Offshoring, functional specialization and economic performance

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Offshoring, Functional Specialization and Economic Performance

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Chapter 1

Introduction

1.1 Background and motivation

Globalization, the growing interaction between countries, is a phenomenon that is centuries if not millennia old. Yet during past decades cross-border economic interrelations intensified greatly and gave rise to the formation of global value chains (GVCs). GVCs refer to production processes that have been 'unbundled' across national borders. This unbundling, it is argued, has been driven by more open economic policies, reductions in transportation costs and are especially due to lower communication and coordination costs (Baldwin, 2016). It has resulted in the rapid expansion of international trade in intermediate inputs and flows of supporting business services, such as back-office and after-sales services.

GVCs are central to this thesis. They are defined in Gerefi and Fernandez-Stark (2016) as: the value chain, which describes the full range of activities that firms and workers perform to bring a product from its conception to end-use and beyond. This includes activities such as research and development (R&D), design, production, marketing, distribution and support to the final consumer. The activities that comprise a value chain can be contained within a single firm or divided among different firms.

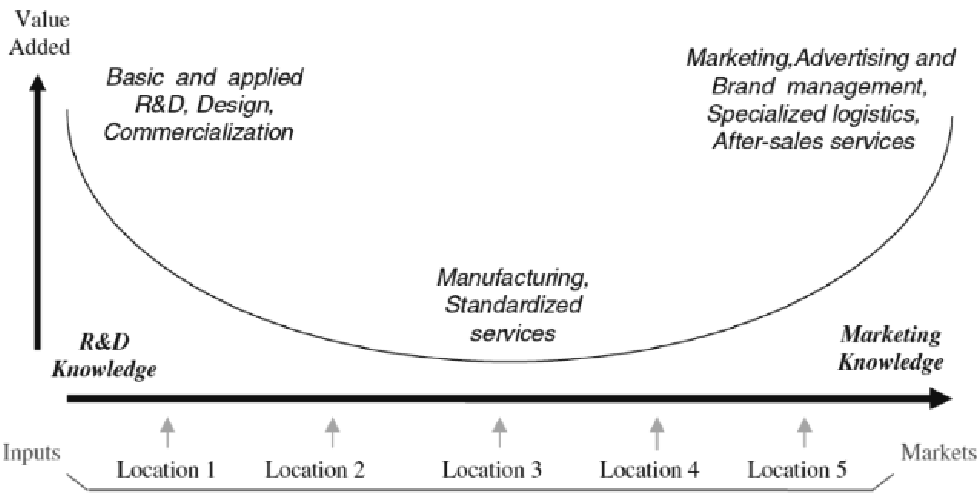
What are the implications of the formation and evolution of GVCs for the levels and growth rates of income, employment, trade, and productivity in countries? These big and important questions motivate this thesis, which aims to provide new empirical insights using a novel task-based GVC perspective.

Until recently, researchers were ill-equipped to study GVCs. This was largely due to data limitations. Macroeconomic frameworks, such as input-output tables and national accounts, describe economic relationships between industries within countries, but not the international linkages between industries which are essential to analyze the size and impact of GVCs. Most firm-level surveys are not insightful either, because when firms organize activities on an international basis, the typical surveys at statistical offices capture only the domestic part of their GVC activities.

In that respect, the creation of multi-regional input-output tables, such as OECD TiVA, the World Input-Output Tables (WIOTs, see Timmer et al. 2015) and others (see overview in Tukker and Dietzenbacher, 2013) has been an important step forward. Such tables provide comprehensive data on the international transactions of goods and services. The tables combine national input-output tables with detailed international trade data. Due to information on supply and use relations between industries and across countries, it allows measuring vertically integrated production structures. This has enabled researchers to analyze the generation of value added by countries in the various production stages.

Yet, current data and tools are organized around products and sectors. They measure the value added by country-industries in value chains. But that does not inform on the specific tasks that are carried out, such as assembly, product design, or marketing tasks (Timmer et al. 2019). Indeed, the above definition of a GVC by Gerefi and Fernandez-Stark (2016) clearly puts the focus on the need to examine business processes and activities.

Figure 1.1: The activities in a GVC



Source: Mudambi (2008)

Figure 1.1 illustrates the activities in a value chain, which can be broadly categorized into those at the upstream and downstream end, with production activities in the middle (Mudambi, 2008). Activities at both ends of the value chain are typically intensive in their application of knowledge and innovation. Upstream activities are supported by R&D knowledge such as basic and applied research and design. Downstream activities are supported by marketing knowledge, such as marketing, advertising, and after-sales services.

The costs of manufacturing and logistics activities in the middle have reduced due to mechanization and standardization (Mudambi, 2008). Furthermore, the opening up of China, India and Eastern Europe in the 1990s implied that low-wage countries with educated workforces emerged as competitive locations for assembly and other routine activities. Competition is fierce among these production activities in the middle of the value chain. The cost reductions arising from increased competition, offshoring and technological change tend to reduce the production activities' share in GVCs.

The changing relative shares of value-added generation, away from production activities and towards knowledge-intensive upstream and downstream activities, was first coined a smile curve by Stan Shih of Acer in 1992 and has been dubbed in subsequent theoretical work 'the smile of value creation' (Mudambi, 2008; Baldwin et al. 2014). Firms are finding that income gains are increasingly concentrated at the upstream and downstream ends of the value chain (Mudambi, 2008).

The contribution of this thesis is to measure and analyze the activities carried out in GVCs. It aims at closely examining 'who is doing what and where', and to reach the end of deepening the understanding of the activities performed, e.g. R&D or fabrication. As a result, measuring and analyzing the activities carried out in GVCs carry implications for the potential of spillovers and productivity growth. It uses a variety of data and quantitative approaches. Moreover, it does so at the macro (country-industry), regional, and micro (firm) level. By way of introduction, we first discuss the current literature. Section 1.2 discusses current approaches to measure and analyze activities carried out in GVCs. Section 1.3 discusses the theory and empirics of the cross-border re-location of activities for levels and growth rates of income and employment. Section 1.4 studies determinants of firm productivity and discusses how the specialization of firms in specific activities might be considered a new determinant of firm productivity. Each subsection selectively reviews relevant literature and discusses how the various thesis chapters relate to this literature. Section 1.5 provides a summary of the chapters in this thesis.

1.2 Conceptualizing business functions

What are business functions and why do we need them?

Business functions are the unit of analysis in GVCs, which originates from the international business (IB) literature, largely due to the scholarly work of Michael Porter (Porter, 1990). In IB, the focus is on firm management and organizational practice, whereby a range of activities (e.g. R&D, fabrication, management, marketing) need to be performed strategically and coordinated in different locations to deliver products most efficiently and profitably.

Hernández and Pedersen (2017) review important IB studies on the orchestration of GVCs. This literature aims to explain why GVCs exist and the main functions involved in it depending on different criteria such as the degree of involvement in the production process. Furthermore, it describes the key decisions firms need to take, which include choosing optimal governance modes, geographical scope, and coordination of activities. Hernández and Pedersen (2017) argue that firms have to combine the decisions on governance mode and location to define the value chain, combining the coordination in a network that interacts with other parties. All these actions are taken at the level of business functions. The GVC configuration is considered to have important implications. To slice the value chain into finer defined activities, firms need to have a better-managed organization to put activities in different locations and coordinate them from afar. Decision making on which activity is the core to be performed at home and which is better outsourced is crucial in a competitive business environment. Furthermore, specialization in different functions gives firms the potential to create a competitive advantage. Hernández and Pedersen (2017) review the literature on the implications of GVC configuration, including firm performance and upgrading processes raising plenty of questions that remain to be explored.

Business functions are also a common unit of analysis in economic geography and urban economics literature. Duranton and Puga (2005) provide striking evidence that shifts in the urban structure have more to do with functional specialization rather than sectoral specialization. Specifically, they find that US cities are increasingly characterized by specialization in supporting business services, with production activities taking place outside cities. Bade et al. (2003) confirm patterns of specialization in functions rather than sectors using data for Germany. This new empirical evidence inspired Duranton and Puga (2005) to develop a general equilibrium model which explains that the change in urban structure from sectoral to functional specialization is due to changes in the firm organization. The main organizational change that has been documented in the model is the separation of management and production. This decision is endogenously made with the operating environment in consideration, for example, headquarters are likely to be located in cities with abundant business services. As many firms make similar strategic decisions on their organizational forms, it leads to functional specialization across geographical locations.

Business functions are related to the concept of tasks in labor and international economics literature. A task is a unit of activity that can be conducted to produce output (Acemoglu and Autor, 2011). In Timmer et al. (2019), a business function is referred to as a set of tasks that are carried out by a specific occupational group of workers. Studying tasks has become relevant and important as firms specialize in different production stages (Baldwin, 2006). There is no standard classification for business functions. However, typically the main distinction is between production and headquarter (Markusen, 2002). In Timmer et al. (2019), they further split headquarter into R&D, management and marketing activities. We will use the business function data constructed by Timmer et al. (2019) in Chapter 2. This type of data is different from measures of skills, approximated by educational attainment. There is not a clear-cut mapping of a business function to factor endowment. For example, Timmer et al. (2019) find that the share of high-skilled workers in the US differs among business functions, with the highest in R&D activities (0.67), the lowest in fabrication activities (0.07) and marketing (0.27) and management activities (0.54) in between.

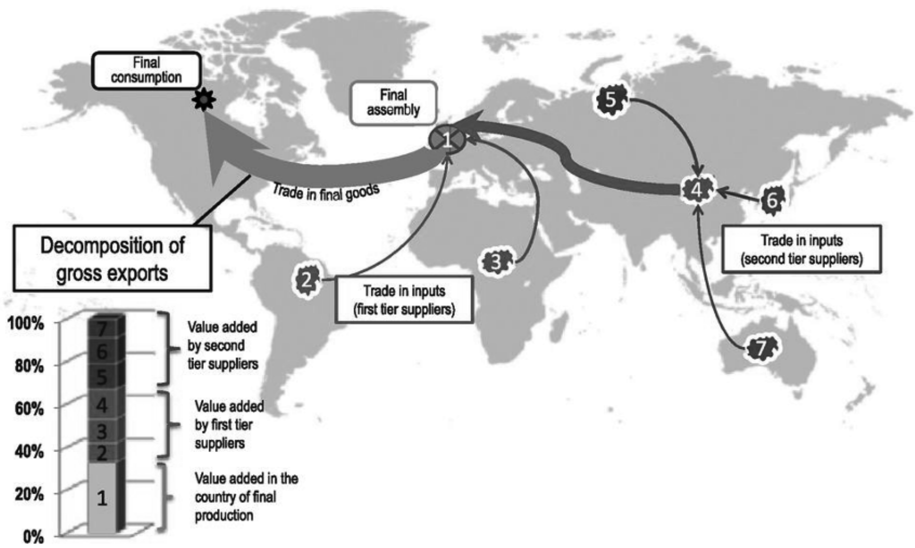
Defever (2006) points out that fabrication is a subset of GVC activities, and a GVC framework should include the full set of activities carried out. This includes fabrication but also supporting business functions. Defever (2006) argues that these supporting business functions have not been widely studied in economics. The reasons could be the lack of data and difficulty in connecting it to theory. To fill this gap, Defever (2006) investigates fragmentation and the co-location of multinational firms' value chain activities in Europe. They use the European Investment Monitor (EIM) database, which provides data that characterizes investments by function such as investments in setting up R&D, logistics, and marketing activities. They find that choosing the location of activities is more influenced by characteristics related to business functions rather than sector characteristics. R&D and fabrication activities appear to be co-located. Barbour and Markusen (2007) find that there is not a clear cut industry-function structure across different geographical regions. Therefore we cannot infer the functional structure of a region from its sectoral structure.

Defever (2006) argues one of the main reasons why business functions have not been widely studied in economics is the lack of data. Brown (2008) and Sturgeon and Gereffi (2009) stress the need to collect new data. The existing literature in economics mainly studies international fragmentation using either industry classification standards, product trade data or input-output statistics. Analysis based on sectors is likely to be ill-advised. For example, a manufacturing firm conducts tasks related to the design, engineering, marketing and distribution of the products it manufactures. It is inadequate to focus on the sector and not dig deeper into what the firm does besides fabricating products.

Similarly, the shortcomings of trade in goods statistics are also widely acknowledged: a country might be a leading exporter of a certain product, but that need not inform on the value it adds to the exported goods. In an often-cited case study, Dedrick et al. (2010) find that even though China is a main exporter of electronics, its contribution to the value-added is minor as the main activity China performs is assembly. Taking the Apple iPod as an example, they document that software is provided by Apple, the main memory chips by Samsung from Korea, and the hard drive by Toshiba from Japan. Each of these activities adds more value than the assembly activities in China. Trade studies based on product data have been doing reasonably well in explaining trade patterns (Timmer et al. 2019). However, they are thought to be less successful in other respects. For example, Sturgeon and Gereffi (2009) argue that trade statistics provide incomplete information on the location where value is added, no information on the ownership of output and how the whole system is coordinated. Product statistics do not directly inform us of the technological content and factor inputs. The technological content of labor and capital can vary by country. A high-tech product like the iPhone may involve technological-intensive activities in the US and low technology assembly activities in China. Furthermore, Sturgeon and Gereffi (2009) indicate that even for an exporter who carries out the production process itself, other activities like design, marketing and management may still be undertaken outside the territory of the exporting country.

Recent studies based on input-output data have emerged to study the domestic value-added content of exports (Hummels et al. 2001; Johnson and Noguera, 2012). The pioneering work of Hummels et al. (2001) proposes a measure of vertical specialization, namely the foreign value-added content embodied in exports. This measure of vertical specialization informs on how much value is added domestically and how much is added abroad. This is crucial to analyze many issues regarding international trade and fragmentation. For example, an increase in the Chinese export of electronics may lead to the conclusion that Chinese exports have become more skill-intensive and sophisticated. However, taking into account the foreign value-added in Chinese export would certainly reach a different conclusion. Much of the value in the Chinese exports used to be added to other advanced economies like the US, Japan, and Korea. This information is not revealed by data on goods trade, but only from tracing the domestic value-added in exports. Similarly, by tracing the foreign content in exports over time, researchers can analyze time-series changes in the contribution to value-added of exporters. For example, Koopman et al. (2012) find that the aggregate domestic content of Chinese manufacturing exports increased from 51% to 60% between 2002 and 2007. Koopman et al. (2014) take the studies of vertical specialization and value-added trade to another level by decomposing gross export into an exhaustive list of components that allows one to trace the value-added from different sources and account for double accounting.

Figure 1.2: Illustration value added in GVC



Source: OECD (2013. Interconnected Economies)

Figure 1.2 illustrates the value-added flows embodied in gross exports. The arrows show flows of intermediate inputs and export of the final product from Europe to the US. Measures and analysis based on gross exports would only tell part of the story. For example, from the perspective of the US, there is only a gross trade flow with Europe. However, it is the final consumption in the US that is driving the creation of value-added in this GVC. The literature on value-added in exports aims to identify these inter-country relationships by breaking down the gross export flow (say from Europe to the US) into the value-added from each of the countries that contributed.

Such measures do not inform on the activities firms carry out, the value-added in particular activities and the organizational and spatial nature of activities concerning decision making (Sturgeon and Gereffi, 2009; Timmer et al. 2019). For example, vertical specialization measures reveal how much value is added in China from its export of a certain product. However, this particular share of Chinese value-added in gross exports may be a result of China's specializing in different functions. Is the value added by China from production, management, R&D or assembly? Questions on what activities a country or a firm does are increasingly relevant and important to understand as they carry important implications for the potential for productivity growth and knowledge spillovers.

Measuring business functions

Several statistical offices and researchers have put in considerable effort to collect new data to measure business functions. Currently, there are two approaches to measure business functions: one is the attempt by statistical offices or census bureaus to conduct firm-level surveys to obtain self-reported information about business functions. The other approach involves collecting detailed information on the occupation and wages of workers and then construct business functions based on the occupation of workers. We describe and outline the strengths and limitations of each approach below.

Brown et al. (2014) use the 2010 National Organizational Survey (NOS) to study outsourcing and offshoring by US organizations. The NOS provides information on eight business functions and the outsourcing and offshoring activities around these functions. Under the aegis of Eurostat, twelve statistical offices in Europe have implemented 'International Sourcing & Global Value Chain Surveys' (ISS) from 2007 onwards. [1] Chapters 3 and 4 of this thesis benefit from using this unique survey from Statistics Netherlands. There are three waves of the survey, which were carried out in 2007, 2012 and 2017. Other statistical offices like Statistics Canada also launched their experiments with international sourcing surveys based on a business function framework (Brown et al. 2014). Other than international sourcing surveys, business function frameworks have also been implemented in surveys dealing with other topics. Defever (2006) uses the European Investment Monitor (EIM) database to study functional fragmentation and the location of multinational firms in Europe as EIM provides investment data distinguished by functions. A key strength of survey data is that they ask managers directly about their business functions and related subjects, which provides firsthand information on business functions and how firms manage it. However, they have the limitation that it is difficult to get these data continuously over time and it is costly and difficult to include a large sample of firms in the survey.

Other studies use census data that provide detailed information on employment and occupation to inform about functional specialization and its impact on economic development. For example, Bernard et al. (2017) propose to rethink deindustrialization as they question the standard classification of firms by manufacturing/non-manufacturing. They argue

[1] These statistical offices are based in Czech Republic, Denmark, Germany, Ireland, Italy, Netherlands, Portugal, Slovenia, Finland, Sweden, United Kingdom and Norway.

that besides manufacturing, manufacturers perform more activities, e.g. design, management, marketing, etc. The operation of (manufacturing) firms consist of a complex combination of different activities. Bernard et al. (2017) use the rich Danish population-level employer-employee data. The employer side of data has detailed information on the economic activity of plants. This information allows the authors to determine if a firm is in the manufacturing sector or not. The employee side of data has information on the occupation of workers, and all workers are linked to the firms they work at with a unique identifier. With detailed information on the occupation of workers, Bernard et al. (2017) classify workers into five business functions according to their occupations: managers, tech workers, support activities, sales activities, and production line workers. By tracing firms and workers over time, the authors can find those firms that switch out of manufacturing and the concomitant changes in their functional structure. They find that the functional structures of switchers have been notably changed and two very different kinds of switchers exist. One switches out of the manufacturing sector and becomes similar to traditional wholesalers as there is an increasing share of sales workers and a reduction of production workers. The other type of switcher continues with manufacturing-related functions like design and R&D. The second type of switchers are also referred to as factory-less goods producing firms (FGPFs). With the detailed occupation data, Bernard et al. (2017) are able to empirically implement a business function framework to inform on what firms do and what happens within (manufacturing) industry during deindustrialization.

Timmer et al. (2019) propose to study trade based on functional specialization. They construct an Occupations Database using detailed census and survey data. They collect detailed time-series data on workers' occupations and wages. They distinguish between four functions according to the occupation of workers, namely R&D, fabrication, marketing, and management. Timmer et al. (2019) propose a Balassa type index of functional specialization at the country level, which compares the share of a function in total export income from a country to the share of this function in total export income for all countries. In order to achieve this, the authors firstly calculate domestic value-added in exports using input-output tables, and then they trace the type of workers that are involved in the production. The value-added contributed by a function is determined by the total income of workers that perform the function. Applying this new functional specialization index, Timmer et al. (2019) find large heterogeneity in functional specialization across countries at similar income levels. The majority of advanced countries specialize in R&D functions. The specialization patterns only change slowly over time for these countries. Chapter 2 of this thesis benefits from using this newly constructed business function data.

Following Timmer et al. (2019), Chen et al. (2018a) investigate the reason behind the increase in China's domestic value-added in export. This is a study that shows how the functional specialization approach by Timmer et al. (2019) can be applied beyond the national level to address regional topics. Chen et al. (2018a) collect detailed data on business functions based on occupations data across 31 Chinese provinces and 42 industries following the identification strategy of Timmer et al. (2019). Combining population census data with inter-provincial input-output tables, they are able to capture the functional specialization of Chinese regions. They find that the increase in China's domestic value-added in exports occurs owing to fabrication activities expansion and it is mainly driven by second-tier provinces. Furthermore, they find that even though the expansion of fabrication activity is important, there is an even faster increase in income from pre- and post-fabrication functions in China and the richest provinces increasingly specialize in these activities. This finding suggests that China is also on the way of transforming itself from a global factory to a participant in GVC that engages in more diverse activities and the roles of regions might differ in this process. Clearly, applying the industry scheme or product data cannot reveal the activities in GVC that Chinese regions specialize in.

A big advantage of using occupation data to approximate business functions is that it allows a time-series economic analysis. However, it is different from business function surveys in which managers answer questions about business functions. Researchers need to put occupations into each business function group to further investigate functions. There is not a clear-cut and unique mapping between occupation and business function and some occupations may qualify to be classified in more than one business function. Therefore, occupations data is an imperfect measure of business functions.

Acknowledging the important advantages of the business function approach in GVC studies and building on the relevant research outlined above, the three remaining chapters of this thesis investigate the functional specialization of countries, sub-national regions and firms in the context of globalization and international fragmentation. We benefit from the international sourcing and labor force surveys from Statistics Netherlands, which provide the opportunity to study the firm and regional level functional specialization and important topics like offshoring and firm productivity. We also benefit from the business function dataset constructed by Timmer et al. (2019), which enables us to investigate cross-country functional specialization patterns.

1.3 Offshoring and onshore labor market effects

The re-location of business functions and production stages abroad is commonly referred to as offshoring (Baldwin, 2006). Offshoring has drawn increasing attention from researchers, media and the general public as it has deep implications for the onshore labor market (Hummels et al. 2018). Fear of potential loss of domestic jobs and an increase in inequality have led to a somewhat strong tone against globalization and offshoring among some political figures and further advocated by mass media. Concerning mechanisms of how offshoring may affect onshore labor markets, important economic theories have been put forward. These will be discussed below. Empirical research will be used to provide evidence on this matter. This field of research is vast and we will only provide a selective review of theoretical and empirical research on the relation between offshoring and onshore labor market outcomes.

Theory

A theoretical foundation is needed to understand the mechanisms at work. The effects of offshoring on onshore labor market outcomes can be traced back to early theory on the wage effects from trade. In the theoretical model of Stolper and Samuelson (1941), two closed economies are included - the North and the South. Both of them use two production factors, namely skilled and unskilled labor to produce two types of goods that differ in skill intensity. The North is a high-skill labor abundant country while the South is an unskilled labor abundant country. When the two countries open up to trade, the North specializes in producing the skill-intensive goods, which leads to a rise in the relative price of the skill-intensive goods and subsequently the skill premium (the relative wage of skilled to unskilled labor). The opposite happens in the South. Their model is among the first to theoretically explain how specialization in international trade affects the onshore labor market.

With increasing production fragmentation, a new theory emerged that examined offshoring within GVCs and its relation to onshore labor demand. Adopting a Heckscher-Olin structure, Feenstra and Hanson (1996) propose an industry model in a North-South setting. In their model, a bundle of intermediate inputs is needed to deliver the single final product to consumers. The intermediate inputs are put in increasing order according to their skill intensity. As in Stolper and Samuelson (1941), there are two countries, the North and the South. The North is skilled labor and capital abundant, whereas the South is unskilled labor abundant. Suppose there is a capital flow from the North to the South, which is identified as an increase of offshoring from the Northern firms. The offshored inputs are less skilled than the inputs remaining in the North but more skilled than the inputs produced in the South. Therefore, both countries see a rise in skill intensity, which increases the relative demand for skilled labor in both.

Besides theories in a North-South setting, other theories try to model the effects of offshoring on labor market outcomes in a North-North setting. Burstein and Vogel (2010) study two identical countries that are both developed North. With a drop in trade costs, both countries start to offshore by exporting intermediate inputs. With the assumption of productivity being skilled labor biased, the less productive firms contract their production, and production resources are redistributed towards the more productive firms. Exporters are those firms with higher productivity in both countries. As a result, the demand for high-skilled labor increases in both countries and so is the skill premium.

The above theoretical research explains reasonably well the increase in skill premiums owing to a rise in offshoring, which is in congruence with the wage changes in the 1980s in the US and other advanced economies. However, what happened in the 1990s is quite different from that in the 1980s and the theories above are not able to explain the 1990s evidence (Feenstra, 2016). There is an increase in the skill premium in US manufacturing but this is accompanied by a decline in the employment of manufacturing workers. This is suggestive of service activities offshoring. As the lower-paid back-office jobs from manufacturing sectors are offshored, the average wages for the nonproduction workers increase, together with a decline in overall manufacturing employment (Feenstra, 2016).

These empirical patterns motivated the theoretical work of Grossman and Rossi-Hansberg (2008), which refer to their theory as a model of 'trade in tasks'. In their two-sector North-South model, instead of intermediate inputs, there is a continuum of tasks carried out by two types of workers - skilled and unskilled ones. They assume that the skilled wages are the same in both countries but unskilled wages are lower in the South, which provides an incentive for the North to offshore unskilled tasks to the South. As the technology of offshoring improves, there is a decline in offshoring costs of unskilled tasks. The wages of the unskilled workers may increase as the cost-saving is attributed to payment to unskilled workers. This saving in costs is similar to an economy-wide increase in unskilled labor productivity, which is therefore named by the authors as 'the productivity effect'. The productivity effect adds a new channel to the other two effects - the relative price effect and the labor supply effect. The relative price effect is similar to the traditional trade theory, which describes that with the decline in offshoring cost, the cost of low skilled tasks also declines. It, therefore, increases the world output of low-skilled labor-intensive goods, which leads to a fall in the relative price of labor-intensive goods. The labor supply effect is similar to the framework of Feenstra and Hanson (1996). As the North offshores unskilled tasks abroad, the onshore unskilled workers are freed and they seek employment elsewhere. This increase in supply leads to a decline in the relative wage of these unskilled workers. The productivity effect proposed by Grossman and Rossi-Hansberg (2008) has important implications as it tells that rather than jeopardizing the low skilled workers, offshoring may even benefit them through an increase in their productivity.

Besides Grossman and Rossi-Hansberg (2008), other extant theories also point out that offshoring needs not to harm the onshore workers even with the offshored activities being labor-intensive. Benz (2013) proposes a dynamic theory of trade in tasks based on the framework of Grossman and Rossi-Hansberg (2008). Other than the three effects of Grossman and Rossi-Hansberg (2008), they propose two other effects: the short-run intertemporal profit effect and the long-run composition effect. Both effects take into account the imitation risk, which is a probability of losing future profits by offshoring to the South. In the short run, the rising discount rate for future profits harms the high-skilled workers. In the long run, however, the endogenous adjustments of both the northern and southern varieties compensate the high-skilled workers for their loss in the short run. With this dynamic setting, Benz (2013) argues that empirical studies aim to identify a stable relation between offshoring and relative wages could be ill-advised as it is more meaningful to investigate the correlation of offshoring and labor wages during different periods. Benz (2013) finds that the intertemporal effect harms the skill premium while the composition effect improves the skill premium. Groizard et al. (2015) propose a theory on offshoring and firm-level employment, they propose three effects of a fall in offshoring costs on firm-level employment. The substitution effect takes place when domestic labor is replaced by foreign ones. Competition effects take place when efficient firms' offshoring leads to a tougher competitive environment. Both effects harm onshore labor. However, similar to the productivity effect of Grossman and Rossi-Hansberg (2008), the third effect, the scale effect, facilitates job creation. The scale effect takes place with the aid of the cost-saving mechanism of offshoring, which expands production and thereby creates more jobs. The theories of the task-based offshoring like Grossman and Rossi-Hansberg (2008) are mostly based on a North-South setting. However, recent research emphasizes that a North-North setting is very important as most trades in intermediate goods are North-North, just like trade in final goods (Hummels et al. 2018). Dluhosch and Hens (2016) develop a theoretical model that focuses on business services offshoring. They discuss that service offshoring need not harm the onshore workers who perform these activities. Whether or not service offshoring would negatively affect the onshore workers who perform these tasks is determined by what factor causes offshoring. Offshoring caused by advancement in ICT is found to be in favor of skill premium through a productivity effect, while offshoring caused by trade integration tends to have the opposite effect as it triggers more fierce competition. Therefore, the important message is that business services offshoring may even benefit onshore labor, and policymakers should be aware of what triggers offshoring.

The research reviewed above suggests that offshoring need not harm onshore workers, whether it is a certain group of workers in terms of a change in skill premium or the onshore employment in general. The task-based framework by Grossman and Rossi-Hansberg (2008) is a groundbreaking theory on offshoring and onshore labor market outcomes, and it is also currently the most important framework to understand the effect of offshoring on labor market outcomes (Barbe and Riker, 2018). The productivity effect of offshoring is also proven to be considerable in empirical works (Amiti and Wei, 2009; Ottaviano et al. 2013). The most important lesson from Grossman and Rossi-Hansberg (2008) model is that the effect of offshoring on the onshore labor market is a mixed result from different channels, and the absolute effect on onshore labor markets is not definite but determined by the net results of all channels.

Empirics

There is a rich literature that provides empirical evidence to the theoretical framework introduced above. They either use industry-level data, firm-level data or worker level data. In the following paragraphs, we will selectively review relevant empirical research.

The common analysis approach in industry level studies is to relate wage bill shares of various groups of workers to relevant variables such as offshoring and the capital to output ratio. Measuring offshoring as the number of foreign plants relative to the number of domestic plants, Feenstra and Hanson (1997) find that the increase in US offshoring to Mexico over 1975-1988 could explain over 50% of the increase in skilled worker wage bill share in Mexico. In Feenstra and Hanson (1999), they measure offshoring as the share of imported intermediate inputs in total costs on non-energy intermediate inputs. This measure later becomes widely used in offshoring research (e.g. Hsieh and Woo, 2005; Hijzen et al. 2005; Amiti and Wei, 2006; Biscourp and Kramarz, 2007), which is the measure we also apply in Chapter 2 of this thesis. Feenstra and Hanson (1999) find that the increase in offshoring accounts for 15-40% of the increase in US high skilled workers' wage bill share. The industry level offshoring research generally concludes that an increase in offshoring leads to a rise in the skill premium in both the North and the South, which supports the theory by Feenstra and Hanson (1996). The challenge of industry-level studies is potential endogeneity issues, which arise when external shocks like technological change might affect the skill premium and offshoring intensity simultaneously (Hummels et al. 2018). Inspired by Hummels et al. (2014), in Chapter 2 of this thesis, we construct an instrumental variable that is potentially correlated with offshoring, but not with the wage structure.

Empirical evidence tends to suggest that offshoring has negative effects on onshore low-skilled workers (Hummels et al. 2014; Wright, 2014). Hummels et al. (2014) find that among high skilled workers, workers with above-the-average routineness suffer wage losses, occupations related to mathematics and social sciences enjoy a wage premium, and natural science occupations are not affected by offshoring. It suggests that dividing workers by their skill level may miss the dynamism of various occupations within each skill level. Chapters 2 and 3 of this thesis make use of a business function framework, in which each business function is an aggregated occupation group. This business function framework allows us to step away from skill groups and brings insights into the dynamism of occupation groups. Chapter 2 closely relates to Hijzen et al. (2005), who study offshoring and the skill structure of labor demand in the UK. They adopt a Seemingly Unrelated Regressions (SUR) technique to estimate a system of equations on the relation between cost shares of various skill groups (high, semi- and low skilled) and offshoring. They use a narrow measure of offshoring from Feenstra and Hanson (1999), which only considers imported intermediate inputs from the same industry. Hijzen et al. (2005) find that offshoring has a significant negative effect on low-skilled labor in the UK manufacturing industries for the period from 1982 to 1996. One important difference between Chapter 2 and Hijzen et al. (2005) is that rather than investigating workers by skill intensity, we focus on the relation between offshoring and demand for labor by activity.

One disadvantage of industry-level studies is that they do not take into account firm heterogeneity. Firms differ in attributes like size, factor use, and productivity levels. Offshoring decisions are made by firms. Focusing on industries as the unit of study may not accurately reflect what firms do, but rather reflect an aggregate scenario of firms within an industry. Being aware of the limitation of industry studies, some researchers have focused their attention on what happens at the firm level using firm-level data. These firm-level studies often adopt similar regression setups to industry-level studies. Many of these studies also make use of the offshoring measure by Feenstra and Hanson (1999), see e.g. Biscourp and Kramarz, 2007; Mion and Zhu, 2013; and Andersson et al. 2017. These studies can take into account firm heterogeneity, therefore being able to capture changes occurring within firms. Firm-level studies generally find that offshoring has an important impact on wages and employment within firms. For example, using French firm data, Biscourp and Kramarz (2007) find that growth in (narrow) offshoring is significant negatively associated with firm employment of unskilled workers. Using Belgian firm-level data, Mion and Zhu (2013) find that offshoring to China leads to a rise in the employment share of non-production workers. Andersson et al. (2017) find that offshoring raises the share of high-skilled workers using Swedish manufacturing firm data.

