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KNOWLEDGE IN ACTION

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DOCTORAL DISSERTATION

Globalization, International Trade and the Risk Position of the Firm - Empirical Evidence from Belgium and the Netherlands

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"Risk comes from not knowing what you're doing."
-Warren Buffet

And when you start a PhD, you do not know what you are doing. At least if I would have known what I would get myself into, I probably would have run for the hills. Few people, maybe even none, believed in the beginning in the probability that I would ever have it in me to finish this PhD journey. Luckily, as John Kenneth Galbraith once stated:

"In Economics, the majority is always wrong."
- John Kenneth Galbraith

Of course in order to prove the majority wrong, I had help. Most of all from Prof. Dr. Mark. Vancauteren, who reminds me of a quote from Edward Deming:

"Without data you're just another person with an opinion."
-Edward Deming

Mark, I would like to thank you for making it possible to give form to my opinion. As my supervisor you gave me a lot of freedom in my work. Without your support, this doctoral dissertation would not have been what it is today. You also encouraged me to develop my own ideas. Your diverse expertise raised my research ideas to a higher level.

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"If you torture the data long enough, it will confess."
-Ronald Coase

Well, Roel, you certainly honored Ronald's statement. Sometimes at night, I can still hear the data cry.

Another quote I would like to share is also from Edward Deming: "If you do not know how to ask the right question, you discover nothing". However, it could easily have been a statement of Prof. Dr. Sigrid Vandemaele, member of my doctoral committee. Sigrid, thank you for learning me the importance of asking the right questions and knowing what to look for. Thank you for being remarkably critical and demanding. You pushed me endlessly to improve my work.
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"Nothing in life that's worth anything is easy."
-Barack Obama

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Another wisdom I would like to share is from Albert Einstein:

"Not everything that can be counted counts, and not everything that counts can be counted."
-Albert Einstein

And something that really counted but is unmeasurable is the support I received from my husband, Steve. Although he is my "bereke" or teddybear, with his patience and understanding, he was always capable to turn bear markets into bull markets. I owe you my deepest gratitude. And of course I may not forget the smallest member of the family, my little dog Billie, who always kept me company and kept my feet warm during the long evenings and nights while I was working. Further, I am very thankful to my grandmother, my mom and Ward for the emotional support and encouragement. I also wrote my thesis in memory of my grandfather, I know he could not have been any prouder of me. Next, I would like to thank my friends, Freya, Michael, Ines, Joost, Thibeault and Vos, who may have wondered if they had to report me as a missing person. I would also like to thank Sarah and Hân, who made the trips to the coffee machine less dull and always let me borrow their coffee key. I am happy to have had you as colleagues and I will miss the happy times we shared in the B58.

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> “Never doubt yourself. Never change who you are. Do not care what people think and just go for it.”
>
> -Britney Spears

Samenvatting (Summary)

Er is een wijdverspreide en groeiende perceptie dat globalisering, hetgeen resulteert in steeds nauwere economische banden tussen landen en continenten, de wereld risicovoller heeft gemaakt. Een bekend voorbeeld is het faillissement van Lehman Brothers, waardoor de wereldwijde financiële markten in de grootste crisis stortten sinds de Grote Depressie. Een ander voorbeeld zijn de buitensporige verplichtingen van Griekenland dat een staatsschuldcrisis veroorzaakte die het voortbestaan van de Europese monetaire unie bedreigde. Bovendien vormt de instabiliteit van valutamarkten in een wereld zonder basisvaluta een permanent risico voor internationaal handelende bedrijven. De economische crises van de afgelopen jaren, van de financiële marktcrisis tot de staatsschuldcrisis, getuigen van de groeiende verwevenheid en kwetsbaarheid van bedrijven in een globaliserende economie. Als gevolg hiervan zijn deze mondiale economische risico's steeds meer in het vizier van de publieke perceptie gekomen. Niettemin lijken mondiale economische mechanismen vaak onvoldoende begrepen en blijft er een gebrek aan empirisch bewijs omtrent globalisering en risico. Bovendien worden de mogelijke risico’s van een globaliserende economie zowel op macro- als microniveau vaak ten onrechte ondenkbaar geacht. Als zodanig blijft risico voor zowel bedrijven als beleidsmakers met betrekking tot hun economische besluitvorming in een globaliserende en soms instabiele wereld, een belangrijk onderzoeksobject.

Daarom tracht dit proefschrift aan de hand van een kruisbestuiving van verscheidene onderzoeksdomeinen, een antwoord te bieden op de vraag of globalisering en de internationale handelsgerelateerde heterogeniteit van bedrijven een invloed heeft op de financiële risicopositie van beursgenoteerde bedrijven. Met andere woorden, dit proefschrift onderzoekt of beursgenoteerde bedrijven, die wereldwijd actief zijn door deel te nemen aan de internationale handel, meer risico's lopen dan bedrijven die minder geglobaliseerd zijn of zich zelfs onthouden van internationale handel. Risico is evenwel een breed begrip waarvan er verscheidene soorten bestaan, zoals operationeel risico, systematisch risico, idiosyncratisch risico, systeemrisico, wisselkoersrisico, enz. Daarom wordt

de focus van dit proefschrift beperkt tot twee specifieke soorten risico's, meer bepaald, systeemrisico en wisselkoersblootstelling. Als zodanig kan het algemene onderzoeksdoel worden beperkt tot de vraag of bedrijven die wereldwijd actief zijn door deel te nemen aan internationale handel, systemisch risicovoller zijn of meer wisselkoersblootstelling ervaren dan bedrijven die minder geglobaliseerd zijn of zich zelfs onthouden van internationale handel. Hiermee vult deze thesis enkele van de bestaande lacunes in de literatuur aan. De algemene onderzoeksvraag zal worden beantwoord aan de hand van drie hoofdstukken.

Hoofdstuk 2 richt zich op de systemische risicobijdragen in de Nederlandse economie van de financiële en niet-financiële sector en de mogelijke systemische rol van globalisering. De resultaten van dit hoofdstuk tonen aan dat systeemrisico's zich niet beperken tot de financiële sector, maar dat ook sectoren uit de reële economie tot dit soort risico bijdragen. Volgens de analyse van de Nederlandse economie behoren de Zakelijke dienstverlening, Vervoer en opslag en Bouwnijverheid tot de sectoren met de grootste risicoafhankelijkheid, vergelijkbaar met het systeemrisico van de Financiële sector. Verder is globalisering, gemeten aan de hand van de handelsintensiteit, of een bedrijf buitenlandse dochterondernemingen heeft, en of het onder buitenlandse controle staat, een belangrijke bepalende factor voor het systeemrisico. Meer specifiek, een hogere handelsintensiteit verlaagt de bijdragen aan het systeemrisico. Handelsintensieve bedrijven kunnen hun bijdrage aan systeemrisico meer neutraliseren dan minder handelsintensieve bedrijven, omdat zij beter in staat zijn om hun activiteiten aan te passen en te optimaliseren als antwoord op vraagschokken. Bovendien blijken bedrijven die internationaal handel drijven productiever en efficiënter te zijn. Deze bedrijven zijn beter bestand tegen schokken en kunnen adequaat reageren, waardoor ze een hogere overlevingskans hebben dan bedrijven die zich primair op binnenlandse markten richten en een lagere handelsintensiteit hebben. Wanneer rekening wordt gehouden met sectorale effecten, blijft deze relatie echter niet langer significant, wat aangeeft dat het effect van handelsintensiteit sectorspecifiek is. Daarnaast, wanneer een bedrijf onder buitenlandse controle staat of buitenlandse dochterondernemingen heeft, stijgt de systemische risicobijdrage. Dit geeft aan dat directe buitenlandse investeringen schokken kunnen kanaliseren en verzenden binnen het internationale organisatorische en operationele netwerk van een bedrijf.

Verder, vanuit een beleidsmatig oogpunt, suggereert dit hoofdstuk dat een uitbreiding van het huidige macroprudentieel regelgevingskader, door het monitoren van systemische risicomaatstaven voor zowel de financiële als niet-financiële sector, noodzakelijk is. In dit hoofdstuk vinden we ook aanwijzingen dat de mate van systemische risicobijdragen wordt gekenmerkt door de conjunctuurcyclus en daarom zeer gevoelig is voor economische omstandigheden. Als zodanig kan een eerste stap in de goede richting worden gezet door bewust te worden van het mogelijke systeemrisico dat bepaalde niet-financiële sectoren dragen. Het is belangrijk om bedrijven en beleidsmakers bewust te maken van het feit dat sectoren die nauwer verbonden zijn met financiële markten, instellingen en hun producten, maar ook sectoren die conjunctuurgevoelige diensten of goederen aanbieden een verhoogd systeemrisico lopen, aangezien de consumptie van hun diensten en goederen als eerste door consumenten wordt uitgesteld tijdens economische recessies. Ten slotte geven onze resultaten aan dat systeemrisico ook een globaal aspect heeft. Als zodanig kan de clustering van buitenlandse directe investeringen in bepaalde geografische gebieden of de concentratie van bepaalde activiteiten tot een klein aantal leveranciers resulteren in het creëren van systeemrisico. De overheid en haar mededingingsbeleid spelen een cruciale rol om ervoor te zorgen dat bepaalde spelers of zelfs locaties niet te belangrijk worden in de toeleveringsketen.

Hoofdstuk 3 onderzoekt wisselkoersblootstelling voor Nederlandse en Belgische beursgenoteerde bedrijven, door cross-sectioneel de associatie tussen de aandeelkoers en de bedrijfsspecifieke, handelsgewogen, effectieve wisselkoersindices op elk punt in de tijd te modelleren voor de periode 2006-2015. De resultaten impliceren dat bedrijven uit gelijkaardige open economieën nog steeds aanzienlijke verschillen kunnen vertonen op het gebied van internationale handel, hetgeen reflecteert in hun wisselkoersblootstelling en als dusdanig eveneens belangrijke beleidsimplicaties kan hebben. Aangezien Nederlandse beursgenoteerde bedrijven uit de steekproef meer handelen buiten de eurozone en een sterkere positieve afhankelijkheid tussen de bedrijfsspecifieke wisselkoersindex en aandelenkoers hebben, zijn deze Nederlandse bedrijven gevoeliger voor het Europese monetair en handelsbeleid dan de Belgische beursgenoteerde bedrijven van de steekproef die zich voornamelijk focussen op de eurozone. Bovendien ondervinden deze Nederlandse bedrijven meer handelstarieven en andere belemmeringen, met als gevolg dat Europese handelsovereenkomsten met landen buiten de unie gunstiger zijn voor deze Nederlandse beursgenoteerde ondernemingen dan voor de Belgische. Deze akkoorden leiden immers tot een verslechtering van de concurrentiepositie van bedrijven die voornamelijk in de eurozone handelen. Vervolgens is de literatuur het eens over het feit dat aandelenrendementen niet normaal verdeeld zijn. In dit onderzoek vinden we bovendien dat extreme gebeurtenissen die fat-tails of staarten veroorzaken en, als zodanig, de niet-normale verdeling van de aandeelkoers, ten minste gedeeltelijk, te wijten zijn aan de internationale handelsactiviteiten van een bedrijf. Omdat de Nederlandse beursgenoteerde bedrijven uit de steekproef meer extreme gebeurtenissen vertonen in hun distributie en deze bedrijven meer buiten de eurozone handelen, is de associatie tussen aandelenrendementen en de bedrijfsspecifieke wisselkoersindex sterker en zijn de staartafhankelijkheden meer uitgesproken dan degene die werden gevonden voor de Belgische beursgenoteerde bedrijven. Als zodanig ervaren de Nederlandse beursgenoteerde handelende bedrijven niet alleen een sterkere verwachte wisselkoersblootstelling dan de Belgische beursgenoteerde handelsfirma's, maar hebben ze ook een meer uitgesproken onverwachte wisselkoersblootstelling. Verder impliceren onze bevindingen dat beursgenoteerde importbedrijven een sterkere wisselkoersblootstelling ervaren dan beursgenoteerde exportbedrijven. Dit resultaat is in overeenstemming met de hypothese van Pritamani et al. (2004) dewelke uitgaat van een dubbel effect van wisselkoerswijzigingen op aandelenkoersen. De hypothese voorspelt dat de wisselkoersblootstelling wordt geaccentueerd voor importeurs en wordt gecompenseerd voor exporteurs vanwege het samenspel tussen de binnenlandse en internationale markt. Tot slot laat dit hoofdstuk zien dat het opportuun is dat beleidsmakers inzicht krijgen in de resultaten van hun monetaire en handelspolitieke acties wanneer zelfs in vergelijkbare open economieën, zoals België en Nederland, beursgenoteerde ondernemingen anders reageren op beleidswijzigingen. Als zodanig kan onze voorgestelde methodologie beleidsmakers helpen de handel in verband te brengen met het monetair beleid en de financiële stabiliteit door een beter begrip van wisselkoersblootstelling op basis van bedrijfsspecifieke handelsgewogen wisselkoersen.

Hoofdstuk 4 onderzoekt de determinanten van wisselkoersblootstelling voor 'enkel-richting' en 'twee-richting' internationale handelaren in Nederland voor de periode 2011-2015. Om de onderliggende dynamieken van wisselkoersblootstelling volledig te begrijpen, is een nieuwe drie stappen-procedure ontwikkeld, die opeenvolgend, vine-copulas, netwerkanalyse en multinomiale logitmodellen toepast. De resultaten geven aan dat bedrijven die zich indekken tijdens een inkrimpende markt, minder wisselkoersblootstelling ervaren. Deze bedrijven hebben een lagere book-to-market-ratio en als zodanig een grotere marktwaarde, grotere hoeveelheden liquiditeit, grotere quick-ratio en/of zijn productiever. Verder wordt het wisselkoersrisico van handelaren die zowel importeren als exporteren ('twee-richting') bepaald door het samenspel van compenserende en accentuerende effecten van export- en importactiviteiten, wat duidt op een meer uitgesproken wisselkoersblootstelling aan de invoerzijde dan aan de exportzijde. De analyse van de multivariate dynamiek van de vine-copula en de multinomial logit modellen bieden empirisch bewijs voor de uitbreiding van de hypothese van Pritamani et al. (2004) voor 'twee-richting' handelaren en bevestigen de bevindingen van Van Cauwenberge et al. (Forthcoming). Meer bepaald, maakt een depreciërende euro/dollar-koers het exporteren naar buitenlandse markten aanvankelijk aantrekkelijker. Het importeren van intermediaire input om het te exporteren goed te fabriceren wordt echter duurder, waardoor het gunstige effect van export wordt gecompenseerd, en exporteren naar de buitenlandse markt terug minder aantrekkelijk wordt. Omdat bedrijven terughoudend zijn om zich uit buitenlandse markten terug te trekken, vanwege de grote reeds niet recupereerbare toetredingskosten, passen ze liever hun intensieve marge aan en optimaliseren ze hun handelsvolumes, in afwachting van een appreciërende euro/dollar-koers. Deze appreciërende wisselkoers maakt de export in eerste instantie minder aantrekkelijk, maar het importeren van intermediaire goederen voor de productie van het product wordt goedkoper. Als zodanig kunnen de negatieve effecten worden gecompenseerd door de lagere productiekosten en te verkopen aan de bloeiende binnenlandse markt. Vervolgens zorgt een verhoogde afhankelijkheid van de buitenlandse markt voor een toename aan wisselkoersblootstelling van de import activiteiten tijdens een inkrimpende markt, maar tijdens expansie kan de onderneming echter profiteren van wisselkoersblootstelling. Het vergroten van de aanwezigheid op exportmarkten zou het risico op wisselkoersblootstelling kunnen compenseren tijdens inkrimpende markten, maar zorgt er ook voor dat bedrijven minder profiteren van wisselkoersrisico tijdens expansie. Daarnaast zal de diversificatie van een groter importaandeel onder meer handelspartners niet leiden tot meer wisselkoersrisico's, omdat in dit geval de buitenlandse afhankelijkheid niet noodzakelijk toeneemt. De mate van buitenlandse afhankelijkheid hangt wel af van de risico-aversie van het bedrijf. Verder hangt de keuze van een 'twee-richting' internationale handelaar om zich in te dekken tegen wisselkoersrisico af van de mate waarin hij eerder import of export gericht is. Indien, bijvoorbeeld bij een depreciërende euro/dollar-koers, de kosten van de blootstelling tot het risico op de binnenlandse markt en invoerzijde groter zijn dan de opbrengsten aan de uitvoerzijde, kan een internationale handelaar, die zowel invoert als uitvoert ('twee-richting'), overwegen om zich in te dekken tegen het risico. 'Enkel-richting' internationale handelaren ondervinden deze keuzeproblemen niet, vermits zij enkel importeren of exporten hoeven zij geen afweging te maken tussen de kosten en opbrengsten van de import en exporteffecten. Ten slotte laat de toepassing van onze methodologie met betrekking tot wisselkoersblootstelling zien dat heterogeen gedrag van bedrijven sterk aanwezig is. Als zodanig kunnen beleidsmakers, in plaats van zich te richten op sectorspecifiek beleid, de voorgestelde methodologie gebruiken om beleidsmaatregelen, zoals belastingen en subsidies, efficiënt af stemmen op relevante bedrijfskarakteristieken door het netwerk van bedrijven bloot te leggen en een gedetailleerde categorisering en profilering van bedrijven te hanteren.

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Chapter 1

General Introduction

Uncertainty is considered to be synonymous with risk. In the early 1920's, however, Knight (1921) introduced an important distinction between these two concepts. Risk is defined as the variability that can be quantified in terms of probabilities, while uncertainty (of the Knightian type) concerns the absence of information about the probability distribution of financial returns (Knight, 1921); the latter is also a driving force behind financial instability. Although very much alike, according to Knight (1921), there is a subtle difference between uncertainty and risk. Only a non-measurable probability can be defined as a 'true uncertainty', every other probability is called a 'risk'.

There is a widespread and growing perception that globalization resulting in increasingly close economic ties between firms, countries and continents, has made the world a 'riskier' place. A well know example is the bankruptcy of Lehman Brothers, which resulted in global financial markets plunging into the most serious turmoil since the Great Depression. Another example are the excessive liabilities of the small Eurozone member, Greece, which triggered a sovereign debt crisis that threatened the very existence of the European monetary union. Moreover, in a world lacking a basic reference currency, the instability of currency markets poses a continuous risk for international traders. The economic crises of recent years, from the financial market crisis to the sovereign debt crisis, testify to the growing interconnectedness and vulnerability of firms within a globalizing economy. As a result, these global economic risks have moved increasingly into the focus of public perception. However, global economic mechanisms often appear to be imperfectly understood by mainstream economic thinking and decision-making. Furthermore, the risks at the macro- and micro-level of a globalizing economy are often wrongfully thought to be perpetually incalculable. Nevertheless, there remains a lack of empirical evidence regarding globalization and risk. As such, the risk for both firms and policymakers regarding their economic decision-making in a globalizing world, which is nowadays increasingly exposed to high levels of instability, remains an important research object.

1.1. Objective of the dissertation

This dissertation brings different strands of research together: the economics of international trade and risk measurement. The overall research question of this dissertation can be formulated as:

“Does globalization and international trade-related firm heterogeneity influence the financial risk position of listed firms?”

In other words, this dissertation investigates whether listed firms, which are globally active by engaging in international trade, are riskier than firms which are less globalized or even refrain from international trade. However, as the general introduction already stated risk is a broad concept. Moreover, many types of risk exist, such as operational risk, systematic risk, idiosyncratic risk, systemic risk, exchange rate risk, etc. Therefore, the focus of this dissertation is narrowed to two specific types of risk, more specifically, systemic risk and the risk involved with exchange rate exposure. As such, the general research purpose can be narrowed to the question whether firms which are globally active by engaging in international trade, are systemically riskier or experience more exchange rate exposure than firms which are less globalized or even refrain from international trade. Hereby, this thesis fills some of the existing research gaps in the literature. The general research purpose will be addressed by focusing on more specific research questions which will be answered relying on a variety of theoretical and methodological approaches.

Overall this dissertation addresses the broad and difficult domain of risk measurement, relying on different methodologies. This dissertation is a bundling of three parts, consisting of three different studies. Through this varied way of addressing the research questions, this dissertation will provide insight in systemic risk and exchange rate exposure differences between firms, taking into account their level of international trade, which will be of great interest for researchers, policy makers and market participants.

1.2. Focus of the dissertation

This doctoral dissertation consists out of two parts. More specifically, this thesis focusses on two specific types of risk any firm which is internationally active on some point in time has to deal with. As such, the first part of this doctoral dissertation will deal with systemic risk (Chapter 2), while the second part of the thesis explores the risk involved with exchange rate exposure (Chapter 3 and 4). Before going any further, we first explore the two risk types of interest in the literature.

1.2.1. Systemic risk

Systemic risk, in the very general sense, is a widely spread phenomenon. Examples can be found in many areas, e.g., in the area of health and epidemic diseases; however, this type of risk also occurs in the field of economics. In economics, systemic risk is often perceived as a special feature of the financial system, particularly the banking system (De Bandt & Hartmann, 2002; Hartmann et al., 2014). Although there is no unanimous definition for systemic risk, and it is often primarily associated with the financial sector, recently many definitions have linked its effects to the real economy. The Group of Ten (2001) emphasized the undesirable real effects in its definition of systemic risk. More specifically, in the absence of an appropriate policy, a systemic financial event must induce substantial reductions in output and employment. In this definition, a systemic event is a financial disruption with an extremely high probability of causing significant disruptions to real economic activity. The Group of Ten (2001) stated that financial firms and markets can be hit by shocks that originate from financial markets, the financial industry, or from within the real economy. Additionally, De Bandt and Hartmann (2002) stated that the contamination effects, which are an important property of systemic risk, can take place in any sector of the economy. Finally, the OECD (2012) stressed that, although a crisis may occur in one sector, its dynamics unfold on different scales within the economy. As such, a financial crisis may provoke an economic recession. However, since this results in less demand for credit, fewer realizations of ideas, less venture capital, etc., there are also feedback loops from a contracting real economy to the financial industry.

Despite the fact that systemic risk is a difficult concept to grasp and, as such, there is no unanimous definition, this dissertation chooses to follow the definition of Adrian and Brunnermeier (2016), who define systemic risk as the risk that the capacity of the entire system is impaired, with potentially adverse consequences for the real economy. The capacity of risk to affect other companies or economic sectors, not directly involved in risky behavior, makes the risk systemic.

1.2.2. Exchange rate exposure

Exchange rate exposure refers to the risk that the value of a firm, that is exposed to a particular currency, is affected by the exchange rate movements between that currency and the firm's domestic currency. Hekman (1983) refers to the sensitivity of a firm's economic value, or stock price, to react to [unanticipated] changes in exchange rates as exchange rate exposure. There are many ways to describe theoretically and analytically how firms are exposed to these currency fluctuations. Stulz and Williamson (1996) distinguished four kinds of exchange rate exposure, more specifically transaction, contractual, translation and competitive exposure. Transaction exposure refers to the exposure and the associated uncertainty firms face regarding already booked activities in foreign currencies. The existence of implicit or explicit agreements or commitments, e.g., price agreements, which are not associated with booked transactions, is called contractual exposure. Further, translation exposure refers to a firm's domestic and foreign assets and liabilities whose values are also affected by currency fluctuations. These aforementioned forms of exposure can be alleviated by well-structured hedging strategies. However, *competitive or economic exposure* is more difficult to hedge correctly and depends on the market in which the firm operates (Di Iorio & Faff, 2000; Marston, 2001; Stulz & Williamson, 1996). It is the latter form of exposure which is of specific interest. In this case, exposure occurs because a firms' competitive position is changed as a consequence of exchange rate variations affecting the relative prices of the goods sold in different countries (Stulz & Williamson, 1996). The traditional approach of using only accounting information to describe the effects of exchange rate changes only is limited to transaction exposure. Moreover, accounting information can be sufficiently distorted to render it almost useless to an investor or corporate manager (Shapiro, 1975).

1.3. Outline of the dissertation

What follows, briefly elaborates on three empirical studies, Chapter 2 to 4, included in this dissertation. In particular, the central research question of each study is introduced and the theoretical rationales behind them are discussed. An extended theoretical discussion and more information about the methodology and empirical results is provided in the respective Chapters. This dissertation also puts forward three standalone papers. There may be some content overlap between the different Chapters, especially in the data description Sections.

1.3.1. Chapter 2

The capacity of risk to affect other firms or economic sectors not directly involved in risky behavior makes risk systemic. (Adrian & Brunnermeier, 2016; Kerste et al., 2015). As such, systemic risk may occur in any sector of the economy and is therefore not exclusively related to the financial sector. Nonfinancial sectors are often not as regulated as the financial sector and, therefore, may also carry systemic risk without being aware of it. Nevertheless, the literature on systemic risk that includes these nonfinancial sectors remains sparse (Bijlsma & Muns, 2011; Harmon et al., 2010; Trapp & Wewel, 2013). Furthermore, most studies focus on the financial sector, financial globalization, and therefore solely investigate classic financial determinants of systemic risk (Acharya et al., 2017; Adrian & Brunnermeier, 2016; Borri et al., 2012; Faia et al., 2018; Girardi & Ergün, 2013). Nonfinancial firms have also become increasingly globally active, through international trade and foreign direct investments, which has resulted in an even more fragile system. However, the role of globalization in systemic risk contributions of the nonfinancial sectors has, to our knowledge, never been thoroughly investigated before and could be an important channel of systemic risk. Furthermore, much of the current research in respect to globalization is limited to international trade (e.g., Baldwin & Taglioni, 2009; Bems et al., 2010, 2011, 2013) and, as such, does not focus on the relationship between the real economy, systemic risk and globalization through international trade and foreign direct investments. Therefore, the main research question in **Chapter 2** is:

"Do global or international activities of financial and non-financial firms influence their systemic risk contributions?"

1.3.2. Chapter 3

Changes in monetary policy[1] may profoundly impact the domestic economy, creating spillover effects to other economies linked through international trade. The modified monetary policy may result in changes in exchange rates which affect the competitive positions of firms, having important implications for financial decision-making and for the profitability and ultimately the value of firms. (Chakraborty et al., 2015). Nevertheless, whether exchange rate changes have measurable effects on firms, is still hard to prove. Empirical research on this issue has produced no convincing unambiguous evidence of exchange rate exposure (e.g., Bini-Smaghi, 1991; Chou et al., 2017; Du et al., 2013; Jorion, 1990, 1991; Muller & Verschoor, 2006a, 2006b; Walid et al., 2011; Zhao, 2010). In Chapter 3 we investigate the estimation of exchange rate exposure and, as such, contribute to the academic debate regarding the exchange rate exposure puzzle. We identify three main methodologically shortcomings in the literature which may explain the inconclusive and inconsistent results. First, research findings depend on the level of aggregation bias, whether country, industry or firm-level (Greenaway & Kneller, 2007). The use of disaggregated firm-level data can avoid the problem of aggregation bias in investigating exchange rate exposure. Second, the choice of an exchange rate index used in modelling the relationship with the value of the firm, influences the observed level of exposure (Dominguez & Tesar, 2006a; Fraser & Pantzalis, 2004). Firms often operate in distinct international locations,

[1] The monetary policy of the European Central Bank tries to maintain price stability within the Eurozone in order to foster economic growth and job creation. The monetary policy affects the economy in general and the price level in particular by, for instance, adjusting official interest rates. The change in the official interest rates affects money-markets interest rates and, indirectly, lending and deposit rates, which are set by banks to their customers. The impact on financing conditions in the economy and on market expectations triggered by monetary policy actions may lead to adjustments in asset prices and the exchange rate. Changes in the exchange rate can affect inflation directly, insofar as imported goods are directly used in consumption, but they may also work through other channels (European Central Bank, 2019b).

as such, taking this into account when choosing an exchange rate index might result in the foreign exchange rate exposure parameter being nonsignificant (Fraser & Pantzalis, 2004). Third, financial time series have important distributional stylized facts, which have major implications on the modelling of their relationship. More specifically, the distributions of stock returns and exchange rates diverge from normality (e.g., Bollerslev et al., 2013; Boothe & Glassman, 1987; Fama, 1965; Huisman et al., 2002; Mandelbrot, 1963). These methodological shortcomings partially explain why the empirical evidence of exchange rate exposure is mixed (e.g., Bergbrant et al., 2014; Bodnar & Gentry, 1993; Dominguez & Tesar, 2006b; Miller & Reuer, 1998; Mohapatra & Rath, 2017; Pantzalis et al., 2001). Therefore, **Chapter 3** addresses these methodological shortcomings in estimating exchange rate exposure and aims at answering the following research question:

"Do we find empirical evidence for the existence of exchange rate exposure when we take firm-level international trade and the stylized facts of financial time series into account in the estimation process?"

1.3.3. Chapter 4

In contrast to the enormous interest on solving the exchange rate exposure puzzle, which focusses on the estimation of exchange rate exposure, the mixed findings on the determinants of exchange rate exposure has received little attention. The most often investigated determinants in the literature are foreign sales, firm size, quick ratio, debt ratio and the book-to-market ratio (e.g., Bartram, 2004; Bodnar & Wong, 2003; Chow et al., 1997; Dominguez & Tesar, 2006a; Doukas et al., 2003; Faff & Marshall, 2005; Lin & Lee, 2017; Pantzalis et al., 2001). However, previous research fails to provide a consensus on the sign of the effect of these determinants on exchange rate exposure. There are three main reasons why empirical research provides inconsistent results. First, former research often uses aggregated data resulting in aggregation bias. We already pointed out the aggregation bias as a limitation of most of the studies on exchange rate exposure (Greenaway & Kneller, 2007). Second, classic ordinary least square (OLS) regression techniques, which are used in most studies, fall short in capturing the complex relationship between exchange rate exposure and its determinants, ignoring the heterogeneity of firm characteristics at different levels of exchange rate exposure (Lin & Lee, 2017). Third, most studies do not include international trade nor trade related variables when they investigate the determinants of exchange rate exposure. More specifically, since firms need to compensate for the sunk entry costs of international trade, the latter is related to higher productivity. International trade will induce only the more productive firms to enter the market. As such, beside international trade playing an important role in determining exchange rate exposure, firm-level variables related to trade behavior, such as productivity, are also interesting to investigate as potential determinants of exchange rate exposure (e.g., Bernard et al., 2007; Doukas et al., 2003; Greenaway & Kneller, 2007; Melitz, 2003; Wagner, 2007, 2012)

As such, the objective of Chapter 4 is to gain a better understanding of the determinants of exchange rate exposure for one-way and two-way traders by filling the aforementioned gaps in the literature. Further, this Chapter elaborates on Chapter 3 by changing the analysis perspective and purpose on investigating exchange rate exposure. Therefore, the main research question in **Chapter 4** is:

"When taking into account international trade in the estimation of exchange rate exposure, which determinants clarify exchange rate exposure of a firm?"

1.3.4. Chapter 5

Finally, **Chapter 5** summarizes the most important empirical findings per Chapter and discusses the most relevant theoretical and methodological implications of this dissertation. To conclude, suggestions for further research are provided.

Chapter 2

International Trade, Foreign Direct Investments and Firms’ Systemic Risk Contributions: Evidence from the Netherlands

Abstract[2]

In this chapter we measure the contribution of financial and non-financial firms to systemic risk. We quantify systemic risk as possible risk spillovers of individual firms that are carried over to an economy by taking time-varying linkages between the economy and a firm into account. Using a novel dataset that combines data on international trade and foreign direct investments with daily stock data for 67 Dutch listed companies over the period 2006-2015, our results indicate that high systemic risk contributions are not only present in the financial sector but also occur in other sectors of the economy. We also find that firms within the financial sector are better capable to revert to their pre-financial crisis level of systemic risk contribution, compared to non-financial firms. Next, we verify the potential role globalization fulfills in determining systemic risk. We find two main opposing effects: first, international trade-intensive firms contribute less to systemic risk and second, systemic risk rises when firms are engaged in foreign direct investment activities, suggesting that systemic risk is more likely to be affected through international networks and global supply chains. These empirical results imply that macro-prudential policy should be extended to non-financial sectors to address financial stability concerns, but also highlight the importance of globalization when monitoring systemic risk.

Keywords: Systemic risk, Delta Conditional Value-at-Risk, Globalization, International trade, Foreign direct investments

JEL: C32, C33, F65, G01

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[2] This Chapter is based on the paper “International Trade, Foreign Direct Investments and Firms’ Systemic Risk Contributions: Evidence from the Netherlands” co-authored with Prof. Dr. Mark Vancauteren, Prof. Dr. Roel Braekers and Prof. Dr. Sigrid Vandemaele which is currently under final review in Economic Modelling. We would like to thank Statistics Netherlands for providing the Dutch trade data. We would like to thank Prof. Dr. Sushanta Mallick and three anonymous referees for their suggestions and thoughtful comments. We would also like to thank all the participants of the 5th International Symposium in Computational Economics and Finance (ISCEF) 2018 in Paris for fruitful discussions.

2.1. Introduction

It is a well-known fact that since the late 19th century, the process of globalization increased the interdependence of nations and societies all over the world. This process accelerated rapidly during the 1990s, both in the financial and the real economy, building up towards the global crisis of 2008-2009 (Baldwin & Taglioni, 2009; Bruno & Shin, 2015; Goldin & Mariathasan, 2014; Lane, 2013; Moshirian, 2015). Since the rise of trade liberalization in the 1990s there is an explosive increase of globalization noticeable, through more international trade, delocalization and the quest for new markets. In the financial economy, the rapid rise of financial globalization connected markets and financial institutions more closely and ultimately resulted in an explosion of cross-border financial flows, foreign direct investments and global imbalances or unusually large current account surpluses and deficits. The capital mobility allowed for savings to be channeled to countries with more productive investment opportunities and for better sharing of macroeconomic risk. However, this financial globalization fueled the asymmetries in credit growth and the propagation of systemic risk. Eventually, the financial crisis of 2008-2009 put a halt to this global financial integration and the steadily increasing global capital flows to and from advanced economies (e.g., Bruno & Shin, 2015; Cetorelli & Goldberg, 2012; Claessens & Van Horen, 2016; Lane, 2013; Mendoza et al., 2009; Milesi-Ferretti et al., 2011; Moshirian, 2015). Considering the real economy, the global crisis of 2008-2009 caused an unprecedented collapse in world trade. There seems to be a consensus that this collapse was demand-driven and the result of growing panic and risk aversion during the fall of 2008. Consumers, firms and investors started simultaneously to postpone consumption in durable goods and investments. This worldwide demand shock led to sharp sales drops and, as such, diminishing international trade. Further reinforced by tumbling commodity prices and a collapse of the production and exports of manufacturing, these demand shocks infected rapidly global nonfinancial firms and their network through their foreign direct investments (Baldwin & Taglioni, 2009; Bems et al., 2013; Bussire et al., 2013; Eaton et al., 2016; Nagengast & Stehrer, 2016).

Although both risk propagating globalization scenarios in the financial and nonfinancial sectors show similarities, only financial globalization and systemic risk have been thoroughly investigated. There is a consensus that the financial sector carries systemic risk, which has been able to spread within the financial sector because of financial globalization (e.g., Acharya et al., 2009; Rossi & Malavasi, 2016; Statistics Netherlands, 2018). However, globalization in the real economy or the non-financial sectors and its relationship with systemic risk has to our knowledge hardly received any attention. Moreover, systemic risk still remains a difficult concept to grasp and, as such, there is no unanimous definition. Therefore, in this research, we follow Adrian and Brunnermeier (2016), who define systemic risk as the risk that the capacity of the entire system is impaired, with potentially adverse consequences for the real economy. The capacity of risk to affect other firms or economic sectors not directly involved in risky behavior makes the risk systemic. In this sense, it can be seen as an externality or a type of market failure that needs to be addressed by regulators and governments (Adrian & Brunnermeier, 2016; Kerste et al., 2015). Systemic risk may occur in any sector of the economy and is therefore not exclusively related to the financial sector. Additionally, certain firms are more closely than other firms related with financial markets, institutions and their products. Examples are the energy, construction, industry and food sectors. Consequently, they may carry an increased degree of systemic risk compared to firms in other nonfinancial sectors (e.g., Bijlsma & Muns, 2011; Dungey et al., 2017; Kerste et al., 2015). Those sectors are often not as regulated as the financial sector and, as such, there is much less general awareness about the systemic risk they carry. Nevertheless, the literature on systemic risk that includes the nonfinancial sector remains sparse (e.g., Dungey et al., 2017; Trapp & Wewel, 2013).

Furthermore, solely quantifying and monitoring systemic risk may not be sufficient to understand systemic risk contributions. The determinants of systemic risk give insight into the sources at play and are an additional important research topic (Basel Committee on Banking Supervision, 2016; Goldin & Mariathasan, 2014; Kerste et al., 2015). Studies focusing on the financial sector and financial globalization have investigated determinants like a firm’s idiosyncratic risk, measured as the Value-at-Risk (VaR), and also leverage and size (Acharya et al., 2017; Adrian & Brunnermeier, 2016; Girardi & Ergün, 2013; Karimalis & Nomikos, 2018). Few studies, have tested foreign expansion, i.e., the number of yearly foreign unit openings, as a potential determinant of a bank's riskiness (e.g., Faia et al., 2018). Next to financial firms, nonfinancial firms have become increasingly globally active, through international trade and foreign direct investments, which has resulted in an even more fragile system. However, the role of globalization in systemic risk contributions of the nonfinancial sectors has to our knowledge never been thoroughly investigated and could be an important channel of systemic risk. Furthermore, much of the current research in respect to globalization is limited to international trade (e.g., Baldwin & Taglioni, 2009; Bems et al., 2013) and, as such, does not focus on its relationship with the real economy and systemic risk.

Accordingly, the present paper aims to ascertain whether nonfinancial firms contribute to systemic risk in a similar way as financial firms and, additionally, to verify the potential role globalization fulfills in determining this systemic risk. Although, there has been important research recently motivated by the growing importance of systemic risk and its determinants, empirical analyses mainly focus on the financial sector, financial globalization and classic financial related determinants. Hardly any attention is paid to the impact of globalization, through international trade and foreign direct investments, on systemic risk in the nonfinancial sectors. The contribution of this paper is to fill this gap in the literature. We proceed as follows: first, by using daily data from 2006 to 2015, we discuss systemic risk contributions from nonfinancial and financial firms over time with the financial crisis of 2008-2009 as a structural breakpoint. Daily systemic risk contributions are computed following the, slightly modified, ΔCoVaR procedure of Girardi and Ergün (2013). We use the ΔCoVaR, defined by Girardi and Ergün (2013), as a parsimonious measure of systemic risk allowing to go further into the tail. By conditioning on a more general case of financial distress, more specifically a firm being at most at its VaR, the definition allows an examination of more severe losses and extreme distress events further in the tail, as opposed to its original definition of Adrian and Brunnermeier (2016). Moreover, the ΔCoVaR makes it possible to combine the macroprudential risk perspective – the systemic risk contributions of individual firms – and complement it with microprudential insights– the idiosyncratic risk of individual firms. The objective of this illustration is to get a proper understanding of systemic risk within the Dutch economy by assessing its course over time and verifying whether nonfinancial sectors play a significant role in this systemic risk. For this research, we choose to analyze the Dutch economy because of its open structure, its large concentrated commercial banking sector and the presence of world's leading multinationals headquarters.[3] Next, in the second part of the paper, we use panel data analysis to verify whether globalization is a determinant of systemic risk. Globalization is measured by three variables, namely, by a firm's trade intensity, the existence of foreign subsidiaries and the presence of foreign control. As such, both international trade activities as well as the international organizational network through foreign direct investments are taken into account. In order to get a proper understanding of the relationship between globalization and systemic risk, we first regress quarterly-aggregated systemic risk contributions to its most common determinants, such as, VaR, size, leverage and beta. Finally, globalization, using the three above-mentioned measures, is added to the panel data analysis to verify whether it is a significant determinant of systemic risk.

Our results imply that the Dutch economy remains systemically riskier after the financial crisis of 2008-2009 compared to the precrisis period; however, this level of risk is also due to the double dip recession of 2011-2012. As such, systemic risk contributions are countercyclical and likely to be affected by the business cycle. Next, we find that systemic risk of firms is sector-specific. High systemic risk contributions are not only present in the financial sector but also occur in other sectors of the real economy. We find that firms within the financial sector are better capable to revert to their pre-financial crisis level of systemic risk contribution, compared to nonfinancial firms. From a policy perspective, this outcome indicates that regulating only the financial sector is insufficient in order to limit systemic risk in the economy. Finally, with respect to the link between

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[3] In the Netherlands, 80% of the total assets are controlled by the largest banks (Bezemer & Muysken, 2015). The worldwide financial crisis of 2008-2009 had a detrimental impact on international trade and economic growth. The Dutch economy contracted, starting from the second quarter of 2008 (See Appendices A2 and A3). The financial crisis of 2008-2009 also had quite an impact on the Dutch international trade; both imports and exports fell sharply (Statistics Netherlands, 2010). Although the Dutch trade recovered more quickly than that of other European countries, it took until the beginning of 2011 to revert to precrisis levels. By the end of 2011, trade growth slowed down again and the Dutch economy went through another recession (Statistics Netherlands, 2014). This was a double-dip recession: from October 2011 until March 2012 and from July 2012 until December 2012 the Dutch GDP shows consecutive negative growth rates. See Table A2 and Figure A3 from respectively Appendix A2 and A3.

globalization and systemic risk contributions, we find evidence suggesting that globalization plays a dual role. More specifically, trade intensive firms are more resilient to systemic risk. However, when taking sectoral effects into account, this relationship becomes insignificant, indicating that the effect of trade intensity is sector specific. Next, when a firm is under foreign control or has foreign subsidiaries, its systemic risk contribution rises, illustrating the overall importance of a firm's international organizational and operational network through foreign direct investments. These results indicate that a firm's systemic risk contribution in nonfinancial sectors is at least partly determined by sector specific demand and supply shocks affecting international trade and is channeled through its foreign direct investments. Finally, these findings imply that current macro-prudential policy should be extended to non-financial sectors and addressing globalization, through trade intensity and the presence of foreign direct investments, when monitoring systemic risk.

The study is organized as follows: Section 2.2 gives a brief introduction on the relationship between globalization and systemic risk, while Section 2.3 describes the data. The empirical framework is explained in Section 2.4. Next, Section 2.5 presents the empirical analysis and results. Finally, the discussion and concluding remarks follow in Section 2.6.

2.2. Globalization and systemic risk

Theoretical and empirical evidence on the relationship between systemic risk contributions and globalization in the nonfinancial sectors is sparse. Nevertheless, the extensive literature on the great trade collapse during the global crisis of 2008-2009 (e.g., Baldwin & Taglioni, 2009; Bems et al., 2013; Bussire et al., 2013; Constantinescu et al., 2018; Eaton et al., 2016; Goldin & Mariathasan, 2014; Nagengast & Stehrer, 2016; Watson, 2019), as well as the research on financial globalization (e.g., Bruno & Shin, 2015; Cetorelli & Goldberg, 2012; Claessens & Van Horen, 2016; Lane, 2013; Mendoza et al., 2009; Milesi-Ferretti et al., 2011; Moshirian, 2015) can provide valuable insights and help to understand the relationship between globalization and systemic risk.

Since systemic risk is countercyclical (Acharya et al., 2009; Adrian & Brunnermeier, 2016; Bisias et al., 2012) and international trade is procyclical (Baldwin & Taglioni, 2009; Constantinescu et al., 2018; Engel & Wang, 2011), a negative relationship between both subjects of interest is to be expected. The countercyclicality of systemic risk – also referred to as the so called "volatility paradox" (Brunnermeier & Sannikov, 2014) - results from firms increasing risk taking behavior during economic expansion, making them extremely vulnerable to adverse shocks. (Adrian & Brunnermeier, 2016). That is, when the economic environment is stable, this may raise further investments which in turn may require credit growth, and risk taking behavior. By underestimating the associated risks, there is a higher probability that firms may end-up investing in lower quality projects or in failed projects. Eventually, an increase of these failed risky investments and the subsequent losses give rise to high volatility, and in a more extreme case, to a financial crisis. For instance, in a banking context, Adrian and Boyarchenko (2013) parametrize an equilibrium model showing that volatility is inversely proportional to leverage through more risky debt issuance. As such, systemic risk is able to build up during good times and is peaking and realized during bad times, resulting in a countercyclical pattern. Next, the argument of international trade being procyclical[4] draws upon demand and supply side effects on international trade. There is a consensus that during recessions trade collapses can mainly be attributed to changes in final expenditure, leading to a fall in sales (Baldwin & Taglioni, 2009; Bems et al., 2013; Bussire et al., 2013; Eaton et al., 2016; Nagengast & Stehrer, 2016). More specifically, out of risk aversion, consumers and firms postpone consumption of durable goods, investments and contingent services,[5] leading to a declining demand. In response to the decreasing consumption, firms adjust their operations and supply downwards (Baldwin, 1988; Chaney, 2008; Engel & Wang, 2011). As a consequence, a firm's future growth prospects will be adjusted downwards, impacting its market value.

[4] Baldwin and Taglioni (2009); Engel and Wang (2011) prove empirically that international trade is highly sensitive for the business cycle. International trade booms during economic good times and falls in crises. Furthermore, Engel and Wang (2011) show that international trade is three times as volatile as GDP and highly sensitive for adverse shocks.

[5] Durable goods are goods, such as, automobiles, electronics, medical equipment, machines, etc. These goods do not wear out quickly and cannot be consumed in one use. During recessions the purchase of these goods is the first to be postponed. The same applies for contingent services which entails non-permanent services and labor supplied by freelancers, temporary contract workers, consultants, etc. These services, often offered by professional or human resources consulting firms, are the first to be cut by firms during recessions (Baldwin & Taglioni, 2009; Engel & Wang, 2011).

Further, firms are reluctant to exit foreign markets and alter the extensive margin of trade,[6] due to the large and sunk market-entry costs, they instead adapt and optimize their operations, waiting for economic upturns (Baldwin, 1988; Chaney, 2008; Engel & Wang, 2011; Goldin & Mariathasan, 2014). Accordingly, a positive relationship between foreign direct investments, through foreign control and foreign subsidiaries, and systemic risk may be prevalent. In essence, firms are unwilling to withdraw foreign direct investments or adapt their extensive margin of trade due to the large sunk costs. As such, firms with foreign subsidiaries or firms under foreign control will remain in their current condition, and rather scale back their operations during economic downturns (Baldwin, 1988; Fontagné & Gaulier, 2009; Schott, 2009). While trade volume is a (repetitive) short term strategic choice in a competitive environment, resulting in variable costs; foreign direct investments are medium to long term strategic choices of a firm, resulting in fixed costs.[7] Foreign direct investments overlap with global value chains, intrinsically creating a network between various countries involved. As such, the choice of, for instance, opening a subsidiary in a foreign market is the result of long-term strategies and maintenance (De Masi & Ricchiuti, 2018). Furthermore, Bems et al. (2013) and Levchenko et al. (2009) indicate that highly integrated

[6] Extensive margin of trade refers to a firm's decision whether or not to enter the market to trade.

[7] A large portion of the existing literature implies FDI and trade to be substitutes, demonstrated by a significant negative correlation, while others come up with opposite results (complements). The relationships between investment and trade are typically viewed from the perspective of the investing or home country (i.e., firms having foreign subsidiaries in our case), the recipient or host country and third-party countries which may be affected by this relationship. According to the substitution theory, firms have two options that would allow them to penetrate a foreign market, export their goods or invest in a foreign affiliate and produce the goods abroad. From the perspective of the investor country, FDI can be seen as substituting for trade as exports are replaced by local sales on foreign markets, particularly in the form of finished goods. This could be detrimental to the investing country's domestic industry, hurting production and employment. The theory of complementation states that there are two main mechanisms through which FDI affects trade positively. FDI and trade can be seen as complementary since investing abroad leads to greater competitiveness in foreign markets, and trade in intermediate goods (inputs) and complementary final products to the affiliate. This type of relationship would be beneficial to exports from the investing country and thus to its industry. For host countries, the relationship between FDI (i.e., firms under foreign control in our case) and trade can be seen to be symmetrical to that of the investing country (Fontagné, 1999; Kawai & Urata, 1998). Empirical evidence on this issue presents mixed results showing the presence of both substituting and complementary effects, highlighting the complexity of this relationship, in which not necessarily a substitution or complementary effect is predominant (e.g., Kawai & Urata, 1998; Swenson, 2004; Y. Wang, 2007). When we look at the correlation matrix of Appendix A10, we see that the FDI variables, being Foreign subsidiaries and Foreign control, are barely correlated with Trade intensity, indicating no collinearity. Neither theories seem to be dominant, the association between Foreign subsidiaries and Trade Intensity gives a slight, but nonsignificant indication of a complementary relationship, while Foreign control has a significant, but neglectable (given the magnitude), substitutional association with Trade intensity.

and tightly synchronized production networks, played a crucial role in rapidly transmitting demand and supply shocks between markets and affecting global firms. Goldin and Mariathasan (2014) acknowledge this, by indicating that supply chain dependent firms are more vulnerable to systemic risk. Moreover, demand shocks reduce the demand for all related intermediate durable inputs, e.g., steel, chemicals, components, affecting the exports of subsidiaries and other supplier firms. In the case of a firm being under foreign control, the firm itself is considered as a subsidiary. As such, foreign direct investments, may not cause risk directly, rather they channel and spread risk through the entire global organization and operations. If foreign direct investments are an important determinant of systemic risk,[8] firms that are part of an international organizational and operational network should exhibit higher levels of systemic risk contributions compared to firms that are not part of a global organization.

2.3. Data

In this chapter we consider stock data of 67 publicly listed Dutch companies and the MSCI Netherlands, which is used as a proxy for the Dutch economy or the system. This index is designed to measure the performance of the entire Dutch market. With 24 constituents,[9] the index covers approximately 85% of the free float-adjusted market capitalization in each industry group in the Netherlands (Morgan Stanley Capital International, 2016). The sample contains daily data from 1/2/2006 to 12/31/2015. There are 2609 observations for each firm. The data are retrieved from DataStream (Thomson Reuters Eikon).[10] Table 2.1 reports the summary statistics of the returns of the firms classified by sector according to the SBI-code[11] and the system or MSCI Netherlands.

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[8] Faia et al. (2018) find that the foreign expansion of banks, through the yearly number of foreign unit openings, has a risk mitigating effect. However, they indicate, following Berger and Udell (2006); Boot and Greenbaum (1993); Vives (2016), that this might not hold for banks mainly operating from countries with highly competitive and concentrated banking systems, such as, the Netherlands.

[9] See also Appendix A1. Adrian and Brunnermeier (2016) construct the overall financial system portfolio (for j = *system*) by computing the average market equity-valued returns of all financial institutions, weighted by the (lagged) market value of their equity. Girardi and Ergün (2013) choose the Dow Jones US Financials Index as a proxy for the financial market. Therefore, in line with these former studies, in this paper we opt for the MSCI Netherlands as proxy for the Dutch system since it covers 85% of the free float-adjusted market capitalization in each industry group in the Netherlands suited to represent data from our sample.

[10] See Appendix A4 for a detailed overview of the company names and their classifications, the variables and their data sources.

[11] Standaard Bedrijfsindeling used by Statistics Netherlands, identical to the NACE-code (rev.2).

Table 2.1 Descriptive statistics for the daily logarithmic returns (EUR) of the firms by sector and the system: entire sample period.

	Mean	St.dev.	Kurtosis	Skewness
1) Administrative & support service activities	-0.00001	0.0260	9.602	-0.116
2) Construction	-0.00097	0.0359	165.944	-2.170
3) Financial & insurance activities	-0.00007	0.0250	16.436	0.129
4) Information & communication	-0.00016	0.0241	18.614	0.036
5) Manufacturing	0.00091	0.0218	96.668	-87.006
6) Professional, scientific & technical activities	-0.00015	0.0265	21.377	-0.027
7)Transportation & storage	0.00001	0.0226	33.655	-0.472
8) Wholesale & retail trade; repair of motor vehicles & motorcycles	-0.00066	0.0292	47.238	-1.301
9) MSCI Netherlands (system)	0.00012	0.0134	9.466	-0.148
Overall	0.00003	0.0256	57.243	-25.021

A relatively large kurtosis is an indication of fat tails and therefore also of relatively high risk; examples are the Construction and Manufacturing sector. Nevertheless, kurtosis does not give a precise indication of upper- or lower-tail risk and therefore can be misleading. However, we can conclude that the kurtosis and skewness presented in Table 2.1 indicate that the normal distribution will be inadequate for further modeling. As such, in this paper we prefer the Student-t distribution to account for the fat-tails. The asymmetry will be addressed by the GJR-GARCH(1,1)-model. Further motivation for this particular model can be found in Section 2.4.1.

Table 2.2 shows the descriptive statistics of the quarterly firm characteristics ($\beta, Leverage\ ratio, Size$) and the $Trade\ Intensity_{i,t}$-variable by sector for the entire sample period. These data, which are quarterly aggregated data, will be used in the panel data model described in Section 2.4.4. All variables are initially retrieved on a daily basis from DataStream (Thomson Reuters Eikon) and Statistics Netherlands.[12] However, since the $Size$ variable changes at most on a quarterly basis, the quarterly average of each of the variables per firm is computed.

[12] See Appendix A4 for a more detailed overview of the variables and their data sources.

Table 2.2 Descriptive statistics of the quarterly firm characteristics ($\beta, Leverage\ ratio, Size$) and $Trade\ Intensity_{i,t}$ by sector: entire sample period.

Panel A

	β				$Leverage\ ratio$			
	Mean β	St.dev. β	Max. β	Min. β	Mean $Leverage\ ratio$	St.dev. $Leverage\ ratio$	Max. $Leverage\ ratio$	Min. $Leverage\ ratio$
1) Administrative & support service activities	1.278	0.094	1.479	1.080	0.350	0.312	1.133	0.00
2) Construction	1.045	0.243	2.067	0.673	1.091	1.356	8.182	0.00
3) Financial & insurance activities	0.947	0.175	1.158	0.591	2.201	3.207	14.217	0.00
4) Information & communication	0.919	0.150	1.108	0.661	0.942	1.339	6.445	0.00
5) Manufacturing	0.886	0.050	0.937	0.787	0.554	0.482	3.998	0.00
6) Professional, scientific & technical activities	0.823	0.061	0.967	0.689	0.725	0.796	3.386	-2.890
7) Transportation & storage	0.963	0.160	1.178	0.686	0.658	1.645	4.175	-4.193
8) Wholesale & retail trade; repair of motor vehicles & motorcycles	0.726	0.057	0.877	0.642	0.659	0.874	4.172	-3.923
Overall	0.844	0.124	1.221	0.726	0.949	1.658	14.217	-4.193

Panel B

	$Size$ (in EUR)				$Trade\ Intensity_{i,t}$ (in EUR)			
	Mean $Size$	St.dev $Size$	Max. $Size$	Min. $Size$	Mean $Trade\ Intensity_{i,t}$	St.dev $Trade\ Intensity_{i,}$	Max. $Trade\ Intensity_{i,t}$	Min. $Trade\ Intensity_{i,t}$
1) Administrative & support service activities	1,919,450	2,433,199	7,300,800	30,293	0.003	0.009	0.061	0
2) Construction	2,599,279	2,246,424	7,086,477	63,904	0.173	0.246	1.095	0.006
3) Financial & insurance activities	140,417,180	339,102,106	1,317,832,000	708	0.004	0.039	0.707	0
4) Information & communication	4,846,576	7,080,242	24,705.000	8289	1.2903	4.105	37.967	0
5) Manufacturing	19,888,264	53,637,152	303,123,204	10,872	0.479	0.589	4.146	0
6) Professional, scientific & technical activities	1,415,370	1,874,911	10,389,801	16,844	0.424	2.980	36.034	0
7) Transportation & storage	4,482,715	1,899,014	8,116,000	1,799,600	2.149	2.563	8.033	0.014
8) Wholesale & retail trade; repair of motor vehicles & motorcycles	12,830,007	27,672,986	95,017,966	328	1.592	3.930	35.100	0
Overall	23,549,855	54,493,254	1,317,832,000	328	0.628	2.404	37.967	0

Column 1 of panel A of Table 2.2 shows the β, which is used as a statistical measure of systematic risk[13] in the Capital Asset Pricing Model (CAPM). The β-coefficient indicates how a given asset is expected to react to changes of the market portfolio. In our sample we find, on average, the most 'aggressive stocks'[14] in the Administrative & support service activities and the Construction sectors. These sectors appear to bear the most systematic risk. Column 2 of Table 2.2 displays the leverage ratio, representing debt over common equity, which is also an indication of risk. Leverage relates to a firm's capital structure, in particular the use of debt financing, which comes with interest expenses and therefore affects the available profits for shareholders. A higher use of debt financing reflected in a higher leverage ratio, more profit variability, and as such, additional risk for shareholders (Brealey et al., 2015). Empirical research concerning the leverage ratio indicates similarities within and persistent differences across industries (Schwartz & Aronson, 1967; Scott, 1972). This outcome is also reflected in our data, for example, on average, the Financial and the Construction sectors have the highest leverage ratio. Further, panel B of Table 2.2 presents statistics on firm size per sector measured as total assets in EUR. Next, we measure globalization on three dimensions: trade intensity, foreign subsidiaries and foreign control. The last column of the table presents the continuous variable $Trade\ Intensity_{i,t}$, which equals total international trade in goods divided by total assets. As such, this indicator can be seen as a firm-level alternative for a commonly used way of the country-level definition of globalization.[15] Obviously, the Financial & insurance activities sector and the Administrative & support activities sector are the least trade intensive since these are heavy service oriented sectors. In our empirical analysis, in addition to sector dummies, we introduce two dichotomous variables ${D_{FS}}_{i,t}$ and ${D_{FC}}_{i,t}$, indicating respectively

[13] In financial portfolio theory systematic risk refers to the market risk that cannot be eliminated through diversification. More specifically, shares have a common exposure to the market and certain disasters (from nature, terrorists, etc.). Systematic risk should not be confused with systemic risk since systemic risk is based on tail dependence rather than average covariance (Acharya et al., 2017).

[14] $\beta_i = \frac{cov(R_i,R_M)}{var(R_M)}$ with R_i the stock return of firm i and R_M the market portfolio. When the β is larger than 1, the stock return tends to be larger than the return of the market portfolio and the stock is called 'aggressive'. Conversely, when β is lower than 1, the stock is labeled 'defensive' (Sollis, 2012).

[15] Globalization is often defined as total trade divided by the country's GDP (Caselli, 2012). In our firm level approach we choose to replace GDP with common assets. An alternative could be turnover, however because of data availability the former was chosen. To capture as many dimensions of globalization as possible, we also take into account whether a firms has foreign subsidiaries and whether it is controlled from abroad. Foreign control and subsidiaries are also used by the OECD in their globalization research (OECD, 2002).

whether the firm has subsidiaries and whether strategic decisions are taken abroad or in the Netherlands[16]. For the remainder of the analysis, the logarithm of both size and leverage is used. We note that log(Size) and log(Leverage) have respectively 16 (1% of sample) and 248 (9% of sample) missing values. $Trade\ Intensity_{i,t}$ has 16 missing values (1% of sample), ${D_{FS}}_{i,t}$ and ${D_{FC}}_{i,t}$ have 605 missing values (23% of sample). Finally, Appendix A4 presents an overview of the variables, their constituents and data sources.

2.4. Empirical framework

2.4.1. Systemic risk measure

Our research builds on the literature presenting measures for systemic risk. Without being exhaustive, we explain a number of risk metrics that are based on market data and study joint tail behavior. First, the Marginal Expected Shortfall (MES) and its extensions, namely Systemic Expected Shortfall (SES) and the Systemic Risk Measure (SRISK), focus on capital shortfall (Acharya et al., 2012; Acharya et al., 2017; Brownlees & Engle, 2012). Finally, Adrian and Brunnermeier (2016) propose the ΔCoVaR as a measure of systemic risk. The main goal of the Conditional Value-at-Risk (CoVaR) is to capture possible risk spillovers of an institution to the system. This metric goes beyond idiosyncratic risk, measured by, e.g., Value-at-Risk (VaR) (Jorion, 2007). Fundamentally based on asset returns, CoVaR assesses the VaR of the financial system conditional on an institution being in financial distress, and hence, it can be used to determine a financial firm's contribution to systemic risk. Subsequently, the ΔCoVaR is defined as the change in the VaR of the system conditional on an institution being in distress relative to its mean state. As such, it captures only extreme variations.

There are two important reasons why the CoVaR measure is preferred above the other metrics mentioned. First, the CoVaR is conditional. The goal of this paper is in line with this conditional property of the CoVaR, namely, the distress of a specific (non)financial firm as condition. Second, the CoVaR is directional (Adrian

[16] Foreign direct investment (FDI) is not directly observed, but measured through the two dichotomous variables foreign control and foreign subsidiaries.

& Brunnermeier, 2016). The directionality implies a major economic interpretational difference with the MES, SES, and SRISK. Conditioning the system on a firm is not the same as the reverse case, more specifically, a firm conditional on the system (Girardi & Ergün, 2013; Mainik & Schaanning, 2012). The goal of this paper is in line with the directional property of the CoVaR. Since one of the fundamental research goals is to compute systemic risk contributions of the financial and nonfinancial sectors, as well as to determine the systemic importance of each firm within the system, the CoVaR is the most appropriate measure to apply. Moreover, in a comparative study, Sedunov (2016) finds that the CoVaR outperforms the SES (and as such also the MES) in forecasting systemic risk.

The original definition of CoVaR as proposed by Adrian and Brunnermeier (2016) assesses the VaR of the system conditional on a firm being at its VaR. However, this definition fails to detect systemic risk when it is most pronounced, resulting in capital requirements that are possibly the outcome of regulatory capital arbitrage[17] (Mainik & Schaanning, 2012). Girardi and Ergün (2013) generalized the definition by conditioning on a more general case of financial distress, more specifically, a firm being at most at its VaR. Not only does the generalized definition allow for more severe losses, but as opposed to its original definition, the CoVaR now also becomes a monotonically increasing function of the dependence parameter (Mainik & Schaanning, 2012). Furthermore, this definition allows an examination of more extreme distress events further in the tail, improves consistency with respect to the dependence parameter between the firm and the system, and allows proper backtesting[18] (Girardi & Ergün, 2013; Mainik & Schaanning, 2012).

[17] Regulatory capital arbitrage is a process in which financial institutions substantially reduce their regulatory measures of risk and capital requirements with little or no corresponding reduction in their overall economic (systemic) risk (Jones, 2000).

[18] The CoVaR definition of Girardi and Ergün (2013) allows for the Kupiec and the superior Christoffersen backtest. These are out-of-sample tests, and to perform proper backtesting with this sample, our sample should be split. However, since the focus of this paper is an historical analysis, in which the financial crisis is a focus point, all the data points will be used to fit the model. As a result, the models will be overfit and unsuitable for forecasting purposes. Models for forecasting should give less weight to extreme events such as the financial crisis, since they are less likely to dominate the future. As such, the Kupiec and Christoffersen backtests become irrelevant, since these chi-squared tests will mostly reject these models (Christoffersen, 1998; Kupiec, 1995).

To determine the CoVaR, Adrian and Brunnermeier (2016) run quantile regressions, in which they incorporate state variables to capture the time-varying effect and also accounting data, which are prone to window dressing. However, linear quantile regressions cannot accommodate structural breaks or nonlinearities and are vulnerable to nonstationarity in macroeconomic and financial time series (Bisias et al., 2012; Liu, 2017). Other ways to estimate the CoVaR are Bayesian inference, copulas and multivariate GARCH models. The latter originate from ARCH and GARCH models, which were initially introduced by Engle (1982) and Bollerslev (1986) respectively to model volatilities for financial time series. In order to cope with the problem of multivariate time series and to keep GARCH models more parsimonious, multivariate GARCH models were created. There are several types of multivariate GARCH models. The DCC specification of Engle (2002) is a generalization of the CCC specification of Bollerslev (1990), the latter not allowing time variation in the conditional correlations. Furthermore, specification difficulties and the large number of parameters to be estimated accompanying the BEKK model proposed by Engle and Kroner (1995), makes the DCC model the preferable choice in practice. As such, Girardi and Ergün (2013) also preferred the DCC-GARCH approach of Engle (2002) to model the time-varying joint distribution of the system and a single firm to calculate systemic risk contributions. Compared to a quantile regression, which is also often used to estimate the ΔCoVaR, the advantage of the DCC-GARCH approach lies in the fact that it allows taking time-varying linkages between the system and a firm into account, without having to rely on systemic state variables. The DCC-model enables us to model contagion during stable and turbulent periods and to reproduce dynamic market correlations. It allows for time-varying contagion effects and for contagion to be asymmetrically transmitted (Hemche et al., 2016). The quantile regression is not able to capture a changing correlation over time between the (economic) system and the firm, and as a result, the effect of VaR on CoVaR stays the same. An advantage of the GARCH estimation is that it captures the dynamic evolution of systemic risk contributions explicitly. When using a GARCH model, a firm's CoVaR and its VaR become time varying due to the time-varying correlation. As such, possible changes over time and linkages between the system and the firm can be detected (Girardi & Ergün, 2013).

Further, Jondeau et al. (2007) found with their explicit parametric model for several equity portfolios much stronger tail dependence on the downside. They found that extreme negative returns are more pronounced than positive ones, which results in asymmetric distributions with heavy tails. More recent work of López-Espinosa et al. (2015) concludes that ignoring the asymmetric feature of tail-interdependences leads to a severe underestimation of systemic risk. Therefore, in this paper we prefer the GJR-GARCH (1,1) specification, which was initially introduced by Glosten et al. (1993). The latter is chosen because of its leverage effect, since it uses dummy variables for negative shocks in the volatility equation. As such, we account for any asymmetry, which ensures that negative shocks are assigned more weight in volatility changes than positive shocks, in order to account for crisis situations or disturbances in the economy. While a GARCH (1,1) process[19] is leptokurtic and, as such, accounts for the heavy tails, the GJR-GARCH(1,1) additionally accounts for the asymmetry by moving the distribution further to the left. Moreover, the standard symmetric GARCH model of Bollerslev (1986) still remains a special case of the GJR-GARCH model. This research uses a DCC-GJR-GARCH model[20] with Student-t distribution. Early empirical evidence (e.g., Fama, 1965; Mandelbrot, 1963) suggests that stock returns are not well described by a Gaussian distribution. Therefore, other fat-tailed distributions were investigated, such as a mixture of normal distributions or Student-t distributions (Barnea & Downes, 1973; Blattberg & Gonedes, 1974). It is now well recognized that the fat-tailed unconditional return distributions may result from the time-varying volatility in the underlying stochastic process governing the stock return dynamics (Bollerslev et al., 2013). Therefore, a DCC-GJR-GARCH model is thus estimated for the returns of each firm and the system. As such, we also allow for asymmetry in conditional variances and covariances (Goeij & Marquering, 2004).

[19] In most financial applications a GARCH(1,1) is found to suffice (Bollerslev et al., 1992). Moreover, an advantage of the GARCH(1,1) is that, according to Hansen (1991), it satisfies under certain conditions near epoch dependence without imposing strict stationarity.

[20] DCC models have several advantages explaining their popularity. More specifically, they are easily extendible to other more complex GARCH-type structures, such as, in this case the GJR-GARCH model. They have an easy two step estimation, which is explained into detail in Bauwens et al. (2006). Using N univariate models and specifying the conditional variances as a GARCH(1,1), the number of parameters in a DCC model is equal to $(N+1)(N+4)/2$, which is smaller than for example the $N(5N+1)/2$ parameters of the BEKK model proposed by Engle and Kroner (1995), making a DCC model the preferable choice in practice (Bauwens et al., 2006).

2.4.2. Definition of Conditional Value-at-Risk

Essential for calculating the CoVaR is the Value-at-Risk or VaR. When r_t^i is defined as the returns of a firm i and the confidence level is given by q, then $VaR_{q,t}^i$ is determined by the q-quantile of the return distribution as is shown below:

$$Pr\left(r_t^i \leq VaR_{q,t}^i\right) = q \tag{1}$$

Adrian and Brunnermeier (2016) define the $CoVaR_{q,t}^{S|i}$ as the VaR of a firm, portfolio of (financial) firms or system S, conditional on another firm i being at its VaR-level.

$$Pr\left(r_t^S \leq CoVaR_{q,t}^{S|i} | r_t^i = VaR_{q,t}^i\right) = q \tag{2}$$

Girardi and Ergün (2013) alter the definition of CoVaR to the VaR of the system conditional on a firm being at most at its VaR-level.

$$Pr\left(r_t^S \leq CoVaR_{q,t}^{S|i} | r_t^i \leq VaR_{q,t}^i\right) = q \tag{3}$$

Only the latter definition is a monotonically increasing continuous function of the dependence parameter between the system and firm i (Mainik & Schaanning, 2012). Conditioning on $r_t^i \leq VaR_{q,t}^i$ constitutes a broader vision on financial distress since it allows for more severe losses further in the tail, namely, those beyond $VaR_{q,t}^i$ (Girardi & Ergün, 2013).

The systemic risk contribution of a particular firm i or ΔCoVaR is defined as the difference between the VaR of the system conditional on the distressed state of a specific firm and the VaR of the system conditional on the benchmark state of that same firm (Adrian & Brunnermeier, 2016). Girardi and Ergün (2013) apply this definition and calculate the ΔCoVaR as a percentage change of the distressed state relative to the benchmark state. It is the latter definition that is applied in this research.

$$\Delta CoVaR_{q,t}^{S|i} = \frac{\left(CoVaR_{q,t}^{S|i} - CoVaR_{q,t}^{S|b^i}\right)}{CoVaR_{q,t}^{S|b^i}} \times 100 \tag{4}$$

Additionally, the benchmark's calculation differs between authors; this study follows the approach of Girardi and Ergün (2013). The benchmark state is calculated as one standard deviation from the mean event, $\mu_t^i - \sigma_t^i \leq r_t^i \leq \mu_t^i + \sigma_t^i$, where μ_t^i and σ_t^i are respectively the conditional mean and the conditional standard deviation of firm i.

2.4.3. The delta Conditional Value-at-Risk procedure

We closely follow the methodology of Girardi and Ergün (2013) and apply their three-step procedure to compute the ΔCoVaR, in which the first two steps involve the DCC-GJR-GARCH estimation and the last step obtaining the ΔCoVaR itself. Due to the time-varying correlation of the GJR-GARCH model, the CoVaR of a firm has a time-varying exposure to its VaR, which is not the case when constructed with a quantile regression as in Adrian and Brunnermeier (2016). Further, we choose a DCC-GJR-GARCH model for estimating the returns of each firm i and the system S. By applying a GJR-GARCH model, we allow asymmetry in the conditional variances and covariances. We specifically prefer this type of model because it weights negative (e.g., crisis events) more heavily than positive events (Goeij & Marquering, 2004).

Let $r_t = \left(r_t^S, r_t^i\right)$ where r_t^S is the log returns of a market index serving as a proxy for the Dutch system and r_t^i represent the log-returns of the stock prices of the publicly listed Dutch firms. The innovation process for the conditional mean $\varepsilon_t \equiv r_t - \mu_t$ has an $(n \times n)$ conditional covariance matrix H_t and in this framework n equals 2. The joint dynamics of r_t are then given by:

Step 1: First, the VaR of each firm i is computed. Next, the following univariate model is estimated.

$$r_t^i = \mu_t^i + \varepsilon_{i,t} \tag{5}$$

Where μ_t^i equals an AR(p)-model of r_t^i and $\varepsilon_{i,t} = z_{i,t}\, \sigma_{i,t}$, where $z_{i,t}$ is i.i.d. with zero mean and unit variance, and the conditional variance has the nonlinear threshold GJR-GARCH (1,1) specification which was initially introduced by Glosten et al. (1993). The latter is chosen because of its leverage effect, since it uses dummy variables for negative shocks in the volatility equation. As such, we account for any asymmetry earlier on in the three-step procedure. In this more flexible model, γ_1 represents the 'leverage' term. Depending on the size of γ_1, the latter ensures that negative shocks are assigned more weight on changes in volatility than positive shocks, in order to account for, e.g., crisis situations or disturbances in the economy. When $I_{t-1} = 0$ the GJR-GARCH boils down to a Bollerslev (1986) standard symmetric GARCH model. Further, the model is also a special case of an asymmetric power ARCH model, more specifically, when the power is 2 the formula is as follows (Ding et al., 1993):

$$\sigma_t^2 = \alpha_0 + \alpha_1 {\varepsilon_{t-1}}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 I_{t-1} \varepsilon_{t-1}^2$$

$$I_{t-1} = \begin{cases} 1 \; if \; \varepsilon_{t-1} < 0 \\ \\ 0 \; if \; \varepsilon_{t-1} \geq 0 \end{cases} \tag{6}$$

In addition, there are the following parameter restrictions for both GJR-GARCH models: $\alpha_0 \geq 0$, $\alpha_1 > 0$, $\beta_1 > 0$ and $\alpha_1 + 0.5\,\gamma_1 + \beta_1 < 1$ to ensure positive and stationary volatility dynamics.

For the returns, an underlying Student-t distribution is assumed in order to account for the fatter tails. Maximum likelihood is used to determine the degrees of freedom. Finally, given a distributional assumption for z, the estimates of each firm i are used to calculate the VaR.

Step 2: In the second step, using the dynamic conditional correlation or DCC specification of Engle (2002), a bivariate DCC-GJR-GARCH model is estimated for the returns of each firm i and the system. As such, we also allow for asymmetry in conditional variances and covariances (Goeij & Marquering, 2004). Let $r_t = \left(r_t^S,\, r_t^i\right)'$, then the error term can be written as follows:[21]

$$\varepsilon_t = \Sigma_t^{1/2}\, z_t \tag{7}$$

[21] The GJR-GARCH models r_t^S and r_t^i constructed in step 1 are in fact the marginals in a copula set up.

Where $\sum_t$ is the (2×2) conditional covariance matrix of the error term ε_t and μ_t is the (2×1) vector of conditional means. The standardized innovation vector $z_t = \sum_t^{-1/2}(r_t - \mu_t)$ is i.i.d. with $E(z_t) = 0$ and $Var(z_t) = I_2$ and v degrees of freedom. D_t is defined as the (2×2) diagonal matrix with the conditional variances $\sigma_{x,t}^2$ and $\sigma_{y,t}^2$ along the diagonal so that $\{D_{xx}\}_t = \{\sum_{xx}\}_t, \{D_{yy}\}_t = \{\sum_{yy}\}_t$ and $\{D_{xy}\}_t = 0$ for $x, y = s, i$. The conditional variances are modelled as GJR-GARCH(1,1):

$$\begin{aligned}\sigma_{x,t}^2 &= \theta_0^x + \left(\theta_1^x + \gamma_1^x I_{x,t-1}\right)\varepsilon_{x,t-1}^2 + \theta_2^x \sigma_{x,t-1}^2 \\ \sigma_{y,t}^2 &= \theta_0^y + \left(\theta_1^y + \gamma_1^y I_{y,t-1}\right)\varepsilon_{y,t-1}^2 + \theta_2^y \sigma_{y,t-1}^2\end{aligned} \tag{8}$$

With $I_{x,t-1} = 1$ when $\varepsilon_{x,t-1}^2 < 0$ and similarly $I_{y,t-1} = 1$ when $\varepsilon_{y,t-1}^2 < 0$, there are the following parameter restrictions for both GJR-GARCH models: $\theta_0 \geq 0$, $\theta_1 > 0$, $\theta_2 > 0$ and $\theta_1 + 0.5\,\gamma_1 + \theta_2 < 1$ to ensure positive and stationary volatility dynamics. The conditional covariance $\sigma_{xy,t}$ is:

$$\sigma_{xy,t} = \rho_{xy,t}\sqrt{\sigma_{x,t}^2 \sigma_{y,t}^2} \tag{9}$$

Let $C_t = D_t^{-1/2} \sum_t D_t^{-1/2} = \{\rho_{xy}\}_t$ be equal to the (2×2) positive definite matrix of conditional correlations of ε_t or the correlation matrix. Following Engle (2002), the conditional correlation matrix and the DCC structure are specified as follows:

$$C_t = diag(\textstyle\sum_t)^{-1/2} \times \sum_t \times diag(\sum_t)^{-1/2} \tag{10}$$

Further, $diag(\sum_t)$ is the (2×2) matrix with the diagonal of $\sum_t$ diagonal and zeros off-diagonal.

$$\textstyle\sum_t = (1 - \delta_1 - \delta_2)\overline{\sum} + \delta_1(u_{t-1}u_{t-1}') + \delta_2 \sum_{t-1} \tag{11}$$

In equation (11) the first part, $(1 - \delta_1 - \delta_2)\overline{\sum}$, represents a constant correlation independent of time. As such, $\overline{\sum}$ equals the unconditional covariance matrix of $u_t = \{\varepsilon_{x,t}/\sigma_{x,t}\}_{x=s,i}$. The second part in the equation above represents the latest shock, while the last part equals an autoregressive part, taking in the information from the past. Since $\sum_t$ depends on time,[22] it is called the conditional covariance matrix of u_t. Finally, δ_1 and δ_2 are non-negative scalar parameters, satisfying $\delta_1 + \delta_2 < 1$.

Step 3: Once the bivariate density $pdf_t\left(r_t^S,\ r_t^i\right)$ for each $r_t = \left(r_t^S,\ r_t^i\right)'$ pair in step 2 is estimated, the $CoVaR_{q,t}^{S|i}$ measure for each firm i and time period t in step 3 is obtained. Given the definition of CoVaR from equation (7), it follows that:

$$Pr\left(r_t^S \leq CoVaR_{q,t}^{S|i} | r_t^i \leq VaR_{q,t}^i\right) = q \tag{12}$$

$$\frac{Pr\left(r_t^S \leq CoVaR_{q,t}^{S|i}, r_t^i \leq VaR_{q,t}^i\right)}{Pr\left(r_t^i \leq VaR_{q,t}^i\right)} = q \tag{13}$$

By definition of $VaR_{q,t}^i$, $Pr\left(r_t^i \leq VaR_{q,t}^i\right) = q$ so

$$Pr\left(r_t^S \leq CoVaR_{q,t}^{S|i}, r_t^i \leq VaR_{q,t}^i\right) = q^2 \tag{14}$$

Given the $VaR_{q,t}^i$ estimates obtained in step 1, and if $x, y = s, i$, the former can be rewritten as a double integral for $CoVaR_{q,t}^{S|i}$ considering the continuous joint probability density function.[23]

$$\int_{-\infty}^{CoVaR_{q,t}^{S|i}} \int_{-\infty}^{VaR_{q,t}^i} pdf_t(x, y) dy, dx = q^2 \tag{15}$$

The former is an equation with only one unknown. Therefore, this double integral can be solved numerically for $CoVaR_{q,t}^{S|i}$ with the Newton method.

[22] As such, the DCC specification of Engle (2002) is a generalization of the constant conditional correlation (CCC) estimation of Bollerslev (1990). The CCC specification does not allow $\sum$ to be time-varying.

[23] The PDF $f(x,y)$ of two continuous variables X and Y is such that:

$f(x, y) \geq 0$

$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx, dy = 1$

$\int_c^d \int_a^b f(x, y) dx, dy = Pr(a \leq x \leq b, c \leq y \leq d)$

In order to compute the $CoVaR_{q,t}^{S|b^i}$ of the benchmark state, the same three-step procedure has to be followed. The only difference is the conditioning event, which is defined as one standard deviation about the mean event or more specifically $\mu_t^i - \sigma_t^i \leq r_t^i \leq \mu_t^i + \sigma_t^i$ instead of $r_t^i \leq VaR_{q,t}^i$. Once the marginal probability $Pr(\mu_t^i - \sigma_t^i \leq r_t^i \leq \mu_t^i + \sigma_t^i) = p_t^i$ is retrieved for each firm i, the $CoVaR_{q,t}^{s|b^i}$ is defined by the following joint probability:

$$Pr\left(r_t^S \leq CoVaR_{q,t}^{S|b^i}, \mu_t^i - \sigma_t^i \leq r_t^i \leq \mu_t^i + \sigma_t^i\right) = p_t^i q \qquad (16)$$

Similar to the $CoVaR_{q,t}^{S|i}$, the following double integral can be solved numerically since the $CoVaR_{q,t}^{S|b^i}$ is the only unknown:

$$\int_{-\infty}^{CoVaR_{q,t}^{S|b^i}} \int_{\mu_t^i - \sigma}^{\mu_t^i + \sigma_t^i} pdf_t(x, y)dy, dx = p_t^i q \qquad (17)$$

Finally, following Girardi and Ergün (2013), the ΔCoVaR is computed by equation (4).

2.4.4. Panel data analysis

Once the ΔCoVaR is estimated, the relationship between systemic risk contributions, and its determinants are investigated in detail by a panel regression analysis. We consider the following linear unobserved effects model for T quarterly time periods:

$$y_{it} = \alpha_i + \boldsymbol{\delta}'\boldsymbol{glob_{it}} + \boldsymbol{\beta}'\boldsymbol{x_{it}} + u_{it}, \qquad t = 1,2, \dots, T \qquad (18)$$

where y_{it} denotes the quarterly-aggregated systemic risk contributions, α_i is the unobserved firm-effect, $\boldsymbol{glob_{it}}$ is the vector of interest that includes the following globalisation variables: trade intensity and two dummy variables that take the value 1 if the firm is foreign owned or has foreign subsidiaries, $\boldsymbol{x_{it}}$ is a vector of additional control variables, δ and β include the unknown parameters and u_{it} is the error term.[24]

We include the following independent variables in the vector $\boldsymbol{x_{it}}$ to explain the firm-level quarterly-aggregated systemic risk contributions: log(VaR), log(Leverage), log (Size) and the firm's equity beta. Further, we control for the sectors, the financial crisis of 2008-2009, the double dip recession of 2011-2012 and other potential market downturns by using dummy variables. The choice of these variables is based on previous studies with respect to explaining systemic risk (Acharya et al., 2017; Adrian & Brunnermeier, 2016; Girardi & Ergün, 2013; Karimalis & Nomikos, 2018). Generally, these studies posit a positive relationship between log(VaR), Size, equity beta and leverage on the one hand and a firm's systemic risk contribution on the other hand. The VaR is often the preferred regulatory measure of systemic risk, and as such, also determines the firm's capital requirements. The latter is obviously linked to Size, which is measured as total assets.[25] Since we define leverage[26] as total debt divided by common equity, we expect the coefficient of log(Leverage), in contrast to Girardi and Ergün (2013), to be negative. When volatility rises, leverage tends to drop. Since the financial crisis, nervous lenders have wanted more collateral for their loans in times when systemic risk rises, and as a result, the leverage ratio has been drastically curtailed (OECD, 2012).

2.5. Empirical analysis

We now turn to the principal interest of this paper, namely uncovering the systemic risk contributions of the financial and nonfinancial sectors and verifying the potential systemic role of globalization in the Netherlands. Subsection 2.5.1.

[24] Table A4.2 from Appendix A4 presents all the variables used in the panel regression analysis, together with brief definitions and data sources.
[25] See also correlation matrix in Appendix A11.
[26] Acharya et al. (2017) define leverage as the quasi-market value of assets divided by market value of equity, where quasi-market value of assets is book value of assets minus book value of equity plus market value of equity. Also Girardi and Ergün (2013) use total assets to book equity. Although it comes down to the same thing, we apply a slightly different definition of leverage, more specifically total debt divided by common equity. When volatility rises leverage tends to drop. Since the financial crisis, nervous lenders have wanted more collateral for their loans in times when systemic risk rises, and as a result, the leverage ratio has been drastically curtailed (OECD, 2012). As such, in this research we expect a negative relationship between systemic risk and leverage.

provides the sectoral analysis of the ΔCoVaRs for the Dutch Economy, while empirical evidence on the systemic role of globalization is provided in Subsection 2.5.2.

2.5.1. Systemic risk contributions of the financial and nonfinancial sectors

The aim of this first empirical analysis is to understand and discuss the behavior of systemic risk contributions from financial and nonfinancial firms over time with the financial crisis of 2008-2009 as a structural breakpoint. Table 2.3 reports the summary statistics of the estimated ΔCoVaR series for all 67 firms (labelled 'Overall') and for firms by sector for the entire sample period using the DCC-GJR-GARCH model. Column 2 represents the standard deviation of the individual firm's ΔCoVaR means, which is a proxy for the dispersion of the average systemic risk contributions. Further, column 3 of Table 2.3 shows the average standard deviation across firms. The latter represents the volatility of systemic risk contributions over time.

Table 2.3 Summary statistics for ΔCoVaR for all firms by sector: overall sample period.

	Mean ΔCoVaR (1)	St.dev. of the ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Maximum ΔCoVaR (4)	Minimum ΔCoVaR (5)
1) Administrative & support service activities	164.85	45.73	37.94	204.90	99.00
2) Construction	147.59	43.82	43.33	199.40	77.92
3) Financial & insurance activities	155.61	82.15	40.03	347.40	84.62
4) Information & communication	117.93	39.82	30.41	184.40	60.69
5) Manufacturing	136.67	55.06	35.13	271.00	65.17
6) Professional, scientific & technical activities	120.02	33.63	32.19	160.20	56.87
7)Transportation & storage	151.10	43.13	37.30	181.60	120.60
8) Wholesale & retail trade; repair of motor vehicles & motorcycles	96.29	28.89	27.16	153.70	64.35
Overall	133.66	51.78	34.87	347.40	56.87

Note: q = 5% and a (multivariate) Student-t distribution is used for all the calculations.

To understand Table 2.3, consider for example the third entry of column 1. When the return of a firm from the Financial & insurance activities sector is equal to or below its 5% VaR, on average, the 5% VaR of the system increases by 155.61%, compared to when this firm would be in its benchmark state. In other words when a firm from the Financial & insurance activities sector is in financial distress, the system (or the Dutch economy) becomes 1.5 times riskier. The second column shows a high standard deviation of the ΔCoVaR means of the financial sector, which means the average systemic risk contribution of this sector is dispersed. Column 4 shows the maximum values of the ΔCoVaR by sector during the entire sample period. The top 3 firms with the highest mean ΔCoVaR are ING, Koninklijke Philips Electronics, and Randstad.[27] Obviously, the ΔCoVaR of these firms is (partially) responsible for the larger dispersion of the average systemic risk contributions in their respective sector. Confirming our expectations, the average standard deviation of the ΔCoVaR across firms (column 3) indicates that the volatility of systemic risk contribution over time is among the highest in the economy for the Financial & insurance activities sector. However, nonfinancial sectors also seem to contribute a significant amount of systemic risk. Table 2.3 shows that the Administrative & support service activities sector is on average the largest risk contributor, while the Construction sector is the most volatile one. Since the consumer is less able to postpone the consumption of goods from the Wholesale & retail sector, it is, as expected, on average the least systemic risk-contributing sector. This result suggests that the distress of a firm in the Administrative & support service or Construction sector results, on average, in higher losses and a higher degree of volatility of the Dutch economy than the distress of a firm in the Wholesale and retail sector.

We split the entire sample into three subsamples to fully understand systemic risk and its relationship to the business cycle per sector. The standard indication of a recession period is two consecutive quarters with negative GDP growth. As Table A2 from Appendix A2 shows, during the selected sample the longest recession period in the Dutch economy lasts from July 2008 to June 2009.[28] Therefore, we decided to split the entire sample into three subsamples based on the longest recession period. More specifically, the first sample comprises the period from 1/2/2006 to 6/30/2008; the second from 7/1/2008 to 6/30/2009 and the third

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[27] The CoVaR of each firm, for each time-period, can be found in Appendix A6.

[28] GDP Netherlands data is obtained from OECD.Stat. Appendix A2 and A3 shows two other recession periods in the sample, namely from October 2011 to March 2012 and from July 2012 to December 2012 (double-dip recession). However, the focus of this paper is on the financial crisis of 2008-2009. See Appendix A9 which adds an additional break in the data in order to analyze the double dip recession of 2011-2012 and tests the robustness of the results.

from 7/1/2009 to 12/31/2015. These subsamples are referred to respectively as precrisis (sample size =651), crisis (sample size =261) and postcrisis period (sample size =1697). As such, different samples for each time period and sector are created, enabling a comparative setup. The Kruskal-Wallis test[29] confirms that for each sector the mean ΔCoVaRs differ significantly from each other over the different subperiods. Next, we perform a post hoc test, using the method described by Siegel and Castellan (1988), to further distinguish the found differences.[30] We find significant differences between time periods for almost every sector. Only the difference between the means of the ΔCoVaR for the crisis and postcrisis period of the Transportation sector is not significant.

Table 2.4 ΔCoVaR results per sector: comparison over time (horizontal).

	Horizontal comparison - change in mean ΔCoVaR over different sample periods		
*Note: Sectors are alphabetically ordered.	Δ precrisis to crisis in %	Δ crisis to postcrisis in %	Δ precrisis to postcrisis in %
Administrative & support service activities	+28.60	-16.44	+7.46
Construction	+50.85	-17.64	+24.24
Financial & insurance activities	+25.74	-17.72	+3.46
Information & communication	+29.39	-10.62	+15.65
Manufacturing	+29.44	-8.97	+17.83
Professional, scientific & technical activities	+46.87	-8.21	+34.81
Transportation & storage	+42.18	+1.49	+44.30
Wholesale & retail trade; repair of motor vehicles & motorcycles	+3.57	-0.80	+2.74
Overall	+31.97	-10.78	+17.74

The (horizontal) comparison over time[31] from Table 2.4 indicates that the postcrisis Dutch economy is still systemically riskier compared to the precrisis period. This outcome is not only due to the aftermath of the financial crisis but also to the double dip recession from 2011-2012.[32] While the Financial & insurance

[29] Because the Levene's test is significant and the data are not normally distributed, we perform the nonparametric Kruskal-Wallis test (Field et al., 2012).
[30] Post hoc test method of Siegel and Castellan (1988): This involves taking the difference between the mean ranks of the different time groups and comparing it to the critical value. The critical value is based on the value corrected for the number of comparisons being done, and a constant based on the total sample size and the sample size in the two groups being compared. The resulting inequality means that if the difference between ranks is bigger than or equal to the critical difference for that comparison, then that difference is significant (Field et al., 2012).
[31] The detailed results of each period for each sector can be found in Appendix A7.
[32] See Appendix A9 which adds an additional break in the data in order to analyze the double dip recession of 2011-2012 and tests the robustness of the results.

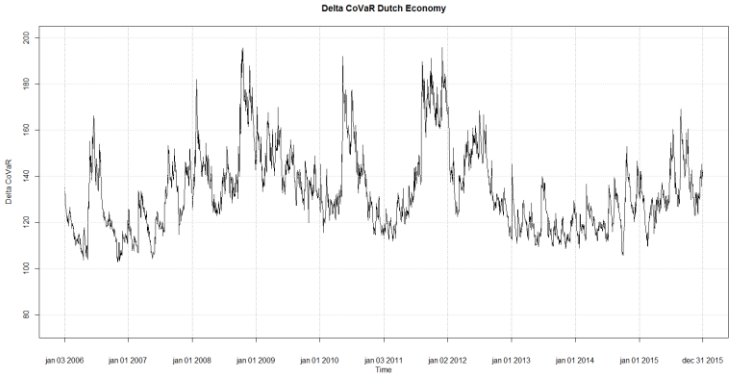
activities sector is still among one of the largest systemic risk contributing sectors of the economy, the sector's contribution reverted more or less back to its precrisis level after the crisis. As such, these findings support the results of Trapp and Wewel (2013), who also find that financial firms recover more quickly after a crisis event compared to non-financial firms. In addition, the systemic risk contribution of the Wholesale & retail trade sector has reverted to its precrisis level. We do not observe this reversion for the Professional, scientific & technical activities, the Construction, and the Manufacturing sectors. The postcrisis systemic risk contributions of these sectors have not yet reverted to their precrisis level. Moreover, the Construction sector, with a systemic risk-contribution increase of almost 25% on average, has become one of the most risk-contributing sectors of the economy. This first empirical analysis shows that systemic risk occurs in any sector of the economy and is therefore not exclusively related to the Financial & insurance activities sector. Moreover, sectors as Construction and the Manufacturing are more closely related with financial markets, institutions and their products compared to other sectors. Furthermore, sectors providing business cycle sensitive services or producing durable goods will show an important increase in systemic risk, since the consumption of these services and goods will be the first to be postponed by the consumer during economic downturns (Baldwin & Taglioni, 2009; Engel & Wang, 2011). An example is the Administrative & support service, which is overall the riskiest sector, containing mainly firms whose core business entails offering contingent services, such as recruitment, supply of temporary workers, etc. As a result, confirming the research of Bijlsma and Muns (2011); Dungey et al. (2017) and Kerste et al. (2015), these sectors carry an increased degree of systemic risk compared to the financial and other nonfinancial sectors.

2.5.2. Globalization as a determinant of systemic risk

2.5.2.1. Descriptive analysis

The ΔCoVaR measure is suitable for detecting sudden shifts in systemic risk. Figure 2.1 clearly shows these sudden shifts in systemic risk. Nevertheless, as systemic risk measures are rarely theoretically grounded or determinant driven, it is usually hard to clarify the source of risk at play (Benoit et al., 2017).

Figure 2.1 Time-series plots of daily ΔCoVaR for the entire Dutch economy



Furthermore, it is impossible to fully understand the financial crisis of 2008-2009 and its associated systemic risk without referring to global trade. As such, this second empirical analysis verifies whether globalization is a determinant of systemic risk.[33] To capture the effect of globalization on systemic risk, we measure globalization on the basis of three dimensions, more specifically $Trade\ Intensity_{i,t}$, the presence of foreign subsidiaries ($D_{FS_{i,t}}$) and foreign control, i.e., whether strategic decisions are taken abroad or in the Netherlands ($D_{FC_{i,t}}$).

Before going to the panel data regressions and controlling for the most common determinants of systemic risk in the literature, we analyze the relationship between globalization and systemic risk in isolation. Based on the time-series, we divide the sample into two subsamples for testing the ΔCoVaR results. More specifically, in order to determine a firm's category, we construct two subgroups based on the median value of $Trade\ Intensity_{i,t}$. Companies above or equal to the median of the entire sample period are considered as high trade intensive firms. As such, different samples for each time period and trade intensity are created, enabling a comparative setup. A similar setup is created for respectively firms with

[33] Globalization is often defined as total trade divided by the country's GDP (Caselli, 2012). In our firm level approach we choose to replace GDP with common assets. An alternative could be turnover, however because of data availability the former was chosen. To capture as many dimensions of globalization as possible, we also take into account whether a firms has foreign subsidiaries and whether it is controlled from abroad. Foreign control and subsidiaries are also used by the OECD in their globalization research (OECD, 2002).

versus firms without foreign subsidiaries and firms that are under foreign control versus firms not under foreign control.

The Kruskal-Wallis test[34] confirms that the mean ΔCoVaRs from Table 2.5[35] differ significantly from each other for every time period and globalization dimension (trade intensity, foreign subsidiaries and foreign control). Next, this paper follows the post hoc method by Siegel and Castellan (1988) which shows that trade intensive firms are less contributing to systemic risk. The opposite results are found for foreign subsidiaries and foreign control,[36] suggesting that firms with subsidiaries and/or under foreign control contribute more to systemic risk. Moreover, every observed difference is larger than the critical differences and, as such, significant for every time period.

Table 2.5 ΔCoVaR results for different globalization status: comparison over time (horizontal)

	Horizontal comparison - change in mean ΔCoVaR over different sample periods		
	Δ precrisis to crisis in %	Δ crisis to postcrisis in %	Δ precrisis to postcrisis in %
High Trade Intensity	+17.35	-6.58	+9.63
Low Trade Intensity	+34.82	-12.83	+17.53
Foreign Subsidiaries	+34.28	-11.63	+18.67
No Foreign Subsidiaries	+16.63	-14.72	-0.54
Foreign Control.	+23.98	-7.87	+14.22
No foreign Control	+31.46	-12.10	+15.55

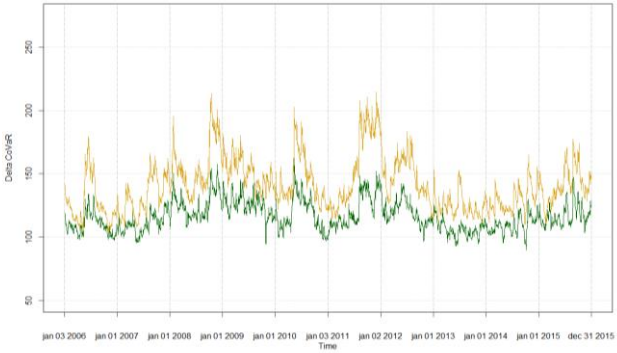
Since evidence suggests that differences in the level of globalization, measured on its three dimensions, between the time periods are significant, the results of Table 2.5 are chronologically examined. During the financial crisis of 2008-2009, Table 2.5 and Figure 2.2 show in general that systemic risk contributions rise, particularly for those firms with lower levels of trade intensity and firms with subsidiaries and under foreign control.[37] In Figure 2.2, we see that the green curves, represent firms with high trade intensity, foreign subsidiaries, and under

[34] Because the Levene's test is significant and the data are not normally distributed, we perform the nonparametric Kruskal-Wallis test (Field et al., 2012).
[35] See also Appendix A8 for the detailed results for each time-period.
[36] Although the relative rise from precrisis to crisis of firms under no-foreign control is higher, the firms under foreign control are already contributing much more systemic risk (see part C of Figure 2.2).
[37] See previous Footnote 34.

foreign control. In part A of Figure 2.2, the green curve lies clearly below the yellow one during the entire sample period. In the part B and C of Figure 2.2, the green curves lie above the yellow one. Further, firms that engage less in trade see their systemic risk contributions rise on average by 35% during the crisis. In the aftermath of the crisis, they are able to lose approximately half of this increase, leaving them still, on average, with 18% higher systemic risk contributions than before the financial crisis of 2008-2009. Companies that trade more also become more systemic risk contributing during the crisis, but only by half as much as the less trade intensive firms. As such, after the crisis the trade intensive firms also remain systemically higher risk contributing than before, but only by 10%. Further, Table 2.5 indicates that the systemic risk contributions of firms with foreign subsidiaries or under foreign control are higher. Firms that are not under foreign control see their systemic risk contributions rise relatively more than firms that are under foreign control. However, because their starting level is much lower, their systemic risk contributions never reach the same heights as firms that are controlled from abroad. Moreover, part C of Figure 2.2 shows that both types of firms have similar systemic risk contributing patterns, but foreign controlled firms are systemically riskier over the entire sample period. Firms with foreign subsidiaries see their systemic risk contributions rise on average by 34% during the financial crisis of 2008-2009. In the aftermath of the crisis, they are able to reduce this percentage, leaving them still, on average, with 19% higher systemic risk contributions than before the financial crisis. Companies without foreign subsidiaries also become more systemic risk contributing during the crisis, but only by half as much as the less trade intensive firms. As such, after the crisis, they even have become less systemic risk contributing than before the financial crisis of 2008-2009, by 0.5%.

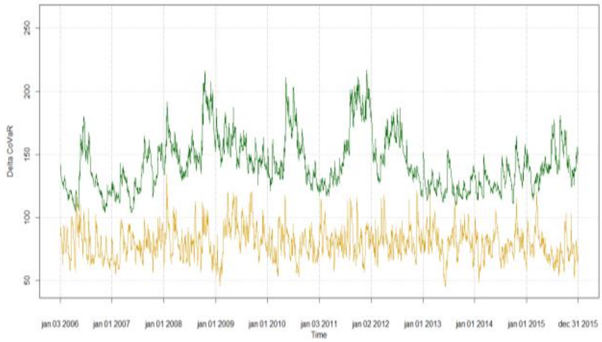
Figure 2.2 Time-series plots of daily ΔCoVaR measures for high and low levels of globalization

Part A: ΔCoVaR and Trade Intensity



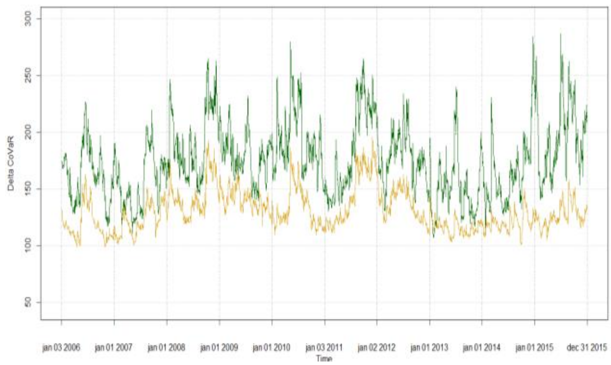
(Green: firms with high trade intensity, yellow: firms with low trade intensity)

Part B: ΔCoVaR and Foreign Subsidiaries



(Green: firms with foreign subsidiaries, yellow: firms without foreign subsidiaries)

Part C: ΔCoVaR and Foreign Control



(Green: firms under foreign control, yellow: firms not under foreign control)

Our findings indicate that globalization might play a dual role through its three dimensions (trade intensity, foreign subsidiaries and foreign control). On the one hand, trade intensive firms contribute less systemic risk. This may be the result of trade intensive firms being able to neutralize their systemic risk contribution more than less trade intensive firms since they are better able to adapt and optimize their operations as a response to negative demand shocks. On the other hand, firms under foreign control and/or having subsidiaries show higher levels of systemic risk. As such, foreign direct investments may channel and spread risk through the entire global organization and operations of a firm. Some relational patterns are noticeable in the former analysis, nevertheless, it is important to undertake a formal panel data regression analysis which controls for other common determinants of systemic risk, in order to verify whether globalization is a significant determinant.

2.5.2.2. Panel data regression results

We now turn to the relationship between systemic risk contributions and its determinants, which is investigated in detail by using a panel regression analysis. Starting the analysis with a fixed effects panel data regression model (FE), we additionally use a feasible generalised least squares (FGLS). Lewis and Linzer (2005) propose FGLS because this approach produces efficient estimates and less overconfident standard errors relative to standard ordinary least squares (OLS) and weighted least squares (WLS) approaches when dealing with estimated dependent variable regressions (EDV). More specifically, when fitting EDV regression models, the variation in the sampling variance of the observations on the dependent variable will induce heteroscedasticity and considerate sampling error. According to Lewis and Linzer (2005), one can correct the inconsistent OLS standard errors by using White's heteroscedastic consistent standard errors estimator or by using standard WLS. Such approaches would generate reliable results but can still give inefficient estimates because partial information about the nature of the heteroscedasticity, i.e., sampling error of the first stage, is not taken into account.

Table 2.6 Determinants of systemic risk – panel regression analysis

Dependent variable	$\Delta CoVaR$		
	(1)	(2)	(3)
$Log(VaR)$	131.793***	104.135***	125.223***
	(4.105)	(0.356)	(0.636)
$Log(Leverage)$	-3.475*	-15.753***	-7.349***
	(1.679)	(0.118)	(0.197)
$Log(Size)$	34.496***	34.355***	35.129***
	(0.091)	(0.091)	(0.207)
$Beta$	3.373 .	52.028***	29.306***
	(1.950)	(4.123)	(0.278)
$D_{\text{Administrative \& support activ.}}$			8.828***
			(1.059)
$D_{\text{Construction}}$			1.155 .
			(0.605)
$D_{\text{Information \& communication}}$			-20.129***
			(1.003)
$D_{\text{Manufacturing}}$			-7.270***
			(0.826)
$D_{\text{Prof,.scien.\& technic.activ.}}$			-9.150***
			(0.678)
$D_{\text{Transport \& storage}}$			2.545***
			(0.749)
$D_{\text{Wholesale \& retail}}$			-12.030***
			(1.031)
$Log(Leverage) \times D_{-r_t^s}$		23.27***	11.246***
		(0.274)	(0.246)
D_{FC}		24.408***	6.145***
		(0.429)	(1.438)
$Trade\ Intensity$		-2.043***	-0.015
		(0.029)	(0.070)
D_{FS}		7.731***	8.542***
		(0.221)	(0.457)
n	66	52	52
T	4-40	4-40	4-40
N	2404	1536	1536
$Durbin\ Watson$ (p-value<2.2e-16)	1.060	1.100	1.123
$Multiple.R^2$	29.91%	63.52%	65.79%

Model (1) is a fixed effect panel model OLS. Models (2) and (3) are FGLS panel models. Models (1)-(3) include time effects, allowing us to study the cross-sectional differences, Model(3) uses time effects and the sector dummies and, as such, allows us to account for the sector heterogeneity. The variables $Log(Leverage)$, $Log(Size)$, D_{FC} and D_{FS} contain missing values (see Section 2.3 for details).
Significance codes: ***0; ** 0.001; * 0.01; . 0.05.

First, in model (1), we relate quarterly-aggregated systemic risk contributions to its most common determinants, i.e., log(VaR), log(Size), log(Leverage) and the firm's beta. Next, in model (2) and (3) we verify whether globalization is a significant determinant of systemic risk. Since the model uses an estimated dependent variable, we prefer to use feasible generalized least squares (FGLS) for the remaining models (2) and (3), in order to correct for heteroscedasticity and serial correlation in the idiosyncratic disturbances. As such, model (2) and (3) are a FGLS models with time fixed effects, with the distinction that to model (3) sector dummies are added to account for sectoral group effects. As such, the difference between model (2) and (3) is that model (2) accounts for individual firm-level effects while model (3) subsumes the individual firm-level effects by sector-level effects.

Model (1) from Table 2.6 shows the fixed effects panel data results with highly significant firm characteristics. Mainly log(VaR) and, to a lesser extent, log(Size) explain systemic risk contributions. In our sample systemic risk seems to be largely determined by idiosyncratic risk. This is already noticeable when we plot the VaR and ΔCoVaR on the same graph. The time-series plots (Appendix A10) of the ΔCoVaR and VaR aggregated by sector show that both time-series have almost a symmetrical course. This outcome suggests a possible strong relationship between the ΔCoVaR and VaR, which can partially be explained by the fact that the VaR is an essential aspect in the ΔCoVaR calculation. Nevertheless, when we take a closer look at the plots, we occasionally notice that the relative increase of the VaR is larger than the increase of the ΔCoVaR, and vice versa. In those situations, the impact of an event is different for the sector itself than for the system. The VaR is seen as an unfit measure since it only measures the isolated or idiosyncratic part of systemic risk. As such, the differences in the plots are an indication that other factors than only idiosyncratic ones determine the contribution to systemic risk or ΔCoVaR. Therefore, only monitoring tail risk may not be sufficient to identify systemic risk contributions (Girardi & Ergün, 2013). Further, our results concerning the effect of firm characteristics on systemic risk are intuitive and are also in line with the literature[38] (e.g., Acharya et al., 2017; Adrian & Brunnermeier, 2016; Girardi & Ergün, 2013; Karimalis & Nomikos, 2018).

In model (2), we introduce globalization by adding the continuous variable $Trade\ Intensity_{i,t}$ and two dichotomous variables, foreign subsidiaries $D_{FS_{i,t}}$ and foreign control $D_{FC_{i,t}}$, to the model.[39] Furthermore, to control for the financial crisis

[38] See also Section 2.4.4. Panel data analysis for a brief exposition of the findings on determinants in past research.

[39] As such, according to model (2) an increase in $Trade\ Intensity_{i,t}$ by 1% results in, on average, a lower ΔCoVaR by 2.043%, ceterus paribus. Furthermore, when that firm is under foreign control, it has, on average, a larger ΔCoVaR by 6.145%, ceterus paribus. If the firm has foreign subsidiaries, its systemic risk or ΔCoVaR rises on average with 8.452%, ceterus paribus. However, according to model (3), in which we force the FGLS panel model into a two-way setting by adding sector dummies to the time fixed effects, the parameter estimate of $Trade\ Intensity_{i,t}$ becomes insignificant. Therefore, primordially the foreign direct investment dimension of globalization matters. More specifically, a firms that is under foreign

of 2008-2009, an interaction variable between log(Leverage) and a dummy indicator of negative market returns (see also Girardi and Ergün (2013)) is included.[40] Model (2) indicates that globalization, on its three dimensions, is a highly significant determinant of systemic risk. The negative coefficient for $Trade\ Intensity_{i,t}$ confirms the earlier found results on the relationship between globalization and systemic risk: trade intensive firms contribute less systemic risk. The firms under foreign control and/or with foreign subsidiaries have higher systemic risk contributions than firms which are not under foreign control and/or do not have foreign subsidiaries. As such, model (2) confirms the significant dual role of globalization in systemic risk contributions.

The figures from Appendix A5 and A10 show that the course of the ΔCoVaR varies per sector. Therefore, we include in model (3) sector dummies. Leaving out the dummy for the Financial & insurance activities sector, we are able to compare the systemic risk contributions of the nonfinancial sectors with that of the Financial & insurance sector. Compared to the Financial & insurance sector, we find the highest systemic risk contributions in the Administrative and support service; the Construction and the Transportation and storage sectors. Overall, systemic risk contributions by sector confirm our previous results discussed in Section 2.5.1. Regarding globalization, after controlling for sectoral effects, two out of three dimensions remain significant, i.e., foreign control and foreign subsidiaries. A firm's $Trade\ Intensity_{i,t}$ no longer plays a significant role because of its sector specific aspect. This nullifies the initially posed duality of globalization in relation to systemic risk. As such, model (3) confirms globalization, through foreign direct investments, as a significant determinant of systemic risk contributions.

2.6. Discussion and conclusion

This study investigates the systemic risk contributions of firms in the financial and nonfinancial sectors and the potential role of globalization in the Netherlands over the period 2006-2015. By using respectively a DCC-GJR-GARCH model and a

control has on average a larger ΔCoVaR by 6.145%, ceterus paribus. If this firms has foreign subsidiaries, its systemic risk contribution or ΔCoVaR rises on average by 8.452%, ceterus paribus.

[40] See also Section 2.4.4. Panel data analysis for a brief exposition on the interaction variable between log(Leverage) and a dummy indicator of negative market returns.

panel data regression, we were able to calculate the ΔCoVaR or systemic risk contributions and test the presence of globalization as a potential determinant of systemic risk.

Our results confirm that systemic risk contributions are countercyclical and, as such, likely to be affected by the business cycle. Moreover, our findings indicate that the Dutch economy remains systemically riskier after the financial crisis of 2008-2009 compared to the precrisis period. However, this increase in risk is also due to the double dip recession of 2011-2012. Our findings suggest two interesting results. First, systemic risk contributions are not limited to firms in the financial sector but also non-financial firms contribute to this type of risk. According to our analysis, firms within the Administrative and support service, Transportation and storage and Construction sectors are among the highest risk contributors in the Dutch economy, comparable with the level of the Financial & insurance activities sector. These firms are closely related with financial markets, institutions and their products. Furthermore, firms belonging to sectors that provide business cycle sensitive services or goods show an important increase in systemic risk, since the consumption of these services and goods will be the first to be postponed by consumers during economic downturns. However, while firms belonging to the Financial & insurance activities sector reverted to their precrisis level of systemic risk contribution, firms in the other nonfinancial sectors remain systemically riskier compared to their precrisis level of systemic risk. Due to their regulatory obligations (such as the Basel accords), firms from the Financial & insurance activities sector may be better able to manage its systemic risk contribution in contrast to nonfinancial firms. As such, our findings are in line with the results of Trapp and Wewel (2013).

Second, globalization, which is measured by trade intensity, the presence (or not) of foreign subsidiaries and whether (or not) a firm is under foreign control, is a significant determinant of systemic risk. More specifically, a higher trade intensity comes with lower systemic risk contribution. Trade intensive firms may be able to neutralize their systemic risk contribution more than less trade intensive firms since they are better able to adapt and optimize their operations as a response to demand shocks. Therefore, trade intensive firms are more resilient to systemic risk. Furthermore, when a firm is under foreign control or has foreign subsidiaries, systemic risk contribution rises. This indicates that foreign direct investments may channel and transmit shocks within a firm's international organizational and operational network. According to Goldin and Mariathasan (2014), systemic risk itself may result from a fragmented supply chain, little inventory and outsourcing. If a subsidiary fails in the supply (chain), it can significantly damage the profitability of a firm. Since, in practice, firms from the same sector often subcontract production to shared producers or at least the same cost-efficient areas, the entire sector bears a similar systemic risk (Battiston et al., 2007; Goldin & Mariathasan, 2014). The effect global supply chains may have on systemic risk contributions is in this research captured by the positive estimates of $D_{FC_{i,t}}$ and $D_{FS_{i,t}}$ which respectively represent whether a firm is under foreign control and/or has foreign subsidiaries. When a link of the value chain is in distress and ultimately fails, systemic risk rises. Moreover, the effect of outsourcing to subsidiaries and subcontracting in global supply chains are in many ways comparable to the effects of securitization and secondary market trading in the financial sector. All of these firms can diversify risk, which may be profitable for them individually, yet they fail to account for the negative externalities and the systemic risk they create for the entire economy (Goldin & Mariathasan, 2014). In addition, according to Battiston et al. (2007), supply and financial networks are not independent. Whenever a commodity is sold from a supplier to a retailer, the supplier faces the risk that the retailer will file for insolvency after obtaining the good but before making the appropriate payment. Battiston et al. (2007) show that supply chain shocks can be transmitted vertically throughout the supply network but also horizontally among competitors. For example, when the insolvency of a major supplier triggers the insolvency of a larger retailer, this can, in turn, affect other suppliers that are not being repaid by the retailer.

Our findings change the perspective on systemic risk from both a research as well as a policy point of view. First, by calculating the ΔCoVaR as a risk metric, policy makers are able to combine macro- and microprudential policy analysis simultaneously. More specifically, the ΔCoVaR itself gives policy makers insights into the systemic risk contributions of a firm (macro), while the metric is based on the VaR, forcing firms to keep their idiosyncratic risk under control (micro).

Currently, both policy perspectives are still carried out separately, which can lead to a fragmented view. Accordingly, we believe that monitoring the ΔCoVaR as an operationalization of macro- and microprudential policy is a first step in tackling this caveat. Second, an important step needs to be taken by policy makers and regulators towards a more comprehensive macroprudential policy by extending it to nonfinancial sectors. Present policy and regulations mainly target the financial sector, which is proven to be insufficient to cover systemic risk. Ideally, all systemically important firms (SIFs) should be addressed by policy makers and not only systemically important financial institutions (SIFIs). Finally, our results imply that globalization, measured as trade intensity and foreign direct investments, cannot be overlooked when studying systemic risk. This has a major implication for the further operationalization of a macroprudential policy including nonfinancial sectors. As such, not only classic indicators, such as leverage, but also globalization can help to identify and monitor SIFs. For instance, globalization, through a firm's foreign direct investments, plays an important role in the contagion of systemic risk within a firm's organizational and operational network. The clustering of foreign direct investments in certain geographic areas or the reliance on a small number of suppliers (i.e., concentration) may result in the contagion or spreading of systemic risk. As such, policy makers and supervisors have a vital role to play in order to ensure that certain players or even locations do not attain too high a weight in the supply chain.

Chapter 3

The Degree of International Trade and Exchange Rate Exposure – Firm-level Evidence from Two Small Open Economies

Abstract[41]

This study investigates cross-sectionally exchange rate exposure by comparing Dutch and Belgian listed firms on each point in time using monthly data from 2006-2015. Gaps in previous research are addressed by using disaggregated firm-level data to construct a firm's trade status and firm-specific effective exchange indices and applying copula theory. Our findings make three contributions to the field. First, extreme events leading to non-normality of stock returns are, at least partially, caused by a firm's international trade status. Second, Dutch listed firms experience stronger expected and unexpected exchange rate exposure since they engage more into trade outside the Eurozone than the Belgian listed firms. The pronounced unexpected exposure indicates that the Dutch listed firms that trade outside the Eurozone experience more extreme events. Third, listed importing firms experience stronger exchange rate exposure than listed exporting firms, indicating a dual effect of exchange rate risk arising from changes in the domestic economy and foreign market. Finally, our proposed methodology helps policy makers link trade with monetary policy and financial stability through a better understanding of exchange rate exposure based on firm-specific trade-weighted exchange rates.

Keywords: Exchange rate exposure, Firm-specific trade-weighted exchange rate, Copula, Belgium, Netherlands.
JEL: C46, C58, F14, F31

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3.1. Introduction

Since the breakdown of the Bretton Wood System in 1973, which resulted in the end of fixed exchange rates, researchers have extensively investigated how movements in exchange rates affect firm value, i.e., exchange rate exposure.[42] Changes in exchange rates have important implications for financial decision-making and for the profitability of firms, since changes in monetary policy[43] profoundly impact the domestic economy, creating spillover effects to other economies linked by international trade (Chakraborty et al., 2015). Eliminating exchange rate risk, to enable European firms to operate free from the uncertainties of changes in relative prices resulting from exchange rate movements, was one of the central motivations to create the euro (Dominguez & Tesar, 2006a). At the macro level, there is evidence that the creation of such currency unions results in a dramatic increase of bilateral trade within the union (Rose, 2000). Following Doukas et al. (2003), firms involved with international trade, i.e., outside the Eurozone, are directly exposed to exchange rate movements. Moreover, sudden extreme changes of exchange rates are more difficult to hedge, creating potential exchange rate risk for a firm's market value (Bartram et al., 2010; Di Iorio & Faff, 2000; Marston, 2001; Stulz & Williamson, 1996). However, evidence on the existence of a relationship between exchange rates and firm value is mixed. Despite the theoretical support (e.g., Allayannis & Ihrig, 2001; Bodnar & Gentry, 1993; Campa & Goldberg, 1995, 1999, 2001;

[42] A firm's exposure to changes in exchange rates is a multifaceted phenomenon and, as such, can be investigated from different perspectives. Stulz and Williamson (1996) distinguish four kinds of exchange rate exposure, more specifically transaction, contractual, translation and economic exposure. Transaction exposure refers to the exposure and the associated uncertainty firms face regarding already booked activities in foreign currencies. The existence of implicit or explicit agreements or commitments, e.g., price agreements, which are not associated with booked transactions, is called contractual exposure. Further, translation exposure refers to a firm's domestic and foreign assets and liabilities whose values are also affected by currency fluctuations. These aforementioned forms of exposure can be alleviated by well-structured hedging strategies. Nevertheless, it is the economic exposure, through a firm's stock price or value, which is of particular interest for this research. Economic exposure, which is the sensitivity of a firm's market value for foreign exchange rate fluctuations, is more difficult to hedge entirely (Bartram et al., 2010; Di Iorio & Faff, 2000; Marston, 2001; Stulz & Williamson, 1996).

[43] The monetary policy of the European Central Bank tries to maintain price stability within the Eurozone in order to foster economic growth and job creation. The monetary policy affects the economy in general and the price level in particular by, for instance, adjusting official interest rates. The change in the official interest rates affects money-markets interest rates and, indirectly, lending and deposit rates, which are set by banks to their customers. The impact on financing conditions in the economy and on market expectations triggered by monetary policy actions may lead to adjustments in asset prices and the exchange rate of the euro. Changes in the exchange rate can affect inflation directly, insofar as imported goods are directly used in consumption, but they may also work through other channels (European Central Bank, 2019b).

Dornbusch & Fischer, 1980; Frankel, 1983; Gavin, 1989), it is still hard to proof whether exchange rates have measurable effect on firms. The majority of the studies find, differing across countries, unidirectional, bivariate or even no causality. Only a small percentage of firms seems to exhibit significant exchange rate exposure. As such, empirical research on this issue has produced no convincing unambiguous evidence of exchange rate exposure. This issue is referred to as the exchange rate puzzle (e.g., Bini-Smaghi, 1991; Bodnar & Wong, 2003; Choi & Prasad, 1995; Chou et al., 2017; De Jong et al., 2006; Dominguez & Tesar, 2006a; Du et al., 2013; El-Masry, 2006; Jorion, 1990, 1991; Muller & Verschoor, 2006a, 2006b; Walid et al., 2011; Zhao, 2010).

There are three main causes why empirical research provides inconclusive and inconsistent results. First, research findings depend on the level of aggregation, namely country, industry or firm-level. Firms that participate in international trade are very heterogeneous and, as such, the country or industry level is too aggregated, causing aggregation bias (Greenaway & Kneller, 2007). Most of the sparse firm-level studies indicate a significant relationship between exchange rate changes and firm value (e.g., Bodnar & Wong, 2003; Choi & Prasad, 1995; De Jong et al., 2006; Di Iorio & Faff, 2000; Dominguez & Tesar, 2006a; Doukas et al., 2003; El-Masry, 2006; Hutson & Stevenson, 2010; Kiymaz, 2003). As such, the use of disaggregated firm-level data can avoid the problem of aggregation bias in investigating exchange rate exposure. Second, the choice of an exchange rate index used in modelling the relationship with firm value, influences the observed level of exposure (Dominguez & Tesar, 2006a; Fraser & Pantzalis, 2004). The bulk of empirical research on currency exposure uses a proxy, i.e., a common exchange rate index, to capture the exchange rate movements for all firms in the sample (Aggarwal & Harper, 2010; Williamson, 2001). However, firms often operate in different, distinct international locations, as such, relying on a common exchange rate index applied to all firms in the sample will often result in the foreign exchange rate exposure parameter being nonsignificant (Fraser & Pantzalis, 2004). Moreover, using common or industry-specific exchange rates does not account for the substantial heterogeneity of a firm’s distribution across export destinations and import countries. Third, financial time series have important distributional stylized facts, which have major implications on the modelling of their relationship. More specifically, the distributions of stock returns and exchange rates diverge from normality (e.g., Bollerslev et al., 2013; Boothe & Glassman, 1987; Fama, 1965; Huisman et al., 2002; Mandelbrot, 1963). Baldwin and Krugman (1989) pointed out the shortcomings of classic econometric assumptions and techniques in modelling exchange rate dynamics and exchange rate exposure. As such, these techniques assume that behavior is often linear, symmetric, represented by continuous functions or that leads and lags follow a fixed structure. Classic techniques, such as ordinary least squares (OLS), do not allow to flexibly model the distribution of each variable independently. Moreover, these conventional methods can only account for general, expected exchange rate exposure, which is hedgable, but fail to capture the unexpected exposure during sudden extreme events (Bartram et al., 2010). The aforementioned methodological shortcomings partially explain why the empirical evidence of exchange rate exposure is mixed (e.g., Bergbrant et al., 2014; Bodnar & Gentry, 1993; Dominguez & Tesar, 2006b; Miller & Reuer, 1998; Mohapatra & Rath, 2017; Pantzalis et al., 2001).

One major motivation of this study is to complement prior studies focusing on the exchange rate puzzle via advanced econometric methodologies which can account for situations in the real world. The objective of this study is to estimate exchange rate exposure by taking firm-level international trade[44] and the stylized facts of financial time series during the estimation process into account. Former research often uses a common exchange rate, is mainly characterized by aggregation bias and relies on classic econometric assumptions. We apply a novel approach on public listed firms from two small open trade intensive economies, i.e., Belgium and the Netherlands, creating a comparative setting. The disaggregated firm-level dataset consists of monthly stock prices, exchange rates, imports and exports. These data are available for Belgium and the Netherlands covering the period 2006-2015. The data allows us to construct firm-specific effective exchange rate indices for import and export activities separately. By taking into account whether

[44] International trade serves as a proxy for the globalization of trade and is, as such, a component of economic globalization. The OECD has proposed a core set of reference indicators to characterize globalization. International trade is one of these indicators (OECD, 2005). When this research mentions (international) trade, it refers to trade outside the Eurozone, since in this case exchange rate exposure is most pronounced.

a firm is trading internationally or refrains from it and by applying copula theory, we cross-sectionally model for each country the comovements between stock returns and, respectively, the import and export firm-specific effective exchange rate indices on each point in time. Since copula techniques permit to estimate both the general association and tail dependence during extreme events, we are able to compare expected and unexpected exchange rate exposure between Dutch and Belgian listed firms. As such, this study makes three contributions to the field.

First, we take into account whether a firm internationally trades or refrains from it, and determine its effect on the distribution of the stock return. While most studies focus on firms that continuously trade, or at least presume that the distribution of a company’s stock return is the same whether it is trading or not, no attempt thus far has been made to verify this assumption. We apply a probabilistic model that indicates the presence of subpopulations within an overall population, as such, this research takes the possibility of a firm’s decision not to trade internationally into account. By comparing different cross-sectional time slots, we show how the probabilities change over time in each country. Second, we construct, consistent with the method of Dai and Xu (2017), firm-specific trade-weighted effective exchange rate indices and investigate the relationship with the stock return. Because firms operate in different international locations and, therefore, are distinctively exposed, we use a firm-specific effective exchange rate index, to examine whether the stock returns are influenced by changes in trade-weighted exchange rates. Third, we use copula theory to model the cross-sectional relationship between the firm-specific exchange rate indices and stock returns on each point in time taking into account both the impact of the decision whether or not to trade and the trade volume. If a firm participates in international trade, we model the comovement between the firm-specific effective exchange rate index and the stock return. More specifically, the general association, i.e., the expected exchange rate exposure, and the tail dependence during extreme events, i.e., the unexpected exchange rate exposure, are estimated and investigated. Comovements between exchange rates and stock prices are likely to vary between firms depending on their participation in international markets. As such, we are able to verify the existence of exchange rate exposure and differences between exchange rate exposure for exporters and importers. Further, we examine whether there are large variations in the comovements over time and according to a firm's trade status (international trade versus no international trade) in particular.

Our results imply that firms from open economies can still have significant international trade differences, which reflected in their exchange rate exposure can have important policy implications. Since the Dutch firms engage more in trade outside the Eurozone and have in general a significant stronger association between the firm-specific exchange rate indices and stock returns than the Belgian firms, the listed firms from the Dutch sample are more susceptible to the European monetary policy which indirectly affects the exchange rate of the euro. Additionally, since the Dutch listed firms from the sample encounter more tariffs and other barriers, because they trade more internationally, European trade agreements with countries outside the union are more beneficial for these Dutch listed firms, than they are for the Belgian ones from the sample. Moreover, such international trade agreements result in a deterioration of the competitive position of those listed firms who trade mainly within the Eurozone. Next, the literature agrees on the fact that stock returns are not normally distributed (e.g., Fama, 1965; Jondeau et al., 2007; Mandelbrot, 1963). However, in this research we find that extreme events causing fat tails and, as such, non-normality for stock returns are, at least partially, caused by a firm's international trade activities. Since the Dutch listed firms from the sample experience more extreme events and these firms trade more outside the Eurozone, the tail dependence between stock returns and the firm-specific exchange rate indices is stronger and more pronounced than the tail dependence found for the Belgian listed firms from the sample. As such, the Dutch listed trading firms not only experience stronger expected exchange rate exposure than the Belgian listed trading firms but also have more pronounced unexpected exchange rate exposure. Further, our findings imply that listed importing firms experience stronger exchange rate exposure than listed exporting firms. This result is in line with the hypothesis[45] of Pritamani et al. (2004) of a dual effect of exchange rate changes on stock returns arising from changes in the domestic economy and foreign market. The hypothesis predicts that exchange rate exposure is accentuated for importers and is offset for exporters because of

[45] See Section 3.2.2 for further details on the dual effect hypothesis.

the interplay between the domestic and international market. Finally, it is expedient that policy makers gain insight into the results of their monetary and trade policy actions when even in similar open economies, such as Belgium and the Netherlands, listed firms may react different to policy changes. As such our proposed methodology can help policy makers link trade with monetary policy and financial stability through a better understanding of exchange rate exposure based on firm-specific trade-weighted exchange rates.

The remainder of this study is organized as follows. Section 3.2 gives a background on past research regarding the measurement of exchange rate exposure and contextualizes the motivation for this study. Next, Section 3.3 presents the data for Belgium and the Netherlands while Section 3.4 discusses the methodology. Section 3.5 presents the results and robustness analysis. Finally, discussion and conclusions follow in Section 3.6.

3.2. Background

3.2.1. Lack of empirical evidence on exchange rate exposure

Hekman (1983) refers to the sensitivity of a firm's economic value, or stock price, to [unanticipated] changes in foreign exchange rates as exchange rate exposure. Several studies show that hedging activities reduce exchange rate exposure (Allayannis & Ofek, 2001; He & Ng, 1998; Pantzalis et al., 2001). However, competitive or economic exposure is more difficult to hedge and depends on the market in which the firm operates (Di Iorio & Faff, 2000; Marston, 2001; Stulz & Williamson, 1996). It is the latter form of exposure which is of specific interest of this research. In this case, exposure occurs because a firm's competitive position is changed as a consequence of exchange rate variations affecting the relative prices of the goods sold in different countries (Stulz & Williamson, 1996).

At the theoretical level, the relationship between exchange rates and firm value, measured by stock prices, is well established. More specifically, two basic approaches describe this relationship. First, Dornbusch and Fischer (1980) proposed the goods market hypothesis, or flow oriented approach. This theoretical approach predicts a positive correlation between exchange rates and stock returns. The theory postulates that a depreciation of the domestic currency improves the competitiveness of local firms, leading to an increase in their exports and future cash flows, which consequently has a positive effect on stock market returns. Second, the stock oriented approach by Frankel (1983), supported by Gavin (1989), is based on the assumption that the exchange rate is determined by the demand and supply of financial assets, such as equities and bonds. Models based on this approach predict a negative correlation between stock returns and exchange rates.[46] Next to the aforementioned basic evidence, others tried to theoretically clarify the effect of exchange rate movements on the firm's returns. For example, Allayannis and Ihrig (2001) analyzed this relationship by developing a theoretical partial equilibrium model. The authors built on the findings of Campa and Goldberg (1995, 1999), who were the first to consider the effect of markups on investment exposure.[47] Campa and Goldberg (1999, 2001) identified three distinct channels of exposure, namely (i) wealth effects or import competition faced in the domestic market, (ii) firm's export sales, and (iii) the firm's imported inputs. By focusing on the effect of exchange rate movements on stock returns rather than on investment, Allayannis and Ihrig (2001) came to a similar conclusion. Beside the theoretical similarities, there also are important differences in investment and stock return exposure. More specifically, in efficient markets, stock returns should adjust instantaneously to an unexpected exchange rate shock, while it takes a considerable amount of time for investments to adjust. This leads to different empirical specifications used to estimate investment and stock return exposure. In particular, both expected and unexpected changes may affect

[46] The flow oriented approach postulates that depreciation of the domestic currency improves the competitiveness of local firms, leading to an increase in their exports and future cash flows, which consequently has a positive effect on stock market returns. More specifically, a depreciation (appreciation) of the domestic currency, makes the exports of domestic firms less (more) expensive and improves (deteriorates) their international competitiveness and their cash flows, thereby increasing (reducing) stock prices (Dornbusch & Fischer, 1980).
The stock oriented approach states that the value of financial assets are determined by the present values of their future cash flows, as such, expectations of relative currency values play a significant role in their future cash flows. Therefore, stock price innovations may affect or be affected by exchange rate dynamics and a reduction in stock prices discourages capital inflows as foreign investor's demand for local assets decreases, thereby reducing the value of the local currency (Frankel, 1983).
[47] Through export sales and imported inputs into production, Campa and Goldberg (1995, 1999) link exchange rates and investments in the U.S. industry. According to the authors, important differences exist across high- and low-price-over-cost markup sectors. In low price-over-cost markup sectors, markups are relatively unresponsive to exchange rate changes, whereas sectoral investment patterns are strongly affected. By contrast, high markup industries absorb much of the exchange rate fluctuations in markups and pass relatively little through to real investments.

investments, while only unexpected changes are important for stock returns (Bodnar & Gentry, 1993). Furthermore, most firms are able to hedge expected exchange rate shocks, nevertheless it is the unexpected exchange rate exposure which is of particular interest (Allayannis & Ihrig, 2001).[48] With the exception of studies such as the one of Campa and Goldberg (1999) most research of exposure tend to ignore import. However, the dual effect hypothesis[49] of Pritamani et al. (2004) states that because of the interplay between the domestic and international market, exchange rate exposure is accentuated for importers and should therefore not be neglected.