The most detailed research on offshoring and labor market outcomes uses worker level data. This line of research has the benefit of incorporating worker heterogeneity in addition to industry and firm-level heterogeneity. These studies are able to examine what happens to individual workers with an increase in offshoring. Some of this research uses open access data like the US Current Population Survey (CPS) that contains detailed worker information on education attainments, earnings, the industry of employment and occupation. In some applications, individuals are matched to detailed firm and trade data using a unique identifier. As a result, researchers can investigate the effect of offshoring on certain groups of workers within occupation spells (see e.g. Liu and Trefler, 2008; Ebenstein et al. 2014). The worker level data that provides the richest source of information is linked employer-employee data. These data combines the rich information from both employer and employee sides and allows one to trace workers and their affiliation over time. Researchers can identify a job spell change in wages and occupations as a result of an increase in firm offshoring (Hummels et al. 2014; Martins and Opromolla, 2009). Therefore, it identifies when there is an exogenous offshoring shock that hits the firm, what is the change in wages for workers in this firm compared to workers of other firms. Hummels et al. (2014) find that offshoring has significantly different wage effects for workers of different skill levels: offshoring improves the wages of skilled workers but lowers wages of unskilled workers.

The most widely used measure of offshoring is based on imported intermediate inputs proposed by Feenstra and Hanson (1999). However, this measure only considers material offshoring - the production stage of the value chain, but not other supporting service activities like design, R&D, management, and marketing. Services offshoring is always more difficult to capture owing to data limitations. In Chapters 3 and 4 of this thesis, we make use of the unique International Sourcing and Global Value Chain survey from Statistics Netherlands. This survey asks firms what activities they offshore, which considers both the production stage and other support business functions. Combining this firm survey with the regional statistics on employment by industry, we construct regional offshoring exposure to different activities of GVC in Chapter 3. With the development of GVC and firms relocating business functions to reduce costs, regions may specialize in a different business function. Examples including Amsterdam's specialization in finance and business activities and the Hague in government institutions. This is suggestive of an important research agenda: what is the relation between offshoring and regional functional specialization? Recent research has paid attention to examine the determinants of firms' local choice of business functions (Defever, 2006, 2012; Markusen and Venables, 2013; Timmer et al. 2019). However, these studies are mainly based on the country level, and we know little about regional functional specialization. Understanding regional functional specialization is relevant. Functions differ in the tasks that are involved and the likelihood to be relocated. For example, compared to assembly, testing and packaging activities, agglomeration forces are stronger for R&D activities (Mudambi et al. 2018). GVC and offshoring have important geographical implications. When taken into account the differences of local area exposure to offshoring and the initial industry structure, there could be a big spatial divergence in functional specialization (Elia et al. 2009). Gagliardi et al. (2015) investigate offshoring and the geography of jobs in the UK. They find that regions that are more exposed to offshoring based on their initial industry structure observe a significant decrease in routine jobs.

1.4 Firm functional specialization, innovation and productivity

The above discussion largely dealt with the impact of GVCs on the levels and growth of income and employment. Specialization in GVCs may also relate to productivity. There is a long line of research that examines the determinants of firm productivity. One important determinant is a firm's innovation efforts. R&D investment or expenditure is often used as a proxy of firms' overall innovative efforts. As theoretically put forward by Griliches (1979), the relation between R&D capital and firm productivity includes two processes: 1) the relation between R&D activity and the innovative achievements; 2) the successful implementation of innovation into the production process. The active learning model of Ericson and Pakes (1992, 1995) explains that successfully invested R&D contributes to an improvement in the efficiency and productivity of firms. Endogenous growth models also state that R&D is the engine of growth (Rochina-Barrachina et al. 2010). Empirical research often confirms that firm innovation and R&D are positively related to firm productivity (Ugur et al. 2016). Product and process innovation can both improve firm productivity (Syverson, 2011). Innovation in product quality improves product price, and therefore, the revenue of the firm. As a result, firm productivity increases as one can think of productivity as units of quality per unit input (Syverson, 2011).

The existing empirical research mainly uses R&D expenditure or investment as a proxy of firm innovation activities. In Chapter 4 of this thesis, we use the unique surveys of Dutch firms that provide information on employment composition by business function to investigate the relationship between functional specialization and firm productivity. We can determine the employment share of R&D workers, and use this as a proxy of innovation activities by firms. Furthermore, we not only focus on R&D activities but also determine functional specialization in marketing and fabrication. As a result, we can provide an alternative angle in looking at R&D activities and also distinguish other business functions.

Investigating the relation between specializing in different business functions and firm productivity is related to the well-known smile curve, where the remuneration for R&D and innovation activities is higher as compared to fabrication activities (Mudambi, 2008; Park et al. 2013). In general, the potential for productivity growth, technology, and knowledge spillovers, and markups is higher for firms that specialize in R&D and marketing activities than fabrication activities. Information technology also plays an important role in explaining differences in productivity growth in the US compared to the European

Union (Jorgenson et al. 2005, 2008; Van Ark et al. 2008). In Chapter 4, the business function 'marketing' encompasses ICT services. Therefore, we also expect specialization in marketing is positively associated with firm productivity.

1.5 Summary and main findings of chapters in this thesis

Chapter 2 investigates the macroeconomic relation between offshoring and the functional structure of labor demand in advanced economies. This chapter provides a country-industry level analysis. We use the business function data constructed by Timmer et al. (2019). We distinguish two types of offshoring, namely intermediate stage offshoring and final stage offshoring. Starting from a translog cost production function, we derive a system of equations on cost shares of different business functions, which we subsequently relate to offshoring indicators and a set of control variables like the ICT capital to output ratio. We estimate the parameters of the system using the Seemingly Unrelated Regression (SUR) technique. We are among the first to investigate the relation between different forms of offshoring and the functional specialization of labor demand in advanced economies. We add to the existing literature with the ability to further differentiate labor in each industry by business function groups using the unique business function data. This is consistent with the argument of Brown (2008) that business functions are operated and organized within each firm regardless of the industry that firm belongs to. Therefore we are able to capture patterns of vertical specialization within and across industries. More importantly, we touch directly upon the most relevant labor content of GVCs, which are the activities that are carried out, by having information on the functional structure of labor demand. We find that final stage offshoring is significant negatively related to fabrication cost share, which suggests that moving the final assembly stage abroad reduces the demand for onshore fabrication workers. On the other hand, intermediate stage offshoring is significant positively correlated with the cost share of R&D activities, but negatively correlated with the cost share of management. Intermediate stage offshoring is not significantly related to the cost share of fabrication or marketing activities. Furthermore, we find that offshoring to different destinations generally have varied and sometimes even opposite effects on the onshore functional demand. For example, intermediate stage offshoring is significant positively associated with the onshore fabrication cost share if destination is high income countries, but the opposite holds if the destination is developing countries. Final stage offshoring is negatively correlated with onshore demand for fabrication activity, whatever the destination is. As a result, we conclude that the impact of offshoring on onshore functional labor demand depends crucially on what stage of production is offshored, and where the offshoring destination is.

Chapter 3 is a regional level analysis, where we study the functional specialization of regions in the Netherlands and how offshoring is related to it. As business functions differ in the potential for productivity growth, tracking the patterns and trends of functional specialization is important to better understand the position of regions in the value chain and the potential for development (Timmer et al. 2019). We use surveys from Statistics Netherlands that provide information on offshoring regarding different business functions. Combing information from the surveys with the regional enterprise database, we are able to measure the offshoring exposure of different business functions for each region. Furthermore, we use the occupation information from the Labor Force Survey to measure the functional structure of labor demand in each region. As a result, we are able to provide key patterns and trends of regional functional specialization in the Netherlands. Furthermore, we relate functional offshoring exposure to functional labor demand in each Dutch region. Our descriptive analysis suggests the following. First, although the functional composition of the Dutch labor force is altering slowly, it is changing decisively away from fabrication and administrative activities towards knowledge-intensive activities such as R&D and technology development, sales and marketing, and management. Second, knowledge-intensive activities are more regionally concentrated compared to other activities. This concentration of knowledge-intensive activities in particular regions within the Netherlands is stable over time. Third, regions differ substantially in their specialization in business functions. Our empirical findings suggest that offshoring is not significantly related to functional specialization patterns in regions. Only for administrative and back-office occupations we find a (weak) statistically significant positive relation between offshoring and reduced labor demand. Investments in R&D and information and communication technologies relate significantly to a decline in fabrication jobs.

Chapter 4 is based on firm level data, and we study functional specialization and its relation to the productivity performance of firms in the Netherlands. In this chapter, we measure functional specialization of firms in three broad functions: fabrication, R&D and marketing. Specifically, we adopt a Balassa-type indicator of specialization where the firm's employment share in a business function is compared to the average employment share of that activity across all firms. Firms are specialized in a function if they have a relatively higher share of workers involved in that function. We then relate the functional specialization index with firm TFP estimated using the Wooldridge (2009) approach. Making use of unique data and proposing a new functional specialization index, we are able to contribute by examining the relation between the functional specialization of firms and their productivity performance. We find that firms specialized in R&D and marketing are significantly more productive compared to firms that specialized in fabrication. These findings are robust to controlling for other potential determinants of productivity. This result suggests returns from R&D as well as building brand names are higher compared to fabrication (Mudambi, 2008; Park et al. 2013). We do not observe a significant relation between functional specialization and mark-ups. Firms covered in the analysis might be more exposed to international competition due to the nature of products produced or function performed, such that these firms face difficulty charging prices above marginal costs.

Chapter 2

Offshoring and the Functional Structure of Labor Demand in Advanced Economies

2.1 Introduction

In this chapter, we analyze the relation between offshoring and onshore labor demand in a country-industry setting. There is a large extant body of literature on this topic that is further discussed below. We contribute to this by analyzing the effects of offshoring in a so-called 'business function' framework. Instead of analyzing the impact of offshoring on demand for workers with particular skills or levels of educational attainment, we analyze the demand for workers who participate in a particular business function group: R&D, fabrication, management or marketing. We show that this offers new, and more nuanced, insights into the effects of offshoring on labor demand in advanced countries.

There is abundant academic research that lays a theoretical foundation of the relationship between offshoring and onshore labor market outcomes, even though the channels and predictions differ by theory. Feenstra and Hanson (1997) model offshoring as trade in intermediate inputs in a two-region (North-South) setting. The developed North is relatively skilled abundant and therefore exports skill-intensive intermediates to the developing South. The model assumes that the offshored intermediates are less skill-intensive than those remaining onshore but more skill-intensive than the production of the intermediates in the South. As a result, the skill intensity of production in both the North and the South increases, driving up demand for skilled labor and accordingly the skill premium in both countries. Other theories try to model the effects of North-North offshoring and labor market outcomes. Burstein and Vogel (2010) study two identical countries that are both advanced. With a drop in trade costs, both countries start to offshore by exporting inputs. With the assumption of productivity being skill labor biased, the less productive firms contract their production, and production resources are redistributed towards the more productive firms. Exporters are those firms with higher productivity in both countries. As a result, the demand for high-skilled labor increases in both countries and so are the skill premiums, as in the Feenstra and Hanson (1997) model. Complementary to Feenstra and Hanson (1997), Grossman and Rossi-Hansberg (2008) provide a theoretical framework that studies 'trade in tasks'. Along a continuum, tasks are performed by increasingly skilled labor. They assume that the wage of skilled labor is the same in both the North and the South but the unskilled wage is lower in the South. The North, therefore, has an incentive to offshore unskilled tasks to the South, with the possibility that it leads to a higher wage level for domestic unskilled workers in the North but with no effect on the wage of high skilled labor. As a result, the skill premium declines in the North. This situation is referred to by the authors as one where the 'productivity effect' dominates the 'relative-price effect' and the 'labor supply effect'.

There is a long list of research that provides empirical evidence to the theoretical predictions, typically trying to identify the relationship between offshoring and the onshore labor market outcomes. The common practice in this research is to use variation at the country-industry level data with a panel structure, and investigate the relationship between changes in offshoring and the relative demand of onshore skilled workers (e.g. Berman et al. 1994; Feenstra and Hanson, 1999; Hsieh and Woo, 2005). These studies typically find the rise in offshoring improves the demand for skilled labor and skill premium in both the North and the South.

In this chapter, we study the relation between offshoring and onshore labor demand across 13 manufacturing industries in 16 developed economies over the years 1999-2007. We provide empirical evidence for both North-North and North-South offshoring by using data from the World Input Output Database (WIOD). We bring two main contributions to the existing (empirical) research on this topic. Offshoring is typically measured by the share of imported intermediate inputs following Feenstra and Hanson (1999), and labor demand is characterized by skill or educational attainment type. We differ, firstly, by considering another type of offshoring, which is what we will call 'the final stage offshoring' measured by intermediate inputs being exported. Secondly, we classify workers by the activity their occupation is associated with rather than their skill levels. In the next paragraph, we will further elaborate on why the two innovations are important and how that enriches the analysis.

We consider two types of offshoring: intermediate stage and final stage offshoring. The first concept is measured by the widely used measure from Feenstra and Hanson (1999), defined by the imported intermediate inputs as a share in total intermediate inputs used. This measure captures the process of offshoring intermediate production stages abroad and imports the intermediate inputs back to the home country to further carry out the final assembly. We refer to this as intermediate stage offshoring. However, this measure does not incorporate another type of offshoring, which is offshoring of the final stage of production. For final stage offshoring, intermediate inputs produced at home are assembled in foreign countries. Therefore, the export of intermediate inputs abroad potentially captures this process. This second type of offshoring is studied in previous works by Liu and Trefler (2008) and Andersson et al. (2017), where it is called, somewhat confusingly, 'inshoring'. In Liu and Trefler (2008), inshoring refers to 'the sale of services produced in the US to unaffiliated parties in low-wage countries', whereas Andersson et al. (2017) extend the definition by including both goods and services, affiliated and unaffiliated groups, and low and high wage countries. In our study, we call this process final stage offshoring, as the final stage assembly of intermediate inputs happens in other countries. We expect that final stage offshoring is negatively related to onshore fabrication cost share, as in particular assembly tasks are performed offshore. For example, Apple puts the assembly plant in China and the fabrication workers who perform assembly activities in the US would relatively decline. We also expect intermediate stage offshoring to be negatively related to onshore fabrication cost share, as it reflects a process of domestic workers who produce those intermediates being replaced by foreign workers.

A second innovation is that we distinguish workers by activities/business functions they perform (we use the two terms interchangeably throughout this chapter) according to their occupation. The common practice of related studies is to distinguish labor by their skill intensity, which is often measured by education attainment. However, the skill intensity of labor does not correspond directly to the offshoring decision of firms. Multinational firms typically organize their activities around business functions such as fabrication, R&D, and management (Porter, 1985; Sturgeon and Gereffi, 2009; Nielsen, 2018). There is not a clear cut mapping between business function and skill intensity. On average, we expect R&D workers to be more skilled than fabrication workers. However, not all fabrication workers are low skilled, and vice versa, not all R&D workers are highly skilled. With management and marketing workers, the relation to skill intensity is even more indecisive (Timmer et al. 2019). If offshoring decision is made about what business function to offshore, then its relation to labor market outcomes should be more about labor related to different business functions rather than their skill levels. As a result, we believe focusing on business function rather than skill level gives us a more direct perspective to investigate production fragmentation using offshoring and the onshore labor market outcomes. Firms in developed countries tend to offshore production and assembly activities to benefit from the low factor costs abroad. As a result, the onshore relative demand for fabrication activity would decline. However, the relative demand for other activities, such as R&D, management or marketing is yet to be determined and depends crucially on the substitution and complementarities across activities that are not well known. For example, Defever (2006) emphasizes the impact of complementarities between R&D and fabrication activities that are carried out in one location and discusses other motives for the co-location of activities. Furthermore, in our analysis, we also distinguish the offshoring destinations in terms of developing countries and developed countries, as some research finds that the destination of offshoring also matters for the impact on onshore labor demand (e.g. Harrison and McMillan, 2011; Ekholm and Hakkala, 2008). Ekholm and Hakkala (2008) find that offshoring to low-income countries is correlated with lower demand for workers with middle education level, but a higher demand for workers with a high education level. However, the opposite result is found for offshoring to high-income countries. We will investigate whether the same variation in impacts is found for different types of workers characterized by the activities their occupations are related to.

Starting from a translog cost production function, we derive a system of equations on cost shares of different business functions, which we subsequently relate to offshoring indicators and a set of control variables like ICT capital to output ratio. We estimate the parameters of the system using the Seemingly Unrelated Regression (SUR) technique. The main results are based on data for manufacturing industries. They indicate that final stage offshoring is significant negatively related to fabrication cost share, which suggests that moving the final assembly stage abroad reduces the demand for onshore fabrication workers. Perhaps more interesting is our finding that intermediate stage offshoring is significant positively correlated with the cost share of R&D activities but negatively correlated with the cost share of management activities. Intermediate stage offshoring is not significantly related to the cost share of fabrication or marketing activities. We show that the results are robust to different specifications. Furthermore, we find that offshoring to different destinations generally has varied and sometimes even opposite effects on the onshore functional demand. For example, intermediate stage offshoring is significant positively associated with the onshore fabrication cost share if the destination is high-income countries, but the opposite holds if the destination is developing countries. Final stage offshoring is negatively correlated with onshore demand for fabrication activity, whatever the destination is. As a result, we conclude that the impact of offshoring on onshore functional labor demand depends crucially on what stage of production is offshored, and where the offshoring destination is.

The rest of the chapter proceeds as follows. Section 2.2 briefly reviews the relevant measures of offshoring. Section 2.3 presents the empirical model based on a translog cost function, and estimates a system of equations using the SUR technique. In section 2.4, we introduce the data sources and provide descriptive statistics on offshoring and functional structure of labor demand with our sample. In section 2.5, we report the baseline results based on the manufacturing industry sample, and the extension results from the non-manufacturing industry sample. Furthermore, we report the results and discussion of the instrumental variable (IV) approach. Section 2.6 concludes.

2.2 Measurement of offshoring

It is important to know what we mean by offshoring before considering how we can measure offshoring. In the spirit of Hummels et al. (2018), we think there are two key elements of offshoring. Firstly, offshoring is related to intermediate inputs that are used in the production process, rather than final goods for consumer demand. Secondly, intermediate inputs should be traded, rather than domestically produced. Put otherwise, offshoring entails the outsourcing of a task initially performed at home, which is now performed abroad and embodied in an import.

A widely used offshoring measure is the one introduced by the pioneering work of Feenstra and Hanson (1999). It is based on information from input-output (IO) tables. The IO table displays how much inputs are used in each sector and their relative importance in cost-shares. The degree of offshoring in an industry is measured as the share of imported intermediates in the value of total (non-energy) intermediates. In Feenstra and Hanson (1999), there are two types of offshoring, namely broad offshoring and narrow offshoring. The narrow definition of offshoring only considers imported intermediate inputs by industry from that same industry as a share in total non-energy intermediates. The broad definition considers all imported intermediate inputs by an industry as a share in total non-energy intermediates. The difference is in the characterization of the input as potentially producible by the industry under consideration. One important advantage of the narrow measure by Feenstra and Hanson (1999) is that the industry is likely to be able to produce the imported input itself. Even though we are not able to observe whether or not the firm could have produced the input by itself, however, narrow offshoring allows us to observe the similarity between the imported intermediate input and the output being produced, as they are both from the same industry (Hummels et al. 2018). It is more likely that a firm would have been able to produce the inputs that are from the same industry to which the main output of the firm belongs.

In this chapter, we apply the offshoring measure of Feenstra and Hanson (1999) using the WIOD. Besides, we also take into account another type of offshoring which we call ‘final stage offshoring’. This has been called ‘inshoring’ by Liu and Trefler (2008) and

Andersson et al. (2017), but we prefer our naming. We define final stage offshoring as the ratio of the export of intermediates by a local industry to that same industry in other countries as a share in total non-energy sales. As this process reflects that firms produce the intermediate inputs themselves and export those inputs abroad for final assembly, therefore we call it final stage offshoring. To distinguish this type of offshoring from the more well-known offshoring type described by Feenstra and Hanson (1999), we call the latter 'intermediate stage offshoring' as firms offshore the intermediate stage production abroad.

Measuring offshoring comes with empirical problems. The most common critique of this method is the use of the 'proportionality assumption' as it is not reflecting reality (e.g. Housman et al. 2011). That is, as data on the imported intermediate inputs by industry is scarce for most of the countries, the common approach in the empirical analysis is to rely on information from IO-tables. However, many IO-tables are constructed based on the assumption that every industry in an economy imports each intermediate input in the same proportion as the economy-wide use of the input (Winkler and Milberg, 2012). This proportionality assumption can be misleading for some industries. Feenstra and Jensen (2012) proposed an alternative method that uses firm-level data on imports and production to construct firm-level IO-tables and further aggregate them to the industry level. They found that at the three-digit industry level, the correlation between offshoring shares measure with and without the proportionality assumption is 0.68, and a higher correlation of 0.87 if the shares are value-weighted. According to Feenstra (2017), an alternative to the proportionality assumption is using the firm-level share of imported inputs, however, the firm-level import data is quite scarce and not available for many countries.

Another critique of the offshoring measure by Feenstra and Hanson (1999) is that they do not address the possibility of goods crossing multiple borders during the production process. It might, for example, be the case that a product imported from China by the US also contains US value-added. To alleviate this concern, a new measure of offshoring has been proposed, which distinguishes between the domestic and foreign value-added in exports (Johnson and Noguera, 2012; Koopmans et al. 2014; Los et al. 2016). The advantage of this method is to indicate how much value is added to the export of a country from foreign countries and home country respectively, which are expressed as foreign value added in exports (FVAiX) and its counterpart domestic value added in exports (DVAiX) respectively. FVAiX and DVAiX indicate the degree that countries are involved in the GVC. With further analysis in the framework of IO-tables, FVAiX and DVAiX can be related to employment, which shows how much employment can be affected by an increase (decrease) in FVAiX or DVAiX. However, this approach of relating FVAiX and DVAiX with employment should be used with care. According to Feenstra (2017), relating FVAiX to employment effects takes the increase in exports as exogenous. In other words, it is an ex-post analysis treating final demand as given, and then using it to derive the demand for jobs. However, the change in exports and their impacts on employment are endogenous and it is unclear how FVAiX affects wages. This is where the measure of Feenstra and Hanson (1999) has an advantage over FVAiX. The research that uses narrow offshoring shows that it acts as a shift parameter in the labor demand and the interaction of prices and quantities can be modeled. For example, consider the model by Feenstra and Hanson (1997) we briefly discussed in the introduction, the developed North offshored intermediate inputs to the developing South. These intermediate inputs are less skill-intensive than the ones remain in the North, but more skill-intensive than the ones produced in the South. As a result, the skill intensity of production in both the North and the South increases, driving up demand for skilled labor and accordingly the skill premium in both countries. This model with offshoring measure as a shift parameter in the demand for labor is compatible with the general equilibrium of the economy (Feenstra, 2017).

There are also other measures of offshoring that are mainly based on firm-level data. For example, Feenstra and Hanson (1997) use the share of foreign plants in total plants within an industry as an indicator of offshoring. Ebenstein et al. (2014) use the growth in employment of affiliates of the US multinational firms as an indicator of offshoring. The idea is that if a firm expands its employment by establishing an affiliate abroad, it is an indication that the inputs or tasks that had been produced within the firm domestically are now being done offshore. The firm-level measures of offshoring avoid the problem with the proportionality assumption. However, according to Hummels et al. (2018), these offshoring measures based on multinational data miss offshoring that does not take place in-house but at arms-length through market transactions.

Another indicator of offshoring is based on information from the so-called ‘factory-less goods producing firms (FGPFs)’ (Bernard and Fort, 2015). FGPFs are firms and plants that do not get involved in the production process themselves but are heavily involved in those activities that are related to the production of goods, like design the goods they sell and coordinate the production activities (Bernard and Fort, 2015). This is a new form of task specialization that separates goods production activity from other supporting service activities. Without task specialization, all these activities should have been produced within the firms in the domestic market (Hummels et al. 2018). Clearly, FGPFs differ from our measure of ‘final stage offshoring’ in that FGPFs do not engage in production activities to produce intermediate goods or assemble final products.

To summarize, among all the offshoring measures we outline above, the industry level offshoring measure from Feenstra and Hanson (1999) is the most widely applied method, but with the limitation that the measurement often relies on information from IO-tables that are frequently based on the proportionality assumption. The FVAiX approach incorporates the possibility of goods crossing multiple borders during the production process. However, the limitation is that it is not consistent with the general equilibrium of the economy. The recent availability of firm data allows researchers to adopt firm-level offshoring measures, which avoids the industry level limitations. However, it is not always possible to apply these measures as detailed firm-level data is not available in many countries.

Furthermore, it is important to remember that offshoring is related to the concept of import competition but these concepts are intrinsically different. For example, Autor et al. (2013) have investigated the effects of exposure to Chinese import competition on the local labor market in the US. They find that local areas that are more exposed to Chinese import competition have both lower employment of manufacturing workers and a decline in wages. However, import competition differs from offshoring as the former involves import of not only intermediate inputs but also final goods. Therefore, both processes affect the local labor market outcomes, but import competition may differ in its effects on the organizational structures of firms and the locations of various activities in the production network compared to offshoring (Hummels et al. 2018).

2.3 Empirical model

In section 2.3.1 we describe the econometric model we use for the baseline empirical analysis. In the baseline, we will focus on manufacturing industries, and in the additional analysis, we will also investigate non-manufacturing industries. In section 2.3.2, we describe our IV approach for the identification analysis of manufacturing industries.

2.3.1 Baseline model

To analyze the role of offshoring on changes in the functional structure of labor demand, we propose to use the translog cost function framework as introduced by Christensen et al. (1973). This framework has frequently been used in studies about the impact of international trade on labor demand, mainly because of its flexibility: it can approximate any functional form and allows for varying elasticities of substitution.

Given that we will distinguish between labor income from four business functions, we will have a system of four equations. Instead of estimating single equations of labor demand as in Michaels et al. (2014), we simultaneously estimate a system of variable functional labor demands using panel data techniques as in Hijzen et al. (2005). The right-hand side variables in the equations are the same. In order to impose cross-equation constraints, we use Iterated Seemingly Unrelated Regressions (iSUR) to estimate the model (Wooldrige, 2011), further discussed below.

The variable factors of labor demand are reflected by labor cost shares of business functions. In our main analysis, we examine R&D, fabrication, management and marketing activities. Together these sum up to the total labor cost share in value-added. We assume the industry cost functions can be approximated by a translog function that is twice differentiable, linearly homogeneous and concave in labor income by business function. We focus on a short-run cost function, keeping capital and output (quasi) fixed. Hence, both output and capital are treated as exogenous in the short run, as in Berman et al. (1994), Feenstra and Hanson (1999), Hijzen et al. (2005) and González-Díaz and Gandoy (2016). The short-run cost function can be expressed as:

$$\begin{aligned} lnC(w,x)_S = \alpha_0 + \sum_{i=1}^{F}\beta_i lnw_{si} + \sum_{k=1}^{K}\beta_k lnx_{sk} + \frac{1}{2}\sum_{i=1}^{F}\sum_{j=1}^{F}\gamma_{si} lnw_{si} lnw_{sj} + \\ \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\gamma_{kl} lnx_{sk} lnx_{sl} + \sum_{i=1}^{F}\sum_{k=1}^{K}\gamma_{ik} lnw_{si} lnx_{sk} \end{aligned} \tag{2.1}$$

Where C refers to total variable costs; w_{si} denotes prices for labor in business functions $i = 1, \ldots, F$ and industry $s = 1, \ldots, N$. It is common to treat labor as a variable input in short-run cost function. However, labor may not be fully flexible in reality (Van Heuvelen et al. 2019), which will be further discussed in Chapter 4. The variable x_{sk} denotes the number of fixed capital inputs or output, and offshoring $k = 1, \ldots, K$ in industry $s = 1, \ldots, N$. We omit time subscripts for simplicity.

We assume cost minimization and take the first order derivative of the cost function, $\frac{\delta lnC_s}{\delta lnw_{si}} = (\frac{\delta C_s}{\delta w_{si}})(\frac{w_{si}}{C_s})$.Using Shephard's lemma it follows that $\frac{\delta lnC_s}{\delta lnw_{si}}$ equals the demand for the chosen business function i in industry s, and hence $\frac{\delta lnC_s}{\delta lnw_{si}} = \frac{L_{si}w_{si}}{C_s} = S_{si}$ equals the payments to business function i in industry s relative to total variable costs in industry s, which we will denote by the cost shares S_{si}. We obtain the following equation to estimate the labor demand by business functions in each industry:

$$S_{si} = \beta_i + \sum_{j=1}^{F}\gamma_{ij} lnw_{sj} + \sum_{k=1}^{K}\gamma_{ik} lnx_{sk} + \varepsilon_i \tag{2.2}$$

Where S_{si} is the labor cost share of a business function in total labor compensation in a certain industry and $\sum_{i=1}^{F} S_{si} = 1$.[2] We impose constant returns to scale to ensure that the cost function is linearly homogeneous in prices of the variable business functions, hence $\sum_{i=1}^{F} \beta_i = 1$ and $\sum_{j=1}^{F} \gamma_{ij} = 0$ for any i. Symmetry implies that $\gamma_{ij} = \gamma_{ji}$. Since the summation of the cost shares of all business functions is equal to one by definition, we have $\sum_{i=1}^{F} \gamma_{ik} = 0$. Furthermore, we also add country, industry and time dummy to equation 2.2.

The relation between the two types of offshoring and functional specialization is of particular interest. As reviewed in the introduction of this thesis, many studies find that intermediate stage offshoring lowers the demand for low-skilled workers while raising the demand for high-skilled workers. Timmer et al. (2019) show that R&D is relatively high-skill intensive while fabrication is relatively low-skill intensive, though it is difficult to assign management and other activities like sales and marketing to particular bundles of factor requirement. We, therefore, expect that intermediate stage offshoring is negatively related to the fabrication cost share, but positively related to labor cost shares of R&D activities. About the final stage offshoring, Andersson et al. (2017) suggest that the impact on labor demand is a priori unclear. [3] Whether or not the offshored activities are high or low skill-intensive is a crucial factor in play. In other words, if the final stage offshoring is mainly related to high skill activities, then the relative demand for high skill workers will increase at home. To the opposite, if final stage offshoring is mainly related to low skill activities, then the onshore relative demand for high skill workers should decrease. We also expect that the destination of the offshoring will play an important role for the potential divergent effects on different types of labor, and will investigate this in the empirical analysis.

Besides trade variables, technology is the most important control variable in our framework, which provides insights on the effect of technological change on functional specialization. We use ICT capital stock to output ratio as a proxy of technological change. The literature has documented a negative relationship between technological change and the low-skilled wage bill shares but a positive relationship between technological change and the high-skilled wage bill share based on the skill-biased technological change and the routine-biased technological change hypothesis (Bernard and Fort, 2015; Feenstra 2017; Hummels et al. 2018). In our study, we expect technological change to be negatively related to labor cost share of fabrication activities, but positively related to labor cost share of R&D activities.

[2] We take logarithms for all explanatory variables in equation 2.2, except for offshoring which is measured as a share.

[3] Andersson et al. (2017) define the export of intermediate inputs inshoring, instead of final stage offshoring.

In our baseline analysis, the system of share equations with the parameter restrictions is estimated by iterating Zellner's method for SUR equations. Since the business function shares sum to one, the disturbance covariance matrix of the system is singular and one equation needs to be dropped. In contrast to standard SUR, the estimation results from the iSUR are invariant to the equation deleted. Therefore, we combine the iSUR estimator with country, industry and time fixed effects to estimate the system given by equation 2.2.[4] The parameter estimates of the cost function are used to examine the effects of the two types of offshoring on the functional structure of labor demand controlling for technology.

Besides reporting the estimated results stated above, we will also report the elasticities of substitution and the elasticities of business function demand. Among others, these are used to determine the economic significance of the regression coefficients. Furthermore, among others, substitution elasticities are used to examine whether two business functions are complementary to each other. Note that the coefficients γ_{ij} in equation 2.2 are the second order derivatives to the business function prices. Hence, a negative estimate of γ_{ij} can loosely be interpreted as a net-complementarity between business function i and j. As it implies a price increase of business function j decreases the cost share paid to business function i and hence the usage of i must decrease. More formally, the substitution elasticities between business functions (σ_{ij}) are given by the Allen-Uzawa partial elasticities of substitution:

$$\sigma_{ij} = \frac{\gamma_{ij}}{s_i s_j} + 1 \; (for \; i \neq j) \tag{2.3}$$

The price elasticity of demand for business function i to the price of $j(\epsilon_{ij})$ is given by:

$$\begin{aligned} \epsilon_{ij} &= \sigma_{ij} s_j = \frac{\gamma_{ij}}{s_i} + s_j \; (for \; i \neq j) \\ \epsilon_{ii} &= \frac{\gamma_{ij}}{s_i} + s_i - 1 \; (for \; i = j) \end{aligned} \tag{2.4}$$

We can use the price elasticity of demand for the business function to check for the concavity of the cost function in factor prices. As is clear from these definitions, elasticities depend on cost shares that vary across observations. We follow common practice (e.g. Hijzen et al. (2005)) and evaluate the elasticities based on the unweighted average cost

[4] The standard one-step SUR combines multiple equations into one stacked form and estimates it using ordinary least squares. The iSUR is estimated using maximum likelihood. We use the latter and although it might not always converge, it did in all our applications in the main analysis. The empirical results from iSUR are close to the standard one-step SUR.

shares across all observations that are included in the regression analysis. [5] We will report the own-price elasticities in the result section.

However, to satisfy the concavity condition in factor prices, all the own-price elasticities being negative is a necessary but not sufficient condition. We need to further check whether the cost function satisfies the cost minimization assumption. The Hessian matrix of second-order derivatives for factor prices must be negative semi-definite for the cost function to be well-behaved. We examined whether the curvature conditions are satisfied at each observation using the approach suggested by Diewert and Wales (1987). The curvature conditions are not satisfied at all points in our estimates, but it is in the majority.

Finally, the economic significance for business function i concerning a change in a fixed variable is given by:

$$\varepsilon_{ik} = \frac{\gamma_{ik}}{s_i} \tag{2.5}$$

Therefore ε_{ik} is the relative change in functional cost shares when there is a unit change in the fixed variable like offshoring and ICT capital stock to output ratio.

2.3.2 Instrumental variable approach

In the econometric model, we can control for industry and country heterogeneity owing to the panel structure of the data. There are still steps to take if we aim to identify the causal relationship between offshoring and the functional specialization across country-industry pairs. As discussed in other literature (see e.g. Autor et al. 2013; Hummels et al. 2014; Andersson et al. 2017), a concern for causal interpretation of the results from the econometric analysis is that both the offshoring measures and labor cost shares in equation 2.2 may correlate with demand or productivity shocks. For example, suppose that new technology like automation of certain tasks in assembling cars through a robot, decreases demand for workers in fabrication activities in the domestic economy and at the same time also makes it easier to offshore assembly lines to other countries. This shock will have an impact on both offshoring (up) and the fabrication wage cost share in the domestic industry (down, assuming wages remain constant) of the relevant country-industry pair. As a result, the OLS estimate is biased due to the simultaneity issue. The direction of the bias depends on the relative effect of productivity shock on offshoring and cost share. The identification challenge is particularly relevant for firm-level studies as firm-level shocks

[5] We use a small letter s in equations 2.3 and 2.5 to denote that the elasticity is evaluated at the mean share for business function i.

to demand or productivity will affect trade and wage-setting simultaneously (Hummels et al. 2014). This endogeneity issue might be much less of a concern on the industry level which we analyze. In any case, we conclude that more generally, intermediate inputs trade and labor cost shares may be correlated due to unobserved industry level demand and productivity shocks, and we will try to solve this problem.

In our study, we try to deal with this endogeneity issue by constructing an instrumental variable (IV). The IV should, in theory, be correlated with the endogenous variable offshoring, but not directly related to cost shares of each country-industry pair. In other words, the connection between the IV and cost shares in a country-industry pair only comes indirectly from the connection between the IV and the endogenous variable. In the spirit of Autor et al. (2013) and Hummels et al. (2014), we construct an IV to identify the causal effect of intermediate stage offshoring on functional specialization. We instrument intermediate stage offshoring using a newly constructed variable which we call the world export supply (WES).[6] The WES captures the change in the world export supply of products by an industry. In general, using WES as an instrument controls for productivity changes from the concerned country-industry pair that would affect both trade in intermediate inputs and wage-setting simultaneously. As a result, the instrument may potentially alleviate endogeneity biases.

To construct the instrument WES for offshoring, we select the top ten countries in export value to measure world export supply as they account for a relatively big share of the international trade value. The ten exporters are China, the US, Germany, Japan, South Korea, France, the Netherlands, Italy, the UK, and Canada. Relevant world export supply (WES_{cdt}) for a particular country c is the total export value from industry d of the ten exporting countries (excluding country c) to the same industry in the world market, minus their exports to industry d in country c, in period t. WES captures global supply shocks regarding products from industry d, which may originate from exogenous productivity shocks in the exporting countries (e.g. liberalization of the Chinese economy leading to productivity growth in Chinese exports). In other words, WES captures the comparative advantage of the exporting countries, which affects offshoring for the focused country-industry pair. However, we exclude the export to the focused country-industry pair from WES, which means WES is not directly related to the wage setting of the focused country-industry. In order to construct WES, we require bilateral intermediate trade flows for country-industry pairs. These are taken from the WIOD. Our indentification strategy also has limitation considering several countries from the top ten exporters are from the EU. This could potentially affect the quality of the IV as the underlying drivers of the

[6] We also construct the IV for final stage offshoring, which is the world import demand (WID). However, the instrument is too weak to work adding both IVs in the regression analysis. WES and WID are the original names of IVs from Hummels et al. (2014).

endogeneity problem may be correlated among these countries.

Since we have a system of equations that relate to each other, it is in our interest to be able to impose cross equation constraints. This means that we need to find an estimation method that allows us to estimate the system of equations simultaneously and can address the endogeneity issue at the same time. Zellner and Theil (1962) introduced Three Stage Least Squares (3SLS), which is generally more efficient than 2SLS when cross equation constraints are needed. 3SLS is a special version of 2SLS that takes advantage of correlations of cross equations. According to Wooldridge (2011), when estimating a system of equations, if all equations are correctly defined, then system estimation like 3SLS is asymptotically more efficient than a single equation estimation like 2SLS. The first stage of 3SLS is to estimate the model in 2SLS, the second stage is to use 2SLS estimates to compute residuals to derive cross equation correlations, and the last stage is to use GLS to estimate the model parameters.

2.4 Data and descriptive statistics

2.4.1 Data construction

We have a panel dataset that includes 16 high-income economies from 1999 to 2007. For each economy, 31 industries are distinguished, including both manufacturing and non-manufacturing industries.[7]

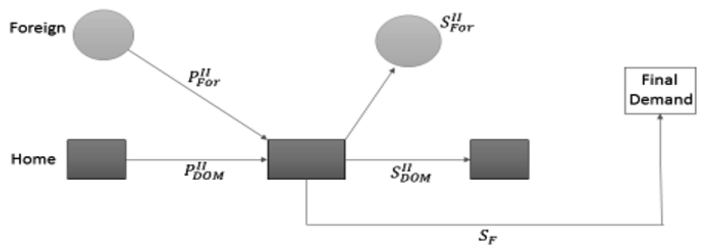
Data for the cost shares of the business functions is obtained from Timmer et al. (2019). They collect detailed information on the income and occupation of workers from detailed surveys and census data for 40 countries and 35 industries. The labor cost shares are calculated using the relative wage and employment share of occupations. The time-series information on occupations and wages of workers is collected. Occupations are mapped to activities using as a guideline according to the list of business functions proposed by Sturgeon and Gereffi (2009), which itself is derived from a list of generic business functions first proposed by Porter (1985). There is no standardized classification of business activities (Brown, 2008), but typically the main distinction is between fabrication and headquarter (Markusen, 2002). Headquarter is further split into R&D, management and other activities which mainly include sales and marketing services. The wage data is from EUKLEMS, where the labor compensation and employment information are provided on the industry level. Combining with the labor cost shares information on business function level from Timmer et al. (2019), we are able to calculate the wages of different business

[7]For the full list of the economies and industries, please refer to Appendix Table 2.A8 and 2.A9.

functions by industry.

We relate changes in functional specialization to trade in intermediate inputs. We distinguish two types of offshoring, namely intermediate stage offshoring (Int-Off) and final stage offshoring (Fin-Off). Figure 2.1 illustrates the mechanisms of the two types of offshoring. Consider a specific industry from home country, on the one hand, it can purchase intermediate inputs from abroad or home country; on the other hand, it can also sell intermediate inputs and final goods abroad or to the home country. It is important to first understand how offshoring is defined and then we will come back to the relation in Figure 2.1.

Figure 2.1: Intermediate stage and final stage offshoring



Note: This figure illustrates the process of the two stages of offshoring. Dark grey box and light grey circle represent home country and foreign country respectively. P and S represent purchase and sales, For and DOM represent foreign and domestic respectively. II refers to intermediate inputs.

Our measures of offshoring are obtained from the annual World Input-Output Tables, release 2013 (Timmer et al. 2015), and include offshoring to foreign affiliates and/or arm's length transactions in intermediates. 'Intermediate stage offshoring' is measured as previously by Feenstra and Hanson (1999). Intermediate stage offshoring is precisely the offshoring defined by Feenstra and Hanson (1999), namely the share of imports in intermediate inputs use. In this chapter, we also consider another type of offshoring, namely 'final stage offshoring', which is closely related to the so-called 'inshoring' concept introduced earlier in Liu and Trefler (2008) and Andersson et al. (2017). To be specific, we define final stage offshoring as the sale of intermediate goods and services produced in the home country abroad. Exporting of intermediate inputs may be the result of quality reputation, firm-level economies of scale or supply of a specific kind of intermediate input (Andersson et al. 2017). Whatever the motivation is, exporting a higher share of intermediate inputs abroad is indicative of the assembly of final production stages. Most existing research mainly focuses on intermediate stage offshoring in the vein of Feenstra and Hanson (1999). However, given the importance of offshoring of final (assembly) stage to especially low cost developing countries, it is relevant and important to also investigate the relationship between this other type offshoring and the onshore functional labor demand. To measure final stage offshoring, we consider intermediate inputs in total sales. So for a particular industry, we define two offshoring indicators: the intermediate (Int-Off) and final stage (Fin-Off) offshoring are defined as follow:

$$Int - Off = \frac{P^{II}_{For}}{P^{II}_{For} + P^{II}_{DOM}} \tag{2.6}$$

$$Fin - Off = \frac{S^{II}_{For}}{S^{II}_{For} + S^{II}_{DOM} + S^{F}} \tag{2.7}$$

Variables P and S represent purchases and sales of Intermediate Inputs (II) from (to) domestic (DOM) and foreign (For) industries. Feenstra and Hanson (1999) provide further refinement of offshoring measures, distinguishing between the so-called 'narrow' and 'broad' measures. The narrow definition of intermediate stage offshoring only considers the traded intermediates by an industry from that same industry as a share in total non-energy intermediates. The broad definition considers all traded intermediates by an industry as a share in total non-energy intermediates. [8] Feenstra and Hanson (1999) prefer to use the narrow definition of offshoring as it is thought to come closer to the essence of fragmentation which takes place within an industry. We follow them and use the narrow measure in our main analysis, but will examine the sensitivity of the results to using the broad measure of offshoring.

We also construct the narrow measure of final stage offshoring, which is the export of intermediates by an industry to that same industry as a share in total non-energy sales (as in Andersson et al. 2017). In addition, we also construct the broad measure of final stage offshoring as all exported intermediates by an industry as a share in total non-energy sales. We focus on the narrow offshoring measure in our analysis and consider the sensitivity of the results to using the broad measure of offshoring.

We will treat capital as quasi-fixed in the short run in our analysis (see section 2.3). With the data at hand, we can distinguish between Information and Communication Technology (ICT) capital stocks and non-ICT capital stocks. We use the real ICT capital

[8] The excluded energy inputs are mining and quarrying (International Standard Industry Classification (ISIC) revision 3, industries 10 to 14), manufacture of coke, refined petroleum products and nuclear fuel (industry 23), and electricity, gas and water supply (industries 40 and 41). This categorization of energy inputs is larger compared to conventional definitions (O'Mahony and Timmer, 2009), which considers ISIC rev. 3 industries 10 to 12, 23 and 40. Our industry data is not disaggregated enough to exactly conform to this definition.

stock to output ratio (in 1995 prices) as the measure of technology development and include non-ICT capital stock to output ratio as a control variable. For most country-industry cells, ICT capital stock information is available until 2007 in the March 2011 update of EUKLEMS (O'Mahony and Timmer, 2009). However, for several countries, the analysis is restricted to 2005 as capital stock data was not updated. [9] The other data needed for our analysis, namely value-added, total labor compensation and employment are taken from the WIOD SEA database. All values are in current US dollars based on official exchange rates (2013 release, Timmer et al. (2015)).

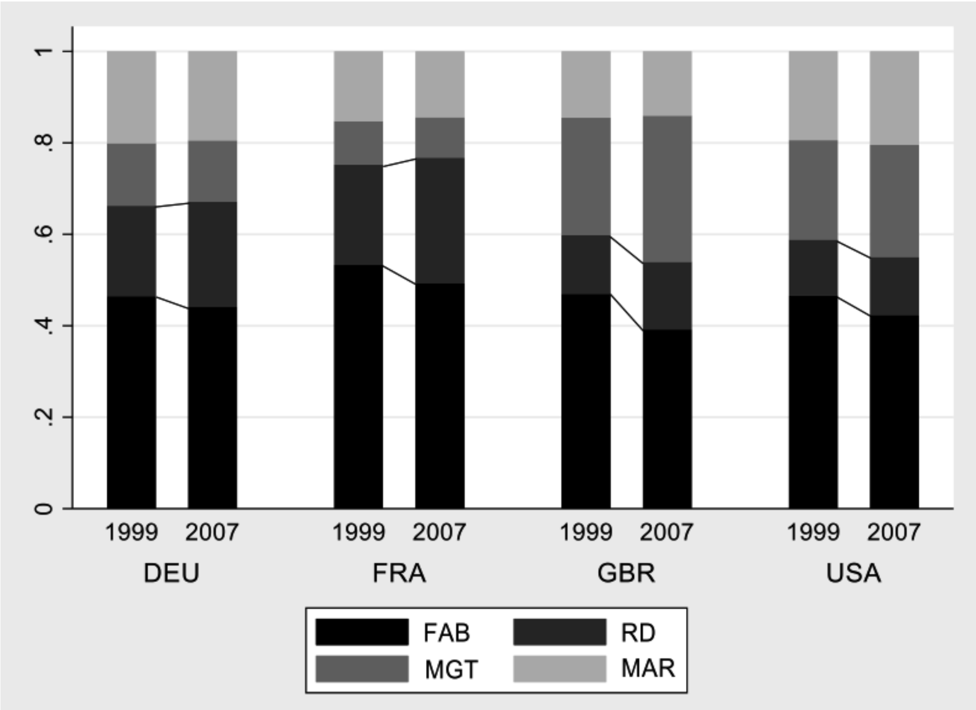
2.4.2 Descriptive statistics

In this section, we will mainly focus on two sets of descriptive statistics. Firstly, we will report descriptive statistics on labor cost shares. Secondly, we will report descriptive statistics on offshoring. In the end, we will have a look at the general patterns of the key variables that will appear in the regression analysis.

First of all, it is interesting to have a look at some general country-industry comparisons with labor cost shares regarding different activities. Figure 2.2 shows the cost share by business functions in the manufacturing industries of four countries, namely Germany, France, the United Kingdom, and the United States in 1999 and 2007. Although the trend of an increasing R&D cost share relative to that of fabrication is observed in each of the countries shown, the levels are rather different. That is, the R&D cost share appears to be higher in Germany and France compared to that in the UK and the US. In contrast, cost shares for management appear to be much higher in the UK and the US. The cost shares of marketing activities are similar across all four countries but that of Germany and the US are slightly higher. This is consistent with the finding of Timmer et al. (2019). They find that there is a high level of heterogeneity in functional specialization across advanced countries with a similar income level. They also find that advanced countries mainly specialize in R&D activities especially countries like France and Germany. Besides, other countries like the UK and the US are mainly specialized in management activities.

[9]These countries are France, Ireland, Luxembourg, and Portugal.

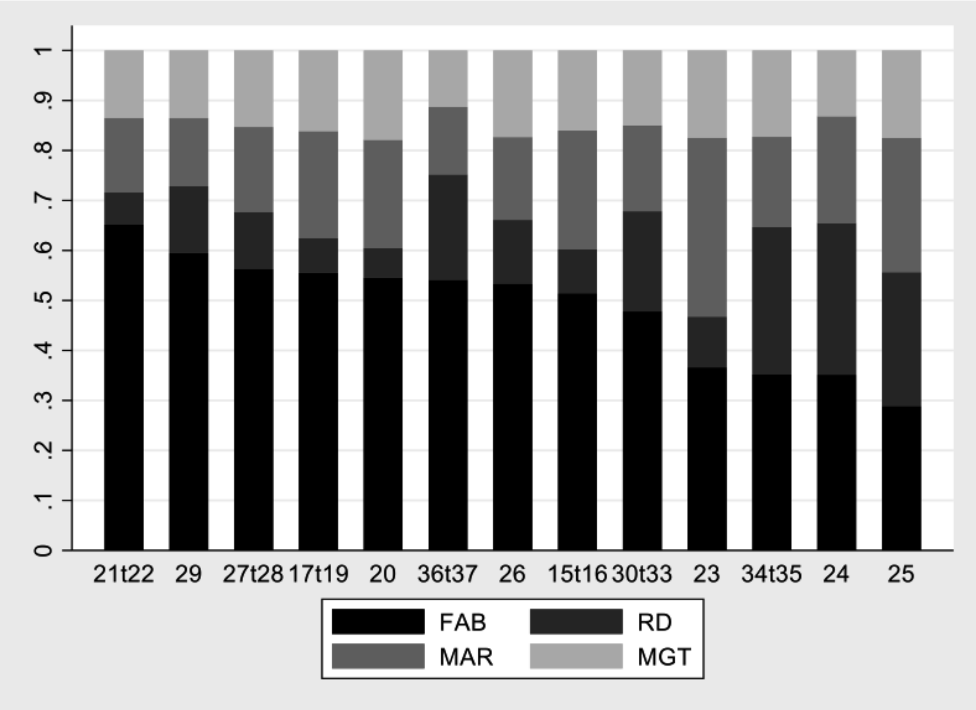
Figure 2.2: Share in domestic labor cost by activity-Manufacturing industries



Note: This graph shows the average functional share of manufacturing industries in 1999 and 2007, for Germany, France, the UK, and the USA. Subscript RD refers to the business function R&D and technology and process development; subscript FAB refers to fabrication activities. Subscript MGT refers to the business functions general and strategic management; subscript MAR is marketing.

Figure 2.3 reports functional labor cost shares in manufacturing industries in 2007, and it is sorted on fabrication share from high to low. These are based on an unweighted average over 21 advanced countries in our sample. We see that there is quite some heterogeneity from industry to industry in terms of fabrication share. Specifically, fabrication share varies from more than 60% in the pulp, paper, printing, and publishing industry to less than 30% in the rubber and plastic industry.

Figure 2.3: Labor cost shares in manufacturing industries, 2007



Note: Labor cost share is sorted on fabrication share from high to low and it is the unweighted average over 21 advanced countries. Subscript RD refers to the business function R&D and technology and process development; subscript FAB refers to fabrication activities. Subscript MGT refers to the business functions general and strategic management; subscript MAR is marketing.

The R&D share is much lower than the fabrication share, however, there is still much heterogeneity across industries. Specifically, R&D share varies from around 30% in the chemical products industry to around 6% in the wood and cork industry. Figure 2.3 indicates that there is not as much heterogeneity across industries for management share compared to fabrication and R&D activities. For all the manufacturing industries, the management share is between 10% and 20%. It is highest for wood and cork industry and lowest for other manufacturing and recycling industry. Figure 2.3 also displays the labor share for marketing and other activities. There is moderate heterogeneity across industries. It ranges from around 35% in coke, refined petroleum and nuclear fuel industry to slightly lower than 15% in other manufacturing and recycling industries.

Table 2.1 reports the average change in functional labor cost share from 1999 to 2007. It is calculated as the average labor cost share in 2007 divided by the average labor cost share in 1999. If the ratio is bigger than 1, it indicates an increase in labor cost share from

1999 to 2007, and it is the other way around if the ratio is smaller than 1. It is clear that over this period, functional specialization has taken place in all manufacturing industries. Specifically speaking, the functional specialization has shifted away from fabrication activities as all industries see a decline in relative labor cost share in fabrication activities. On the other hand, the functional specialization has shifted towards an increased cost share of R&D and management activities. Marketing activities appear no clear common pattern in the functional specialization.

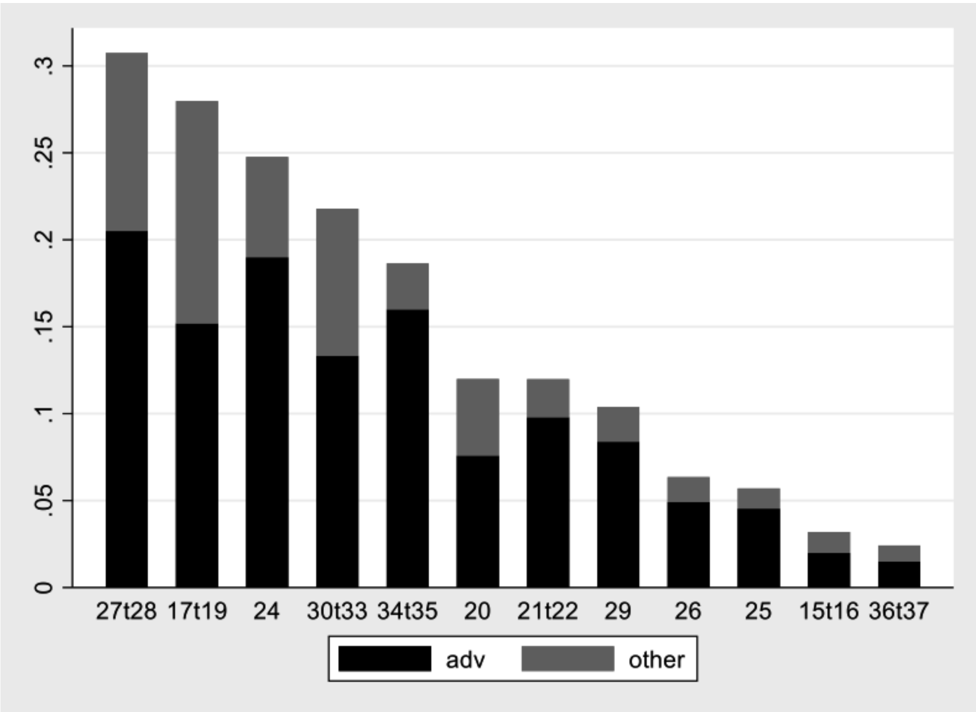
Table 2.1: Change in labor cost shares, 2007 over 1999

Industry	MGT	RD	MAR	FAB
15t16	**1.12**	**1.31**	**1.02**	0.93
17t19	**1.22**	**1.08**	**1.19**	0.89
20	**1.10**	**1.71**	**1.27**	0.86
21t22	**1.19**	**1.28**	0.90	0.97
23	**1.17**	**1.31**	**1.06**	0.84
24	0.99	**1.19**	0.84	0.99
25	**1.10**	**1.13**	**1.07**	0.82
26	**1.35**	**1.18**	0.95	0.91
27t28	**1.12**	**1.20**	0.97	0.95
29	**1.19**	**1.26**	**1.00**	0.92
30t33	**1.08**	**1.04**	**1.01**	0.96
34t35	**1.16**	**1.07**	**1.02**	0.88
36t37	0.91	**1.27**	0.95	0.95

Note: The change in labor cost share is calculated as an unweighted average of the average share of 2007 divided by the average share in 1999 over 21 advanced countries. Numbers>1 are in bold. Subscript RD refers to the business function R&D and technology and process development; subscript FAB refers to fabrication activities. Subscript MGT refers to the business functions general and strategic management; subscript MAR is marketing.

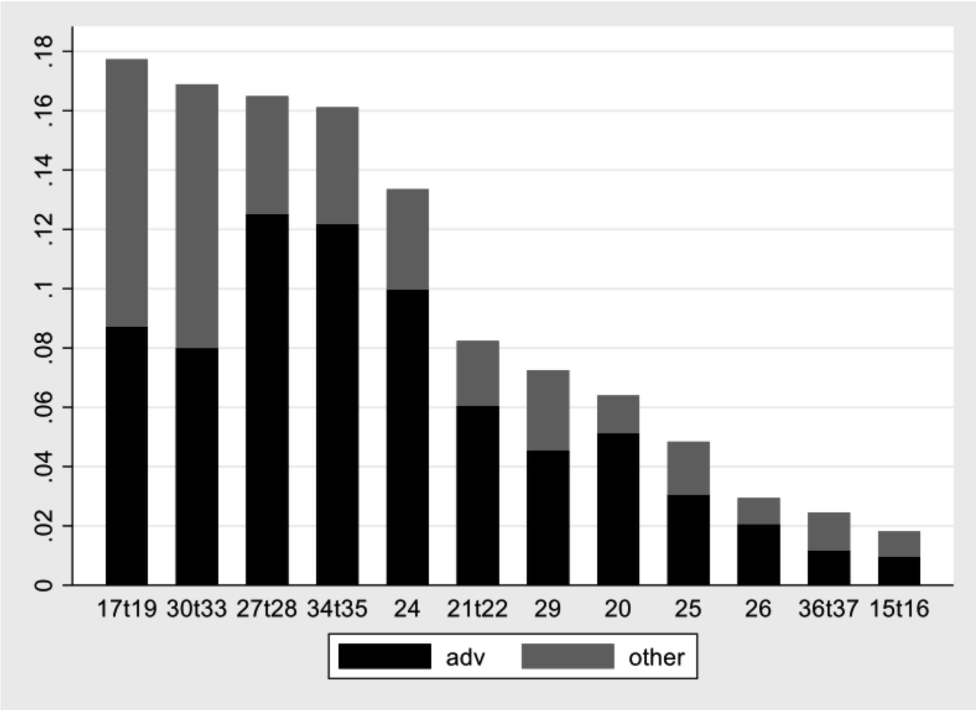
Figures 2.4 and 2.5 report descriptive statistics of narrow offshoring, distinguishing two sets of offshoring destinations: 21 advanced countries and other countries. Figure 2.4 is for the intermediate stage offshoring and Figure 2.5 for the final stage offshoring in 2007. Figure 2.4 shows that there is large heterogeneity across industries regarding intermediate stage offshoring. It is quite low for the food industry but high for textile and metal industries. For all manufacturing industries, the intermediate stage offshoring to advanced countries is more important than to other countries. Offshoring to other countries is relatively more important in the textile industry than in other industries. For transport equipment (e.g. car) industry, it is the other way around as intermediate inputs are mostly sourced from other advanced countries. So, making this distinction in offshoring destination is empirically highly relevant. Similarly, Figure 2.5 also suggests a large heterogeneity across industries in terms of final stage offshoring. It is also low for the food industry and high for the textile industry. However, a bit different from intermediate stage offshoring, final stage offshoring is also relatively high in electrical and optical equipment. It indicates that the final assembly is often offshored abroad for electronics just like Apple puts its assembly plant in China. For most industries, the final stage offshoring to advanced countries is more important than to other countries. However, textile and electronics industries are exceptions. For these two, offshoring to other countries is more important than to advanced countries. To the opposite, for metal and car industries, the final stage offshoring is mostly to advanced countries. For the car industry, there seems to be specialization across advanced countries going on in a global production network (see e.g. Sturgeon et al. 2008).

Figure 2.4: Int-Off by destination-Manufacturing industries in 2007



Note: Int-Off is the unweighted average over 21 advanced countries. The calculation is based on the narrow measure of Int-Off by destination: advanced countries (adv) and other countries (other).

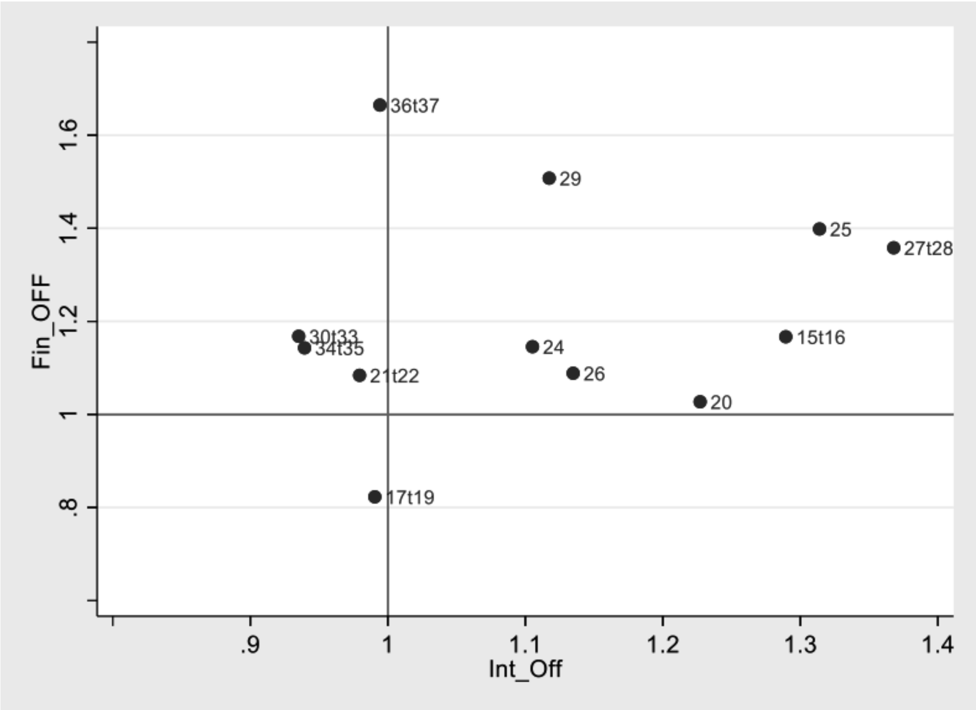
Figure 2.5: Fin-Off by destination-Manufacturing industries in 2007



Note: Fin-Off is the unweighted average over 21 advanced countries. The calculation is based on the narrow measure of Fin-Off by destination: advanced countries (adv) and other countries (other).

Figure 2.6 displays the change in the narrow offshoring index over the period 1999-2007 for 12 manufacturing industries. It is calculated as the ratio between 2007 and 1999. It shows that intermediate stage offshoring declined for some industries over this period, most notably electronics and car industries. To the opposite, it increased rapidly in the rubber and plastic industry. The final stage offshoring increased in all industries except for the textile industry. Among all industries, the highest increase appears to be in other manufacturing and machinery industries. Besides, there is a relatively high positive correlation between intermediate stage offshoring and final stage offshoring in the cross-section (the correlation is 0.66 in 2007), however, this is not the case over time as Figure 2.6 suggests. Hence we will include the two types of offshoring separately and combined in the regression analysis later.

Figure 2.6: Change in offshoring-Manufacturing industries, 1999-2007



Note: This figure illustrates the change in the offshoring index over the period 1999-2007(ratio of 2007/1999) for manufacturing industries. It is the change in the final stage offshoring on the vertical axis and the change in intermediate stage offshoring on the horizontal axis. The numbers are calculated as an unweighted average over 21 advanced countries.

Table 2.2 shows the descriptive statistics of the variables used in the regression analysis: mean values and average annual changes for the key variables of interest for manufacturing industries. The top rows show the business function shares. S_{RD} is the labor cost share of R&D activities; S_{FAB} is the labor cost share of fabrication activities; S_{MGT} is the labor cost share of management activities; and S_{MAR} is the labor cost share of marketing activities. The changes in the labor cost share of a certain function indicate the changes in functional specialization of industry. In Table 2.2 we focus on the general patterns of the average value of cost shares and offshoring and their average annual changes as these are closely related to the regression analysis in the next section.

Table 2.2: Average cost shares and average annual changes for manufacturing industries

	Levels			Annual Change		
	Obs	Mean	SD	Obs	Mean	SD
S_{RD}	1637	14.3%	0.108	1445	0.003	0.041
S_{FAB}	1637	50.3%	0.148	1445	-0.007	0.055
S_{MGT}	1637	15.9%	0.076	1445	0.005	0.055
S_{MAR}	1637	19.5%	0.084	1445	-0.001	0.054
Narrow Int_Off share	1637	11.5%	0.114	1445	0.001	0.017
_To advanced economies	1637	8.7%	0.093	1445	-0.001	0.014
_To developing countries	1637	2.8%	0.034	1445	0.002	0.007
Broad Int_Off share	1637	32.1%	0.188	1445	0.006	0.025
_To advanced economies	1637	22.4%	0.159	1445	0.000	0.019
_To developing countries	1637	9.7%	0.091	1445	0.006	0.019
Narrow Fin_Off share	1637	7.8%	0.079	1445	0.001	0.021
_To advanced economies	1637	5.6%	0.063	1445	0.000	0.008
_To developing countries	1637	2.2%	0.024	1445	0.001	0.007
Broad Fin_Off share	1637	24.4%	0.169	1445	0.006	0.043
_To advanced economies	1637	17.5%	0.144	1445	0.000	0.022
_To developing countries	1637	6.9%	0.048	1445	0.003	0.016

Note: Subscript RD refers to the business function R&D and technology and process development; subscript FAB refers to fabrication activities. Subscript MGT refers to the business functions general and strategic management; subscript MAR is marketing.

The mean values indicate that R&D constitutes about 14.3% of the total labor cost. Fabrication constitutes about 50.3% of labor costs. 15.9% of labor cost is related to management and 19.5% of labor cost is related to marketing.

Over time, we observe an increase in the average cost share of R&D and a decline in fabrication activities. This finding indicates a change in the functional specialization that is in favor of R&D but against fabrication activity, as also noted above. It is a general pattern across all 16 countries included in our study, although the level and pace appear to differ across countries.

The bottom rows of Table 2.2 display the average levels and annual change of the two types of offshoring, distinguishing between narrow and broad measures, and destinations. The correlation between the two types of narrow offshoring for manufacturing industries is 0.68. It suggests that industries that import more intermediate inputs also tend to export more intermediate inputs. Generally speaking, we would expect industries located relatively downstream in the production chain to have a higher correlation between intermediate stage and final stage offshoring. This is because downstream industries need more intermediate inputs to undertake production and they are also closer to the final assembly stage so more prone to final stage offshoring. In our data, among all manufacturing industries, Other non-metallic mineral (0.77), basic metals and fabricated metal (0.75) and other manufacturing and recycling (0.67) have the highest correlation between the two types of offshoring. On the other hand, textile and leather products (-0.10), and pulp, paper, and printing (0.23) have the lowest correlation between the two types of offshoring.