At the empirical level, a vast literature studying exchange rate exposure exists using classical ordinary least squares (OLS) approaches and elaborating on Adler and Dumas (1984) and Jorion (1990). By examining the monthly stock returns of 287 U.S. multinationals, Jorion (1990) found no conclusive evidence of a statistical significant influence of nominal exchange rate movements on stock returns. Jorion (1991) confirmed these findings in a subsequent paper where he examined the pricing of exchange rate risk in the U.S. stock market, by using two-factor and multi-factor arbitrage pricing models. Since OLS techniques do not seem to lead to conclusive answers, several other methods have been explored. Phylaktis and Ravazzolo (2005) used cointegration methodology and multivariate Granger causality tests on a group of Pacific Basin countries over the period 1980–1998. Their evidence suggests that stock and foreign exchange markets are positively related. This result is in contrast with the findings of Aloui (2007), who used the Johansen cointegration test to reveal no long-run equilibrium relationship between the non-stationarity stock indices and exchange rates. Additionally, Zhao (2010) found no stable long-term equilibrium relationship between the RMB real effective exchange rate and stock prices. However, according to Aloui (2007), in the short term, the stock and foreign exchange markets do seem to be integrated.

[48] For reasons of consistency, nominal exchange rates are preferred in the literature. The underlying motivation is that monthly inflation differentials have a low variability compared to exchange rate movements, implying that the nominal dominate the real exchange rate movements (e.g., Bodnar and Gentry (1993); Chamberlain et al. (1997); Choi and Prasad (1995); Griffin and Stulz (2001)). This was empirically proven by Mark (1990) who showed that contemporaneous movements in real and nominal exchange rates are almost perfectly correlated for seven currencies examined. As a consequence, the use of real versus nominal exchange rates has a negligible effect on exposure estimates. Finally, exchange rate exposure is time-varying, therefore the observation frequency of deflators might be problematic, since they are composed on a yearly basis (Ekholm et al., 2012).

[49] See Section 3.2.2 for further details on the dual effect hypothesis.

According to their empirical evidence, stock markets are less affected by exchange rate movements, than reversed. Nevertheless, the findings of Pan et al. (2007) suggest it is the other way around. For their dataset of Asian countries, the authors found no significant causality from stock prices to exchange rates, while a causal relation from exchange rates to stock prices is found for all countries. Pan et al. (2007) suggested that their findings also are an indication that linkages could possibly vary across economies with respect to exchange rate regimes, the trade size, etc. Additionally, Walid et al. (2011) provided strong evidence that the relationship between stock and foreign exchange markets is regime dependent, and stock-price volatility responds asymmetrically to events in the foreign exchange market. They demonstrated that foreign exchange rate changes have a significant impact on the probability of transition across regimes. According to Bergbrant et al. (2014), who used a survey of firm-level data from 55 countries, exchange rate exposure varies with foreign involvement. More specifically, exposure is found to be higher for import-only firms than for export-only firms. This is in agreement with Chou et al. (2017), who found not only the influences of exchange rate fluctuation on stock returns to vary enormously for different currencies, but also the level of foreign sales to be a key determinant of economic exposure.

In summary, all the aforementioned contributions indicate that estimating exchange rate exposure depends on a large number of parameters. However, since there is no consensus concerning the estimation of exchange rate exposure, there exists no unique model integrating all the complexity of the effects of exchange rate shocks on firm value. Despite the theoretical support that there is a relationship between stock prices and exchange rates, the exchange rate puzzle remains largely unsolved. Some studies of causality provide evidence, differing across countries, of no causality, unidirectional causality or bivariate causality. Most of the firm level studies indicate a significant relationship (e.g., Bodnar & Wong, 2003; Choi & Prasad, 1995; De Jong et al., 2006; Di Iorio & Faff, 2000; Dominguez & Tesar, 2006a; Doukas et al., 2003; El-Masry, 2006; Hutson & Stevenson, 2010; Kiymaz, 2003), however, only for a minority of the firms. As such, there seem to be some essential pieces missing of the exchange rate puzzle in order to find unanimous convincing empirical evidence of currency exposure.[50]

3.2.2. Importance of a firm-specific trade-weighted exchange rate index

The empirical literature agrees that multinational firms tend to exhibit higher stock return volatility than non-multinational firms because selling abroad is also a source of risk exposure to firms (Bernard et al., 2005; Fillat & Garetto, 2015; Riahi-Belkaoui, 1999). Following a negative shock, these firms are reluctant to exit the foreign market because they would forgo the cost they paid to enter (Fillat & Garetto, 2015; Franke, 1991). Additionally, Girma et al. (2016) find that a greater reliance on foreign markets increases a firm's risk and as such the volatility of its stock returns. Moreover, greater reliance on foreign trade increases firm-level volatility by intensifying the sensitivity of business cycle conditions.

At the theoretical level, the view that exchange rate risk adversely affects trade seems reasonable. Exchange rate risk causes the level of trade to become sensitive to exchange rate uncertainty, reduces the level of trade, and increases the terms of the tradeoff of expected profit for a reduction in risk (e.g., Clark, 1973; Ethier, 1973; Hooper & Kohlhagen, 1978). However, the more speculative or risk seeking the firm, the less significant this relationship will be. Moreover, the hypothesis is based on the assumption that firms cannot alter factor inputs in order to optimally adjust and take into account exchange rate movements. Nevertheless, when this assumption is relaxed, and one or more production factors can respond to increased exchange rate variability, profit opportunities can arise. As a result, rather than impeding trade, increased exchange rate risk may increase trade (e.g., Broll & Eckwert, 1999; De Grauwe, 1988; Franke, 1991; Sercu, 1992; Viaene & de Vries, 1992). As such, the existence of a positive relationship between exchange rate volatility and exports has been theoretically confirmed. Nevertheless, Sercu and Uppal (2003) were able to show, that it is possible to have either a negative or a positive relationship between trade and

[50] For additional information concerning exchange rate exposure, see also the exhaustive literature review of Muller and Verschoor (2006b).

exchange rate volatility, depending on the source underlying the exchange rate risk. This is in line with the dual effect hypothesis of Pritamani et al. (2004) which elaborates on the flexible price monetary model[51] by incorporating international trade and exchange rate exposure. More specifically, exporting firms undergo offsetting effects since the adverse consequences of a strengthening domestic currency in its foreign market is at least partially mitigated by the gains of a stronger domestic economy. Similarly, when the domestic currency depreciates, the effects of a weaker domestic economy are partially offset by a stronger position of exporting firms in foreign markets. Importing firms benefit from an appreciating domestic currency in both the domestic and foreign market, while during times of a depreciating home currency, they are adversely affected in both markets (Pritamani et al., 2004). These two accentuating effects suggest more pronounced exchange rate exposure at the importing side than the exporting side. Further, our sample mainly consists out of two-way traders, which are firms that export a large share of their output but also import a large share of their intermediate input. Elaborating on the dual effect hypothesis for two-way traders, a depreciating domestic currency may make exporting to foreign markets more attractive. However, importing the intermediate inputs to fabricate the exporting good becomes more expensive, offsetting the beneficial effect of export, making exporting to the foreign market less attractive. Since the exporting activities cannot entirely offset the accentuating effects of the importing side and domestic market, two-way traders are still left exposed, i.e., exchange rate exposure is not entirely neutralized. An appreciating domestic currency makes exporting less attractive, but importing the intermediary goods for producing the product becomes cheaper, as such, the adverse effects may be offset by selling at lower production cost to the booming domestic market. Moreover, these firms are now able to export at a lower cost, making them again more attractive on the foreign market.

Despite the fact that the empirical literature has not yet been able to provide evidence which would clarify the relationship between trade and exchange rate exposure, it is clear that trade can play an important role when estimating

[51] The flexible price monetary model states that there exists a positive association between growth in the domestic economy and domestic currency movements (Mussa, 1976).

exchange rate exposure. Therefore, this research chooses to build firm-specific trade-weighted exchange rates indices which are composed of bilateral exchange rates of all countries based on a company's trade activities. Most studies use a common exchange rate index for all firms in the sample. The aggregate exchange rate does not effectively capture changes in industry competitive conditions induced by moves in specific bilateral exchange rates. Moreover, the choice of an exchange rate index used to capture exposure, influences the observed level of exposure (Dominguez & Tesar, 2006a; Fraser & Pantzalis, 2004). Empirical research on currency exposure often uses a proxy to capture the exchange rate movements affecting firm value. Three different types of proxies are used. First, a bilateral currency exchange rate based on the single currency method is used when the dominance of one country as trading partner or a currency is assumed. As such, primarily one currency is considered to affect the value of the firm in the sample. Obviously, this method neglects a firm's exposure to other currencies (Aggarwal & Harper, 2010; Williamson, 2001). Second, other studies employ trade-weighted exchange rates. These trade-weighted exchange rates are based on macroeconomic data which are computed with price and trade flow series at the national level. Weighted indices may underestimate exposure since they have the tendency to average out the competitive effects resulting from bilateral exchange rate shocks (Choi & Prasad, 1995; Dominguez & Tesar, 2006a; Du et al., 2013; Tang, 2015; Williamson, 2001). Third, few studies build firm-specific exchange rates indices which are composed of bilateral exchange rates of all countries based on a company's trade activities or subsidiaries (Dai & Xu, 2017; Ekholm et al., 2012; Fraser & Pantzalis, 2004; Ihrig, 2001).[52] However, the time slots when a company only imports or exports or even refrains from trading are

[52] Because of the scarcity in the literature, not all cited studies, using firm-specific exchange rates, focus on the relationship between exchange rate movements and firm value. More specifically, Ekholm et al. (2012) use firm-level data to investigate the impact of a sharp real appreciation of the Norwegian Krone in the early 2000s on investment demand by Norwegian manufacturing firms, which differ substantially in their trade orientation. As they make use of extensive micro data with detailed information on individual firms' exports and imports of intermediates, they manage to calculate precise measures of a firm's net currency exposure (which take into account the share of exports in total output and the share of imported inputs in total costs).
Also Dai and Xu (2017) examine how exchange rate shocks affect intra-industry labor reallocation across firms. The authors use comprehensive Chinese firm-level data to examine the employment response to exchange rates of firms. They construct firm-specific effective exchange rates to accurately measure exchange rate shocks pertinent to individual firms. The study shows that exchange rate movements induce significant labor reallocation across firms with different degrees of external orientation and with different trading partners. Compared with effective exchange rate measures at more aggregate levels, using firm-specific effective exchange rates generates estimation results more consistent with theory and substantially increases the estimated impact.

often ignored. While most studies focus on companies that continuously trade or at least presume that the distribution of a company's stock return is the same whether it is trading or not, this research investigates the correctness of this assumption. No attempt thus far has been made to take this issue into account.

Because firms often operate in different international locations, relying on a common exchange rate index applied to all firms in the sample will often result in the foreign exchange rate exposure parameter being nonsignificant (Fraser & Pantzalis, 2004). The industry-level studies on the economic impact of exchange rate movements have generally adopted industry-specific exchange rates that are constructed using industry level trade weights. Nevertheless, using industry-specific exchange rates does not account for the substantial heterogeneity of a firm's distribution across export destinations and import countries (Dai & Xu, 2017). Firms exposed because of their trade activities still react very differently when they are hit by an exchange rate shock. Even when these firms belong to the same (export) industry, they may be affected very differently. For example, an appreciation of the home currency, will increase the competitive pressure for exporting firms. However, firms that sell a large share of their output, often import a large share of their intermediate inputs. Because of the real appreciation, the latter tends to become cheaper, as such the exchange rate shock has an ambiguous effect on profitability and firm performance. Furthermore, according to Baldwin and Krugman (1989), a decision to enter a foreign market[53] is a type of investment and a decision to abandon a market amounts to capital consumption. The authors highlighted the difficulty of properly modeling trade effects of exchange rate dynamics since they cannot be captured by the usual econometric assumptions that behavior can be represented by continuous functions and a fixed structure of leads and lags. As such, unconventional statistical techniques may be necessary. Additionally, Alessandria and Choi (2007) emphasized the importance of the entry and exit decisions of firms into foreign markets for trade and real exchange rate dynamics. According to the authors, exporters continue to export as long as the value of doing so exceeds the continuation cost. The value of entering the foreign market varies across non-exporters and the value of continuing in the foreign market varies across

[53] The extensive margin of trade refers to a firm's decision whether or not to enter a foreign market.

exporters. These values change over time and generate a time-varying distribution of exporters and non-exporters. Nevertheless, most literature is based on data at the industry-level, while more recent contributions are based on firm-level data. However, some researchers believe that aggregation reduces the statistical significance of the results (Allayannis, 1997). It is more precise to use the firm-level data to construct an extensive microdata set in order to calculate precise measures of exposure. This method accounts for the heterogeneity across firms with respect to their currency exposure, taking into account the share of exports in total output as well as the share of imported inputs in total costs. As such, it overcomes a severe shortcoming of previous analyses of exchange rate shocks, namely, the lack of detailed firm-specific measures of exposure (Ekholm et al., 2012).

3.2.3. Methodological evolutions

3.2.3.1. Distribution of the stock returns and exchange rates

Before modeling the economic relationship between exchange rates and stock returns, we need to know more about their distributions. It is well known that the normal distribution is inadequate to model the skewed behavior and kurtosis, or fat tails, of stock returns. Early empirical evidence, suggesting that stock returns are not well described by a Gaussian distribution, was given by Mandelbrot (1963) and Fama (1965). It is now well recognized that the fat-tailed unconditional stock return distributions may result from the time-varying volatility in the underlying stochastic process governing the stock return dynamics (Bollerslev et al., 2013). For example, Jondeau et al. (2007) also found, with their explicit parametric model for several equity portfolios, much stronger tail dependence on the downside. In addition, correlations between equity returns tend to be higher during sharp market declines than during “normal” periods. While there is a bulk of empirical evidence confirming that stock returns have distributions with heavier tails than those of the normal distribution, this does not imply that the normal distribution should not be considered when trying to properly fit the distribution of stock returns. For example, according to Fukuda (2009b), the possibility of distribution switching of stock returns could be easily examined by calculating the excess kurtosis for the subsamples. Empirical results show that in two out of the six countries, the monthly time series of stock returns are generated from the normal distribution before the switch point and from the Student-t distribution after the switch point. Both the switch points were caused by international economic crises. In another paper, Fukuda (2009a) investigated a new method for detecting regime switches between different magnitudes of volatility and, as such, the switches between Gaussian and Cauchy[54] distributions. He finds that after an international financial crisis the volatility should be described by a Cauchy distribution instead of a Gaussian one. Except for the work by Fukuda (2009a, 2009b), regime switches between different distributions is not considered in the literature. Our research also includes a switching point concerning the trade decision. More specifically, when a firm prefers not to trade, we expect less volatility in the stock returns and, as such, a different distribution than when the firm decides to trade. Without being exhaustive, the review of the previous research shows that the Student-t distribution is one of the most favored distributions in modelling stock returns.

Empirical studies also find the distributions of exchange rate returns too fat-tailed, or leptokurtic, to satisfy normality (Boothe & Glassman, 1987; McFarland et al., 1982; Rana, 1981; Rogalski & Vinso, 1978; Tucker & Pond, 1988; Westerfield, 1977). According to Huisman et al. (2002), who investigated the currencies of 16 countries, measured against both U.S. dollar and Deutsche mark for the period 1979-1996, the distribution is asymmetric. Their research showed significant differences between the left and right tail and, as such, found the assumption of an underlying symmetric distribution inappropriate. Next, for eight exchange rates, Gurrola (2008) compared the unbounded Johnson family to the normal mixture and the Skewed Student-t distributions. Since the examined cases contained higher kurtosis, it seemed that the power of the Skewed Student-t density, which provided the best fit of the empirical distribution, increased as departures from normality were greater. More recently, Corlu and Corlu (2015) investigated the performance of the Generalized Lambda distribution to capture the skewed and leptokurtic behavior of exchange returns. They compared this

[54] The complete specification of the Cauchy distribution requires a location parameter, δ, and a scale parameter, θ. However, the standard Cauchy distribution is also a special case of the Student-t distribution with one degree of freedom (Fabozzi & Pachamanova, 2016).

distribution to the Skewed Student-t, the unbounded Johnson family and the Normal Inverse Gaussian distributions. The authors found that in terms of overall fit, all methods perform similarly to each other. However, the Normal Inverse Gaussian, the Skewed Student-t and the Generalized Lambda distribution do a better job in capturing tail behavior of the exchange rates. Nadarajah et al. (2015) comment on these findings by reanalyzing the data. They show that Student-t and Skewed Student-t distributions always gave the best or second best fits. As such, according to Nadarajah et al. (2015), a simpler distribution than those preferred by Corlu and Corlu (2015) often fits the data at least as well. Without being exhaustive, the review of the previous research shows that the Skewed Student-t distribution is one of the most favored distributions in modelling exchange rates.

3.2.3.2. Copula functions

Baldwin and Krugman (1989) already pointed out the shortcomings of classic econometric assumptions and techniques in modelling exchange rate dynamics and exchange rate exposure. These techniques assume that behavior is often linear, symmetric, time invariant, represented by continuous functions or that leads and lags follow a fixed structure. Moreover, classic techniques, such as OLS, do not allow to flexibly model the distribution of each variable independently. Further, conventional methods can only account for general, expected exchange rate exposure, which is hedgeable, but fail to capture the unexpected exposure during sudden extreme events (Bartram et al., 2010). These methodological shortcomings partially explain why the empirical evidence of exchange rate exposure is mixed (e.g., Bergbrant et al., 2014; Bodnar & Gentry, 1993; Dominguez & Tesar, 2006b; Miller & Reuer, 1998; Mohapatra & Rath, 2017; Pantzalis et al., 2001).

In this research we prefer to use the copula technique to model exchange rate exposure and tackle the aforementioned methodological shortcomings. Copulas are the part of a multivariate distribution function that fully captures the cross-sectional dependence between the variables of interest. It can be seen as the joint distribution function of a set of uniformly [0,1] distributed random variables, or simply as a function, which joins the marginal distributions with their multivariate distribution function. The copula technique not only allows to express the marginal behavior of each variable, but also the association between two or more variables in a common, shared function whereby the marginal distributions of each variable can be chosen separately from the association structure between the variables. This aforementioned key characteristic of copulas, differentiating them from classic multivariate normal and Student-t distributions, enables the construction of flexible models (Joe, 1997; Nelsen, 2006).[55] As such, copulas are ideal to model comovement between stock returns and exchange rates since empirical research shows that asset returns and exchange rates have skewed and leptokurtic marginal distributions (Härdle & Okhrin, 2010; Manner, 2007).

Few studies use copula techniques to examine the dependence structure between stock and exchange rate markets. For example, static and flexible copulas were used with monthly data over the 1995-2006 period by Michelis and Ning (2010) to characterize the tail dependence between aggregate stock returns and foreign exchange rate markets. More specifically, they investigated the dependence structure between the aggregate real Canadian stock returns and the real USD/CAD exchange rate returns. The authors found more dependence in the left than in the right tail of their joint distribution, resulting in a significant asymmetric tail dependence over time. On the same note, Y. Wang et al. (2013) developed a dependence-switching copula model to describe the dependence structure between the stock and foreign exchange markets. The authors discussed tail dependence for bear and bull markets associated with currency depreciation and appreciation using daily stock returns and exchange rate changes for six major industrial countries over the 1990–2010 period. They found that a positive and negative correlation between the exchange rates and stock returns results in different tail dependence structures. Their results suggested that analyzing cross-market linkages within a time-invariant copula framework may not be appropriate. More recently, Kamal and Haque (2016) studied the degree of dependence of the bivariate distributions of stock market and foreign exchange market returns of three South Asian countries. The results from their copula-GARCH models indicate the existence of asymmetric dependence structures, with upper tail dependence for all pairs, implying dependence increases in bull market situations. Further,

[55] A more extensive introduction into copulas can be found in Appendix B25.

Reboredo et al. (2016) examined the interrelationship and dynamic changes between the exchange rates and stock prices of emerging countries. The research focused on the dependence structure between currency and stock returns using copulas, and computed downside and upside value-at-risk and conditional value-at-risk. They found evidence of a positive relationship between stock prices and exchange rates. Their analysis also showed downside and upside spillover risk from currencies to stock returns and vice versa. Reboredo et al. (2016) found asymmetries in upside and downside risk spillovers and asymmetric differences in the size of risk spillovers when the domestic currency values against the U.S. dollar and the euro. However, no research yet has modelled the comovement between trade-weighted firm-specific effective exchange rates and the stock returns.

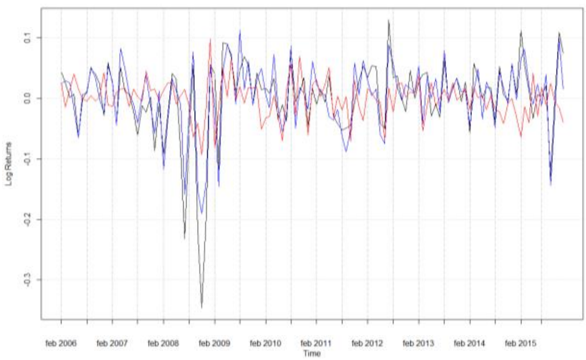
3.2.4. Exchange rate exposure in open economies: comparing Belgium and the Netherlands

Many studies focus on U.S. financial markets,[56] however in search of empirical evidence of exchange rate exposure theory, other countries are also explored. Researchers argue that currency risk exposure might be better investigated in an open economy because of its stronger ties with foreign trading activities (Chamberlain et al., 1997; Friberg & Nydahl, 1999; He & Ng, 1998; Hutson & Stevenson, 2010; Muller & Verschoor, 2006b). It is logical to assume, other factors being equal, that firms in open economies experience greater exposure than those in closed economies, simply because they engage more in international trade. The Belgian economy has a strong international focus and can be considered as a hub of international contacts. Not only EU institutions but also more than a thousand international public and private organizations have their headquarters or a permanent secretariat in Belgium. However, this role as a regional logistical hub makes its economy vulnerable to shifts in foreign demand. In 2014, multinationals represented in Belgium 2% of the non-financial enterprises in the private sector. Together with their associated companies, they create 45% of value added and employ around 37% of wage earners. Their small

[56] Examples are: Bartov et al. (1996); Bodnar et al. (1998); Choi and Prasad (1995); Chou et al. (2017); Chow et al. (1997); Fraser and Pantzalis (2004); Gao (2000); Howton and Perfect (1998); Jorion (1990, 1991); Koutmos and Martin (2003); Pantzalis et al. (2001).

number combined with their economic importance indicates that the multinationals are relatively large. Since their share of value added outweighs their share of employees, it also can be said that the apparent productivity of wage earners in multinationals is relatively high. However, the Belgian economy is heavily dependent on small and medium enterprises (Statistics Belgium, 2015). The Netherlands, which is the sixth-largest economy in the EU, also plays an important role as a European transportation hub. The Dutch economy persistently has a high trade surplus, stable industrial relations, and low unemployment. It also is strongly internationally oriented, since some of the world's leading multinationals are headquartered in the Netherlands. In 2014, 2% of all firms was a multinational, accounting for 40% of the private sector employment. These multinationals provide more than 80% of international trade in goods (Statistics Netherlands, 2015).

Figure 3.1 MSCI Belgium (blue), MSCI Netherlands (black) and the euro-dollar exchange rate (red) from 01/01/2006 to 12/31/2015



(Datasource: DataStream/Thomson Reuters Eikon)

Since this research focuses on Belgian and Dutch listed firms, it enables a comparative perspective on exchange rate exposure. For the sake of an overall comparison, Figure 3.1 plots the MSCI[57] of both countries and the euro-dollar exchange rate in log returns. As the figure shows, the MSCI indices of Belgium

[57] MSCI Belgium: This index is designed to measure the performance of the large and mid-cap segments of the Belgium equity market. With 10 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in Belgium.
MSCI Netherlands: This index is designed to measure the performance of the large- and mid-cap segments of the Dutch market. With 24 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in the Netherlands (Morgan Stanley Capital International, 2016).

and the Netherlands have a similar course and volatility.[58] Nevertheless, in periods of strong volatility, e.g., during the financial crisis 2008-2009, we see that the Dutch MSCI index shows more extremes. However, by only using macro data, it is impossible to verify what caused the Dutch MSCI index to take on a more volatile course compared to the Belgian one. Insights into micro economic data may be very useful in explaining their differences. Additionally, Figure 3.1 indicates that even in periods when volatility rises, the euro-dollar exchange rate and the MSCI indices seem to move together, which might be an indication of a positive relationship. This indicates that shocks to open economies which also affect exchange rates can have severe consequences, as we saw during the financial crisis of 2008-2009.

Despite the fact that volatility is similar and some patterns may be noticeable in Figure 3.1, it is nevertheless important to undertake a formal analysis in order to confirm their nature, since they could be due to random variation rather than changes in the underlying process. Furthermore, both countries are part of the euro area, and face common external exchange rates which are sometimes a source of asymmetric shocks. As such, the monetary policy of the European Central Bank, indirectly leading to adjustments of the exchange rate of the euro, may have a more powerful impact on firms of member countries that trade more outside the Eurozone than those that trade less outside the Eurozone (Angeloni & Ehrmann, 2004; Lane, 2006). The measures from Figure 3.1 are too aggregated to be able to determine why both economies may react differently in terms of exchange rate exposure. Disaggregated and tailor-made measures for firms in both countries could enable us to more accurately investigate and determine the dynamics behind exchange rate exposure for both countries.

[58] Volatility refers to the dispersion or standard deviation of a financial return. As such, it is a statistical property of a return (Sollis, 2012). The empirical models in this research are based on returns, however, in order to describe the results volatility is also discussed. Furthermore, in this research volatility does not limit itself to financial returns. As such, we expand the definition of volatility to the dispersion of the subject to which is it applied.

3.3. Data

To estimate exchange rate exposure we primarily require exchange rates, stock returns and trade data, presented in this Section.

3.3.1. Trade data

For the Netherlands, trade data of 82 publicly listed firms are obtained from Statistics Netherlands spanning the period 2006-2015. This dataset is a comprehensive panel of monthly trade flows by firm, exports by destination and imports by source country. The data are customs data from the International Trade in Goods statistics, which contain import and export data and follow the Eurostat European Regulation. The figures based on this Regulation follow the principle of crossing borders. As such, the value of import as well as the value of export is recorded at the Dutch border for the Dutch National Accounts. This means that imports are valued at the border of the importing country (i.e., cif-value: value, cost, insurance and freight) and exports are valued at the border of the exporting country (i.e., fob-value: free on board).[59] Transit trade is not included in the dataset. Statistics Netherlands gave us access to the relevant data for this research which enables us to calculate firm-level exports by destination and imports by source country, which will be used to construct firm-specific trade-weighted exchange rates. The level of granularity of the Dutch data is at the listed firm which is not necessarily the enterprise group firm.

The necessary Belgian trade data were obtained from the National Bank of Belgium for 88 publicly listed firms spanning the period 2006-2015. The Belgian import and export data are collected separately at firm level for extra-EU (Extrastat) trade as well as intra-EU trade (Intrastat). Companies report their transactions monthly. There are two kinds of declarations, the standard one and the extended declaration. Both declarations report the product code, the type of transaction, and the destination or origin of the goods, the value, the net mass and units. Companies whose annual receipts or shipments exceed the threshold

[59] The difference between the cif- and the fob-value of imports concerns the costs incurred in transporting the intermediate route (the border between the exporting country and the Dutch border). These are mainly transport and insurance costs.

of 25 million euro for their annual receipts or shipments must fill up the extended declaration. The extended declaration includes, in addition to the same common variables of the standard declaration, also the means of transport and the conditions of delivery. The data is collected by customs agents and centralized at the National Bank of Belgium. This also means, similar as for the Dutch trade data, that imports are valued at the border of the importing country and exports are valued at the border of the exporting country. The Extrastat data records all flows, unless their value is smaller than 1000 euro or their weight smaller than one ton. Transit trade is also not included in the dataset. The National Bank of Belgium provided us with the firm-specific trade-weighted exchange rates for the 88 publicly listed firms spanning the period 2006-2015.

For Belgium and the Netherlands, the listed firms are identified by respectively the VAT number and the Chamber of Commerce number. Trade outside the European Union is collected by the customs office where large traders send the data to Statistics Netherlands directly. This is on detailed country and product level. We note that for the Netherlands the National Accounts also use the same data. However, concerning trade in goods they have many different other sources to create a complete image of the Dutch economy. They harmonize concepts and classifications and integrate the data to obtain a consistent view. Since we use firm-level data, this is less of an issue. Since in both cases the trade data are collected at respectively the Belgian and Dutch border by customs agents in the context of the National Accounts, these data are comparable across the countries of interest.

3.3.2. Stock prices and exchange rate data

Bartov and Bodnar (1994) suggest that previous weak findings of exchange rate exposure are due to the poor sample selection criteria, whereby firms with no ex ante exposure are included. In order to account for this issue, we include only trading companies that were publicly listed for at least 100 months during the period 2006-2015 in the sample. As such, starting from at least 100 observations, only long-living firms are used for our sample composition. This is necessary in order to collect cross-sectionally enough datapoints to construct reliable marginals for the copula models from Section 3.4. The Dutch and Belgian datasets cover respectively 82 and 88 stock market returns from publicly listed firms. The second dataset contains nominal exchange rate data from their 245 trading partners, euro expressed in foreign currency, spanning the period from 01/01/2006 until 12/31/2015. We downloaded monthly stock prices and nominal exchange rate data from Thomson Reuters DataStream. For the monthly data, prices and rates on every first day of the month are taken in consideration.

3.3.3. Matching the datasets and sample construction

Based on the initial trade data sample described in Section 3.3.1, we construct for the Netherlands a second trade dataset, containing only transactions with non-Euro member countries. This dataset serves for the computation of the trade-weighted exchange rates. In order to properly calculate firm level trade-weighted exchange rates per month, the exchange rate data are merged with the aforementioned trade dataset using respectively the country code and the date variable. After computation, the firm dataset contains 9758 observed trade-weighted exchange rates for 82 firms and will be used further for modelling purposes. We notice 4498 not available (NA) values when no export and 3531 NA values when no import was registered. In one case there was no exchange rate change observed, which resulted in a 0 for the trade-weighted index. Finally, the stock prices are matched with their specific trade-weighted exchange rate using the firm names and date variable.

Similarly for the Belgian case we construct identical datasets containing 10,472 observations for 88 firms. In this case we observe 5692 NA values when no export transaction and 5257 NA values when no import transaction has taken place. The only observed 0 was the result of no exchange rate change. The fact that a large amount of NA values is observed for both countries will play an important part in the explanation of the methodology.

The tables from Appendix B1-B4 give an overview of the sample specifics and the cross-sectional summary statistics of the key variables. Table B1 gives us already and indication about the non-normal distribution which is suspected.[60] Table B2 presents the sample composition for both Belgium and the Netherlands into more detail. For both countries the majority of the traders are two-way traders while the remainder of the sample are importers. Being solely an exporter is an exception, since there are none in the Dutch sample and only two in the Belgian sample. Since import is important to almost every firm of the sample, this also implies that both country samples are extremely vulnerable to changes in foreign supply. Further, Tables B3 and B4 demonstrate that Belgian listed firms mostly trade with European countries, while Dutch listed firms mainly trade with non-European countries. Furthermore, while the number of firms in both samples is more or less the same, the total non-European imported value is three times and the total non-European exported value is four and a half times as high for the Dutch firms compared to the Belgian firms for the entire sample period (Table B4). The former indicates that, while both countries are open economies, the Dutch sample has a more global focus than the Belgian sample. Finally, the probability and density plots of the key variables are presented and discussed in Section 3.5.1.

3.4. Methodology

3.4.1. Firm-specific trade-weighted effective exchange rate index

The bulk of the literature, with some exceptions, looks at exposure using a common foreign exchange rate index. This is in contrast to the methodology adopted in this research, which is the construction of firm-specific trade-weighted foreign exchange indices. The construction of the index is consistent with the method of Dai and Xu (2017) and provides further evidence on exchange rate exposure and the role indices play in the subsequent analysis.

[60] More specifically, the null hypothesis of the Jarque-Bera test cannot be rejected for the firm-specific export-weighted exchange rate (later referred to as $\Delta EXER_{i,t}$) for 67 of the Belgian and 58 of the Dutch months out of 119 months totally. Similarly, the aforementioned null hypothesis cannot be rejected for the firm-specific import-weighted exchange rate (later referred to as $\Delta IMER_{i,t}$) for 74 of the Belgian and 41 of the Dutch months out of 119 months totally. The results are available upon request.

Before constructing the necessary variables for this research, every nominal exchange rate is scaled relatively to the base value, of January 2006, which is set equal to 100. Further, we construct the following three variables in our panel dataset $\left(R_{i,t},\ \Delta EXER_{i,t},\ \Delta IMER_{i,t}\right)$ for the different firms $(i = 1, \dots, n)$ over a period of T months $(t = 1, \dots, T)$.

$$R_{i,t} = \left(\frac{S_{i,t} - S_{i,t-1}}{S_{i,t-1}}\right)$$

$$\Delta ln\left(e_{k,t}\right) = ln\left(\frac{e_{k,t}}{e_{k,t-1}}\right)$$

$$\Delta EXER_{i,t} = \sum_{k=1}^{K}\left[EX_{i,k,t-1}\Big/\sum_{k^*}^{K} EX_{i,k^*,t-1}\right]\Delta\, ln\left(e_{k,t}\right) \tag{19}$$

$$\Delta IMER_{i,t} = \sum_{k=1}^{K}\left[IM_{i,k,t-1}\Big/\sum_{k^*}^{K} IM_{i,k^*,t-1}\right]\Delta\, ln\left(e_{k,t}\right) \tag{20}$$

with:

- $R_{i,t}$ equals to the stock price return of firm i at time t ($S_{i,t}$ is the stock price)
- $\Delta EXER_{i,t}$ is the weighted effective export exchange rate index of firm i at time t.
- $\Delta IMER_{i,t}$ is the weighted effective import exchange rate index of firm i at time t.
- $EX_{i,k,t-1}$ equals the total value of exported goods of firm i to country k at time $t-1$.
- $IM_{i,k,t-1}$ equals the total value of imported goods of firm i from country k at time $t-1$.
- $\Delta ln\left(e_{k,t}\right)$ represents the bilateral exchange rate change with country k ($e_{k,t}$ is the exchange rate with country k at time t).

In equations (19) and (20), we note that the exchange rate indices are weighted averages of the bilateral exchange rate changes over the different countries. Hereby, we note that the weights for firm i are based on the value of trade that this firm has in a certain country k in a given month $t-1$:

$w_k^{i,t} = \frac{EX_{i,k,t-1}}{\sum_{k^*}^{K} EX_{i,k^*,t-1}}$ or $w_k^{i,t} = \frac{IM_{i,k,t-1}}{\sum_{k^*}^{K} IM_{i,k^*,t-1}}$ $,\forall k = 1, \dots, K.$

In case of continuous trade, we see that these weights are properly defined: $w_k^{i,t} \geq 0, \forall k = 1, \ldots, K$ and $\sum_{k=1}^{K} w_k^{i,t} = 1$.

Nevertheless, several firms do not trade (either export and/or import) every month. Therefore we note that in such months all weights are equal to zero and do not sum up to one. In this situation, the firm-specific exchange rate index of a firm is not properly defined and generate a NA value for these months. Although in this way, we have a lot of missing values for the firm-specific exchange rate indices of our dataset, we can still use the information on whether a NA value is observed to model the probability of whether a firm will trade or not during a given month. Hereto we define two new indicator variables ($Export_{i,t}$ and $Import_{i,t}, \forall i, t$) as:

$$Export_{i,t} = I(\Delta EXER_{i,t} \neq NA) = \begin{cases} 1 & \Delta EXER_{i,t} \neq NA \\ 0 & \Delta EXER_{i,t} = NA \end{cases}$$

$$Import_{i,t} = I(\Delta IMER_{i,t} \neq NA) = \begin{cases} 1 & \Delta IMER_{i,t} \neq NA \\ 0 & \Delta IMER_{i,t} = NA \end{cases}$$

We see that these indicator variables have a Bernoulli distribution with the probability on respectively export and import trade for a company as parameters. We expect this to have implications for the distribution of the stock return. More specifically, in the event a firm prefers not to trade, we expect less volatility in the stock returns and as such a different distribution compared to the periods the firm decides to trade.

Therefore, we observe the following five variables $(R_{i,t}, \Delta EXER_{i,t}, \Delta IMER_{i,t}, Export_{i,t}, Import_{i,t})$ in the panel data set for the different firms $(i = 1, \ldots, n)$ over a period of T months $(t = 1, \ldots, T)$.

3.4.2. Modelling the association

In this Section, we want to study the association between the stock price returns and each of the different trade-weighted firm-specific effective exchange rate indices. Hereto we will consider copula functions to introduce models for this association. The advantage of using copula functions in analyzing tail dependence is multifold. First, by specifying different copulas, we are able to separately model the marginal behavior and dependence structure between variables. Second, linear correlation is unable to provide information about the (a)symmetrical properties of the dependence and the tail dependence, whereas copula models estimate directly asymmetric tail dependence and give a succinct and exact representation of the dependencies between the underlying variables, irrespective of their marginal distributions. Third, copulas do not require normality of the variables of interest. This makes them a reliable alternative dependence measure for correlation, since the latter can only be used for elliptical distributions, with the normal distribution being a special case. Finally, the copula function is invariable to transformation of the underlying variables, which otherwise causes problems for correlation. Transformation can affect correlation estimates, potentially rendering the numerical value of the correlation meaningless (Ning, 2010).

Since we are interested in the exchange rate exposure of the entire sample for each point in time per country, we model the association between the stock returns and firm-specific exchange rate indices cross-sectionally. Such an approach allows us to distinguish trading periods from non-trading periods per firm over the entire sample and consecutively build dynamic subsamples of trading firms per point in time in order to estimate their exchange rate exposure. As such, we obtain both the general association, i.e., the expected exchange rate exposure and tail dependence, i.e., the unexpected exchange rate exposure, by applying the copula theory cross-sectionally. This approach permits us to investigate exchange rate exposure more accurately by not assuming that all firms continuously trade and accounting for extreme events.

Hereby, we first ignore the missing values and consider $\left(R_{i,t}\,, \Delta EXER_{i,t}\right)$ respectively $\left(R_{i,t}\,, \Delta IMER_{i,t}\right)$, $i = 1, \ldots, n$ as a sample for the cross-sectional variables $(R_t\,, \Delta EXER_t)$ respectively $(R_t\,, \Delta IMER_t)$. We define for each of the firm-specific effective exchange rates a copula model by assuming that the joint distribution function of these vectors is written as:

$$F_{R_{t,\Delta EXER_t}}(r,x) = P(R_t \leq r, \Delta EXER_t \leq x) = C_t\left(F_{R_t}(r), F_{\Delta EXER_t}(x)\right)$$

$$F_{R_{t,\Delta IMER_t}}(r,x) = P(R_t \leq r, \Delta IMER_t \leq x) = C_t^*\left(F_{R_t}(r), F_{\Delta IMER_t}(x)\right)$$

with:

- F_{R_t} representing the distribution of the stock price return at time t.
- $F_{\Delta EXER_t}$ equals the distribution of the weighted firms-specific export exchange rate index at time t.
- $F_{\Delta IMER_t}$ equals the distribution of the weighted firms-specific import effective exchange rate index at time t.
- $C_t : [0,1] \times [0,1] \rightarrow [0,1]$ and $C_t^* : [0,1] \times [0,1] \rightarrow [0,1]$ copula functions which join both variables together.

However, due to the missing values, we cannot always observe the vectors $(R_t, \Delta EXER_t)$ and $(R_t, \Delta IMER_t)$. Instead, we look at the vectors $(R_t, \Delta EXER_t, Export_t)$ and $(R_t, \Delta IMER_t, Import_t)$ in which $Export_t$ and $Import_t$ represent indicator variables for the missing values. The joint distribution of these vectors depends on the value of $Export_t$ and $Import_t$.

- If $Export_t = 0$ or $Import_t = 0$, we have a missing value for the weighted firm-specific effective exchange rate and the joint distribution is given by:

$$\begin{aligned}
&P(R_t \leq r, \Delta EXER_t = NA, Export_t = 0) \\
&= P(R_t \leq r, \Delta EXER_t = NA | Export_t = 0)P(Export_t = 0) \\
&= \int_{-\infty}^{+\infty} P\,(R_t \leq r, \Delta EXER_t = x | Export_t = 0)dx \times P(Export_t = 0) \\
&= P(R_t \leq r | Export_t = 0)P(Export_t = 0) \\
&= F_{R_t|Export_t}(r|0)\; P(Export_t = 0)
\end{aligned}$$

$$\begin{aligned}
&P(R_t \leq r, \Delta IMER_t = NA, Import_t = 0) \\
&= P(R_t \leq r, \Delta IMER_t = NA | Import_t = 0)\; P(Import_t = 0) \\
&= \int_{-\infty}^{+\infty} P\,(R_t \leq r, \Delta IMER_t = x | Import_t = 0)dx \times P(Import_t = 0) \\
&= P(R_t \leq r | Import_t = 0)P(Import_t = 0) \\
&= F_{R_t|Import_t}(r|0)\; P(Import_t = 0)
\end{aligned}$$

We note from these expressions that, when the firm-specific effective exchange rate is missing we are still able to get an idea about the distribution for the stock price return for firms that have not traded in the previous month. Furthermore, we have information on the probability of trade amongst the different firms.

- If $Export_t = 1$ or $Import_t = 1$, we get that the joint distribution is given by:

$$
\begin{aligned}
&P(R_t \leq r, \Delta EXER_t \leq x, Export_t = 1) \\
&= P(R_t \leq r, \Delta EXER_t \leq x | Export_t = 1)\ P(Export_t = 1) \\
&= C_t\big(P(R_t \leq r | Export_t = 1), P(\Delta EXER_t \leq x | Export_t = 1)\big)\ P(Export_t = 1) \\
&= C_t\left(F_{R_t|Export_t}(r|1), F_{\Delta EXER_t|Export_t}(x|1)\right) P(Export_t = 1)
\end{aligned}
$$

$$
\begin{aligned}
&P(R_t \leq r, \Delta IMER_t \leq x, Import_t = 1) \\
&= P(R_t \leq r, \Delta IMER_t \leq x | Import_t = 1)\ P(Import_t = 1) \\
&= C_t^*\big(P(R_t \leq r | Import_t = 1), P(\Delta IMER_t \leq x | Import_t = 1)\big)\ P(Import_t = 1) \\
&= C_t^*\left(F_{R_t|Import_t}(r|1), F_{\Delta IMER_t|Import_t}(x|1)\right) P(Import_t = 1)
\end{aligned}
$$

From these expressions, we note that we can estimate the association between the stock price return and the firm-specific effective exchange rate for the subgroup of firms which have traded. This association can change over time. Additionally, we calculate the probability of trade.

From the given data set with its possible missing values, we are still able to estimate several quantities and associations. By using the $Export_t$ or $Import_t$ indicators of the different companies, we estimate the probabilities of export or import trade. Comparing the different cross-sectional time slots, we can show how these probabilities change over time. Next, from the companies that have missing values for the effective exchange rates, we can estimate the distribution of the stock price return in the subgroup of firms: $F_{R_t|Export_t}(r|0)$ or $F_{R_t|Import_t}(r|0)$. From the subgroup of companies that have non-missing values for the effective exchange rates, we estimate the distribution of the stock price return for trading firms: $F_{R_t|Export_t}(r|1)$ or $F_{R_t|Import_t}(r|1)$; the distribution of the firm-specific effective exchange rate $F_{\Delta EXER_t|Export_t}(x|1)$ or $F_{\Delta IMER_t|Import_t}(x|1)$ and the association between the stock price return and the firm-specific effective exchange rate; i.e., C_t and C_t^*.

Furthermore, to estimate the different quantities, we can explore the hypothesis whether the distribution of the stock price return is different for firms that trade versus firms that did not trade:

$$H_0 : F_{R_t|Export_t}(r|1) = F_{R_t|Export_t}(r|0) \ vs. \ H_1 : F_{R_t|Export_t}(r|1) \neq F_{R_t|Export_t}(r|0)$$

or

$$H_0 : F_{R_t|Import_t}(r|1) = F_{R_t|Import_t}(r|0) \ vs. \ H_1 : F_{R_t|Import_t}(r|1) \neq F_{R_t|Import_t}(r|0)$$

Finally, we model the association between stock price return and firm-specific effective exchange rate as bivariate T-copulas C_t and C_t^*.

3.4.3. Robustness

In order to verify whether our results are stable, we perform three additional robustness analyzes. First, we test the strength and validity of the firm-specific exchange rate indices by re-estimating exchange rate exposure using respectively a common exchange rate, i.e., the euro-dollar exchange rate, and a common weighted exchange rate, i.e., nominal effective exchange rate (NEER) of the euro and comparing it with our initial results. According to Amiti et al. (2018), the U.S. dollar and the euro are the dominant invoicing currencies in both Belgium's exports and imports, with substantial variation in currency choice across firms and products, even within narrowly defined manufacturing industries. The dominance of the United States as a trading partner and U.S. dollar as exchange rate is also reflected in the trade data of the Dutch sample in Table B3 of Appendix B3. The NEER[61] of the euro is a weighted average of nominal bilateral rates between the

[61] The NEER of the euro is defined as: $NEER_t = \prod_{i=1}^{N} \left(e_{i,euro}^t\right)^{w_i}$ where N stands for the number of trading partners in the reference group, $e_{i,euro}^t$ is an index of the average exchange rate of the currency of trading partner i vis-à-vis the euro in period t and w_i is the trade weight assigned to the currency of trading partner i. The NEER of the euro includes the following trading partners: Bulgaria, Czech Republic, Denmark, Hungary, Poland, Romania, Sweden, United Kingdom, Australia, Canada, China, Hong Kong, Japan, Norway, Singapore, South Korea, Switzerland, United States, Algeria, Argentina, Brazil, Chile, Croatia, Iceland, India, Indonesia, Israel, Malaysia, Mexico, Morocco, New Zealand, the Philippines, Russia, South Africa, Taiwan, Thailand, Turkey and Venezuela (European Central Bank, 2019a). Further, we scale the NEER relatively to the base value of January 2006, which is set equal to 100, and compute $\Delta ln(NEER_t) = ln\left(\frac{NEER_t}{NEER_{t-1}}\right)$.

euro and a basket of 38 foreign currencies of principal trading partners constructed by the European Central Bank. We downloaded monthly euro-dollar exchange rates and NEERs of the euro from Thomson Reuters DataStream.

Second, we re-estimate the $\Delta EXER_{i,t}$ and $\Delta IMER_{i,t}$ for the manufacturing sector only. Since our data only accounts for trade in goods, the cross-sectional monthly samples will contain a majority of listed manufacturing firms. We expect that by including the remaining sectors of the economy results are averaged out. Third, we modify formulas (19) and (20) from Section 3.4.1. into formulas (21) and (22) by using lagged firm-level year trade data instead of lagged monthly data as a weighting scheme. When a firm trades with a specific country, the entire previous year is taken into account instead of only the previous month, which gives more weight to the trade history with this country as a trading partner.

$$\Delta EXER_{i,t} = \sum_{k=1}^{K} \left[\sum_{t-n}^{12} EX_{i,k,t-n} \middle/ \sum_{t-n}^{12} \sum_{k^*}^{K} EX_{i,k^*,t-n} \right] \Delta\, ln(e_{k,t}) \tag{21}$$

$$\Delta IMER_{i,t} = \sum_{k=1}^{K} \left[\sum_{t-n}^{12} IM_{i,k,t-n} \middle/ \sum_{t-n}^{12} \sum_{k^*}^{K} IM_{i,k^*,t-n} \right] \Delta\, ln(e_{k,t}) \tag{22}$$

This modified firm-specific trade-weighted effective exchange rate is then used to re-estimate the relationship with stock returns.

3.5. Empirical analysis

We now turn to the principal interest of this research, namely investigating exchange rate exposure by modelling the association between stock returns and firm-specific trade-weighted effective exchange rate indices on each point in time or cross-sectionnally. Subsection 3.5.1. provides a descriptive analysis on the probabilities of trade and their impact on the distribution of the stock returns, while empirical evidence on the association between firm-specific exchange rate indices and stock returns is provided in Subsection 3.5.2. Finally, in Subsection 3.5.3, the robustness analysis is discussed.

3.5.1. Trade probabilities and the stock return distribution

From the given dataset with its possible missing values, we are still able to estimate several quantities and associations. By using the $Export_t$ or $Import_t$ indicators of the different firms, we estimate the probabilities to export or import outside the Eurozone. Comparing the different cross-sectional time slots, we can show how these probabilities change over time. These results can be found in Appendix B6-B7 and B9-B10, where the probability of trade, for import and export, is plotted over time for the Belgian and Dutch samples. For Belgium, we observe a 45% chance of import at the beginning of the sample period. This likelihood only increases slightly and remains between 50 and 55%. The probability to export on the other hand seems to be more volatile, with an average probability around 45% for the entire sample period. For the Netherlands, we see an almost linear, upward trend for both export and import, implying a probability between 45 and 55% of trade during the beginning of the crisis. However, the slope for import seems to be steeper, since the probability rises toward 75% for import, while for export the probability of trade remains around 60% towards the end of the sample.

Furthermore, increased exchange rate volatility is likely to affect trade. More specifically, when exchange rate uncertainty rises, it can reduce the level of trade, and increase the terms of trade-off of expected profit for a reduction in risk (Clark, 1973; Ethier, 1973; Hooper & Kohlhagen, 1978). However, exchange rate uncertainty can also create trade when it implies a higher probability that the exchange rate will deviate enough from commodity price parity,[62] so it may exceed tariffs and transportation costs in order to trigger international trade (Franke, 1991; Sercu, 1992). Exchange rate volatility contains risks and opportunities for firms deciding whether or not to trade. When a firm does not decide to trade because of the increased exchange rate volatility, it eliminates

[62] Or purchasing power parity: if the currencies of two countries are valued for the goods that can be purchased with them, then the nominal exchange rate between the two currencies will be equal to the purchasing power (PP) between the two countries in arbitrage equilibrium (Cassel, 1918). This statement is also known as the absolute version of purchasing power parity (APPP) or the law of one price (LOP) (Ayala et al., 2016).

exchange rate risk, but also misses the potential profit it could have gained from trading. As such, with every decision to trade, a firm has to make a trade-off. When volatility rises, this trade-off changes, since the possible risk but also the possible profit gains rise. Therefore, we should see notable changes in the probability of trade when exchange rate volatility increases. When we compare for the Netherlands Figures B7 with B8 and Figures B10 with B11 from the Appendix, we see that both the trade probability plots have an increasing cascading pattern. Next to Figure B7 and B10 indicating a higher probability in trade throughout the sample period, we notice higher exchange rate volatility in Figure B8 and B11 during the financial crisis of 2008-2009 and the double dip recession of 2011-2012. These are periods where the Netherlands also experiences negative GDP growth.[63] Although the Dutch trade probabilities generally have an increasing pattern, we see a stagnation in their growth and an increase in the volatility during these crisis periods, which can be an indication of uncertainty about the decision to trade outside the Eurozone. Similarly, for Belgium we can respectively compare Figure B6 with B8 and B9 with B11. While the Dutch trade probabilities seem to have an increasing trend with periods of stagnation, this seems to be absent for Belgium. The Belgian trade probabilities are, however, more volatile. The pattern is also less related with the firm-specific exchange rate from Figures B8 and B11, which might indicate that trade outside the Eurozone plays a less pronounced role for the listed firms in Belgium than it does for the Netherlands.[64]

Further, in Appendix B14 the median quantile graph of the Belgian stock returns suggests that the financial crisis impacts listed importing firms (red dotted line) more severely during their trading periods than the listed importing firms during their non-trading period (blue dotted line).[65] The median quantile plot from Appendix B17 of the Belgian exporting firms during their trading and non-trading period shows a similar pattern although it is less pronounced. The same plots (solid lines in Figures B14 and B17 from Appendix) for the Dutch listed firms indicate more negative than positive outliers for trading firms, pointing out the

[63] See growth rates Appendix B5.
[64] This is in line with Appendix B4 since the listed firms in the Netherlands trade more outside the Eurozone than the Belgian listed firms.
[65] For sample composition regarding importers and exporters see Appendix B2.

additional risk which accompanies international trade. In general, the Dutch plots seem more volatile compared to the Belgian quantile plots, possibly reflecting that the Dutch listed firms are more internationally focused. More specifically, the higher Dutch volatility can be explained by the fact that Dutch listed firms have more global trading partners while Belgian listed firms choose their trading partners within the Eurozone.[66]

Additionally, to formally verify the different quantities, we explore the hypothesis whether the distribution of the stock price return is the same during trading periods versus non-trading periods. If the null hypothesis is true, then the decision of a firm to trade or not has no impact on the distribution of stock returns. The density and median quantile plots[67] from the Appendix give the impression that the distribution for trading periods is probably different from non-trading periods of a firm. To verify this presumption, we perform the Kolmogorov-Smirnov-test to compare the distributions of stock price returns for trading periods versus non-trading periods. In our case the null hypothesis is always rejected at the 5% significance level. Further, the Shapiro-Wilk test is performed, in order to verify whether the sample at hand comes from a normally distributed population. In most of the cases, the null hypothesis, stating that the sample is normally distributed, is rejected at the 5% significance level for both the Belgian and Dutch stock returns and exchange rates,[68] which is in line with the theoretical and empirical findings in the literature on the distributions of stock returns and exchange rates from Section 3.3.3. Only during the non-trading periods, the Belgian and Dutch listed import and export firms seem to have normally distributed data. Moreover, the Kolmogorov-Smirnov test indicates that the data during the non-trading periods for Belgium and the Netherlands come from the same distribution. Therefore, we conclude that the Belgian and Dutch non-trading data are normally distributed. This indicates that extreme events in the stock returns are only found during trading periods. We also note that this is visible on the quantile plots (Appendix B14 and B17), which also show a much more volatile pattern for trade (red) versus non-trade (blue). Moreover, this finding might

[66] See also Appendix B3.
[67] See plots in Appendix B12, B14, B15 and B17.
[68] The results of Kolmogorov-Smirnov test and Shapiro-Wilk test are available upon request.

explain partly why empirical research, which presumes that firms continuously trade, find less pronounced exchange rate exposure. Extreme variations might be averaged out, leading to weaker results.

3.5.2. Association between stock returns and firm-specific exchange rate indices

The former Section implies that we need to determine the most appropriate distribution for the data when firms are trading, or more specifically, we need to estimate the distribution $F_{R_t|Export_t}(r|1)$; $F_{R_t|Import_t}(r|1)$; and the distribution of $F_{\Delta EXER_t|Export_t}(x|1)$; $F_{\Delta IMER_t|Import_t}(x|1)$. The aforementioned already indicated that the data of the listed trading firms are not normally distributed (see Figures B12 and B15), both Belgian and Dutch stock returns are mainly negatively skewed and have a leptokurtic non-normal distribution. Next, as already indicated by the Shapiro-Wilk test, the Belgian and Dutch firm-specific exchange rates are also not normally distributed. Although their density plot shows a relatively symmetrical plot of the Belgian and Dutch firm-specific import and export exchange rates, the data still seems to contain a leptokurtic non-normal distribution (see Figures B13 and B16). In order to capture the behavior of our data, we fit five distributions; the Generalized Lambda distribution (GλD), the Normal Inverse Gaussian distribution (NIG), the Johnson family distribution, the Skewed Student-t distribution and the Student-t distribution to our dataset. We follow the fitting methods of Corlu and Corlu (2015).[69] To identify the most suitable distribution, we calculate the goodness-of-fit by using the Kolmogorov-Smirnov test statistic and the Anderson Darling test statistic (see Tables B18-B19 from the Appendix). We find that the Normal Inverse Gaussian and the Skewed Student-t distributions are in general the preferred distributions for both the stock returns and the firm-specific exchange rate data. Further, to decide in an objective manner an appropriate selection from the possible combinations of marginals, we use simple deduction and the Kolmogorov-Smirnov test. As such, keeping in mind the findings from Appendix B18-19, we conclude that the following combinations of distributions for the marginals, as presented in Table 3.1, are most adequate:

[69] For technical details on these flexible distributions we refer to Corlu and Corlu (2015).

Table 3.1 Combinations of distributions for marginals

		Distribution stock returns	Distribution firm-specific exchange rate
Belgium	Import	Skewed Student-t	NIG
	Export	NIG	Skewed Student-t
Netherlands	Import	Student-t[70]	NIG
	Export	NIG	Skewed Student-t

By using the Skewed Student-t and/or the Normal Inverse Gaussian distributions as its marginals, we model the association between stock price returns and firm-specific effective exchange rates as bivariate T-copulas C_t and C_t^*.[71] Next, we discuss the results[72] of the estimated T-copulas, which are fitted using the maximum likelihood method. More specifically, Table 3.2 shows the average estimated dependency[73] ($\overline{\rho_t}$) and accompanying tail dependencies (τ_t). However, since a T-copula was fitted on each point in time, the results in Table 3.2 hide a lot of important time varying information. As such, Figures 3.2 until 3.6 below visually represent the complete set of (tail) dependencies over time for the Belgian and Dutch listed importing and exporting firms.

Table 3.2 Descriptive results T-copula

T-copula $C_t(u, v; \rho, d)$		$\overline{\rho_t}$	Max ρ_t	Min ρ_t	Max τ_t
Belgium	Import (Skewed Student-t - NIG)	0.01606	0.42085	-0.44136	0.16888
	Export (NIG - Skewed Student-t)	-0.01406	0.44136	-0.46846	0.17515
Netherlands	Import (Student-t - NIG)	0.02341	0.54557	-0.65890	0.23240
	Export (NIG - Skewed Student-t)	-0.00246	0.58845	-0.50694	0.25893

[70] The Student-t is a special case of a Skewed Student-t distribution where alpha is kept equal to 0 to insure symmetry.
[71] Appendix B25 reviews the relevant bivariate copula functions for this research.
[72] The results for each point in time are significant at 1% level. The results of Cramér-von-Mises goodness-of-fit test can be found in Appendix B20. This test is based on the empirical process comparing the empirical copula with the parametric estimate of the copula derived under the null hypothesis (Genest et al., 2009). Since we are unable to reject the null hypothesis, we can conclude that the fitted copulas are suitable to estimate the dependencies in which we are interested in.
[73] Figures B21-B24 from the Appendix also show the sample version of Kendall's tau and are comparable to the Figures 3.2 and 3.4 presenting the rho of the estimated T-copulas. These figures are almost identical to the rho of the T-copulas, proving the robustness of the chosen model.

The dependency between stock returns and firm-specific exchange rates for Belgian listed importing firms are represented by an estimated average $\bar{\rho_t}$ of 0.01606. Similarly, the dependence for the Dutch listed importing firms is slightly higher for the entire sample period with an estimated average $\bar{\rho_t}$ of 0.02341. However, because these results are averages, they mask the time variability.

Figure 3.2(a) Rho T-copula for Dutch listed trading importing firms with 95% confidence bounds*

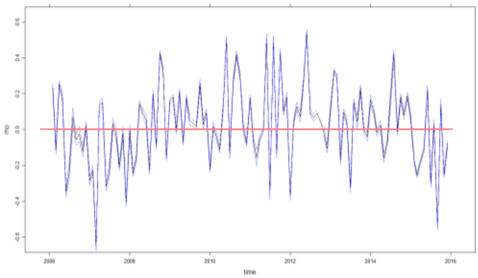


Figure 3.2(b) Rho T-copula for Belgian listed trading importing firms with 95% confidence bounds*

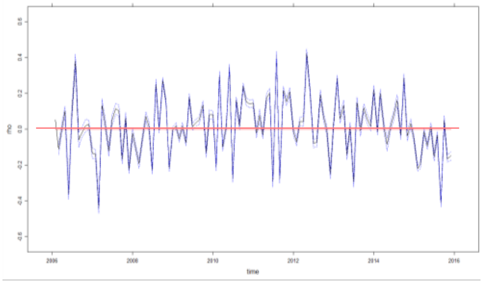


Figure 3.2(a) and (b) show the dependence, or general association, between the firm-specific exchange rates and the stock returns, expressed as rho, representing the expected exchange rate exposure for Belgian and Dutch listed trading importing firms.[74] As shown, both countries experienced peaks of positive dependence alternated with negative ones during the sample period. The most pronounced negative dependence is observable at the beginning (2007) and the end of the sample (2015). During the entire sample period the negative dependencies are balanced out by positive ones for both countries, with on average a slightly positive end result. As such, from Table 3.2, it is possible to conclude that the dependence between stock returns and firm-specific import exchange rates is on average positive. Positive dependence means that large changes of the stock returns and firm-specific exchange rate indices occur together and similarly for small changes.[75] An appreciation of the domestic currency, more specifically in our case a strengthening euro, results in a upward

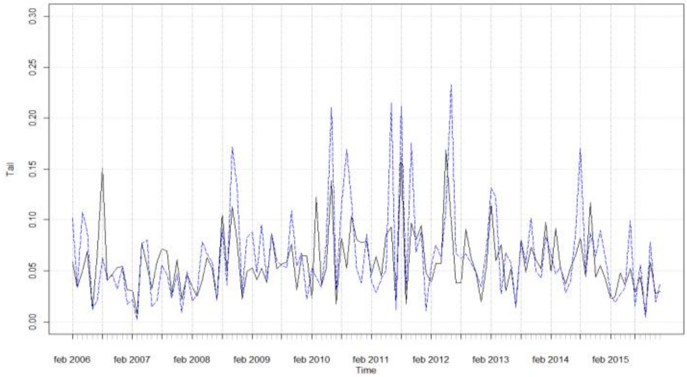
[74] The results for each point in time are significant at 1% level. The results of the Cramér-von-Mises goodness-of-fit test can be found in Appendix B20. This test is based on the empirical process comparing the empirical copula with the parametric estimate of the copula derived under the null hypothesis (Genest et al., 2009). Since we are unable to reject the null hypothesis, we can conclude that the fitted copulas are suitable to estimate the dependencies in which we are interested in.
[75] Also known as concordance. See also explanation Kendall's tau in Appendix B25.

adjustment of the exchange rate, which makes importing more attractive. The former yields favorable profit prospects and results in an upward adjustment of the stock return of importing firms. However, the average (positive) expected exchange rate exposure is small, making an analysis of the tail dependence, or unexpected exposure during extreme events, over time even more important.

Figure 3.3 shows that periods characterized by more dependence are often accompanied with more extreme events. For the Belgian case, according to Figure 3.2(b) and 3.3, peaks of high positive dependence such as the one at the end of 2006 are accompanied with higher tail dependence. Similarly for the Netherlands, Figure 3.3, shows the highest tail dependencies during the period 2010 – 2012, which is also a period characterized by higher volatility in the dependence. The levels of tail dependence never reach similar heights for Belgium as they do for the Netherlands. Therefore, we can presume that the Dutch listed firms experience significantly more extreme events than the Belgian listed firms, since their higher tail dependence indicates a higher probability of extremely large (or small) changes of stock returns and firm-specific exchange rates appearing together.[76] From the data description in Section 3.3 and Appendix B4, we conclude that the Dutch listed firms are more involved in extra-euro area trade than the Belgian listed firms from the sample, which may explain to some extent the higher tail dependence the Dutch listed importing firms experience. This finding is in line with the dual effect hypothesis of Pritamani et al. (2004), which suggests an accentuating effect of exchange rate changes of the domestic currency on listed importing firms. The Dutch listed trading firms experience a stronger accentuating effect since they import more from outside the Eurozone than the Belgian listed trading firms.

[76] By performing a t-test, we verify the hypothesis whether the tails of the trading importing listed Dutch firms are larger than the tails of the trading importing listed Belgian firms at the 5% significance level. The t-test (t = 2.054; p-value 0.021) indicates that the tails of the Dutch firms are significantly 11% stronger than the tails found for the Belgian firms.

Figure 3.3 Tail dependence T-copula Belgian and Dutch listed trading importing firms*



*Netherlands in dashed blue line; Belgium in black line; Skewed and Student-t distribution for the stock returns, Normal Inverse Gaussian distribution for the firm-specific exchange rates.

Figure 3.4(a) and 3.4(b) show that dependencies between the stock returns and the firm-specific exchange rates of the Dutch listed exporting firms, i.e., the expected exchange rate exposure, positively peak around June 2010, and shows for both countries a period of higher positive dependence during the second half of 2011.[77] This period is also characterized by higher tail dependence in Figure 3.5. In the Dutch case, however, these tail dependencies are more pronounced with the highest peak in June 2010. Further, for both countries, we observe the strongest negative dependence in September 2015. The dependence of both countries is, on average, negative. Negative dependence implies that large changes of the one occur together with small of the other and vice versa.[78] A depreciation of the domestic currency, results in a downward adjustment of the exchange rate, more specifically in our case a weakening euro, which makes the exporting more attractive. The former yields favorable profit prospects and results in an upward adjustment of the stock return of exporting firms. The average dependence over the entire sample period is closer to zero for the listed firms in Belgium than the ones in the Netherlands, but they are both small and slightly negative. Once again, this makes an analysis over time of the tail dependence or unexpected exchange rate exposure important.

[77] The results for each point in time are significant at 1% level. The results of Cramér-von-Mises goodness-of-fit test can be found in Appendix A20. This test is based on the empirical process comparing the empirical copula with the parametric estimate of the copula derived under the null hypothesis (Genest et al., 2009). Since we are unable to reject the null hypothesis, we can conclude that the fitted copulas are suitable to estimate the dependencies in which we are interested in.
[78] Also known as discordance. See also explanation Kendall’s tau in Appendix B25.

Figure 3.4(a): Rho T-copula Dutch listed trading exporting firms with 95% confidence bounds*

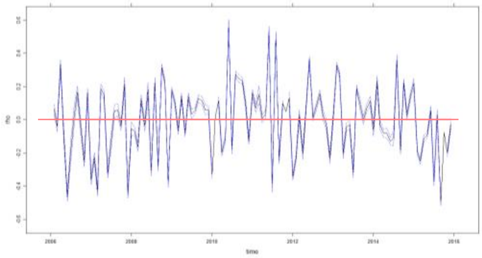
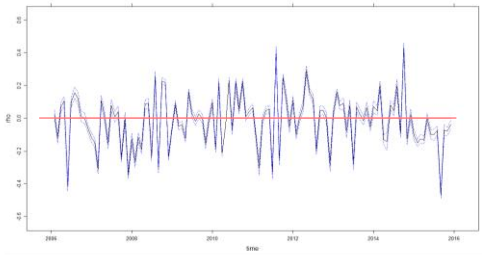


Figure 3.4(b): Rho T-copula Belgian listed trading exporting firms with 95% confidence bounds*



*Normal Inverse Gaussian distribution for the stock returns and Skewed Student-t distribution for the firm-specific exchange rates.

Figure 3.5 shows that there have been extreme events for both countries throughout the entire sample period. More extreme and pronounced dependencies can be found more frequently for the listed firms in the Netherlands. As a result, the tail dependence from these Dutch listed firms is significantly higher than the one for the Belgian listed firms, which indicates that the listed firms in the Netherlands experience more extreme events.[79] These results might indicate that the Dutch listed firms have a higher level of involvement in extra-euro area trade compared to the Belgian listed firms from the sample and therefore are more susceptible to, for example, monetary and trade policy actions of respectively the European Central Bank and the European Commission. Dutch listed firms trade more outside the Eurozone and benefit more from trade agreements (e.g., reducing or abolishing tariffs, limiting devaluation of partner currencies, etc.) which limit exchange rate volatility. Belgian listed firms prefer to stay closer to home and trade within the Eurozone, as such, trade agreements heighten competition from abroad, worsening their competitive position in the market. A contractionary monetary policy shock leads to a decrease in price level, a decrease in output, an appreciation in exchange rate (in our case a strengthening euro), and an improvement in trade balance. This affects Dutch listed firms more than it affects Belgium listed firms from our sample, since the latter are less affected by

[79] By performing a t-test, we verify the hypothesis whether the tails of the trading exporting listed Dutch firms are larger than the tails of the trading exporting listed Belgian firms at the 5% significance level. The t-test (t = 2.026; p-value 0.022) indicated that the tails of the Dutch firms are significantly 12% stronger than the tails found for Belgian ones.

the exchange rate appreciation, because they trade more in their own currency, the euro.

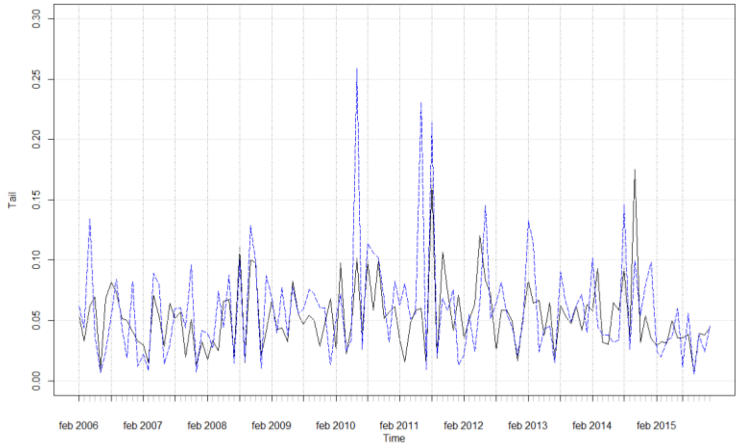
Further, it should be noted that the general dependencies, or expected exchange rate exposure, of listed importing and exporting firms have opposite signs and differ significantly.[80] Moreover, trading importing firms experience more pronounced expected exposure than trading exporting firms. The positive dependence found for importing firms on the one hand is an indication that on average exchange rate changes and stock return changes of importing firms move together in the same direction. For example, an appreciating domestic currency, adjusting the exchange rate upwards, makes importing cheaper and more attractive and as such yields future profit prospects for importing firms, adjusting their stock return upwards. Moreover, an appreciating home currency indicates a domestic market in upturn, which additionally implies that the domestic market holds beneficial profit opportunities for the importing firms. As such, the appreciation of the domestic currency is accentuated for the importing firms in both the foreign and domestic market. The negative dependence found for the exporting firms on the other hand is an indication that on average exchange rate changes and stock return changes of exporting firms move in opposite directions. For example, an appreciating domestic currency, adjusting the exchange rate upwards, makes exporting more expensive and less attractive and, as such, yields less future profit prospects for exporting firms, adjusting their stock return downwards. However, an appreciating home currency indicates a domestic market in upturn, which means that firms are able to sell more on the domestic market and, as such, can mitigate the former negative effect that the appreciating domestic currency has on exporting firms (Pritamani et al., 2004). Additionally, the tail dependence, or unexpected exchange rate exposure, for exports in both countries is significantly weaker than the tail dependence for import.[81] This

[80] By performing a t-test, we verify the hypothesis whether the difference between the general associations, or rho's, for trading exporting and importing listed firms is different from zero at the 5% significance level. The t-test for the Dutch firms (t = 2.38; p-value 0.02) and Belgian firms (t = 3.42; p-value 0.00) indicate that trading importing firms and exporting firms significantly differ regarding their expected exchange rate exposure.

[81] By performing t-tests, we verify the hypothesis whether the tails of the trading importing listed firms are larger than the tails of the trading exporting listed firms at the 5% significance level. The t-test for the Dutch firms (t = 2.32; p-value 0.01) and Belgian firms (t = 3.31; p-value 0.00) indicate that the tails of trading importing firms are significantly 9%, in the Dutch case, and 10%, in the Belgian case, stronger than the tails found for trading exporting firms.

illustrates that the listed firms with importing activities are more sensitive to extreme events since they have a higher probability of extremely large (or small) changes of stock returns and firm-specific exchange rates appearing together. This finding is also in line with the dual effect hypothesis of Pritamani et al. (2004), which suggests an accentuating effect of exchange rate changes of the domestic currency on listed importing firms.

Figure 3.5 Tail dependence T-copula Belgian and Dutch listed trading exporting firms*



*Netherlands in dashed blue; line Belgium in black line; Normal Inverse Gaussian distribution for the stock returns and Skewed Student-t distribution for the firm-specific exchange rates.

Finally, Figures 3.6(a) and (b) verify whether the behavior of Belgian and the Dutch listed firms is significantly different regarding the expected exchange rate exposure. Figures 3.6(a) and (b) represent both the confidence interval[82] of the difference in dependence between both countries. The behavior of both countries is significantly different at the 5% level when zero is not part of the confidence interval. We find for the large majority of the point estimates in time significant differences in behavior for respectively listed trading importing and exporting firms, indicating that the Dutch listed firms experience more expected exchange

[82] Since the dependence is estimated using maximum likelihood we can state:

$$\hat{\rho}_t^{Bel} - \hat{\rho}_t^{Ned} \cong N\left(\rho_t^{Bel} - \rho_t^{Ned}, SE\left(\rho_t^{Bel} - \rho_t^{Ned}\right)\right)$$

$$\cong \left(\rho_t^{Bel} - \rho_t^{Ned}\right) \pm 1{,}96 \times \sqrt{\left[\left({}^{Var(Bel)_t}/_{n}\right) + \left({}^{Var(Ned)_t}/_{n}\right)\right]}$$

rate exposure than the Belgian listed firms.[83] Only sporadically, zero is part of the confidence interval, resulting in an insignificant difference at that point in time. Next to the aforementioned findings regarding expected exchange rate exposure, we already pointed out that the Dutch listed firms also have stronger tail dependencies during extreme events and, as such, experience more unexpected exchange rate exposure.

Figure 3.6(a): Confidence interval of the difference in Rho between Belgium and Netherlands for listed trading importing firms

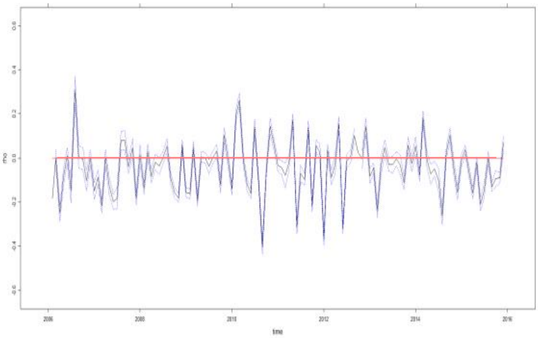
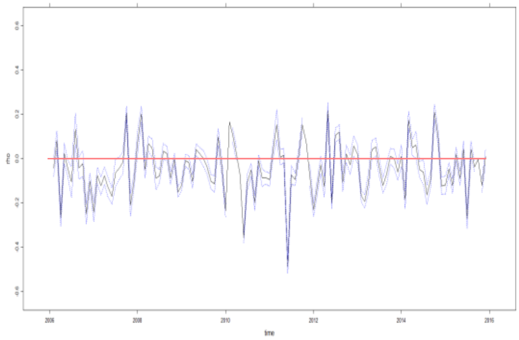


Figure 3.6(b): Confidence interval of the difference in Rho between Belgium and Netherlands for listed trading exporting firms



3.5.3. Robustness

This Section discusses alternative specifications and additional results to check the robustness of our main results from Section 3.5.2. First, we test the strength and validity of the firm-specific exchange rate indices by re-estimating exchange rate exposure using respectively a common exchange rate, i.e., the euro-dollar exchange rate, and a common weighted exchange rate, i.e., the nominal effective exchange rate (NEER) of the euro and comparing it with our initial results. Figures 3.7(a) to 3.7(f) show the results for NEER, while Figures 3.8(a) to 3.8(f) present the results for the euro-dollar exchange rate. For both the general associations, or rho's, and the extreme events, or tail dependencies, we test whether the original results, obtained by using the $\Delta EXER$ and $\Delta IMER$ for the Dutch and Belgian samples, are significantly stronger and more pronounced than the results obtained

[83] By performing t-tests, we verify the hypothesis whether the difference between the rho's of the Belgian and Dutch samples are different from zero at the 5% significance level. For both the trading importing (t = 3.95; p-value 0.00) and exporting firms (t = 4.05; p-value 0.01), the expected exchange rate exposure of the Dutch samples is more pronounced than the exposure of the Belgian samples.

by applying the NEER and euro-dollar exchange rate. When using the NEER or euro-dollar exchange rate instead of the proposed firm-specific trade-weighted exchange rate indices, in estimating exchange rate exposure, we are no longer able to distinguish between the exposure on the import and export side. As such, the estimates of exchange rate exposure in this robustness analysis will provide less information than our original results using the $\Delta EXER$ and $\Delta IMER$, since the NEER and euro-dollar exchange rate are only able to provide a general view on exchange rate exposure. Furthermore, both expected and unexpected exchange rate exposure using the NEER[84] are on average significantly weaker than our results obtained by using the $\Delta EXER$ and $\Delta IMER$.[85]

Figure 3.7(a) Confidence interval of the difference in Rho between $\Delta EXER_{i,t}$ for Dutch listed exporting firms and NEER

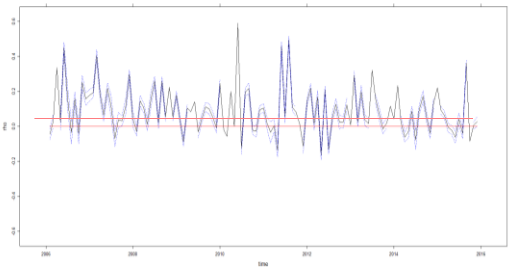
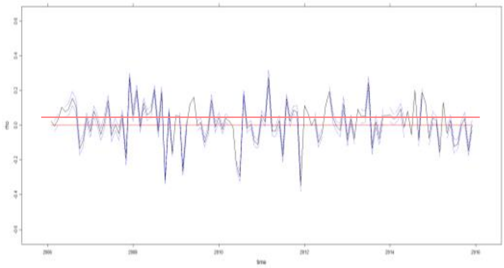


Figure 3.7(d) Confidence interval of the difference in Rho between $\Delta EXER_{i,t}$ for Belgian listed exporting firms and NEER



[84] We compare $\Delta ln(NEER_t)$ with $\Delta EXER_{i,t}$ and $\Delta IMER_{i,t}$, as such, both indices are expressed as changes. Similarly for the euro-dollar exchange rate.

[85] By performing t-tests, we verify the hypothesis whether the rho's and the tails of our initial results, obtained by the $\Delta EXER$ and $\Delta IMER$, are stronger than the rho's and the tails using the NEER at the 5% significance level. For the Dutch sample, the rho's of $\Delta EXER$ (t = 7.26; p-value 0.00) and $\Delta IMER$ (t = 7.00; p-value 0.00) are significantly stronger than the rho's of the NEER. Also the tails are significantly larger, respectively 16% for the $\Delta EXER$ (t = 2.20; p-value 0.01) and 25% for the $\Delta IMER$ (t = 3.41; p-value 0.00) compared to the tails of the NEER. For the Belgian sample, the rho's are significantly stronger for $\Delta IMER$ (t = 1.77; p-value 0.04) and $\Delta EXER$ (t = 1.50; p-value 0.06), the latter on a 10% significance level. Compared to the tails of the NEER, the tail dependence of the $\Delta IMER$ is 21% significantly bigger (t = 1.87; p-value 0.03), while the tails of the $\Delta EXER$ (t = 1.45; p-value 0.07) are 12% stronger at the 10% significance level.

Figure 3.7(b) Confidence interval of the difference in Rho between $\Delta IMER_{i,t}$ for Dutch listed importing firms and NEER

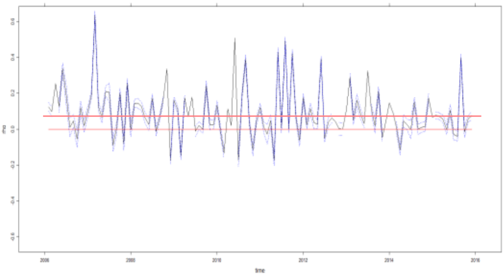
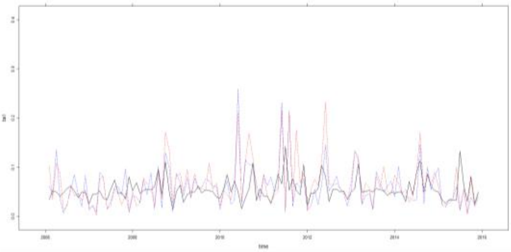


Figure 3.7(c) Tail dependence Dutch listed trading $\Delta IMER_{i,t}$ importing and $\Delta EXER_{i,t}$ exporting firms and NEER*



*Tails NEER in black full line; Tails $\Delta EXER_{i,t}$ exporting firms in dashed blue; Tails $\Delta IMER_{i,t}$ importing firms in dashed red.

Figure 3.7(e) Confidence interval of the difference in Rho between $\Delta IMER_{i,t}$ for Belgian listed importing firms and NEER

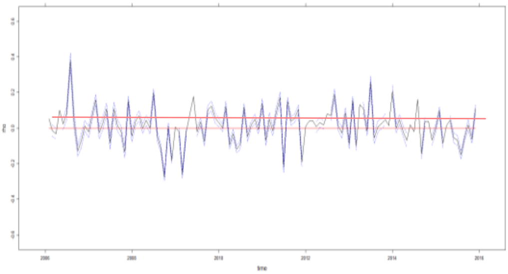
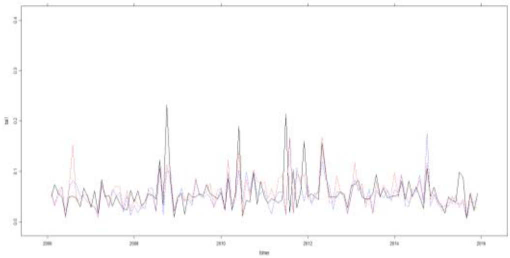


Figure 3.7(f) Tail dependence Belgian listed trading $\Delta IMER_{i,t}$ importing and $\Delta EXER_{i,t}$ exporting firms and NEER*



*Tails NEER in black full line; Tails $\Delta EXER_{i,t}$ exporting firms in dashed blue; Tails $\Delta IMER_{i,t}$ importing firms in dashed red.

Additionally, the robustness analysis using the euro-dollar exchange rate indicates significant weaker results regarding the expected exchange rate exposure compared to the $\Delta EXER$ and $\Delta IMER$. However, we only find significant stronger unexpected exchange rate exposure for the Belgian $\Delta IMER$, while the other tests on the tail dependencies rendered insignificant differences.[86] As such, the euro-dollar exchange rate can be an appropriate alternative common exchange rate to estimate unexpected exchange rate exposure for firms that trade considerably in

[86] By performing t-tests, we verify the hypothesis whether the rho's and the tails of our initial results, obtained by the $\Delta EXER$ and $\Delta IMER$, are stronger than the rho's and the tails using the euro-dollar exchange rate at the 5% significance level. For the Dutch sample, the rho's are significantly stronger for $\Delta EXER$ (t = 3.81; p-value 0.00) and $\Delta IMER$ (t = 4.72; p-value 0.00). Although, the tails are bigger for the initial results using the $\Delta EXER$ and $\Delta IMER$, they are not significantly different than the results obtained by using the euro-dollar exchange rate. For the Belgian sample, the rho's are significantly stronger for $\Delta IMER$ (t = 1.73; p-value 0.04) and $\Delta EXER$ (t = 1.60; p-value 0.05), the latter on a 10% significance level. Only the tail dependence of the $\Delta IMER$ is significantly 7% larger (t = 1.87; p-value 0.03) than the results obtained by using the euro-dollar exchange rate.

U.S. dollar (or in currencies strongly related to the U.S. Dollar). Nevertheless, this does not seem to be the case for the Belgian import sample.[87] This first robustness analysis shows the strength and validity of the firm-specific exchange rate index and the accompanying empirical strategy in estimating exchange rate exposure.

Figure 3.8(a) Confidence interval of the difference in Rho between $\Delta EXER_{i,t}$ for Dutch listed exporting firms and U.S. dollar

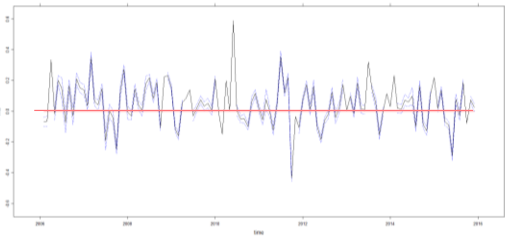


Figure 3.8(b) Confidence interval of the difference in Rho between $\Delta IMER_{i,t}$ for Dutch listed importing firms and euro-dollar

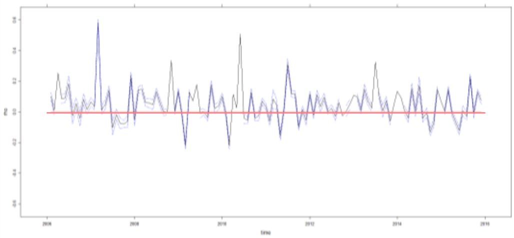
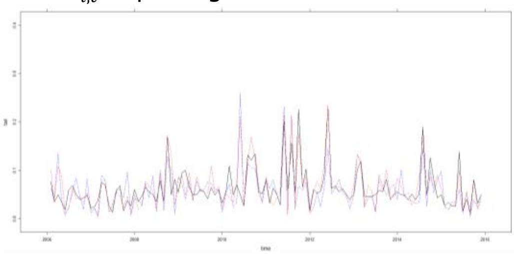


Figure 3.8(c) Tail dependence Dutch listed trading $\Delta IMER_{i,t}$ importing and $\Delta EXER_{i,t}$ exporting firms and U.S. dollar*



*Tails NEER in black full line; Tails $\Delta EXER_{i,t}$ exporting firms in dashed blue; Tails $\Delta IMER_{i,t}$ importing firms in dashed red.

Figure 3.8(d) Confidence interval of the difference in Rho between $\Delta EXER_{i,t}$ for Belgian listed exporting firms and U.S. dollar

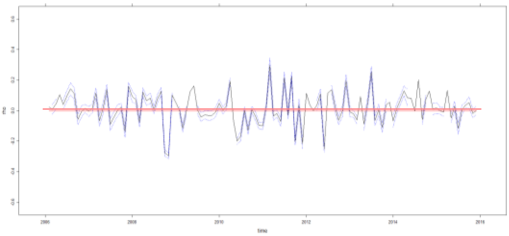


Figure 3.8(e) Confidence interval of the difference in Rho between $\Delta IMER_{i,t}$ for Belgian listed importing firms and U.S. dollar

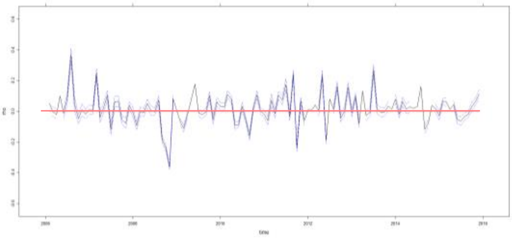
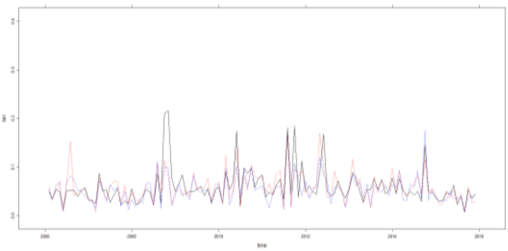


Figure 3.8(f) Tail dependence Belgian listed trading $\Delta IMER_{i,t}$ importing and $\Delta EXER_{i,t}$ exporting firms and U.S. dollar*

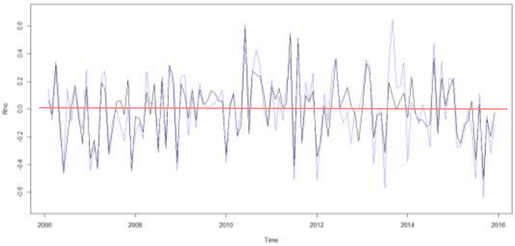


*Tails NEER in black full line; Tails $\Delta EXER_{i,t}$ exporting firms in dashed blue; Tails $\Delta IMER_{i,t}$ importing firms in dashed red.

[87] See Appendix B3 Table B3.

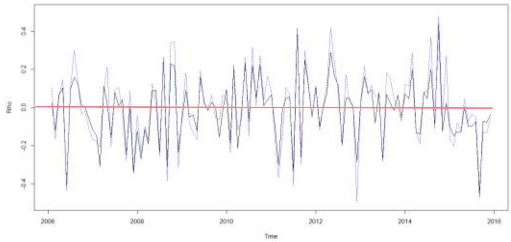
Second, we re-estimate the $\Delta EXER_{i,t}$ and $\Delta IMER_{i,t}$ for the manufacturing sector exclusively. Since our data only accounts for trade in goods, the cross-sectional monthly samples will contain a majority of listed manufacturing firms. By including the remaining sectors of the economy results are averaged out. This is also represented in the Figures 3.9(a) to 3.9(d) and 3.9(e) to 3.9(h) below, where the $\Delta EXER_{i,t}$ and $\Delta IMER_{i,t}$ are estimated solely for the Manufacturing industry.

Figure 3.9(a) Rho Dutch listed trading exporting Manufacturing firms*



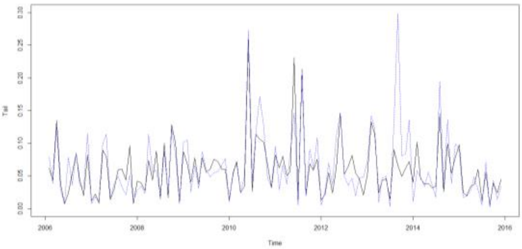
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.9(e) Rho Belgian listed trading exporting Manufacturing firms*



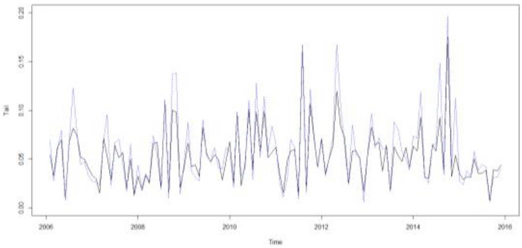
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.9(b) Tail dependence Dutch listed trading exporting Manufacturing firms*



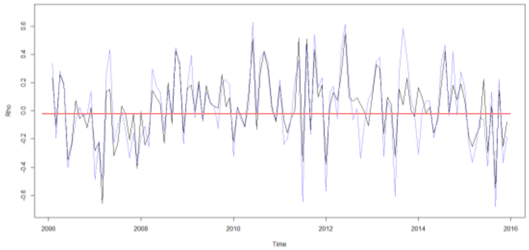
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.9(f) Tail dependence Belgian listed trading exporting Manufacturing firms*



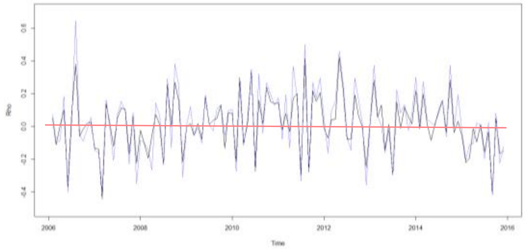
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.9(c) Rho Dutch listed trading importing Manufacturing firms*



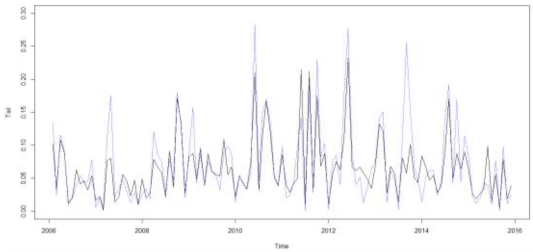
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.9(g) Rho Belgian listed trading importing Manufacturing firms*



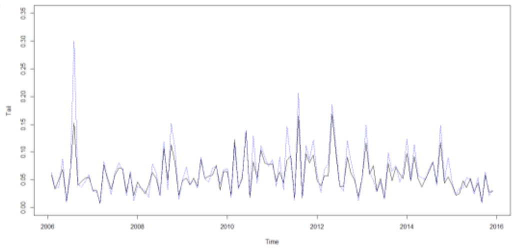
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.9(d) Tail dependence Dutch listed trading importing Manufacturing firms*



*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.9(h) Tail dependence Belgian listed trading importing Manufacturing firms*

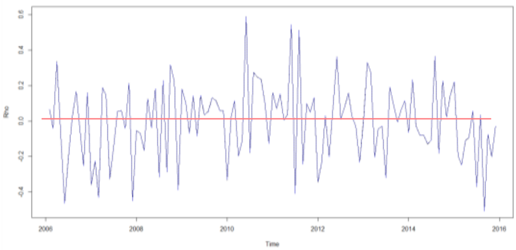


*Baseline estimations in black full line; robustness check in dashed blue line.

The Figures 3.9(a) to 3.9(h) reveal for both export and import and for both countries a similar pattern compared to the baseline results. However, focusing on the Manufacturing sector in particular, the results are more pronounced. This suggests that by including the remaining sectors of the economy, the results are averaged out. As such, the general conclusions of this research still hold, especially for the manufacturing sector in which trade in goods is most important.

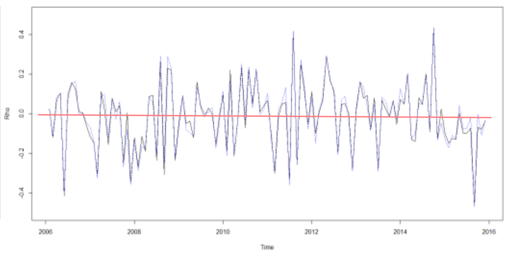
In the third robustness analysis, we give more weight to the trade history of a country as a trading partner by using yearly trade data as weighting scheme in the firm-specific effective exchange rate. Figures 3.10(a) to 3.10(d) and 3.10(e) to 3.10(f) reveal for both export and import and for both countries a very similar pattern compared to the baseline results. Moreover, for the Netherlands, the full line of the baseline results and the dashed line of the robustness estimations can barely be distinguished from each other. This outcome results from the fact that the Dutch listed firms from the sample hardly switch in their international trading partners over time. Furthermore, the proportional weight barely changes, which ensures that the trade history becomes less important. The latter also makes the Dutch listed firms more prone to exchange rate exposure. When in time exchange rate volatility rises, shifting to other trading partners with a more stable currency is a possible hedging strategy. However, since the trade weights or proportions of the trade-weighted index of the Dutch listed firms barely differ from the baseline index, we can derive that the Dutch listed firms stay loyal to their trading partners. For the Belgian case we can distinguish between the baseline and the robustness estimations, which indicates that Belgian listed firms are relatively less loyal to their international trading partners compared to the Dutch listed firms from the sample. However, generally, the figures indicate that the trade history with the trading partners is not a big issue in terms of influencing the exchange rate exposure and that the results from Section 3.5.2. are robust.

Figure 3.10(a) Rho T-copula Dutch listed trading exporting firms*



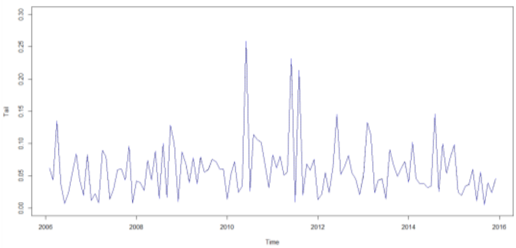
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.10(e) Rho T-copula Belgian listed trading exporting firms*



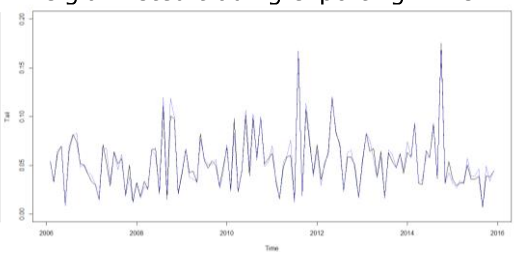
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.10(b) Tail dependence Dutch listed trading exporting firms*



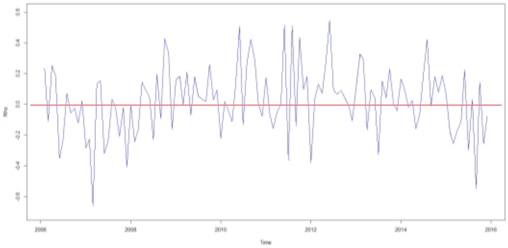
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.10(f) Tail dependence Belgian listed trading exporting firms*



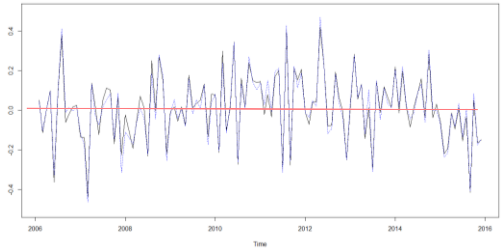
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.10(c) Rho T-copula Dutch listed trading importing firms*



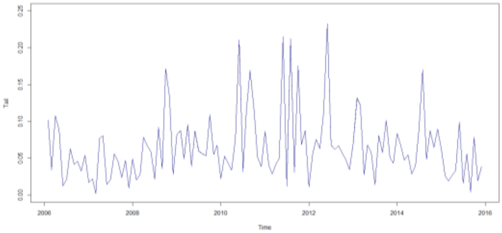
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.10(g) Rho T-copula Belgian listed trading importing firms*



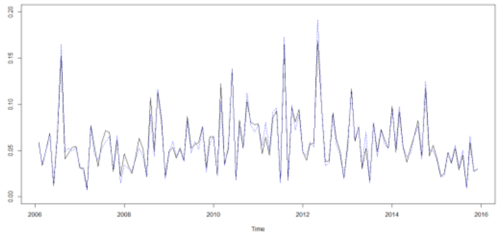
*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.10(d) Tail dependence Dutch listed trading importing firms*



*Baseline estimations in black full line; robustness check in dashed blue line.

Figure 3.10(h) Tail dependence Belgian trading importing firms*



*Baseline estimations in black full line; robustness check in dashed blue line.

3.6. Discussion and conclusion

Because of the worldwide breakdown of tariff and non-tariff barriers, new production techniques and better means of transportation, firms are increasingly able to outsource part of their production process to cheaper producers or locations in foreign countries. Although this internationalization of the production process is a universal phenomenon, it seems particularly relevant for small open economies such as Belgium and the Netherlands. These countries are too small to reap all the scale economies of keeping the entire production chain within their domestic borders (Burger & Haagsma, 2007). Nevertheless, when engaging in international trade outside the Eurozone, a firm's value becomes exposed to exchange rate movements. Therefore, this study investigates exchange rate exposure by cross-sectionally modelling the association between stock returns and firm-specific trade-weighted effective exchange rate indices on each point in time, comparing Dutch and Belgian listed firms over the period 2006-2015. Former research often uses a common exchange rate, is mainly characterized by aggregation bias, and relies on classic econometric assumptions leading to inconclusive, ambiguous results. The disaggregated firm-level data allow us to construct firm-specific effective exchange indices for import and export activities separately, consistent with the method of Dai and Xu (2017). Additionally, the research takes into account whether a firm internationally trades or refrains from it. Next, by applying copula theory, it cross-sectionally investigates the comovements between stock returns and, respectively, the import and export firm-specific effective exchange rate indices on each point in time. Since copula techniques permit to estimate both the general association and tail dependence during extreme events, this study is able to compare expected and unexpected exchange rate exposure between Dutch and Belgian listed firms. Four key findings characterise this research.

First, the literature agrees on the fact that stock returns are not normally distributed (e.g., Fama, 1965; Jondeau et al., 2007; Mandelbrot, 1963). However, in this study we find that extreme events causing fat tails and, as such, non-normality for stock returns are, at least partially, caused by a firm's international trade activities. The results of the Shapiro-Wilk and Kolmogorov-Smirnov test, indicate that the stock returns for Belgian and Dutch listed firms during non-trading periods are normally distributed and extreme events are only found during trading periods. As such, stock returns diverge from normality when firms are trading outside the Eurozone. This finding might explain partly why empirical research, which presumes that firms continuously trade, find less pronounced exchange rate exposure. Moreover, extreme variations might be averaged out, leading to weaker results.

Second, open economies can have international trade differences, which reflected in their exchange rate exposure may have important implications on their reaction to monetary and trade policy. Despite the fact that both Belgium and the Netherlands are open economies, the listed firms of our Dutch sample are still more involved in trade outside the Eurozone compared to listed firms of our Belgian sample. As a result, we find significant stronger dependence between the firm-specific exchange rate indices and stock returns for the listed firms in the

Netherlands than for the listed firms in Belgium. This finding is in line with the literature which suggests a positive relationship between exchange rate exposure and the openness of industrialized countries. More specifically, Friberg and Nydahl (1999) found a positive relationship between market-level exchange rate exposure and the openness of industrialized countries. Hutson and Stevenson (2010) confirmed this relationship at the firm-level. Hutson and O'Driscoll (2010) showed that after the introduction of a single currency, firm-level exchange exposure for Eurozone and non-Eurozone European firms has increased, but this rise was smaller for Eurozone than non-Eurozone firms. Furthermore, at the firm-level, Bergbrant et al. (2014) found exchange rate exposure varying with the degree of foreign involvement. It is logical to assume, other factors being equal, that firms in open economies experience greater exposure than those in closed economies, simply because they engage more in trade. Since the Dutch listed firms engage more into trade outside the Eurozone compared to the Belgian listed firms, the Dutch firms become more susceptible to the European trade and monetary policy, the latter indirectly leading to adjustments of the exchange rate of the euro. Additionally, the Dutch listed firms also encounter more tariffs and other barriers to international trade. As such, European trade agreements with countries outside the union are more beneficial for the listed firms from the Netherlands, than they are for those from Belgium, since they result in a deterioration of the competitive position of those firms who trade mainly within the Eurozone. This finding is in line with Valta (2012) who states that a reduction of the import tariffs and other barriers to international trade affect the operations of domestic firms in U.S. manufacturing industries by an increase of foreign competitors. For instance, lower import tariffs could generate more complaints by domestically active firms implying that customs or foreign trade regulations negatively affect their operations and increase exchange rate exposure. The lower import tariffs are beneficial for foreign exporting firms who want to penetrate the domestic market. As such, competition on the domestic market increases at the expense of local firms who are active on that same domestic market. However, trade agreements mostly contain an advantage for domestic firms who export to the foreign market as well, when for instance import tariffs in the foreign market are lowered as a counter measure for lowering the import tariffs in the domestic market. In such a scenario, trade agreements are beneficial for firms who trade internationally in comparison with firms who remain mostly operating on the domestic market. Obviously, the extent to which a firm's foreign trade with other countries is regulated will influence its exchange rate exposure (Bergbrant et al., 2014).

Third, the Dutch listed trading firms not only experience stronger expected exchange rate exposure than Belgian listed trading firms but also have more pronounced unexpected exchange rate exposure. Distinguishing the general association between stock returns and firm-specific effective exchange rate indices and their tail dependence is key in order to account for both the general relationship and the association during sudden, extreme events. As such, the tail dependence for the listed Dutch firms is stronger than the one for the Belgian listed trading firms, which indicates that for the Dutch listed trading firms more extreme events occur. The Dutch firms in our sample trade more outside the Eurozone than Belgian listed firms, making their stock returns more sensitive for extreme events. As such, there are more extreme and pronounced dependencies to be found for the listed firms from the Dutch sample than for the Belgian sample.

Fourth, listed importing firms experience stronger and more pronounced exchange rate exposure than listed exporting firms. This result is in line with the dual effect hypothesis of Pritamani et al. (2004) which predicts an accentuating effect of exchange rate changes of the domestic currency on importing firms. On the one hand, an appreciating domestic currency is beneficial for both the importer's activities on the domestic and foreign market, resulting in positive profit expectation which may also be reflected in the stock return. On the other hand, negative profit prospects may result from a depreciating domestic currency because of its adverse effects on an importer's activities on both the domestic and foreign market. As a result of these accentuating effects exchange rate exposure is more pronounced for importing firms.

Furthermore, we find that mainly Dutch listed importers engage more in international trade than exporters, influencing their exchange rate exposure. According to the dual effects hypothesis exporters should be able to counter exchange rate exposure by relying interchangeably on the domestic and foreign market. Two-way traders may remain exposed, more specifically, a depreciating domestic currency may make exporting to foreign markets more attractive, but makes importing the intermediate inputs to fabricate the exporting goods more expensive, offsetting the beneficial effect of export. Since the exporting activities cannot entirely offset the two accentuating effects of importing, the two-way traders are still left exposed, but in a lesser extent than a sole importer. Furthermore, the tail dependence for exports in both the Dutch and Belgian cases seems to be lower than the tail dependence for import. This illustrates that the firms with importing activities are more sensitive to extreme events since they have a higher probability of extremely large (or small) changes of stock returns and firm-specific exchange rates appearing together. This finding is also in line with, e.g., Bergbrant et al. (2014), who found exposure to be higher for import-only firms than for export-only firms. Similarly, Crowley and Habibdoust (2013) also showed at longer horizons a stronger sensitivity to exchange rate volatility for importing firms than for exporting firms. Finally, also Amiti et al. (2018) concluded more recently in related research on a Belgian dataset of currency invoicing,[88] that import-intensive[89] firms exhibit very low pass-through which according to the theoretical model of Bodnar et al. (2002)[90] can be related to higher exchange rate exposure. The authors found high-pass through for non-import-intensive firms because they mainly invoice their exports in euros and as such not only exhibit nearly complete exchange rate pass-through but are also hardly exposed.

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[88] Invoicing data were not available for both Belgium and the Netherlands for our data sample and time period.

[89] In this Chapter import and export are handled separately, in chapter 4, import-intensive firms can also be distinguished in the multinomial logit model.

[90] Bodnar et al. (2002) set up a duopoly model with an exporting firm and an import competing foreign firm, and show that exchange rate pass-through and exposure are negatively correlated across industries. According to the authors, when the substitutability between the domestically produced good and the imported good increases in an industry, the price elasticity of demand for the firms increases and both firms have greater incentives to stabilize prices, hence, exchange rate pass-through falls. Nevertheless, profits become more sensitive to exchange rate changes, so exposure increases. One should therefore see a negative relationship between exchange rate pass-through and exposure across industries, if industries differ mainly in the substitutability between domestically produced and imported goods. According to Flodén et al. (2008), the negative relationship between exchange rate exposure and pass-through might sometimes not hold in practice because an increase in the convexity of costs mostly reduces both pass-through and exposure. The correlation between pass-through and exposure should therefore be positive across industries if cost functions differ across these industries. This effect can be mitigated by the aforementioned negative correlation between pass-through and exposure induced by changes in the price elasticity of demand. Furthermore, exchange rate pass-through and exchange rate exposure do not have a one-to-one relationship with each other. While the first is more closely related to, e.g., market-power and elasticities, the latter concept is broader and relates closer to macro-economic conditions.

Additionally, our findings have implications for policy makers. Since there is no active exchange rate policy, policy makers influence currencies with their monetary policy. The effect of monetary policy also has repercussions on a national trade balance, which can be described by the J-curve hypothesis, and has been proven multiple times empirically (e.g., Nadenichek, 2006; Nektarios, 2018; Syed & Sajid, 2018). According to this hypothesis, a depreciation of domestic currency lowers the relative price of domestically produced goods, which in turn increases the exports and reduces the imports of the country. Therefore, trade balance of the country moves toward a surplus in the long-run. However, the aforementioned process is not immediate. If the quantities of imports and exports do not adjust immediately to the depreciation of domestic currency, the trade balance moves towards a deficit. This means that the trade balance deteriorates due to the depreciation of domestic currency in the short run. As time passes the quantity of imports falls and that of exports rises. This implies that the trade balance improves due to the depreciation of domestic currency in the long run. To sum up, the effect of an expansionary monetary policy on trade balance gives an impression of a J-shaped curve: initially causing a trade deficit and consecutively leading to a trade surplus (Ivrendi & Guloglu, 2010). Calculating exchange rate exposure using firm-specific trade-weighted exchange rates can help policy makers, since it gives insight into how importers and exporters their stock returns are exposed to particular exchange rate changes. As such, it allows National Banks to be equipped to estimate financial repercussions in terms of exposure related to national trade balance deficits and make a time estimate of how quickly the gap can be closed, which may result from monetary and/or trade policy measures from respectively the European Central Bank and the European Commission. Firm-level information concerning the amount of trading partners gives an insight in the amount of transaction costs it will take to adjust to the new policy. Accordingly, exchange rate exposure based on firm-specific trade-weighted exchange rates can help policy makers link trade with monetary policy and financial stability.

Chapter 4

Determinants of Exchange Rate Exposure- Firm-level Evidence using a Novel Methodological Approach

Abstract[91]

This study investigates the determinants of exchange rate exposure for one-way and two-way international traders in the Netherlands using weekly data from 2011-2015. In order to fully understand the underlying firm-level forces of exchange rate exposure, this research puts forward a novel approach using a three-step procedure applying, consecutively, vine copulas, network analysis and multinomial logit models. By exposing the network and using a fine-grained categorization or profiling of firms, our methodology allows policy makers to adapt policy measures, such as taxes and subsidies, more efficiently. Our findings constitute three contributions to the field. First, firms that hedge during market downturns, experience less exchange rate exposure and are characterized by a lower book-to market-ratio, possess large amounts of liquidity and/or have a high level of productivity. Second, exchange rate exposure of two-way traders is determined by the interplay of offsetting and accentuating effects of export and import activities, indicating a more pronounced exchange rate exposure at the importing side than the exporting side. Finally, exchange rate exposure is determined by the level of foreign dependence on the import side. The exchange rate exposure may be decreased by increasing foreign dependence on the export side or by diversifying import among a larger number of importers. Whether a firm is willing to follow this hedging strategy depends on the risk-aversion of the firm.

Keywords: Exchange rate exposure, Determinants, Trade, Vine copula, Network analysis.
JEL: C38, C49, F14, F31

[91] This Chapter is co-authored with Prof. Dr. Mark Vancauteren, Prof. Dr. Roel Braekers and Prof. Dr. Sigrid Vandemaele.

4.1. Introduction

It is generally accepted in micro-economic theory that a firm's profitability is affected by uncertainties such as exchange rate fluctuations. As such, measuring exchange rate exposure of firms[92] has been a subject of research interest over the last three decades. Nevertheless, the search for statistically significant and economically meaningful exposure estimates in the literature has been largely unsuccessful. The studies on exchange rate exposure in the vast literature can be divided in two strands, namely research on the measurement of exchange rate exposure and studies investigating determinants of exchange rate exposure (Lin & Lee, 2017). Despite the fact that the sensitivity of the value of a firm for exchange rate changes has been investigated extensively, with most of the firm-level studies indicating a significant relationship (e.g., Bodnar & Wong, 2003; Choi & Prasad, 1995; De Jong et al., 2006; Di Iorio & Faff, 2000; Dominguez & Tesar, 2006a; Doukas et al., 2003; El-Masry, 2006; Hutson & Stevenson, 2010; Kiymaz, 2003), the exchange rate exposure puzzle remains largely unsolved (e.g., Bini-Smaghi, 1991; Chou et al., 2017; Du et al., 2013; Jorion, 1990, 1991; Muller & Verschoor, 2006a, 2006b; Walid et al., 2011; Zhao, 2010). The puzzle refers to the common finding in many empirical studies that only a minority of firms experience significant exchange rate exposure. The issue of this puzzle is mostly attributed to hedging practices which partly eliminates exchange rate risk (e.g., Bartov et al., 1996; Bartram & Bodnar, 2007; Hutson & Stevenson, 2010; Levi, 1994; Lin & Lee, 2017). Moreover, Bartram et al. (2010) argue that firms, in addition to hedging, can pass through a proportion of currency changes to customers, reducing the exchange rate exposure by 70%. However, sudden extreme changes of exchange rates are more difficult to hedge, creating the remaining exchange rate risk (Bartram et al., 2010; Di Iorio & Faff, 2000; Marston, 2001; Stulz & Williamson, 1996; Van Cauwenberge et al., Forthcoming). Next to hedging, there are also methodological issues causing empirical research to provide inconsistent results. First, when measuring exchange rate exposure, ordinary least squares (OLS) fails to account for the extreme, non-linear and

[92] A firm's exposure to changes in exchange rates is a multifaceted phenomenon and, as such, can be investigated from different perspectives, but it is the economic exposure, through a firm's stock price or value, which is of particular interest in this study.

asymmetric relationship between exchange rates and stock prices (Baldwin & Krugman, 1989; Lin & Lee, 2017; Van Cauwenberge et al., Forthcoming). Second, most studies do not account for the dynamics between international imports and exports when estimating exchange rate exposure; instead they analyze imports and exports separately. Nevertheless, Aristei et al. (2013) state that most trading firms both export and import. Therefore, it is quintessential to include international trade or more specifically export and import simultaneously while modelling exchange rate exposure in order not to ignore two-way traders (Pritamani et al., 2004; Van Cauwenberge et al., Forthcoming).

In contrast to the enormous interest on solving the exchange rate exposure puzzle, the mixed findings on the determinants of exchange rate exposure has received little attention (Lin & Lee, 2017). Most studies report a significant relationship between exchange rate exposure and five, often investigated, determinants, namely, foreign sales , firm size, quick ratio, debt ratio and the book-to-market ratio[93] (e.g., Bartram, 2004; Bodnar & Wong, 2003; Chow et al., 1997; Dominguez & Tesar, 2006a; Doukas et al., 2003; Faff & Marshall, 2005; Lin & Lee, 2017; Pantzalis et al., 2001). However, previous research fails to provide a consensus on the sign of the effect of these determinants on exchange rate exposure.

There are three main causes why empirical research provides inconsistent results. First, classic OLS regression techniques, which are used in most studies, fall short in capturing the complex relationship between exchange rate exposure and its determinants. When verifying the effects of the determinants of exchange rate exposure, these classic econometric techniques ignore the heterogeneity of firm characteristics at different levels of exchange rate exposure and average out the effects of determinants (Lin & Lee, 2017). Second, most studies do not include international trade nor trade related variables when they investigate the determinants of exchange rate exposure. More specifically, since firms need to compensate for the sunk entry costs of international trade, the latter is related to higher productivity. International trade will induce only the more productive firms to enter the market, while less productive firms continue to produce only for the

[93] For details concerning the calculations of these determinants, see Appendix C5.

domestic market, and will simultaneously force the least productive firms to exit. As such, beside international trade playing an important role in determining exchange rate exposure, firm-level variables related to trade behavior, such as productivity, are also interesting to investigate as a potential determinant of exchange rate exposure (e.g., Bernard et al., 2007; Doukas et al., 2003; Greenaway & Kneller, 2007; Melitz, 2003; Wagner, 2007, 2012). Finally, a common limitation on the majority of studies on the measurement and the determinants of exchange rate exposure is the aggregation bias. Firms that participate in international trade are very heterogeneous and, as such, the industry level is too aggregated (Greenaway & Kneller, 2007). One must go deep into the microeconomic level to understand the relationship between exchange rate exposure and different types of firms with different productivity levels, import and export orientations (Dominguez & Tesar, 2006a). Furthermore, low-frequency data might additionally suppress and distort empirical evidence. According to Boswijk and Klaassen (2006); Shaar and Khaled (2017) the relationship between exchange rate changes and trade should be investigated using at least monthly data. These authors argue that using high-frequency data allows a better understanding of the dynamics of the relationship. The use of disaggregated, high frequency data can avoid the problem of aggregation bias in testing this relationship, that is, when insignificant associations are offset by significant ones (e.g., Bahmani-Oskooee & Hegerty, 2007; Byrne et al., 2008; Tsen, 2016).

Accordingly, the objective of this study is to gain a better understanding of the determinants of exchange rate exposure for one-way and two-way traders by filling the aforementioned gaps in the literature. Therefore, this study elaborates on the research of Van Cauwenberge et al. (Forthcoming),[94] which focused on resolving the exchange rate exposure puzzle. Through the use of copula theory and by using monthly data on both imports and exports, Van Cauwenberge et al. (Forthcoming) investigate the cross-sectional comovements between stock returns and firm-specific effective exchange rates on each point in time. However, in this research we rotate the cross-sectional outlook into a time-series perspective, permitting us to investigate firm-level heterogeneity and determinants of exchange rate exposure. Next, as opposed to Van Cauwenberge

[94] Chapter 3 of this dissertation.

et al. (Forthcoming) who analyze exchange rate exposure by using an import- and export-weighted firm-specific effective exchange rate separately, this study investigates exchange rate exposure by accounting for import and export simultaneously, making it possible to investigate two-way traders.

The contribution of this research to the field is three-fold: first, we contribute to the literature by introducing a new three step procedure to uncover firm-level determinants of complex concepts such as exchange rate exposure. We investigate the determinants of exchange rate exposure, by successively combining vine-copulas with network analysis and a multinomial logit model. Vine-copulas permit us to estimate exchange rate exposure conditional on the intensive margin of international trade,[95] i.e., accounting for import and export activities, during extreme events. Next, elaborating on the results of the vine-copulas, network analysis allows us to distinguish different groups of firms based on their exchange rate exposure level, while consecutively the multinomial logit model is used to investigate the determinants on different levels of exchange rate exposure. This three step procedure is applied on disaggregated firm-level data. The dataset consists out of weekly stock prices, exchange rates and unique trade data supplemented with additional firm-level monthly and yearly data. These data are available for the Netherlands covering the period 2011-2015. Our second contribution to the field is the estimation of exchange rate exposure for two-way traders. This research models the exchange rate exposure conditional on the intensive margin of international trade by using vine-copulas and, as such, is able to uncover the impact of the import and export dynamics on exchange rate exposure for two-way traders. By elaborating on the dual effect hypothesis[96] of Pritamani et al. (2004), we verify for two-way traders whether import or export drives the international trade behavior and, as such, clarify the association with exchange rate exposure. Furthermore, this enables us to investigate how firms react during domestic and foreign market up- and downturns. Third, we contribute to the existing research by verifying the significance and effect of both already

[95] Intensive margin of trade refers to a firm's decision to change their trade volume, while the extensive margin refers to a firm's decision whether or not to enter the market.
[96] Monetary theory, embodied by the flexible price monetary model, states that there exist a positive association between growth in the domestic economy and domestic currency movements (Mussa, 1976). In their dual effect hypothesis, Pritamani et al. (2004) elaborate on this theory by incorporating international trade and exchange rate exposure. See Section 4.2 for further details.

established and potential new determinates of exchange rate exposure. By using a network analysis we are able to identify different groups of firms based on their level of exchange rate exposure and through testing these groups on their determinants in a multinomial logit model, we are able to verify which firm characteristics contribute significantly to a certain level of exchange rate exposure. Next to investigating foreign sales, firm size, quick ratio, debt ratio and the book-to-market, we introduce four new determinants. More specifically, we evaluate the impact of the trade status of a firm by verifying whether a firm proportionally mainly imports or exports. Next, the extensive margin, or the decision whether or not to trade, is investigated as well as a potential determinant of exchange rate exposure. Additionally, Héricourt and Nedoncelle (2016) already investigated the relationship between firm-level performance and real effective exchange rate changes and how this relationship is shaped by the number of trade-destinations. By elaborating on their work, we verify whether diversifying the intensive margin across multiple destinations or trade partners has a mitigating effect on exchange rate exposure. Finally, productivity is also examined as potential determinant of interest.

Our results indicate that firms that hedge during domestic market downturns, experience less exchange rate exposure. These firms have a lower book-to market-ratio and, as such, a greater market value, large amounts of liquidity, a larger quick ratio, and/or are more productive. Further, we show that exchange rate exposure of two-way traders is determined by the interplay of offsetting and accentuating effects of export and import activities, indicating a more pronounced exchange rate exposure at the importing side than the exporting side. The multivariate dynamics in the vine copulas provide empirical evidence on our elaboration of the dual effect hypothesis of Pritamani et al. (2004) for two-way traders and confirm the findings of Van Cauwenberge et al. (Forthcoming). Moreover, a weakening euro makes exporting to foreign markets more attractive. However, importing the intermediate inputs to fabricate the exporting good becomes more expensive, offsetting the beneficial effect of export, making exporting to the foreign market less attractive and leaving the firm exposed. Since firms are reluctant to exit foreign markets or alter the extensive margin of trade, due to the large and sunk market-entry costs, they instead adapt and optimize their intensive margin, waiting for an appreciating euro-dollar exchange rate or strengthening euro (Baldwin, 1988; Chaney, 2008). An appreciating euro-dollar exchange rate makes exporting initially less attractive, but importing the intermediary goods for producing the product becomes cheaper, as such, the adverse effects may be offset by selling at lower production cost to the booming domestic market. Moreover, these firms are now able to export at a lower cost, making them again more attractive on the foreign market. Next, increasing the dependence on the foreign market on the import side puts a firm at risk when the market is contracting and exposes it to exchange rate risk. During market upturns, however, the firm is able to profit from exchange rate exposure. Increasing the presence in export markets might mitigate this risk during domestic market downturns, but also deprives it from the possible benefits when the domestic market is in upturn. Similarly, the diversification of a bigger import share among more trading partners will not induce more exchange rate risk since it does not increase foreign dependence. The extent of the foreign dependence depends on the risk-aversion of the firm. Finally, the application of our methodology on exchange rate exposure shows that heterogeneous firm behavior is prevalent when looking at exchange rate exposure. As such, instead of targeting policy based on, e.g., sector affiliation, policy makers can use the proposed methodology to efficiently adapt policy measures, such as taxes and subsidies, according to relevant firm-characteristics by exposing the network and using a fine-grained categorization or profiling of firms.

The study is organized as follows: Section 4.2 gives a brief background on the determinants of exchange rate exposure, while Section 4.3 explains the data. Further, the empirical framework is presented in Section 4.4. Next, Section 4.5 presents the empirical analysis and results. Finally, the discussion and concluding remarks follow in Section 4.6.

4.2. Determinants of exchange rate exposure

There exists a vast literature at the empirical level studying exchange rate exposure using classical OLS approaches, elaborating on Adler and Dumas (1984) and Jorion (1990, 1991). Since OLS techniques do not seem to lead to conclusive answers, several other methods have been explored (Aloui, 2007; Pan et al., 2007; Phylaktis & Ravazzolo, 2005; Walid et al., 2011; Zhao, 2010). Despite the theoretical support that there is a relationship between stock prices and exchange rates, there exists no unique model integrating all the complexity of the effects of exchange rate shocks on firm value, resulting in mixed evidence (e.g., Bodnar & Wong, 2003; Choi & Prasad, 1995; De Jong et al., 2006; Di Iorio & Faff, 2000; Dominguez & Tesar, 2006a; Doukas et al., 2003; El-Masry, 2006; Hutson & Stevenson, 2010; Kiymaz, 2003).

Nevertheless, the literature agrees that exchange rate exposure depends on a large number of parameters. As such, solely quantifying exchange rate exposure may not be sufficient to understand the sensitivity of firms to exchange rate changes. The determinants of exchange rate exposure give insight into the firm-level forces at play and are, next to estimating exchange rate exposure, an important research domain. Since most studies focus on financial determinants, measures like foreign sales, firm size, quick ratio, debt ratio and the book-to-market ratio are often investigated. Foreign sales is mainly used as an approximation of the degree of foreign involvement. The majority of studies which find evidence of a significant relationship suggest that exchange rate exposure increases with foreign sales. (e.g., Bartram, 2004; Bodnar & Wong, 2003; Chow et al., 1997; Dominguez & Tesar, 2006a; Doukas et al., 2003; Pantzalis et al., 2001). Further, the research on the effect of a firm's size on exchange rate exposure is ambiguous. Bartram (2004); Chow et al. (1997); Dominguez and Tesar (2006a); Nance et al. (1993) argue that firms will only start to hedge exchange rate risk when the benefits exceeds the costs. As such, bigger firms are less sensitive for exchange rate changes. However, some studies provide evidence against these deterministic findings, stating that larger firms do not automatically hedge because they reach a certain level of economy of scale and that exchange rate exposure is not necessarily negatively associated with firm size (Doidge et al., 2006; He & Ng, 1998; Lin & Lee, 2017). Another investigated determinant of exchange rate exposure is the quick ratio, which is a measure of short-term liquidity used to manage short term cash flow needs (Lin & Lee, 2017). Also for this determinant the evidence is inconclusive. He and Ng (1998) state that a positive relationship between exchange rate exposure and the quick ratio exist since firms with lower short-term liquidity have a greater motivation to hedge exchange rate risk. However, Bartram (2004) disagrees stating that firms with a higher quick ratio have a greater flexibility to withstand imminent cash flow needs and exchange rate risk. As such, according to Bartram (2004) the quick ratio affects exchange rate exposure negatively. Few studies additionally investigate the debt ratio and book-to-market ratio as determinants. Doukas et al. (2003) and He and Ng (1998) find evidence of a negative relationship between debt ratio and exchange rate exposure. They argue that the incentive to hedge, in order to reduce the impact of exchange rate risk, increases with a higher debt ratio and likelihood of financial distress. Regarding the book-to-market ratio, He and Ng (1998) and Nance et al. (1993) demonstrate that a positive link between book-to-market and exchange rate exposure exist since firms with lower book-to-market, i.e., more growth opportunities, have more incentives to hedge exchange rate risk. The main culprit of the inconclusive results regarding the aforementioned five determinants is the methodological reliance on OLS regression techniques which fails to unambiguously capture the complex asymmetric relationship between exchange rate exposure and its determinants. OLS models are only able to estimate the average effects under strict assumptions and, as such, are not able to fully distinguish differences in firms' characteristics at various levels of exchange rate exposure (Lin & Lee, 2017; Yuan et al., 2014). Furthermore, firms try to hedge exchange rate risk and, additionally, can pass through a proportion of currency changes to their customers, reducing exchange rate exposure significantly (Bartram et al., 2010; Nance et al., 1993). Consequently, a nonhedgeable portion of exchange rate risk remains, making an analysis of exchange rate exposure during sudden extreme events necessary (Lin & Lee, 2017).

Another important limitation of previous empirical research on determinants of exchange rate exposure, is the lack of taking into account international import and export decisions when measuring exchange rate exposure in a first stage and verifying determinants in a second stage (Van Cauwenberge et al., Forthcoming). According to Doukas et al. (2003); Hutson and Stevenson (2010); Pritamani et al. (2004), firms involved with international trade experience exchange rate exposure. The sparse empirical research, which estimates exchange rate exposure and accounts for international trade, investigates import and export decisions separately by using a trade-weighted exchange rate (Van Cauwenberge et al., Forthcoming). Therefore, they are not able to capture the dynamics between import and export activities for international two-way traders and their sensitivity for exchange rate changes (Pritamani et al., 2004; Van Cauwenberge et al., Forthcoming). Moreover, Pritamani et al. (2004) argue that a dual effect, through domestic and international activities, occur at a firms' exporting and import side when the domestic currency appreciates or depreciates.[97] Exporting firms, on the one hand, undergo offsetting effects since the adverse consequences of a strengthening domestic currency in its foreign markets is at least partially mitigated by the gains of a stronger domestic economy and higher consumer income. Similarly, when the domestic currency depreciates, the effects of a weaker domestic economy and lower consumer income are partially offset by a stronger position of exporting firms in foreign markets. Import oriented firms, on the other hand, benefit from an appreciating domestic currency in both the domestic and foreign markets, while during times of a depreciation they are adversely affected in both markets (Pritamani et al., 2004). These two accentuating effects indicate a more pronounced exchange rate exposure at the importing side than the exporting side, a finding which is confirmed by Van Cauwenberge et al. (Forthcoming). Therefore, it is important when investigating exchange rate exposure to account for trade-related determinants, such as the trade profile, the intensive and extensive margin of trade. According to Dekle et al. (2016); Greenaway and Kneller (2007), exchange rate sensitivity is more related with the intensive rather than the extensive margin of trade. Since firms are reluctant to exit foreign markets or alter the extensive margin of trade, due to the large and sunk market-entry costs, they instead adapt and optimize their intensive margin (Baldwin, 1988; Chaney, 2008). Further, although not directly related with exchange rate exposure, several studies on international trade and exchange rate changes provide interesting perspectives and, as such, potential determinants of interest to investigate regarding exchange rate exposure. Héricourt and Nedoncelle (2016) focus in their study on the trade-deterring effect of real exchange rate volatility on firm-destination exports. The authors find that

[97] In their dual effect hypothesis, Pritamani et al. (2004) elaborate on the flexible price monetary model by incorporating international trade and exchange rate exposure. The flexible price monetary model states that a positive association between growth in the domestic economy and domestic currency movements exists (Mussa, 1976).

more destination-diversified firms are better able to handle exchange rate changes. As such, trade destinations might be an interesting exchange rate risk mitigating determinant to investigate. Next, productivity might also be an interesting variable which to our knowledge, has never been investigated as a determinant of exchange rate exposure. Empirical evidence has shown that firms engaging in international trade differ on various dimensions, confirming mostly a positive relationship between export activities and productivity (e.g., Bernard et al., 2007; Greenaway & Kneller, 2007; Melitz, 2003; Wagner, 2007, 2012). Moreover, a productive firm's international export activities are less impacted by exchange rate changes (Berthou & Dhyne, 2018). Although, little evidence on import behavior exist, importers seem to exhibit a number of the same performance differences as exporters. More specifically, importers are bigger, more productive, pay higher wages and are more skill- and capital- intensive than nonimporters (Andersson et al., 2008; Castellani et al., 2010; Halpern et al., 2005; Wagner, 2012).

4.3. Data

This study considers stock data and unique trade data for 81 publicly listed Dutch companies and the euro-dollar exchange rate, in order to first estimate exchange rate exposure taking into account the intensive margin of international trade. The sample contains weekly data from 1/2/2011 to 12/31/2015. There are 260 observations for each variable. The stock and exchange rate data are retrieved from Thomson Reuters DataStream. Because of the dominance of the U.S. dollar in international trade, this research only takes the euro-dollar exchange rate into account.[98] Further, the nominal euro-dollar exchange rate is scaled relatively to the base value, namely the first week of 2011, which is set equal to 100. Next, we construct $\Delta log(e_t)$ as follows: $log(e_t/e_{t-1})$. Similarly, the logarithmic difference

[98] According to Goldberg (2011), evidence show that the U.S. dollar continues to be the leading transaction currency in the foreign exchange markets and a key invoicing currency in international trade. The dominance of the U.S. dollar has proven to be very resilient, with an 85 percent share of foreign exchange transaction volume, which is more than twice the share of the euro. As such, it remains the leading currency used in international trade, primary commodities are generally priced in U.S. dollar on world exchanges and central banks and governments hold the bulk of their foreign exchange reserves in U.S. dollar. In addition, in some countries dollars are accepted for making transactions and sometimes even preferred over the domestic currency (Pollard, 2001). Furthermore, the robustness results in Section 3.5.3 from Chapter 3 indicated that the euro-dollar might be a decent alternative if one would not opt for a firm-specific trade-weighted exchange rate. However, this is not always the case, see, e.g., the robustness results in the same Section for Belgium.

of the stock return is constructed as follows: $\Delta log(R_{i,t}) = log(r_{i,t}/r_{i,t-1})$ for the different firms $(i = 1, \dots, n)$ and over a period of T months $(t = 1, \dots, T)$. For the weekly data, prices and rates on every Friday are taken in consideration.