We see that the levels of final stage offshoring are lower than the levels of intermediate stage offshoring, for both narrow and broad measures. It suggests that on average, industries in advanced countries export a smaller share of intermediate inputs abroad for further assembly than they import intermediate inputs from abroad. Besides, on average, both types of offshoring increase annually during the 1999-2007 period. The average annual increase in the narrow measure of both offshoring types is 0.1 percentage points, and it is higher in the broad measure of offshoring (0.6). Furthermore, most of the offshoring goes to advanced economies. However, from 1999 to 2007, all increase in offshoring goes to developing countries.

Descriptive statistics for the full industry sample, including also non-manufacturing industries, is displayed in Appendix Table 2.A1. The mean values show that R&D constitutes about 12.8% of the total labor cost share. On average, it is higher for manufacturing industries than for non-manufacturing industries. Fabrication constitutes about 40% of labor costs. 17.8% of labor is related to management and appears not to differ much between manufacturing and non-manufacturing industries. 29.4% of labor cost is related to marketing activities. Over time, we observe an increase in the average cost share of R&D and management activities, but a decline in fabrication and marketing activities. Both narrow and broad offshoring increase during the period. The increase appears to be mainly driven by an increase in offshoring to developing countries. The decline in fabrication and the increase in offshoring to developing countries provide circumstantial evidence of the trend that firms in advanced economies offshore fabrication activities to developing countries.

We will present the relation between offshoring and functional structure of labor demand, and control for technology in the next section.

2.5 Empirical Results

This section reports the results of estimating the system of equations using the fixed effects iSUR. [10] From econometric theory, using iSUR and OLS would give us the same results as the independent variables are identical in all the equations. We apply iSUR in the baseline analysis mainly to impose the cross-equation constraints (Wooldridge, 2011). Cost functions are well behaved if they are concave in wages. That is, the Hessian matrix of second-order derivatives concerning factor prices must be negative semi-definite. For each regression, we examine whether the curvature conditions are satisfied on average as is standardly done (eg. Hijzen et al. 2005). More stringently, one would like to have curvature conditions satisfied at each observation using the approach suggested by Diewert and Wales (1987). We find that the curvature conditions are not satisfied at all points in our estimates, but it is in the majority.

The role of wage changes on changing demand for business functions can be inferred from the parameter estimates. However, the interpretation of these (and the structural) parameters is not straightforward, because the factor prices on the right-hand side are in natural logarithms whereas the dependent variables are not. Instead, we calculate the wage elasticities that are reported in Table 2.3. A necessary (but not sufficient) condition for concavity in factor prices is that all the own-price elasticities are negative. The signs on the main diagonal indeed reveal that elasticities are negative, while the cross-wage elasticities are positive in all cases, which is as expected, except for the marketing-R&D pair. Interestingly, own-price elasticities are high for management and R&D activities. For workers in management and R&D activities, the own-price elasticities are -1.290 and -0.678 respectively, which means that a 1 percent decrease in the wage of management/R&D workers corresponds to a 1.290/0.678 percentage point increase in the respective cost share. These elasticities are much higher compared to the own-price elasticities for fabrication and marketing workers (-0.202 and -0.192).

[10] We estimated the system of equations using the industry to total economy value added share as analytical weights to account for differences in economic importance of industries and measurement error. We also check robustness of the unweighted regression analysis.

Table 2.3: Wage elasticities

	RD	FAB	MGT	MAR
RD	-0.678			
FAB	0.155	-0.202		
MGT	0.433	0.021	-1.290	
MAR	-0.282	0.026	0.388	-0.192

Note: The elasticity results correspond to the regression results in Table 2.5 using the narrow offshoring measure. RD refers to the business function R&D; FAB to fabrication; MGT to management and MAR to marketing.

Of additional interest for our analysis is the viscidity of business functions. The elasticities of substitution among business functions are shown in Table 2.4. An elasticity below one indicates that the two business functions are complementary, otherwise they are substitutes. The substitution elasticity between activities provides us with information on relationships between business functions. If two activities are complementary, the change in demand for both would go in the same direction; if the two are substitutes, then the change in demand for both would go in opposite directions. R&D activities appear to be complementary to marketing activities, and fabrication activities are also complementary to management activities. The substitution elasticity between fabrication and R&D is smaller than, but close to one (0.951), which suggests that there is a weak complementary relationship between the two activities. This is in line with micro-evidence from the firm-level analysis by Defever (2012), which also finds that firms co-locate R&D and fabrication activities when investing abroad. The substitution elasticity between fabrication activities with management (0.186) and marketing activities (0.155) is much lower, which suggests that they are particularly complementary. A similar complementary relationship is also found between R&D and marketing activities. On the other hand, management activities are strong substitutes for R&D and marketing activities.

Table 2.4: Implied elasticity of substitution

	RD	FAB	MGT	MAR
RD				
FAB	0.951			
MGT	3.813	0.186		
MAR	-1.727	0.155	3.412	

Note: The elasticity results correspond to the regression results in Table 2.5 using the narrow offshoring measure. RD refers to the business function R&D; FAB to fabrication; MGT to management and MAR to marketing.

The main results are discussed in two sections. In section 2.5.1 we present our baseline results based on manufacturing industries. In section 2.5.2 we present an additional analysis based on non-manufacturing industries. Furthermore, in section 2.5.3 we present results from the IV approach.

2.5.1 Results for manufacturing industries

Table 2.5 displays the main results from estimating equation 2.2. We consider the relationship between the cost shares of functions and the narrow measures of intermediate stage offshoring and final stage offshoring. As discussed in section 2.4, Feenstra and Hanson (1999) prefer to use the narrow definition of offshoring as it is thought to come closer to the essence of fragmentation which takes place within an industry. [11] We also focus on narrow offshoring in the main analysis. Results based on the broad measure of offshoring serve for comparison and robustness checks to the baseline results. To control for time-invariant fixed effects, country, industry as well as year dummies are included in the regression.

The results suggest that intermediate stage offshoring is significantly related to higher R&D cost share but to lower management cost share. On the other hand, final stage offshoring is significant positively related to R&D, management and marketing cost shares, but negatively related to fabrication cost share. The negative relation between final stage offshoring and fabrication cost share is in line with our expectations. Developed countries normally offshore the final stage to developing countries to benefit from lower unskilled wages. As a result, demand for onshore workers who perform assembly (fabrication) related tasks would decline. Both types of offshoring are significant positively correlated with R&D cost share, which suggests that onshore demand for R&D workers would increase whatever the stage of production that is offshored.

[11] Full list of results (including wage terms) are presented in Appendix Table 2.A2 and 2.A3.

Table 2.5: The relation between trade, technology and business function shares-Manufacturing industries

	Cost share of:			
	R&D	Fabrication	Management	Other
Intermediate Stage Offshoring	0.087***	0.020	-0.098***	-0.009
	(0.020)	(0.025)	(0.020)	(0.019)
Final Stage Offshoring	0.105***	-0.294***	0.080***	0.108***
	(0.030)	(0.037)	(0.030)	(0.028)
ICT	0.021***	-0.028***	0.006***	0.002
	(0.002)	(0.003)	(0.002)	(0.002)
non-ICT	-0.019***	0.049***	-0.035***	0.005***
	(0.002)	(0.003)	(0.002)	(0.002)
Constant	0.465***	0.696***	-0.424***	0.263***
	(0.039)	(0.049)	(0.040)	(0.037)
Observations	1,637	1,637	1,637	1,637
R^2	0.797	0.816	0.601	0.585

Note: This table reports estimations of the relation between (narrow) intermediate stage offshoring, final stage offshoring and business function shares for the manufacturing-only sample. Analytical weight is used in the regression analysis (value added shares of industries in country's GDP). Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Country, industry and time dummies inclued in all regressions.

We report the elasticities in Table 2.6 to discuss the economic significance. These elasticities are calculated based on coefficients from Table 2.5 and we focus on those coefficients that are statistically significant. We are particularly interested in the elasticities for intermediate stage and final stage offshoring. Our main finding is that the type of offshoring has a major impact on the effects on labor demand. Industries with 1 percentage point higher intermediate stage offshoring, on average, have a 0.530 percentage point higher R&D cost share, but 0.863 percentage point lower management cost share. For final stage offshoring, on the other hand, industries with 1 percentage point higher offshoring, on average, have higher R&D, management and marketing cost shares (respectively 0.645, 0.704 and 0.655 percentage points), but lower cost shares for fabrication (0.527 percentage point).

The relation between technology and functional specialization is consistent with our predictions. Industries with a higher ICT capital stock to output ratio have a significant higher cost share in R&D and management activities, but lower cost share in fabrication activities. Quantitatively speaking, if an industry has 1 percentage point higher ICT capital to output ratio, the R&D cost share is on average 0.128 percentage point higher but the fabrication cost share is 0.050 percentage point lower than other industries.

Table 2.6: The elasticity of demand for business function-Economic significance-Manufacturing industries

	RD	FAB	MGT	MAR
Intermediate Stage Offshoring	0.530	0.037	-0.863	-0.054
Final Stage Offshoring	0.645	-0.527	0.704	0.655
ICT capital	0.128	-0.050	0.050	0.009
Non ICT capital	-0.118	0.088	-0.305	0.031
Output	-0.072	0.009	0.068	-0.007

Note: The elasticity results correspond to the regression results in Table 2.5 using the narrow offshoring measure. RD refers to the business function R&D; FAB to fabrication; MGT to management and MAR to marketing.

As a robustness check, we also run the above regression using unweighted equations and replace narrow offshoring with broad offshoring. The regression results are reported in Table 2.7. Generally speaking, the results from unweighted regressions and using the broad measure of offshoring suggest that the baseline results are quite robust. The magnitude and significance of the coefficients mostly hold. In Table 2.8, we report the elasticity of demand for business function concerning different types of offshoring. Table 2.8 indicates the economic significance of the relationship. We focus our attention on those results with statistically significant relationships. Compared to the baseline results, the elasticity of demand for R&D function is lower with broad unweighted offshoring measure (0.338 vs. 0.530). The elasticity of demand for R&D is also much lower with broad final stage offshoring than narrow offshoring. This indicates that final stage offshoring to the same industry has a higher economic effect on R&D demand than to other industries. The negative elasticity of demand for fabrication activity is much bigger with the narrow measure of final stage offshoring than the broad measure. This suggests that final stage offshoring to the same industry has a bigger negative impact on fabrication demand than offshoring to other industries.

Table 2.7: The relation between trade, technology and business function shares-Manufacturing industries robustness checks

	RD	FAB	MGT	MAR
Intermediate stage offshoring				
(narrow, weighted) Baseline	0.087***	0.020	-0.098***	-0.009
	(0.020)	(0.025)	(0.020)	(0.019)
(narrow, unweighted)	0.099***	0.016	0.085***	0.002
	(0.023)	(0.030)	(0.022)	(0.022)
(broad, weighted)	0.087***	-0.022	-0.089***	0.024
	(0.021)	(0.026)	(0.021)	(0.019)
(broad, unweighted)	0.055***	-0.054***	-0.052***	0.051***
	(0.018)	(0.024)	(0.018)	(0.017)
Final stage offshoring				
(narrow, weighted) Baseline	0.105***	-0.294***	0.080***	0.108***
	(0.030)	(0.037)	(0.030)	(0.028)
(narrow, unweighted)	0.129***	-0.195***	0.053*	0.013
	(0.032)	(0.043)	(0.032)	(0.031)
(broad, weighted)	0.049**	-0.124***	0.051***	0.024*
	(0.014)	(0.018)	(0.014)	(0.013)
(broad, unweighted)	0.072***	-0.091***	0.022	-0.003
	(0.014)	(0.019)	(0.014)	(0.013)

Note: This table reports estimations of the relation between offshoring and functional specialization for the manufacturing-only sample. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Country, industry and time dummies added in all regressions.

Table 2.8: The elasticity of demand for business function-Robustness checks

	RD	FAB	MGT	MAR
Intermediate stage offshoring				
(narrow, weighted) Baseline	0.530	0.037	-0.863	-0.054
(narrow, unweighted)	0.598	-0.029	-0.729	0.012
(broad, weighted)	0.534	-0.040	-0.782	0.146
(broad, unweighted)	0.338	-0.097	-0.459	0.310
Final stage offshoring				
(narrow, weighted) Baseline	0.645	-0.527	0.704	0.655
(narrow, unweighted)	0.782	-0.350	0.453	0.079
(broad, weighted)	0.302	-0.222	0.448	0.144
(broad, unweighted)	0.440	-0.163	0.192	-0.015

Note: The elasticity results correspond to the regression results in Table 2.7. RD refers to the business function R&D; FAB to fabrication; MGT to management and MAR to marketing.

To sum up, the results based on our sample of manufacturing industries indicate that intermediate stage offshoring is significant positively correlated with R&D cost share but negatively correlated with management cost share. It is not significantly related to the cost share of fabrication or marketing activities. In contrast, final stage offshoring is significant negatively related to fabrication cost share, which suggests moving the final assembly stage abroad reduces the demand for onshore fabrication workers. The results are robust to unweighted regression and the broad measure of offshoring. We conclude that the impact of offshoring on onshore functional labor demand depends crucially on what stage of production is offshored.

Some research finds that the destination of offshoring may also matter for the impact on onshore labor demand (e.g. Harrison and McMillan, 2011; Ekholm and Hakkala, 2008). To investigate this further, we distinguish between two sets of the offshoring destinations: other high-income countries and developing countries. In Table 2.9, we report the results from regression when we enter variables that distinguish between the destinations of (narrow) offshoring.

We compare Table 2.9 with Table 2.7 and find that offshoring to different destinations is related to different results for onshore functional demand. The significant positive relation between intermediate stage offshoring and R&D share happens when the offshoring destination is high-income countries. Interestingly, intermediate stage offshoring is significant positively related to fabrication share when the destination is high-income countries but negatively related to fabrication share when the destination is developing countries. However, the significance is only at the 10% level. It suggests that only when the intermediate stage offshoring is to developing countries, the onshore fabrication share sees a decline. For management activities, there is a significantly negative correlation between intermediate stage offshoring and the management share when the offshoring destination is high-income countries. If the destination is developing countries, the correlation is positive but only at the 10% significance level. This suggests that offshoring to advanced countries probably decreases the onshore demand for management workers as maybe more management tasks are carried out in other advanced countries. However, offshoring to developing countries requires more management work at home, congruent with a story in which multinational companies relocate activities abroad while expand coordination activities in the home country.

For final stage offshoring, the destination also matters. Different from intermediate stage offshoring, final stage offshoring is significant positively related to R&D share when the destination is developing countries. This fits the narrative of factory-less goods producing firms (FGPFs) like Apple. FGPFs do not get involved in production process themselves, but are heavily involved in those activities that are related to the production of goods, like design the goods they sell and coordinate the production activities (Bernard and Fort, 2015). When Apple puts assembly plants in China, it specializes in R&D so that R&D share at home in the States will increase. For fabrication activities, on the other hand, final stage offshoring is significant negatively related to fabrication share wherever the destination is. This indicates that offshore the final stage abroad would always negatively associate with onshore demand for fabrication workers. Final stage offshoring is significant positively correlated with management share when the destination is high-income countries but negatively related when the destination is developing countries. Besides, final stage offshoring is significant positively related to marketing share when the destination is high-income countries. Table 2.10 reports the economic significance of the above results. Interestingly, the relative increase in R&D is quite big when the final assembly offshoring destination is developing countries, which may indicate that FGPFs have a strong specialization in R&D activities while they offshore the final assembly stage to developing countries. We conclude that offshoring to different destinations generally has different and even opposite effects on the onshore functional demand. This holds not true for fabrication activities when offshoring is in the final stage though: final stage offshoring is negatively correlated with onshore demand for fabrication activity, whatever the offshoring destination is.

Table 2.9: The relation between trade, technology and business function shares-Manufacturing industries, narrow offshoring measures distinguishing offshoring destinations

	Cost share of:			
	R&D	FAB	MGT	MAR
Int_Off to:				
High-income countries	0.105***	0.048*	-0.144***	-0.009
	(0.023)	(0.028)	(0.023)	(0.021)
Developing countries	0.060	-0.161*	0.119*	-0.018
	(0.068)	(0.086)	(0.069)	(0.064)
Fin_Off to:				
High-income countries	0.012	-0.320***	0.188***	0.120***
	(0.035)	(0.045)	(0.035)	(0.033)
Developing countries	0.496***	-0.242***	-0.311***	0.058
	(0.079)	(0.098)	(0.079)	(0.074)
Constant	0.503***	0.662***	-0.422***	0.256***
	(0.041)	(0.052)	(0.041)	(0.039)
Observations	1,637	1,637	1,637	1,637
R^2	0.799	0.811	0.552	0.594

Note: This table reports estimations of the relation between (narrow) offshoring and business function shares for the manufacturing-only sample. RD refers to the business function R&D; FAB to fabrication; MGT to management and MAR to marketing. Int_Off and Fin_Off represent intermediate stage and final stage offshoring respectively. Analytical weight is used in the regression analysis. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Country, industry and time dummies included in all regressions.

Table 2.10: The elasticity of demand for business function-Economic significance-Manufacturing industries, distinguishing offshoring destinations

	RD	FAB	MGT	MAR
Int_Off_total	0.530	0.037	-0.863	-0.054
Int_Off_adv	0.647	0.086	-1.244	-0.055
Int_Off_dev	0.372	-0.289	1.028	-0.110
Fin_Off_total	0.645	-0.527	0.704	0.655
Fin_Off_adv	0.075	-0.575	1.631	0.724
Fin_Off_dev	3.059	-0.435	-2.693	0.348

Notes: The elasticity results correspond to the regression results in Table 2.9 using the narrow offshoring measure. RD refers to the business function R&D; FAB to fabrication; MGT to management and MAR to marketing. Int_Off and Fin_Off represent intermediate stage and final stage offshoring, and adv for advanced countries, dev for developing countries as destinations respectively.

2.5.2 Extension to non-manufacturing industries

In the main analysis discussed in section 2.5.1, we focus on manufacturing industries as they are more prone to offshoring than (most) other industries in the economy. In this subsection, we extend the analysis to non-manufacturing industries as some of these appear to be increasingly involved in offshoring (Geishecker and Görg, 2013). We also compare the results to those from manufacturing industries.[12] For non-manufacturing industries, the concept of fabrication activities is not as intuitive as for manufacturing industries. However, non-manufacturing industries can also get involved in fabrication activities. On the one hand, firms are classified into industries by the primary activities they undertake. Besides the primary service activities, firms in service industries may also perform fabrication activities. For example, an IT company can also package their software and a restaurant may also have their production line of a branding lunch box. On the other hand, FGPFs are classified into the wholesale industry as they are like the traditional manufacturing firms but outsource the entire production line. The transition process from manufacturing to wholesale firms happens gradually and some firms in this process are classified into services but may still undertake fabrication activities.

In our baseline analysis, we take the narrow measure of offshoring with analytical weights. The main regression results for non-manufacturing industries are displayed in Table 2.11, together with alternative results based on using the broad measure of offshoring with(out) weight. The baseline results indicate that intermediate stage offshoring is significant positively related to R&D and marketing cost shares but negatively related to fabrication share; final stage offshoring is significant negatively related to R&D and fabrication shares,

[12]We report the results that distinguish offshoring destinations in the Appendix Tables 2.A6 and 2.A7.

but positively related to management share. These results are robust in other settings for fabrication and management shares when offshoring is on the final stage, and for marketing share when offshoring is on the intermediate stage. It suggests that final stage offshoring is always negatively related to onshore demand for fabrication workers, but positively related to onshore management workers. This is the same finding for the manufacturing sample. The main difference from the manufacturing sample is on the relation between intermediate stage offshoring and onshore fabrication share. For non-manufacturing industries, narrow offshoring is significant negatively related to domestic fabrication share. However, broad offshoring is positively related to domestic fabrication share. It is perhaps because the wider variety of imported inputs raises the learning opportunity or quality of domestic production within non-manufacturing industries. Table 2.12 reports the economic significance of the relationship between offshoring and onshore functional demand in terms of elasticity. For the baseline analysis, we see that industries with 1 percentage point higher intermediate stage offshoring have 1.315 percentage point lower fabrication cost share and 0.288 (0.470) percentage point higher R&D (marketing) cost shares. On the other hand, industries with 1 percentage point higher final stage offshoring have 2.525 percentage point higher management cost share and 0.555 (2.536) percentage point lower R&D (fabrication) cost shares. Compared to manufacturing industries, the negative relation between final stage offshoring and onshore fabrication cost share is much bigger for non-manufacturing industries. This could be partly driven by some FGPFs that outsource the entire production line abroad and domestic demand for assembly could decline considerably.

To sum up, the main difference between the non-manufacturing sample from the manufacturing sample is when offshoring is at the intermediate stage, onshore fabrication cost share is negatively related to narrow offshoring, but positively related to broad offshoring. We think that learning from a wide set of imported inputs from many industries might partially account for this. On the other hand, as we found for manufacturing, final stage offshoring is significant negatively related to onshore fabrication cost share for non-manufacturing industries.

Table 2.11: The relation between trade, technology and business function shares- non-Manufacturing industries

	RD	FAB	MGT	MAR
Intermediate stage offshoring				
(narrow, weighted) Baseline	0.061**	-0.226***	-0.041	0.205***
	(0.029)	(0.044)	(0.044)	(0.041)
(narrow, unweighted)	0.006	-0.199***	-0.038	0.230***
	(0.031)	(0.053)	(0.051)	(0.046)
(broad, weighted)	0.004	0.052**	-0.098***	0.043**
	(0.013)	(0.021)	(0.020)	(0.019)
(broad, unweighted)	-0.005	0.058***	-0.100***	0.048***
	(0.013)	(0.022)	(0.021)	(0.019)
Final stage offshoring				
(narrow, weighted) Baseline	-0.118*	-0.435***	0.451***	0.102
	(0.063)	(0.098)	(0.096)	(0.089)
(narrow, unweighted)	-0.136**	-0.482***	0.510***	0.108
	(0.064)	(0.112)	(0.107)	(0.095)
(broad, weighted)	-0.008	-0.114***	0.151***	-0.029
	(0.013)	(0.021)	(0.020)	(0.019)
(broad, unweighted)	0.031***	-0.166***	0.159***	-0.024
	(0.012)	(0.021)	(0.020)	(0.018)

Note: This table reports estimations of the relation between offshoring and business function shares for the non-manufacturing sample. RD refers to the business R&D; FAB to fabrication; MGT to management and MAR to marketing. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Country, industry and time dummies added in all regressions.

Table 2.12: The elasticity of demand for business function- non-Manufacturing industries

	RD	FAB	MGT	MAR
Intermediate stage offshoring				
(narrow, weighted) Baseline	0.288	-1.315	-0.230	0.470
(narrow, unweighted)	0.032	-1.074	-0.214	0.529
(broad, weighted)	0.017	0.279	-0.563	0.101
(broad, unweighted)	-0.026	0.298	-0.581	0.113
Final stage offshoring				
(narrow, weighted) Baseline	-0.555	-2.536	2.525	0.232
(narrow, unweighted)	-0.671	-2.602	2.886	0.247
(broad, weighted)	-0.036	-0.614	0.861	-0.068
(broad, unweighted)	0.150	-0.855	0.920	-0.057

Notes: The elasticity results correspond to the regression results in Table 2.11. RD refers to the business function R&D; FAB to fabrication; MGT to management and MAR to marketing.

2.5.3 IV estimation

Estimates for the relation between offshoring and the functional labor demand might be affected by endogeneity issues as discussed in section 2.3. In our setting, the identification challenge is possibly the industry-level shocks to demand or productivity which affect offshoring and labor cost shares simultaneously. Controlling for industry fixed effects and technological change as we have done so far might not be sufficient to address this issue. Inspired by the identification strategy of Autor et al. (2013) who use Chinese imports to other eight developed countries as IV for Chinese imports to the US, we aim to identify the causal effect of offshoring on functional specialization. We follow Autor et al. (2013) and Hummels et al. (2014) in constructing the instrumental variable WES (for a detailed construction of the IV see section 2.3).

We use the same regression specification with the baseline analysis in terms of control variables and industry, country and time fixed effects. We aim to identify the causal effect of offshoring on functional cost shares, imposing cross equation constraints based on 3SLS for our IV estimation.

Table 2.13: The relation between trade, technology and business function shares-Manufacturing industries based on 3SLS estimator

	Cost share of:			
	R&D	FAB	MGT	MAR
Int_Off	0.284	-0.520**	0.271	-0.035
	(0.247)	(0.262)	(0.192)	(0.168)
Fin_Off	-0.140	0.140	-0.123	0.124
	(0.154)	(0.165)	(0.121)	(0.106)
ICT	0.013***	-0.016***	-0.003	0.007**
	(0.003)	(0.004)	(0.003)	(0.003)
Constant	0.190***	0.680***	-0.026	0.156***
	(0.037)	(0.048)	(0.038)	(0.033)
Observations	1,637	1,637	1,637	1,637
R^2	0.809	0.799	0.603	0.616

Note: This table reports estimations of the relation between (narrow) offshoring and business function shares for the manufacturing-only sample. The coefficients are based on 3SLS estimate. Offshoring is instrumented by WES, which is explained in the main text.

The first stage F statistic is smaller than the 10% critical value, which indicates that we unfortunately still suffer from a problem with a weak instrument, such that the results of the IV analysis should be treated with great care. The results are given in Table 2.13. We find that intermediate stage offshoring is significant negatively related to fabrication cost share, while in the baseline analysis, the relationship is insignificant. This suggests that we underestimate the coefficient in the baseline analysis, even though caveat should be given with the weak instrument.

2.6 Conclusion

In this chapter, we study the relation between offshoring and the onshore labor market outcomes across 13 manufacturing industries in 16 advanced countries over the years 1999-2007. We make two main contributions to the strand of literature. Firstly, we explicitly distinguish between different types of offshoring based on the activity that is offshored. We think that the offshoring measure that is proposed by Feenstra and Hanson (1999) and which is most commonly used in the empirical literature is a valid measure of intermediate stage offshoring. Inspired by the inshoring concept from Liu and Trefler (2008) and Andersson et al. (2017), we propose a second type of offshoring, which involves the offshoring of the final assembly stage. It is measured by the share of exported intermediate inputs in total sales. Secondly, we distinguish workers by their occupations rather than the skill levels as firms typically make offshoring decisions around the activities (business functions) they undertake and not around types of workers. This is relevant, given that there is not a one to one mapping from the educational attainment of a worker and the type of activity (s)he undertakes. We distinguish four different types of activities, based on the occupational classification of the workers.

We work with a translog cost function and estimate a system of share equations on business function cost shares with the two types of offshoring as independent variables. We find that intermediate stage offshoring is significant positively correlated with the cost share of R&D activities but negatively correlated with the cost share of management activities. Intermediate stage offshoring is not significantly related to the cost share of fabrication or marketing activities. In contrast, final stage offshoring is significant negatively related to fabrication cost share, which suggests, not surprisingly, that moving the final assembly stage abroad reduces the demand for onshore fabrication workers. Interestingly, we also find that the destination of offshoring matters for the result. Intermediate stage offshoring is significant positively associated with onshore fabrication cost share if the destination is high-income countries, but the opposite holds if the destination is developing countries. However, final stage offshoring is negatively correlated with onshore demand for fabrication activity, whatever the destination is. This indicates that the effects of offshoring on onshore labor demand are rather nuanced and should be evaluated in the context of the type of offshoring, as well as the offshoring destination.

This chapter aims to take the first step in investigating the relationship between two types of offshoring and onshore functional cost shares. The analysis carried out so far is based on correlation and we could not establish a strong causal relationship. We tried to find suitable instruments to deal with the possible omitted variable problem but did not succeed. The challenge for future work would be to find a strong IV to identify the causal relationship between offshoring and onshore labor demand. Furthermore, our study is on the industry level, therefore firm heterogeneity is not taken into account. The firm-level studies generally find that offshoring has an important impact on wage and employment of firms, typically a negative impact on demand for unskilled and production workers but positive for those of high skilled workers (e.g. Biscourp and Kramarz, 2007; Mion and Zhu, 2013; Andersson et al. 2017). Future work could make use of firm-level trade in intermediate goods and occupation data to explore the mechanism at the firm level, considering two types of offshoring and labor structure in a business function framework.

2.7 Appendix: additional tables

Table 2.A1: Average cost shares and average annual changes for all industries

	Average			Annual changes		
	Obs	Mean	SD	Obs	Mean	SD
S_{RD}	3725	12.8%	0.113	3294	0.2%	0.041
in others	2088	11.7%	0.116	1849	0.1%	0.041
S_{FAB}	3725	40.0%	0.238	3294	-0.5%	0.048
in others	2088	32.0%	0.264	1849	-0.3%	0.042
S_{MGT}	3725	17.8%	0.107	3294	0.4%	0.051
in others	2088	19.2%	0.123	1849	0.3%	0.047
S_{MAR}	3725	29.4%	0.193	3294	-0.1%	0.049
in others	2088	37.1%	0.217	1849	-0.1%	0.054
Narrow intermediate stage offshoring share	3725	6.5%	0.098	3294	0.1%	0.015
to advanced economies	3725	5.0%	0.079	3294	0	0.013
to developing economies	3725	1.6%	0.027	3294	0.1%	0.006
Broad intermediate stage offshoring share	3725	25.8%	0.222	3294	0.4%	0.026
to advanced economies	3725	18.6%	0.183	3294	0	0.023
to developing economies	3725	7.2%	0.076	3294	0.4%	0.016
Narrow assembly share	3725	6.5%	0.098	3294	0.1%	0.015
to advanced economies	3725	5.0%	0.079	3294	0	0.013
to developing economies	3725	1.6%	0.027	3294	0.1%	0.010
Broad assembly share	3725	25.8%	0.222	3294	0.4%	0.026
to advanced economies	3725	19.1%	0.261	3294	0	0.051
to developing economies	3725	10.4%	0.183	3294	0.4%	0.043

Note: Subscript RD refers to the business function R&D; subscript FAB refers to fabrication activities. Subscript MGT refers to the business functions general and strategic management; subscript MAR is marketing.

Table 2.A2: Fixed effects iSUR-Manufacturing industries

	(1)	(2)	(3)	(4)
$\gamma_{RD,RD}$	0.026**	0.027**	0.036***	0.040***
$\gamma_{RD,FAB}$	-0.004	-0.012	-0.022**	-0.030**
$\gamma_{RD,MGT}$	0.052***	0.049***	0.059***	0.051***
$\gamma_{RD,MAR}$	-0.074***	-0.065***	-0.073***	-0.061***
$\gamma_{RD,ICT}$	0.021***	0.015***	0.022***	0.014***
$\gamma_{RD,nonICT}$	-0.019***	-0.013***	-0.017***	-0.010***
$\gamma_{RD,Y}$	-0.012***	-0.008***	-0.007***	-0.005***
$\gamma_{RD,Off_{broad}}$			0.087***	0.055***
$\gamma_{RD,In_{broad}}$			0.049***	0.072***
$\gamma_{RD,Off_{narrow}}$	0.087***	0.099***		
$\gamma_{RD,In_{narrow}}$	0.105***	0.129***		
$\gamma_{FAB,FAB}$	0.134***	0.140***	0.155***	0.167***
$\gamma_{FAB,MGT}$	-0.052***	-0.053***	-0.053***	-0.053***
$\gamma_{FAB,MAR}$	-0.078***	-0.075***	-0.080***	-0.085***
$\gamma_{FAB,ICT}$	-0.028***	-0.024***	-0.031***	-0.025***
$\gamma_{FAB,nonICT}$	0.049***	0.045**	0.048***	0.042***
$\gamma_{FAB,Y}$	0.005***	0.005***	0.001	-0.0002
$\gamma_{FAB,Off_{broad}}$			-0.022	-0.054***
$\gamma_{FAB,In_{broad}}$			-0.124***	-0.091***
$\gamma_{FAB,Off_{narrow}}$	0.020	-0.016		
$\gamma_{FAB,In_{narrow}}$	-0.294***	-0.195***		
Observations	1,637	1,637	1,637	1,637
R^2_{RD}	0.798	0.790	0.799	0.790
R^2_{FAB}	0.819	0.802	0.819	0.805

Note: Estimation of parameters determining factor cost shares in the system of equations as given in equation 2.2 as shown. The first 2 columns are based on the narrow measure of offshoring and the last 2 columns broad offshoring. Columns 1 and 3 are results with analytical weights and columns 2 and 4 unweighted. All regressions include country, industry and year dummies. ***,** and * refer to 1%, 5% and 10% significance levels. Subscript RD refers to the business functions R&D; subscript FAB refers to fabrication activities. The R^2 is reported for each regression equation.