Import and export data are obtained from Statistics Netherlands. This firm-level dataset is a comprehensive panel of weekly trade flows, i.e., exports by destination and imports by source country. The weekly data contains information about trade flows outside the Eurozone. The data are customs data from the International Trade in Goods statistics, which contain import and export data and follow the Eurostat European Regulation. The figures based on this Regulation follow the principle of crossing borders. As such, the value of import as well as the value of export is recorded at the Dutch border. This means that imports are valued at the border of the importing country (i.e., cif-value: value, cost, insurance and freight) and the exports are valued at the border of the exporting country (i.e., fob-value: free on board).[99] Statistics Netherlands gave us access to the relevant data for this research, which enables us to calculate firm-level exports and imports, which will be used to construct the logarithmic difference for trade (e.g., for export $\Delta log(Export_{i,t}) = log(Export_{i,t}/Export_{i,t-1})$). Further, 65 firms (80%) in the sample are two-way traders, while 16 firms (20%) only import. For the weekly data, trading ends on every Friday of the week. Because the trade data are confidential, the firms are anonymized and referred to by simply numbering them randomly from f1 to f81.[100]

Table 4.1 reports the summary statistics of the logarithmic difference of stock prices, euro-dollar exchange rate, import and export. A larger kurtosis is an indication of fatter tails and therefore of extreme events; e.g., the stock returns are clearly leptokurtic. Nevertheless, kurtosis does not give an indication of upper or lower tail risk and therefore can be misleading. However, we can conclude that the kurtosis and skewness presented in Table 4.1 indicate that the normal distribution will be inadequate for further modeling. As such, this research prefers

[99] The difference between the cif- and the fob-value of imports concerns the costs incurred in transporting the intermediate route (the border between the exporting country and the Dutch border). These are mainly transport and insurance costs.
[100] Table C6.1 of Appendix C6 gives an overview of the sector affiliation of the firms in the sample.

the Student-t distribution to account for the fat-tails for these four variables of interest.[101]

Table 4.1 Descriptive statistics for the weekly logarithmic differences (EUR) of stock prices, EUR/USD, import and export: entire sample period.

	Mean	St.dev.	Kurtosis	Skewness
Stock Returns	-0.0004	0.026	249.464	-5.340
EUR/USD	-0.0009	0.031	4.038	-0.271
Import	0.0027	1.401	9.230	0.124
Export	0.0009	1.393	10.775	-0.007

The descriptive statistics of the twelve investigated firm-level determinants of exchange rate exposure for the entire sample period are shown in Table C6.2 of Appendix C6. These data will be used in the multinomial logit model in Section 4.4.3. All variables are initially retrieved on a weekly, monthly or yearly basis from Thomson Reuters DataStream, Statistics Netherlands or Orbis Global (Bureau Van Dijk). Next, the variables of interest are constructed and finally aggregated over the entire sample period. An overview of these variables, their definitions, initial data frequency and data sources, can be found in Table C5.1 from Appendix C5. Further, we employ foreign net revenue as an approximation for the foreign sales variable. The latter is often calculated as a ratio of foreign sales divided by total sales (Bartram, 2004; Bodnar & Wong, 2003; Chow et al., 1997; Dominguez & Tesar, 2006a; Doukas et al., 2003; Faff & Marshall, 2005; Lin & Lee, 2017; Pantzalis et al., 2001). Since data on foreign sales were not available for most of the firms, we instead divide the foreign net revenue by the total net revenue. This ratio accounts for the share of the total net revenue generated outside the Netherlands in the total net revenue. As such, it represents the net revenue generated within and outside the Eurozone including foreign subsidiaries as well; a further distinction in the data, accounting solely for the net revenue outside the Eurozone was not possible.

[101] Shapiro-Wilk normality tests confirmed that stock returns, euro-dollar exchange rate, import and export are not normal distributed. Furthermore, the literature agrees on the general appropriateness of the Student-t distribution for modelling these kind of financial data (Van Cauwenberge et al., Forthcoming).

In order to investigate trade related characteristics, we construct variables such as the extensive margin, the number of trade destinations, labor productivity and the trade status of a firm by calculating its import share. When we divide the total import outside the Eurozone by the total trade outside the Eurozone, we obtain a proportion which indicates whether a firm is rather an importer or an exporter during our sample period. Next, by counting the number of weeks when a firm participates in import or export activities, the extensive margin of respectively import and export is constructed. Additionally, trade destinations and differences in labor productivity, based respectively on weekly and yearly data, are added to the analysis. In order to measure labor productivity, the firm's output is measured by value added. As such, labor productivity is the ratio of value added to the total number of employees (FTE's) (e.g., Datta et al., 2005; Freeman, 2008; Rai et al., 1997; Wagner, 2002). Value added is the firm's total revenue minus its costs of nonlabor inputs. This measure is preferred to the alternative of measuring labor productivity as the ratio of firm sales to the number of employees since value added excludes taxes and controls for potential increases in nonlabor costs that may accompany revenue generation (Datta et al., 2005; Freeman, 2008). However, regarding the labor productivity variable, there is a selection bias. Since all firms in the sample are publicly listed and participate in international trade, firms already have achieved a certain level of productivity (Dominguez & Tesar, 2006b; Helpman et al., 2004; Melitz, 2003). As such, it becomes very difficult to distinguish large different productivity levels on a continuous scale. In order to accommodate this issue, firms are categorized according to different levels of productivity in the sample. More specifically, the 25% or the 17 least productive firms are marked as 'low', the 25% or the 17 most productive firms are marked as 'high', the remaining 50% or 34 firms of the sample are marked 'medium' productive. Further, we note that, concerning the measurement of labor productivity, the Financial and insurance activities sector is excluded from this analysis since these firms have productivity measures that are barely comparable to those used in other sectors (Bhatia et al., 2018). Finally, we mention that Quick ratio, Debt ratio and Book-to-market each have 15 (18% of sample) missing values. Foreign net revenue and productivity have respectively 16 (19% of sample) and 13 (16% of sample) missing values.

4.4. Empirical framework

The research methodology can be divided into three steps permitting us to investigate the determinants of exchange rate exposure. The first step of this novel three-step procedure aims to estimate firm-level exchange rate exposure taking into account the intensive margin of trade by using vine-copulas. In the next step, networks of firms are constructed based on the estimated exchange rate exposure. The goal of this second step is to identify whether distinguishable communities, or subgroups of firms, exist within the constructed networks based on the level of their exchange rate exposure. Finally, we apply a multinomial logit model in order to investigate the determinants of the different communities of firms found in the network analysis.

4.4.1. Step 1: Vine copulas, estimating exchange rate exposure

The first step of this novel three-step procedure aims to estimate exchange rate exposure taking international import and export into account. Classic OLS regression techniques, which are mostly used to estimate exchange rate exposure, fall short in modelling such extreme nonhedgeable exchange rate changes causing non-linear and asymmetric behavior (Bartram et al., 2010; Di Iorio & Faff, 2000; Lin & Lee, 2017; Marston, 2001; Stulz & Williamson, 1996; Van Cauwenberge et al., Forthcoming). Copulas are flexible models which are able to overcome these issues. In our research we have four variables of interest, more specifically stock returns, export, import and exchange rates. Most studies use the wide variety of bivariate copulas, since the available multivariate copulas are rather limited (e.g. Liebscher, 2008). Moreover, next to one-way traders, we also want to investigate two-way traders by including import and export in the model of exchange rate exposure. Capturing the dynamics between import and export and, as such, investigating two-way traders, can never be properly done with a trade-weighted index since this implies that export and import must always be investigated separately (Van Cauwenberge et al., Forthcoming). In order to accommodate for these constraints, we suggest the use of vine copulas, through which it is possible to display the multivariate structure between stock returns, the euro-dollar exchange rate, imports and exports. Vine copulas are a probabilistic construction of multivariate distributions based on a cascade of bivariate copulas or pair copulas which are in fact the building blocks. Vine copulas allow to add multiple dimensions, and as such, to capture the behavior of two-way traders.

Vines are a graphical representation of pair copula constructions (PCCs) (Czado et al., 2012). For the presentation we follow Aas et al. (2009) and Czado (2010) but the idea of vine copulas was first developed by Joe and Xu (1996) for cumulative distribution functions (CDF). Further, Bedford and Cooke (2001, 2002) added a graphically organization using densities and a sequence of nested trees. The class of multivariate copulas constructed in such a way are called regular vines. There are two types of regular vines: the canonical vines (C-vines) and the drawable vines (D-vines).[102] While D-vines only give temporal information on the vine-construction, the C-vine is preferred when one wants information on the importance of the relations. As such, this study only presents the results of the C-vine, more information on the D-vine and its results can be found in Appendix C2 and C7. Before building the pair copulas in order to construct the vine models, the stock returns, exports, imports and euro-dollar exchange rate data are log transformed and made stationary. Next, an ARMA(1,1)-GARCH(1,1) with Student-t distribution is adopted to remove time dependence in each of the marginal time series. Furthermore, we take the various standardized residuals to transform them into appropriate uniform margins [0,1].

Let $X = (X_1, X_2, X_3, X_4) \sim F$ with the marginal distribution functions F_1, F_2, F_3, F_4 and the cumulative distribution functions $cdf\ F_{1234}$, we can express the probability density function as follows:

$$f(x_1, x_2, x_3, x_4) = f_{4|123}(x_4|x_1, x_2, x_3) f_{3|12}(x_3|x_1, x_2) f_{2|1}(x_2|x_1) f_1(x_1) \tag{23}$$

By the repeated use of Sklar's theorem (Sklar, 1959) the density in (1) can be represented as a product of pair copula densities. There are several possibilities for building vines, one possible decomposition is the following pair copula construction (PCC) for a C-Vine:

---

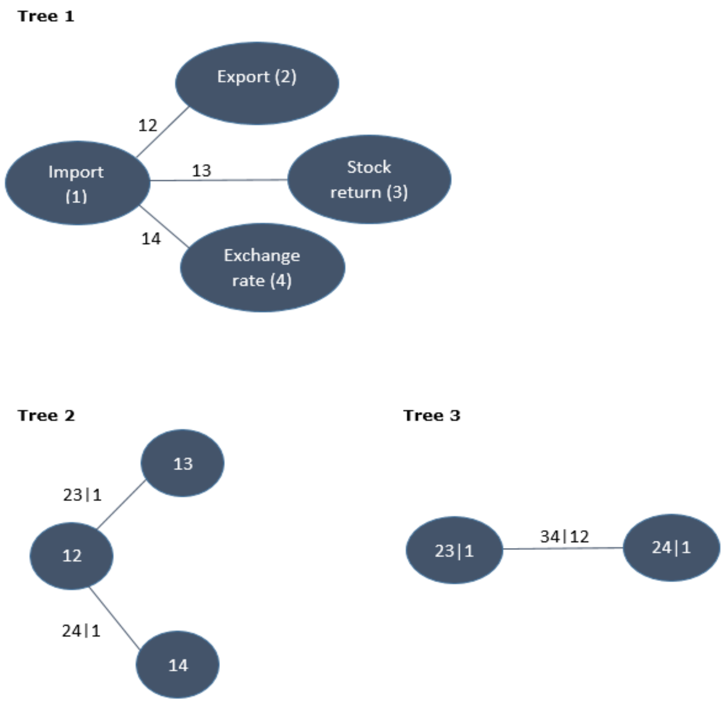
[102] D-vines are explained in Appendix C2. The results of the D-vine can be found in Appendix C7 and serve as robustness.

$$
\begin{aligned}
f_{1234}(x_1,x_2,x_3,x_4) = \quad & \textit{(marginals)} \\
& f_1(x_1)f_2(x_2)f_3(x_3)f_4(x_4) \\
& \textit{(unconditional copulas)} \\
& .\, c_{12}\big(F_1(x_1),F_2(x_2)\big) \\
& .\, c_{13}\big(F_2(x_2),F_3(x_3)\big) \\
& .\, c_{14}\big(F_3(x_3),F_4(x_4)\big) \\
& \textit{(conditional copulas)} \\
& .\, c_{23|1}\left(F_{1|2}(x_1|x_2),F_{3|2}(x_3|x_2)\right) \\
& .\, c_{24|1}\left(F_{1|3}(x_1|x_3),F_{4|3}(x_4|x_3)\right) \\
& .\, c_{34|12}\left(F_{3|12}(x_3|x_1,x_2),F_{4|12}(x_4|x_1,x_2)\right)
\end{aligned}
\tag{24}
$$

The unconditional copulas can be found in the first tree, while the conditional copulas are constructed in the second and the third tree. In order to construct a C-vine, we can choose between a data-driven and an economic-driven approach, which will be briefly explained hereafter.

The C-vine structure assumes that in an n-dimensional structure with n variables, there is one variable that can be used as a starting variable with $n-1$ edges, on which the further structure (or trees) can be built. The first tree of a C-vine can be determined by a data- or dependence-driven approach. The data-driven approach only looks at the dependence between the variables, regardless of their meaning. The highest dependence between the possible pairs is then placed in the first tree. Subsequently, building on the first tree by consecutive trees, the complete multivariate copula is constructed. The disadvantage of such an approach, however, is that the structure not always makes much sense. This approach may result in a multivariate copula in the last tree which makes no sense and cannot be explained economically. However, since the purpose and nature of this study is economical and not mathematical, we prefer a substantive, economically driven approach to build the order of the variables and pair copulas in the vine structure. Therefore, an economic approach to order the first tree can also be applied. In this case, the C-vine is composed using substantive, economically driven intuition in order to build the order of the variables and pair copulas in the vine structure.

Figure 4.1 Canonical Vine (C-Vine)



In Figure 4.1 the C-vine is presented, the third tree represents exchange rate exposure conditional on the intensive margin of international trade. We start our C-vine with import because of the dual effect hypothesis of Pritamani et al. (2004). Exchange rate exposure should be most pronounced for the importing activities of a firm since the dual effect hypothesis suggests an accentuating effect of exchange rate exposure for importing activities. More specifically, a firm with importing activities benefits from a strengthening euro in both the foreign and domestic markets and is adversely affected in both markets by a weakening domestic currency[103] (Pritamani et al., 2004). Furthermore, since the dataset used for this research consists only out of two-way traders and importers, there are no

[103] See Section 4.2 for a detailed discussion on the dual effect hypothesis.

sole exporters and every firm has at least some importing activities. Therefore, we start from a firm's importing activities in order to make the association with the remaining variables. More specifically, the first tree of the C-vine (Figure 4.1) starts with import changes and the association with export, respectively stock return, and exchange rate changes. In the second tree, two conditional copulas are made, namely, conditional on the fact that every firm imports, the relationship between export and respectively stock return changes and exchange rate changes is investigated. As such, conditional on the fact that a firm imports the second tree investigates the effect firms experience when they engage in exporting activities as well. Finally, the third and last tree represents the conditional dependence of the association between stock return and exchange rate changes on the relationship between import and export changes. The latter tree constructs exchange rate exposure conditional on the intensive margin of international trade. When a firm is not involved in exporting, the last tree boils down to $(34|1)$ or the association between stock return and exchange rate changes conditional on import changes.

The third tree provides information on how the volume of international trade influences the (tail) dependence between stock returns and the euro-dollar exchange rate. As such, this tree, with all the underlying trees or relations, gives insight into the import and export dynamics of two-way traders and the effects on their exchange rate exposure. Moreover, the obtained exchange rate exposure conditional on the intensive margin of international trade is of main interest for the second step in the three-step procedure since we distinguish different levels of exchange rate exposure by using network analysis. We compare the relationship, obtained in the third tree, between firms based on their general dependence (ρ) or Kendall's tau[104] and tail dependencies during extreme events. However, the upper and lower tail dependencies of this relationship are only comparable between firms when the constructed copulas are the same. Therefore, we force all the (conditional) associations in the trees into Symmetrical Joe-

[104] Kendall's tau coefficient, also called the Kendall rank correlation coefficient, is a non-parametric measure of linear correlation. As such, it measures the general dependence or association between the variables of interest without imposing strict normality assumptions to the distribution of the data (Field et al., 2012).

Clayton (SJC) copulas (Patton, 2006).[105] As such, the results of the vines are comparable, the upper and lower tail dependencies are captured and it is possible to see whether a relationship exists between a firm's intensive margin of international trade and exchange rate exposure during extreme events. Certain firms will, to a certain level, experience exchange rate exposure while others will not be exposed.

4.4.2. Step 2: Dependence networks, distinguishing levels of exchange rate exposure

The methodological reliance on OLS regression techniques which fail to unambiguously capture the complex relationship between exchange rate exposure and its determinants, is the main reason for inconclusive results in the literature. OLS models are only able to estimate the average effects under strict assumptions and, as such, are not able to fully distinguish differences in firms' characteristics at different levels of exchange rate exposure (Lin & Lee, 2017; Yuan et al., 2014). As such, to be able to detect whether different groups of firms are present at various levels of exchange rate exposure, we use network analysis. We apply network analysis to the vine copula results obtained from step one of the three-step procedure. The vine copula has enabled us to capture exchange rate exposure at extreme events, making it possible to construct networks of firms based on their (tail) dependence of exchange rate exposure taking the intensive margin of trade into account. We construct the Minimum Spanning Tree (MST) and the Planar Maximally Filtered Graph (PMFG) based on the Kendall's tau (τ_n) and the lower respectively upper tail dependencies of the vines. From the PMFG's, we are able to identify the community structure by using the Louvain approach.[106] The ultimate goal of this second step is to identify, whether distinguishable communities, or subgroups of firms, exist within the constructed networks, based

[105] See also Appendix C1. For this research we prefer the SJC copula since it accommodates tail independence as well as tail dependence, ranging patterns with lower and upper tails. Furthermore, it allows asymmetric tail dependence and symmetric tail dependence, which is nested as a special case. Because of these advantages, the SJC copula has become recently more widely applied in finance and economics (Patton, 2006; G. Wang & Xie, 2016).
[106] The Louvain approach is a greedy optimization approach, developed to optimize the modularity of a partition of the network (Blondel et al., 2008; G. Wang & Xie, 2015, 2016). Modularity processes the portion of internal links in the whole network over all the communities and then the corresponding proportion of links in a comparable network is estimated and subtracted (Labatut & Balasque, 2013).

on their level of exchange rate exposure conditional on the intensive margin of international trade.

In this second step of our three-step procedure we focus on the conditional dependence constructed in the third tree of the vine copula in order to construct the network. Correlation or dependence based networks are used to reduce the complexity of financial dependencies in order to understand the behavior and dynamics in financial markets. Before constructing financial networks, one should build a dependence or correlation matrix in order to determine the similarity between the agents or firms at hand. To filter or select the most important information presented in this matrix, different approaches can be used to build a dependence network. Mantegna (1999) proposed a Minimum Spanning Tree[107] (MST) which is a hierarchical arrangement of, for example, stocks obtained from their complete network of correlations. The MST is attractive because it provides an arrangement of firms which selects the most relevant connections while remaining as simple as possible. However, the condition that the extracted MST network should be a tree is a strong limitation. Definitely, when firms are involved in similar activities which have strong dependent behaviors, the constraint of the MST network becomes apparent. In the MST construction, not every firm can be directly connected with an edge. Ideally, one would like to be able to maintain the same powerful filtering properties of the MST but also allow the presence of extra links, cycles and cliques[108] in a controlled manner. As such, Tumminello et al. (2005) introduced the algorithm to filter out complex networks at a chosen level. The graph is embedded on a surface with genus[109] (g) and a certain level of complexity. By increasing g, the level of complexity rises and more information about the formed clusters is revealed, while containing the same hierarchical tree. A surface with genus equal to zero results in the simplest form of the graph or the

[107] Unlike traditional clustering algorithms, the minimum spanning tree clustering algorithm is known to be capable of detecting clusters with irregular boundaries. The MST clustering algorithm does not assume a spherical shaped clustering structure of the underlying data (Grygorash et al., 2006). See Appendix C3 for more information on the Minimum Spanning Tree.

[108] An n–clique is a complete sub graph on n vertices such that every two vertices in the sub-graph are linked by an edge. In our practical case a clique in our network refers to a set of firms with similar behavior, i.e., changes in exchange rate exposure of one firm in a clique is closely related or similar to the behavior of other firms in that clique (Aste et al., 2010).

[109] Roughly speaking, the genus of a surface is the number of holes in the surface: g = 0 corresponds to the embedding on a topological sphere; g = 1 on a torus, g = 2 on a double torus, etc. (Aste et al., 2010).

Planar Maximally Filtered Graph (PMFG).[110] The PMFG allows extra links, loops and cliques and the MST is always a subgraph of the PMFG.

In this research we choose to use the MST and the PMFG, which can be constructed in two ways (G. Wang & Xie, 2016). It is possible to construct the network based on the estimated general dependence or Kendall's tau, however this approach only takes into account the linear relationship between the variables of interest and fails to capture non-linear dependence during for instance extreme events. Alternatively, the network can also be built upon tail dependence, accounting for extreme events, as described by G. Wang and Xie (2016). Tail dependence refers to the level of dependence in the lower and upper quadrant tails of a multivariate distribution, so it is a suitable measure of the dependence of extreme events. Furthermore, domestic exchange rate changes are associated with changes in growth in the domestic economy (Mussa, 1976). As such, tail dependence, which can be divided into two measures, namely the lower tail dependence and upper tail dependence, can be used respectively to investigate the joint extreme events in stock returns and exchange rates during the market downturns and market upturns (Hu, 2010). Nevertheless, this can only be done if tail dependencies are comparable across firms, and, as such, the estimated copulas are identical. In this research we combine both proposed approaches in calculating a novel distance metric. Both general association and tail dependence are equally taken into account in calculating the distance. As such, our metric is able to take into account firms with strong tails but weak general associations, and reversed. In order to execute our proposed technique, we forced the vine copulas in our first step from our three-step procedure to use the Symmetrical Joe-Clayton (SJC) copula to estimate its (tail) dependence structure and enable comparability. The estimated tail dependence coefficients of the SJC-copula from the third tree represent extreme movements between the stock return of firm i and the exchange rate conditional on the firm's intensive margin of international trade. Since this type of copula is capable of constructing both the upper- and lower tail dependence of firm i, we can construct upper and lower tail dependence matrices, denoted as t_i^U and $t_{i,}^L$, for I firms, in our case 81. According to Mantegna (1999), who introduced

[110] See Appendix C4 for more information on the Planar Maximally Filtered Graph.

the original application of the MST, the dependence coefficient should be transformed into a distance. Therefore, we match for each firm their Kendall's tau (τ_i) and lower, respectively upper, tail dependencies with those of the other firms in order to calculate the Euclidian distance. As such we are able to construct unique distances or dissimilarity measures between all firms, more specifically $d_{i,n}^U = \sqrt{(\tau_i - \tau_n)^2 + \left(t_i^U - t_n^U\right)^2}$ and $d_{i,n}^L = \sqrt{(\tau_i - \tau_n)^2 + \left(t_i^L - t_n^L\right)^2}$. We are able to construct two distance matrices of $\boldsymbol{D}^U$ and $\boldsymbol{D}^L$ with both a size $i \times i$, or in this case 81×81. Since the distances in the matrices are unique, we are able to construct unique lower and upper tail dependence MSTs and PMFGs. These methods are explained more in detail in Appendix C3 and C4.

4.4.3. Step 3: The multinomial logit model, investigating determinants of exchange rate exposure

In the third step of our three-step approach, the determinants of exchange rate exposure are investigated.

By elaborating on the subgroups of firms found by the dependence network analysis in step two, the multinomial logit model allows us to test determinants on these communities of firms found in the network analysis. Furthermore, the multinomial logit model uses maximum likelihood estimation, which implies that we are able to determine the odds that a firm belongs to a detected community if it has a certain characteristic. We select 12 variables and verify whether the firms from the different communities are significantly different based on these determinants. We test the attributes from Table C5.1 from Appendix C5, the choice of these variables and approach is justified from past empirical research.[111] More specifically, the majority of studies which find evidence of a significant relationship suggest that exchange rate exposure increases with foreign sales (Bartram, 2004; Bodnar & Wong, 2003; Chow et al., 1997; Dominguez & Tesar, 2006a; Doukas et al., 2003; Pantzalis et al., 2001). Further, the few studies which investigate the debt ratio and book-to-market ratio find respectively a negative and a positive relationship with exchange rate exposure, the findings on the

[111] See also Section 4.2 Determinants of exchange rate exposure.

effects of a firm's size and the quick ratio are ambiguous (e.g., Bartram, 2004; Dominguez & Tesar, 2006a; Doukas et al., 2003; He & Ng, 1998; Nance et al., 1993). Regarding our trade related variables, exchange rate changes are more likely to cause changes in the intensive rather than the extensive margin (Dekle et al., 2016; Greenaway & Kneller, 2007), and firms with a higher import share than export and, as such, more pronounced importing activities, are more sensitive to exchange rate exposure (Van Cauwenberge et al., Forthcoming). Next, destination diversified firms are better able to handle exchange rate risks (Héricourt & Nedoncelle, 2016). Further, interactions are constructed between the import share and respectively the import destinations and export destinations. Furthermore, since the interaction between import share and export destinations only exist for two-way traders, we are able to distinguish two-way traders from one-way traders. Finally, highly productive firms are less sensitive to exchange rate exposure (Berthou & Dhyne, 2018).

The multinomial logit model for verifying the relationship between firm heterogeneity and exchange rate exposure is constructed as follows:

$$y_{ij} = log\frac{\pi_{ij}}{\pi_{iJ}} = \alpha_j + \beta_j x_i' + \varepsilon_{ij} \tag{25}$$

With α_j is the constant and β_j is a vector of regression coefficients for $j = 1, \dots, J - 1$. Further, x_i' is a vector of Z observed firm characteristics or variables that explain y_{ij} or the log-odds that a firm i is part of community j versus reference community J and, finally, ε_{ij} is the error term. The multinomial logistic regression model is identical to the binomial logistic regression, except that the probability distribution of the response multinomial results in $J - 1$ equations instead of one. The $J - 1$ equations contrast each category with the reference category J. As such, one community will always serve as a reference community (Field et al., 2012).

4.5. Empirical analysis

We now turn to the principal interest of this research, namely investigating the determinants of exchange rate exposure. The structure of this empirical analysis follows the subsequent three-step procedure of our novel empirical approach.

Subsection 4.5.1. provides the results and analysis of the estimation of exchange rate exposure conditional on the intensive margin of international trade through the use of vine copulas, while, by applying network analysis, empirical evidence on the existence of distinguishable communities of firms based on the level of their exchange rate exposure is provided in Subsection 4.5.2. Finally, in Subsection 4.5.3., the results of the multinomial logit model are discussed in order to investigate the determinants of the different communities of firms found in the network analysis.

4.5.1. Results step 1: estimating exchange rate exposure

The aim of this first step is to estimate exchange rate exposure conditional on the intensive margin of international trade, which is obtained in the third and last tree of the vine copulas. However, we first analyze the entire vine structure since it provides useful insights on the multivariate relationship between import, export, the euro-dollar exchange rate and stock returns. In the remaining two steps of our three-step procedure the underlying trees of the third tree, will not be considered any further since they do not contribute to building the networks in step two.

Table 4.2 shows the basic descriptive statistics of the results of the entire C-vine copula. We only discuss the C-vine results, the D-vine results, which can be interpreted in a similar way, can be found in Appendix C7.[112] The dataset used for this research consists out of two-way traders and sole importers. There are no sole exporters, but every firm has at least some importing activities. Furthermore, as already mentioned in Section 4.4.1, by elaborating on the dual effect hypothesis of Pritamani et al. (2004), the C-vine starts from a firm's imports in order to make the association with the remaining variables. More specifically, the first tree of the C-vine starts with import changes and the association with respectively export changes, stock returns, and euro-dollar exchange rate changes. As such, the first tree represents the relationship a firm's importing

[112] Since the D-vine is constructed using the data-driven approach, the economic meaning of this vine structure is only temporarily and less relevant, the results can therefore be obtained in Appendix C7. The C-vine is composed using substantive, economically driven approach to build up the order of the variables and pair copulas in the vine structure. As such, the D-vine is used as a robustness check for the C-vine. Both the C- and D-vine show similar results, indicating that the results of the C-vine are robust.

activities have with the remaining variables. The associations in this first tree are, on average, positive. This indicates that for the majority of the time import changes move together and are positively related with respectively export changes $C_{SJC}(1,2)$, stock returns $C_{SJC}(1,3)$, and euro-dollar exchange rate changes $C_{SJC}(1,4)$.

Table 4.2 Results C- vine with import (1), export (2), stock return (3) and exchange rate (4)

Tree 1

$C_{SJC}(1,2)$		$C_{SJC}(1,3)$		$C_{SJC}(1,4)$	
Max λ_L	0.481018	Max λ_L	0.102659	Max λ_L	0.114882
Max λ_U	0.763059	Max λ_U	0.068923	Max λ_U	0.092509
$\bar{\rho}$	0.047505	$\bar{\rho}$	0.001618	$\bar{\rho}$	0.023274
Min ρ	-0.246167	Min ρ	-0.105814	Min ρ	-0.077681
Max ρ	0.599023	Max ρ	0.088652	Max ρ	0.112902

Tree 2

$C_{SJC}(2,3\|1)$		$C_{SJC}(2,4\|1)$	
Max λ_L	0.106446	Max λ_L	0.081711
Max λ_U	0.119174	Max λ_U	0.120492
$\bar{\rho}$	0.000974	$\bar{\rho}$	0.021963
Min ρ	-0.103830	Min ρ	-0.084104
Max ρ	0.122201	Max ρ	0.096919

Tree 3

$C_{SJC}(4,3\|1,2)$	
Max λ_L	0.102555
Max λ_U	0.065135
$\bar{\rho}$	0.002570
Min ρ	-0.123073
Max ρ	0.103211

However, the minimum of ρ shows that there are also firms for which import changes and respectively the export changes $C_{SJC}(1,2)$, stock returns $C_{SJC}(1,3)$ or euro-dollar exchange rate changes $C(1,4)$ move in opposite directions. The upper tail (λ_U) and lower tail (λ_L) are both large for $C_{SJC}(1,2)$ and, as such, import and export rise and decline together or follow each other in extreme moments. Since the lower tail is smaller than the upper tail, the decline of import and export together is less pronounced in extreme moments than their joint increase during extreme events. For the other associations in the first tree, more specifically, import and the stock return or $C_{SJC}(1{,}3)$, and import and the exchange rate or $C_{SJC}(1{,}4)$, both pair of variables decline mostly together in extreme moments since their lower tail (λ_L) is larger than their upper tail (λ_U). Taking a closer look at $C_{SJC}(1{,}2)$ and $C_{SJC}(1{,}4)$ these associations can be explained by the dual effect hypothesis and the behavior of two-way traders. According to this hypothesis, exchange rate exposure should be most pronounced for the importing firms because of the accentuating effect of exchange rate exposure for importing activities. More specifically, a firm with importing activities benefits from a strengthening euro in both the foreign and domestic markets and is adversely affected in both markets by a weakening euro (Pritamani et al., 2004). As such, expanding imports and a strengthening euro will have a positive association, which is confirmed in $C_{SJC}(1{,}4)$. Further, the dataset used to construct this C-vine mainly consists largely out of two-way traders. When the demand for export rises, as a result of a weakening euro, two-way traders will have to augment their imports because this is often their source of (raw) materials or intermediary goods in order to produce the exported good. This positive association between import and export $C_{SJC}(1{,}2)$ indicates that export activities, at least partly, determine import activities for two-way traders. Additionally, the associations between import and stock return or $C_{SJC}(1{,}3)$ is positive. This implies that a firm with increasing importing activities, also may adjust its profit expectations upwards, because the additional import will either be resold at a profit margin or used as an intermediary good in the production process to add value. Increasing these activities should, therefore, result in increased profits. Higher profit expectations result in higher stock returns, hence, the positive association.

The second tree $C_{SJC}(2{,}4|1)$, which represents the association between export changes and the euro-dollar exchange rate changes conditional on import changes, is on average positive and therefore indicates that both export and the euro-dollar exchange rate move together. The lower tail dependence implies a depreciating euro-dollar exchange rate and declining exports in extreme moments. However, the upper tail dependence is more pronounced, pointing to a jointly appreciating euro-dollar exchange rate and increasing exports in extreme moments. The behavior found in $C_{SJC}(2,4|1)$ can also be explained by elaborating on the dual effect hypothesis for two-way traders (Pritamani et al., 2004). For instance, a depreciating euro-dollar exchange rate makes exporting to foreign markets more attractive. However, importing the intermediate inputs to fabricate the exporting good becomes more expensive, offsetting the beneficial effect of export, making exporting to the foreign market less attractive and leaving the firm exposed. Since firms are reluctant to exit foreign markets or alter the extensive margin of trade, due to the large and sunk market-entry costs, they instead adapt and optimize their intensive margin, waiting for an appreciating euro-dollar exchange rate or strengthening euro (Baldwin, 1988; Chaney, 2008). An appreciating euro-dollar exchange rate makes exporting initially less attractive, but importing the intermediary goods for producing the product becomes cheaper, as such, the adverse effects may be offset by selling at lower production cost to the booming domestic market. Moreover, these firms are now able to export at a lower cost, making them again more attractive on the foreign market. The other remaining conditional association in the second tree $C_{SJC}(2,3|1)$ presents the association between export changes and the stock return conditional on import changes. This association $C_{SJC}(2,3|1)$ is less strong than the association $C_{SJC}(2,4|1)$ but is on average still slightly positive. Both upper and lower tail dependence have a similar size. This is an indication that foreign involvement by importing and exporting activities are related with higher profit expectations which result in higher stock returns, hence, the positive association.

Finally, the third and last tree $C_{SJC}(4,3|1,2)$ shows that there is on average a positive association between stock returns and exchange rate changes conditional on international trade, which indicates that for the majority of the time changes move together. The monetary theory of Mussa (1976) and the dual effect hypothesis of Pritamani et al. (2004) further explain $C_{SJC}(4,3|1,2)$ from a business cycle perspective. More specifically, demand and supply side effects are driven by the business cycle. During market downturns,[113] trade collapses can mainly be

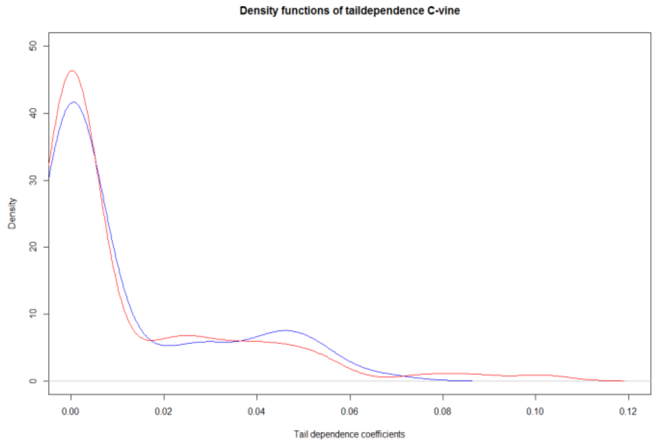
[113] Monetary theory, embodied by the flexible price monetary model, states that there exist a positive association between growth in the domestic economy and domestic currency movements (Mussa, 1976). As such, an appreciating euro-dollar exchange rate embodies a domestic market upturn, while a depreciating euro-dollar exchange rate represent a domestic market downturn.

attributed to changes in final expenditure, leading to a decreasing demand (Baldwin & Taglioni, 2009; Bems et al., 2013; Bussire et al., 2013; Eaton et al., 2016; Nagengast & Stehrer, 2016). Although a depreciating euro-dollar exchange rate might trigger a demand on the foreign market (export) and might mitigate partly the exposure on the importing side and the weakening domestic market, it still leaves the firm exposed, i.e., exchange rate exposure is not entirely neutralized. In response to these effects, firms adjust their operations and supply downwards (Baldwin, 1988; Chaney, 2008; Engel & Wang, 2011). As a consequence, a firm's future growth prospects will be adjusted downwards, impacting its market value. The opposite is true when the euro appreciates. In such a situation, the domestic market strengthens and the domestic demand increases. Albeit an appreciating euro-dollar exchange rate makes exporting initially less attractive, importing the intermediary goods for producing the product becomes cheaper and selling at lower production cost to the booming domestic market offset the adverse effects on the exporting side. Moreover, two-way traders are now able to export at a lower cost, making them again more attractive on the foreign market. A firm's future growth prospects will be adjusted upwards, impacting its market value. Moreover, since exchange rate changes embody domestic market up- and downturns (Mussa, 1976), we might derive that firms who have on average a positive association between their stock returns and exchange rate conditional on international trade are more sensitive to the business cycle than firms who have no or a negative association between these variables of interest.

Further, the maxima of the lower and upper tail dependence of the third and final tree $C_{SJC}(4,3|1,2)$ show that the upper tail dependence coefficients are on average smaller than the lower tail dependence, implying that firms experience stronger and more volatile exchange rate exposure during domestic market downturns than during domestic market upturns.[114] This behavior becomes much clearer when plotting the density function of the tail dependencies of the third tree.

[114] Monetary theory, embodied by the flexible price monetary model, states that there exist a positive association between growth in the domestic economy and domestic currency movements (Mussa, 1976). As such, an appreciating euro-dollar exchange rate embodies a domestic market upturn, while a depreciating euro-dollar exchange rate represent a domestic market downturn.

Figure 4.2 Density functions tail dependence C-vine



(Upper tail =blue; lower tail = red)

Figure 4.2 presents the density functions of the upper- and lower tail dependencies of the C-vine of the third tree, namely the estimated exchange rate exposure conditional on the intensive margin of international trade. Lower tail dependencies stands for jointly declining stock returns, import, export and a depreciating euro-dollar exchange rate, while upper tail dependencies represent jointly increasing stock returns, import, export and an appreciating euro-dollar exchange rate. Next, both figures indicate that the two tail dependence distributions (red and blue line) are different since they have hardly any overlapping parts. Further, the figure shows larger lower tail than upper tail dependence since the red curve is longer than the blue one. This indicates that most variability in exchange rate exposure can be found in lower tail dependence. The difference in tail dependence[115] structure suggests that firms react differently to changes in market conditions and, as such, confirming Lin and Lee (2017), different levels of exchange rate exposure exist. Furthermore, Figure 4.2 justifies the use of the SJC-copula, since it emphasizes the importance of treating upper and lower tail separately.

As mentioned before, we are able to construct unique distances or dissimilarity measures between firms based on the results of the third and last tree, more

[115] Figure 4.2 also shows the importance of using the SJC-copula which enables us to distinguish upper from lower tail dependence. This information would remain unexposed if one would use, e.g., elliptical copulas.

specifically $d_{i,n}^U = \sqrt{(\tau_i - \tau_n)^2 + \left(t_i^U - t_n^U\right)^2}$ and $d_{i,n}^L = \sqrt{(\tau_i - \tau_n)^2 + \left(t_i^L - t_n^L\right)^2}$. As such, we construct two distance matrices of $\boldsymbol{D}^U$ and $\boldsymbol{D}^L$ resulting in both 3240 distances (i.e., $i(i-1)/2$). When comparing the d^U and d^L we find that 20% of the upper and lower tail distances are equal while the remaining 80% of the observations determine the difference in upper and lower tail structure of exchange exposure.

4.5.2. Results step 2: distinguishing levels of exchange rate exposure

In the second step of our three-step procedure, networks of firms are constructed based on the estimated exchange rate exposure from step one. The goal is to identify whether distinguishable communities, or subgroups of firms, exist within the constructed networks based on the level of their exchange rate exposure. We construct upper and lower tail dependence networks for both MST and PMFG approaches. The results of the MST are discussed first, followed by the PMFG.

4.5.2.1. Lower and upper tail dependence Minimum Spanning Trees

The figures below show the lower and upper tail dependence MSTs of 81 firms analyzed during the period 2011-2015. The obtained MSTs are unique since taking the tail dependences as well as the Kendall's tau into account, while calculating the Euclidian distances, results in unique distances. The lower tail dependence MST differs from the upper tail dependence MST as the former clusters firms based on a depreciating euro-dollar exchange rate and a declining stock return while the latter clusters firms based on an appreciating euro-dollar exchange rate and a rising stock return. The MSTs of Figures 4.3 and 4.4 show two obvious clusters of weaker and stronger lower, respectively, upper tail dependence. This already confirms the preconceived assumption that different subgroups of firms according to their exchange rate exposure conditional on the intensive margin of international trade are distinguishable. Next, the nodes or firms in Figure 4.3 and 4.4 are depicted larger when the upper or lower tail dependence is larger and as such firms are more subject to extreme changes of the market conditions. The left cluster represents the weaker tail dependence or lower risk, while the right cluster stands for stronger tail dependence and, as such, higher risk. However, we notice that in both graphs the center nodes, which also connect both clusters, seem to be strangers in their cluster.[116] These kind of nodes and links have a special role in a network. In our networks these nodes are placed central because they represent the firms with the most extreme distances, in other words opposites attract. More specifically, these are the firms with the weakest and the strongest lower and upper tail dependence. For example, this explains why in Figure 4.3 the very large node f35, representing the strongest lower tail dependence, is placed central in the left cluster among firms with weak tail dependence. As such, firm f35 represents an extreme in our sample and is linked with the right cluster with stronger lower tail dependencies. The connection to the other (right) community is more relevant for f35 than the surrounding relationships from its own community on the left. Further, since our distance metric also takes the Kendall's tau into account, this explains why f76 is placed central instead of for example f3. Whereas, the tail dependence of f3 is greater than the one of f76, the latter has a larger Kendall's tau indicating a stronger general association between the stock return and an appreciating euro-dollar exchange rate conditional on the intensive margin of international trade. This last example shows why it is also important to take the Kendall's tau, or the strength of the relationship, into account when composing the distance metric.

[116] According to Alvarez-Socorro et al. (2015) nodes linking neighboring nodes in different clusters or communities are more relevant than nodes with neighborhoods fully included in the same cluster. Similar, links with both extreme nodes in the same module are less relevant than links with extreme nodes in different clusters or communities.

Figure 4.3 Lower tail dependence MST with tails marked

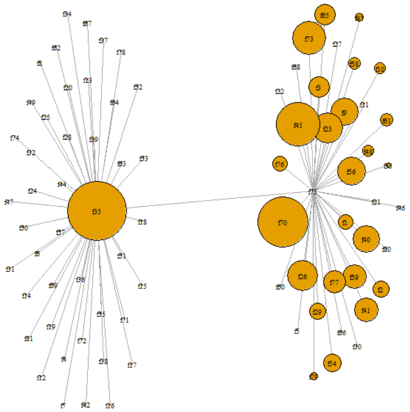


Figure 4.4 Upper tail dependence MST with tails marked

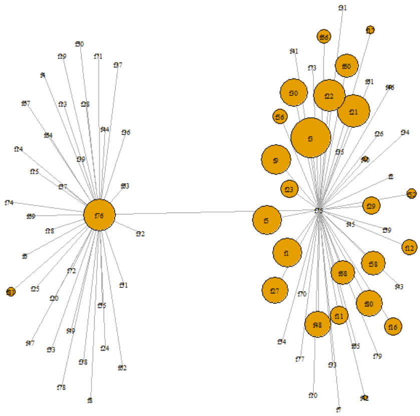


Figure 4.5 and 4.6 show that the association of the relationship, or the Kendall's tau, is also reflected in the clusters. The left cluster, which was already identified as a cluster with weaker tail dependence, shows mainly the firms with negative Kendall's taus. The right cluster, which represents stronger tail dependence, contains mainly firms with a positive association. The firms with a positive association experience exchange rate exposure, since the stock return changes and exchange rate changes move in the same direction. When we take a look back to Figure 4.3 and 4.4, these firms also have tail dependence. Firms with no or even a negative association experience little or no exchange rate exposure since the stock return and euro-dollar exchange rate changes do not move together and do not seem to be related at all.

When we take a look at the lower and upper tail MSTs from Figure 4.5 and 4.6, they look very similar. However, there are some slight differences between the two networks. More specifically, 9 firms move from the left cluster in the lower tail dependence to the right cluster in the upper tail dependence MST, meaning that these firms have hardly any lower but have high upper tail dependence. These firms are able to control their exchange rate exposure during domestic market downturns and are able to take advantage of exchange rate changes during domestic market upturns. These firms have a profound market understanding and can be considered as winners. Only one firm makes the opposite movement and goes from the right cluster in the lower tail dependence MST to the left cluster in the upper tail MST. As such, this firm experiences exchange rate exposure during domestic market downturns and is not able to take advantage of a strengthening euro during domestic market upturns. This firm is not resilient to exchange rate exposure and can be considered as a loser in the market. The remaining 71 firms stay in the same cluster as they were before. This implies that firms which are initially in the left cluster and do not experience much exchange rate exposure, also do not take advantage of an appreciating euro-dollar exchange rate. The firms in the right cluster experience exchange rate risk during market downturn, but, when the domestic economy restores and booms, they are also able to take advantage of market upturns.

Figure 4.5 Lower tail dependence MST Kendall's taus marked

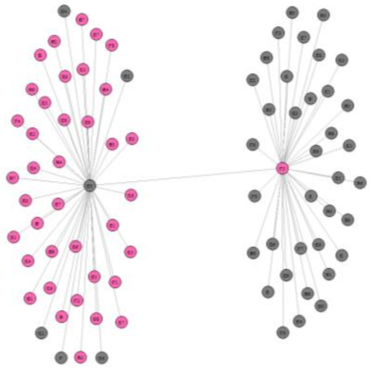
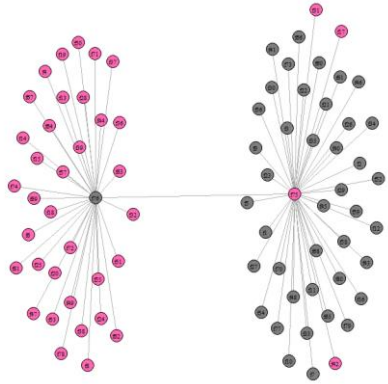


Figure 4.6 Upper tail dependence MST Kendall's taus marked



The firms in Figures 4.5 and 4.6 are marked as follows: positive Kendall's tau in grey and negative Kendall's tau in pink.

Our sample consists out of 65 two-way traders and 16 sole importers. In Figure 4.7 and 4.8 we mark these two types of traders. In the lower tail dependence MST, the importers and two-way traders seem to be scattered over the two clusters. More specific, 55% of the two-way traders seem to experience almost no lower tail dependence and are not affected by exchange rate risk during market downturns and also the exclusive importers are distributed equally over both clusters. In the upper tail dependence MST, the exclusive importers mainly occur in the right cluster. The right cluster represents stronger tail dependence and a positive Kendall's tau. As such, we can assume that although not all exclusive importers are able to avoid exchange rate risk during market downturns, the majority, or 81%, is able to take advantage of exchange rate exposure during market upturns. Import oriented firms clearly benefit from an appreciating euro-dollar exchange rate in both the domestic and foreign markets, confirming the economic intuition of the dual effect hypothesis (Pritamani et al., 2004). The two-way traders are almost equally distributed over the left and the right cluster of the upper tail dependence MST.

Figure 4.7 Lower tail dependence MST with two-way traders and sole importers marked

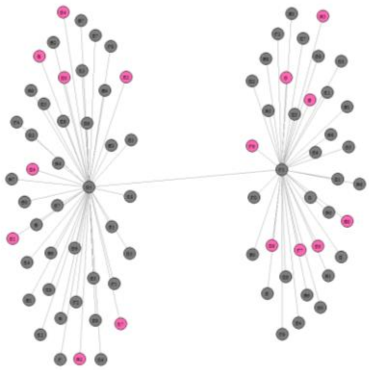
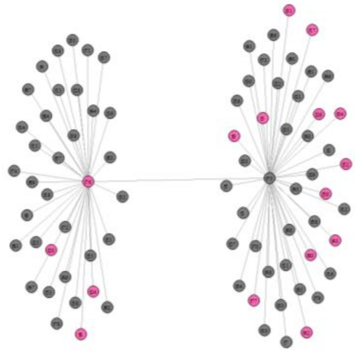


Figure 4.8 Upper tail dependence MST with two-way traders and sole importers marked



The firms in Figures 4.7 and 4.8 are marked as follows: two-way traders in grey and sole importers in pink.

Finally, in Figure 4.9 and 4.10, the 8 different sectors are marked with each a specific color. Both networks show two distinctive clusters. Confirming the findings of Dominguez and Tesar (2006a, 2006b), firms of different sectors are scattered among the two clusters, indicating that sector affiliation is not a potential determinant of exchange rate exposure.

Figure 4.9 Lower tail dependence MST with the sectors marked

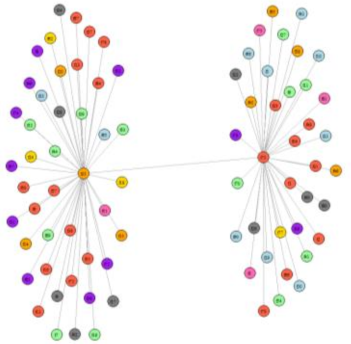
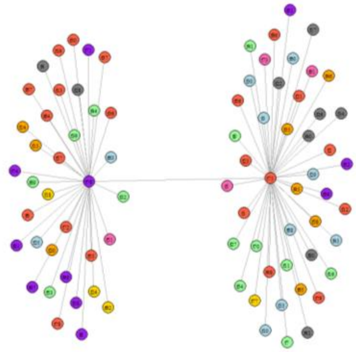


Figure 4.10 Upper tail dependence MST with the sectors marked



The firms in Figures 4.9 and 4.10 are marked as follows: The Financial & insurance sector (grey); Industry (red); Administrative and service sector (yellow); Professional, scientific & technical sector (blue); Wholesale and retail sector (green); Information & communication sector (purple); Construction (orange); Transportation & storage (pink).

4.5.2.2. Lower and upper tail dependence Planar Maximally Filtered Graph

The figures below show the lower and upper tail dependence PMFGs of 81 firms analyzed during the period 2011-2015. The MST is always a subgraph of the PMFG, but a PMFG[117] has 3 times the number of edges than the MST. This also implies that the conclusions for the MST networks also apply for the PMFGs. However, the PMFG contains extra information, since cycles, 3- and 4-cliques are allowed, enabling us to find more meaningful information in the network, in order to investigate the determinants of exchange rate exposure in the last step of our three-step procedure (Aste et al., 2010; Tumminello et al., 2005). Furthermore, the 3- and 4-cliques between the lower- and upper tail dependence PMFGs are almost completely different. Market participants and policy makers should be aware of the 3- and 4-cliques in the PMFGs to adjust their decision making. Moreover, firms from the same 3- or 4-clique react highly similar to exchange rate exposure in different market situations. As such, while assembling portfolios, one should choose firms from different cliques. However, policy makers should focus on firms of the same 3- and 4-clique when making policy decisions. The firms of

[117] We calculate 200 3-cliques and 42 4-cliques in the lower tail dependence PMFG and respectively 193 and 35 in the upper tail dependence PMFG. This is still far smaller than the number of possible 3- and 4-cliques in a fully linked graph, which is C_{81}^{3} or 85,320 and C_{81}^{4} or 1,663,740, indicating the efficiency and meaningfulness of the obtained structure of the PMFGs.
$C_{81}^{3} = 81!/(3!\,(3-81)!) = 85{,}320$ and $C_{81}^{4} = 81!/(4!\,(4-81)!) = 1{,}663{,}740$.

these cliques do not always come from the same sector, as we already noted while studying the MSTs from the previous Section.

When we compare Figure 4.11 and 4.12 with the previous MSTs, such as Figure 4.9 and 4.10, the MST structure in both PMFG graphs is recognizable. However, we notice in the lower tail dependence PMFG more distinguishable subgroups of firms than in the upper tail dependence PMFG. As such, an analysis on its clique and community structure is an important topological feature as input to later on investigate the determinants of exchange rate exposure. Moreover, the detailed subgroups or communities obtained from the PMFGs will be used in the third step of the three-step procedure, namely the multinomial logit model.

Figure 4.11 General lower tail dependence PMFG

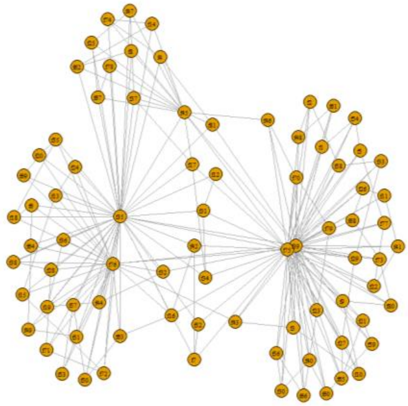
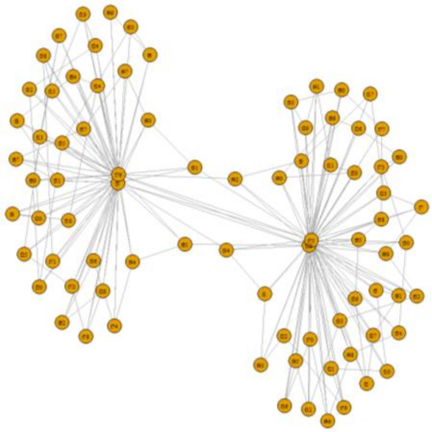


Figure 4.12 General upper tail dependence PMFG



The community structure shows the emergence of clusters of firms in a complex network that are more densely or compactly linked internally than the rest of the complex network. To identify the community structure in the tail dependence PMFGs, the Louvain approach is used as proposed by Blondel et al. (2008). Figures 4.13 to 4.16 present the communities of firms of the lower and upper tail dependence PMFGs respectively. Three communities (C1 grey, C2 yellow and C3 pink) are found in the lower tail dependence PMFG network. While only two communities (C1 grey, C2 yellow) are detected in the upper tail dependence PMFG. Next to the presence of 3- and 4-cliques, market participants and policy makers should also be aware of the community structure in the PMFGs while making their decisions. The size of the communities is larger than the 3- and 4-cliques. Some of the 3-cliques and 4-cliques are covered in the same community (G. Wang & Xie, 2015, 2016). As such, firms in the same community will react similar to exchange rate exposure.

Figure 4.13 Lower tail dependence PMFG with communities marked

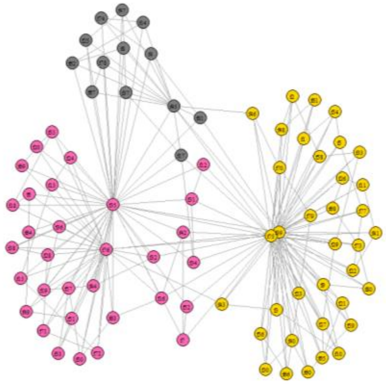


Figure 4.14 Upper tail dependence PMFG with communities marked

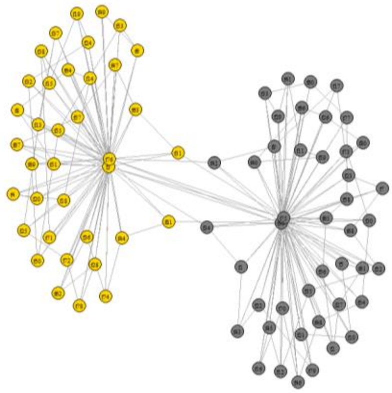


Figure 4.15 Lower tail dependence PMFG with communities separated

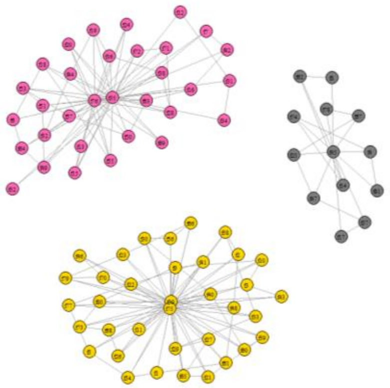
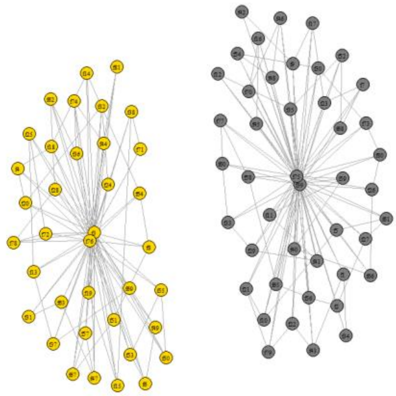


Figure 4.16 Upper tail dependence PMFG with communities separated



The communities or clusters in Figures 4.13 and 4.15 are marked as follows: C1 in grey equals the non-exposure group; C2 in yellow is the heavy exposure group; C3 in pink equals the low exposure group. The communities or clusters in Figures 4.14 and 4.16 are marked as followed: C1 in yellow is the low exposure group; C2 in grey equals the heavy exposure group.

Table 4.3 presents the descriptive statistics of the three communities found in the lower tail dependence PMFG. The table indicates that community C1, or the non-exposure group in grey, has no tail dependence and a negative association, from which we conclude that the firms from this community have no exchange rate risk in the lower tail, or in other words are not exposed during domestic market downturns. Community C2, or the heavy exposure group in yellow, is the opposite case, with stronger tails and positive dependence. The firms from this community experience exchange rate exposure during domestic market downturns and are, as such, much riskier. Further, since the first community is torn from the third, while constructing the PMFG, these two have more similarities with each other than with the second community. More specifically, just like in the first community, we also find negative dependence in the third. However, the firms in the third community C3, or the low exposure group in pink, do have tails, yet, they are very small.

Table 4.3 Descriptive statistics lower tail dependence PMFG communities

	Kendall's tau			
	Mean	St.dev.	Min.	Max.
Non-exposure group (C1 in grey)	-0.0157362	0.0069004	-0.0238237	-0.0027109
Heavy exposure group (C2 in yellow)	0.0513144	0.0235912	0.0115640	0.1066817
Low exposure group (C3 in pink)	-0.0459011	0.0375588	-0.1229201	0.0055226
	Lower tail dependence			
	Mean	St.dev.	Min.	Max.
Non-exposure group (C1 in grey)	0	0	0	0
Heavy exposure group (C2 in yellow)	0.0280164	0.0258777	0.0000489	0.1013733
Low exposure group (C3 in pink)	0.0000435	0.0001702	0	0.0006922

Table 4.4 presents the descriptive statistics of the two communities found in the upper tail dependence PMFG. The table indicates that firms from community C1, the low exposure group in yellow, have small tails and negative association, which means that they do not take advantage of exchange rate swings in a booming market, but are also not exposed to exchange rate risk. Community C2, which is the heavy exposure group in grey, includes firms with stronger tails and positive dependence. These firms make use of exchange rate exposure during domestic market upturns but can also be seen as riskier.

Table 4.4 Descriptive statistics upper tail dependence PMFG communities

	Kendall's tau			
	Mean	St.dev.	Min.	Max.
Low exposure group (C1 in yellow)	-0.0451927	0.0329062	-0.1229201	-0.0014471
Heavy exposure group (C2 in grey)	0.0434794	0.0282763	-0.0027109	0.1066817
	Upper-tail dependence			
	Mean	St.dev.	Min.	Max.
Low exposure group (C1 in yellow)	0.0004324	0.0026304	0.0000000	0.0160000
Heavy exposure group (C2 in grey)	0.0215316	0.0214452	0.0006922	0.0676217

We conclude that, while assembling portfolios, one should not only choose firms from different cliques but also different communities. However, policy makers should focus on firms from the same 3- and 4-clique within the same community when making policy decisions. The firms of these cliques do not always come from the same sector as we pointed out while studying the MSTs from the previous Section.

The community structure shows the emergence of clusters of firms in a complex network that are more densely or compactly linked internally than the rest of the network. The network analysis on the MSTs and PMFGs shows that significant subgroups of firms can be distinguished based on their exchange rate exposure conditional on the joint dynamics of international export and import changes. These obtained insights and information of the network analysis, e.g., communities, are used in the next step of the three-step procedure, namely the multinomial logit model.

4.5.3. Results step 3: investigating determinants of exchange rate exposure

In the last step of our three-step approach, we investigate the determinants of exchange rate exposure. Therefore, we select twelve firm-level variables to verify whether the firms from the different communities are significantly different based on these variables. Table C5.1 from Appendix C5 presents all the variables used in this third step of the empirical analysis, together with a brief definition and data sources. All the variables are examined using a multinomial logit model with the different lower- or upper tail communities as dependent variable. Table 4.5 (part A to C) shows the individual parameter estimates of the multinomial logit regression using the communities of the lower tail PMFG as dependent variable, while Table 4.6 investigates the communities of the upper tail PMFG. In Table C9.1 and C9.2 of Appendix C9 are alternative multinomial logit models presented, where determinants for which no effect was found (i.e., debt ratio, foreign net revenue, extensive margin) are excluded. Appendix C9 confirms that our results are robust.

Table 4.5 Multinomial logistic regression communities lower tail dependence PMFG

PART A

Non-exposure versus heavy exposure group (C1 versus C2)	$\hat{\beta}$	Odds ratio[118]
Intercept	11.711	121,916.500
Log size	-1.430	0.239
Quick ratio	-3.451	0.032
Debt ratio	1.429	4.176
Book-to-market	-0.655	0.519
Foreign net revenue	6.281	534.242
Extensive margin import	0.045	1.046
Extensive margin export	0.037	1.037
Import share	-16.156	0.000
Import destinations outside Eurozone	-0.952	0.386
Export destinations outside Eurozone	-0.039	0.961
Import share × Import destinations outside Eurozone	0.907*	2.478
Import share × Export destinations outside Eurozone	-0.1634	0.849
Highly productive firms	9.866*	19,273.740
Medium productive firms	4.118	61.439

Significance codes 0.001 '***'; 0.01 '**'; 0.05 '*'; Log-likelihood: -26.814; McFadden R^2: 0.56
Likelihood ratio test: chi-square: 68.838 (p-value: 0.000).

Part A of Table 4.5 compares community C1, which is a non-exposed community, with the most exposed community of the lower tail dependence PMFG, i.e., community C2. We find significant results for two variables distinguishing C1 from C2, namely the productivity dummy ($\hat{\beta}$ = 9.866, p<0.05) and the interaction between the import share and importing destinations outside the Eurozone ($\hat{\beta}$ = 0.907, p<0.05). Taking into account, although not significant, that increasing the

[118] In general odds are defined as follows: $Odds = \frac{P(event)}{P(no\ event)}$ (Field et al., 2012). For Table 4.5 this implies for the first part of the table the odds are equal to $\frac{P(C_1)}{P(C_2)}$ the second part of the table the odds are equal to $\frac{P(C_3)}{P(C_2)}$ and finally the third part of the table the odds are equal to $\frac{P(C_3)}{P(C_1)}$.

import share or the number of import partners outside the Eurozone separately would heighten the possibility of firms belonging to the heavy exposure group, combining both activities seems to significantly mitigate risk. More specifically, the odds ratio of the interaction indicates that when the import share increases with one unit in combination with an increase of import destinations outside the Eurozone, the change in odds of being part of the non-exposure community C1 compared to being part of the heavy exposure group C2 is 2.478, ceteris paribus. In other words, the risk of importing is mitigated by diversifying along more import destinations outside the Eurozone. This might indicate that the findings of Héricourt and Nedoncelle (2016), who state that that more destination-diversified firms are better able to handle exchange rate changes, are confirmed when comparing community C1 to C2. Additionally, productivity seems to play a significant role in explaining the community structure. A productivity dummy is added in the multinomial regression, excluding the first category representing the 25% least productive firms of the sample. More productive firms tend to end up in less risky communities. The odds ratio shows a highly significant result when a firm moves from the least productive to the highest productive category of the sample, ceteris paribus. This implies that a firm belonging to the 25% highest productive firms of the sample, is most likely to be part of the non-exposure community C1. This confirms the findings of Berthou and Dhyne (2018) stating that productive firms are better able to handle exchange rate risk since they are more efficient in adapting their operations in changing market conditions.

Next, in part B of Table 4.5 we compare community C3, which is a low exposed or low risk bearing community, with the most exposed or risky community, i.e., community C2. It is important to note that the firms in both communities experience exchange rate exposure, however these two communities differ in intensity. Nine variables are found to be significant in predicting whether a firm belongs to community C3 or C2, more specifically, size, quick ratio, book-to-market, import share, import and export destinations outside the Eurozone, the interaction between import share and import destinations outside the Eurozone and finally, the interaction between import share and export destinations outside the Eurozone and productivity.

Table 4.5: Multinomial logistic regression communities lower tail dependence PMFG

PART B

Low exposure versus heavy exposure group (C3 versus C2)	$\hat{\beta}$	Odds ratio
Intercept	-1.114	0.328
Log size	-1.366*	0.255
Quick ratio	4.192***	66.155
Debt ratio	-1.384	0.251
Book-to-market	-3.611**	0.003
Foreign net revenue	-0.862	0.422
Extensive margin import	-0.006	0.994
Extensive margin export	0.025	1.025
Import share	8.653**	5724.868
Import destinations outside Eurozone	-0.154**	0.857
Export destinations outside Eurozone	0.138***	1.149
Import share × Import destinations outside Eurozone	0.239**	1.270
Import share × Export destinations outside Eurozone	-0.275**	0.760
Highly productive firms	4.838***	126.198
Medium productive firms	0.443	1.557

Significance codes 0.001 '***'; 0.01 '**'; 0.05 '*'; Log-likelihood: -26.814; McFadden R^2: 0.562; Likelihood ratio test: chi-square: 68.838 (p-value: 0.000).

According to the odds ratio of 0.255, larger firms are more likely to end up in the heavy exposure group. When a firm's size ($\hat{\beta}$ = -1.366, p<0.05) increases with one unit, the change in the odds of being part of the low exposure group versus the heavy exposure group is 0.255, ceteris paribus. In short, larger firms are more likely to be part of the heavy exposure group. However, size is defined as total assets, which only gives the book value of a firm's total resources but does not indicate the market value of a firm. The book-to-market, which equals equity book value divided by equity market value, gives a more complete view on the value of a firm. When we take a closer look at the book-to-market ratio ($\hat{\beta}$ = -3.611, p<0.01), we notice that an increase of one unit book-to-market changes the odds of being part of the low exposure group versus the heavy exposure group with 0.003, ceteris paribus. As such, firms with lower book-to-market, i.e., more growth opportunities, are more likely to be part of the low exposure group since they have more incentives to hedge exchange rate risk (He & Ng, 1998; Nance et al., 1993). Furthermore, because of the scale of their operations, larger firms are more likely to experience exchange rate exposure, however, larger firms do not automatically hedge because they reach a certain level of economy of scale (Bartram, 2004; Chow et al., 1997; Dominguez & Tesar, 2006a; Nance et al., 1993). Baldwin (1988) and Berthou and Dhyne (2018) argue that the ability of a firm to manage its resources and operations efficiently does matter when it comes to reducing or even eliminating exchange rate sensitivity. In line with the latter perspectives, our results imply that more productive firms ($\hat{\beta}$ = 4.838, p<0.001) tend to end up in less exposed communities. The difference is most pronounced and found significant between the least productive and the most productive firms from the sample. Stated differently, when a firm belongs to the 25% highest productive firms of the sample, it is most likely that it belongs to the low exposed community C3.

Next, when the quick ratio ($\hat{\beta}$ = 4.192, p<0.001), which measures short-term liquidity used to manage short-term cash flow needs, increases, firms are more likely to be part of the low exposure group versus the heavy exposure group, ceteris paribus. Firms with a higher quick ratio have a greater flexibility to withstand imminent cash flow needs and exchange rate risk (Bartram, 2004). Conclusively, the firms from the low exposed group are firms with upcoming growth opportunities for which they keep on high liquidity and which they try to safeguard by hedging in order to keep risks such as exchange rate exposure as low as possible.

Further, when the import share increases ($\hat{\beta}$ = 8.653, p<0.01), firms are more likely part of the low exposure group versus the heavy exposure group, ceteris paribus. However, this effect is superseded by the interaction between import share and respectively import and export destinations. Additionally, the odds ratio indicates that when adding an import destination outside the Eurozone ($\hat{\beta}$ = -0.154, p<0.01), the change in the odds of being part of the low exposure community C3 compared to being part of the high exposure community C2 becomes 0.857. More specifically, when the number of import destinations outside the Eurozone rises, it is less likely that firms are going to stay in the low exposed group C3. This is in line with the dual effect hypothesis of Pritamani et al. (2004), increasing the dependence on the foreign market on the import side will result in higher exchange rate exposure because of the accentuating effect. Next, when a firm adds one export destination outside the Eurozone ($\hat{\beta}$ = 0.138, p<0.001), the odds of being part of the low exposure group versus the heavy exposure group is

1.149. In short, a firm is less likely to be part of the highly exposed group C2 than the low exposure bearing community C3, when having more export destinations outside the Eurozone. This finding also supports the dual effect hypothesis of Pritamani et al. (2004), which suggests that the foreign market on the export side may mitigate the accentuating effects of exchange rate exposure on the import side; increasing the access to foreign markets on the export side, further limits exchange rate exposure. Nevertheless, the effects of respectively import and export destinations outside the Eurozone are each superseded by their interaction with import share. The odds ratio of the first interaction ($\hat{\beta}$ = 0.239, p<0.01) indicates that as the import share increases with one unit in combination with an increase of import destinations outside the Eurozone, the change in odds of being part of low exposed community C3 compared to being part of highly exposed community C2 is 1.270, ceteris paribus. Although importing does not seem to induce exposure for this group of firms, adding trading partners does. However, firms who combine an increase of their import share with an increase in importing destinations outside the Eurozone are able to spread the risk of being exposed and as such do not necessarily increase their foreign dependence. Next, when a firm increases its import share, and as such lowers its export share,[119] with one unit in combination with adding an export destination outside the Eurozone ($\hat{\beta}$ = -0.275, p<0.01), the odds of being part of the low exposed group C3 compared to being part of highly exposed group C2 is 0.760, ceteris paribus. This is an effect that only can occur for a two-way trader. Since Table 4.5 concerns lower tail dependence, it shows a market in downturn, and as such, a weakening euro will be beneficial for the exporting activities of two-way traders, giving them no incentive to hedge. However, the importing activities of two-way traders remain exposed while the domestic market is weakened, placing them in the heavy exposure group. As such, a weakening euro might trigger a demand on the foreign market (export) and might mitigate partly the exposure on the importing side and the weakening domestic market, it still leaves the two-way trader exposed if he does not hedge, i.e., exchange rate exposure is not entirely neutralized. The choice of a two-way trader to hedge depends on how much import or export oriented the two-way trader is and accordingly, if the costs of being exposed to

[119] 1 - Import share = Export share. Since we know that: Import share + export share = total international trade (100%). See also Appendix C5.

the domestic market and importing side are higher than the benefits at the export side, a two-way trader might better hedge. Sole importers find these market conditions less beneficial for their activities, i.e., they do not have the potential benefices of exporting for the foreign market like a two-way trader, and will sufficiently hedge their trading activities, placing them rather in the low exposure group.

Table 4.5 Multinomial logistic regression communities lower tail dependence PMFG

PART C

Low exposure versus non-exposure group (C3 versus C1)	$\hat{\beta}$	Odds ratio
Intercept	-12.825	0.000
Log size	0.063	1.066
Quick ratio	7.643*	2086.822
Debt ratio	-2.814	0.060
Book-to-market	-2.956	0.052
Foreign net revenue	-7.143	0.001
Extensive margin import	-0.051	0.951
Extensive margin export	-0.012	0.988
Import share	24.809**	5.949e+10
Import destinations outside Eurozone	0.798	2.221
Export destinations outside Eurozone	0.178*	1.195
Import share × Import destinations outside Eurozone	-0.669	0.512
Import share × Export destinations outside Eurozone	-0.111	0.895
Highly productive firms	-5.029	0.007
Medium productive firms	-3.675	0.025

Significance codes 0.001 '***'; 0.01 '**'; 0.05 '*'; Log-likelihood: -26.814; McFadden R^2: 0.562; Likelihood ratio test: chi-square: 68.838 (p-value: 0.000).

In part C of Table 4.5, we compare community C3, which is a low exposed community, with the non-exposed community, i.e., community C1. We find significant results for three variables distinguishing C3 from C1, namely the quick ratio, import share and export destinations outside the Eurozone. A firm is more likely to be part of the low exposed community C3 than the non-exposed community C1, when having a larger import share ($\hat{\beta}$ = 24.809, p<0.01), ceteris paribus. This result indicates that importing bears risk during a depreciating euro-dollar exchange rate. Next, adding export destinations ($\hat{\beta}$ = 0.178, p<0.05), makes a firm more likely to be part of the low exposed group, ceteris paribus. Increasing the number of export trading partners, increases dependence on foreign demand. Moreover, we have no indication that these firms take advantage of the decreasing euro-dollar exchange rate in foreign markets, in order to offset the risk at their import activities. Further, the low exposed community C3 is able to control the exchange rate risk, which might be explained by the quick ratio. An increase in the quick ratio ($\hat{\beta}$ = 7.643, $p<0.05$), which measures short-term liquidity used to manage short term cash flow needs, makes firms more likely to be part of the low exposure group versus the non-exposure group, ceteris paribus. Firms with a higher quick ratio have a greater flexibility to withstand imminent cash flow needs and exchange rate risk (Bartram, 2004).

Table 4.6 Multinomial logistic regression communities upper tail dependence PMFG

Heavy exposed versus low exposed (C2 versus C1)	$\hat{\beta}$	Odds ratio
Intercept	-2.217	0.109
Log size	0.564	1.758
Quick ratio	-0.920	0.399
Debt ratio	-0.640	0.528
Book-to-market	0.559	1.749
Foreign net revenue	0.456	1.577
Extensive margin import	0.004	1.004
Extensive margin export	-0.003	0.997
Import share	0.513	1.670
Import destinations outside Eurozone	0.109**	1.115
Export destinations outside Eurozone	-0.081***	0.922
Import share × Import destinations outside Eurozone	-0.172**	0.842
Import share × Export destinations outside Eurozone	0.127	1.136
Highly productive firms	-2.499**	0.082
Medium productive firms	-0.237**	0.789

Significance codes 0.001 '***'; 0.01 '**'; 0.05 '*'; Log-likelihood: -32.38; McFadden R^2: 0.25; Likelihood ratio test: chi-square: 21.125 (p-value: 0.048).

Table 4.6 compares community C2, which is the heavy exposed community, with the low exposed group of firms of the upper tail dependence PMFG, i.e., community C1. The firms from C2 are labelled as more exposed because they have upper tails, as such, they bear more risk but are also able to profit from an strengthening euro. We find significant results for five variables distinguishing C2 from C1, namely, import and export destinations outside the Eurozone, the interaction between import share and import destinations outside the Eurozone and the productivity dummy.

The odds ratio shows that adding an import destination outside the Eurozone ($\hat{\beta}$ = 0.109, p<0.01), results in the odds of being part of the C2 compared to the C1 community of 1.115, ceteris paribus. More specifically, when the number of import destinations outside the Eurozone rises, it is more likely that firms are going to be part of the heavy exposed community C2. Since the link with foreign markets increases, it is also more likely to be exposed. This is in line with the dual effect hypothesis of Pritamani et al. (2004), increasing the dependence of the foreign market on the import side will result in higher exchange rate exposure because of the accentuating effect. Next, the number of exporting destinations outside the Eurozone significantly predicts whether a firm belongs to community C2 or C1. When a firm adds one export destination outside the Eurozone ($\hat{\beta}$ = -0.081, p<0.001), the odds of being part of the heavy exposure group versus the low exposure group is 0.992, ceteris paribus. In short, a firm is less likely to be part of the heavy exposed group C2 than the low exposure bearing community C1, when having more export destinations outside the Eurozone. This finding also supports the dual effect hypothesis of Pritamani et al. (2004), which suggests that the presence in foreign markets at the export side may mitigate the positive effects of an appreciating euro-dollar exchange rate; increasing the access to foreign export markets, offsets exchange rate exposure. Nevertheless, the effects of import destinations outside the Eurozone are superseded by their interaction with the import share ($\hat{\beta}$ = -0.172, p<0.001). The odds ratio of the interaction shows that when the import share increases with one unit in combination with an increase of import destinations outside the Eurozone, the change in odds of being part of highly exposed community C2 compared to being part of the low exposed community C1 is 0.842, ceteris paribus. Therefore, firms who combine an increase of their import share with an increase in importing destinations outside the Eurozone are less likely to be part of the highly exposed group. This might indicate that diversifying a higher import share over more foreign import markets might reduce the benefits of an appreciating euro-dollar exchange rate. Further, since Table 4.6 concerns upper tail dependence, it shows a market in upturn, and as such, a strengthening euro will be beneficial for the importing activities of two-way traders. Nevertheless, the exporting activities of two-way traders mitigate this beneficial exposure, placing them in the lower exposed group than sole importers.[120] Finally, when a firm does not belong to the 25% least productive firms of the sample, the firm is more likely to be part of the low exposed group C1. Stated differently, the most productive ($\hat{\beta}$ = -2.499, p<0.01) and medium productive firms ($\hat{\beta}$ = -0.237, p<0.01) of the sample are less likely to be part of the highly exposed community C2 than the low exposed community C1, ceteris paribus. Productive firms are better able to control exchange rate risk since they are more efficient in adapting their operations in changing market conditions, however in doing so they are also less likely to take advantage of an appreciating euro-dollar exchange rate.

Finally, both in the lower- and upper tail dependence PMFGs, four variables did not generated any significant effects, namely debt ratio, foreign net revenue and the extensive margin of import and export. Regarding the extensive margin, our insignificant results are supported by the findings of, among others, Dekle et al. (2016); Greenaway and Kneller (2007) who stated that firms are less responsive to exchange rate shocks because firms tend to adjust their intensive margin instead of adjusting their extensive margin of trade. Next, in line with Doukas et al. (2003); He and Ng (1998) our overall results indicate a potential negative relationship between debt ratio and exchange rate exposure, indicating that a higher debt ratio increases the incentive to hedge and as such reduces exchange rate exposure. However, the other determinants are more explanatory in the model than the insignificant debt ratio, implying that debt ratio is not a determinant of exchange rate exposure. Further, foreign net revenue did also not render significant results as a determinant of exchange rate exposure. The insignificance might be explained by the construction of this variable. Moreover, this ratio accounts for the share of the total net revenue generated outside the Netherlands in the total net revenue. As such, it represents the net revenue generated within and outside the Eurozone including foreign subsidiaries as well; a further distinction in the data, accounting solely for the net revenue outside the Eurozone was not possible.

[120] Figure 4.8 shows the majority (81%) of sole importers in the exposed cluster (right side) of the MST.

4.6. Discussion and conclusion

This study investigates the determinants of exchange rate exposure for one-way and two-way traders in the Netherlands over the period 2011-2015. In order to fully understand the firm-level forces underlying exchange rate exposure, this research puts forward a novel approach through a three-step procedure by consecutively combining vine-copulas with network analysis and a multinomial logit model. The contribution of this study to the field is three-fold.

The first contribution of this research is the introduction of a novel empirical three-step approach to uncover determinants of complex concepts such as exchange rate exposure. In this study our novel three-step procedure contributes to the literature by estimating the exchange rate exposure for one-way and two-way traders and giving insight into the determinants of this exposure. More specifically, in a first step, we estimate exchange rate exposure conditional on the intensive margin, or trade volume, of international import and export by vine copulas. Vine copulas permit to construct the multivariate dependence structure between stock returns, euro-dollar exchange rate changes, import changes and export changes. In the third tree of the vine copula structure the general association and tail dependence between these variables of interest are obtained, representing exchange rate exposure conditional on the intensive margin of international trade. By forcing the vine structure to use the Symmetrical Joe-Clayton copula to estimate the multivariate dependence between the variables of interest, the tail dependence coefficients become comparable among firms. Next, by applying the Euclidian norm, the general association and respectively upper and lower tail dependence measures of each firm are used to calculate a distance metric. In the second step of this novel approach, Minimum Spanning Tree (MST) and Planar Maximally Filtered Graph (PMFG) networks are constructed using these distance metrics. As such, these networks allow to distinguish and analyze subgroups or communities of firms based on their level of exchange rate exposure. In a third and final step, the communities of the PMFG network are used in a multinomial logit model to test the determinants of exchange rate exposure.

Second, our results indicate that the exchange rate exposure of two-way traders is determined by the interplay of offsetting and accentuating effects of export and import activities, indicating a more pronounced exchange rate exposure at the importing side than the exporting side. As such, our results empirically confirm the results of Amiti et al. (2018), who concluded in their related research on a Belgian dataset of currency invoicing,[121] that import-intensive firms exhibit very low pass-through which according to the theoretical model[122] of Bodnar et al. (2002) can be related to higher exchange rate exposure. Furthermore, the analysis of the multivariate dynamics in the vine copulas and multinomial logit model provide empirical evidence on our elaboration of the dual effect hypothesis of Pritamani et al. (2004) for two-way traders and confirm the findings of Van Cauwenberge et al. (Forthcoming). More specifically, a weakening euro (as in the lower tail) makes exporting to foreign markets more attractive. However, importing the intermediate inputs to fabricate the exporting good becomes more expensive, offsetting the beneficial effect of export, making exporting to the foreign market less attractive and leaving the firm exposed. Since firms are reluctant to exit foreign markets or alter the extensive margin of trade, due to the large and sunk market-entry costs, they instead adapt and optimize their intensive margin, waiting for an appreciating euro-dollar exchange rate (Baldwin, 1988; Chaney, 2008). A strengthening euro (as in the upper tail) makes exporting initially less attractive, but importing the intermediary goods for producing the product becomes cheaper, as such, the adverse effects may be offset by selling at lower production cost to the booming domestic market. Moreover, these firms are now able to export at a lower cost, making them again more attractive on the foreign market.

[121] Invoicing data were not available for both Belgium and the Netherlands for our data sample and time period.

[122] Bodnar et al. (2002) set up a duopoly model with an exporting firm and an import competing foreign firm, and show that exchange rate pass-through and exposure are negatively correlated across industries. According to the authors, when the substitutability between the domestically produced good and the imported good increases in an industry, the price elasticity of demand for the firms increases and both firms have greater incentives to stabilize prices, hence, exchange rate pass-through falls. Nevertheless, profits become more sensitive to exchange rate changes, so exposure increases. One should therefore see a negative relationship between exchange rate pass-through and exposure across industries, if industries differ mainly in the substitutability between domestically produced and imported goods. According to Flodén et al. (2008), the negative relationship between exchange rate exposure and pass-through might sometimes not hold in practice because of an increase in the convexity of costs mostly reduces both pass-through and exposure. The correlation between pass-through and exposure should therefore be positive across industries if cost functions differ across these industries. This effect can be mitigated by the aforementioned negative correlation between pass-through and exposure induced by changes in the price elasticity of demand.

Third, trade related decisions and productivity, next to financial measures as quick ratio and book-to-market, are the most pronounced determinants of exchange rate exposure. The MST and PMFG networks provide evidence that distinguishable subgroups or communities of firms exist based on their level of exchange rate exposure. Within the lower tail dependence PMFG, three communities were detected, while in the upper tail two subgroups were identified. Financial variables, which are an indication of hedging activities, are only significant determinants in the lower tail or during market downturns, showing the asymmetry with the upper tail or during market upturns. As such, during market downturns, firms with low exposure seem to have a significant lower book-to-market ratio. The latter is an indication of growth opportunities, in order to safeguard these opportunities these firms have an incentive to hedge. As such, they keep large amounts of liquidity, resulting in a significant larger quick ratio, to withstand exchange rate risk. Furthermore, the growth opportunities result in a significant greater market value for these firms. The market value differs from size measured as total assets. Firms with a larger scale of operations are more likely to experience exchange rate exposure but not necessarily hedge efficiently. In line with the findings of Berthou and Dhyne (2018), more productive firms seem to end up in less exposed communities. As such, also the level of productivity is an important determinant to take into account. This is the case during market upturns (strengthening euro) and market downturns (weakening euro).

From these findings, we conclude that productive firms are barely affected by exchange rate changes of the euro. However, this has an up- and a downside. The upside is that during a weakening euro, productive firms barely experience exposure, the downside is that they do not benefit from a strengthening euro when looking at exposure in the upper tail network. As such, highly productive firms are resilient to exchange rate risk. This can possibly be explained by highly productive firms being better able, than less productive firms, to adapt their operations and supply to changes in demand from the foreign and domestic market, which is also assumed by Berthou and Dhyne (2018). Furthermore, productive firms will also apply hedging strategies in order to safeguard their productivity gains and profit margins. However, hedging means that exposure during both market downturns and upturns is neutralized.

Next, foreign dependence on trading partners seems to be important in determining exchange rate exposure during market down- and upturns. Our results in the lower tail support the dual effect hypothesis of Pritamani et al. (2004). More specifically, increasing the dependence on the foreign market on the import side will result in higher exchange rate exposure because of the accentuating effect during market downturns. The foreign market on the export side may mitigate these accentuating effects of exchange rate exposure on the import side, as such, increasing the access to foreign markets on the export side, further limits exchange rate exposure. Nevertheless, firms who combine an increase of their import share with an increase in importing destinations outside the Eurozone are able to spread the risk of being exposed and as such do not necessarily increase their foreign dependence. Further, the choice of a two-way trader to hedge depends on how much import or export oriented the two-way trader is. If, for instance, during a weakening euro, the costs of being exposed to the domestic market and importing side are higher than the benefits at the export side, a two-way trader might better hedge. One-way traders do not experience these issues, since they do not have to balance the effects between importing and exporting and make a trade-off in their decisions. Additionally, our results in the upper tail or during market upturns support the dual effect hypothesis of Pritamani et al. (2004). To be specific, the dependence on the foreign market on the import side will result in higher exchange rate exposure because of the accentuating effect during market upturns. However, the presence in foreign markets at the export side may mitigate the exposure and as such the positive effects of an appreciating euro-dollar exchange rate. By increasing access to foreign export markets exchange rate exposure is offset in the upper tail. Firms who combine an increase of their import share with an increase in importing destinations outside the Eurozone are less likely to be part of the highly exposed group. This might indicate that diversifying a higher import share over more foreign import markets reduces the benefits of an appreciating euro-dollar exchange rate in an upturning market. The position a firm should take in the foreign market depends on their risk-aversion.

Our applied novel methodology and findings have implications for researchers, policy makers and portfolio managers. First, the empirical framework, whereby consecutively vine-copulas are combined with network analysis and a multinomial logit model, can assist to link trade policy and monetary policy with financial stability and facilitate decision making. As such, making the three-step procedure dynamic or time-driven and setting the focus on specific trade partners can reveal early warning patterns, for instance when productive firms start moving from not to exposed lower tail communities. Furthermore, instead of targeting policy based on, e.g., sector affiliation, our methodology allows policy makers to efficiently adapt policy measures, such as taxes and subsidies, according to relevant firm-characteristics by exposing the network and using a fine-grained categorization or profiling of firms. Second, the application of our methodology on exchange rate exposure shows that heterogeneous firm behavior is prevalent when looking at exchange rate exposure. As a consequence, it is expedient that European policy makers changing trade and monetary policy, the latter indirectly influencing the exchange rate of the euro, are aware of the subtle differences that exist between their member states and their respective domestic firms. Even in an open economy such as the Netherlands, listed firms may react different to policy actions. As such, it is quintessential to take into account the different characteristics, trading profiles and sensitives to exchange rate exposure of European firms when drawing up policy. It is the European monetary and trade policy that will encourage countries to stimulate their domestic firms to go global or stay within the borders of the Eurozone. A proper understanding why some firms of certain countries benefit from policy measures while others do not is therefore quintessential for policy makers. With 19 Eurozone member states and a large amount of trade active listed firms per member state, the heterogeneity may be too large for the European monetary and trade policy to have favorable effects on every firm. Therefore, policy makers should choose a moderate middle ground so that no pronounced losers or winners are created as a result. Our proposed methodology enables policy makers to identify the winners and losers, in case of an imbalance, national policy is still able to counter the possible negative effects of European policy measures through an optimal trade strategy where for instance, firms employ built-in hedging and exchange rate risk mitigating strategies in order to reduce the potential unfavorable effects of exchange rate volatility. Finally, the proposed three-step procedure, can be easily applied to other complex concepts, such as systemic risk, and used for other purposes than merely academic, such as portfolio construction and market valuation. Additionally, introducing a dynamic SJC-copula to account for time dynamics in the vine-copula of the first step, can be an interesting path for further research.

Chapter 5

Conclusions

5.1. Outline

The purpose of this dissertation is to ameliorate our understanding of how international trade and, more generally, globalization can explain the risk position of listed firms. By means of three separate studies, this dissertation gains more insight into two specific types of risk a firm involved in international trade may encounter. First, this thesis investigates systemic risk, its quantification and its determinants, for both financial and non-financial firms. Second, the risk of a firm being exposed to exchange rate changes, which additionally may affect the value of the firm is examined through the use of firm-specific trade-weighted exchange rate indices and copula theory. Next, exchange rate exposure is further investigated by taking a closer look at its determinants. While the next Section, Section 5.2, highlights the main results and findings of each Chapter, Section 5.3 and 5.4 summarize respectively the theoretical and methodological implications of this dissertation, the final concluding Section offers suggestions for future research.

5.2. Summary of results

Chapter 2 focusses on systemic risk contributions in the Dutch economy of the financial and nonfinancial sector and the potential systemic role of globalization. The results of this Chapter show that systemic risk contributions are not limited to the financial sector, but also real economy sectors contribute to this type of risk. According to the analysis of the Dutch economy, the Administrative and support service, Transportation and storage and Construction sectors are among the highest risk contributing, comparable with the level of the Financial & insurance activities sector. Further, globalization, which is measured by trade intensity and whether a firm has foreign subsidiaries and is under foreign control, is a significant determinant of systemic risk. More specifically, higher trade intensity lowers systemic risk contributions. Trade intensive firms may be able to neutralize their systemic risk contribution more than less trade intensive firms since they are better able to adapt and optimize their operations as a response to demand shocks. Moreover, firms that trade internationally are found to be more productive and efficient. These firms are more resilient to demand shocks and can react appropriately, making them less risky. They have a higher probability of survival than firms that focus primarily on domestic markets and have a lower trade intensity, which makes them less of a systemic threat (e.g., Andersson et al., 2008; Baldwin, 1988; Bernard et al., 2007, 2012; Greenaway & Kneller, 2007; Melitz, 2003; Wagner, 2007, 2012). Therefore, trade intensive firms are more resilient to systemic risk. However, when taking sectoral effects into account, this relationship becomes insignificant, indicating that the effect of trade intensity is sector specific. Furthermore, when a firm is under foreign control or has foreign subsidiaries, systemic risk contribution rises. This indicates that foreign direct investments may channel and transmit shocks within a firm's international organizational and operational network.

Further, from a regulatory point of view, this Chapter suggests that current macroprudential policy should be extended to non-financial sectors and addressing globalization, through trade intensity and the presence of foreign direct investments, when monitoring systemic risk. In this Chapter we also find evidence that the degree of systemic risk contributions is characterized by the business cycle and is therefore highly sensitive to economic conditions. As such, a first step can be taken in the right direction by raising awareness of the possible systemic risk that certain nonfinancial sectors carry. It is important to make firms and policy makers aware of the fact that sectors which are more closely related with financial markets, institutions and their products, but also sectors providing business cycle sensitive services or goods, will have an increased systemic risk, since the consumption of their services and goods will be the first to be postponed by consumers during economic downturns. Finally, our results indicate that systemic risk also has a global aspect. As such, the clustering of foreign direct investments in certain geographic areas or the concentration of certain activities to a small number of suppliers may result in the creation of systemic risk. The government and its competition policy has a vital role to play in order to ensure that certain players or even locations do not become too important in the supply chain.

Chapter 3 investigates exchange rate exposure by cross-sectionally modelling the association between stock returns and firm-specific trade-weighted effective exchange rate indices on each point in time, comparing Dutch and Belgian listed firms over the period 2006-2015. The results imply that firms from similar open economies can still have significant international trade differences, which reflected in their exchange rate exposure can have important policy implications. Since the Dutch listed firms from the sample engage more in trade outside the Eurozone and have a stronger positive dependence between the firm-specific exchange rate indices and stock returns, these Dutch firms are more susceptible than the listed firms from the Belgian sample to the European monetary and trade policy which affects respectively the exchange rate of the euro and the competitive position of firms. Additionally, the Dutch firms from the sample encounter more tariffs and other barriers to international trade. As a result, European trade agreements with countries outside the union are more beneficial for these Dutch listed firms, than they are for the Belgian ones from the sample, since they result in a deterioration of the competitive position of those firms who trade mainly within the Eurozone. Next, the literature agrees on the fact that stock returns are not normally distributed (e.g., Fama, 1965; Jondeau et al., 2007; Mandelbrot, 1963). However, in this research we find that extreme events causing fat tails and, as such, non-normality for stock returns are, at least partially, caused by a firm's international trade activities. Since the Dutch listed firms from the sample experience more extreme events and these firms trade more outside the Eurozone, the tail dependence between stock returns and the firm-specific exchange rate indices is stronger and more pronounced than the tail dependence found for the Belgian listed firms from the sample. As such, the Dutch listed trading firms not only experience stronger expected exchange rate exposure than Belgian listed trading firms but also have more pronounced unexpected exchange rate exposure. Further, our findings imply that listed importing firms experience stronger exchange rate exposure than listed exporting firms. This result is in line with the hypothesis[123] of Pritamani et al. (2004) of a dual effect of exchange rate changes

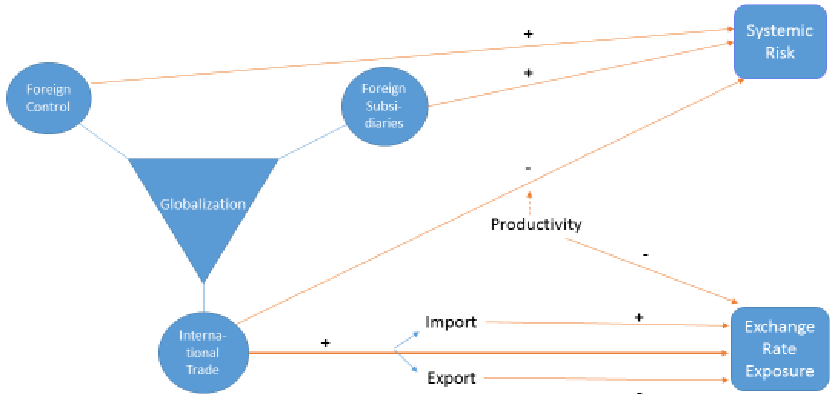
[123] See Section 3.2.2 for further details on the dual effect hypothesis of Pritamani et al. (2004).

on stock returns arising from changes in the domestic economy and foreign market. The hypothesis predicts that exchange rate exposure is accentuated for importers and is offset for exporters because of the interplay between the domestic and international market. Finally, this Chapter shows that it is expedient that policy makers gain insight into the results of their monetary and trade policy actions when even in similar open economies, such as Belgium and the Netherlands, listed firms may react different to policy changes. As such, our proposed methodology can help policy makers link trade with monetary policy and financial stability through a better understanding of exchange rate exposure based on firm-specific trade-weighted exchange rates.

Chapter 4 investigates the determinants of exchange rate exposure for one-way and two-way international traders in the Netherlands from 2011-2015. In order to fully understand the underlying firm-level forces of exchange rate exposure, a novel three-step procedure is developed, applying consecutively vine copulas, network analysis and multinomial logit models. The results indicate that firms that hedge during market downturns, experience less exchange rate exposure. These firms have a lower book-to-market ratio and, as such, a greater market value, large amounts of liquidity, a larger quick ratio, and/or are more productive. Further, exchange rate exposure of two-way traders is determined by the interplay of offsetting and accentuating effects of respectively export and import activities, indicating a more pronounced exchange rate exposure at the importing side than the exporting side. The analysis of the multivariate dynamics in the vine copula and the multinomial logit model provide empirical evidence on the elaboration of the dual effect hypothesis of Pritamani et al. (2004) for two-way traders and confirm the findings of Van Cauwenberge et al. (Forthcoming). More specifically, a depreciating euro-dollar exchange rate makes exporting to foreign markets more attractive. However, importing the intermediate inputs to fabricate the exporting good becomes more expensive, offsetting the beneficial effect of export, making exporting to the foreign market less attractive and leaving the firm exposed. Since firms are reluctant to exit foreign markets or alter the extensive margin of trade, due to the large and sunk market-entry costs, they instead adapt and optimize their intensive margin, waiting for an appreciating euro-dollar exchange rate (Baldwin, 1988; Chaney, 2008). This appreciating euro-dollar exchange rate makes exporting initially less attractive, but importing the intermediary goods for producing the product becomes cheaper, as such, the adverse effects may be offset by the lower production costs and selling to the booming domestic market. Moreover, these firms are now able to export at a lower cost, making them again more attractive on the foreign market. Next, increasing the dependence on the foreign market on the import side puts a firm at risk when the market is contracting and exposes it to exchange rate risk. During market upturns, however, the firm is able to profit from exchange rate exposure. Increasing the presence in export markets might mitigate this risk during market downturns, but also deprives it from the possible benefits when the market is in upturn. Similarly, the diversification of a bigger import share among more trading partners will not induce more exchange rate risk since it does not increase foreign dependence. The extent of the foreign dependence depends on the risk-aversion of the firm. Further, the choice of a two-way trader to hedge depends on how much import or export oriented the two-way trader is. If, for instance, during a weakening euro, the costs of being exposed to the domestic market and importing side are higher than the benefits at the export side, a two-way trader might better hedge. One-way traders do not experience these issues, since they do not have to balance the effects between importing and exporting and make a trade-off in their decisions. Finally, the application of our methodology on exchange rate exposure shows that heterogeneous firm behavior is prevalent when looking at exchange rate exposure. As such, instead of targeting policy based on, e.g., sector affiliation, policy makers can use the proposed methodology to efficiently adapt policy measures, such as taxes and subsidies, according to relevant firm-characteristics by exposing the network and using a fine-grained categorization or profiling of firms.

Figure 5.1 gives a schematic overview of the main relationships found in this dissertation. Although it is obvious that Figure 5.1 remains a partial representation of reality, some common denominators such as international trade and productivity are found in both risk subjects. Bringing the conclusions of the Chapters together, enables us to answer the overall research question whether international trade and trade-related firm-heterogeneity explains the financial risk position of listed firms.

Figure 5.1 Overview main findings



The results of Chapter 2 can be found in the left part of Figure 5.1. The large triangle representing globalization indicates the three dimensions which measure this concept. Foreign direct investments, which comprises foreign direct control and foreign subsidiaries, heighten systemic risk, while participating in international trade lowers this type of risk. Firms participating in international trade are found to be more productive and more resilient to failure and as such pose less a systemic threat. Productivity also influences exchange rate exposure (Chapter 3 and mainly Chapter 4), more productive firms are less exposed to exchange rate risk. Additionally, international trade is related to exchange rate exposure, since trading increases the probability of being exposed to exchange rate fluctuations. Moreover, it matters whether a firm is an importer, exporter or two-way trader, since importing activities appear to be more sensitive to exchange rate risk.

5.3. Theoretical implications

Systemic risk is an externality or market failure, which, when it is not internalized by governmental action, will not be addressed by firms (Kerste et al., 2015). This is not the case for exchange rate risk since it may affect the value of the firm. As such, it is in the direct interest of firms to address this type of risk. In this dissertation we contributed to the systemic risk literature by showing that globalization increases systemic risk through a firm's foreign direct investments. Foreign direct investments, measured by foreign control and foreign subsidiaries, do not cause risk directly, rather they channel and spread risk through the entire global organization and operations. In the second part of the dissertation, we found a partly similar but inverse pattern when looking at exchange rate risk, namely exchange rate exposure is determined by the level of foreign dependence. We contributed to the literature on exchange rate exposure by stating that this risk may be decreased by increasing foreign dependence on the export side or by diversifying import among a larger number of importers. Whether a firm is willing to follow this hedging strategy depends on the risk-aversion of the firm. Notwithstanding, foreign dependence and foreign direct investment are not the same, it is not farfetched to consider that both subjects are related. As such, a firm might be inclined to increase foreign trading partners, and in extension in the future their foreign direct investments, in order to mitigate exchange rate exposure. As a consequence, this may increase the possible channels through which systemic risk may spread. Until today it remains unclear whether firms sensitive to exchange rate exposure also contribute more systemic risk and, as such, exchange rate exposure and systemic risk are related.

5.4. Methodological implications

Each Chapter has in common that it specifically accounts for the distributional stylized facts of financial time series when estimating risk. Classic econometric techniques, often used in the literature, fail to capture sufficiently the non-linear, asymmetric dynamics of financial time series. As such, we use techniques which allow to properly model these dynamics and profoundly estimate risk. Next, in each Chapter we elaborate on this empirical strategy by adding additional approaches in order to build a unique methodological framework and adding in this way to the existing methodological literature.

In **Chapter 2** we prefer the DCC specification of Engle (2002), to model the time-varying joint distribution of the system and a single firm to calculate systemic risk contributions. The DCC model itself is a generalization of the CCC specification of Bollerslev (1990), only the latter does not allow time variation in the conditional correlations. The DCC specification is a type of multivariate GARCH model which was created in order to cope with the problem of multivariate time series and to keep GARCH models more parsimonious. The latter originate from ARCH and GARCH models which were initially introduced by Engle (1982) and Bollerslev (1986) respectively to model volatilities for financial time series. Furthermore, DCC models are in practice the preferable choice amongst multivariate GARCH models because of specification difficulties and the large number of parameters to be estimated accompanying the alternative BEKK models proposed by Engle and Kroner (1995). Compared to a quantile regression, which is also often used to estimate the ΔCoVaR, the advantage of the DCC-GARCH approach lies in the fact that it allows taking time-varying linkages between the system and a firm into account, without having to rely on systemic state variables. The DCC model enables us to model contagion during stable and turbulent periods and to reproduce dynamic market correlations. It allows for time-varying contagion effects and for contagion to be asymmetrically transmitted (Hemche et al., 2016). Further, we prefer the GJR-GARCH (1,1) specification, which was initially introduced by Glosten et al. (1993). The latter is chosen because of its leverage effect, since it uses dummy variables for negative shocks in the volatility equation. As such, we account for any asymmetry, which ensures that negative shocks are assigned more weight in volatility changes than positive shocks, in order to account for crisis situations or disturbances in the economy. While a GARCH (1,1) process[124] is leptokurtic and, as such, accounts for the heavy tails, the GJR-GARCH(1,1) additionally accounts for the asymmetry by moving the distribution further to the left. Moreover, the standard symmetric GARCH model of Bollerslev (1986) still remains a special case of the GJR-GARCH model. As such, by applying a DCC-GJR-GARCH model for the returns of each firm and the system, we also allow for asymmetry in conditional variances and covariances (Goeij & Marquering, 2004).

Finally, the relationship between systemic risk contributions and globalization is investigated in detail by a panel data regression analysis. Since this panel data

[124] In most financial applications a GARCH(1,1) is found to suffice (Bollerslev et al., 1992). Moreover, an advantage of the GARCH(1,1) is that, according to Hansen (1991), it satisfies under certain conditions near epoch dependence without imposing strict stationarity.

model uses an estimated dependent variable, we used fixed effects feasible generalized least squares. In the first stage of the research, observed data are used to estimate the values of the dependent variable, more specifically the ΔCoVaR. In the second stage, estimated dependent variable (EDV) regression models are used to regress these values of the dependent variable against several independent variables to generate the coefficients of interest. When fitting EDV regression models, the variation in the sampling variance of the observations on the dependent variable will induce heteroscedasticity, i.e., estimates and sample sizes per sector and per firm differ, as such, standard errors of the dependent variables vary and affect the t-statistic. Next, since the focus of this study is an historical analysis, in which the financial crisis is a focus point, all the data points will be used to fit the first stage model to compute the dependent variable, i.e., the ΔCoVaR. As a result, the models will be suited for such a historical analysis but will result in an overfit when used for forecasting purposes. Models for forecasting should give less weight to extreme events such as the financial crisis, since they are less likely to dominate the future. Therefore, we need to account for this in our second stage model by assuming that there will be a considerate sampling error. According to Lewis and Linzer (2005), one can correct the inconsistent OLS standard errors by using White's heteroscedastic consistent standard errors estimator in order to mitigate this issue. Such an approach would generate reliable results but can still give inefficient OLS estimates. OLS is inefficient because partial information about the nature of the heteroscedasticity, i.e., sampling error of the first stage, is not taken into account. To overcome the aforementioned issues, Lewis and Linzer (2005) propose FGLS because this approach produces efficient estimates (relative to OLS) and less overconfident standard errors than OLS and WLS approaches.

The methodology adopted in **Chapter 3**, which is the construction of firm-specific foreign exchange indices, is consistent with the method of Dai and Xu (2017) and provides further evidence on exchange rate exposure. However in our dataset we notice that several companies do not trade (either export and/or import) every month. Therefore we note that in such months all weights are equal to zero and do not sum up to one. In this situation, the firm-specific exchange rate indices for a company are not properly defined and generate a not available (NA) value for these months. Although in this way, we have a lot of missing values for the firm-specific exchange rate indices in our dataset, we can still use the information on whether a NA value is observed to model the probability of whether a company will trade or not during a given month. The probability of a firm deciding to participate in international trade is determined for every point in time, including the financial crisis. Moreover, when the firm-specific effective exchange rate is missing we are still able to get an idea about the distribution for the stock price return for companies that have not traded in the previous month. Only during the non-trading periods, the Belgian and Dutch import and export firms seem to have normally distributed data. This indicates that extreme events in the stock returns are only found during trading periods. We can estimate cross-sectionally the association, by applying copula theory, between the stock price returns and the firm-specific effective exchange rate indices on each point in time for the subgroup of firms which have traded. We model the association between stock price returns and firm-specific effective exchange rates as bivariate T-copulas, which are fitted using the maximum likelihood method. Since copula techniques permit to estimate both the general association and tail dependence during extreme events, we are able to compare expected and unexpected exchange rate exposure between Dutch and Belgian listed firms.

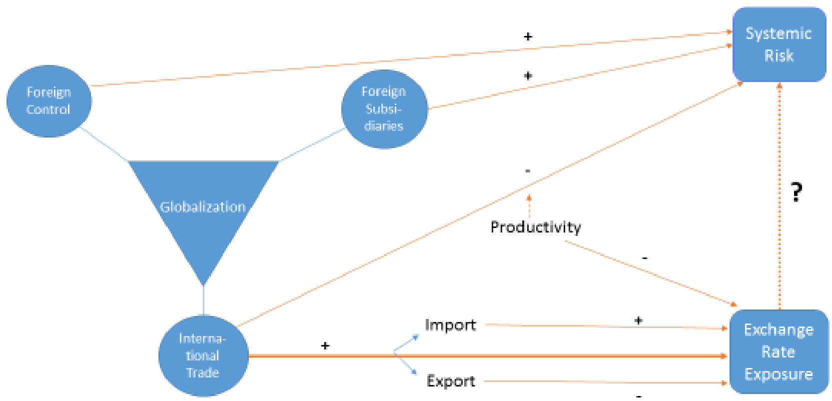
Chapter 4 introduces a novel empirical three-step approach to uncover determinants of complex concepts such as exchange rate exposure. More specifically, in a first step, we estimate exchange rate exposure conditional on the intensive margin, or trade volume, of international import and export by vine copulas. Vine copulas permit us to construct the multivariate dependence structure between stock returns, euro-dollar exchange rate changes, import changes and export changes. In the third tree of the vine copula structure the general association and tail dependence between these variables of interest are obtained, representing exchange rate exposure conditional on the intensive margin of international trade. By forcing the vine structure to use the Symmetrical Joe-Clayton copula to estimate the multivariate dependence between the variables of interest, the tail dependence coefficients become comparable among firms. Next, by applying the Euclidian norm, the general association and respectively upper and lower tail dependence measures of each firm are used to calculate a distance metric. In the second step of this novel approach, Minimum Spanning Tree (MST) and the Planar Maximally Filtered Graph (PMFG) networks are constructed using these distance metrics. As such, these networks allow us to distinguish and analyze subgroups or communities of firms based on their level of exchange rate exposure. In a third and final step, the communities of the PMFG network are used in a multinomial logit model to test the determinants of exchange rate exposure.

5.5. Suggestions for future research

To finalize this dissertation, some interesting pathways for future research are outlined. This thesis examines the influence of globalization through international trade on the risk position of the firm and, more specifically, on systemic risk and exchange rate exposure. Apart from the theoretical and methodological implications mentioned in the previous sections, each Chapter is to our knowledge one of the first to provide empirical evidence. More specifically, Chapter 2 is one of the first in its domain to provide empirical evidence on the link between globalization and systemic risk contributions in the non-financial sector. Additionally, Chapter 3 and Chapter 4 are pioneers in their domain by providing methodological and empirical evidence on respectively the estimation of exchange rate exposure and relating firm-level determinants to a firm's sensitivity for exchange rate changes. Yet, as this is grounded research, there is a definite need for a follow-up study to confirm the exploratory results. Furthermore, the studies included in this dissertation are based on evidence collected from a specific geographical region, i.e., the Netherlands and Belgium. In how far these findings are generalizable to other regions, remains to be explored in future research. Countries have cultural differences, which may influence the openness, productivity, and importance of sectors and firms in general. Such an institutional perspective could add further insights on how systemic risk contributions and exchange rate exposure varies across regions and improves our understanding of the cultural context. Furthermore, Chapter 4 proposes a novel three step-procedure which opens up various research path; not only can the three step procedure be further explored on other complex (risk) subjects, but there also remain some methodologically interesting possibilities. More specifically, the three step procedure, as described momentarily, is static and does not take into account time variation. However, by integrating a dynamic Symmetrical Joe Clayton Copula, it would be possible to construct dependence networks which would be able to adapt over time dynamically.

Finally, bringing the conclusions of the several Chapters together, we may conclude that an internationally active, listed firm is subject to different dynamics that influence systemic risk and exchange rate exposure. The Figure 5.1 already presented the possible interplay between the two types of risk based on the main results of this dissertation. Although it is obvious this is only a partial representation of reality, some common denominators such as international trade and productivity are found in both risk subjects. Nevertheless, more research concerning the role of productivity needs to be done relating to both risk subjects. Furthermore, it would be interesting to investigate the relation between the distinct risk topics simultaneously, as presented in Figure 5.2, and verify the exact role these common denominators might play in the determining the risk position for a firm.

Figure 5.2 Possible future research



Furthermore, it would be interesting to search for the association between systemic risk and exchange rate exposure. The proposed methodology of Chapter 4 may be an ideal stepping stone to investigate the complex interactions between these two different risk subjects and their determinants.

References

Aas, K., Czado, C., Frigessi, A., & Bakken, H. (2009). Pair-Copula Constructions of Multiple Dependence. *Insurance Mathematics and Economics, 44*(2), 182-198.

Acharya, V., Engle, R., & Richardson, M. (2012). Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks. *American Economic Review, 102*(3), 59-64.

Acharya, V., Pedersen, L., Philippon, T., & Richardson, M. (2017). Measuring Systemic Risk. *The Review of Financial Studies, 30*(1), 2-47.

Acharya, V., Philippon, T., Richardson, M., & Roubini, N. (2009). The Financial Crisis of 2007-2009: Causes and Remedies. In V. V. Acharya & M. P. Richardson (Eds.), *Restoring Financial Stability: How to Repair a Failed System* (pp. 1-56). Hoboken, New Jersey: John Wiley & Sons.

Adler, M., & Dumas, B. (1984). Exposure to Currency Risk: Definition and Measurement. *Financial Management*, 41-50.

Adrian, T., & Boyarchenko, N. (2013). Intermediary Leverage Cycles and Financial Stability. *Federal Reserve Bank of New York Staff Report*. New York.

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review, 106*(7), 1705-1741.

Aggarwal, R., & Harper, J. (2010). Foreign Exchange Exposure of "Domestic" Corporations. *Journal of International Money and Finance, 29*(8), 1619-1636.

Alessandria, G., & Choi, H. (2007). Do Sunk Costs of Exporting Matter for Net Export Dynamics? *The Quarterly Journal of Economics, 122*(1), 289-336.

Allayannis, G. (1997). *The Time-variation of the Exchange Rate Exposure: An Industry Analysis.* Paper presented at the 57th Annual American Finance Association Conference,(New Orleans), January.

Allayannis, G., & Ihrig, J. (2001). Exposure and Markups. *Review of Financial Studies, 14*(3), 805-835.

Allayannis, G., & Ofek, E. (2001). Exchange Rate Exposure, Hedging, and the Use of Foreign Currency Derivatives. *Journal of International Money and Finance, 20*, 273-296.

Aloui, C. (2007). Price and Volatility Spillovers between Exchange Rates and Stock Indexes for the Pre-and Post-Euro Period. *Quantitative Finance, 7*(6), 669-685.

Alvarez-Socorro, A. J., Herrera-Almarza, G. C., & González-Díaz, L. A. (2015). Eigencentrality Based on Dissimilarity Measures Reveals Central Nodes in Complex Networks. *Scientific Reports, 5*(1).

Amiti, M., Itskhoki, O., & Konings, J. (2018). Dominant Currencies. How Firms Choose Currency Invoicing and Why It Matters. *NBB. Working Papers. Research and Document Series 353.*

Andersson, M., Lööf, H., & Johansson, S. (2008). Productivity and International Trade: Firm Level Evidence from a Small Open Economy. *Review of World Economics, 144*(4), 774-801.

Angeloni, I., & Ehrmann, M. (2004). Euro Area Inflation Differentials. Frankfurt: European Central Bank.

Aristei, D., Castellani, D., & Franco, C. (2013). Firms' Exporting and Importing Activities: Is There a Two-Way Relationship? *Review of World Economics, 149*(1), 55-84.

Aste, T., Shaw, W., & Di Matteo, T. (2010). Correlation Structure and Dynamics in Volatile Markets. *New Journal of Physics, 12*.

Ayala, A., Blazsek, S., Cuñado, J., & Gil-Alana, L. (2016). Regime-switching Purchasing Power Parity in Latin America: Monte Carlo Unit Root Tests with Dynamic Conditional Score. *Applied Economics, 48*(29), 1-22.

Bahmani-Oskooee, M., & Hegerty, S. (2007). Exchange Rate Volatility and Trade Flows: a Review Article. *Journal of Economic Studies, 34*(3), 211-255.

Baldwin, R. (1988). Hysteresis in Import Prices: the Beachhead Effect. *American Economic Review, 78*(4), 773-785.

Baldwin, R., & Krugman, P. (1989). Persistent Trade Effects of Large Exchange Rate Shocks. *Quarterly Journal of Economics, 104*(4), 635-654.

Baldwin, R., & Taglioni, D. (2009). The Great Trade Collapse and Trade Imbalances. In R. Baldwin (Ed.), *The Great Trade Collapse: Causes, Consequences and Prospects* (pp. 47-59). London: VoxEU Publication, Centre For Trade and Economic Integration.

Barnea, A., & Downes, D. (1973). A Reexamination of the Empirical Distribution of Stock Price Changes. *Journal of the American Statistical Association, 68*(342), 348-350.

Bartov, E., & Bodnar, G. (1994). Firm Valuation, Earnings Expectations, and the Exchange-rate Exposure Effect. *Journal of Finance, 49*(5), 1755-1785.

Bartov, E., Bodnar, G., & Kaul, A. (1996). Exchange Rate Variability and Riskiness of U.S. Multinational Firms: Evidence From the Breakdown of the Bretton Woods system. *Journal of Financial Economics, 42*, 105-132.

Bartram, S. (2004). Linear and Nonlinear Foreign Exchange Rate Exposures of German Nonfinancial Corporations. *Journal of International Money and Finance, 23*(4), 673-699.

Bartram, S., & Bodnar, G. (2007). The Exchange Rate Exposure Puzzle. *Managerial Finance, 33*(9), 642-666.

Bartram, S., Brown, G., & Minton, B. (2010). Resolving the Exposure Puzzle: The Many Facets of Exchange Rate Exposure. *Journal of Financial Economics, 95*(2), 148-173.

Basel Committee on Banking Supervision. (2016). Minimal Capital Requirements for Market Risk (Vol. January). Basel: Bank for International Settlements.

Battiston, S., Gatti, D., Gallegati, M., Greenwald, B., & Stiglitz, J. (2007). Credit Chains and Bankruptcy Propagation in Production Networks. *Journal of Economic Dynamics and Control, 31*(6), 2061-2084.

Bauwens, L., Laurent, S., & Rombouts, J. (2006). Multivariate GARCH Models: a Survey. *Journal of Applied Econometrics, 21*(1), 79-109.

Bedford, T., & Cooke, R. (2001). Probability Density Decomposition for Conditionally Dependent Random Variables Modeled by Vines. *Annals of Mathematics and Artificial Intelligence, 32*(1), 245-268.

Bedford, T., & Cooke, R. (2002). Vines - A New Graphical Model for Dependent Random Variables. *Annals of Statistics, 30*(4), 1031-1068.

Bems, R., Johnson, R., & Yi, K. (2010). Demand Spillovers and the Collapse of Trade in the Global Recession. *IMF Economic Review, 58*(2), 295-326.

Bems, R., Johnson, R., & Yi, K. (2011). Vertical Linkages and the Collapse of Global Trade. *American Economic Review, 101*(3), 308-312.

Bems, R., Johnson, R., & Yi, K. (2013). The Great Trade Collapse. *Annual Review of Economics, 5*(1), 375-400.

Benoit, S., Colliard, J., Hurlin, C., & Perignon, C. (2017). Where the Risks Lie: A Survey on Systemic Risk. *Review of Finance, 21*(1), 109-152.

Bergbrant, M., Campbell, K., & Hunter, D. (2014). Firm-level Competition and Exchange Rate Exposure: Evidence from a Global Survey of Firms. *Financial Management, 43*(4), 885-916.

Berger, A. N., & Udell, G. F. (2006). A More Complete Conceptual Framework for SME Finance. *Journal of Banking & Finance, 30*(11), 2945-2966.

Bernard, A., Jensen, B., Redding, S., & Schott, P. (2007). Firms in International Trade. *Journal of Economic Perspectives, 21*(3), 105-130.

Bernard, A., Jensen, B., Redding, S., & Schott, P. (2012). The Empirics of Firm Heterogeneity and International Trade. *Annual Review of Economics, 4*, 283-313.

Bernard, A., Jensen, B., & Schott, P. (2005). Importers, Exporters, and Multinationals: A Portrait of Firms in the U.S. that Trade Goods. *NBER Working Paper Series* (Vol. w11404).

Berthou, A., & Dhyne, E. (2018). Exchange Rate Movements, Firm-level Exports and Heterogeneity. *Working Paper Nr. 660*: Banque de France, Eurosystème.

Bezemer, D., & Muysken, J. (2015). Dutch Financial Fragilities *Working Paper*. The Hague: WRR The Netherlands Scientific Council for Governement Policy.

Bhatia, V., Basu, S., Mitra, S., & Dash, P. (2018). A Review of Bank Efficiency and Productivity. *OPSEARCH, 55*(3), 557-600.

Bijlsma, M., & Muns, S. (2011). Systemic Risk Across Sectors; are Banks Different? *CPB Discussion Paper 175*. The Hague, The Netherlands: CPB Netherlands Bureau for Economic Policy Analysis.

Bini-Smaghi, L. (1991). Exchange Rate Variability and Trade: Why is it so Difficult to Find any Empirical Relationship? *Applied Economics, 23*, 927-936.

Bisias, D., Flood, M. D., Lo, A. W., & Valavanis, S. (2012). A Survey of Systemic Risk Analytics. *Annual Review of Financial Economics, 4*(0001), 255-296.

Blattberg, R., & Gonedes, N. (1974). A Compariscon of the Stable and Student Distributions as Statistical Models for Stock Prices. *The Journal of Business, 47*(2), 244-280.

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast Unfolding Communities in Large Networks. *Journal of Statistical Mechanics: Theory and Experiment, 2008(10)*, P10008 (10012pp).

Bodnar, G., Dumas, B., & Marston, R. (2002). Pass-through and Exposure. *The Journal of Finance, 57*(1), 199-231.

Bodnar, G., & Gentry, W. (1993). Exchange Rate Exposure and Industry Characteristics**:** Evidence from Canada, Japan, and the USA. *Journal of International Money and Finance, 12*, 29-45.

Bodnar, G., Hayt, G., & Marston, R. (1998). Wharton Survey of Financial Risk Management by US Non-financial Firms. *Financial Management, 27*, 70-91.

Bodnar, G., & Wong, F. (2003). Estimating Exchange Rate Exposures: Issues in Model Structure. *Financial Management, 32*(1), 35-67.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327.

Bollerslev, T. (1990). Modelling the Coherence in Short-run Nominal Exchange Rates: a Multivariate Generalized ARCH Model. *The Review of Economics and Statistics, 72*(3), 498.

Bollerslev, T., Chou, R., & Kroner, K. (1992). ARCH Modeling in Finance: a Review of the Theory and Empirical Evidence. (Autoregressive Conditional Heteroskedasticity model) (ARCH Models in Finance). *Journal of Econometrics, 52*(1 2), 5.

Bollerslev, T., Todorov, V., & Li, S. Z. (2013). Jump Tails, Extreme Dependencies, and the Distribution of Stock Returns. *Journal of Econometrics, 172*(2), 307-324.

Boot, A., & Greenbaum, S. (1993). *Bank Regulation, Reputation and Rents: Theory and Policy Implications*. Cambridge Cambridge University Press.

Boothe, P., & Glassman, D. (1987). The Statistical Distribution of Exchange Rates: Empirical Evidence and Economic Implications. *Journal of International Economics, 22*, 297-319.

Borri, N., Caccavaio, M., Di Giorgio, G., & Sorrentino, A. M. (2012). Systemic Risk in the European Banking Sector. *CASMEF Working Paper Series No.11*. Rome: Arcelli Centre for Monetary and Financial Studies.

Boswijk, H., & Klaassen, F. (2006). Why Frequency Matters for Unit Root Testing. *Tinbergen Institute Discussion Paper; Nr. TI 2004-119/4*. Amsterdam: Tinbergen Institute.

Brealey, R., Myers, S., & Marcus, A. (2015). *Fundamentals of Corporate Finance* (Vol. 8). New York: McGraw Hill Education.

Broll, U., & Eckwert, B. (1999). Exchange Rate Volatility and International Trade. *Southern Economic Journal, 66*, 178-185.

Brownlees, C. T., & Engle, R. F. (2012). Volatility, Correlation and Tails for Systemic Risk Measurement *Working Paper*. New York: New York University.

Brunnermeier, M. K., & Sannikov, Y. (2014). A Macroeconomic Model with a Financial Sector. *The American Economic Review, 104*(2), 379-421.

Bruno, V., & Shin, H. (2015). Cross-border Banking and Global Liquidity. *The Review of Economic Studies, 82*(2), 535-564.

Burger, K., & Haagsma, R. (2007). International Outsourcing in the Netherlands. In W. Heijman (Ed.), *Regional Externalities*. Verlag Berlin Heidelberg: Springer.

Bussire, M., Callegari, G., Ghironi, F., Sestieri, G., & Yamano, N. (2013). Estimating Trade Elasticities: Demand Composition and the Trade Collapse of 2008-2009. *American Economic Journal: Macroeconomics, 5*(3), 118-151.

Byrne, J., Darby, J., & Macdonald, R. (2008). US Trade and Exchange Rate Volatility: A Real Sectoral Bilateral Analysis. *Journal of Macroeconomics, 30*(1), 238-259.

Campa, J., & Goldberg, L. (1995). Investment in Manufacturing, Exchange Rates and External Exposure. *Journal of International Economics, 38*, 297-320.

Campa, J., & Goldberg, L. (1999). Investment, Pass-through, and Exchange Rate: A Cross-country Comparison. *International Economic Review, 40*(2), 287-314.

Campa, J., & Goldberg, L. (2001). Employment Cersus Wage Adjustment and the U.S. Dollar. *The Review of Economics and Statistics, 83*(3), 477-489.

Caselli, M. (2012). *Trying to Measure Globalization: Experiences, Critical Issues and Perspectives*. Dordrecht: Springer.

Cassel, G. (1918). Abnormal Deviations in International Exchanges. *The Economic Journal, 28*(112), 413-415.

Castellani, D., Serti, F., & Tomasi, C. (2010). Firms in International Trade: Importers' and Exporters' Heterogeneity in Italian Manufacturing Industry. *World Economy, 33*(3), 424-457.

Cetorelli, N., & Goldberg, L. (2012). Liquidity Management of U.S. Global Banks: Internal Capital Markets in the Great Recession. *Journal of International Economics, 88*(2), 299-311.

Chakraborty, S., Tang, Y., & Wu, L. (2015). Imports, Exports, Dollar Exposures, and Stock Returns. *Open Economies Review, 26*(5), 1059-1079.

Chamberlain, S., Howe, J., & Popper, H. (1997). The Exchange Rate Exposure of U.S. and Japanese Banking Institutions. *Journal of Banking & Finance, 21*(6), 871-892.

Chaney, T. (2008). Distorted Gravity: The Intensive and Extensive Margins of International Trade. *American Economic Review, 98*(4), 1707-1721.

Choi, J., & Prasad, A. (1995). Exchange Risk Sensitivity and its Determinants: A Firm and Industry Analysis of U.S. Multinationals. *Financial Management, 24*(3), 77-88.

Chou, D., Lin, L., Hung, P., & Lin, C. (2017). A Revisist to Economic Exposure of U.S. Multinational Corporations. *North American Journal of Economics and Finance, 39*, 273-287.

Chow, E., Lee, W., & Solt, M. (1997). Exchange Risk Sensitivity and its Determinants: a Firm and Industry Analysis of U.S. Multinationals. *Financial Management, 24*, 77-88.

Christoffersen, P. (1998). Evaluating Interval Forecasts. *International Economic Review, 39*, 841–862.

Claessens, S., & Van Horen, N. (2016). The Impact of the Global Financial Crisis on Banking Globalization. *IMF Economic Review, 63*(4), 868-918.

Clark, P. (1973). Uncertainty, Exchange Risk, and the Level of International Trade. *Western Economic Journal, 11*(3), 302-313.

Constantinescu, C., Mattoo, A., & Ruta, M. (2018). The Global Trade Slowdown: Cyclical or Structural? *The World Bank Economic Review*, 1-22.

Corlu, C., & Corlu, A. (2015). Modelling Exchange Rate Returns: Which Flexible Distribution to Use? *Quantitative Finance, 15*(11), 1851-1864.

Crowley, P., & Habibdoust, A. (2013). Assessing the Exchange Rate Exposure of U.S. Multinationals. In R. D. Papers (Ed.). St Louis: Federal Reserve Bank of St Louis, 34/2013.

Czado, C. (2010). Pair-copula Constructions of Multivariate Copulas. In P. Jaworski (Ed.), *Copula Theory and its Applications, Lecture Notes in Statistics* (Vol. 198, pp. 93–109). Berlin: Heidelberg: Springer-Verlag.

Czado, C., Schepsmeier, U., & Min, A. (2012). Maximum Likelihood Estimation of Mixed C-vines with Application to Exchange Rates. *Statistical Modelling, 12*(3), 229-255.

Dai, M., & Xu, J. (2017). Firm-specific Exchange Rate Shocks and Employment Adjustment: Theory and Evidence. *Journal of International Economics, 108*, 54-66.

Datta, D., Guthrie, J., & Wright, P. (2005). Human Resource Management and Labor Productivity: Does Industry Matter? *Academy of Management Journal, 48*, 135-145.

De Bandt, O., & Hartmann, P. (2002). Systemic Risk in Banking: A Survey. In C. Goodhart & G. Illing (Eds.), *Financial Crises, Contagion and the Lender of Last Resort, A Reader*. New York: Oxford University Press.

De Grauwe, P. (1988). Exchange Rate Variability and the Slowdown in the Growth of International Trade. *Staff Papers (International Monetary Fund), 35*(1), 63-84.

De Jong, A., Ligterink, J., & Macrae, V. (2006). A Firm-specific Analysis of the Exchange-rate Exposure of Dutch Firms. *Journal of International Financial Management & Accounting, 17*(1), 1-28.

De Masi, G., & Ricchiuti, G. (2018). EU FDI Network and Systemic Risks *Working Papers N. 27/2018 - Economics*: Universita' degli Studi di Firenze, Dipartimento di Scienze per l'Economia e l'Impresa (DISEI).

Dekle, R., Jeong, H., & Ryoo, H. (2016). Firm-level Heterogeneity and the Aggregate Exchange Rate Effect on Exports. *Economic Record, 92*(298), 435–447.

Di Iorio, A., & Faff, R. (2000). An Analysis of Asymmetry in Foreign Currency Exposure of the Australian Equities Market. *Journal of Multinational Financial Management, 10*, 133-159.

Ding, Z., Granger, C. W. J., & Engle, R. F. (1993). A Long Memory Property of Stock Market Returns and a New Model. *Journal of Empirical Finance, 1*(1), 83-106.

Doidge, C., Griffin, J., & Williamson, R. (2006). Measuring the Economic Importance of Exchange Rate Exposure. *Journal of Empirical Finance, 13*(4-5), 550-576.

Dominguez, K., & Tesar, L. (2006a). Exchange Rate Exposure. *Journal of International Economics, 68*(1), 188-218.

Dominguez, K., & Tesar, L. (2006b). Trade and Exposure. *American Economic Review, 91*(2), 367-370.

Dornbusch, R., & Fischer, S. (1980). Exchange Rates and the Current Account. *The American Economic Review, 70*(5), 960-971.

Doukas, J., Hall, P., & Lang, L. H. P. (2003). Exchange Rate Exposure at the Firm and Industry Level. *Financial Markets, Institutions & Instruments, 12*(5), 291-346.

Du, D., Ng, P., & Zhao, X. (2013). Measuring Currency Exposure with Quantile Regression. *Review of Quantitative Finance and Accounting, 41*(3), 549-566.

Dungey, M., Matei, M., Luciani, M., & Veredas, D. (2017). Surfing Through the GFC: Systemic Risk in Australia. *Economic Record, 93*(300), 1-19.

Eaton, J., Kortum, S., Neiman, B., & Romalis, J. (2016). Trade and the Global Recession. *American Economic Review, 106*(11), 3401-3438.

Ekholm, K., Moxnes, A., & Ulltveit-Moe, K. (2012). Manufacturing Restructuring and the Role of Real Exchange Rate Shocks. *Journal of International Economics, 86*(1), 101-117.

El-Masry, A. (2006). The Exchange Rate Exposure of U.K. Nonfinancial Companies: Industry Level Analysis. *Managerial Finance, 32*(2), 115-136.

Engel, C., & Wang, J. (2011). International Trade in Durable Goods: Understanding Volatility, Cyclicality, and Elasticities. *Journal of International Economics, 83*(1), 37-52.

Engle, R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50*(4), 987-1007.

Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics, 20*(3), 339-350.

Engle, R., & Kroner, K. (1995). Multivariate Simultaneous Generalized ARCH. *Econometric Theory, 11*(1), 122-150.

Ethier, W. (1973). International Trade and the Forward Exchange Market. *American Economic Review, 63*(3), 494-503.

European Central Bank. (2019a). Statistics Bulletin: Statistical Data Warehouse.

European Central Bank. (2019b). Transmission Mechanism of Monetary Policy. Retrieved from https://www.ecb.europa.eu/mopo/intro/transmission/html/index.en.html

Fabozzi, F., & Pachamanova, D. (2016). *Portfolio Construction and Analytics*. New Jersey: John Wiley & Sons.

Faff, R. W., & Marshall, A. (2005). International Evidence on the Determinants of Foreign Exchange Rate Exposure of Multinational Corporations. *Journal of International Business Studies, 36*(5), 539-558.

Faia, E., Ottaviano, G., & Laffitte, S. (2018). Foreign Expansion, Competition and Bank Risk *Working Paper Series Federal Reserve Bank of St Louis*. St. Louis.

Fama, E. (1965). The Behavior of Stock-Market Prices. *The Journal of Business, 38*(1), 34-105.

Field, A., Miles, J., & Field, Z. (2012). *Discovering Statistics Using R*. London: Sage Publications Ltd.

Fillat, J., & Garetto, S. (2015). Risk, Returns, and Multinational Production. *Quarterly Journal of Economics, 130*(4), 2027.

Flodén, M., Simbanegavi, W., & Wilander, F. (2008). When Is a Lower Exchange Rate Pass-Through Associated with Greater Exchange Rate Exposure? *Journal of International Money and Finance, 27*(1), 124-139.

Fontagné, L. (1999). Foreign Direct Investment and International Trade: Complements or Substitutes? *OECD Science, Technology and Industry Working Papers 1999/03*. Paris: OECD.