Table 2.A3: Fixed effects iSUR-Manufacturing industries

	(1)	(2)	(3)	(4)
$\gamma_{MGT,MGT}$	-0.046***	-0.027***	-0.054***	-0.034***
$\gamma_{MGT,MAR}$	0.045***	0.031***	0.048***	0.036***
$\gamma_{MGT,ICT}$	0.006***	0.006***	0.006***	0.007***
$\gamma_{MGT,nonICT}$	-0.035***	-0.032***	-0.037***	-0.033***
$\gamma_{MGT,Y}$	0.008***	0.007***	0.006***	0.005***
$\gamma_{MGT,Off_{broad}}$			-0.089***	-0.052***
$\gamma_{MGT,In_{broad}}$			0.051***	0.022
$\gamma_{MGT,Off_{narrow}}$	-0.098***	-0.085***		
$\gamma_{MGT,In_{narrow}}$	0.080***	0.053*		
$\gamma_{MAR,MAR}$	0.106***	0.109***	0.105***	0.110***
$\gamma_{MAR,ICT}$	0.002	0.003	0.002	0.003
$\gamma_{MAR,nonICT}$	0.005***	0.000	0.006***	0.002
$\gamma_{MAR,Y}$	-0.001	-0.003***	0.000	-0.0001
$\gamma_{MAR,Off_{broad}}$			0.024	0.051**
$\gamma_{MAR,In_{broad}}$			0.024*	-0.003
$\gamma_{MAR,Off_{narrow}}$	-0.009	0.002		
$\gamma_{MAR,In_{narrow}}$	0.108***	0.013		
Observations	1,637	1,637	1,637	1,637
R^2_{MGT}	0.603	0.589	0.602	0.587
R^2_{OTH}	0.586	0.686	0.584	0.688

Note: Estimation of parameters determining factor costs shares in the system of equations as given in equation 2.2 as shown. The first 2 columns are based on the narrow measure of offshoring and the last 2 columns broad offshoring. Columns 1 and 3 are results with analytical weights and columns 2 and 4 unweighted. All regressions include country and industry dummies. ***,** and * refer to 1%, 5% and 10% significance levels. Subscript MGT refers to the business functions general and strategic management; subscript MAR is marketing. The R^2 is reported for each regression equation.

Table 2.A4: Fixed effects iSUR-Manufacturing industries, distinguishing offshoring destinations

	(1)	(2)	(3)	(4)
$\gamma_{RD,RD}$	0.030***	0.029***	0.034***	0.036***
$\gamma_{RD,FAB}$	-0.005	-0.011	-0.019*	-0.028**
$\gamma_{RD,MGT}$	0.050***	0.046***	0.058***	0.052***
$\gamma_{RD,MAR}$	-0.074***	-0.064***	-0.074***	-0.060***
$\gamma_{RD,ICT}$	0.021***	0.015***	0.022***	0.015***
$\gamma_{RD,nonICT}$	-0.020***	-0.014***	-0.018***	-0.011***
$\gamma_{RD,Y}$	-0.014***	-0.010***	-0.008***	-0.003**
$\gamma_{RD,Off_{broad,adv}}$			0.137***	0.137***
$\gamma_{RD,Off_{broad,dev}}$			-0.007	-0.007
$\gamma_{RD,In_{broad,adv}}$			-0.001	0.012
$\gamma_{RD,In_{broad,dev}}$			0.253***	0.254***
$\gamma_{RD,Off_{narrow,adv}}$	0.105***	0.121***		
$\gamma_{RD,Off_{narrow,dev}}$	0.060	0.075		
$\gamma_{RD,In_{narrow,adv}}$	0.012	0.035		
$\gamma_{RD,In_{narrow,dev}}$	0.496***	0.495***		
$\gamma_{FAB,FAB}$	0.138***	0.141***	0.167***	0.167***
$\gamma_{FAB,MGT}$	-0.056***	-0.054***	-0.062***	-0.054***
$\gamma_{FAB,MAR}$	-0.078***	-0.076***	-0.086***	-0.085***
$\gamma_{FAB,ICT}$	-0.029***	-0.024***	-0.030***	-0.024***
$\gamma_{FAB,nonICT}$	0.048***	0.045**	0.045***	0.041***
$\gamma_{FAB,Y}$	0.006***	0.006***	0.002	0.0002
$\gamma_{FAB,Off_{broad,adv}}$			0.033	-0.031
$\gamma_{FAB,Off_{broad,dev}}$			-0.241***	-0.074**
$\gamma_{FAB,In_{broad,adv}}$			-0.151***	-0.106***
$\gamma_{FAB,In_{broad,dev}}$			-0.058	-0.044
$\gamma_{FAB,Off_{narrow,adv}}$	0.048*	0.024		
$\gamma_{FAB,Off_{narrow,dev}}$	-0.161*	-0.258***		
$\gamma_{FAB,In_{narrow,adv}}$	-0.320***	-0.203***		
$\gamma_{FAB,In_{narrow,dev}}$	-0.242***	-0.154		
Observations	1,637	1,637	1,637	1,637
R^2_{RD}	0.802	0.793	0.804	0.795
R^2_{FAB}	0.819	0.802	0.822	0.805

Note: Estimation of parameters determining factor costs shares in the system of equations as given in equation 2.2 as shown. The first 2 columns are based on the narrow measure of offshoring and the last 2 columns broad offshoring. adv and dev are abbreviations for advanced and developing countries as offshoring destinations respectively. Columns 1 and 3 are results with analytical weights and columns 2 and 4 unweighted. All regressions include country, industry and year dummies. ***,** and * refer to 1%, 5% and 10% significance levels. Subscript RD refers to the business functions R&D; subscript FAB refers to fabrication activities. The R^2 is reported for each regression equation.

Table 2.A5: Fixed effects iterated SUR-Manufacturing industries, distinguishing offshoring destinations

	(1)	(2)	(3)	(4)
$\gamma_{MGT,MGT}$	-0.041***	-0.023***	-0.047***	-0.032***
$\gamma_{MGT,MAR}$	0.047***	0.032***	0.051***	0.034***
$\gamma_{MGT,ICT}$	0.006***	0.006***	0.006***	0.007***
$\gamma_{MGT,nonICT}$	-0.033***	-0.031***	-0.034***	-0.033***
$\gamma_{MGT,Y}$	0.009***	0.008***	0.005***	0.004***
$\gamma_{MGT,Off_{broad,adv}}$			-0.169***	-0.104***
$\gamma_{MGT,Off_{broad,dev}}$			0.130***	-0.021
$\gamma_{MGT,In_{broad,adv}}$			0.115***	0.070***
$\gamma_{MGT,In_{broad,dev}}$			-0.186***	-0.136***
$\gamma_{MGT,Off_{narrow,adv}}$	-0.144***	-0.119***		
$\gamma_{MGT,Off_{narrow,dev}}$	0.119*	0.023		
$\gamma_{MGT,In_{narrow,adv}}$	0.188***	0.142***		
$\gamma_{MGT,In_{narrow,dev}}$	-0.311***	-0.297		
$\gamma_{MAR,MAR}$	0.105***	0.109***	0.108***	0.111***
$\gamma_{MAR,ICT}$	0.001	0.003	0.002	0.003
$\gamma_{MAR,nonICT}$	0.005***	0.0003	0.007***	0.002
$\gamma_{MAR,Y}$	-0.001	-0.004***	0.000	-0.002
$\gamma_{MAR,Off_{broad,adv}}$			-0.001	-0.002
$\gamma_{MAR,Off_{broad,dev}}$			0.118***	0.102***
$\gamma_{MAR,In_{broad,adv}}$			0.037***	0.024
$\gamma_{MAR,In_{broad,dev}}$			-0.009	-0.073**
$\gamma_{MAR,Off_{narrow,adv}}$	-0.009	-0.026		
$\gamma_{MAR,Off_{narrow,dev}}$	-0.018	0.161***		
$\gamma_{MAR,In_{narrow,adv}}$	0.120***	0.026		
$\gamma_{MAR,In_{narrow,dev}}$	0.058	-0.043		
Observations	1,637	1,637	1,637	1,637
R^2_{MGT}	0.610	0.592	0.620	0.594
R^2_{OTH}	0.586	0.687	0.586	0.690

Note: Estimation of parameters determining factor costs shares in the system of equations as given in equation 2.2 as shown. The first 2 columns are based on the narrow measure of offshoring and the last 2 columns broad offshoring. adv and dev are abbreviations for advanced and developing countries as offshoring destinations respectively. Columns 1 and 3 are results with analytical weights and columns 2 and 4 unweighted. All regressions include country and industry dummies. ***,** and * refer to 1%, 5% and 10% significance levels. Subscript MGT refers to the business functions general and strategic management; subscript MAR is marketing. The R^2 is reported for each regression equation.

Table 2.A6: The relation between trade, technology and business function shares- non-Manufacturing industries, narrow offshoring measures distinguishing offshoring destinations

	Cost share of:			
	R&D	FAB	MGT	MAR
Int_Off to:				
High-income countries	0.145***	-0.291***	-0.054	0.201***
	(0.037)	(0.057)	(0.056)	(0.052)
Developing countries	-0.315***	0.070	0.022	0.222
	(0.109)	(0.169)	(0.167)	(0.155)
Fin_Off to:				
High-income countries	-0.089	-0.474***	0.501***	0.062
	(0.072)	(0.112)	(0.110)	(0.103)
Developing countries	-0.111	-0.367	0.214	0.264
	(0.171)	(0.266)	(0.262)	(0.243)
Constant	0.608***	0.296***	-0.137***	0.826***
	(0.033)	(0.051)	(0.051)	(0.047)
Observations	2,088	1,637	2,088	2,088
R^2	0.818	0.811	0.554	0.850

Note: This table reports estimations of the relation between (narrow) offshoring and functional specialization for the manufacturing-only sample. RD refers to the business function R&D; FAB to fabrication; MGT to management and MAR to marketing.Int_Off and Fin_Off represent intermediate stage and final stage offshoring respectively. Analytical weight is used in the regression analysis. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Country, industry and time dummies added in all regressions.

Table 2.A7: The elasticity of demand for business function-Economic significance- non-Manufacturing industries, distinguishing offshoring destinations

	RD	FAB	MGT	MAR
Int_Off_total	0.288	-1.315	-0.230	0.470
Int_Off_adv	0.681	-1.689	-0.306	0.458
Int_Off_dev	-1.485	0.409	0.126	0.508
Fin_Off_total	-0.555	-2.536	2.525	0.232
Fin_Off_adv	-0.418	-2.754	2.819	0.142
Fin_Off_dev	-0.522	-2.133	1.204	0.603

Note: The elasticity results correspond to the regression results in Table 2.A6 using the narrow offshoring measure. RD refers to the business function R&D; FAB to fabrication; MGT to management and MAR to marketing. Int_Off and Fin_Off represent intermediate stage and final stage offshoring, and adv for advanced countries, dev for developing countries as destinations respectively.

Table 2.A8: Economy list

Economy	Dev (0) /Adv (1)	In our sample
Australia	1	+
Austria	1	+
Belgium	1	
Brazil	0	
Bulgaria	0	
Canada	1	
China	0	
Cyprus	0	
Czech Republic	0	
Denmark	1	+
Estonia	0	
Finland	1	+
France	1	+
Germany	1	+
Greece	1	
Hungary	0	
India	0	
Indonesia	0	
Ireland	1	+
Italy	1	+
Japan	1	+
Latvia	0	
Lithuania	0	
Luxembourg	1	+
Malta	0	
Mexico	0	
Netherlands	1	+
Poland	0	
Portugal	1	+
Romania	0	
Russian Federation	0	
Slovak Republic	0	
Slovenia	0	
South Korea	1	
Spain	1	+
Sweden	1	+
Taiwan	1	
Turkey	0	
United Kingdom	1	+
United States	1	+

Note: All 40 economies are in the sample of WIOT (2013 release), which we use to calculate intermediate stage and final stage offshoring. We include 16 developed economies in our sample since there is also ICT capital information for these economies.

Table 2.A9: Industry list

Code	Industry Name
AtB	Agriculture, Hunting, Forestry and Fishing
C	Mining and Quarrying
15t16*	Food, Beverages and Tobacco
17t19*	Textiles and Textile Products; Leather, Leather and Footwear
20*	Wood and Products of Wood and Cork
21t22*	Pulp, Paper, Paper , Printing and Publishing
23*	Coke, Refined Petroleum and Nuclear Fuel
24*	Chemicals and Chemical Products
25*	Rubber and Plastics
26*	Other Non-Metallic Mineral
27t28*	Basic Metals and Fabricated Metal
29*	Machinery, Nec
30t33*	Electrical and Optical Equipment
34t35*	Transport Equipment
36t37*	Manufacturing, Nec; Recycling
E	Electricity, Gas and Water Supply
F	Construction
50	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
51	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
52	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
H	Hotels and Restaurants
60t63	Transportation
64	Post and Telecommunications
J	Financial Intermediation
70	Real Estate Activities
71t74	Renting of M&Eq and Other Business Activities
L	Public Admin and Defence; Compulsory Social Security
M	Education
N	Health and Social Work
O	Other Community, Social and Personal Services
P	Private Households with Employed Persons

Note: This is a list of industries that are included in the WIOD (2013 release) by ISIC rev. 3 industry classification code. The ones with a * represent they are manufacturing industries.

Chapter 3

Functional Specialization of Regions in the Netherlands and the Role of Offshoring[13]

3.1 Introduction

This chapter examines functional specialization of regions in the Netherlands during the period from 2006 to 2014. Our main goal is to describe for the first time trends and patterns. In particular, we will also explore whether regional changes in employment by business function have been shaped by the international fragmentation of production.

The typical production process involves a set of business functions that range from R&D, fabrication and assembly, to branding and distribution (Coe and Hess, 2013). As firms re-locate business functions in order to reduce costs, regions may specialize in one or more of these business functions. Several examples of regional functional specialization are well known, including New York's specialization in finance and business activities and that of San Francisco in R&D and technology development.

Recently, scholars have started to examine the determinants of the spatial location of business functions (Defever 2006, 2012; Markusen and Venables, 2013; Timmer et al. 2019). These studies are mainly conducted at the country level and suggest a distribution of business functions within production networks that are shaped by opportunities for offshoring and other factors such as scale economies, institutions, market proximity, and factor endowments. So far, however, we know relatively little about the patterns of

[13] The data that support the findings of this study are available from Statistics Netherlands. Restrictions apply to the availability of part of these data, which were used under license for this study.

regional functional specialization. How does it develop over time and what forces drive it? This chapter aims to provide a first step towards answering this question focusing in particular on the role of offshoring.

The measurement and causes of regional specialization is of long-standing interest in geographical economics, see e.g. the contributions of Glaeser and Resseger (2010), Groot et al. (2014), Hummels et al. (2018), and Mudambi et al. (2018). Characterizing regional specialization patterns by business function is relevant for various reasons. First, functions may differ in their use of skilled and unskilled workers as well as in the likelihood to be relocated. For example, Mudambi et al. (2018) argue that agglomeration forces are stronger for R&D activities compared to assembly, testing or packaging activities and therefore less likely to be relocated. Second, business functions may differ in their potential for productivity improvements as well as the generation of knowledge and spillovers. Measures of specialization in functions are therefore important to understand the position of a region in global production networks and its potential for future development (Timmer et al. 2019).

This chapter studies regional functional specialization in the Netherlands. We study the Netherlands which is a very open economy, reflected in trade accounting for a substantial share of income earned. The open economy and the active engagement of firms in production networks make it likely that production fragmentation has impacted and shaped functional specialization patterns of Dutch regions. We use information from a unique survey, called 'International Organization and Sourcing of Business Activities' (abbreviated as International Sourcing Survey (ISS) from here onwards) that was administered by Statistics Netherlands. This survey has been conducted on a quinquennial basis since 2007. Typically, the majority of surveyed firms indicate they did not offshore: only about ten percent offshored a business activity during the surveyed period (Bongaard et al. 2013). Offshoring was mainly to other European countries, and Asia, with a reduction in labor costs as the main motivation for doing so. The most likely activities to be moved abroad was in fabrication activities, followed by support type of activities such as ICT and administration (Bongaard et al. 2013). Therefore, we expect that labor markets in regions with a higher share of fabrication and administrative jobs have been more affected by offshoring.

We first examine the functional specialization of the forty regions in the Netherlands. These regions are identified at the NUTS 3 level and commonly known as COROP regions. Its name derives from a commission that proposed the regions on the basis of commuter flows (COördinatiecommissie Regionaal Onderzoeks Programma). The COROP regions are a common subnational level of analysis by scholars and in data published by Statistics Netherlands. The scale of COROP regions was originally designed such that most travel to work takes place within these regions.

Scholars that study regional specialization in the Netherlands usually take industries as the unit of observation. In their historical analysis of Dutch regional development, De Jong and Stelder (2019) point out that wages were lower in provinces other than the urbanized western part of the country, and because of lower wages they specialized in manufacturing industries. The urbanized western provinces were more engaged in the provision of services. Indeed, Groot et al. (2014) find that even nowadays, relatively more and a larger variety of manufacturing industries are observed outside the urbanized Randstad area. The creative industry, but also ICT and financial and business services, is concentrated in several neighboring regions, namely Amsterdam, Gooi and Vechtstreek, Haarlem, and Utrecht (Rasp and Van den Berge, 2010).

Yet, while 'industries' or 'sectors' are a useful instrument to classify firms for the purpose of statistical measurement, they do not play a role in actual decision making of firms. Multi-plant firms decide on the type of activities they want to perform, and at which location. Activities are located where they can be performed at the best price to quality ratio. The biggest problem for interpretation of industry statistics is that various activities can take place within an industry. There is not a one-to-one mapping from industries to activities. A good example is provided in Los et al. (2014) who point at the production of cars by Nedcar in Born (in the Southern region Zuid-Limburg). Activities that are undertaken at this location include assembly, logistics, and sales. Other activities, such as R&D are done elsewhere. In another example, Philips recently announced it will close its factory in Glemsford (U.K.) and move fabrication activities of baby bottles and teat to Drachten (in the Northern region Zuidoost-Friesland). The design department for those products will not move as that was already done elsewhere. What these examples illustrate is that it matters to examine what is actually being done where and how it evolves over time. At a minimum, charting regional functional specialization offers a complementary perspective to a traditional analysis based on industry classifications.

To do so, we measure specialization in functions using information on the occupations of workers. We aim to move beyond the common dichotomous classification of headquarter and fabrication activities that is common in urban studies (Markusen 2002). We consider trends in the following eight business functions: R&D; Fabrication; Transport, logistics, and distribution; Sales and marketing; Technology and process development; Administrative and back-office; General and strategic management; and Others. These groups constitute a relevant level of analysis as multinational firms typically organize their activities around these functions due to internal economies of scale (Porter, 1985). They also allow us to explore the relationship between specialization and offshoring, further discussed below. A business function can be conceived of as a set of tasks carried out by a firm. In theoretical work, a 'task' is a narrow stage of production typically modeled as a continuum (Grossman and Rossi-Hansberg, 2008). For empirical analysis, we would like to set a level of aggregation that does not preclude measurement. We define the employment share of an activity in a region as the number of workers that perform it divided by the total number of workers in that region. This allows us to trace functional specialization across regions. We use labor force surveys (in Dutch: Enquête Beroepsbevolking) for the period from 2006 to 2014. This is the only source that provides representative information on the occupations of workers in the Netherlands.

Our descriptive analysis suggests the following. First, although the functional composition of the Dutch labor force is altering slowly, it is changing decisively away from fabrication and administrative activities towards knowledge-intensive activities such as R&D and technology development, sales and marketing, and management. Second, knowledge-intensive activities are more regionally concentrated compared to other activities. This concentration of knowledge-intensive activities in particular regions within the Netherlands is stable over time. Third, regions differ substantially in their specialization in business functions. Some regions, such as Amsterdam and Delft, have a relatively high share of workers involved in R&D and technology development activities, and others, such as Zaanstreek and Hilversum, in sales and marketing.

Next, this chapter explores whether changes in regional functional specialization relate to offshoring. We measure a firm's offshoring behavior using data from surveys in which Dutch firms were asked whether they relocated an activity to a foreign location. This relocation could occur within or outside the boundary of the firm, that is inside multinationals or between arm's length firms, and covers only those activities that were previously performed in the Netherlands. This measure for the re-location of business functions is clearly different from measures of international competition that are based on imported goods that feature prominently in recent studies of changes in labour demand (e.g. Autor et al. 2013, see Hummels et al. (2018) for overview). Standard measures of import competition contain imports that the firm does and does not produce, thereby confounding the effects of import competition and offshoring (Bernard et al. 2017). Our approach aims to examine regional functional employment implications from the firm's offshoring decisions regarding business functions. It is possible that shocks, e.g. a technology shock, influence both offshoring decisions and patterns of regional functional employment. To mitigate such concerns, we adapt an identification strategy used in Gagliardi et al. (2015), further discussed below.

The surveys we use are administered by Statistics Netherlands and sent to a representative sample of private firms with at least 50 employees. We combine these data with information from labor force surveys and the location of firms to create a novel dataset to explore the impact of offshoring. The ISS indicates that the likelihood to offshore a function depends on the industry as the nature of some industries makes them more prone to offshoring compared to others. In general, manufacturing firms are more likely to offshore compared to services firms (Möhlman and De Groot, 2013). But also within manufacturing, we find substantial differences in the likelihood of offshore. Firms in manufacturing industries like computers, electronic and optical products manufacturing, and motor vehicles and other transport equipment manufacturing are more likely to offshore fabrication activities compared to firms in food, beverages and tobacco manufacturing. In industries such as the manufacturing of coke, petroleum, chemical and pharmaceutical products we observe a higher propensity to offshore R&D activities compared to other manufacturing industries.

The ISS does not allow us to directly measure from which region a business function was offshored. This is because the survey is a relatively small sample of large and medium firms, and it is firms that report on offshoring. These firms have multiple establishments spreading across the various regions of the Netherlands. Therefore, to examine regional labor market effects we have to develop an identification approach. We use the information on the location of firms to document that regions in the Netherlands differ in terms of their industry composition. This provides a region by industry classification of workers. We combine this with the likelihood of offshoring business functions that differs across industries, based on Netherlands wide information. This offshoring has thus only an industry dimension. We combine this with our information on workers classified by activity and region described above. Using all three data sets one can investigate whether exposure of a particular group of workers in a region to offshoring depends on the industry composition of that region. For example, workers involved in fabrication activities in a region that manufactures relatively more transport products (an industry in which offshoring of fabrication activities is more prevalent) are expected to be more exposed to offshoring compared to fabrication workers in a region that manufactures relatively more processed food and beverages (an industry where offshoring of fabrication activities is less prevalent). To examine the relation between offshoring and demand for workers involved in functions across regions, we econometrically exploit cross-regional variation in offshoring exposure stemming from regional differences in industry composition. This identification approach is akin to that developed in Autor et al. (2013).

In general, we do not find evidence for a relationship between offshoring and functional specialization patterns in regions. Only for administrative and back-office occupations, we find a (weak) statistically significant relation between offshoring and reduced labor demand. In contrast, investments in R&D and ICT relate significantly to a decline in fabrication jobs. There are several ways to interpret these results. One is that the data is simply too noisy or that the time period covered is too short to pick up any effects of offshoring. It is likely also difficult to empirically identify any effects since most firms did not offshore activities, such that regional effects are likely to be modest at best. Alternatively, it might be the case that many of the major developments in reorganizing production systems of Dutch firms have already played out earlier, e.g. during the East-European enlargement of the European Union, see Marin (2006). Another is that offshoring of an activity may not significantly influence jobs as when the composition of the activity changes, its overall size does not change. For example, a firm may offshore its assembly activities but expand other fabrication activities, such as customized work and the provision of critical parts and components due to the decline in costs of offshored activities. As such, the overall size of fabrication activities carried out domestically is not necessarily decreasing (Grossman and Rossi-Hansberg, 2008). [14]

This chapter relates to several strands of literature. First, it relates to literature that examines business functions. Bernard et al. (2017) and Bloom et al. (2019) study how manufacturing firms in Denmark and the U.S. changed to research, design, management or wholesale activities under competitive pressures, notably from China. Timmer et al. (2019) characterize the functional specialization of countries in exports, and Chen et al. (2018a) the functional specialization of Chinese regions in exports. We provide a description of regional functional specialization in the Netherlands. Second, this chapter relates to studies on offshoring and onshore labor market outcomes, which include industry-level studies (Feenstra and Hanson, 1997, 1999; Hsieh and Woo, 2005; Hijzen et al. 2005; Michaels et al. 2014), firm-level studies (Biscourp and Kramarz, 2007; Amiti and Davis, 2011; Mion and Zhu, 2013) and the recent matched worker-firm studies (Martins and Opromolla, 2009; Liu and Trefler, 2011; Ebenstein et al. 2014; Hummels et al. 2014). We aim to contribute by exploring the effects of offshoring on onshore regional labor demand cross-classified by functions. Third, this chapter relates to literature that examines outcomes of import competition in local areas (Autor et al. 2013; Gagliardi et al. 2015). We aim to explore implications from the firm's offshoring behavior. Fourth, surveys of international sourcing activities have been used to examine the impact on firm productivity (Möhlman and De Groot, 2013). We use these surveys to examine whether regional specialization relates to offshoring.

The remainder of this chapter is organized as follows. Section 3.2 describes the data used. Section 3.3 presents trends in the regional functional specialization. Section 3.4 outlines the methodological approach and section 3.5 empirical results. Section 3.6 provides concluding remarks.

[14] Such substitution effects within fabrication activities are documented by Berghuis and den Butter (2013), based on firm interviews.

3.2 Data sources

For the analysis, we bring together three data sources from Statistics Netherlands. In section 3.2.1 we describe the Labor force survey used to measure functional specialization in local areas. Section 3.2.2 describes the regional enterprise database, which we use to obtain information on the industry composition of local areas. Section 3.2.3 describes the ISS, which provide unique information on the offshoring of business functions by firms.

3.2.1 Labor force surveys

Information on the occupation and other characteristics of workers are obtained from the Labor Force Survey (LFS). The LFS is a continuous quarterly survey of the Dutch population aged between 15 and 65 years. It is a rotating survey and in principle, each individual participates for 5 consecutive quarters in the survey and then drops out.

The sampling framework of the LFS is based on the geographical base register. This register includes all addresses by postal code in the Netherlands. The survey base includes a set of addresses drawn up by postal code in combination with the population register. Private households are included in the sample. The sampling plan is a two-stage stratified probability sample of addresses: the primary sampling units are the municipalities and the secondary sampling units are the addresses. Municipalities are selected with a probability proportional to their population and mailing addresses are selected systematically from a mailing list by postal code. In each quarter, the sample consists of around 50,000 households, which corresponds to a quarterly population sampling rate of about 0.7%. The variables we use from the LFS are information on the occupation, education, and location of work for each individual. Individuals report on their location of work in the first quarter round of the LFS during the years up to 2009 and from 2010 onwards they report the location of work in the second quarter round of the LFS. For the construction of our variables, we therefore use information from the first quarter of the LFS for the period up to 2009 and from 2010 onwards from the second quarter of the LFS. This sub-sample selection deals with the issue of missing information of working addresses in the other quarters, and also gets rid of redundant information on the same individuals over successive quarters. We exclude workers who live in the Netherlands but work abroad. [15]

An important step in our analysis is the mapping of occupations to particular functions, such as mapping occupations into fabrication, administration, and R&D. We map oc-

[15]We also exclude individuals who are unemployed or not in the labor force. The final sample size we use is about 30,000 workers annually.

cupations into the set of business functions put forth by Sturgeon and Gereffi (2009), itself based on Porter (1985). In particular, we match an occupation to a specific business function by the most closely related task description that applies to both. Consider the following examples. Electrotechnology engineers are mapped into R&D of products, services, or technology activities. Machinery mechanics and repairers are mapped into fabrication activities. Sales, marketing and public relations professionals are mapped into sales and marketing activities. However, It is not always straightforward to match an occupation to a certain business function group since there is not a clear-cut relationship between the two. Therefore, we need to make a choice by checking the similar task description of both the occupation and business function, which is open for more discussion in the future research.[16] In total, we have data on more than 100 occupations. To reduce the dimensions we map these occupational categories into eight business function categories which are clearly heterogeneous while still easy to interpret. We consider eight functions that are also distinguished in the ISS: 1) R&D; 2) Fabrication; 3) Transport, logistics, and distribution; 4) Sales and marketing; 5) Technology and process development; 6) Administrative and back-office; 7) General and strategic management; and 8) Others. Our mapping of occupations to these activities is exhaustive and similar to that in Timmer et al. (2019), although more detailed. However, it is difficult to classify all occupations to specific activities. These are put into the category 'others'. There are however ongoing efforts in the statistical community (in particular at Eurostat) that seek to provide a standardized mapping of occupations to business functions. Appendix Table 3.A2 displays the mapping of each 3 digit ISCO occupation to a particular function.

The use of occupational data to identify functions has some precursors in previous empirical work. Bernard et al. (2017) use occupations to identify activities by Danish firms and examine functional specialization patterns of firms that switch out of manufacturing into services. Maurin and Thesmar (2004) study the business function structure of French manufacturing firms using the information on the occupations of workers. Duranton and Puga (2005) show how cities in the U.S. specialize in management activities based on the occupational structure of the labor force. For the Netherlands, Berghuis and den Butter (2013) discuss how occupations may relate to business functions of firms on the basis of their own survey and interviews of managers. However, they do not create an actual mapping of occupations to business functions and do not provide an empirical analysis as done in this chapter.

[16]For example, we classify occupation librarians into the business function group of fabrication. The tasks related to librarians are designing and developing database architecture, data structures, dictionaries and naming conventions for information systems projects; designing, constructing, modifying, integrating, implementing and testing database. The similar task description in fabrication are the fabrication or transformation of materials and codification of information to render them suitable for use in operations. Activities that transform inputs into final outputs, either goods or services. This includes the detailed management of such operations.

The LFS data allows us to estimate the employment share by business function in each of the 40 COROP regions of the Netherlands. In Appendix Figure 3.A1 we show a map of the regions in the Netherlands. To obtain the number of jobs in business function b in region a at time t, denoted $Y_t^{a,b}$, we multiply the business function employment shares by region with the number of full-time equivalent (fte) jobs in each region. [17]

3.2.2 The regional enterprise database

We use the regional enterprise database to measure the industrial employment composition of regions. The regional enterprise dataset provides yearly information of all active local business units (LBU). An LBU corresponds to one or more subdivisions of an enterprise (e.g. a factory, warehouse, or office), which is located in a geographically identifiable place. An enterprise may consist of one or more LBUs, and in principle, each of the LBUs can be linked to a different sector. The postal code of the LBU is a full code with six characters, by which regional divisions can easily be made.

In order to measure the industry composition in local areas, we aggregate information from the LBUs. The main variables we take from the regional enterprise database are: 1) The number of people employed by the enterprise in the relevant statistical year; 2) A distribution key, which is the percentage of persons employed by the LBU with respect to the entire business unit; 3) Industry classification, which is the code for main economic activity of the LBU, according to the 2008 Standard Industrial Classification. [18] Combining the above information, we are able to measure the employment shares by sector in each region. We will denote this as $Employment\ share_t^{a,s}$, which is the employment share of sector s in region a at time t, where $\sum_{s=1}^{S} Employment\ share_t^{a,s} = 1$.

Regions differ substantially in their industry composition. For example, the East-Groningen region (in the northeast of the Netherlands) has a very different industrial employment composition compared to the region of Amsterdam. The share of workers employed in manufacturing is 19.43 percent in East-Groningen compared to 4.98 percent in Amsterdam. Vice versa, Amsterdam has a much bigger business services sector. Compared to East-Groningen, the employment share of ICT services is about 8.5 percent in Amsterdam but only 1 percent in East-Groningen. [19] This regional division in the location of the manufacturing and services sectors is broadly consistent with what has been docu-

[17] The number of full-time equivalent (fte) jobs by region is available from the statistical office at http://statline.cbs.nl/Statweb/.

[18] The Dutch Standaard Bedrijfs Indeling (SBI) 2008 is based on the industry classification of the European Union (NACE) and the classification of the United Nations (ISIC). The first 4 digits of SBI are the 4 digits of NACE. The first 2 digits of SBI and ISIC are the same.

[19] Employment shares by sector for each region are not shown, but available from the author upon request.

mented by De Jong and Stelder (2019). We will exploit cross-regional variation in industry specialization in our empirical analysis below.

3.2.3 International sourcing surveys

The third source of data are the ISS. In this chapter, we use the 2007 and 2012 ISS. These surveys provide unique information on the international sourcing of business functions by Dutch firms. For the ISS, Statistics Netherlands surveys firms with 50 or more persons employed, which results in a target population of about 4,600 enterprises. The 2007 (2012) ISS survey includes a representative set of responses from 1,002 (1,370) enterprises. Note two shortcomings of this data when used to analyze detailed regional developments. First, it is based on enterprises which can consist of various LBUs operating in different regions. Second, it is a sample and only covers medium and large-sized firms such that detail by region would quickly lead into samples being too small to be used in further econometric analysis.