Fontagné, L., & Gaulier, G. (2009). French Exporters and the Global Crisis. In R. Baldwin (Ed.), *The Great Trade Collapse: Causes, Consequences and Prospects* (pp. 143-150). London: VoxEU Publication, Centre For Trade and Economic Integration.

Franke, G. (1991). Exchange Rate Volatility and International Trading Strategy. *Journal of International Money and Finance, 10*, 292-307.

Frankel, J. (1983). Monetary and Portfolio-balance Models of Exchange Rate Determination. In J. Bhandari & B. Putnam (Eds.), *Economic Interdependence and Flexible Exchange Rates.* (Vol. 1). Cambridge, Massachusetts: MIT.

Fraser, S., & Pantzalis, C. (2004). Foreign Exchange Rate Exposure of U.S. Multinational Corporations: A Firm-Specific Approach. *Journal of Multinational Financial Management, 14*(3), 261-281.

Freeman, R. (2008). Labour Productivity Indicators. Comparison of Two OECD Databases, Productivity Differentials and the Balassa-Samuelson Effect: OECD Statistics Directorate, Division of Structural Economic Statistics.

Friberg, R., & Nydahl, S. (1999). Openness and the Exchange Rate Exposure of National Stock Markets. *International Journal of Finance and Economics, 4*(1), 55-62.

Fukuda, K. (2009a). Distribution Switching in Financial Time Series. *Mathematics and Computers in Simulation, 79*(5), 1711-1720.

Fukuda, K. (2009b). Distribution Switching of Stock Returns: International Evidence. *Applied Financial Economics, 19*(5), 371-377.

Gao, T. (2000). Exchange Rate Movements and the Profitability of U.S. Multinationals. *Journal of International Money and Finance, 19*, 117-134.

Gavin, M. (1989). The Stock Market and Exchange Rate Dynamics. *Journal of International Money and Finance, 8*(2), 181-200.

Genest, C., Rémillard, B., & Beaudoin, D. (2009). Goodness-of-fit Tests for Copulas: A Review and a Power Study. *Insurance: Mathematics and Economics, 44*, 199-213.

Girardi, G., & Ergün, A. T. (2013). Systemic Risk Measurement: Multivariate GARCH Estimation of CoVaR. *Journal of Banking & Finance, 37*(8), 3169-3180.

Girma, S., Lancheros, S., & Riaño, A. (2016). Global Engagement and Returns Volatility. *Oxford Bulletin of Economics and Statistics, 78*(6), 814-833.

Glosten, L., Jagannathan, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance, 48*(5), 1779-1801.

Goeij, P., & Marquering, W. (2004). Modeling the Conditional Covariance between Stock and Bond Returns: a Multivariate GARCH Approach. *Journal of Financial Econometrics, 2*, 531-564.

Goldberg, L. (2011). The International Role of the Dollar: Does it Matter if this Changes? *Staff Reports October*. New York: Federal Reserve Bank of New York.

Goldin, I., & Mariathasan, M. (2014). *The Butterfly Defect: How Globalization Creates Systemic Risks, and What to Do About It* (Vol. 3). Princeton, New Jersey: Princeton University Press.

Greenaway, D., & Kneller, R. (2007). Firm Heterogeneity, Exporting and Foreign Direct Investment. *The Economic Journal, 117*, F134-F161.

Griffin, J., & Stulz, R. (2001). International Competition and Exchange Rate Shocks: A Cross-country Industry Analysis of Stock Returns. *The Review of Financial Studies, 14*(1), 215-241.

Group of Ten. (2001). Report on Consolidation in the Financial Sector (I. M. Fund, Trans.) (pp. 459). Washington: International Monetary Fund.

Grygorash, O., Yan Zhou, Z., & Jorgensen, Z. (2006). *Minimum Spanning Tree Based Clustering Algorithms.* Paper presented at the 18th IEEE International Conference on Tools with Artificial Intelligence.

Gurrola, P. (2008). Capturing Fat-tail Risk in Exchange Rate Returns Using SU Curves: A Comparison with the Normal Mixture and Skewed Student Distributions. *Journal of Risk, 10*(2), 73-100.

Halpern, L., Koren, M., & Szeidl, A. (2005). Imports and Productivity *IDEAS Working Paper Series from RePEc*. St Louis: Federal Reserve Bank of St Louis.

Hansen, B. (1991). GARCH(1,1) Processes Are Near Epoch dependent. *Economic Letters, 36*, 181-186.

Härdle, W., & Okhrin, O. (2010). De Copulis Non Est Disputandum. *Advances in Statistical Analysis, 94*(1), 1-31.

Harmon, D., Stacey, B., Bar-Yam, Y., & Bar-Yam, Y. (2010). Networks of Economic Market Interdependence and Systemic Risk *NECSI Report*. Cambridge: New England Complex Systems Institute.

Hartmann, P., De Bandt, O., & Peydró, J. L. (2014). Systemic Risk in Banking after the Great Financial Crisis. In A. N. Berger, P. Molyneux, & J. O. S. Wilson (Eds.), *The Oxford Handbook of Banking* (Vol. 2). Oxford Handbooks Online: Oxford University Press.

He, J., & Ng, L. (1998). The Foreign Exchange Exposure of Japanese Multinational Corporations. *The Journal of Finance, 53*(2), 733-753.

Hekman, C. (1983). Measuring Foreign Exchange Exposure: A Practical Theory and Its Application. *Financial Analysts Journal, 39*(5), 59-65.

Helpman, E., Melitz, M., & Yeaple, S. (2004). Export Versus FDI with Heterogeneous Firms. *American Economic Review, 94*(1), 300-316.

Hemche, O., Jawadi, F., Maliki, S., & Cheffou, A. (2016). On the Study of Contagion in the Context of the Subprime Crisis: a Dynamic Conditional Correlation–Multivariate GARCH Approach. *Economic Modelling, 52*(PA), 292-299.

How Multi-destination Firms Shape the Effect of Exchange Rate Volatility on Trade: Micro Evidence and Aggregate Implications, Centre d'Etudes Prospectives et d'Informations Internationales (2016).

Hooper, P., & Kohlhagen, S. (1978). The Effect of Exchange Rate Uncertainty on the Prices and Volumes of International Trade. *Journal of international Economics, 8*(483-511).

Howton, S., & Perfect, S. (1998). Currency and Interest Derivatives Use in U.S. Firms. *Financial Management, 27*, 111-121.

Hu, J. (2010). Dependence Structures in Chinese and U.S. Financial Markets: a Time-Varying Conditional Copula Approach. *Applied Financial Economics, 20*(7), 561-583.

Huisman, R., Koedijk, K., Kool, C., & Palm, F. (2002). Notes and Communications: The Tail-fatness of FX Returns Reconsidered. *De Economist, 150*(3), 299-306.

Hutson, E., & O'Driscoll, A. (2010). Firm-level Exchange Rate Exposure in the Eurozone. *International Business Review, 19*, 468-478.

Hutson, E., & Stevenson, S. (2010). Openness, Hedging Incentives and Foreign Exchange Exposure: A Firm-level Multi-country Study. *Journal of International Business Studies, 41*(1), 105-122.

Ihrig, J. (2001). Exchange-rate Exposure of Multinationals: Focusing on Exchange-rate Issues *International Finance Discussion Papers*. Washington: Board of Governors of the Federal Reserve System.

Ivrendi, M., & Guloglu, B. (2010). Monetary Shocks, Exchange Rates and Trade Balances: Evidence from Inflation Targeting Countries. *Economic Modelling, 27*(5), 1144-1155.

Joe, H. (1997). *Multivariate Models and Dependence Concepts* (Vol. 1). London: Chapman & Hall.

Joe, H., & Xu, J. (1996). The Estimation Method of Inference Functions for Margins for Multivariate Models *Technical Report, Nr.166*. Vancouver, Canada: The University of British Columbia, The Department of Statistics.

Jondeau, E., Poon, S., & Rockinger, M. (2007). *Financial Modeling under Non-Gaussian Distributions*. Londen: Springer.

Jones, D. (2000). Emerging Problems with the Basel Capital Accord: Regulatory Capital Arbitrage and Related Issues. *Journal of Banking & Finance, 24*, 35-58.

Jorion, P. (1990). The Exchange-rate Exposure of U.S. Multinationals. *Journal of Business*, 331-345.

Jorion, P. (1991). The Pricing of Exchange Rate Risk in the Stock Market. *Journal of Financial and Quantitative Analysis, 26*(03), 363-376.

Jorion, P. (2007). *Value at Risk*. New York: McGraw-Hill.

Kamal, J., & Haque, A. (2016). Dependence between Stock Market and Foreign Exchange Market in South Asia: A Copula-GARCH Approach. *The Journal of Developing Areas, 50*(1), 175-195.

Karimalis, E., & Nomikos, N. (2018). Measuring Systemic Risk in the European Banking Sector: A Copula CoVaR Approach. *The European Journal of Finance, 24*(11), 944-975.

Kawai, M., & Urata, S. (1998). Are Trade and Direct Investments Substitutes or Complements? An Empirical Analysis of Japanese Manufacturing Industries. In H. Lee & D. Roland-Holst (Eds.), *Economic Development* *and Cooperation in the Pacific Basin: Trade, Investment, and Environmental Issues* Cambridge University Press.

Kerste, M., Gerritsen, M., Weda, J., & Tieben, B. (2015). Systemic Risk in the Energy Sector — Is There Need for Financial Regulation? *Energy Policy, 78*, 22-30.

Kiymaz, H. (2003). Estimation of Foreign Exchange Exposure: An Emerging Market Application. *Journal of Multinational Financial Management, 13*(1), 71-84.

Knight, F. H. (1921). *Risk, Uncertainty and Profit*. Boston: Houghton Mifflin.

Koutmos, G., & Martin, A. (2003). First and Second Moment Exchange Rate Exposure: Evidence from U.S. Stock Returns. *Financial Review, 38*, 455-471.

Kruskal, J. (1956). On the Shortest Spanning Subtree of a Graph and the Traveling Salesman Problem. *Proceedings of the American Mathematical Society, 7*(1), 48-50.

Kupiec, P. (1995). Techniques for Verifying the Accuracy of Risk Measurement Models. *Journal of Derivatives, 73–84*(3).

Labatut, V., & Balasque, J. M. (2013). *Detection and Interpretation of Communities in Complex Networks: Practical Methods and Application* (Vol. 9781447140481). Londen: Springer.

Lane, P. (2006). The Real Effects of European Monetary Union. *The Journal of Economic Perspectives, 20*(4), 47-66.

Lane, P. (2013). Financial Globalisation and the Crisis. *Open Economies Review, 24*(3), 555-580.

Levchenko, A., Lewis, L., & Tesar, L. (2009). The Collapse of U.S. Trade: In Search of the Smoking Gun. In R. Baldwin (Ed.), *The Great Trade Collapse: Causes, Consequences and Prospects* (pp. 71-78). London: VoxEU Publication, Centre for Trade and Economic Integration.

Levi, M. (1994). Exchange Rates and the Valuation of Firms. In Y. Amihud & R. Levich (Eds.), *Exchange Rates and Corporate Performance*. Washington, D.C.: New York University.

Lewis, J., & Linzer, D. (2005). Estimating Regression Models in Which the Dependent Variable Is Based on Estimates. *Political Analysis, 13*(4), 345-364.

Liebscher, E. (2008). Construction of Asymmetric Multivariate Copulas. *Journal of Multivariate Analysis, 99*(10), 2234-2250.

Lin, L., & Lee, C. I. (2017). Unmasking the Relationships Between Exchange Rate Exposure and Its Determinants: A More Complete Picture from Quantile Regressions. *Review of Pacific Basin Financial Markets and Policies, 20*(04), 1-28.

Liu, X. (2017). Measuring Systemic Risk with Regime Switching in Tails. *Economic Modelling, 67*, 55-72.

López-Espinosa, G., Moreno, A., Rubia, A., & Valderrama, L. (2015). Systemic Risk and Asymmetric Responses in the Financial Industry. *Journal of Banking and Finance, 58*(C), 471-485.

Mainik, G., & Schaanning, E. (2012). On Dependence Consistency of CoVaR and Some other Systemic Risk Measures. St. Louis: Federal Reserve Bank of St Louis.

Mandelbrot, B. (1963). The Variation of Certain Speculative Prices. *The Journal of Business, 36*(3), 394-419.

Manner, H. (2007). Estimation and Model Selection of Copulas with an Application to Exchange Rates *METEOR Research Memorandum RM/07/056*: Maastricht University.

Mantegna, R. (1999). Hierarchical Structure in Financial Markets. *The European Physical Journal B, 11*(1), 193-197.

Mark, N. (1990). Real and Nominal Exchange Rates in the Long Run: an Empirical Investigation. *Journal of International Economics, 28*, 115-136.

Marston, R. (2001). The Effects of Industry Structure on Economic Exposure. *Journal of International Money and Finance, 20*, 149-164.

McFarland, J., Pettit, R., & Sung, S. (1982). The Distribution of Foreign Exchange Price Changes: Trading Day Effects and Risk Measurement. *The Journal of Finance, 37*(3), 693-715.

Melitz, M. (2003). The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity. *Econometrica, 76*(6), 1695-1725.

Mendoza, E., Quadrini, V., & Ríos-Rull, J. (2009). Financial Integration, Financial Development, and Global Imbalances. *Journal of Political Economy, 117*(3), 371-416.

Michelis, L., & Ning, C. (2010). The Dependence Structure between the Canadian Stock Market and the USD/CAD Exchange Rate: a Copula Approach. *Canadian Journal of Economics/Revue Canadienne d'Économique, 43*(3), 1016-1039.

Milesi-Ferretti, G., Tille, C., Ottaviano, G., & Ravn, M. (2011). The Great Retrenchment: International Capital Flows during the Global Financial Crisis. *Economic Policy, 26*(66), 285-342.

Miller, K., & Reuer, J. (1998). Firm Strategy and Economic Exposure to Foreign Exchange Rate Movements. *Journal of International Business Studies, 29*(3), 493-513.

Mohapatra, S., & Rath, B. (2017). Exchange Rate Exposure and its Determinants: Evidence from Indian Firms. *The International Trade Journal, 31*(2), 197-211.

Morgan Stanley Capital International. (2016, 30/11/2016). MSCI Netherlands. Retrieved from https://www.msci.com/documents/10199/aa1d6a82-5c8b-447d-89b3-df9a6bbc8e0d

Moshirian, F. (2015). Global Governance and Financial Stability. *Journal of Banking & Finance, 55*, 358-360.

Muller, A., & Verschoor, W. (2006a). European Foreign Exchange Risk Exposure. *European Financial Management, 12*(2), 195-220.

Muller, A., & Verschoor, W. (2006b). Foreign Exchange Risk Exposure: Survey and Suggestions. *Journal of Multinational Financial Management, 16*(4), 385-410.

Mussa, M. (1976). The Exchange Rate, the Balance of Payments and Monetary and Fiscal Policy under a Regime of Controlled Floating. *The Scandinavian Journal of Economics, 78*(2), 229-248.

Nadarajah, S., Afuecheta, E., & Chan, S. (2015). A Note on "Modelling Exchange Rate Returns: Which Flexible Distribution to Use?". *Quantitative Finance*, 1-9.

Nadenichek, J. (2006). The J-curve Effect: An Examination Using a Structural Vector Error Correction Model. *International Journal of Applied Economics, 3*(2), 34-47.

Nagengast, A. J., & Stehrer, R. (2016). The Great Collapse in Value Added Trade. *Review of International Economics, 24*(2), 392-421.

Nance, D., Smith, C., & Smithson, C. (1993). On the determinants of corporate hedging. *The Journal of Finance, 48*(1), 267-284.

Nektarios, M. (2018). Estimating a Bilateral J-curve between the U.K. and the Euro Area. *The Manchester School, 86*(6), 757-769.

Nelsen, R. (2006). *An Introduction to Copulas*. New York: Springer Science & Business Media.

Ning, C. (2010). Dependence Structure between the Equity Market and the Foreign Exchange Market– A Copula Approach. *Journal of International Money and Finance, 29*(5), 743-759.

OECD. (2002). *Measuring Globalisation: The Role of Multinationals in OECD Economies (Two-volume Set)*. Paris: Organisation for Economic Co-operation and Development: Publishing.

OECD. (2005). *Measuring Globalisation. OECD Handbook on Economic Globalisation Indicators.* Paris: Statistics. OECD Publishing.

OECD. (2012). Systemic Financial Risk OECD Reviews of Risk Mangement Policies, Paris: OECD Publishing.

Pan, M., Fok, R., & Liu, Y. (2007). Dynamic Linkages Between Exchange Rates and Stock Prices: Evidence from East Asian Markets. *International Review of Economics & Finance, 16*(4), 503-520.

Pantzalis, C., Simkins, B., & Laux, P. (2001). Operational Hedges and the Foreign Exchange Exposure of U.S. Multinational Corporations. *Journal of International Business Studies, 32*(4), 793-812.

Patton, A. (2001). Modelling Time-Varying Exchange Rate Dependence Using the Conditional Copula. *IDEAS Working Paper Series from RePEc*.

Patton, A. (2006). Modelling Asymmetric Exchange Rate Dependence. *International Economic Review, 47*(2).

Phylaktis, K., & Ravazzolo, F. (2005). Stock Prices and Exchange Rate Dynamics. *Journal of International Money and Finance, 24*(7), 1031-1053.

Pollard, P. (2001). The Creation of the Euro and the Role of the Dollar in International Markets. *Review-Federal Reserve Bank of Saint Louis, 83, september-oktober*(5), 17-36.

Pritamani, M. D., Shome, D. K., & Singal, V. (2004). Foreign Exchange Exposure of Exporting and Importing Firms. *Journal of Banking & Finance, 28*(7), 1697-1710.

Rai, A., Patnayakuni, R., & Patnayakuni, N. (1997). Technology Investment and Business Performance. *Communications of the ACM, 40*(7), 89-97.

Rana, P. (1981). Exchange Rate Risk Under Generalized Floating: Eight Asian Countries. *Journal of International Economics, 11*, 459-466.

Reboredo, J., Rivera-Castro, M., & Ugolini, A. (2016). Downside and Upside Risk Spillovers Between Exchange Rates and Stock Prices. *Journal of Banking & Finance, 62*, 76-96.

Riahi-Belkaoui, A. (1999). The Degree of Internationalization and the Value of the Firm: Theory and Evidence. *International Accounting, Auditing & Tacation, 8*(1), 189-196.

Rogalski, R., & Vinso, J. (1978). Empirical Properties of Foreign Exchange Rates. *Journal of International Business Studies, 9*, 69-79.

Rose, A. (2000). One Money, One Market: the Effect of Common Currencies on Trade. *Economic Policy*(30), 7-45.

Rossi, S., & Malavasi, R. (2016). *Financial Crisis, Bank Behaviour and Credit Crunch* (Vol. 1). Switzerland: Springer International Publishing.

Schott, P. (2009). U.S. Trade Margins During the 2008 Crisis. In R. Baldwin (Ed.), *The Great Trade Collapse: Causes, Consequences and Prospects* (pp. 127-142). London: VoxEU Publication, Centre For Trade and Economic Integration.

Schwartz, E., & Aronson, J. R. (1967). Some Surrogate Evidence in Support of the Concept of Optimal Financial Structure. *The Journal of Finance, 22*(1), 10-18.

Scott, D. F. (1972). Evidence On the Importance of Financial Structure. *Financial Management, 1*(2), 45.

Sedunov, J. (2016). What Is the Systemic Risk Exposure of Financial Institutions? *Journal of Financial Stability, 24*(C), 71-87.

Sercu, P. (1992). Exchange Risk, Exposure, and the Option to Trade. *Journal of International Money and Finance, 11*(8), 579-593.

Sercu, P., & Uppal, R. (2003). Exchange Rate Volatility and International Trade: A General-Equilibrium Analysis. *European Economic Review, 47*, 429-441.

Shaar, K., & Khaled, M. (2017). Why You Should Use High Frequency Data to Test the Impact of Exchange Rate on Trade. *Applied Economics Letters*, 1-4.

Shapiro, A. (1975). Exchange Rate Changes, Inflation, and the Value of the Multinational Corporation. *The Journal of Finance, 30*(2), 485-502.

Siegel, S., & Castellan, N. (1988). *Nonparametric Statistics for the Behavioral Sciences* (Vol. 2). New York: McGraw-Hill.

Sklar, A. (1959). Fonctions de Répartition à N Dimensions et Leurs Marges. *Publications de l'Institut Statistique de l'Université de Paris*(8), 229-231.

Sollis, R. (2012). *Empirical Finance: for Finance and Banking*. United Kingdom: Wiley.

Statistics Belgium. (2015). Kerncijfers, Statistisch Overzicht van België. Brussel: FOD Economie, KMO Middenstand en Energie.

Statistics Netherlands. (2010). *Internationalisation Monitor 2010.* Den Haag/Heerlen/Bonaire.

Statistics Netherlands. (2014). *Internationalisation Monitor 2014.* (Vol. 3). Den Haag/Heerlen/Bonaire.

Statistics Netherlands. (2015). *Internationaliseringsmonitor*. Den Haag/Heerlen/Bonaire.

Statistics Netherlands. (2018). *Internationalisation Monitor 2018. Globalisation.* (Vol. 4). Den Haag/Heerlen/Bonaire.

Stulz, R., & Williamson, R. (1996). *Identifying and Quantifying Exposures*. Ohio: Fisher College of Business, The Ohio State University.

Swenson, D. (2004). Foreign Investment and Mediation of Trade Flows. *Review of International Economics, 12*(4), 609-629.

Syed, Z., & Sajid, A. (2018). Anticipated versus Unanticipated Terms of Trade Shocks and the J-curve Phenomenon. *Journal of International Money and Finance, 81*, 1-19. doi:10.1016/j.jimonfin.2017.10.003

Tang, B. (2015). Exchange Rate Exposure of Chinese Firms at the Industry and Firm Level. *Review of Development Economics, 19*(3), 592-607.

Trapp, M., & Wewel, C. (2013). Transatlantic Systemic Risk. *Journal of Banking & Finance, 37*(11), 4241-4255.

Tsen, W. (2016). Exchange Rate Volatilities and Disaggregated Bilateral Exports of Malaysia to the United States: Empirical Evidence. *Eurasian Economic Review, 6*(2), 289-314.

Tucker, A., & Pond, L. (1988). The Probability Distribution of Foreign Exchange Price Changes: Tests of Candidate Processes. *The Review of Economics and Statistics, 70*(4), 638-647.

Tumminello, M., Aste, T., Di Matteo, T., & Mantegna, R. N. (2005). A Tool for Filtering Information in Complex Systems. *Proceedings of the National Academy of Sciences of the United States of America, 102*(30), 10421-10426.

Valta, P. (2012). Competition and the Cost of Debt. *Journal of Financial Economics, 105*, 66-682.

Van Cauwenberge, A., Vancauteren, M., Braekers, R., & Vandemaele, S. (Forthcoming). An Empirical Study of Exchange Rate Exposure - the Case of Belgium and the Netherlands *Working Paper Series*. Brussels: National Bank Belgium.

Viaene, J.-M., & de Vries, C. (1992). International Trade and Exchange Rate Volatility. *European Economic Review, 36*(August), 1311-1321.

Vives, X. (2016). *Competition and Stability in Banking: The Role of Regulation and Competition Policy*. Princeton: Princeton University Press.

Wagner, J. (2002). The Causal Effects of Exports on Firm Size and Labor Productivity: First Evidence From a Matching Approach. *Economics Letters, 77*(2), 287-292.

Wagner, J. (2007). Exports and Productivity: A Survey of the Evidence from Firm-level Data. *World Economy, 30*(1), 60-82.

Wagner, J. (2012). International Trade and Firm Performance: a Survey of Empirical Studies Since 2006. *Review of World Economics, 148*(2), 235-267.

Walid, C., Chaker, A., Masood, O., & Fry, J. (2011). Stock Market Volatility and Exchange Rates in Emerging Countries: A Markov-state Switching Approach. *Emerging Markets Review, 12*(3), 272-292.

Wang, G., & Xie, C. (2015). Correlation Structure and Dynamics of International Real Estate Securities Markets: A Network Perspective. *Physica A: Statistical Mechanics and its Applications, 424*, 176-193.

Wang, G., & Xie, C. (2016). Tail Dependence Structure of the Foreign Exchange Market: A Network View. *Expert Systems With Applications, 46*, 164-179.

Wang, Y. (2007). On the Relationship Between Overseas Direct Investment and Trade. *The Chinese Economy, 40*(4), 56-69.

Wang, Y., Wu, J., & Lai, Y. (2013). A Revisit to the Dependence Structure between the Stock and Foreign Exchange Markets: A Dependence-switching Copula Approach. *Journal of Banking & Finance, 37*(5), 1706-1719.

Watson, A. (2019). Financial Frictions, the Great Trade Collapse and International Trade over the Business Cycle. *Open Economies Review, 30*(1), 19-64.

Watts, D., & Strogatz, S. (1998). Collective Dynamics of 'Small-world' Networks. *Nature, 393*(6684), 440-442.

Westerfield, J. (1977). An Examination of Foreign Exchange Risk under Fixed and Floating Rate Regimes. *Journal of International Economics, 7*, 181-200.

Williamson, R. (2001). Exchange Rate Exposure and Competition: Evidence from the Automotive Industry. *Journal of Financial Economics, 59*, 441-475.

Yuan, X., Sriboonditta, S., Wu, B., & Tang, J. (2014). Evaluating Co-movements with the Total Value of Import and Export with Exchange Rate in Yunnan Province. In J. Watada, B. Xu, & B. Wu (Eds.), *Innovative Management in Information and Production*. New York: Springer.

Zhao, H. (2010). Dynamic Relationship between Exchange Rate and Stock Price: Evidence from China. *Research in International Business and Finance, 24*(2), 103-112.

Appendices

Appendix Chapter 2

A1 MSCI Netherlands: constituents

Table A1: List of constituents MSCI Netherlands

Security Name	Closing Weight
1. UNILEVER NV (NL) CERT	17.94%
2. ING GROEP	12.83%
3. ASML HLDG	10.66%
4. NXP SEMICONDUCTORS	7.04%
5. KONINKLIJKE PHILIPS	6.74%
6. AHOLD DELHAIZE	6.51%
7. HEINEKEN NV	4.42%
8. RELX (NL)	4.10%
9. AKZO NOBEL	4.00%
10. WOLTERS KLUWER	2.87%
11. KONINKLIJKE DSM	2.77%
12. NN GROUP	2.32%
13. KONINKLIJKE KPN	2.23%
14. AEGON	2.23%
15. ALTICE A	1.87%
16. HEINEKEN HOLDING	1.78%
17. COCA-COLA EUROPEAN PTNRS	1.75%
18. AERCAP HOLDINGS NV	1.65%
19. RANDSTAD HOLDING	1.62%
20. ABN AMRO GROUP	1.54%
21. GEMALTO (NL)	1.12%
22. BOSKALIS WESTMINSTE CERT	0.78%
23. KONINKLIJKE VOPAK	0.70%
24. ALTICE B	0.55%

*Note: Weights are rounded to six decimal points. Totals may not add up to 100%.

A2 GDP growth rates

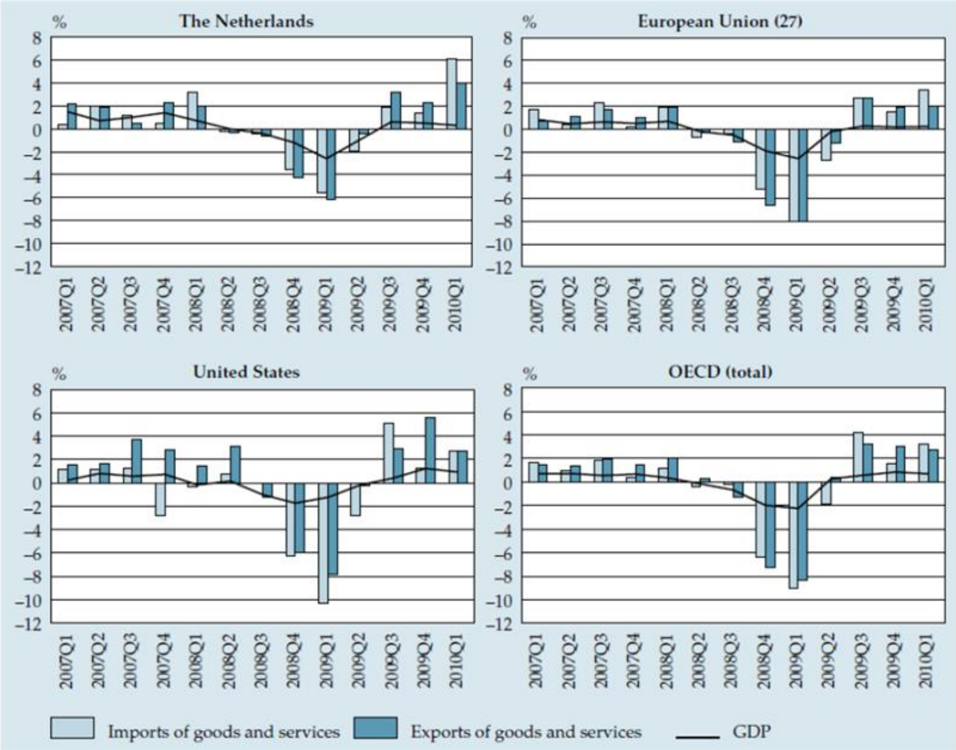
Table A2 : GDP growth rate (%) compared to previous quarter, seasonally adjusted

Period	Nether-lands	Euro area	Period	Nether-lands	Euro area
2006 Q1	0.8	0.9	2011 Q1	0.7	0.8
2006 Q2	1.5	1.0	2011 Q2	-0.1	0.0
2006 Q3	0.5	0.6	2011 Q3	0.0	0.0
2006 Q4	0.8	1.1	2011 Q4	**-0.7**	**-0.4**
2007 Q1	1.1	0.8	2012 Q1	**-0.2**	**-0.2**
2007 Q2	0.5	0.6	2012 Q2	0.1	**-0.3**
2007 Q3	1.2	0.5	2012 Q3	**-0.4**	**-0.1**
2007 Q4	1.5	0.5	2012 Q4	**-0.8**	**-0.4**
2008 Q1	0.0	0.5	2013 Q1	0.4	**-0.3**
2008 Q2	0.4	**-0.3**	2013 Q2	-0.2	0.4
2008 Q3	**-0.3**	**-0.6**	2013 Q3	0.6	0.3
2008 Q4	**-0.8**	**-1.7**	2013 Q4	0.6	0.2
2009 Q1	**-3.2**	**-3.0**	2014 Q1	-0.2	0.3
2009 Q2	**-0.2**	**-0.2**	2014 Q2	0.5	0.2
2009 Q3	0.3	0.3	2014 Q3	0.4	0.4
2009 Q4	0.5	0.5	2014 Q4	1.1	0.4
2010 Q1	-0.1	0.5	2015 Q1	0.6	0.8
2010 Q2	0.6	1.0	2015 Q2	0.1	0.4
2010 Q3	0.4	0.4	2015 Q3	0.2	0.3
2010 Q4	1.2	0.6	2015 Q4	0.3	0.5

(Metadata were obtained from OECD.stat)

A3 GDP and trade Growth

Figure A3: GDP and trade growth (% change previous quarter)



(This table is extracted from a study of Statistics Netherlands (2010))

A4 Classifications of firms and variables according to data source

Table A4.1: Names and classifications of firms

Sector (NACE-Code rev.2, 2 digit)	Firm
1) Administrative & support service activities (77-82)	Brunel International DPA Group Randstad USG People
2) Construction (41-43)	Ballast Nedam Batenburg Techniek Heijmans Koninklijke BAM Groep Koninklijke Boskalis Westminster Royal Imtech
3) Financial & insurance activities (64-66)	Aegon BinckBank Eurocommercial Proporties Gemalto ING Groep Kardan Kas Bank Nieuwe Steen Unibail-Rodamco Value 8 Vastned Retail
4) Information & communication (58-63)	AND International Publishers ICT Automatisering Koninklijke Brill Koninklijke KPN Ordina RELX Telegraaf Media Groep TomTom Wolters Kluwer
5) Manufacturing (10-33)	Aalberts industries Accell Group AkzoNobel ASM International ASML Holding BESI Corbion Docdata Heineken
5) Manufacturing (10-33)	Koninklijke DSM Nedap Neways Electronics RoodMicrotec Royal Dutch Shell Royal Ten Cate Royal Wessanen TKH Group Unilever Koninklijke Philips Electronics
6) Professional, scientific & technical activities (69-75)	Arcadis Fugro Galapagos Grontmij Kendrion Oranjewoud A Pharming Group SBM Offshore
7) Transportation & storage (49-53)	Koninklijke Vopak Post NL
8) Wholesale & retail trade; repair of motor vehicles & motorcycles (45-47)	Amsterdam Commodities ArcelorMittal Beter Bed Inverko Koninklijke Ahold Macintosh Retail Group Sligro Food Group Stern Groep

A4 Classifications of firms and variables according to data source

Table A4.2: List of variables and data sources

Variable	Definition	Source
CoVaR	The $VaR^{s}_{q,t}$ of the system conditional on a firm being at most at its $VaR^{j}_{q,t}$-level.	DataStream
VaR	$VaR^{j}_{q,t}$ is determined by the q-quantile of the return distribution. The $VaR^{j}_{q,t}$ is a firm i's maximums loss at time t at confidence level q.	DataStream
Beta	A measure of market risk which shows the relationship between the volatility of the stock and the volatility of the market. The beta factor is derived by performing a least squares regression between adjusted prices of the stock and the corresponding DataStream market index.	DataStream
Leverage	Total Debt / Common equity	DataStream
Size	The sum of total current assets.	DataStream
Trade Intensity	= (Export + Import)/Total Assets	Statistics Netherlands
Sector dummy	= 1 the sector according to which the firm belongs = 0 the remaining sectors	Statistics Netherlands
Foreign control dummy	= 1 if firm is foreign controlled, strategic decisions are taken abroad = 0 if firm is controlled by a Dutch company/owner, strategic decisions are taken in the Netherlands Data available for 2006-2014, imputation for 2015.	Statistics Netherlands
Foreign Subsidiary dummy	= 1 if the firm has at least one foreign subsidiary = 0 otherwise	Statistics Netherlands

Note: Logarithms are used to scale the parameters and to potentially solve the outlier problems.
*The dummy variable Foreign Subsidiary has only 1756 observations, out of which 94%, or 1652 observations indicate the presence of at least one foreign subsidiary.

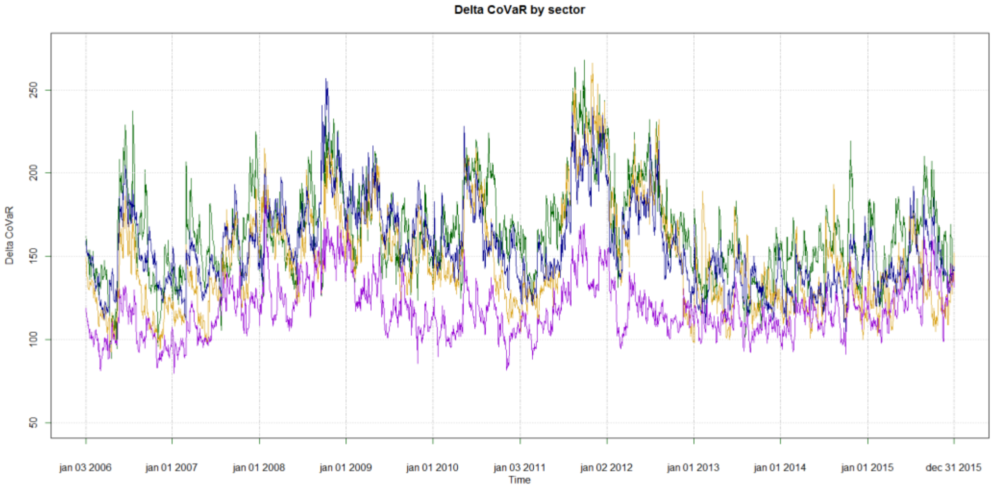
Table A4.3: Constituents of the variables from table A4.2

Variable	Definition	Source
Export**	Value of exported goods recorded at the Dutch border.	Statistics Netherlands
Import**	Value of imported goods recorded at the Dutch border.	Statistics Netherlands
Total assets	The sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets.	DataStream
Common equity	Total amount that shareholders, with the exception of preferred shareholders, have invested in a company. Also the common shares themselves, retained earnings, additional paid-in capital are included.	DataStream

** The International Trade in Goods statistics contain the used import and export data and follow the Eurostat European Regulation. The figures based on this Regulation follow the principle of crossing borders. As such, the value of import and as well as the value of export is recorded at the Dutch border. This means that imports at the border of the importing country are valued (i.e., cif-value: value, cost, insurance and freight) and the export at the border of the exporting country (i.e., fob-value: free on board). However, in the national accounts, the value of both imports and exports is based on the fob-value (i.e., both at the border of the exporting country). This means that the input value has to be corrected. The difference between the cif- and the fob-value of imports concerns the costs incurred in transporting the intermediate route (the border between the exporting country and the Dutch border). These are mainly transport and insurance costs (Statistics Netherlands, Den Haag/Heerlen)

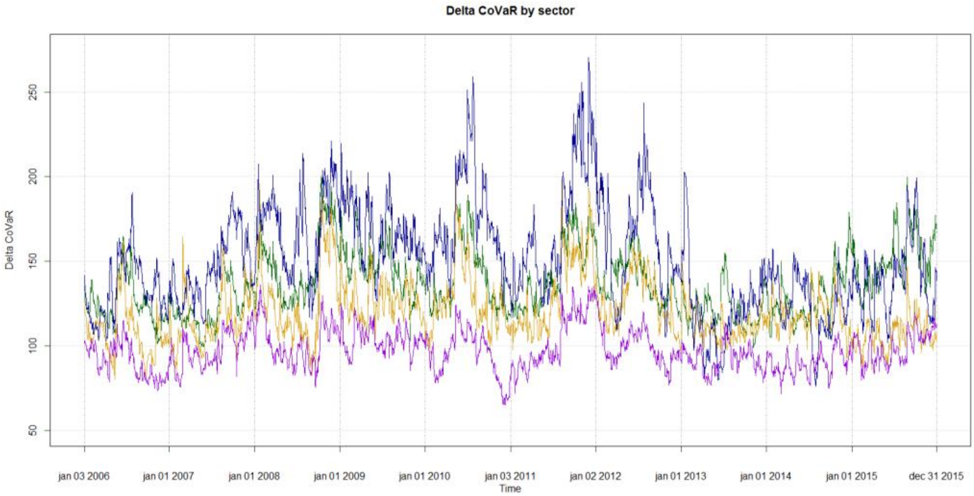
A5 Time-series plots of daily ΔCoVaR measures aggregated by sector

Figure A5.1. Time-series plots of daily ΔCoVaR measures aggregated by sector (part1)



(Green: Administrative & support service activities , yellow: Construction, blue: Financial & insurance activities, purple: Information & communication)

Figure A5.2.: Time-series plots of daily ΔCoVaR measures aggregated by sector (part2).



(Green: Manufacturing, yellow: Professional, scientific & technical activities, blue: Transportation & storage , purple: Wholesale & retail trade; repair of motor vehicles & motorcycles)

A6 ΔCoVaR

Table A6.1: ΔCoVaR Entire sample Period (January 2006 – December 2015)

Sector (NACE-code rev.2, 2 digit)	Firm	Mean ΔCoVaR	St.dev.
1) Administrative & support service activities (77-82)	Brunel International	178.10	33.40
	DPA Group	99.00	24.15
	Randstad	204.90	48.34
	USG People	177.40	45.85
2) Construction (41-43)	Ballast Nedam	120.10	30.79
	Batenburg Techniek	77.92	17.80
	Heijmans	142.30	35.97
	Koninklijke BAM Groep	172.70	47.07
	Koninklijke Boskalis Westminster	173.10	61.67
	Royal Imtech	199.40	60.67
3) Financial & insurance activities (64-66)	Aegon	257.00	77.18
	BinckBank	188.60	43.93
	Eurocommercial Proporties	113.00	29.94
	Gemalto	123.70	23.87
	ING Groep	347.40	92.13
	Kardan	164.40	39.88
	Kas Bank	84.62	18.59
	Nieuwe Steen	89.15	24.12
	Unibail-Rodamco	149.00	41.42
	Value 8	88.91	28.38
	Vastned Retail	105.90	20.91
4) Information & communication (58-63)	AND International Publishers	117.60	24.14
	ICT Automatisering	90.75	19.75
	Koninklijke Brill	60.69	12.07
	Koninklijke KPN	118.30	31.98
	Ordina	138.80	38.28
	RELX	133.10	35.54
	Telegraaf Media Groep	67.51	14.79
	TomTom	184.40	49.05
	Wolters Kluwer	150.20	48.08
5) Manufacturing (10-33)	Aalberts industries	178.60	55.52
	Accell Group	83.08	14.56
	AkzoNobel	185.10	56.33
	ASM International	133.40	25.03
	ASML Holding	160.50	55.52
5) Manufacturing (10-33)	BESI	137.10	35.64
	Corbion	134.30	26.83
	Docdata	83.84	18.90
	Heineken	114.60	21.75
	Koninklijke DSM	164.60	30.14
	Nedap	271.00	53.84
	Neways Electronics	65.17	46.42
	RoodMicrotec	103.70	13.08
	Royal Dutch Shell	103.30	21.88
	Royal Ten Cate	114.20	24.59
	Royal Wessanen	125.50	42.38
	TKH Group	132.30	37.47
	Unilever	124.30	26.56
	Koninklijke Philips Electronics	182.20	32.40
6) Professional, scientific & technical activities (69-75)	Arcadis	129.90	32.42
	Fugro	160.20	61.51
	Galapagos	110.90	18.80
	Grontmij	109.70	21.08
	Kendrion	99.81	25.56
	Oranjewoud A	56.87	16.45
	Pharming Group	135.80	32.52
	SBM Offshore	157.00	49.17
7) Transportation & storage (49-53)	Koninklijke Vopak	120.60	26.25
	Post NL	181.60	48.35
8) Wholesale & retail trade; repair of motor vehicles & motorcycles (45-47)	Amsterdam Commodities	84.41	20.44
	ArcelorMittal	153.70	60.51
	Beter Bed	84.82	23.54
	Inverko	101.30	19.07
	Koninklijke Ahold	124.40	36.96
	Macintosh Retail Group	88.75	17.28
	Sligro Food Group	76.60	15.38
	Stern Groep	64.35	24.06

A6 ΔCoVaR

Table A6.2: ΔCoVaR: Precrisis period (January 2006-June 2008)

Sector (NACE-code rev.2, 2 digit)	Firm	Mean ΔCoVaR	St.dev.
1) Administrative & support service activities (77-82)	Brunel International	153.10	26.83
	DPA Group	89.28	27.11
	Randstad	156.70	26.69
	USG People	149.90	28.17
2) Construction (41-43)	Ballast Nedam	107.90	13.20
	Batenburg Techniek	64.46	11.71
	Heijmans	131.30	22.04
	Koninklijke BAM Groep	167.20	41.72
	Koninklijke Boskalis Westminster	120.80	31.40
	Royal Imtech	106.60	37.71
3) Financial & insurance activities (64-66)	Aegon	222.90	65.97
	BinckBank	142.60	43.97
	Eurocommercial Proporties	105.30	22.94
	Gemalto	139.30	13.16
	ING Groep	333.30	81.24
	Kardan	116.80	24.89
	Kas Bank	90.31	22.05
	Nieuwe Steen	89.86	21.30
	Unibail-Rodamco	107.10	26.66
	Value 8	88.60	27.22
	Vastned Retail	102.30	28.00
4) Information & communication (58-63)	AND International Publishers	95.74	23.70
	ICT Automatisering	92.41	17.34
	Koninklijke Brill	56.08	15.46
	Koninklijke KPN	125.80	30.14
	Ordina	127.20	32.77
	RELX	123.90	30.25
	Telegraaf Media Groep	75.15	15.51
	TomTom	122.00	39.68
	Wolters Kluwer	122.40	32.73
5) Manufacturing (10-33)	Aalberts industries	144.50	40.94
	Accell Group	95.28	22.41
	AkzoNobel	137.70	39.70
	ASM International	120.70	19.53
	ASML Holding	131.20	31.95
5) Manufacturing (10-33)	BESI	103.90	11.26
	Corbion	131.60	12.91
	Docdata	74.46	10.24
	Heineken	83.28	16.12
	Koninklijke DSM	125.90	22.32
	Nedap	219.40	30.79
	Neways Electronics	49.68	9.56
	RoodMicrotec	110.00	18.22
	Royal Dutch Shell	106.80	17.94
	Royal Ten Cate	82.34	37.93
	Royal Wessanen	99.77	11.86
	TKH Group	116.80	17.51
	Unilever	124.70	24.74
	Koninklijke Philips Electronics	168.30	41.83
6) Professional, scientific & technical activities (69-75)	Arcadis	113	34.17
	Fugro	96.12	16.75
	Galapagos	65.29	11.78
	Grontmij	86.69	19.18
	Kendrion	76.67	13.26
	Oranjewoud A	77.36	14.85
	Pharming Group	123.3	37.64
	SBM Offshore	100.1	18.71
7) Transportation & storage (49-53)	Koninklijke Vopak	100.70	13.81
	Post NL	103.60	12.07
8) Wholesale & retail trade; repair of motor vehicles & motorcycles (45-47)	Amsterdam Commodities	56.33	5.16
	ArcelorMittal	104.20	22.15
	Beter Bed	134.60	18.71
	Inverko	97.38	17.71
	Koninklijke Ahold	124.30	20.76
	Macintosh Retail Group	104.10	18.17
	Sligro Food Group	99.05	10.28
	Stern Groep	43.87	24.57

A6 ΔCoVaR

Table A6.3: ΔCoVaR: Crisis period (July 2008-June 2009)

Sector (NACE-code rev.2, 2 digit)	Firm	Mean ΔCoVaR	St.dev.
1) Administrative & support service activities (77-82)	Brunel International	99.25	16.71
	DPA Group	90.43	19.64
	Randstad	226.10	11.85
	USG People	279.30	36.44
2) Construction (41-43)	Ballast Nedam	124.40	24.84
	Batenburg Techniek	71.39	16.91
	Heijmans	267.60	89.47
	Koninklijke BAM Groep	249.70	9.51
	Koninklijke Boskalis Westminster	191.20	31.82
	Royal Imtech	149.00	10.43
3) Financial & insurance activities (64-66)	Aegon	342.90	15.65
	BinckBank	164.70	37.88
	Eurocommercial Proporties	103.00	8.32
	Gemalto	141.60	5.04
	ING Groep	366.90	73.65
	Kardan	205.40	27.80
	Kas Bank	128.80	11.65
	Nieuwe Steen	119.30	32.19
	Unibail-Rodamco	145.90	6.10
	Value 8	114.00	27.98
	Vastned Retail	102.00	7.90
4) Information & communication (58-63)	AND International Publishers	117.20	38.06
	ICT Automatisering	115.60	17.18
	Koninklijke Brill	38.17	13.37
	Koninklijke KPN	88.93	26.23
	Ordina	230.70	22.85
	RELX	165.10	19.80
	Telegraaf Media Groep	82.74	21.43
	TomTom	212.80	24.30
	Wolters Kluwer	166.00	20.97
5) Manufacturing (10-33)	Aalberts industries	200.40	10.53
	Accell Group	86.59	19.85
	AkzoNobel	192.10	15.91
	ASM International	130.80	19.97
	ASML Holding	141.60	5.04

Sector (NACE-code rev.2, 2 digit)	Firm	Mean ΔCoVaR	St.dev.
5) Manufacturing (10-33)	BESI	127.70	19.46
	Corbion	140.90	30.18
	Docdata	80.69	33.19
	Heineken	106.30	28.93
	Koninklijke DSM	220.30	28.78
	Nedap	337.00	17.71
	Neways Electronics	99.44	20.22
	RoodMicrotec	107.90	17.81
	Royal Dutch Shell	162.90	10.30
	Royal Ten Cate	164.80	64.23
	Royal Wessanen	140.50	9.51
	TKH Group	149.50	12.22
	Unilever	132.80	28.41
	Koninklijke Philips Electronics	159.60	37.41
6) Professional, scientific & technical activities (69-75)	Arcadis	134.90	10.85
	Fugro	169.20	63.53
	Galapagos	121.50	18.10
	Grontmij	130.90	29.46
	Kendrion	66.12	34.51
	Oranjewoud A	69.46	12.79
	Pharming Group	147.30	37.96
	SBM Offshore	245.30	82.33
7) Transportation & storage (49-53)	Koninklijke Vopak	110.60	23.56
	Post NL	179.80	9.27
8) Wholesale & retail trade; repair of motor vehicles & motorcycles (45-47)	Amsterdam Commodities	72.61	19.59
	ArcelorMittal	203.80	65.68
	Beter Bed	77.59	9.31
	Inverko	90.03	19.56
	Koninklijke Ahold	94.49	7.59
	Macintosh Retail Group	72.17	8.68
	Sligro Food Group	85.03	15.37
	Stern Groep	95.34	31.32

A6 ΔCoVaR

Table A6.4: ΔCoVaR: Postcrisis period (July 2009- December 2015)

Sector (NACE-code rev.2, 2 digit)	Firm	Mean ΔCoVaR	St.dev.
1) Administrative & support service activities (77-82)	Brunel International	141.9	22.78
	DPA Group	77.64	18.7
	Randstad	193.2	41.35
	USG People	177.1	44.73
2) Construction (41-43)	Ballast Nedam	103.4	27.95
	Batenburg Techniek	79.29	20.03
	Heijmans	138.6	35.77
	Koninklijke BAM Groep	164.7	43.39
	Koninklijke Boskalis Westminster	180.8	58.78
	Royal Imtech	200.6	73.2
3) Financial & insurance activities (64-66)	Aegon	243.5	71.11
	BinckBank	149.1	31.09
	Eurocommercial Proporties	108.4	31.4
	Gemalto	130.2	27.02
	ING Groep	335.3	79.2
	Kardan	146.9	35.59
	Kas Bank	67.88	13.53
	Nieuwe Steen	88.14	20.77
	Unibail-Rodamco	152.2	35.94
	Value 8	70.07	20.13
	Vastned Retail	99.98	17.82
4) Information & communication (58-63)	AND International Publishers	122.1	22.67
	ICT Automatisering	82.06	14.07
	Koninklijke Brill	68.33	12.53
	Koninklijke KPN	116.7	31.85
	Ordina	166.6	45.1
	RELX	129.3	33.01
	Telegraaf Media Groep	64.83	10.9
	TomTom	180.6	43.48
	Wolters Kluwer	157.5	54.85
5) Manufacturing (10-33)	Aalberts industries	189.9	54.31
	Accell Group	83.76	13.97
	AkzoNobel	200.1	53.43
	ASM International	142.9	23.62
	ASML Holding	171.6	32.51

Sector (NACE-code rev.2, 2 digit)	Firm	Mean ΔCoVaR	St.dev.
5) Manufacturing (10-33)	BESI	36.930	36.93
	Corbion	21.350	21.35
	Docdata	23.990	23.99
	Heineken	31.370	31.37
	Koninklijke DSM	60.990	60.99
	Nedap	42.330	42.33
	Neways Electronics	10.970	10.97
	RoodMicrotec	17.460	17.46
	Royal Dutch Shell	19.740	19.74
	Royal Ten Cate	28.560	28.56
	Royal Wessanen	45.250	45.25
	TKH Group	26.370	26.37
	Unilever	32.230	32.23
	Koninklijke Philips Electronics	97.170	97.17
6) Professional, scientific & technical activities (69-75)	Arcadis	123.60	26.24
	Fugro	163.60	67.48
	Galapagos	114.70	18.43
	Grontmij	122.90	24.48
	Kendrion	106.90	26.82
	Oranjewoud A	59.36	17.01
	Pharming Group	142.30	29.82
	SBM Offshore	162.30	51.12
7) Transportation & storage (49-53)	Koninklijke Vopak	121.3	26.14
	Post NL	173.5	38.86
8) Wholesale & retail trade; repair of motor vehicles & motorcycles (45-47)	Amsterdam Commodities	88.26	23.84
	ArcelorMittal	164.40	63.29
	Beter Bed	74.99	19.81
	Inverko	103.40	19.54
	Koninklijke Ahold	120.90	38.37
	Macintosh Retail Group	79.33	18.72
	Sligro Food Group	84.24	18.51
	Stern Groep	69.04	17.70

A7 ΔCoVaR results per sector

Table A7: Summary statistics for ΔCoVaR per sector: precrisis, crisis, postcrisis and horizontal comparison.

Precrisis period						**Crisis period**					
*Note: Sectors are ordered descending on Mean ΔCoVaR.	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)	*Note: Sectors are ordered descending on Mean ΔCoVaR and numbered according to the Precrisis period ranking.	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)
1) Financial & Insurance	139.87	75.91	18.88	333.30	88.60	2) Admin. & support service	176.51	93.76	14.60	279.30	90.43
2) Admin. & support service	137.25	32.10	19.78	156.70	89.28	1) Financial & Insurance	175.87	93.53	12.39	366.90	102.00
3) Manufacturing	117.17	37.00	10.52	219.40	49.68	4) Construction	175.54	75.35	18.93	267.60	71.39
4) Construction	116.37	33.73	19.44	167.20	64.46	3) Manufacturing	151.67	58.27	10.44	337.00	80.69
5) Information & commun.	104.52	25.98	13.47	127.20	56.08	6)Transportation & storage	145.22	48.93	12.24	179.80	110.60
6)Transportation & storage	102.14	2.05	10.23	103.60	100.70	8) Professional, scientific & technical	135.59	56.98	24.15	245.30	66.12
7) Wholesale & retail trade	95.47	30.99	7.83	134.60	43.87	5) Information & commun.	135.24	63.25	11.46	230.70	38.17
8) Professional, scientific & technical	92.32	19.62	12.39	123.30	65.29	7) Wholesale & retail trade	98.88	43.37	9.54	203.80	72.17
Overall	113.14	42.94	22.36	333.30	43.87	Overall	149.31	68.71	29.31	366.90	38.17

Postcrisis period						**Vertical comparison - change in mean ΔCoVaR over different sample periods**			
*Note: Sectors are ordered descending on Mean ΔCoVaR and numbered according to the crisis period ranking.	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)	*Note: Sectors are alphabetically ordered.	Δ precrisis to crisis in %	Δcrisis to postcrisis in %	Δ precrisis to postcrisis in %
1) Admin. & support service	147.49	51.24	24.01	193.20	77.64	Administrative & support service	**+28.60**	**-16.44**	**+7.46**
5)Transportation & storage	147.39	36.91	26.57	173.50	121.30	Construction	**+50.85**	**-17.64**	**+24.24**
2) Financial & Insurance	144.71	80.23	21.55	335.30	67.88	Financial & Insurance	**+25.74**	**-17.72**	**+3.46**
3) Construction	144.58	46.58	31.93	200.60	79.29	Information & commun.	**+29.39**	**-10.62**	**+15.65**
4) Manufacturing	138.06	48.74	18.13	252.20	66.54	Manufacturing	**+29.44**	**-8.97**	**+17.83**
6) Professional, scientific & technical	124.46	33.65	18.37	163.60	59.36	Professional, scientific & technical	**+46.87**	**-8.21**	**+34.81**
7) Information & commun.	120.88	42.57	14.80	180.60	64.83	Transportation & storage	**+42.18**	**+1.49**	**+44.30**
8) Wholesale & retail trade	98.09	31.54	12.51	164.40	69.04	Wholesale & retail trade	**+3.57**	**-0.80**	**+2.74**
Overall	133.21	51.08	27.28	335.30	59.36	Overall	**+31.97**	**-10.78**	**+17.74**

A8 ΔCoVaR results for different globalization status

Table A8.1: Summary statistics for ΔCoVaR for different globalization status: precrisis, crisis, postcrisis and horizontal comparison.

PART A

	Precrisis period					**Crisis period**				
	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)
High Trade Intensity	105.14	37.57	41.33	219.38	49.68	123.38	68.33	69.58	337.00	38.17
Low Trade Intensity	118.22	44.84	53.91	333.31	43.87	159.39	65.99	74.03	366.88	66.12

	Postcrisis period					**Vertical comparison - change in mean ΔCoVaR over different sample periods**		
	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)	Δ precrisis to crisis in %	Δ crisis to postcrisis in %	Δ precrisis to postcrisis in %
High Trade Intensity	115.26	48.16	55.33	252.25	66.84	**+17.35**	**-6.58**	**+9.63**
Low Trade Intensity	138.94	51.15	65.37	335.29	59.36	**+34.82**	**-12.83**	**+17.53**

Table A8.1: Summary statistics for ΔCoVaR for different globalization statuses

PART B

	Precrisis period					Crisis period				
	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)
Foreign Subsidiaries	119.13	47.99	55.51	575.48	11.82	159.97	72.76	79.04	646.14	12.97
No foreign Subsidiaries	77.40	29.45	32.55	187.12	5.68	90.27	5.16	23.46	220.14	21.40

	Postcrisis period					Vertical comparison - change in mean ΔCoVaR over different sample periods		
	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)	Δ precrisis to crisis in %	Δ crisis to postcrisis in %	Δ precrisis to postcrisis in %
Foreign Subsidiaries	141.37	55.46	68.81	638.51	18.40	**+34.28**	**-11.63**	**+18.67**
No Foreign Subsidiaries	76.98	7.63	19.36	178.29	27.40	**+16.63**	**-14.72**	**-0.54**

	Precrisis period					Crisis period				
	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)
Foreign Control	155.72	93.61	94.76	575.48	44.17	193.06	89.45	92.98	646.14	49.52
No Foreign Control	110.60	36.50	45.02	461.28	5.68	145.39	69.98	75.43	525.08	12.98

	Postcrisis period					Vertical comparison - change in mean ΔCoVaR over different sample periods		
	Mean ΔCoVaR (1)	St.dev. ΔCoVaR means (2)	St.dev. ΔCoVaR (3)	Max ΔCoVaR (4)	Min ΔCoVaR (5)	Δ precrisis to crisis in %	Δ crisis to postcrisis in %	Δ precrisis to postcrisis in %
Foreign Control.	177.86	82.24	96.34	638.51	41.64	**+23.98**	**-7.87**	**+14.22**
No foreign Control	127.80	48.89	60.09	481.92	18.40	**+31.46**	**-12.10**	**+15.55**

A9 Double dip recession and robustness

The (horizontal) comparison over time from Table 2.4 (see section 2.5.1. in chapter 2 of thesis) indicates that the postcrisis Dutch economy is still systemically riskier compared to the precrisis period. This outcome is not only due to the aftermath of the financial crisis but also to the double dip recession from 2011-2012. In order to have a better view on the events during the post-financial crisis period (from 07/1/2009 to 12/31/2015, sample size = 1697) we added an additional analysis focusing on the double dip recession from 10/1/2011 to 12/31/2012. More specifically, we divided the post-financial crisis period (from 07/1/2009 to 12/31/2015) into three sub-periods, namely the pre-double dip period (from 07/1/2009 to 9/30/2011, sample size = 588), the double dip recession (from 10/1/2011 to 12/31/2012, sample size = 326) and the post-double dip (from 1/1/2013 to 12/31/2015, sample size = 783). We estimated the ΔCoVaR for each sector and the overall economy and computed the changes of the ΔCoVaR between each of the consecutive sub-periods. The results which are presented in Table A9.1 show how the double dip recession slowed down the recovery from the financial crisis.

Table A9.1 ΔCoVaR results per sector during the post-financial crisis period: comparison over time with focus on the double dip recession.

	Horizontal comparison - change in mean ΔCoVaR over different sub-samples during the post-financial crisis period		
*Note: Sectors are alphabetically ordered.	Δ pre-double dip to double dip in %	Δ double dip to post-double dip in %	Δ pre-double dip to post-double dip in %
Administrative & support service activities	+8.27	-18.88	-12.17
Construction	+20.68	-29.02	-14.34
Financial & insurance activities	+8.81	-19.30	-12.19
Information & communication	+5.50	-4.72	+0.52
Manufacturing	+3.90	-6.20	-2.54
Professional, scientific & technical activities	+6.62	-16.76	-11.24
Transportation & storage	+7.07	-22.70	-17.23
Wholesale & retail trade; repair of motor vehicles & motorcycles	+8.23	-12.05	-4.81
Overall	+7.75	-14.15	-7.49

During the post-financial crisis period, the double dip recession leads to increasing systemic risk contributions of every sector and the overall economy, postponing the recovery from the financial crisis. The Construction sector, with a systemic risk contribution increase of, on average, almost +21%, suffered the most from the double dip recession. After the double dip recession, all sectors manage to initiate a recovery from respectively the financial crisis and double dip recession.

In order to verify the initial results of the ΔCoVaR changes from the financial crisis period to the post-financial crisis period, we conducted a robustness analysis. First, we computed the ΔCoVaR changes from the financial crisis period to respectively each of the three sub-periods per sector during the post-financial crisis period. Second, we calculate the weighted average of the changes in ΔCoVaR from the financial crisis period to the three sub-periods per sector. Since the sample of each sub-period has a different size within the post-financial crisis period, we compute a weighted average, where we weigh each ΔCoVaR change according to the sub-sample size. The results are presented in Table A9.2. Third, we compare the obtained average ΔCoVaR change per sector with the initial results from the financial crisis period compared to the post-financial crisis period (see Table 2.4 column 2). By applying a paired two-tailed t-test we verify whether or not there is a significant difference between both results. Since the t-test is nonsignificant (p-value > 0.10) we can state that our initial results of the changes of the ΔCoVaR between the financial crisis and the post-financial crisis still hold and are robust.