The relevant question in the ISS we use for measuring offshoring is: *did your enterprise group internationally source a certain business activity in the period <2001-2006> (2007 ISS survey) or <2009-2011> (2012 ISS survey)?*[20] The survey defines international sourcing as the total or partial movement of business functions currently performed in-house or currently domestically sourced by the resident enterprise to enterprises within or outside of the enterprise group located abroad. If the answer on offshoring is yes, enterprises are further asked about what type of business function(s) they offshored. Here, the ISS distinguishes between core and support functions. The core business function is the main activity of the enterprise, related to the production of a final good or service. Support functions are conducted by enterprises to facilitate the production of final goods or services. These include activities such as distribution and logistics; marketing, sales and after sales services; ICT services; administration and management; R&D, engineering and related technical services, and other support functions. Note these business functions as defined in this survey correspond closely to the characterization we propose of functional specialization in regions. This is not a coincidence. The same literature on business functions (Porter, 1985; Sturgeon and Gereffi, 2009) was used to guide the formulation of questions in the ISS. [21]

The measure of offshoring that we obtain from the ISS is imperfect since it is a binary

[20] The period refers to 2001 to 2006 in the 2007 ISS and 2009 to 2011 in the 2012 ISS. See Sturgeon et al. (2013) for more information on the ISS.

[21] An exception is administrative and back-office, which are not distinguished from management. In the econometric analysis we will measure the likelihood to offshore these activities, and examine their individual effect on demand for administrative and back-office jobs and management jobs.

measure and it is measured over a relatively large time frame. From the 2007 ISS (2012 ISS), we only know whether a firm offshored between 2001 and 2006 (between 2009 and 2011), but not when it happened and how much. In addition, one cannot observe whether a firm outsources only once or multiple times during this period.

Regional functional specialization may have been shaped by the offshoring of business functions. We describe our identification strategy in section 3.4. However, changes in labor demand may also relate to other drivers, such as technological change (Autor et al. 2013; Gagliardi et al. 2015). To control for the effects of technological change in the regression analysis, we consider two indicators reflecting investments in computer software and innovation, both are measured in constant prices. The Dutch statistical office collects information on fixed capital formation in computer software and databases, as well as investment in R&D. These data are available annually for each of the 40 COROP regions. Fixed capital formation measures the value of acquisitions of new or existing fixed assets by the business sector less disposals of fixed assets. Specifically, the fixed capital formation of computer software and databases includes investment in computer programs, program descriptions and supporting materials for both systems and applications of software. The initial development and subsequent extensions of software and acquisition of computer software assets are also included. R&D incorporates the value of expenditure on creative work undertaken on a systematic basis to increase the stock of knowledge and the use of knowledge to devise new applications.

3.3 Functional specialization in the Netherlands

This section presents trends in functional specialization for the Netherlands. Section 3.3.1 presents aggregate trends. Due to offshoring, but also agglomeration externalities, geographical characteristics as well as historical development paths, we expect to observe spatial (inter-regional) differences in the share of workers by business functions, which is examined in section 3.3.2. Section 3.3.3 provides a measure for the exposure of regions to offshoring of business functions. This measure will be used in section 3.5 to explore whether regional functional job patterns relate to offshoring.

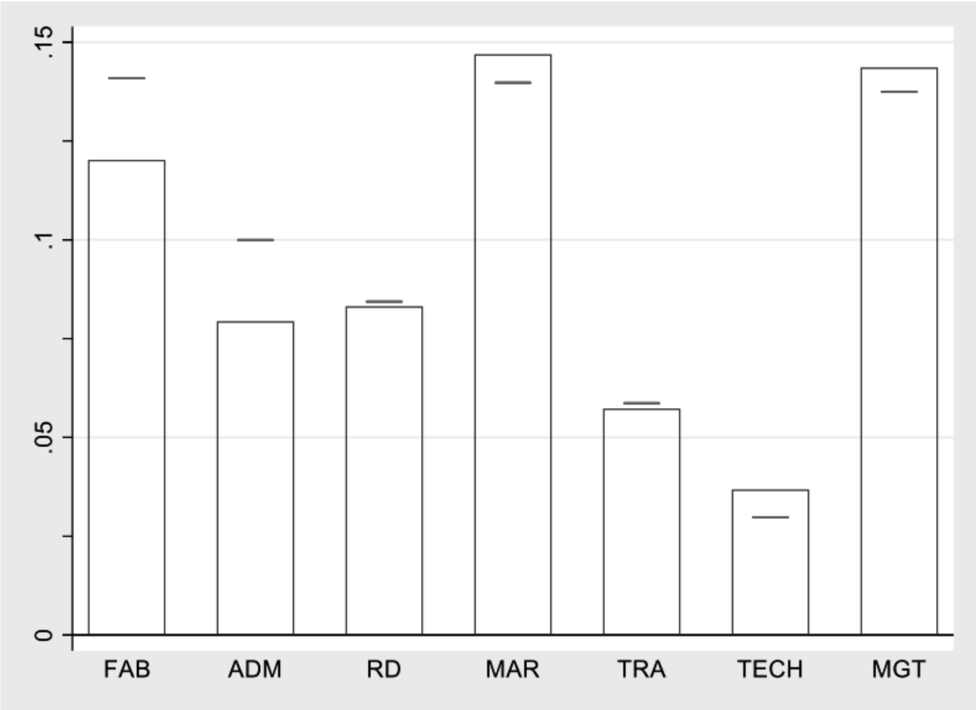
3.3.1 Aggregate trends in business functions

Figure 3.1 provides aggregate trends in employment shares by business function for 2006 and 2014. This figure is based on the annual Dutch LFS whereby the occupations of workers are mapped to business functions (as described in section 3.2). Bars are shares in 2014 and horizontal (red) line are shares in 2006.

Between 2006 and 2014 we observe a decline in the employment share of workers involved in fabrication and administration and back-office. In contrast, the share of workers involved in technology development, sales and marketing, and management increased. By 2014, we observe that more workers are involved in sales and marketing and management compared to fabrication. This is a fundamental change in the functional composition of the Dutch labor force.

Clearly, however, changes in the employment share by a business function are a slow moving process. For example, the share of workers involved in fabrication activities declined by less than three percentage points between 2006 and 2014. Also, the share of workers involved in management activities was high in both the initial and final year for which we have data. This aggregate pattern is complementary information to what is observed in Timmer et al. (2019). Timmer et al. (2019) examine functional specialization in exports, which is only a subset of all activities in the Dutch economy, namely those that are involved in the production for export. The patterns described in this chapter reflect employment shares by business function in traded and non-traded goods and services and as such is a much wider set of activities. Timmer et al. (2019) present a transition matrix that compares functional specialization in exports from 1999 to 2011 for forty countries in the world. For both the initial and final years of their analysis, they find that, compared to the rest of the world, the Netherlands is specialized in management activities in international trade.

Figure 3.1: Aggregate trends by business function for 2006 and 2014

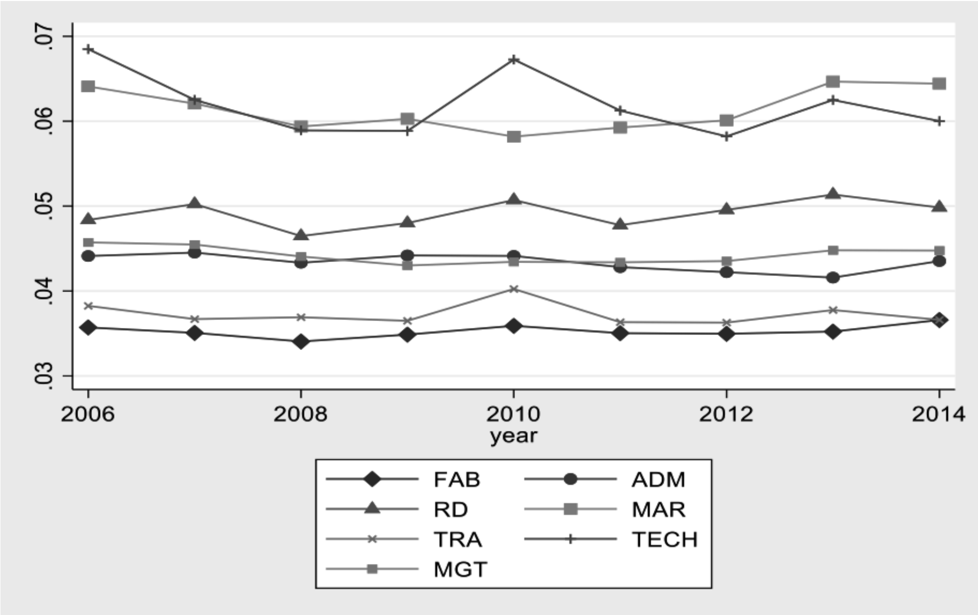


Note: Employment share by business function in the Netherlands. Bars are shares in 2014 and horizontal (red) lines are shares in 2006. R&D (RD); Fabrication (FAB); Transport, logistics, and distribution (TRA); Sales and marketing (MAR); Technology and process development (TECH); administrative and back-office (ADM); and General and strategic management (MGT). Other activities (OTH) not included in the figure. *Source:* LFS.

What is the geographical concentration of business functions across Dutch regions? A standard measure used is the Herfindahl Index (HI). The HI of a business function is defined as the sum of squared employment shares for each of the forty COROP regions. Figure 3.2 presents the HI by business function for the period from 2006 to 2014.

Two findings stand out. First, the higher HI for knowledge-intensive activities, such as R&D, technology development, and sales and marketing suggests they are stronger geographically concentrated in the Netherlands compared to fabrication. This is compatible with the view about the relevance of agglomeration whereby proximity helps spread knowledge (Glaeser and Resseger, 2010). The wider regional spread of fabrication that we document also relates to the spatial dispersion of manufacturing firms in the Netherlands as found in Groot et al. (2014). Second, we do not find a strong trend in the concentration of business functions in particular regions within the Netherlands. Figure 3.1 shows that business function employment shares only move slowly. Here we add to this finding that there is not a lot of reallocations across regions within the Netherlands, and therefore there is also not a strong increase in functional concentration.

Figure 3.2: Geographical concentration of business functions



Note: the Herfindahl Index (HI) is calculated as follows: $HI = \sum_{a=1}^{A} s_{ab}^2$, where s_{ab} is the share of COROP region a in total employment of business function b in the Netherlands. A higher (lower) HI indicates a business function is more (less) regionally concentrated. R&D (RD); Fabrication (FAB); Transport, logistics, and distribution (TRA); Sales and marketing (MAR); Technology and process development (TECH); administrative and back-office (ADM); General and strategic management (MGT). Other activities (OTH), not included in the figure. *Source:* LFS.

3.3.2 Regional functional specialization

Regional differences in wages (De Jong and Stelder, 2019), geographical characteristics, as well as historical built up of capabilities and networks (Markusen and Venables, 2013) are all likely to influence the specialization of regions in business functions. Consider the port of Rotterdam. It dates back to the 14th century and its location near the North Sea has led to the accumulation of knowledge and expertise in logistics activities. Therefore, once we move beyond studying aggregate trends, we expect to observe differences in the relative importance of activities across regions.

To examine regional functional specialization, we propose a Functional Specialization

(FS) index. This index compares the region's functional employment share to the weighted average functional employment share in the Netherlands. If the FS index is above (below) 1 it suggests the activity is relatively more (less) present in a region. The FS index has intuitive appeal as a measure of specialization, but should not be straightforwardly interpreted as a measure of (revealed) comparative advantage, because we do not examine functional specialization in regional exports. Also, it should be noted that the FS index is related to concentration indices traditionally used in economic geography, for example, the HI based on the distribution of employment across business functions in a region as discussed in section 3.3.1. Yet, the FS index is different as it is based on a comparison of shares, not distributions (Timmer et al. 2019).

Table 3.1 shows the FS index by region for 2014 (see Appendix Table 3.A1 for the employment shares by business function and region in 2014). Regional functional specialization is visualized in choropleth graphs, see Figure 3.3. As expected, we indeed observe substantial differences in the regional functional specialization. In discussing the results, it is helpful to distinguish between the urban (Randstad) area, the intermediate zone directly surrounding the Randstad area, and the 'periphery', see Appendix Figure 3.A2. Typically, we do not observe functional specialization in fabrication activities in the Randstad and surrounding areas. For example, the FS index for fabrication activities is below one in Utrecht, Groot-Amsterdam, and Agglomeration Haarlem. It is substantially above one in regions like Zuidwest-Friesland, Noord-Limburg, and Kop Van Noord-Holland. In contrast, the share of workers involved in R&D is relatively high in regions like Groot-Amsterdam (FS index is 1.4), Agglomeration's-Gravenhage (1.3), and Delft and Westland (1.3). Yet the FS index for R&D is low in peripheral regions like Oost-Groningen (0.4) and Noord-Friesland (0.6).

Table 3.1: Functional specialization index, by region in 2014

COROP region	RD	FAB	TRA	MAR	TECH	ADM	MGT	OTH
Oost-Groningen	0.4	**1.4**	0.8	**1.1**	0.3	0.7	0.8	**1.2**
Delfzijl en omgeving	0.7	**1.1**	**2.0**	0.8	0.5	**1.1**	0.8	1.0
Overig Groningen	**1.2**	0.8	0.9	1.0	0.7	0.9	1.0	**1.1**
Noord-Friesland	0.6	**1.4**	**1.1**	0.8	0.7	1.0	1.0	**1.1**
Zuidwest-Friesland	0.7	**1.6**	**1.1**	0.9	1.0	0.7	0.7	**1.1**
Zuidoost-Friesland	0.8	**1.3**	**1.2**	**1.1**	0.8	1.0	0.8	1.0
Noord-Drenthe	**1.1**	**1.1**	0.7	0.8	0.9	0.9	**1.2**	**1.1**
Zuidoost-Drenthe	0.8	**1.5**	**1.5**	0.9	0.7	0.8	1.0	0.9
Zuidwest-Drenthe	**1.1**	**1.3**	**1.3**	0.8	0.3	0.8	0.7	**1.1**
Noord-Overijssel	0.7	**1.3**	**1.3**	0.9	0.6	1.0	0.9	**1.1**
Zuidwest-Overijssel	1.0	1.0	**1.3**	1.0	0.8	1.0	0.9	**1.1**
Twente	0.9	**1.2**	0.8	0.9	0.8	1.0	0.9	**1.1**
Veluwe	0.9	**1.2**	0.9	1.0	**1.2**	0.9	0.9	1.0
Achterhoek	0.6	**1.3**	**1.3**	1.0	0.7	**1.2**	0.9	1.0
Arnhem/Nijmegen	**1.1**	0.7	1.0	1.0	1.0	1.0	**1.1**	**1.1**
Zuidwest-Gelderland	0.8	**1.5**	**1.4**	0.9	0.9	1.0	1.0	0.9
Utrecht	**1.2**	0.7	0.8	**1.1**	**1.7**	1.0	**1.1**	0.9
Kop Van Noord-Holland	0.9	**1.7**	0.8	0.8	0.5	0.9	0.9	1.0
Alkmaar en omgeving	1.0	0.8	1.0	**1.1**	0.9	1.0	0.9	**1.1**
IJmond	0.9	**1.1**	1.0	0.8	0.6	0.8	**1.1**	**1.1**
Agglomeratie Haarlem	**1.1**	0.5	0.5	**1.2**	**1.2**	0.6	**1.3**	**1.1**
Zaanstreek	0.9	0.8	**1.8**	**1.3**	0.8	1.0	0.7	0.9
Groot-Amsterdam	**1.4**	0.5	0.7	**1.1**	**1.4**	**1.1**	**1.1**	1.0
Het Gooi en Vechtstreek	0.9	0.6	0.7	1.0	**1.3**	0.7	**1.1**	**1.2**
Agglomeratie Leiden en Bollenstreek	**1.2**	1.0	0.8	0.9	0.9	0.9	0.9	**1.1**
Agglomeratie 's-Gravenhage	**1.3**	0.5	0.6	1.0	**1.6**	0.9	**1.4**	0.9
Delft en Westland	**1.3**	**1.3**	1.0	**1.1**	**1.1**	**1.1**	0.8	0.9
Oost-Zuid-Holland	0.7	**1.1**	**1.4**	1.0	1.0	0.9	1.0	1.0
Groot-Rijnmond	1.0	0.9	1.0	1.0	0.9	**1.2**	1.0	1.0
Zuidoost-Zuid-Holland	0.9	**1.1**	**1.1**	0.9	0.7	**1.1**	**1.2**	1.0
Zeeuwsch-Vlaanderen	0.8	**1.4**	**1.6**	0.9	0.6	1.0	0.8	1.0
Overig Zeeland	0.9	**1.2**	**1.1**	0.9	0.4	1.0	1.0	**1.1**
West-Noord-Brabant	0.9	**1.1**	**1.3**	**1.2**	0.7	1.0	0.9	0.9
Midden-Noord-Brabant	1.0	**1.1**	**1.5**	0.9	0.5	**1.2**	0.9	1.0
Noordoost-Noord-Brabant	0.8	**1.2**	**1.2**	1.0	0.8	**1.1**	0.9	1.0
Zuidoost-Noord-Brabant	**1.1**	**1.3**	0.9	1.0	**1.3**	0.9	1.0	0.9
Noord-Limburg	0.7	**1.6**	**1.4**	0.9	0.8	1.0	0.9	0.9
Midden-Limburg	0.9	**1.2**	**1.3**	1.0	0.6	**1.1**	0.9	1.0
Zuid-Limburg	1.0	1.0	0.9	1.0	0.7	1.0	0.9	**1.1**
Flevoland	0.8	**1.1**	**1.3**	**1.1**	**1.1**	1.0	0.9	1.0

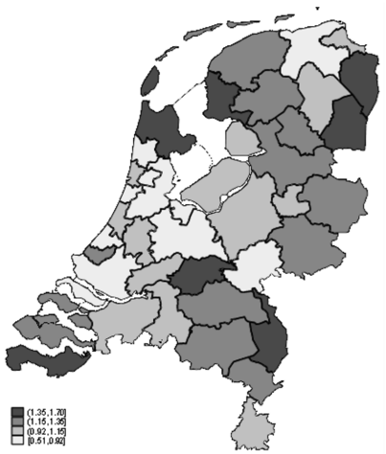
Note: The FS index compares the region's functional employment share to the weighted average functional employment share in the Netherlands. If the FS index is above (below) 1 it suggests the activity is relatively more (less) present in a region. These are visualized in bold font. R&D (RD); Fabrication (FAB); Transport, logistics, and distribution (TRA); Sales and marketing (MAR); Technology and process development (TECH); administrative and back-office (ADM); General and strategic management (MGT); and. Other activities (OTH). *Source*: LFS.

We observe functional specialization in transport, logistics, and distribution workers in Rijnmond (Rotterdam). This is not observed for Groot-Amsterdam (which includes Schiphol) but is observed for Delfzijl and surroundings, and the Zaanstreek. Also, we observe a functional specialization in sales and marketing in the Gooi and Vechtstreek. Note, however, the FS index is a relative measure: it is based on a comparison of employment shares of various activities within a region and is silent on the overall level of activity in a region. It has, therefore, to be interpreted in conjunction with other information on the overall number of workers involved in activities, which is examined below. Furthermore, the standard deviation of the calculated specialization index is larger in less populated regions, which is a potential limitation of the analysis.

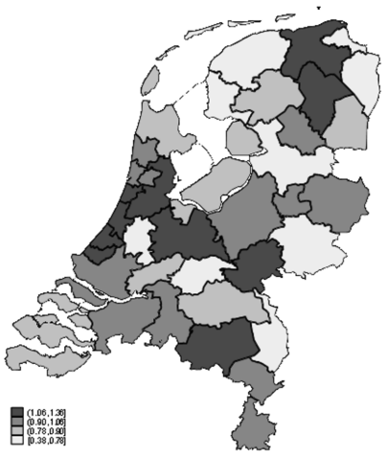
Figure 3.4 shows growth rates in functional employment by region between 2006 and 2014. Section 3.3.1 documents that in the aggregate the changes are moderate (see Figure 3.1). Figure 3.4 examines growth rates at the regional level. We observe much more regional variation. Panel (a) of Figure 3.4 visualizes growth rates in fabrication employment. In the aggregate, the level decreased, and we also observe a decrease in most regions. However, fabrication employment did not decrease in all regions. In particular, in Delfzijl and Zuidwest-Friesland it increased. Also, growth in fabrication employment differs substantially across regions. This regional variation is also observed for other business functions. For example, panel (e) shows employment growth in technology and process development. Most regions experienced an increase in this activity, but the increase differs by region and is not confined to regions in the Randstad.

Figure 3.3: Choropleth maps of the FS index, by region in 2014

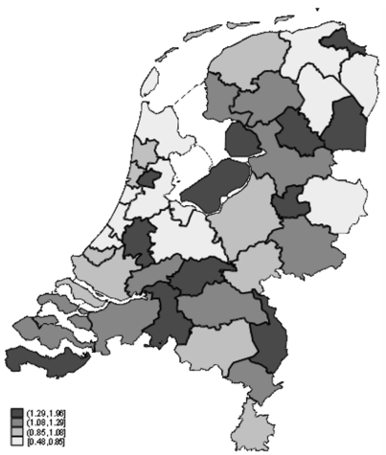
(a) Fabrication activities



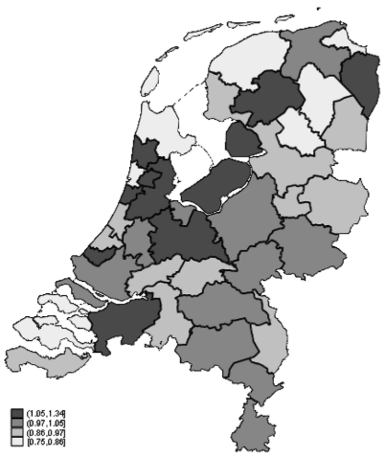
(b) R&D activities



(c) Logistics and distribution activities

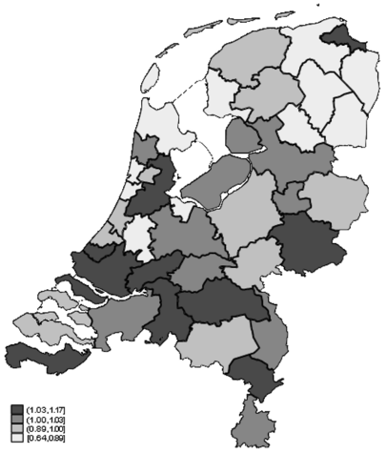


(d) Sales and marketing activities

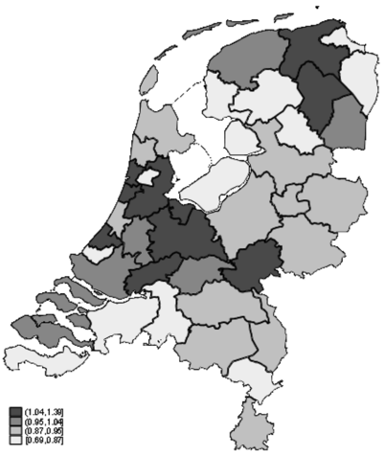


(e) Technology and process development activities

(f) Administrative and back-office activities



(g) Management activities



(h) Other activities

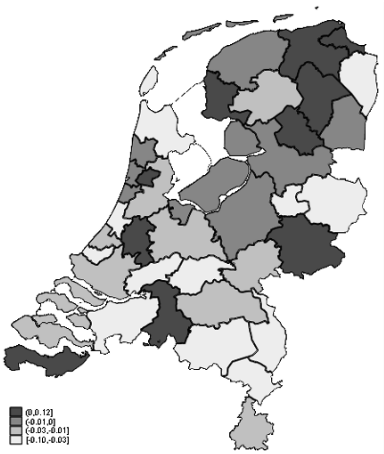
Note: The FS index compares the region's functional employment share to the weighted average functional employment share in the Netherlands. If the FS index is above (below) 1 it suggests the activity is relatively more (less) present in a region. Darker (lighted) shaded areas indicate a higher (lower) FS index. *Source:* LFS.

Figure 3.4: Growth rates in functional employment, 2006 to 2014

(a) Fabrication activities

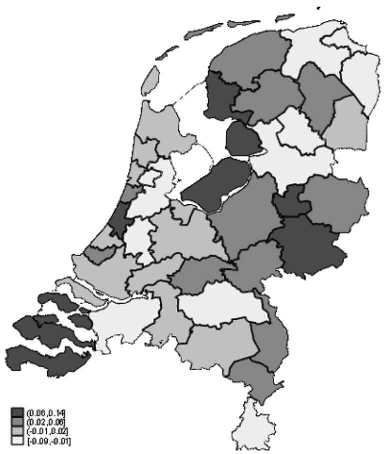
(b) R&D activities

(c) Logistics and distribution activities

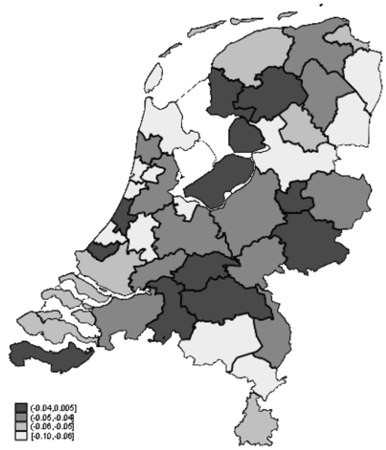


(d) Sales and marketing activities

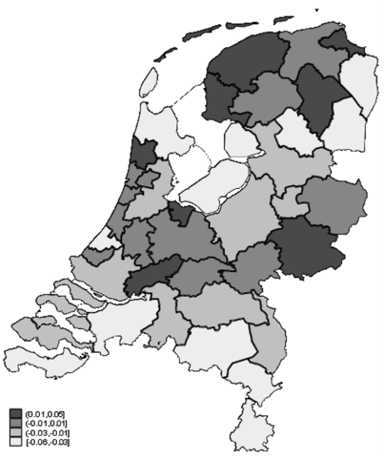
(e) Technology and process development activities



(f) Administrative and back-office activities



(g) Management activities



(h) Other activities

Note: Regional employment growth rate by function, between 2006 and 2014. *Source:* LFS.

3.3.3 The exposure of regions to offshoring of business functions

What is driving changes in business function employment and the functional specialization of regions that we documented in the previous section? One prominent hypothesis in the literature is offshoring. Presumably, offshoring is activity-biased. Bernard et al. (2017) examine the occupational structure of Danish firms and document that many Danish manufacturing firms offshored fabrication activities and specialized in related activities such as R&D, design, sales and marketing.

Table 3.2 confirms this bias in the case of Dutch firms. It shows the shares of firms that offshored by business function. Not surprisingly, most international sourcing was of fabrication activities (9.7 percent of firms in the 2007 ISS, 4.5 percent in the 2012 ISS). But 4 percent of firms report they internationally sourced technology and process services in the 2007 wave of the ISS (3.2 percent in the second wave). 3.4 percent of firms reported offshoring of administrative and management services in the first wave of the ISS (3.1 percent in the second wave).

Bongaard et al. (2013) document that foreign controlled enterprises are more often involved in international sourcing than Dutch controlled enterprises. This is perhaps because they are less sensitive to social and political pressure to save domestic jobs or face lower thresholds when moving functions abroad since they already have foreign affiliates. About 80 percent of offshoring is within the enterprise group (2012 ISS). In the 2007 and 2012 ISS, the EU-countries were the main destinations for offshoring (67 percent in the 2012 ISS), indicating that activities were not massively moved to Asia.

Perhaps most surprising is that the ISS uncovered that only a limited fraction of firms engage in offshoring. The 2007 ISS asks firms on their offshoring during the period from 2001 to 2006. The share of firms offshoring is low and falls further in the 2012 ISS (which asks firms on their offshoring during 2009-2011). Offshoring data is not available by region. We aim to address this issue by using an approximation based on the industry composition in a region and the likelihood of offshore an activity that varies by industry, discussed next.

Table 3.2: Offshoring shares by business function

Business function	2007 ISS	2012 ISS
Fabrication	9.7 (97)	4.5 (61)
Transport, logistics, and distribution	3.1 (31)	1.2 (17)
Sales and marketing	2.3 (23)	1.9 (26)
Technology and process development	4.0 (40)	3.2 (44)
Administrative and back-office; General and strategic management	3.4 (34)	3.1 (43)
R&D	3.4 (34)	0.9 (12)
Others	0.4 (4)	1.3 (18)

Note: This table reports the percentage share of firms that report offshoring a business function. The number of firms that report offshoring a business function in brackets. Firms may offshore multiple business functions. Sources: 2007 and 2012 ISS.

We construct a measure of the likelihood of firms to offshore a particular business function. This likelihood, or propensity, to offshore a business function, which we name it by $Offshoring\ propensity_t^{b,s}$, is calculated as the number of firms in sector s that reported in the ISS they offshored business function b divided by the total number of firms in this sector s.[22] We use the total number of firms in industry s that report in the ISS. So if 5 out of 20 firms in sector s report they offshored business activity b, the offshoring propensity of that activity in sector s is 5/20=0.25. This is an unweighted offshoring propensity measure. In what follows we consider a weighted offshoring propensity measure, where we weight by firm's employment size for our baseline estimates and examine whether results are different from unweighted ones. For several services sectors and also for agriculture and mining sector we do not observe information on offshoring propensity, because no firms active in these sectors were included in the ISS. These sectors of the economy are excluded from the analysis in this chapter. [23]

Table 3.3 shows the offshoring propensity by industry and business activity based on the 2007 ISS. The propensity to offshore differs across industries, as the nature of some industries makes them more prone to offshoring compared to others. For example, using the 2007 ISS, outsourcing by firms that provide business services is lower compared to manufacturing firms (reported in column 1 of Table 3.3, see also Möhlman and De Groot (2013)), which is not surprising since manufacturing firms are able to offshore fabrication activities and their products tend to be more internationally contestable. Column 1 in Table 3.3 suggests that services firms also offshore fabrication activities. Note that fabrication activities refer to the core activity of the firm. The core business function is the main revenue-producing activity of the enterprise. In most cases, it equals the main activity of the enterprise, but it may include other activities, including the production of intermediate inputs if the enterprise considers these to comprise part of their core set of functions (Sturgeon 2018).

Within manufacturing industries, we find substantial variation in offshoring propensity. For the 2007 ISS, we find that firms in industries like manufacturing of computers, electronic and optical products (a weighted offshoring propensity measure of 0.577), manufacturing of machinery and equipment (0.417) and manufacturing of motor vehicles and other transport equipment (0.401) have the highest propensity to offshore fabrication activities.[24] In other industries, such as the manufacturing of coke, petroleum; chemical

[22]The ISS only covers large enterprises. This may lead to an overestimation of the sourcing propensity because of a positive correlation between firm size and international sourcing behavior (Hummels et al. 2014). Note, however, that in the empirical analysis below we will compare the effects of international sourcing on employment across regions, and therefore instead of using absolute international sourcing propensity (which is biased upwards due to the coverage of only large firms), we compare relative exposure to international sourcing across regions (which is less likely to be biased).

[23]Sectors included in the analysis are manufacturing industries and market-based services sectors, except for financial and insurance, see Table 3.3.

[24]If we do not weight by firm size, offshoring propensity of motor vehicles and other transport equipment manufacturers (0.435) tops all other sectors. Offshoring propensity of computers, electronic and optical products (0.278) and manufacturing of machinery and equipment (0.288) are lower compared to the weighted measure, but still rank in the top 3.

and pharmaceutical products we observe a higher propensity to offshore R&D activities (0.422). The final column in Table 3.3 shows the number of firms reporting offshoring in the survey by industry. The limited number of firms reporting offshoring is likely to affect the statistical significance for identification from offshoring on changes in business function employment shares.

The next sections use these sectoral differences in the propensity to offshore business functions. Regions differ in terms of their sector composition. Since the propensity to offshore a business function differs across sectors, this will result in differential exposure of regions to offshoring. Our econometric identification strategy is described in the next section.

Table 3.3: Offshoring propensity by industry and business function, 2007 ISS

Industry	FAB	TRA	MAR	TECH	RD	ADM & MGT	OTH	# Firms reporting offshoring
Mfr of food, beverages and tobacco products	0.059	-	0.016	0.019	-	0.013	-	7
Mfr of textiles, wearing apparel, footwear and leather	X	X	X	X	X	X	X	X
Mfr of wood, paper, printing and recorded media	0.084	0.058	0.048	0.252	0.078	0.111	-	7
Mfr of coke, petroleum; chemical and pharmaceutical products	0.076	0.189	0.058	0.422	0.191	0.168	-	13
Mfr of rubber and plastic products; other non-metallic mineral products	0.120	-	0.025	0.154	-	0.154	-	7
Mfr of basic and fabricated metals, except machinery and equipment	0.244	0.115	0.012	0.010	-	0.105	-	9
Mfr of computers, electronic and optical products; electrical equipment	0.577	0.387	0.009	0.100	0.073	0.396	-	11
Mfr of machinery and equipment n.e.c.	0.417	0.049	0.044	0.289	0.244	0.038	0.024	22
Mfr of motor vehicles and other transport equipment	0.401	0.025	0.067	0.122	0.024	0.000	0.000	10
Mfr of furniture and other products n.e.c.; repair and installation of machinery and equipment	0.066	0.009	-	0.027	0.027	0.007	0.010	9
Electricity, gas and water supply	-	-	-	-	-	-	-	0
Construction	X	X	X	X	X	X	X	X
Wholesale and retail trade; repair of motor vehicles and motorcycles	0.048	0.026	0.010	0.071	0.017	0.034	-	20
Transportation and storage services	0.024	0.053	0.000	0.007	-	0.015	-	7
Accommodation and food services	X	X	X	X	X	X	X	X
Information and communication services	0.033	0.039	0.020	0.111	0.011	0.204	-	11
Renting, buying and selling of real estate	-	-	-	-	-	-	-	0
Consultancy, research and other specialized business services	0.063	0.002	0.024	0.040	0.015	0.042	0.002	14
Renting and leasing of tangible goods and other business support services	X	X	X	X	X	X	X	X

Note: The propensity to offshore a business function is calculated as the number of firms in sector s that internationally sourced business function b divided by the total number of firms in this sector s included in the survey. We weight by firm size based on the number of persons employed. A '-' indicates no observation to calculate the offshoring propensity. X indicates value is not disclosed due to confidentiality reasons. The last column reports the number of firms in a corresponding industry that report they offshore a business function R&D (RD); Fabrication (FAB); Transport, logistics, and distribution (TRA); Sales and marketing (MAR); Technology and process development (TECH); Administrative and back-office (ADM) and General and strategic management (MGT); and Other activities (OTH). See Appendix Table 3.A3 for results based on the 2012 ISS. *Source:* 2007 ISS.

3.4 Econometric methodology

We aim to econometrically examine whether changes in jobs by business function and region as described in the previous section are related to offshoring. For that, we propose a measure of the exposure of regions to offshoring. This will be our key independent variable in the regression model. The relation between changes in jobs and offshoring is subject to endogeneity concerns. This is because offshoring may influence changes in jobs and vice versa, the presence of certain jobs may affect whether offshoring actually takes place. To mitigate issues of endogeneity and resulting bias in estimated coefficients in the regressions, we construct offshoring exposure as the interaction between the region's industry composition and the industry's offshoring propensity.

This methodological approach is akin to a differences-in-differences method (see e.g. Gagliardi et al. (2015)). Regions differ in terms of sector composition. In turn, the propensity to offshore a business function differs by sector. Hence, workers in regions with a stronger presence of sectors that are more likely to offshore activities are relatively more exposed to offshoring. Formally, we measure regional exposure to offshoring as follows:

$$Offshoring\ Exposure_t^{a,b} = \sum_s (Employment\ share_t^{a,s} \times Offshoring\ propensity_t^{b,s}) \tag{3.1}$$

where $Offshoring\ Exposure_t^{a,b}$ is our preferred measure of region a's exposure to offshoring a certain business function b in year t. This measure is constructed as an interaction term. It takes into account the conditional effect of the initial industry composition of local areas a, ($Employment\ share_t^{a,s}$), on offshoring propensity by sector s and business function b ($Offshoring\ propensity_t^{b,s}$). $Offshoring\ propensity_t^{b,s}$ is a country-wide measure of offshoring for different business functions by sector. The sectoral employment shares of a region are measured using the regional enterprise database (see section 3.2.2). Offshoring propensity is as shown in Table 3.3.

Since we have two editions of the ISS, we estimate initial regional exposure to offshoring for t=2006 using offshoring propensity from the 2007 ISS and for t=2011 using offshoring propensity from the 2012 ISS. In our econometric analysis, we examine whether this initial exposure is associated with changes in the regional functional employment structure in subsequent years. We relate the 2006 initial exposure to occupational employment changes for the years 2006 to 2008, and the 2011 initial exposure to changes in the period from

2011 to 2013.

Constructed this way, the variable meets certain exogeneity conditions. That is, it attributes a national trend (offshoring propensity identified using the ISS) to regions based on their initial sector composition. This limits simultaneity concerns between sector composition and offshoring. However, it is still possible that the identification of effects is driven by omitted variables. To alleviate this concern, we include investments in ICT and R&D as well as other control variables at the regional level.

Our econometric estimation strategy follows Gagliardi et al. (2015) and takes the following reduced form:

$$\Delta Y_T^{a,b} = \alpha + \beta \times Offshoring\ Exposure_{initial}^{a,b} + \theta \times Tech\ inv_{initial}^{a} + \gamma \times X_{initial}^{a} + \delta T + \varepsilon_t^{a,b} \tag{3.2}$$

$\Delta Y_T^{a,b}$ is the dependent variable that measures the average annual growth rate of jobs involved in business function b in region a. We pool the average annual growth rate of jobs in activity b in area a during the period T which can be 2006-2008 or 2011-2013. We also include a period dummy T. Standard errors are conservatively clustered at the NUTS 2 level since errors are potentially correlated within regions due to agglomeration of activities. $Offshoring\ Exposure^{a,b}$ is the exposure of region a to the offshoring of a particular business function b at the start of the period examined. The effect from technology investment is measured using the information on investment by regions in computer assets, software and databases or R&D investment in the initial year of the period considered (2006 or 2011), divided by gross value added of the region.

We also include several common spatial/geographic control variables at the regional level. These are a port dummy variable that takes a value of 1 for all regions that are coastal or located along one of the four big seaports of the Netherlands (Amsterdam, Moerdijk, Rotterdam, and Terneuzen), and a metropolitan dummy variable that takes a value of 1 for all metropolitan districts—the Randstad regions (see Appendix Figure 3.A2).

Furthermore, the experience and education of workers may affect the regional occupational employment composition. We therefore include proxies for average age and education level by region as control variables in our econometric analysis. The variable for young workers is measured as the share of young workers (aged between 15 and 35) in the working population of a region; the share of high-skilled workers is measured as the number of workers with higher educational attainment (HBO and above) divided by the working population in a region.

Table 3.4 shows descriptive statistics of the variables used in the econometric analysis. Our dependent variable is the regional annual employment growth in a business function during the period 2006-2008 and 2011-2013. This growth rate shows substantial variation across regions and is on average positive in activities like R&D, sales and marketing, and management. The average growth rate is negative for fabrication and administrative activities, but with substantial variation across regions as discussed in section 3.3.2. Average offshoring exposure is highest for fabrication activities (0.055), and is also high for R&D activities (0.046). ICT and R&D investment show substantial variation across regions. We normalize this variable by dividing by regional gross value added. Other control variables also show substantial variation across regions.

Table 3.4: Descriptive statistics of variables included in the regression analysis

Variable	# obs	Mean	St. Dev.	Min	Max
Average annual employment growth in:					
R&D	80	0.006	0.017	-0.034	0.040
Fabrication	80	-0.001	0.097	-0.218	0.303
Administrative and back-office	80	-0.042	0.099	-0.438	0.208
Management	80	0.030	0.086	-0.191	0.231
Technology and process development	79†	0.006	0.017	-0.034	0.040
Sales and marketing	80	0.009	0.072	-0.199	0.174
Transportation, logistics, and distribution	80	-0.027	0.127	-0.361	0.350
Other	80	0.015	0.038	-0.094	0.109
Offshoring exposure by business function:					
R&D	80	0.046	0.008	0.032	0.079
Fabrication	80	0.055	0.015	0.033	0.128
Transportation, logistics, and distribution	80	0.019	0.013	0.003	0.073
Sales and marketing	80	0.016	0.006	0.009	0.037
Technology and process development	80	0.043	0.009	0.028	0.084
Administrative and back-office	80	0.011	0.010	0.001	0.039
Other	80	0.019	0.008	0.007	0.042
Investment in R&D / gross value added	80	0.020	0.007	0.010	0.060
Investment in computer assets and software / gross value added	80	0.040	0.007	0.022	0.069
Big Sea Port (dummy variable)	80	0.125	0.333	0	1
Metropolitan region (dummy variable)	80	0.300	0.461	0	1
Share of high-skilled workers	80	0.283	0.061	0.151	0.439
Share of young workers	80	0.340	0.024	0.264	0.395

Note: average annual employment growth is calculated for the period 2006-2008 and 2011-2013. Offshoring exposure is measured using the 2007 and 2012 ISS. † For one region-year we do not observe technology and process development jobs. Sources: see section 3.2.

3.5 Results

3.5.1 Basic results

Before we examine regression results, we first explore partial correlations between offshoring exposure and regional growth of employment by business function. Figure 3.5 plots the relationship between offshoring exposure to a particular business function (horizontal axis) and regional growth in employment by business function (vertical axis). Remember that we have 80 observations in total: two observations (for the periods 2006-2008 and 2011-2013) for each of the forty COROP regions. A linear fit is shown in each panel. We expect to observe a negative relationship between employment growth and offshoring exposure in each of the panels of Figure 3.5. Such a relation would capture the direct effect of jobs moving out of the region to a foreign location. Some business functions are complements, and hence the re-location of a business function may indirectly affect jobs of a complementary function. For example, the re-location of fabrication may indirectly affect product development especially if both activities take place under the same roof.[25] These indirect effects due to the complementarity of functions are not studied here but in Chapter 2.

The exploratory analysis suggests that there is not a strong relationship between offshoring exposure and employment changes in our dataset. Indeed, a relation is virtually absent for fabrication (panel a). For some business functions, we observe a negative relation between offshoring exposure and changes in employment, in line with our expectations. These include R&D as well as logistics and distribution. However, for other business functions, such as sales and marketing, management, and administrative and back-office, this is not observed.

Table 3.5 more formally examines the relationship between offshoring and employment. It shows regression results based on equation 3.2. We run regressions for each of the 8 business functions. Our estimates are conservative as we cluster observations at the NUTS 2 level and control for heteroscedasticity. The adjusted R^2 for several regressions suggests that much of the variance in employment growth by business function is explained by the regression model, although this is less the case for administration (column 6) and management (column 7).[26]

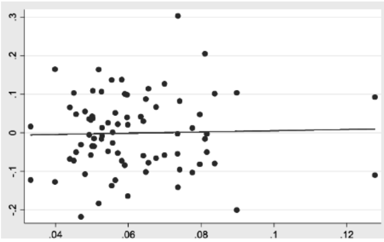
Our key independent variable is a measure of regional offshoring exposure. In each regres-

[25]In the introduction we discussed the example of Philips in Drachten. Besides the fabrication of shavers, this factory also hosts a product development division for shavers.

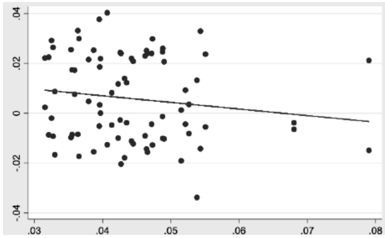
[26]The definition of the adjusted R^2 allows it to be negative and suggests a simpler model with less predictors or a model with more observations is preferable.

Figure 3.5: Correlation between offshoring exposure and growth of employment by business function

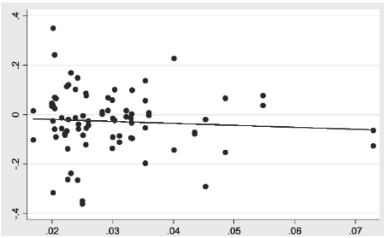
(a) Fabrication



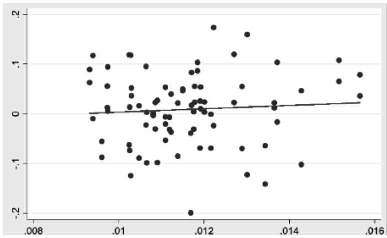
(b) R&D



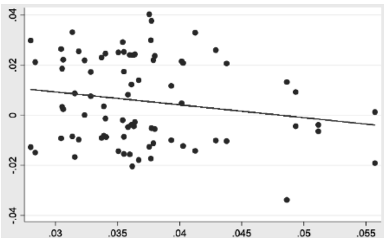
(c) Logistics and distribution



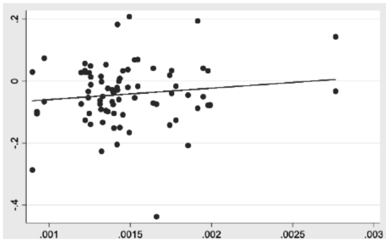
(d) Sales and marketing



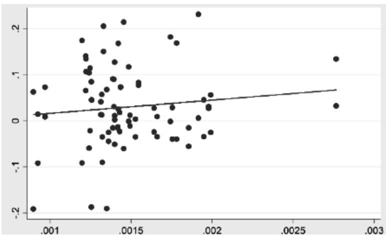
(e) Technology and process development



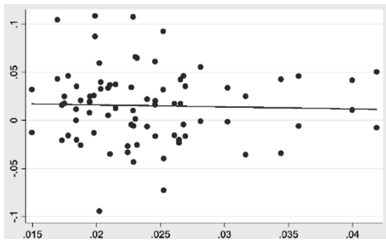
(f) Administrative and back-office



(g) Management



(h) Other



Note: On the horizontal axis is the measure of offshoring exposure by business function, see equation 3.1. On the vertical axis is the average annual growth in employment by business function for each of the forty regions and for the period 2006-2008 and 2011-2013. *Source:* see section 3.2.

sion in Table 3.5, the coefficient for offshoring exposure is negative, suggesting a negative relationship between changes in jobs and offshoring. This is consistent with our expectations. It is also observed in alternative model specifications (not shown), for example in regressions without control variables. The coefficient varies substantially, ranging from

-0.205 for fabrication (column 2) to -9.663 for administration and back-office activities (column 6). Yet, for most regressions, we do not observe a significant relation and actual change in offshoring is small such that the effect is generally modest. There are two exceptions. We do find a statistically significant relation for changes in administrative and back-office jobs, and sales and marketing jobs.[27] Taken together these findings are suggestive (weak) evidence on the employment effects of offshoring on support services activities. Amiti and Wei (2005) have pointed at the small but rapid expansion of support services offshoring in the US and the UK. They document that most advanced economies import and export computing and business services and are net exporters of these services. Amiti and Wei (2005) analyze the effects of services outsourcing on employment growth in the UK and do not find evidence that offshoring results in employment losses. Our analysis provides a more direct approach to examine offshoring and changes in jobs by business function across regions in the Netherlands.

[27]Results are qualitatively similar if we include initial ICT investment as a proxy for technological change instead of initial R&D investment.

Table 3.5: OLS regression results by business function

	Dependent variable is average annual growth rate of jobs in:							
	RD	FAB	TRA	MAR	TECH	ADM	MGT	OTH
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial Offshoring exposure	-0.223	-0.205	-2.376	-5.127*	-0.237	-9.663**	-0.210	-0.514
	(0.205)	(0.537)	(1.772)	(2.650)	(0.182)	(4.183)	(4.562)	(0.706)
Initial R&D investment	-0.021	-2.269**	-0.714	1.810*	0.009	0.995	-1.145	0.998*
	(0.199)	(0.896)	(2.104)	(0.959)	(0.188)	(0.904)	(1.959)	(0.529)
Initial share of young	0.074*	0.135	-0.649	-0.370	0.081**	0.763**	-0.019	0.201
workers	(0.036)	(0.357)	(0.745)	(0.303)	(0.037)	(0.335)	(0.441)	(0.194)
Initial share of high-skilled	0.035*	-0.146	-0.224	0.313**	0.039*	0.343**	-0.195	-0.017
workers	(0.017)	(0.094)	(0.189)	(0.142)	(0.020)	(0.131)	(0.171)	(0.064)
Randstad	-0.002	-0.002	0.024	-0.027*	-0.002	-0.016	0.031*	-0.004
	(0.001)	(0.019)	(0.025)	(0.014)	(0.001)	(0.012)	(0.016)	(0.007)
Sea Port	0.0001	-0.003	0.013	0.029**	0.000	-0.004	-0.028	-0.003
	(0.003)	(0.015)	(0.021)	(0.013)	(0.003)	(0.021)	(0.033)	(0.013)
Constant	-0.004	0.120	0.387	0.049	-0.009	-0.408***	0.116	-0.040
	(0.016)	(0.116)	(0.319)	(0.133)	(0.014)	(0.118)	(0.181)	(0.074)
Observations	80	80	80	80	79	80	80	80
Adjusted R^2	0.756	0.459	0.141	0.199	0.751	0.048	-0.039	0.125

Note: Dependent variable is the regional average annual growth rate of jobs in R&D (RD); Fabrication (FAB); Transport, logistics, and distribution (TRA); Sales and marketing (MAR); Technology and process development (TECH); Administrative and back-office (ADM); General and strategic management (MGT); and Other activities (OTH) during the period 2006-2008 and 2011-2013. A period dummy is included in all regressions. Robust standard errors in parentheses are clustered at the NUTS 2 level. *** p<0.01, ** p<0.05, * p<0.1.

Various control variables are included in the regressions presented in Table 3.5. In particular, we have included a proxy for investment in new technologies. There is a burgeoning literature on the impact of technologies on jobs. One of the key recent insights in this literature is that automation is substituting for routine tasks. Autor (2015) argues that occupations related to fabrication and administration are typically more routine task-intensive and therefore more likely to be substituted. Our results appear to confirm this as an investment in R&D significantly relates to lower growth rates of jobs in fabrication. In regressions with investment in IT (not shown) instead of R&D investment we also observe a negative relation to fabrication jobs, although not significant at conventional probability levels. For other occupations that are more complementary to automation, such as R&D and marketing, we observe either no relation or a significant positive relation. The results align with those presented in Chapter 2, where we study how IT investment relates to business function employment changes in a cross-country analysis. However, the results presented here are less strong for reasons discussed earlier.

The share of young workers is significant and positively related to the growth of knowledge intensive jobs such as those in R&D, and technology and process development, but also administrative jobs. A positive relation is also observed for the share of high-skilled workers in a region, suggesting that regions with a higher share of educated workers also have higher employment growth in R&D, technology and administrative jobs. In addition, we observe a positive and significant relation to sales and marketing jobs.

The geographical control variables, namely the dummies for regions in the Randstad and regions with a major seaport or located at the coast, suggest there is a positive relationship between growth in management jobs when the region is located in the Randstad. The relation between sales and marketing jobs and metropolitan regions is negative and significant. For regions that are located to the sea or have a prominent harbor, we observe a higher growth in sales and marketing jobs.

3.5.2 Extensions

So far, the econometric analysis has focused on the effects of offshoring exposure on jobs by business function. One of the extensions we consider here is the relation of offshoring to skills. Fabrication is typically associated with unskilled (blue-collar) labor, whereas R&D activities are much more skill-intensive (Feenstra and Hanson, 1997). Yet other activities, such as management and marketing, do not map easily into particular sets of factor requirements. The analysis presented previously is therefore distinct from a large literature that examined the effects of offshoring on jobs by skill type (see e.g. Foster-McGregor et al. 2013).

In columns 1 and 2 of Table 3.6, we regress regional employment growth rates of low- and high-skilled workers on offshoring exposure and initial R&D investment. The offshoring exposure in column 1 is based on fabrication and administrative and back-office activities and column 2 is based on all other business functions. We do not find significant effects of offshoring exposure on labor growth based on skill classification, also in specifications where we consider initial ICT investment instead of R&D investment (not shown, results available upon request). Empirical findings for a dichotomous classification of workers by skills in Table 3.6 suggest recent technological change is not significantly related to labor demand by skill type. These findings do not tally well with the literature about offshoring and the demand for skills, and may arise due to issues discussed previously.

Table 3.6: OLS regression results, extensions

	Dependent variable is average annual growth rate of			
	Low-skilled workers	High-skilled workers	Unemployment	Working age population
	(1)	(2)	(3)	(4)
Initial offshoring exposure	0.894	-0.321	-0.106	0.050**
	(0.616)	(0.407)	(0.166)	(0.022)
Initial R&D investment	0.127	1.698	0.731***	-0.156***
	(0.662)	(1.212)	(0.233)	(0.048)
Initial share of young workers	0.347	0.969	0.181	0.012
	(0.328)	(0.657)	(0.114)	(0.042)
Initial share of high-skilled workers			-0.015	0.038***
			(0.034)	(0.008)
Randstad	0.009	-0.001	-0.0002	-0.001
	(0.017)	(0.021)	(0.005)	(0.003)
Sea Port	0.009	-0.005	-0.005	-0.001
	(0.012)	(0.020)	(0.005)	(0.001)
Constant	-0.070	-0.191	-0.217***	0.005
	(0.128)	(0.255)	(0.053)	(0.015)
Observations	80	80	80	80
Adjusted R^2	0.723	0.301	0.982	0.481

Note: Dependent variables are the average annual growth rate of the corresponding variable described in each column, during the period 2006-2008 and 2011-2013. In columns 1, 3 and 4, offshoring exposure is based on fabrication and administrative and back-office activities. In column 2, offshoring exposure is based on all other business functions. A period dummy is included in all regressions. Robust standard errors in parentheses are clustered at the NUTS 2 level. *** p<0.01, ** p<0.05, * p<0.1.

The final columns in Table 3.6 examine the effect of offshoring and technological change on unemployment and the working age population in regions. For the effects of unemployment, recent research suggests that offshoring and technological change may contribute to an increase in unemployment in regions (Autor et al. 2015). We indeed find that recent investment in R&D is significantly related to regional unemployment.

In the final column of Table 3.6, the dependent variable is the working age population. We use regions for our empirical analysis. The classification of the 40 regions in the Netherlands was developed based on commuting flows. However, given the small area size of the Netherlands and its well-developed infrastructure, part of the workforce commutes and lives in a different area as to where they work (Terzidis et al. 2017). As a result, local employment effects from exposure to offshoring and technological change may diffuse across space when workers relocate to a different region after a layoff. To explore whether COROP regions provide a reasonable approximation, we regress offshoring and investment in new technologies on the size of the working-age population in a region. If offshoring and technological change do not relate to the size of the working-age population, local employment effects are less likely to spatially diffuse. Both Offshoring exposure and technological change are significantly related to the working-age population in local areas. This suggests that employment effects due to offshoring and technological change may indeed lead to a relocation of labor across regions, which is a potential limitation of our analysis.

3.6 Concluding remarks

This chapter examines functional specialization patterns across regions in the Netherlands. We measure specialization using the information on the occupations of workers and provide trends for eight business functions: R&D; Fabrication; Transport, logistics, and distribution; Sales and marketing; Technology and process development; Administrative and back-office; General and strategic management; and Others. We document substantial heterogeneity in functional specialization across local areas in the Netherlands.

Measuring specialization in business functions is relevant as it provides policy insights into the type of occupations demanded as well as reflecting the potential for growth and job dynamics. For example, R&D is more knowledge-intensive which will have implications for the jobs demanded and the potential for productivity growth in a region.

We then use cross-area variation in industry composition such that regions are differentially exposed to offshoring trends and investments in new technologies. We do not find a statistically significant relation between offshoring and functional employment changes, apart from significant effects that offshoring relates to lower demand for administrative and back-office jobs.

The limited significant results on the relation between offshoring and functional employment changes could imply that offshoring is not related to a decrease or increase in jobs (for this, see also Temmink and Lemmers (2015) with firm-level findings for the Netherlands). When firms offshore activities, they may lower costs and thereby improve their competitiveness, resulting in an initial reduction in employment but a later expansion of production and employment (Grossman and Rossi-Hansberg, 2008). Offshoring an activity may also induce a change in the composition within that activity, but no overall change in jobs involved in the activity. For example, the composition may shift away from assembly towards other fabrication activities, such as customized work and the provision of critical parts and components (Berghuis and den Butter, 2013).

Our measurement of specialization in regions and the econometric approach to investigate the drivers are exploratory. The Netherlands is geographically small and therefore there are few regions, which limits the degrees of freedom and scope for alternative econometric identification strategies. The measurement and analysis can be extended to other countries as the ISS was conducted by various statistical offices across Europe (see Sturgeon et al. 2013). Extending the scope may improve upon identification and allow capturing other determinants that drive certain activities to cluster geographically, such as spillovers and returns to scale (Gervais et al. 2016).

Furthermore, cross-area variation in industry specialization may be used to examine the effects of activity re-location and technological change on other socio-economic and political outcomes. A recent wave of research has started to use cross-area variation in offshoring exposure and import competition to examine its impact on elections (Autor et al. 2016; Colantone and Stanig, 2018) or uses information on the routine task-intensity of occupations to examine preferences for redistribution (Thewissen and Rueda, 2019). These are interesting areas for further research.

3.7 Appendix: additional tables and figures

Table 3.A1: Employment shares by business function and region in the Netherlands, 2014

COROP region	FAB	ADM	RD	MAR	TRA	TECH	MGT	OTH
Achterhoek	0.15	0.09	0.05	0.15	0.07	0.02	0.13	0.32
Agglomeratie ’s-Gravenhage	0.06	0.07	0.11	0.14	0.04	0.06	0.20	0.31
Agglomeratie Haarlem	0.06	0.05	0.09	0.18	0.03	0.04	0.18	0.37
Agglomeratie Leiden en Bollenstreek	0.12	0.07	0.09	0.13	0.04	0.03	0.13	0.36
Alkmaar en omgeving	0.09	0.08	0.08	0.16	0.05	0.03	0.13	0.36
Arnhem/Nijmegen	0.08	0.08	0.09	0.15	0.06	0.04	0.15	0.35
Delft en Westland	0.15	0.08	0.11	0.16	0.06	0.04	0.12	0.28
Delfzijl en omgeving	0.14	0.09	0.06	0.12	0.11	0.02	0.11	0.33
Flevoland	0.13	0.08	0.07	0.16	0.07	0.04	0.12	0.32
Groot-Amsterdam	0.07	0.08	0.11	0.16	0.04	0.05	0.16	0.32
Groot-Rijnmond	0.11	0.09	0.09	0.14	0.06	0.03	0.14	0.32
Het Gooi en Vechtstreek	0.08	0.06	0.07	0.15	0.04	0.05	0.16	0.39
IJmond	0.13	0.06	0.08	0.11	0.06	0.02	0.15	0.37
Kop Van Noord-Holland	0.20	0.07	0.07	0.12	0.05	0.02	0.13	0.32
Midden-Limburg	0.14	0.09	0.08	0.15	0.07	0.02	0.12	0.33
Midden-Noord-Brabant	0.13	0.09	0.08	0.13	0.08	0.02	0.12	0.32
Noord-Drenthe	0.13	0.07	0.09	0.11	0.04	0.03	0.16	0.35
Noord-Friesland	0.16	0.08	0.05	0.11	0.06	0.03	0.14	0.36
Noord-Limburg	0.18	0.08	0.06	0.13	0.08	0.03	0.13	0.30
Noord-Overijssel	0.15	0.08	0.05	0.13	0.07	0.02	0.13	0.35
Noordoost-Noord-Brabant	0.14	0.09	0.07	0.15	0.07	0.03	0.13	0.32
Oost-Groningen	0.17	0.06	0.03	0.16	0.05	0.01	0.12	0.40
Oost-Zuid-Holland	0.13	0.07	0.05	0.15	0.08	0.04	0.14	0.34
Overig Groningen	0.10	0.07	0.10	0.15	0.05	0.03	0.15	0.35
Overig Zeeland	0.15	0.08	0.07	0.12	0.06	0.01	0.15	0.35
Twente	0.15	0.08	0.08	0.13	0.05	0.03	0.13	0.35
Utrecht	0.08	0.08	0.10	0.15	0.04	0.06	0.16	0.31
Veluwe	0.14	0.07	0.07	0.15	0.05	0.04	0.13	0.33
West-Noord-Brabant	0.13	0.08	0.08	0.17	0.07	0.02	0.12	0.31
Zaanstreek	0.09	0.08	0.08	0.19	0.10	0.03	0.10	0.31
Zeeuwsch-Vlaanderen	0.17	0.08	0.06	0.13	0.09	0.02	0.12	0.32
Zuid-Limburg	0.11	0.08	0.08	0.14	0.05	0.03	0.13	0.36
Zuidoost-Drenthe	0.18	0.07	0.07	0.13	0.08	0.03	0.14	0.30
Zuidoost-Friesland	0.16	0.08	0.06	0.15	0.07	0.03	0.11	0.33
Zuidoost-Noord-Brabant	0.15	0.07	0.09	0.15	0.05	0.05	0.14	0.30
Zuidoost-Zuid-Holland	0.13	0.09	0.07	0.13	0.07	0.03	0.17	0.32
Zuidwest-Drenthe	0.15	0.06	0.09	0.12	0.08	0.01	0.10	0.37
Zuidwest-Friesland	0.19	0.05	0.06	0.13	0.06	0.04	0.10	0.36
Zuidwest-Gelderland	0.17	0.08	0.06	0.14	0.08	0.03	0.14	0.29
Zuidwest-Overijssel	0.12	0.08	0.09	0.14	0.07	0.03	0.12	0.35

Note: R&D (RD); Fabrication (FAB); Transport, logistics, and distribution (TRA); Sales and marketing (MAR); Technology and process development (TECH); Administrative and back-office (ADM); General and strategic management (MGT); and Other activities (OTH). *Sources:* author’s calculations using the Dutch LFS.

Table 3.A2: Mapping occupations to business functions

Occupation	ISCO 08 code	Business function
Physical and earth science professionals	211	Research and development of products,services, or technology
Mathematicians, actuaries and statisticians	212	,,
Life science professionals	213	,,
Engineering professionals (excluding electro technology)	214	,,
Electro technology engineers	215	,,
Architects, planners, surveyors and designers	216	,,
University and higher education teachers	231	,,
Finance professionals	241	,,
Legal professionals	261	,,
Physical and engineering science technicians	311	,,
Life science technicians and related associate professionals	314	,,
Financial and mathematical associate professionals	331	,,
Librarians, archivists and curators	262	Fabrication
Building and housekeeping supervisors	515	,,
Market gardeners and crop growers	611	,,
Animal producers	612	,,
Mixed crop and animal producers	613	,,
Forestry and related workers	621	,,
Fishery workers, hunters and trappers	622	,,
Subsistence crop farmers	631	,,
Subsistence livestock farmers	632	,,
Subsistence mixed crop and livestock farmers	633	,,
Subsistence fishers, hunters, trappers and gatherers	634	,,
Building frame and related trades workers	711	,,
Building finishers and related trades workers	712	,,
Painters, building structure cleaners and related trades workers	713	,,
Sheet and structural metal workers, moulders and welders, and related workers	721	,,
Blacksmiths, toolmakers and related trades workers	722	,,
Machinery mechanics and repairers	723	,,
Handicraft workers	731	,,
Printing trades workers	732	,,
Electrical equipment installers and repairers	741	,,
Electronics and telecommunications installers and repairers	742	,,
Food processing and related trades workers	751	,,

Continuation of Table 3.A2

Occupation	ISCO 08 code	Business function
Wood treaters, cabinet-makers and related trades workers	752	,,
Garment and related trades workers	753	,,
Other craft and related workers	754	,,
Mining and mineral processing plant operators	811	,,
Metal processing and finishing plant operators	812	,,
Chemical and photographic products plant and machine operators	813	,,
Rubber, plastic and paper products machine operators	814	,,
Textile, fur and leather products machine operators	815	,,
Food and related products machine operators	816	,,
Wood processing and papermaking plant operators	817	,,
Other stationary plant and machine operators	818	,,
Agricultural, forestry and fishery labourers	921	,,
Mining and construction labourers	931	,,
Manufacturing labourers	932	,,
Assemblers	821	,,
Sales, marketing and development managers	122	Sales and marketing
Sales, marketing and public relations professionals	243	,,
Sales and purchasing agents and brokers	332	,,
Street and market salespersons	521	,,
Shop salespersons	522	,,
Cashiers and ticket clerks	523	,,
Other sales workers	524	,,
Locomotive engine drivers and related workers	831	Transportation, logistics, and distribution
Car, Van and motorcycle drivers	832	,,
Heavy truck and bus drivers	833	,,
Mobile plant operators	834	,,
Ships' deck crews and related workers	835	,,
Transport and storage labourers	933	,,
Sports and fitness workers	342	Customer and after-sales services
Client information workers	422	,,
Travel attendants, conductors and guides	511	,,
Software and applications developers and analysts	251	Technology and process development
Database and network professionals	252	,,

Continuation of Table 3.A2

Occupation	ISCO 08 code	Business function
Information and communications technology operations and user support technicians	351	,,
Telecommunications and broadcasting technicians	352	,,
General office clerks	411	Administration and back-office
Secretaries (general)	412	,,
Keyboard operators	413	,,
Tellers, money collectors and related clerks	421	,,
Numerical clerks	431	,,
Material-recording and transport clerks	432	,,
Other clerical support workers	441	,,
Commissioned armed forces officers	11	General and strategic management
Non-commissioned armed forces officers	21	,,
Armed forces occupations, other ranks	31	,,
Legislators and senior officials	111	,,
Managing directors and chief executives	112	,,
Business services and administration managers	121	,,
Production managers in agriculture, forestry and fisheries	131	,,
Manufacturing, mining, construction, and distribution managers	132	,,
Information and communications technology service managers	133	,,
Professional services managers	134	,,
Hotel and restaurant managers	141	,,
Retail and wholesale trade managers	142	,,
Other services managers	143	,,
Administration professionals	242	,,
Mining, manufacturing and construction supervisors	312	,,
Regulatory government associate professionals	335	,,
Legal, social and religious associate professionals	341	,,
Medical doctors	221	Others
Nursing and midwifery professionals	222	,,
Traditional and complementary medicine professionals	223	,,
Paramedical practitioners	224	,,
Veterinarians	225	,,
Other health professionals	226	,,
Vocational education teachers	232	,,
Secondary education teachers	233	,,
Primary school and early childhood teachers	234	,,
Other teaching professionals	235	,,

Continuation of Table 3.A2

Occupation	ISCO 08 code	Business function
Social and religious professionals	263	,,
Authors, journalists and linguists	264	,,
Creative and performing artists	265	,,
Process control technicians	313	,,
Ship and aircraft controllers and technicians	315	,,
Medical and pharmaceutical technicians	321	,,
Nursing and midwifery associate professionals	322	,,
Traditional and complementary medicine associate professionals	323	,,
Veterinary technicians and assistants	324	,,
Other health associate professionals	325	,,
Business services agents	333	,,
Administrative and specialized secretaries	334	,,
Artistic, cultural and culinary associate professionals	343	,,
Cooks	512	,,
Waiters and bartenders	513	,,
Hairdressers, beauticians and related workers	514	,,
Other personal services workers	516	,,
Child care workers and teachers' aides	531	,,
Personal care workers in health services	532	,,
Protective services workers	541	,,
Domestic, hotel and office cleaners and helpers	911	,,
Vehicle, window, laundry and other hand cleaning workers	912	,,
Food preparation assistants	941	,,
Street and related service workers	951	,,
Street vendors (excluding food)	952	,,
Refuse workers	961	,,
Other elementary workers	962	,,

Note: The occupations are classified to a business function group that has the most similar descriptions on the tasks involved.