Table A9.2 Robustness analysis on the post-financial crisis period

	Horizontal comparison - change in mean ΔCoVaR from financial crisis to each sub-period during the post-financial crisis period			
*Note: Sectors are alphabetically ordered.	Δ crisis to pre-double dip in % (sample = 588)	Δ crisis to double dip in % (sample = 326)	Δ crisis to post-double dip in % (sample = 783)	**Weighted average**
Administrative & support service activities	-12,93%	-5,73%	-23,53%	**-16,44%**
Construction	-15,40%	2,09%	-27,53%	**-17,66%**
Financial & insurance activities	-14,35%	-6,81%	-24,79%	**-17,72%**
Information & communication	-11,76%	-6,91%	-11,30%	**-10,63%**
Manufacturing	-8,59%	-5,02%	-10,91%	**-8,98%**
Professional, scientific & technical activities	-4,47%	1,86%	-15,21%	**-8,21%**
Transportation & storage	8,66%	16,35%	-10,07%	**1,51%**
Wholesale & retail trade; repair of motor vehicles & motorcycles	-0,16%	8,05%	-4,97%	**-0,81%**
Overall	-9,91%	-2,92%	-16,65%	**-11,68%**

A10 Time-series plots ΔCoVaR and VaR measures*

Figure A10.1: Administrative & support service activities

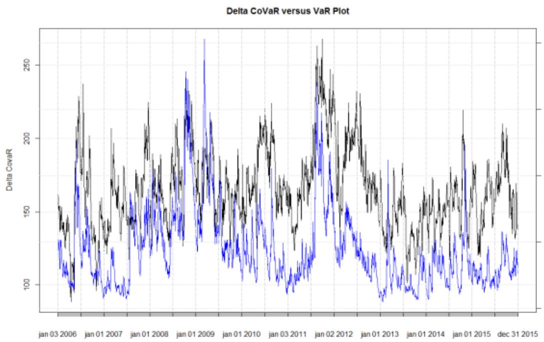


Figure A10.2: Construction

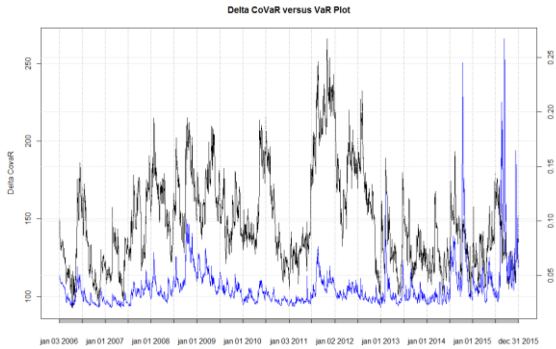


Figure A10.3: Financial & insurance activities

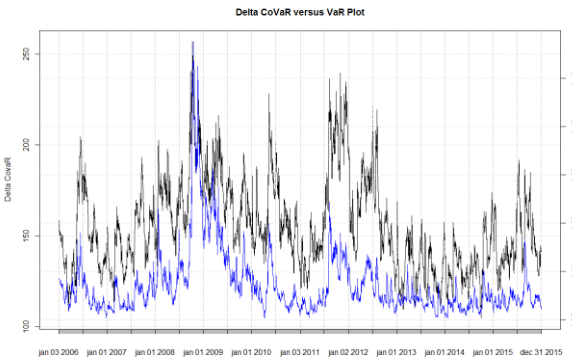
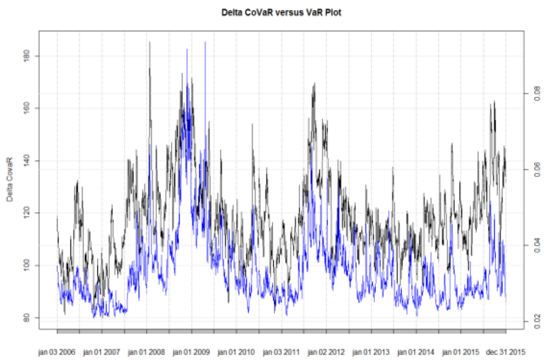


Figure A10.4: Information & communication



*ΔCoVaR series (black) are plotted on the left vertical axis and the VaR series (blue) on the right vertical axis

A10 Time-series plots ΔCoVaR and VaR measures*

Figure A10.5: Manufacturing

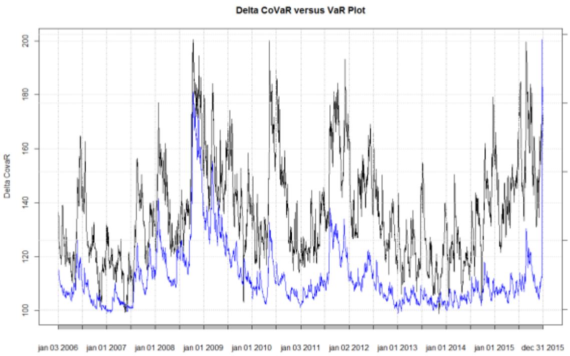


Figure A10.6: Professional, scientific & technical activities

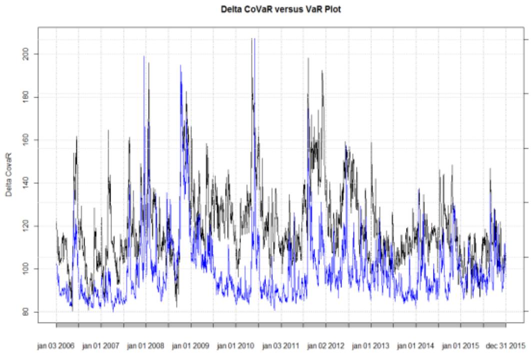


Figure A10.7: Transportation & storage

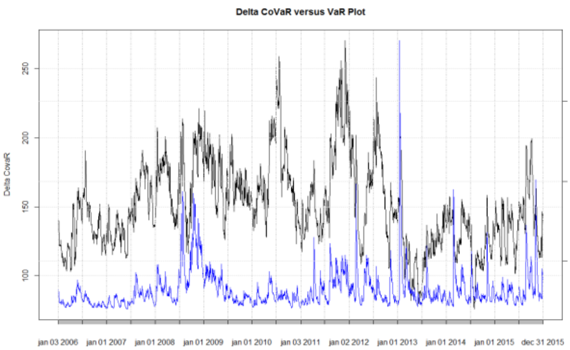
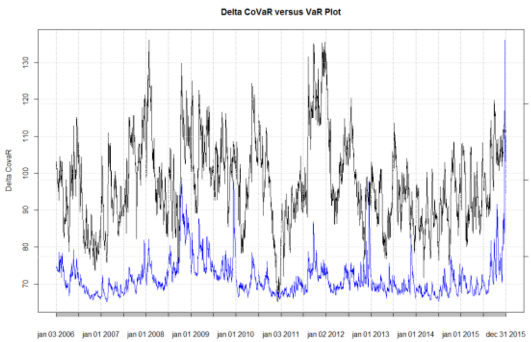


Figure A10.8: Wholesale & retail trade; repair of motor vehicles & motorcycles



*ΔCoVaR series (black) are plotted on the left vertical axis and the VaR series (blue) on the right vertical axis

A11 Correlation matrix

Table A11: Correlation matrix

	$\Delta CoVaR$	D_{Year}	D_{Sector}	$Beta$	$Log(Size)$	$Log(Leverage)$	$Log(VaR)$	$Trade\ Intensity$	$D_{Foreign\_subsidiary}$	$D_{Foreign\ control}$	$Log(Leverage) \times D_{-r_t^S}$
$\Delta CoVaR$	1.0000										
D_{Year}	-0.0141	1.0000									
D_{Sector}	-0.2900*	0.0000	1.0000								
$Beta$	0.5238*	0.1087*	-0.2215*	1.0000							
$Log(Size)$	0.5581*	0.0480*	-0.1287*	0.2701*	1.0000						
$Log(Leverage)$	0.1480*	-0.0779*	-0.0164	0.0669*	0.2701*	1.0000					
$Log(VaR)$	0.3534*	-0.0877*	-0.0711*	0.3297*	-0.2185*	0.0411*	1.0000				
$Trade\ Intensity$	-0.1645*	0.0239	0.2016*	-0.1523*	-0.2401*	-0.0496*	-0.0089	1.0000			
$D_{Foreign\_subsidiary}$	0.2448*	-0.0014	-0.3228*	0.2197*	0.1646*	-0.0608*	0.1599*	0.0224	1.0000		
$D_{Foreign\ control}$	0.0894*	-0.0248	0.1469*	0.0449*	0.1869*	-0.1122*	0.0856*	-0.0825*	0.0420	1.0000	
$Log(Leverage) \times D_{-r_t^S}$	0.0778*	-0.0221	-0.0046	-0.0389	0.1613*	0.5154*	-0.0483*	-0.0308	-0.0299	-0.0505*	1.0000

Note: *Correlation is significant at the 0.05 level

Appendix Chapter 3

B1 Sample specifics: Four moments

Table B1: Four moments of the entire sample

	Belgium				
	n	Mean (μ)	Standard deviation (σ)	Skewness (σ^3)	Kurtosis (σ^4)
Stock returns	10,324	-0.00237	0.112673	-0.23492	5.745888
$\Delta IMER$	5303	-0.00036	0.01641	0.35346	2.40307
$\Delta EXER$	4780	0.00080	0.01647	0.51183	2.729534
	Netherlands				
	n	Mean (μ)	Standard deviation (σ)	Skewness (σ^3)	Kurtosis (σ^4)
Stock returns	9685	-0.00335	0.109748	-0.59176	4.81147
$\Delta IMER$	6227	-0.00036	-0.01526	-0.01526	1.11068
$\Delta EXER$	5260	0.00007	0.01623	0.25423	2.08999

B2 Sample composition

Table B2: Sample composition 2006-2015

SECTOR (NACE-code rev.2, 2digit)	Belgium				Netherlands			
	Importers	Exporters	2-Way	Total	Importers	Exporters	2-Way	Total
Manufacturing (10-33)	3	0	35	**38**	0	0	24	**24**
Information & communication (58-63)	2	0	7	**9**	3	0	11	**14**
Financial & insurance activ. (64-66)	3	1	4	**8**	5	0	6	**11**
Real estate activ. (68)	9	0	1	**10**	0	0	0	**0**
Professional, scientific & technical activ. (69-75)	3	0	4	**7**	2	0	7	**9**
Wholesale & retail trade; repair of motor vehicles & motorcycles (45-46)	0	1	7	**8**	0	0	9	**9**
Construction (41-43)	0	0	0	**0**	1	0	7	**8**
Administrative & support service activ. (77-82)	0	0	0	**0**	1	0	3	**4**
Transportation & storage (49-53)	0	0	4	**4**	1	0	2	**3**
Mining and quarrying (05-09)	0	0	2	**2**	0	0	0	**0**
Electricity, gas, steam and air conditioning (35)	0	0	2	**2**	0	0	0	**0**
Grand Total	**20**	**2**	**66**	**88**	**13**	**0**	**69**	**82**
	23%	2%	75%	100%	16%	0%	84%	100%

B3 Top 5 Non-Euro Trading partners

Table B3: Top 5 Non-Euro trading partners Export and Import sample 2006-2015 for Belgium and the Netherlands (in €1B)

Export			
Belgium		Netherlands	
1. United Kingdom	7.5	1. United States	29.7
2. United States	5.2	2. Taiwan	13.8
3. China	2.5	3. South Korea	13.6
4. Switzerland	1.5	4. United Kingdom	13.2
5. Republic of Korea	1.3	5. China	8.5
Import			
Belgium		Netherlands	
1. Norway	27.5	1. Russia	27.3
2. United Kingdom	13.9	2. United Kingdom	21.1
3. Bulgaria	2.7	3. Saudi-Arabia	20.9
4. Czech Republic	2.5	4. Norway	14.6
5. United States	2.4	5. United States	14.2

B4 Trade in goods

Table B4: Dutch and Belgian trade in goods sample 2006-2015 (in €1M)

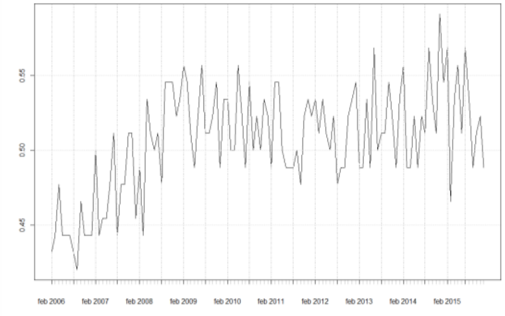
SECTOR (NACE-code rev.2, 2digit)	Netherlands				Belgium			
	IMPORT		**EXPORT**		**IMPORT**		**EXPORT**	
	EURO	Non-EURO	EURO	Non-EURO	EURO	Non-EURO	EURO	Non-EURO
Manufacturing (10-33)	57,902	152,207	109,125	119,831	19,343	21,341	24,806	27,078
Electricity, gas, steam and air conditioning (35)	-	-	-	-	40,118	39,705	44,861	3335
Wholesale & retail trade (45-46)	8266	4733	1945	850	24,064	3793	2813	316
Transport & storage (49-53)	279	26,013	359	14732	71	13	0	16
Information & communication (58-63)	2135	3342	4412	2279	1859	417	387	100
Construction (41-43)	893	817	387	1,258	-	-	-	-
Professional scientific & technical activ. (69-75)	30	104	30	432	76	78	209	191
Mining and quarrying (05-09)	-	-	-	-	210	31	782	97
Real estate activ. (68)	-	-	-	-	50	9	73	0,6
Financial & insurance activ. (64-66)	39	17	65	1	1.4	0.2	0	0.1
Administration & support service (77-82)	0	3	2.5	1.5	-	-	-	-
Total	69,543	187,236	116,326	139,385	85,793	65,388	73,931	31,135
SHARE	**27%**	**73%**	**45%**	**55%**	**57%**	**43%**	**70%**	**30%**

B5 GDP Growth rates

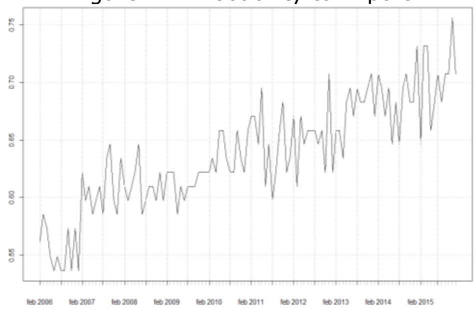
Table B5: GDP growth rate (%) compared to previous quarter, seasonally adjusted

Period	Belgium	Netherlands	Euro area	Period	Belgium	Netherlands	Euro area
2006 Q1	0,6	0.8	0.9	2011 Q1	0,6	0.7	0.8
2006 Q2	0,3	1.5	1.0	2011 Q2	0,3	**-0.1**	0.0
2006 Q3	0,8	0.5	0.6	2011 Q3	0,2	0.0	0.0
2006 Q4	1,1	0.8	1.1	2011 Q4	0,1	**-0.7**	**-0.4**
2007 Q1	1,3	1.1	0.8	2012 Q1	0,2	**-0.2**	**-0.2**
2007 Q2	0,4	0.5	0.6	2012 Q2	**-0,2**	0.1	**-0.3**
2007 Q3	0,8	1.2	0.5	2012 Q3	0.0	**-0.4**	**-0.1**
2007 Q4	0,5	1.5	0.5	2012 Q4	**-0,1**	**-0.8**	**-0.4**
2008 Q1	0,6	0.0	0.5	2013 Q1	**-0,3**	0.4	**-0.3**
2008 Q2	0,2	0.4	**-0.3**	2013 Q2	0,6	**-0.2**	0.4
2008 Q3	**-0,5**	**-0.3**	**-0.6**	2013 Q3	0,4	0.6	0.3
2008 Q4	**-2,1**	**-0.8**	**-1.7**	2013 Q4	0,3	0.6	0.2
2009 Q1	**-1,2**	**-3.2**	**-3.0**	2014 Q1	0,2	**-0.2**	0.3
2009 Q2	**-0,1**	**-0.2**	**-0.2**	2014 Q2	0,2	0.5	0.2
2009 Q3	1,1	0.3	0.3	2014 Q3	0,5	0.4	0.4
2009 Q4	0,8	0.5	0.5	2014 Q4	0,5	1.1	0.4
2010 Q1	0,5	**-0.1**	0.5	2015 Q1	0,4	0.6	0.8
2010 Q2	1.0	0.6	1.0	2015 Q2	0,6	0.1	0.4
2010 Q3	0,5	0.4	0.4	2015 Q3	0,2	0.2	0.3
2010 Q4	0,4	1.2	0.6	2015 Q4	0,5	0.3	0.5

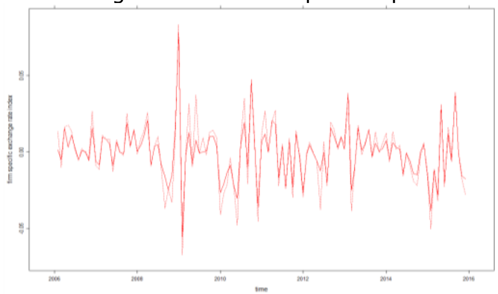
B6 Belgian listed firms
Figure B6: Probability to import



B7 Dutch listed firms
Figure B7: Probability to import

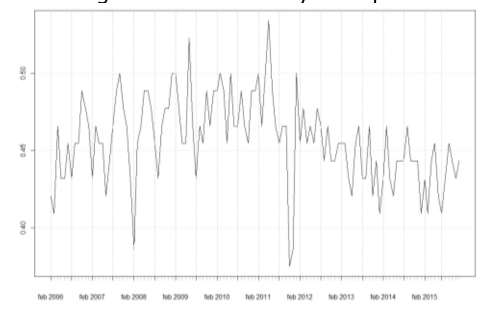


B8 Firm-specific exchange rate index for listed trading importing Belgian and Dutch firms*
Figure B8: Median quantile plot

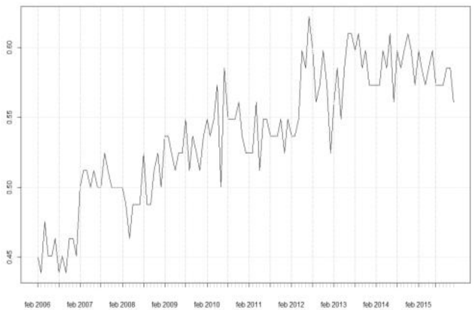


*red= importing firm; dotted line =Belgium, solid line= Netherlands

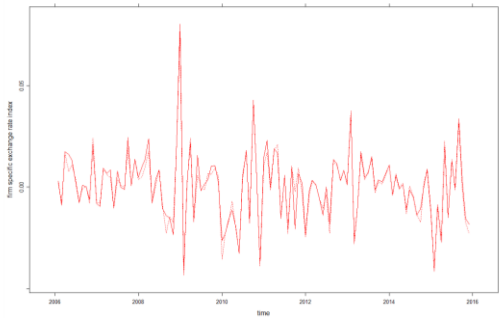
B9 Belgian listed firms
Figure B9: Probability to export



B10 Dutch listed firms
Figure B10: Probability to export



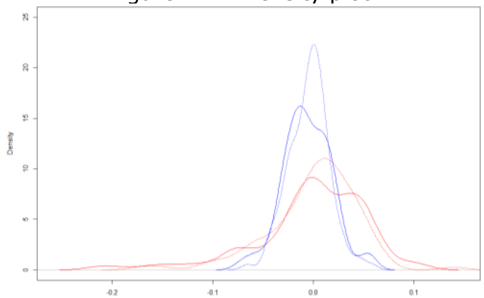
B11 Firm-specific exchange rate for listed trading exporting Belgian and Dutch firms*
Figure B11: Median quantile plot



*red= importing firm; dotted line =Belgium, solid line= Netherlands

B12 Stock returns for Belgian and Dutch listed importing firms during trading and non-trading periods*

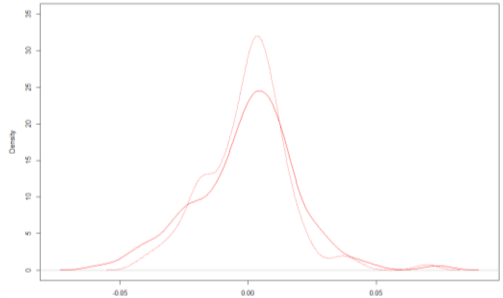
Figure B12: Density plot



*red= importing firm; blue= non-importing firm; dotted line =Belgium, solid line= Netherlands

B13 Firm-specific exchange rate index for Belgian and Dutch listed trading importing firms*

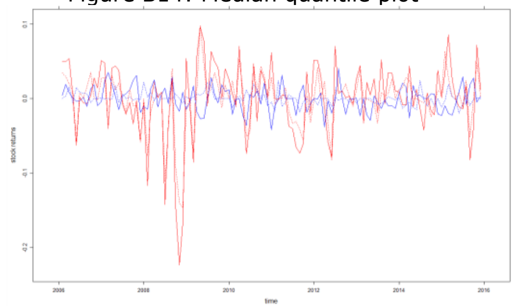
Figure B13: Density plot



*red= importing firm; dotted line =Belgium, solid line= Netherlands

B14 Stock returns for Belgian and Dutch listed importing firms during trading and non-trading periods*

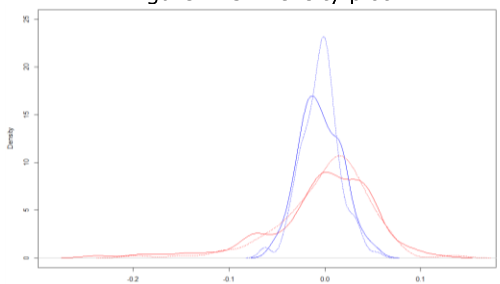
Figure B14: Median quantile plot



*red= importing firm; blue= non-importing firm; dotted line =Belgium, solid line= Netherlands

B15 Stock returns for Belgian and Dutch listed exporting firms during trading and non-trading periods *

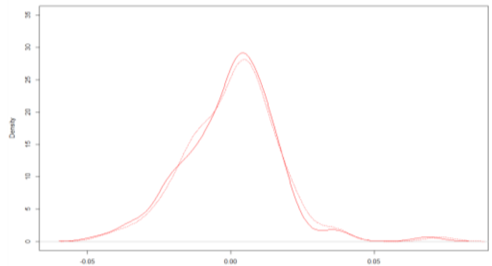
Figure B15: Density plot



*red= exporting firm; blue= non-exporting firm; dotted line =Belgium, solid line= Netherlands

B16 Firm-specific exchange rate index for Belgian and Dutch listed trading exporting firms*

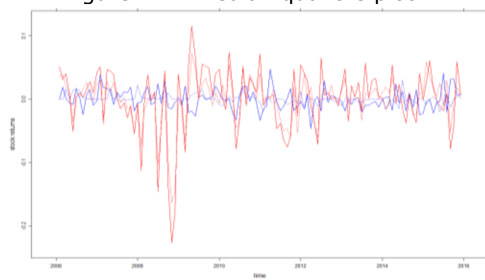
Figure B16: Density plot



*red= exporting firm; dotted line =Belgium, solid line= Netherlands

B17 Stock returns for Belgian and Dutch listed exporting firms during trading and non-trading periods*

Figure B17: Median quantile plot



*red= exporting firm; blue= non-exporting firm; dotted line =Belgium, solid line= Netherlands

B18 Results Kolmogorov-Smirnov and Anderson Darling test of stock returns for Belgian and Dutch importing and exporting firms

Table B18.1: Kolmogorov-Smirnov test statistic (p-value between brackets)

		Generalized Lambda	Normal inverse Gaussian	Johnson SU	Skewed Student-t	Student-t	Normal
Stock return	Belgium import	0.06916	**0.03648**	0.31660	**0.04158**	0.05697	0.11870
		(0.6197)	(0.9974)	(8.625e-1)	(0.9863)	(0.8346)	(0.0699)
	Belgium Export	0.19069	**0.03736**	0.33497	**0.03935**	0.05389	0.10691
		(0.0003)	(0.9963)	(5.054e-12)	(0.9928)	(0.8800)	(0.1317)
	Netherlands import	0.43087	**0.07527**	0.07344*	0.07645	**0.07122**	0.12592
		(<2.2e-16)	(0.5103)	(0.5422)	(0.5464)	(0.5821)	(0.0459)
	Netherlands Export	0.38056	**0.05552**	0.07180**	**0.05540**	0.08298	0.13292
		(2.109e-15)	(0.8568)	(0.5716)	(0.8585)	(0.3856)	(0.0298)

*Johnson SL with quantile fit; **Johnson SU with quantile fit

Table B18.2: Anderson-Darling test statistic (p-value between brackets)

		Generalized Lambda	Normal inverse Gaussian	Johnson SU	Skewed Student-t	Student-t	Normal
Stock return	Belgium import	Inf	**0.15258**	26.91800	**0.14533**	0.82807	1.84330
		(5.042e-06)	(0.9984)	(5.042e-06)	(0.9989)	(0.4610)	(0.1123)
	Belgium Export	Inf	**0.12685**	33.15300	**0.12716**	0.76274	1.75080
		(5.042e-06)	(0.9997)	(5.042e-06)	(0.9997)	(0.5084)	(0.1266)
	Netherlands import	60.33600	**0.44214**	0.71464*	**0.43942**	1.16240	2.69260
		(5.042e-06)	(0.8058)	(0.5464)	(0.8086)	(0.2822)	(0.0394)
	Netherlands Export	39.67400	**0.39727**	0.46990	**0.40352**	1.27110	2.93710
		(5.042e-06)	(0.8512)	(0.7773)	(0.8450)	(0.2419)	(0.0295)

*Johnson SL with quantile fit; **Johnson SU with quantile fit

B19 Results Kolmogorov-Smirnov and Anderson Darling test of firm-specific exchange rates for Belgian and Dutch importing and exporting firms

Table B19.1: Kolmogorov-Smirnov test statistic (p-value between brackets)

		Generalized Lambda	Normal inverse Gaussian	Johnson SU	Skewed Student-t	Student-t	Normal
Firm-specific exchange rate	Belgium import	0.10828	**0.06421**	0.09933	**0.07286**	0.07464	0.09229
		(0.1227)	(0.7105)	(0.1909)	(0.5527)	(0.5212)	(0.2629)
	Belgium Export	0.07423	**0.04896**	0.08812	**0.05161**	0.05479	0.27900
		(0.5284)	(0.9379)	(0.3138)	(0.9091)	(0.8673)	(1.784e-08)
	Netherlands import	0.09565	**0.05422**	0.09421	**0.06186**	0.07568	0.24969
		(0.2263)	(0.8754)	(0.2414)	(0.7526)	(0.5032)	(7.194e-07)
	Netherlands Export	0.08420	**0.04442**	0.06496	**0.04765**	0.06291	0.30837
		(0.3677)	(0.9730)	(0.6968)	(0.9499)	(0.7339)	(2.966e-10)

Table A19.2: Anderson-Darling test statistic (p-value between brackets)

		Generalized Lambda	Normal inverse Gaussian	Johnson SU	Skewed Student-t	Student-t	Normal
Firm-specific exchange rate	Belgium import	1.04130	**0.51607**	2.08470	**0.47906**	0.80043	1.21600
		(0.3361)	(0.7301)	(0.08266)	(0.7679)	(0.4805)	(0.2615)
	Belgium Export	0.56704	**0.32924**	1.9847	**0.30390**	0.35600	18.541
		(0.6793)	(0.9145)	(0.0937)	(0.9351)	(0.8908)	(5.042e-06)
	Netherlands import	0.78376	**0.32099**	0.77535	**0.33323**	0.65101	17.99000
		(0.4926)	(0.9214)	(0.4989)	(0.9111)	(0.6008)	(5.042e-06)
	Netherlands Export	0.83952	**0.38050**	1.11890	**0.32838**	0.61138	22.86700
		(0.4531)	(0.8676)	(0.3004)	(0.9152)	(0.6369)	(5.042e-06)

B20 Results Cramér-von-Mises goodness-of-fit test

The Cramér-von-Mises goodness-of-fit test was performed on every C_t. However, for each point in time, the goodness-of-fit test resulted in identical parameters and test statistics; only the p-values differed slightly. Therefore, for editorial reasons, the table below only shows the average p-value, since the difference with the true p-value for each observation in time is negligible.

Table B20: Cramér-von-Mises goodness-of-fit test results

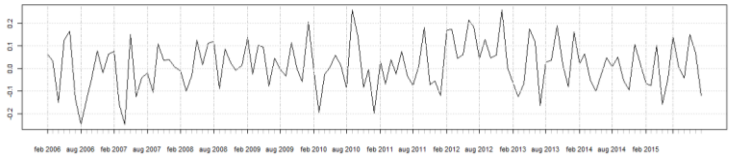
		Parameter for hypothesized copula (θ)	Test statistic (S_n)	Average p-value
Belgium	Import (Skewed Student-t - NIG)	0.20497	0.03458	0.32008
	Export (NIG - Skewed Student-t)	-0.01656	0.02185	0.95920
Netherlands	Import (Student t-NIG)	0.08705	0.04080	0.21849
	Export (NIG - Skewed Student-t)	0.06874	0.03376	0.43405

B21 Sample version of Kendall’s tau between stock returns and the firm-specific exchange rate $\Delta IMER_{i,t}$ for Belgium (only trading firms)

Figure B20: Kendall’s tau Belgium (importing firms)

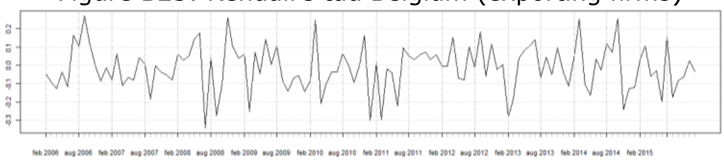
B22 Sample version of Kendall’s tau between stock returns and the firm-specific exchange rate $\Delta IMER_{i,t}$ for the Netherlands (only trading firms)

Figure B22: Kendall’s tau the Netherlands (importing firms)



B23 Sample version of Kendall’s tau between stock returns and the firm-specific exchange rate $\Delta EXER_{i,t}$ for Belgium (only trading firms)

Figure B23: Kendall’s tau Belgium (exporting firms)



B24 Sample version of Kendall’s tau between stock returns and the firm-specific exchange rate $\Delta EXER_{i,t}$ for the Netherlands (only trading firms)

Figure B24: Kendall’s tau the Netherlands (exporting firms)

B25 Copula theory Part 1

The remainder of this Section is primarily based on the research of Härdle and Okhrin (2010) and Manner (2007) and presents an overview of the copula theory and the main copula classes. A more detailed discussion with proofs and mathematical treatment can be found in e.g., Joe (1997) and Nelsen (2006). Also proofs for most of the results mentioned can be found there.

1. Preliminaries

Before introducing the copula functions, some properties need to be presented.

Definition 1: Let $\boldsymbol{S_1}$ and $\boldsymbol{S_2}$ be nonempty subsets of $\overline{\mathbb{R}}$, and let H be a 2–place real function such that DomH = $S_1 \times S_2$. Let $B = [x_1, x_2] \times [y_1, y_2]$ be a rectangle all of whose vertices are in DomH. Then the H-volume of B is given by:

$$V_H(B) = H(x_2, y_2) - H(x_2, y_1) - H(x_1, y_2) + H(x_1, y_1) \tag{26}$$

When H is a distribution function, the H-volume represents the probability of an event occurring in the region specified. In the 2-dimensional case, this region is a rectangle.

Definition 2: A 2-place real function H is 2-increasing if $V_H(B) \geq 0$ for all rectangles B whose vertices lie in DomH. Suppose S_1 has a least element a_1 and that S_2 has a least element a_2. We say that function H from $S_1 \times S_2$ into $\mathbb{R}$ is grounded if $H(x, a_2) = 0 = H(a_1, y)$ for all (x, y) in $S_1 \times S_2$. A 2-increasing function H is nondecreasing in each argument. The one dimensional marginal are then given by $F(x) = H(x, b_2)$ and $G(y) = H(b_1, y)$.

The definition of a copula becomes:

Definition 3: A 2-dimensional copula is a function C from $\mathbf{I}^2$ to $\mathbf{I}$ such that:

1. For every u, v in $\mathbf{I}$ C is grounded and 2-increasing.
2. $C(u, 1) = u$ and $C(1, v) = v$; (margins)

More specifically, a copula is a function with $\mathbf{I}^2$ as its domain, $\mathbf{I}$ as its range, is increasing in each element and has marginals. The main result about copula functions is the theorem of Sklar (1959), which shows why copulas are so useful for modeling multivariate distribution function.

Theorem 1: Let H be a joint distribution function with margins F and G. Then there exists a copula C such that for all x, y in $\overline{\mathbb{R}}$ (Sklar, 1959):

$$H(x,y) = C(F(x), G(y)), \quad \forall (x,y) \in \overline{\mathbb{R}} \times \overline{\mathbb{R}} \tag{27}$$

If F and G are continuous then C is unique; otherwise C is uniquely determined on $\mathrm{Ran}F \times \mathrm{Ran}G$. Conversely, if C is a copula and F and G are univariate distribution functions then the function H defined by (27) is a joined distribution function with margins F and G.

The joint distribution can be represented separately by the marginal distribution functions and the copula, which completely describes the dependence between the i.i.d. random variables *X* and *Y*. The converse turns out to be very useful in the construction of multivariate distribution functions, since we can take now any pair of marginal distributions and any copula to construct a bivariate distribution. This allows for an easy construction of a large number of multivariate distribution functions. A useful corollary to Sklar's theorem, allows us to represent the copula by the joint distribution function and the inverses of the marginals. However, if a margin is not strictly increasing, then it does not possess an inverse in the usual sense. To ensure the existence of the inverses a new concept of the inverse of a function is required, the latter is called the quasi-inverse.

Definition 4: Let F be a distribution function. Then a quasi-inverse of F is any function $F^{(-1)}$ with domain $\mathbf{I}$ such that

1. if r is in $\mathrm{Ran}F$, then $F^{(-1)}(r)$ is any number x in $\overline{\mathbb{R}}$ such that $F(x) = r$, i.e., for all r in $\mathrm{Ran}F$,
   $F\left(F^{(-1)}(r)\right) = r;$
2. if r is not in $\mathrm{Ran}F$, then
   $F^{(-1)}(r) = inf\{x|F(x) \geq r\} = sup\{x|F(x) \leq r\}.$
   If F is strictly increasing, then it has but a single quasi-inverse, which is of course the ordinary inverse, for which we use the customary notation F^{-1}.

Corollary 1: Let H be any bivariate distribution function with continuous margins F and G. Let $F^{(-1)}$ and $G^{(-1)}$ denote the (quasi-) inverses of the marginal distributions. Then there exists a unique copula C from $\mathbf{I}^2$ to $\mathbf{I}$ such that:

$$C(u,v) = H\left(F^{(-1)}(u), G^{(-1)}(v)\right), \quad \forall(u,v) \in \mathbf{I}^2 \tag{28}$$

Copulas have an upper and lower bound. More specifically:

Theorem 2: Frèchet-Hoeffding bounds inequality. For every copula C and every (u,v) in $\mathbf{I}^2$,

$$W(u,v) = max(u+v-1,0) \leq C(u,v) \leq min(u,v) = M(u,v),$$

$W(u,v)$ is known as the Frèchet-Hoeffding lower bound $M(u,v)$ as the Frèchet-Hoeffding upper bound. As such one can conclude that an arbitrary copula C reflects dependence which lies between the perfect negative and positive one. The upper bound corresponds to perfect positive dependence between two variables, the lower bound to perfect negative dependence. Additionally, consider the product copula $\prod(u,v) = uv$ which corresponds to independence. In the bivariate case these three important functions are copulas. For $n \geq 3$, however, the function W is not a copula. Finally, consider the function:

$$\hat{C}(u,v) = u + v - 1 + C(1-u, 1-v), \tag{29}$$

This is known as the survival or rotated copula.

Copulas are mostly used to model dependency. Traditionally, dependence between two random variables is measured by the linear correlation coefficient. However, when the dependence is not described by an elliptical distribution, using linear correlation can be quite misleading. As such, it might be more reasonable to use copula based measures of dependence. One of these more robust copula based measures is Kendall's tau. This measure of overall dependence relies on the concept of concordance. Let (x_i, y_i) and (x_j, y_j) denote two observations from a vector of (X, Y) of continuous random variables. We say that (x_i, y_i) and (x_j, y_j) are concordant if $(x_i - x_j)(y_i - y_j) > 0$. Similarly, we say that (x_i, y_i) and (x_j, y_j) are discordant if $(x_i - x_j)(y_i - y_j) < 0$. A pair of random variables are concordant if "large" values of one tend to be associated with "large" values of the other, and "small" values of one with "small" values of the other. The sample version of the Kendall's tau is defined as the fraction of concordant pairs of observations in the sample minus the fraction of discordant pairs of observations. The population version of Kendall's tau is defined as the difference between the probability of concordance and the probability of discordance.

$$\tau = \tau_{X,Y} = P[(X_1 - X_2)(Y_1 - Y_2) > 0] - P[(X_1 - X_2)(Y_1 - Y_2) < 0] \tag{30}$$

Kendall's tau[125] may be represented as a function of the expected value of a copula as follows.

$$\tau_C = 4E\big(C(U,V)\big) - 1 \tag{31}$$

Another frequently encountered and important dependence concept, which is relevant when modeling extreme events, is tail dependence. Tail dependence describes the non-zero probability of extremely large (or small) values of one random variable appearing together with extremely large (or small) values of the other. The concept of bivariate tail dependence measures the amount of dependence between the variables in the upper-quadrant tail or lower-quadrant tail of a bivariate distribution.

Definition 5: Let X and Y be continuous random variables with distribution functions F and G, respectively. The upper tail dependence parameter λ_U is the limit (if it exists) of the conditional probability that Y is greater than the $100u$-th percentile of G given that X is greater than the $100u$-th percentile of F as u approaches 1, i.e.,

$$\lambda_U = \lim_{u \to 1^-} P\big[Y > G^{(-1)}(u) \big| X > F^{(-1)}(u)\big] \tag{32}$$

Similarly, the lower tail dependence parameter λ_L is the limit (if it exists) of the conditional probability that Y is less than or equal to the $100u$-th percentile of G given that X is less than or equal to the $100u$-th percentile of F as u approaches 0, i.e.,

$$\lambda_L = \lim_{u \to 0^+} P\big[Y \le G^{(-1)}(u) \big| X \le F^{(-1)}(u)\big] \tag{33}$$

These parameters are nonparametric and depend only on the copula of X and Y:

Theorem 3: Let C be the copula of X and Y, with diagonal section δ_C. If the limits in λ_U and λ_L from definition (10) exist, then:

$$\lambda_U = \lim_{u \to 1^-} \frac{1 - 2u + C(u,u)}{1 - u} \tag{34}$$

[125] In Appendix B21-B24, the Kendall’s tau can be found between the stock returns and foreign exchange rate indices for Belgium and the Netherlands.

and

$$\lambda_L = \lim_{u \to 0^+} \frac{C(u,u)}{u} \tag{35}$$

C is said to have lower (upper) tail dependence if $\lambda_L \neq 0$ ($\lambda_U \neq 0$). The interpretation of the coefficients of tail dependency is that it measures the probability of two random variables both taking extreme values.

2. Elliptical copulas

We present in this Section the commonly used elliptical copulas and their properties. For a more exhaustive list of copula functions and various methods for constructing copulas we refer to Joe (1997) and Nelsen (2006).

Elliptical copulas are able to model multivariate distributions and characterize them by an elliptical distribution even when the marginals are not the same or not from the same family of distributions. The elliptical copulas are easy to sample but lack a closed form expression and their symmetrical property is a major drawback. Both the Gaussian and the (Student-) t copula fall into the class of elliptically symmetric copulas.

The bivariate normal copula with dependence parameter $\rho \in (-1,1)$ is given by:

$$C_{Ga}(u,v;\rho) = \int_{-\infty}^{\phi^{-1}(u)} \int_{-\infty}^{\phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(-\frac{s^2 - 2\rho st + t^2}{2(1-\rho^2)}\right) dsdt \tag{36}$$

The Gaussian copula has zero tail dependence.

The bivariate t copula, which is also easy to sample, is given by:

$$C_T(u,v;\rho,d) = \int_{-\infty}^{t_d^{-1}(u)} \int_{-\infty}^{t_d^{-1}(v)} \frac{1}{2\pi\sqrt{1-\rho^2}} \left(1 + \frac{s^2 - 2\rho st + t^2}{d(1-\rho^2)}\right)^{-(d+2)/2} dsdt \tag{37}$$

with $\rho \in (-1,1)$ corresponding to the dependence parameter and t_d to the univariate t distribution with $d \in (0,\infty)$ degrees of freedom. There is symmetrical dependence and, as such, both lower and upper tail dependence are given by $\tau^L = \tau^U = 2t_{d+1}\left(-\sqrt{d+1}\sqrt{1-\rho}/\sqrt{1+\rho}\right)$.

Appendix Chapter 4

C1 Copula theory Part 2

1. Archimedean copulas: One-parameter families

The class of Archimedean copulas is a large family of copulas with the ability to capture a large number of (asymmetric) dependence structures. Most Archimedean copulas have closed form expressions, more specifically, these copulas often have a generator function satisfying the following conditions:

1) φ is a continuous, strictly decreasing and convex function from $\mathbf{I}$ to $[0,\infty]$
2) $\varphi(0) = \infty$ and,
3) $\varphi(1) = 0$.

Theorem 4: Let φ be a continuous strictly decreasing function from $\mathbf{I}$ to $[0,\infty]$ such that $\varphi(1) = 0$, and let $\varphi^{[-1]}$ be the pseudo- inverse of φ. Let C be the function from $\mathbf{I}^2$ to $\mathbf{I}$ given by:

$$C(u,v) = \varphi^{[-1]}(\varphi(u) + \varphi(v)) \tag{38}$$

Then C is a copula if and only if φ is convex.

Different generators lead to different types of Archimedean copulas. If $\varphi(0) = \infty$, φ is a strict generator and $\varphi^{[-1]} = \varphi^{-1}$ and $C(u,v)$ is said to be a strict Archimedean copula. Finally, Archimedean copulas have specific properties:

Theorem 5: Let C be an Archimedean copula with generator φ, then:

1) C is symmetric; i.e. $C(u,v) = C(v,u)$ for all u,v in $\mathbf{I}$;
2) C is associative, i.e. $C(C(u,v)w) = C\big(u, C(v,w)\big)$ for all u,v,w in $\mathbf{I}$;
3) If $c > 0$ is any constant then $c\varphi$ is also a generator of C.

Another reason why Archimedean copulas are easy to work with, is the fact that the Kendall's tau can be expressed in term of the generation function:

$$\pi_C = 1 + 4\int_0^1 \frac{\varphi(t)}{\varphi'(t)}dt \tag{39}$$

The same can be done for the tail dependencies. These expressions are:

$$\lambda_U = 2 - \lim_{t \to 1^-} \frac{1 - \varphi^{[-1]}\big(2\varphi(t)\big)}{1 - t} \tag{40}$$

and

$$\lambda_L = \lim_{t \to 0^+} \frac{\varphi^{[-1]}\big(2\varphi(t)\big)}{t} \tag{41}$$

1.1. Clayton copula

The Clayton copula with generator function:

$$\varphi_\theta(t) = \tfrac{1}{\theta}\left(t^{-\theta} - 1\right), \qquad \theta \in [-1, \infty) \tag{42}$$

and distribution function:

$$C_\theta(u, v) = \left[max\left(u^{-\theta} + v^{-\theta} - 1, 0\right)\right]^{-1/\theta} \tag{43}$$

For $\theta > 0$ is the Clayton copula strict and has lower tail dependence $\left(\lambda_L = 2^{-1/\theta}\right)$. The Clayton copula cannot have positive dependence ($\lambda_U = 0$)

1.2. Gumbel copula

The Gumbel copula with generator function:

$$\varphi_\theta(t) = (-\ln t)^\theta \qquad \theta \in [1, \infty) \tag{44}$$

and distribution function:

$$C_\theta(u, v) = \exp\left(-\left[(-\ln u)^\theta + (-\ln v)^\theta\right]^{1/\theta}\right) \tag{45}$$

Gumbel copulas are strict and have for $1 \leq \theta \leq \infty$ upper tail dependence $\left(\lambda_U = 2 - 2^{-1/\theta}\right)$ but no lower tail dependence ($\lambda_L = 0$). As such, neither the Clayton, nor the Gumbel copula can capture simultaneously lower and upper tail dependence.

1.3. Frank copula

The Frank copula with generator function:

$$\varphi_\theta(t) = -\ln \frac{e^{-\theta t} - 1}{e^{-\theta} - 1} \quad \theta \in (-\infty, \infty) \backslash \{0\} \tag{46}$$

and distribution function:

$$C_\theta(u, v) = -\frac{1}{\theta} \ln\left(1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{(e^{-\theta} - 1)}\right) \tag{47}$$

Frank copulas are strict and display the property of radial symmetry $\left(C(u, v) = \hat{C}(u, v)\right)$ and do not have any tail dependence ($\lambda_L = \lambda_U = 0$). In fact, it can be shown that the Frank copula is the only Archimedean copula that has radial symmetry.

1.4. Joe copula

The Joe copula with generator function:

$$\varphi_\theta(t) = -\ln\left[1-(1-t)^\theta\right] \quad \theta \in [1,\infty) \tag{48}$$

and distribution function:

$$C_\theta(u,v) = 1-\left[(1-u)^\theta+(1-v)^\theta-(1-u)^\theta(1-v)^\theta\right]^{1/\theta} \tag{49}$$

Similarly to the Gumbel copula, the Joe copula cannot have negative dependence. It allows for stronger upper tail dependence $\left(\lambda_U = 2-2^{-1/\theta}\right)$ and in the positive dependence case, the Joe copula is closer to being the reverse of the Clayton copula. The Joe copula shows independence when $\theta = 1$.

2. Archimedean copulas: Two-parameter families

Two parameter families are used to capture more than one type of dependence. Examples are one parameter for upper tail dependence and one for lower tail dependence.

2.1 Symmetrical Joe-Clayton Copula

After obtaining the marginal distributions for trade and the exchange rates, a copula function is used to estimate the tail dependencies. Tail dependence quantifies the probability that both variables are in their upper or lower tail (Ning, 2010). In general, two sorts of tail dependence are identified, upper and lower.

Let X and Y be continuous random variables with distribution functions F and G, respectively. The upper tail dependence parameter λ_U is the limit (if it exists) of the conditional probability that Y is greater than the $100u$-th percentile of G given that X is greater than the $100u$-th percentile of F as t approaches 1, i.e.,

$$\lambda_U = \lim_{u\to 1^-} P\left[Y > G^{(-1)}(u) \middle| X > F^{(-1)}(u)\right] \tag{50}$$

Similarly, the lower tail dependence parameter λ_L is the limit (if it exists) of the conditional probability that Y is less than or equal to the $100u$-th percentile of G given that X is less than or equal to the $100u$-th percentile of as approaches 0, i.e.,

$$\lambda_L = \lim_{u \to 0^+} P\left[Y \le G^{(-1)}(u) \middle| X \le F^{(-1)}(u)\right] \tag{51}$$

These parameters are nonparametric and depend only on the copula of X and Y: Let C be the copula of X and Y, with diagonal section δ_C. If the limits in λ_U and λ_L exist, then:

$$\lambda_U = \lim_{u \to 1^-} \frac{1 - 2u + C(u,u)}{1 - u} \tag{52}$$

and

$$\lambda_L = \lim_{u \to 0^+} \frac{C(u,u)}{u} \tag{53}$$

C is said to have lower (upper) tail dependence if $\lambda_L \neq 0$ $(\lambda_U \neq 0)$. The interpretation of the coefficients of tail dependency is that it measures the probability of two random variables both taking extreme values.

However, not every copula (family) measures the same type of tail dependence. Elliptical copulas capture no or only symmetrical tail dependence and, as such, are insufficient for this research. More specifically, the bivariate Gaussian copula has lower and upper tail dependence equal to zero, meaning that in the extreme tails of the distribution the variables are independent. Similarly, the Student-t copula captures cannot distinct upper from lower tail dependence since it only captures symmetrical tail dependency. Therefore, Archimedean copulas with the ability to capture a large number of (asymmetric) dependence structures are a better choice. For example, the Joe-Clayton copula estimates upper and lower tail dependence ranging anywhere from zero to one. The Joe-Clayton copula with distribution function as follows:

$$C^{JC}_{\lambda_U,\lambda_L}(u,v) = 1 - \left(1 - [[1 - (1-u)^{\kappa}]^{-\gamma} + [1 - (1-v)^{\kappa}]^{-\gamma} - 1]^{-1/\gamma}\right)^{1/\kappa} \tag{54}$$

where

$$\kappa = \frac{1}{\log_2(2-\lambda_U)}$$
$$\gamma = -\frac{1}{\log_2(\lambda_L)}$$

and $\lambda_U \in (0,1)$, $\lambda_L \in (0,1)$.

The two parameters of the copula measure the upper $\left(\lambda_U = 2 - 2^{-1/\theta}\right)$ and lower tail dependence $\left(\lambda_L = 2^{-1/\theta}\right)$ respectively. When $\lambda_U = 0$ the Joe-Clayton copula collapses to the Clayton copula. As one of the coefficients approaches 1, the copula approaches the Frèchet-Hoeffding upper bound (Härdle & Okhrin, 2010; Joe, 1997; Manner, 2007; Nelsen, 2006). Nevertheless, a major drawback of this copula is that even when the two tail dependence measures are equal, there is still some (slight) asymmetry. To attain this desirable property, Patton (2001, 2006) introduced the symmetrized version of the Joe-Clayton copula, which mixes the Joe-Clayton copula with its Survival copula.

$$C^{SJC}_{\lambda_U,\lambda_L}(u,v) = 0.5\left(C_{JC}(u,v|\lambda_U,\lambda_L) + C_{JC}(1-u,1-v|\lambda_U,\lambda_L) + u + v - 1\right) \tag{55}$$

The symmetrized Joe-Clayton (SJC) copula is clearly only a slight modification of the original Joe-clayton, and nests by construction symmetry as a special case when $\lambda_U = \lambda_L$.

C2 D-vine

In order to construct D-vines, a data-driven approach can be applied, which will be briefly explained hereafter. In a D-vine, a certain order is placed in the first tree structure, with each variable, or node, having a maximum of 2 edges. When following a data-driven approach, one uses only mathematical or statistical evidence in determining the imposed structure for the first tree of the D-vine. One can follow the approach of Aas et al. (2009) who put the strongest bivariate dependencies in the first tree of the D-vine specification. The strongest bivariate dependencies within the copula distribution can be measured by Kendall's tau or the tail dependence (Czado, 2010). The imposed structure then determines the subsequent structure in the remaining trees. As such, the outer nodes of the first tree will always form the dependency or pair copula to be obtained. However, D-vines give only a temporal vine-construction. As such, C-vines are preferred when one wants information on the importance of the relations.

We take the various standardized residuals to transform them into appropriate uniform margins [0,1].

Let $X = (X_1, X_2, X_3, X_4) \sim F$ with the marginal distribution functions F_1, F_2, F_3, F_4 and the cumulative distribution functions $cdf\ F_{1234}$, we can express the probability density function as follows:

$$f(x_1, x_2, x_3, x_4) = f_{4|123}(x_4|x_1, x_2, x_3) f_{3|12}(x_3|x_1, x_2) f_{2|1}(x_2|x_1) f_1(x_1) \tag{56}$$

By the repeated use of Sklar's theorem (Sklar, 1959) the density in (1) can be represented as a product of pair copula densities. There are several possibilities for building vines, Another possible decomposition is the following pair copula construction (PCC) for a D-Vine:

$$f_{1234}(x_1, x_2, x_3, x_4) = \quad \textit{(marginals)} \tag{57}$$

$$f_1(x_1)f_2(x_2)f_3(x_3)f_4(x_4)$$

$$\textit{(unconditional copulas)}$$

$$.\, c_{12}\big(F_1(x_1), F_2(x_2)\big)$$

$$.\, c_{23}\big(F_2(x_2), F_3(x_3)\big)$$

$$.\, c_{34}\big(F_3(x_3), F_4(x_4)\big)$$

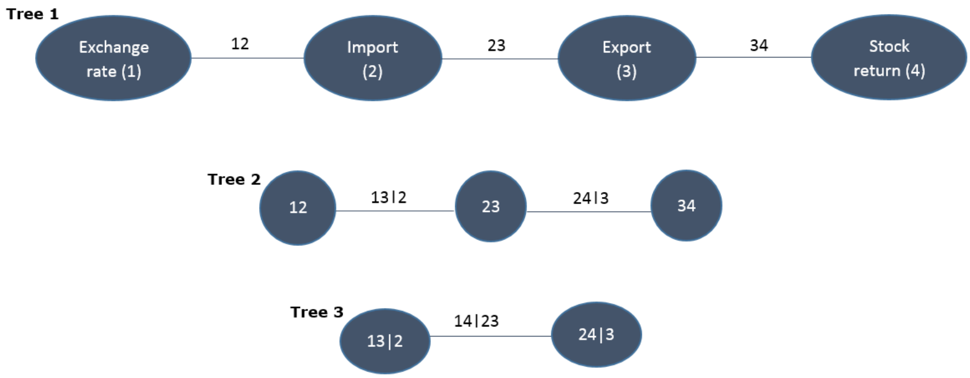
$$\textit{(conditional copulas)}$$

$$.\, c_{13|2}\left(F_{1|2}(x_1|x_2), F_{3|2}(x_3|x_2)\right)$$

$$c_{24|3}\left(F_{1|3}(x_1|x_3), F_{4|3}(x_4|x_3)\right)$$

$$c_{14|23}\left(F_{1|23}(x_1|x_2, x_3), F_{4|23}(x_4|x_2, x_3)\right)$$

Figure C2.1: Drawable Vine (D-Vine)



The D-vine (Figure C2.1) constructs in the first tree the association between the different variables, more specifically exchange rate and export changes, export and import changes, import and stock returns changes. In the second tree, two conditional copulas are made, namely the association between exchange rate and import changes conditional on export changes, and the association between stock return and export changes conditional on import changes. The last tree represents the conditional dependence of the association between stock return and exchange rate changes on the relationship between import and export changes. The D-vine is constructed using the data-driven approach, the economic meaning of the vine structure will therefore not be explained any further. Nevertheless, since the third and last three of the D- and C-vine is the same in both structures, the result of the third tree should be similar and the D-vine can be used as a robustness check for the C-vine.

C3 Minimum Spanning Tree

The tail dependence MST network filters the tail distance matrix and links all i nodes, in this case firms, with $i-1$ stronger edges such that the sum of all distances is the minimum. In other words, the MST tries to reduce the number of $i(i-1)/2$ elements originally contained in the distance matrix to reduce to only the $i-1$ most important links. In this study we use the algorithm of Kruskal (1956) to construct the MST network. Aste et al. (2010) described the general approach to construct a MST as to connect the pairs while constraining the graph to be a tree, as follows:

Step 1: Create an ordered list of edges by pair of firms i and n ranking them by increasing distance. *Step 2*: Take the first element, i.e., the element with the smallest distance, in the list and add the edge to the graph.

Step 3: Take the next element and add the edge if the resulting graph is still a forest or a tree and as such does not result in loops or cliques; otherwise discard the element.

Step 4: Iterate the process from step three until all pairs have been exhausted.

The MST is attractive because it provides an arrangement of firms which selects the most relevant connections while remaining as simple as possible. We can determine from the MST the subdominant ultrametric distance matrices, $\boldsymbol{D}^{<U}$ and $\boldsymbol{D}^{<L}$. These matrices are obtained by defining the subdominant ultrametric distance $d^{<U}(i,n)$ and $d^{<L}(i,n)$ between i and n as the maximum value of any distance detected by moving in single steps from n to m through the shortest path connecting the firms n and m in the MST (Mantegna, 1999). Mantegna (1999) points out that by using the detected subdominant ultrametric space it is possible to obtain a taxonomy of the investigated elements which is uniquely defined without any further assumption.

C4 Planar Maximally Filtered Graph (PMFG)

The condition that the extracted MST network should be a tree (step three from the MST procedure) is a strong limitation, the PMFG does not have this constraint. Nevertheless, the tail dependence PMFG network has the same filtering ability as the MST network while containing extra links, loops and cliques. Definitely, when firms are involved in similar activities which have strong dependent behaviors, the constraint of the MST network becomes apparent. In the MST construction, not every firm can be directly connected with an edge. However, firms can form cycles or cliques in the filtered graph, which are not allowed in a tree. Ideally, one would like to be able to maintain the same powerful filtering properties of the MST but also allow the presence of extra links, cycles and cliques in a controlled manner. A recently proposed solution consists in building graphs embedded on surfaces with a given genus. The algorithm to build such a graph is identical to the one for the MST discussed previously, except that in step three (from the previous Section) the condition to accept the link now only requires that the resulting graph must be embeddable on a surface of genus g. The resulting graph has $3i - 6 + 6g$ edges. The simplest graph is called a planar maximally filtered graph and is associated with genus equal to zero (g = 0). The MST is always a subgraph of the PMFG. A PMFG has 3 times the number of edges as the MST; cycles are admitted; the number of 3-cliques[126] must be larger or equal to $2i - 4$; and 4-cliques can be present (Aste et al., 2010; Tumminello et al., 2005).

[126] An n–clique is a complete sub graph on n vertices such that every two vertices in the sub-graph are linked by an edge. In our practical case a clique in our network refers to a set of firms with similar behavior, i.e., changes in exchange rate exposure of one firm in a clique is closely related or similar to the behavior of other firms in that clique (Aste et al., 2010).

C5 Definition firm characteristics and data sources

Table C5.1: Definition determinants and their data source

Nr.	Variable	Explanation (for sample between 2011-2015)	Data Frequency	Data source
1	Log size	Logarithm of the average total assets during the sample period of the firms in EUR	Monthly	Datastream
2	Quick ratio	Average of the quick ratio during the sample period of the firms. The quick ratio is computed by (current assets– inventory)/current liabilities	Yearly	Statistics Netherlands
3	Debt ratio	Average of the debt ratio during the sample period of the firms. The debt ratio is computed by total debt/total assets.	Yearly	Statistics Netherlands
4	Book-to-market	Average of the book-to-market during the sample period of the firms. The book-to-market is computed by equity book value/equity market value.	Yearly	Statistics Netherlands
5	Foreign net revenue	Average of the foreign net revenue during the sample period of the firms. The foreign net revenue is computed by foreign net revenue/total net revenue.	Yearly	Statistics Netherlands
6	Import share	Total volume import divided by the total volume of trade per firm in EUR.	Weekly	Statistics Netherlands
7	Import destinations outside Eurozone	Total number of destination countries outside the Eurozone from which is imported.	Weekly	Statistics Netherlands
8	Extensive margin week import	Number of weeks in which import occurred.	Weekly	Statistics Netherlands
9	Export share	Total volume export divided by the total volume of trade per firm in EUR or the inverse proportion of import share (1-Import share).	Weekly	Statistics Netherlands
10	Export destinations outside Eurozone	Total number of destination countries outside the Eurozone from which is exported.	Weekly	Statistics Netherlands
11	Extensive margin week export	Number of weeks in which export occurred.	Weekly	Statistics Netherlands
12	Productivity dummy	Productivity is measured as Value-added/Number of employees. The productivity dummy divides the sample in three levels of productivity. More specifically, category 1 denoting the 25% least productive firms, category 2 representing the 25% highest productive firms and category 3 indicating the remaining 50% of the sample or average productive firms[127].	Weekly	Orbis

[127] Financial and insurance firms are not included, since the measurement of their productivity occurs entirely different. Including these firms might otherwise result in outliers.

C6 Summary statistics for firm characteristics (1)

Table C6.1: Summary statistics for sector affiliation*

Sectors	Nr. of Firms
Administrative & support service activities	4
Construction	8
Financial & insurance activities	9
Industry	22
Information & communication	11
Professional, scientific & technical activities	10
Transportation & storage	4
Wholesale & retail trade; repair of motor vehicles & motorcycles	13

*Based on the Standaard Bedrijfsindeling used by Statistics Netherlands, identical to the NACE-code (rev.2).

Table C6.2: Descriptive statistics of the investigated firm-level determinants of exchange rate exposure: entire sample period

	Mean	St. dev.	Min.	Max.
Log Size	6.159	1.016	3.663	9.029
Quick ratio	1.479	2.948	0.123	18.635
Debt ratio	0.535	0.372	0.014	3.046
Book-to-market	0.699	0.557	-0.278	3.406
Foreign net revenue	0.374	0.336	0	1
Import share	0.536	0.388	0.00008	1
Export share	0.464	0.388	0	0.999
Import destinations outside Eurozone	30	28	1	100
Export destinations outside Eurozone	37	40	0	168
Extensive Margin Week import	136	102	1	252
Extensive Margin Week export	133	116	0	260

C6 Summary statistics for firm heterogeneity and node attributes (2)

Table C6.3: Summary statistics for firm heterogeneity and node attributes based on monthly dataset

	Mean (EUR)	Minimum (EUR)	Maximum (EUR)	Standard deviation (EUR)	Skewness	Kurtosis
Average Size per firm	27,222,276	4604	1,069,889,200	128,265,483	7.218	56.601
Import	2,009,906,329	55	99,116,948,766	11,124,981,851	8.537	75.115
Export	1,973,983,546	0	64,417,802,136	8,084,354,922	6.472	46.639
EU Trade	1,437,125,366	0	65,061,002,772	7,345,775,906	8.355	72.745
Outside EU Trade	2,546,764,510	86	98,473,748,130	11,745,523,024	7.247	57.482
Trading Partners	56	1	195	49	0.729	-0.183
Extensive Margin Week	161	1	260	109	-0.442	-1.644
Extensive Margin Month	45	1	60	22	-1.063	-0.582

Table C6.4: Summary statistics for firm heterogeneity and node attributes based on weekly data set

	Mean	Minimum	Maximum	Standard deviation	Skewness	Kurtosis
Stock Returns	-0.0004	-0.865	0.798	0.026	-5.340	246.464
EUR-USD exchange rate	-0.0003	-0.0161	0.014	0.006	-0.193	-0.034
Import	0.0027	-6.894	7.911	1.401	0.124	6.230
Export	0.0009	-7.891	7.852	1.393	-0.007	7.775

C6 Summary statistics for firm heterogeneity and node attributes (3)

Table C6.5: Summary statistics for firm heterogeneity and node attributes (PART C)

Sectors	Nr. of Firms
Administrative & support service activities	4
Construction	8
Financial & insurance activities	9
Industry	22
Information & communication	11
Professional, scientific & technical activities	10
Transportation & storage	4
Wholesale & retail trade; repair of motor vehicles & motorcycles	13

C7 Results D-vine (tree 1, 2 and 3)

Table C7.1: Results D- vine with exchange rate (1), import (2), export (3) and stock return (4)

Tree 1					
$C_{SJC}(1,2)$		$C_{SJC}(2,3)$		$C_{SJC}(3,4)$	
Max λ_L	0.114882	Max λ_L	0.481018	Max λ_L	0.111487
Max λ_U	0.092509	Max λ_U	0.763059	Max λ_U	0.121654
$\bar{\rho}$	0.023530	$\bar{\rho}$	0.047505	$\bar{\rho}$	0.000819
Min ρ	-0.077681	Min ρ	-0.246167	Min ρ	-0.101059
Max ρ	0.112902	Max ρ	0.599023	Max ρ	0.116383
Tree 2					
$C_{SJC}(1,3\|2)$		$C_{SJC}(2,4\|3)$			
Max λ_L	0.104552	Max λ_L	0.084854		
Max λ_U	0.066216	Max λ_U	0.119240		
$\bar{\rho}$	0.000559	$\bar{\rho}$	0.021634		
Min ρ	-0.112989	Min ρ	-0.084826		
Max ρ	0.086888	Max ρ	0.096173		
Tree 3					
$C_{SJC}(1,4\|2,3)$					
Max λ_L	0.103202				
Max λ_U	0.065108				
$\bar{\rho}$	0.002351				
Min ρ	-0.123552				
Max ρ	0.105538				

C8 Topological properties and robustness of MST and PMFG

In this Section we discuss the network's topological properties which determine the function and the behavior of the networks. As such, we can determine whether the networks contain significant, valid and robust structures and patterns to investigate. Two common topological features are the average path length (L_{APL}) and the average clustering coefficient (L_{ACC}).[128] The average path length (L_{APL}) refers to the average number of intermediates between any two firms and characterizes the size of the network. Each firm and its directly connected firms make up a neighborhood group. The density and compactness of the network resulting from this clustering behavior is represented by the average clustering coefficient (L_{ACC}) (G. Wang & Xie, 2016).

Table C8.1: The average degree $\langle k \rangle$, average path length L_{APL} and average clustering coefficient L_{ACC} of lower and upper tail dependence MSTs and PMFGs and a random graph

	$\langle k \rangle$	L_{APL}	L_{ACC}
Lower tail dependence MST	1.9753	2.4531	0
Upper tail dependence MST	1.9753	2.4507	0
Lower tail dependence PMFG	5.8519	2.2528	0.1617
Upper tail dependence PMFG	5.8519	2.3342	0.1478
Random graph	5.8519	2.6299	0.0566

Table C8.1 presents the results of lower and upper tail dependence MSTs and PMFGs and a random graph, more specifically, the average degree $\langle k \rangle$, average path length L_{APL} and average clustering coefficient L_{ACC}. On average, each vertex has only one or two neighbors in the tail dependence MST network, while in the PMFG network this number rises to five or six neighbors. The average path length indicates that the size of the upper and lower tail dependence networks are both similar. Further, the average clustering coefficient of the tail dependence MST network equals zero since loops are not allowed. Concerning the PMFG, the average clustering coefficient suggests that the lower tail dependence network is

[128] $L_{APL} = \frac{2}{N(N-1)} \sum_{i<j} l_{ij}$ is the average path length with N being the number of vertexes. If vertexes v_i and v_j are directly connected then the shortest path length is given by l_{ij}.
$L_{ACC} = \frac{1}{N} \sum_{i=1}^{N} C_i$ is the average clustering coefficient with N being the number of vertexes and C_i is given by $C_i = \frac{2E_i}{k_i(k_i-1)}$. E_i are the edges among k_i vertexes. The latter, k_i, is the degree of vertex v_i, or in other words, v_i has k_i neighbors (G. Wang & Xie, 2016).

denser and more compact than the upper-tail network. Finally, as a validity and robustness analysis, Table C8.1 also includes the results for a random graph which is created with the same number of vertexes and average degree. As such, we are able to examine whether the tail dependence PMFGs are small-world networks or rather random. A small world network is, as suggested by Watts and Strogatz (1998), a kind of graph in which majorities of vertexes are not neighbors of one another, but majorities of vertexes are reachable from the remaining vertexes by a small number of steps. According to these authors, the average path length of a small-world network is close to that of a random graph, while the average clustering coefficient is far larger than the one from a random graph. From the aforementioned, we can conclude that the two tail dependence PMFGs are small-world networks, indicating that significant, robust and valid structures are present (G. Wang & Xie, 2016; Watts & Strogatz, 1998).

C9 Multinomial logistic regression remaining attributes communities (1)

In Table C9.1 and C9.2 are alternative multinomial logit models presented, where determinants for which no effect was found (i.e., debt ratio, foreign net revenue, extensive margin) are excluded. The results remain robust.

Table C9.1: Multinomial logistic regression on lower tail dependence PMFG communities

C1 versus C2	β	Odds ratio
Intercept	12.144*	188,055.100
Log size	-1.739*	0.176
Quick ratio	-0.304	0.738
Book-to-market	-1.211	0.298
Import share	-6.075**	0.002
Import destinations outside Eurozone	-0.261**	0.770
Export destinations outside Eurozone	0.087	1.091
Import share × Import destinations outside Eurozone	0.402**	1.495
Import share × Export destinations outside Eurozone	-0.153	0.858
Highly productive firms	4.374**	79.324
Medium productive firms	1.573	4.819
C3 versus C2	β	Odds ratio
Intercept	2.078	7.985
Log size	-1.488**	0.226
Quick ratio	4.039***	56.758
Book-to-market	-2.919**	0.054
Import share	4.988**	146.644
Import destinations outside Eurozone	-0.138**	0.871
Export destinations outside Eurozone	0.140***	1.151
Import share × Import destinations outside Eurozone	0.239**	1.270
Import share × Export destinations outside Eurozone	-0.207**	0.812
Highly productive firms	4.301***	73.745
Medium productive firms	0.058	1.060
C3 versus C1	β	Odds ratio
Intercept	-10.067	424,597.300
Log size	0.251	1.286
Quick ratio	4.343**	76.913
Book-to-market	-1.707	0.181
Import share	11.063***	63796.020
Import destinations outside Eurozone	0.123	1.131
Export destinations outside Eurozone	0.053	1.055
Import share × Import destinations outside Eurozone	-0.163	0.849
Import share × Export destinations outside Eurozone	-0.055	0.947
Highly productive firms	-0.073	0.930
Medium productive firms	-1.514	0.220

Significance codes 0.001 '***'; 0.01 '**'; 0.05 '*'; Log-likelihood: -31.853; McFadden R^2: 0.480; Likelihood ratio test: chi-square: 58.764 (p-value: 0.000).

C9 Multinomial logistic regression remaining attributes communities (2)

Table C9.2: Multinomial logistic regression on upper tail dependence PMFG communities

C1 versus C2	β	Odds ratio
Intercept	-1.999	0.135
Log size	0.484	1.623
Quick ratio	-0.773	0.462
Book-to-market	0.454	1.575
Import share	0.653	1.921
Import destinations outside Eurozone	0.107**	1.113
Export destinations outside Eurozone	-0.076***	0.927
Import share × Import destinations outside Eurozone	-0.163**	0.850
Import share × Export destinations outside Eurozone	0.120*	1.127
Highly productive firms	-2.348**	0.096
Medium productive firms	-0.282	0.754

Significance codes 0.001 '***'; 0.01 '**'; 0.05 '*'; Log-likelihood: -32.563; McFadden R^2: 0.24; Likelihood ratio test: chi-square: 20.760 (p-value: 0.023).