Table 3.A3: Offshoring propensity using the 2012 ISS

Industry	FAB	TRA	MAR	ADM & MGT	TECH	R&D	OTH
Mining of minerals	-	-	-	0.086	0.161	-	-
Mfr of food, beverages and tobacco products	0.059	-	0.021	0.113	0.060	-	-
Mfr of textiles, wearing apparel, footwear and leather	X	X	X	X	X	X	X
Mfr of wood, paper, printing and recorded media	0.079	-	-	-	0.066	0.033	-
Mfr of coke, petroleum; chemical and pharmaceutical products	0.205	0.160	0.181	0.208	0.476	0.268	0.160
Mfr of rubber and plastic products; other non-metallic mineral products	0.132	0.162	0.000	0.064	0.092	-	0.030
Mfr of basic and fabricated metals, except machinery and equipment	0.210	0.015	0.010	-	0.014	-	0.010
Mfr of computers, electronic and optical products; electrical equipment	0.587	-	0.440	-	0.702	0.351	-
Mfr of machinery and equipment n.e.c.	0.130	0.088	0.080	-	0.021	-	-
Mfr of motor vehicles and other transport equipment	0.105	-	-	-	0.014	0.014	0.015
Mfr of furniture and other products n.e.c.; repair and installation of machinery and equipment	-	-	0.030	0.030	-	-	-
Electricity, gas and water supply	-	-	0.051	-	0.051	-	-
Construction	X	X	X	X	X	X	X
Wholesale and retail trade; repair of motor vehicles and motorcycles	0.004	0.002	0.002	0.021	0.019	0.002	0.023
Transportation and storage	0.015	0.014	0.009	0.073	0.038	-	0.005
Accommodation and food service activities	X	X	X	X	X	X	X
Information and communication	0.296	0.003	0.007	0.139	0.243	0.003	0.092
Renting, buying and selling of real estate	0.000	-	-	-	-	-	-
Consultancy, research and other specialised business services	0.040	0.002	0.050	0.104	0.106	0.010	0.046
Renting and leasing of tangible goods and other business support services	X	X	X	X	X	X	X

Note: The propensity to offshore a business activity, the international sourcing propensity, is calculated as the number of firms in industry s that internationally sourced business activity b divided by the total number of firms in this industry s included in the survey. We weight by firm size based on the number of employed persons. A '-' indicates no observation to calculate the offshoring propensity. X indicates value is not disclosed due to confidentiality reasons. R&D (RD); Fabrication (FAB); Transport, logistics, and distribution (TRA); Sales and marketing (MAR); Technology and process development (TECH); Administrative and back-office (ADM); General and strategic management (MGT); and Other activities (OTH). *Source:* 2012 ISS.

Figure 3.A1: Forty COROP regions of the Netherlands

Note: 40 COROP (COördinatiecommissie Regionaal OnderzoeksProgramma) regions of the Netherlands.
Source: http://en.wikipedia.org/wiki/COROP.

Figure 3.A2: The Randstad

Source: Groot et al. (2014).

Chapter 4

Firm Productivity and Functional Specialization[28]

4.1 Introduction

Improvements in communication and management systems have allowed firms to functionally specialize in the value chain (Feenstra, 1998; Dedrick et al. 2010; Bernard et al. 2017; Wood, 2017; Timmer et al. 2019). This specialization in production networks, which Hummels et al. (2001) refer to as vertical specialization, has been related to productivity and wages in theoretical work (Costinot et al. 2013; Fally and Hillberry, 2017).

This chapter proposes a straightforward yet novel approach to measure the specialization of firms and provides an empirical test of its relation to productivity and mark-ups. We adopt a Balassa-type indicator of specialization where the firm's employment share in a function is compared to the average employment share of that activity across all firms. In this approach, firms are specialized in a function if they have a relatively higher share of workers involved in that function.

We measure the functional specialization of firms using unique data from two survey rounds, held in 2012 and 2017, in which Dutch firms report on the composition of their employees by function. There is no standardized classification of business functions, but typically the main distinction is between fabrication and headquarter (Markusen, 2002). We keep that distinction, and further split headquarter into R&D and marketing. The

[28] This chapter is co-authored with Oscar Lemmers, Shang-Jin Wei, and Gaaitzen De Vries. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the Central Bureau of Statistics. The data that support the findings of this study are available from the Central Bureau of Statistics. Restrictions apply to the availability of these data, which were used under license for this study.

surveys we use were administered by Statistics Netherlands and sent to private firms with at least 50 employees. We combine these surveys with detailed statistics on firm employment, sales, production, input usage, imports, and exports. This allows us to measure firm productivity and price mark-ups over marginal costs.

We find that firms specialized in R&D and marketing are significantly more productive compared to firms that specialized in fabrication. These findings are robust to controlling for other potential determinants of productivity. This result suggests returns from R&D as well as building brand names are higher compared to fabrication (Mudambi, 2008; Park et al. 2013). We do not observe a significant relationship between functional specialization and mark-ups. Firms covered in the analysis might be more exposed to international competition due to the nature of products produced or function performed, such that these firms face difficulty charging prices above marginal costs.

There is an emerging literature that provides empirical measures of the relative production line position of firms (Chor et al. 2014), industries (Fally, 2012; Antràs et al. 2012), or even entire countries (Costinot et al. 2013; Fally and Hillberry, 2017). The production line position is imputed based on input-output tables. Such measures are commonly referred to as upstreamness and downstreamness measures (Fally, 2012; Antràs et al. 2012; Antràs and Chor, 2018). In this approach, the upstreamness or downstreamness (the average distance from final use) is decided on the basis of the products produced. In some applications, discussed in section 4.2, empirical measures of the production line position are interpreted to reflect functional specialization in production networks.

However, measures of upstreamness (or downstreamness) do not inform on the activities of firms. We argue that input-output based measures are useful for understanding where goods-producing firms operate along the production line, but not for what firms do. For example, cotton is a relatively upstream product as it is typically an intermediate product, often used to produce clothing. Clothing is a more downstream product because clothing is typically for final use by consumers. Thus, the cotton production of a farmer is relatively upstream. And the clothing product of a textile firm is relatively downstream. But that does not inform on what the textile firm actually does. The textile firm might be involved in the design of a tee-shirt, do the cut, make and trim assembly or nurture a brand name by focusing on marketing. These are very different activities and likely to differ in the potential for productivity growth and knowledge spillovers. In support of this view, the empirical analysis in this chapter suggests that input-output based measures for firms' position in production networks do not significantly relate to firm productivity and price mark-ups over marginal costs. Furthermore, the analysis suggests that measures of upstreamness are unrelated to measures of functional specialization.

This chapter closely relates to Timmer et al. (2019), who propose to measure the functional specialization of countries in international trade using the information on the occupations of workers. In this approach, the occupation of a worker informs on the nature of the activity performed. Our approach is very similar but at the firm level. We determine the specialization of a firm based on the composition of its workforce over functions.

The inference of activities from labor data is well-known in urban economics and economic geography. For example, Maurin and Thesmar (2004) study the business functions of French manufacturing firms using the information on the occupations of workers. Duranton and Puga (2005) show how cities in the U.S. specialize in headquarter activities, while fabrication activities concentrate in less urbanized regions. Harrigan et al. (2016) argue that technology adoption is mediated by technically qualified managers and technicians ('techies'), and use the firm-level employment share of techies as a measure for the propensity to adopt new technology.

Our analysis also relates to recent work that examines structural change within firms. Ding et al. (2019) examine the characteristics of manufacturing firms that have establishments providing professional services. They develop a model and examine US firms in which technical professionals complement physical production, and where reductions in the price of intermediate goods induce firms to reallocate towards the provision of services. Bernard et al. (2017) examine Danish firms that switch out of manufacturing. They define a firm that switches out when it no longer reports any establishment in a manufacturing industry but continues operations in services. Bernard et al. (2017) document that the occupational employment composition of switchers is concentrated in non-fabrication professional activities, such as managers, sales, and tech workers. Switchers are found to have higher labor productivity compared to firms that did not switch out of manufacturing. The analysis in this chapter abstracts from changes within firms, as it is based on cross-sections from two survey waves for Dutch firms.

Also, this chapter relates to a rich body of literature that examines the relation between firm innovation and productivity. A broad consensus in this literature is that R&D investment and the adoption of new technologies relate positively to firm productivity (e.g. Aw et al. 2011; Syverson, 2011). Often, R&D investment is observable and reflected in expenditures (Syverson, 2011). However, many firms undertake different types of innovation, such as process and product innovation without formally reporting R&D spending. The standard way of R&D expenditure reported in national accounts starts from the labor costs of scientists, engineers and technicians and adds other costs related to R&D labs. Our conceptualization of R&D based on the firm's employment share in R&D activities provides an alternative view of R&D activities and also helps distinguish it from other innovative activities, such as marketing and building brand names. Therefore it is complementary to the literature on the relation between R&D and productivity.

This chapter proceeds as follows. Section 4.2 outlines and describes the data and index to measure functional specialization. We contrast functional specialization to measures of upstreamness and downstreamness based on input-output tables. Section 4.3 discusses the measurement of firm productivity and mark-ups. Section 4.4 provides descriptive statistics. Section 4.5 econometrically examines the relation between the functional specialization of firms, productivity, and mark-ups. Section 4.6 concludes.

4.2 Measuring the functional specialization of firms

To measure the functional specialization of firms we use information from several waves of a unique survey. This is described in section 4.2.1. In section 4.2.2 we discuss a common set of upstreamness and downstreamness measures based on input-output tables that focus on the relative production line position of products. We argue these are not informative regarding the activities that firms actually do because they have a different purpose and interpretation.

4.2.1 The functional specialization of firms

Under the aegis of Eurostat, various statistical offices in Europe have implemented 'International Sourcing & Global Value Chain Surveys (ISS)' (Nielsen, 2018). The surveys were held in 2007, 2012 and 2017. Its focus is to map aspects of globalization, such as the relocation of business functions abroad and motives for and barriers against sourcing internationally, but it also collects other interesting information. A question on the employment composition by function was asked in the survey waves 2012 and 2017, which will be used in this chapter.

We consider question 2.2: 'Please give your best estimate of the employment in your enterprise at the end of 20[xx]'.[29] For this question, the manager is asked to only include employment in her own enterprise, not employment at affiliates abroad. Persons undertaking more than one activity are included according to their main activity. Managers who complete such surveys indicate that the allocation of their employees across business functions is a natural way for them to categorize their workers (Sturgeon and Gereffi, 2009). Indeed, business functions are a relevant unit of analysis as (multinational) firms

[29]For the 2012 survey, it is the employment distribution at the end of 2011. For the 2017 survey it is the distribution at the end of 2016. Therefore, in the empirical analysis we will relate functional specialization to productivity and mark-ups in cross-sections for the years 2011 and 2016.

typically organize their activities around these (Sturgeon and Gereffi, 2009). However, as usual in surveys, the quality of the information provided by the firm varies depending on whether the person completing the survey is knowledgeable on the subject.

Response rates are high. Sampling is based on the general business register, and hence representative of firms that meet the size threshold (CBS, 2018).[30] The trade data for these firms in the sample shows they are actively involved in international trade, with most of them both importing and exporting goods.

A common approach to characterize activities has been tracking the establishments in which the value is added, as in Ding et al. (2019). Value-added from manufacturing establishments is then equated with fabrication activities and value-added from establishments in specific services sectors with professional services. However, functions are not the same as sectors (Duranton and Puga, 2005). Establishments, be they classified in manufacturing or services, typically perform various functions and combine these in-house. Over time, this mix has been changing, sometimes denoted as the 'servicification of manufacturing' (Fontagné and Harrison, 2017). This indicates that we cannot rely on a mere statistical classification of sectors to understand the functional specialization of firms. Instead, we prefer to measure specialization in functions based on the activities workers perform.

Table 4.1 shows the potential allocation of workers in the survey questionnaire. The workers can be either allocated to a core or a support business function, and the latter is then split further. The core function refers to the primary activity of the enterprise. It includes the production of goods or services intended for the market or third parties carried out by the enterprise. We will refer to these as fabrication activities. Support business functions facilitate the production of goods or services. These business functions are grouped into R&D and marketing, see the final column in Table 4.1.[31] We aggregate these business functions to three broad groups to distinguish these functions by their sequential location in the production process, namely whether the function is before or after production stage. Furthermore, the functions in the same group tend to be bundled more compared to others. For example, firms that market their brands, typically also orchestrate the value chain and therefore also handle the logistics.

[30]The response rate is 81.6 percent for the 2017 ISS. The 2017 survey sampled firms from the universe of Dutch firms with 50 or more employees. It includes firms in manufacturing and market-based services while excluding firms in agriculture, finance, government, education, health, and other social and personal services. The 2012 survey sampled firms with 100 or more employees. Sample weights are by industry and size class. Only very few firms in the 2012 survey are also sampled in the 2017 survey.

[31]It is difficult to decide where to draw the boundaries between functions that go together and those that are different (Kemeny and Storper, 2015). We take a pragmatic solution and closely follow the set of functions distinguished by Bernard et al. (2017) and Timmer et al. (2019). The category 'other support functions' has been excluded as it does not easily map in one of the three activities.

Table 4.1: Question on employment by business function in the survey

	Number of persons employed	Business function aggregation
TOTAL (all functions)	[_ _ _ _ _]	
Core business function		
- production of goods for the market	[_ _ _ _ _]	Fabrication
- production of services for the market	[_ _ _ _ _]	Fabrication
Support business functions		
- Distribution and logistics	[_ _ _ _ _]	Marketing
- Marketing, sales services and after sales services, incl. help desks and call centers	[_ _ _ _ _]	Marketing
- ICT services	[_ _ _ _ _]	Marketing
- Administrative and management functions	[_ _ _ _ _]	Marketing
- Engineering and related technical services	[_ _ _ _ _]	R&D
- Research & Development	[_ _ _ _ _]	R&D
- Other support functions	[_ _ _ _ _]	Excluded

Note: Question 2.2 in the ISS 2012 and 2017. The final column shows the aggregation of business functions to R&D, fabrication, and marketing.

We use a straightforward yet novel approach to measure the functional specialization of a firm, adapting the Balassa (1965) indicator. That is, we compare the firm's employment share (emp_k) in activity a to the average employment share for that activity across all firms in the survey:

$$SI_k^a = \frac{(emp_k^a / \sum_a emp_k^a)}{(\sum_k emp_k^a / \sum_k \sum_a emp_k^a)} \tag{4.1}$$

The highest index across all possible activities is used to determine the Specialization Index (SI) of the firm. E.g. if the SI of firm k is above one for R&D activities, but not for fabrication and marketing, the firm is said to be specialized in R&D activities.

The specialization index can be easily implemented and is straightforward to interpret. It is akin to the functional specialization index introduced in Timmer et al. (2019). In particular, note that the SI is related to concentration indices such as the Herfindahl index. However, the Herfindahl index and other concentration indices are based on the distribution of employment, whereas the specialization index is based on a comparison of shares.

4.2.2 Upstreamness and downstreamness

Scholars have proposed empirical measures for the production line position of products, counting the number of steps away from final consumption and weighting each stage by its output value (Fally, 2012; Antràs et al. 2012; Antràs and Chor, 2013). In this setup, a good that is used for final consumption is more downstream. Likewise, a good is more upstream if it is used to produce intermediate inputs (that are then used to produce intermediate inputs etcetera). In Appendix A we provide a formal exposition of upstreamness and downstreamness measures (see also Johnson, 2018).

The production line position of a firm can be based on direct observation of the firm's industry classification for which upstreamness or downstreamness is calculated. But firms may produce multiple products. Therefore, Chor et al. (2014) propose measures based on the product composition of the firms' exports. We follow Chor et al. (2014) and measure the upstreamness and downstreamness of firm k based on the export value of its products, W_{ks}. That is,

$$U_k = \sum_{s=1}^{S} \frac{W_{ks}}{W_k} U_s, D_k = \sum_{s=1}^{S} \frac{W_{ks}}{W_k} D_s \tag{4.2}$$

where $W_k = \sum_{s=1}^{S} W_{ks}$, U_s the upstreamness, and D_s the downstreamness of a product from industry s.

Intuitively, upstreamness or downstreamness appears to relate to functional specialization. Indeed, when Antràs and Chor (2013) develop measures of the production line position they write in the introduction that they consider sequential production processes where 'at a broad level, the process of manufacturing cannot commence until the efforts of R&D centers in the development or improvement of products have proven to be successful, while the sales and distribution of manufactured goods cannot be carried out until their production has taken place (page 2127).'

Upstreamness and downstreamness are used in empirical applications for which they are not intended. For example, scholars aim to provide empirical content to the smile curve using estimates of upstreamness (or downstreamness). The well-known 'smile curve' of GVCs originally proposed by Stan Shih of Acer in 1992 states that fabrication activities typically have the lowest remuneration relative to other activities in the chain (Mudambi, 2008; Park et al. 2013). In the applications, upstreamness is estimated and ordered on the horizontal axis.[32] Implicit in this approach is that if a firm is near the origin on the horizontal axis, it is involved in activities like the conception, R&D of a product. A firm that is further to the right on the horizontal axis is assumed to be involved in downstream activities like sales and marketing.

Yet, input-output measures relate to production stages only. They are informative about the relative production line position of products. As discussed in the introduction, cotton is relatively upstream whereas clothing is more downstream, because clothing is closer to final use by consumers. Yet, textile firms can be involved in the design activities of a tee-shirt, do the assembly or marketing. Hence, the product of a textile firm is downstream, but that does not inform on what the textile firm actually does.

Appendix A describes measures of upstreamness using input-output tables. We use the 2016 release of the World Input-Output Tables (WIOTs), which provide tables for the period from 2000 to 2014 (Timmer et al. 2016). These tables give information on input purchases, the parent (downstream) industry, as well as source country and industry. U_s and D_s statistics are calculated at the level of country-industry pairs. We focus here on the length and position of industries for products that are finalized in the Netherlands. The WIOTs distinguish two services sectors that are of interest, namely 'Scientific research and development' (the 'R&D' sector) and 'Advertising and market research' (the 'Advertising' sector). At face value these two sectors might be considered to be upstream (R&D) and downstream (Advertising), as e.g. in Rungi and Del Prete (2018). However, the findings suggest that the R&D sector is one of the most downstream industries (see the row in italics in Appendix Table 4.A1). The upstreamness measure U_s for the advertising sector suggests it is one of the most upstream industries (also in italics in Appendix Table 4.A1).

One reason why these findings do not conform with standard expectations is due to the definition of R&D in the System of National Accounts 2008 (SNA 2008, see UN et al. 2009). The SNA 2008 recognizes R&D as an investment, a produced asset in the economy. Most spending on R&D is treated as investment in R&D assets. In input-output tables, investments are part of final demand. Hence, the R&D sector in the input-output tables is mainly delivering investments that are for final demand. From this point of view, the

[32] See for instance Baldwin et al. 2015; Baldwin 2016; and Degain et al. 2017. Baldwin et al. (2015) and Baldwin (2016) put the change in the value added share on the y-axis. Degain et al. (2017) put the value added to gross output share on the vertical axis.

R&D sector is downstream.[33]

Estimates of upstreamness for manufacturing products are more intuitive. For example, manufactured basic metals are more upstream compared to motor vehicles (see Appendix Table 4.A1). This is one reason why scholars usually only report upstreamness for manufacturing products (see e.g. Antràs et al. 2012). The next sections make comparisons between firm upstreamness (U_k) (and downstreamness (D_k)) calculated according to equation 4.2 and the functional specialization index (SI_k), see equation 4.1 for Dutch firms. Since scholars tend to focus on measures of upstreamness for manufacturing, we will focus on comparisons for manufacturing firms and show that functional specialization is not related to measures of upstreamness.

4.3 Productivity and mark-ups

In the empirical analysis below, we relate specialization to productivity and mark-ups. This section describes the estimation of Total Factor Productivity (TFP) using the econometric approach suggested by Wooldridge (2009), with a price mark-up correction from De Loecker and Warzynski (2012). We adopt this econometric approach because estimating a production function using OLS to derive TFP results in biased coefficients due to endogeneity issues. Endogeneity issues arise, because of the correlation between factor inputs and unobservable productivity shocks (Syverson, 2011).

There are several solutions to endogeneity problems when estimating production functions. The most common solutions are the two control function approaches put forth by Olley and Pakes (1996, hereafter OP) and by Levinsohn and Petrin (2003, hereafter LP). A key assumption in these two approaches is that firm-level investments (OP) or purchases of intermediate inputs (LP), conditional on the capital stock, can be related to unobserved firm-level productivity shocks. Under this strict monotonicity, one is able to invert the investment or intermediate input demand function. The form of the control function is nonparametric in capital, and investment (OP) or intermediate inputs (LP).

[33] More generally, input-output tables that are used to calculate up- and downstreamness have to create consistency between the prices that producers charge and the prices that are paid by consumers (2008 System of National Accounts, UN et al. 2009). The recommend price basis for producers is the basic price, the so-called factory gate price. This is the appropriate price basis when applying the Leontief inverse (Miller and Blair, 2009). Hence, input-output analyses trace back the steps that are involved in the product that is produced and valued at factory gate (or basic) prices. But any margins that are levied on the product before it is consumed may not be taken into account (Chen et al. 2018b; Ahmad, 2018). In their famous decomposition of the value of the iPod, Dedrick et al. (2010) document that the factory gate price was about half the final (purchasers') price paid by consumers. The profits to Apple, basically the compensation for its research, design, and marketing activities are not included in the factory gate price. Therefore, upstreamness measures that use input-output tables at factory gate (basic) prices may not include income from R&D and marketing.

The control function is estimated in two stages. The first stage estimates the labor coefficient in the production function. In the second stage, the estimates from the first stage are plugged in to estimate capital, and investment or intermediate inputs coefficients.

Ackerberg et al. (2015) point out that both OP and LP suffer from a functional dependence problem from estimating the first stage. Wooldridge (2009) suggests solving the problem by replacing the two-step estimation procedure with a generalized method of moments (GMM) setup. Specifically, Wooldridge (2009) proposes an alternative moment that minimizes the first and second stage moments simultaneously. Apart from avoiding the functional dependence problem in the first stage, the joint estimation approach is also more efficient than previous control function approaches. We, therefore, use the method of Wooldridge (2009) to estimate TFP in our baseline analysis.

We run the Prodest program in Stata written by Mollisi and Rovigatti (2017) for the Wooldridge approach specifying a value-added based production function, wherein labor is treated as a flexible input. We estimate a Cobb-Douglas production function by industry from 2009 to 2016 (at the two-digit industry level and in logs, further discussed below):

$$v_{kst} = \beta_0 + \beta_1 Capital_{kst} + \beta_2 Labor_{kst} + \omega_{kst} + \vartheta_{kst} \tag{4.3}$$

where v is value-added of firm k in industry s at time t, and ω is unobserved productivity. The sequence $\{\omega_{kst} : t = 1, \ldots, T\}$ is unobserved productivity, and $\{\vartheta_{kst} : t = 1, 2, \ldots, T\}$ is a sequence of shocks that are assumed to be conditional mean independent of current and past inputs (Wooldridge, 2009). Value added is in values rather than in quantities owing to the absence of information on prices and quantities of goods sold. Our TFP estimate is therefore revenue based. This is a common limitation of firm-level production data when estimating TFP. It is acceptable and even desirable when firm-level prices fully reflect product quality differences (Syverson 2011). However, it creates problems in estimating TFP whenever prices reflect differences in market power across firms. In that case, the estimated revenue based TFP may reflect differences in market power rather than differences in production efficiency across firms.

To separate mark-ups from TFP, we follow the approach by De Loecker and Warzynski (2012) to calculate firm- and time-specific mark-ups, μ_{kst}. The mark-up corrected firm-level TFP is derived as follows:

$$TFP^{adj}_{kst} = log(TFP_{kst}) - log(\mu_{kst}) \tag{4.4}$$

TFP^{adj}_{kst} separates the price influence caused by market power differences. The key assumption to do so is that at least one factor input is fully flexible, which is labor in our setting. The mark-up is derived from minimizing the firm's cost with respect to the flexible input for a Cobb Douglas production function:

$$\mu_{kst} = \frac{P_{kst}}{MC_{kst}} = \frac{Labor\ elasticity_{kst}}{Labor\ share_{kst}} \tag{4.5}$$

Where P is the output price and MC is marginal cost. The elasticity of labor is the estimate for β_2 in equation 4.3. The labor share is obtained by dividing labor costs by a corrected value-added measure. This corrected value-added measure arises because of the assumption that when making optimal input decisions, firms do not observe unanticipated shocks to production. Specifically, firms minimize costs according to a prediction of output, and the prediction is based on fitting equation 4.3 to a polynomial output function in terms of factor inputs:

$$v_{kst} = h(Capital_{kst}, Labor_{kst}) + \vartheta_{kst} \tag{4.6}$$

where the function h() includes the factor inputs and interactions with first- and second-order terms. Following De Loecker and Warzynski (2012), the predicted output is computed as: $\hat{v_{kst}} = \frac{v_{kst}}{exp(\hat{\vartheta_{kst}})}$, where $\hat{\vartheta_{kst}}$ is the first stage error term using the control function approaches of OP and LP and v_{kst} is the observed value-added. The labor coefficient β_2 is estimated for each industry s. Hence, the variation of firm-level mark-ups within an industry is determined by the expenditure share of labor input in total expenditure.

One potential advantage of using value-added production function is that by excluding intermediate inputs from the production function it avoids the identification problem raised by Ackerberg et al. (2015). However, treating labor as a flexible input that can be easily adjusted without incurring costs is debatable. It depends on the actual labor market situation and might well differ by country. For example, Van Heuvelen et al. (2019) argue that the assumption of labor being flexible is unlikely to hold in the Netherlands. Labor adjustment involves hiring and firing costs, which are typically substantial. Therefore, Van Heuvelen et al. (2019) argue that using intermediate inputs as a flexible input in production is more reasonable. However, as De Loecker and Warzynski (2012) have pointed out, there is a tradeoff between applying a gross output function with intermediate inputs as flexible input and being able to accurately identify the coefficients of factor inputs.

Appendix B sets out our estimation using a gross output setting with intermediate inputs as the flexible input. As discussed by Gandhi et al. (2017), whatever the motivation behind the choice of a gross output or value-added production function, productivity estimates are fundamentally different in these two settings. This is due to the econometric estimation of TFP. Gandhi et al. (2017) discuss the differences between value-added and gross output production functions in a restricted profit value-added approach and a structural value-added approach. In the first approach, they show that the finding by Bruno (1978), which states that one can simply rescale with the firm-level share of intermediate inputs to obtain the estimates of gross output production function regarding factor coefficients and productivity from a value-added production function, does not hold. In the second approach, they discuss that the often made assumptions in empirical literature regarding perfect complements of factor inputs do not always hold unless one assumes that capital or labor is flexible. Otherwise, it may be in the firm's interest to opt to hold a bigger stock of capital and labor than a combination of all three inputs (capital, labor and intermediate inputs) as capital/labor is costly to adjust. The discussions on both approaches indicate that the value-added setting cannot be used to infer characteristics (including productivity) from the gross output production function, and vice versa. The empirical finding from Gandhi et al. (2017) confirms that features of interests (including productivity) from a value-added production function are different from those from a gross output production function. Since we have difficulty accurately identifying the coefficients of factor inputs in a gross output setting, we report on it in Appendix B and do not use it for our baseline estimates. We do consider these alternative estimates of TFP in robustness analysis.

The data to estimate firm TFP and mark-ups are obtained from the Production Statistics (PS) provided by Statistics Netherlands.[34] PS is a yearly enterprise survey. Firms with less than 50 employees are sampled, but all enterprises with 50 or more employees are included. Since firms in the surveys we use to measure functional specialization are sampled from firms with at least 50 employees, we have matching data from PS for all firms. The variables we use are: gross output at basis prices, gross value added at basic prices, intermediate consumption costs, persons employed (FTEs), depreciation of fixed assets, and turnover.[35] The variables in value terms are deflated using industry price deflators.[36] The data includes other firm characteristics as well, such as age, size, and exports, which will be used in the empirical analysis.

The PS data does not include information on capital stocks. Broersma et al. (2003) propose the 'booked depreciation method' to derive a long investment series based on

[34]We are grateful to Michael Polder for sharing his Stata codes for collecting and harmonizing data from the production statistics.

[35]Gross output and intermediate input costs are net of trading goods.

[36]Variables are deflated using 2-digit industry deflators.

depreciation reported by Dutch firms. This method is based on a standard accounting rule, namely linear depreciation. This rule indicates that an investment in year t will be depreciated uniformly over the lifetime of the asset. Therefore, the depreciation of the asset in year t is a function of the flow of investments in previous years. Broersma et al. (2003) use investment data for the period 1988-1994. However, this period is not included in our analysis and investment data is only provided from 1988-1994 and not for the years thereafter. Therefore, we are unable to obtain investment data from PS, which leaves using depreciation of capital as a proxy for capital input. Using capital depreciation as a proxy for capital input may be reasonable as capital stocks and depreciation costs are positively correlated. A similar approach has been adopted by other researchers, see e.g. Mohnen et al. (2018).

For each 2-digit industry we estimate TFP using OLS, the approach by Wooldridge (2009) outlined here and Ackerberg et al. (2015) described in Appendix B. Coefficient estimates are industry specific, which aims to control for potential heterogeneity in production technologies across industries.

4.4 Descriptive analysis

Table 4.2 reports estimates of input coefficient for manufacturing industries using OLS and Wooldridge (2009). Endogeneity of factor inputs biases the flexible input coefficient upwards in OLS regressions (Syverson, 2011; Gandhi et al. 2017; Van Biesebroeck, 2008). In the value-added setting labor is the flexible input, and compared to capital, labor responds more quickly to productivity shocks (Gandhi et al. 2017). The results reported in Table 4.2 indeed suggest that labor coefficients are higher if estimated on the basis of OLS. The capital coefficients are relatively less affected by endogeneity bias and go in either direction.

We also report returns to scale based on the coefficient estimates using the Wooldridge (2009) approach. Among all the manufacturing industries, only the manufacturing of tobacco products shows increasing returns to scale but all the others show decreasing returns to scale. Considering there are only 65 observations when estimating the production function for the tobacco industry, the accuracy of the estimation for this industry might be affected by measurement error. Rizov et al. (2012) also use value-added production function for Dutch firms for the period of 1997-2006 and find that the returns to scale of food, beverage and tobacco industry is 0.92. In our case, we find that the weighted average of the three industries is 0.68 for the period of 2009-2016. The average returns to scale of all manufacturing industries in our sample are 0.81 and 0.92 in Rizov et al. (2012).

Both results suggest manufacturing firms in the Netherlands have decreasing returns to scale.

Table 4.2: Coefficient estimates OLS and Wooldridge (2009) for value added production function

SBI code	Industry description	β_k_wdrg	β_k_ols	β_l_wdrg	β_l_ols	RTS_wdrg	Obs
10	Manufacture of food products	0.19*** (0.01)	0.34*** (0.01)	0.47*** (0.01)	0.70*** (0.01)	0.66	7,046
11	Manufacture of beverages	0.36*** (0.06)	0.34*** (0.04)	0.50*** (0.03)	0.84*** (0.05)	0.87	412
12	Manufacture of tobacco products	0.24 (0.20)	0.13*** (0.10)	1.12*** (0.23)	1.29*** (0.15)	1.37	65
13	Manufacture of textiles	0.10*** (0.04)	0.23*** (0.02)	0.68*** (0.02)	0.89*** (0.03)	0.77	1,050
15	Manufacture of leather, products of leather and footwear	0.17*** (0.02)	0.21*** (0.03)	0.71*** (0.02)	0.97*** (0.04)	0.88	799
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	0.17*** (0.01)	0.30*** (0.01)	0.59*** (0.01)	0.73*** (0.01)	0.76	4,561
17	Manufacture of paper and paper products	0.13*** (0.02)	0.22*** (0.01)	0.70*** (0.03)	0.85*** (0.02)	0.82	1,067
18	Printing and reproduction of recorded media	0.22*** (0.02)	0.20*** (0.01)	0.68*** (0.02)	0.87*** (0.02)	0.91	1,506
19	Manufacture of coke and refined petroleum products	0.34** (0.17)	0.25*** (0.04)	0.60*** (0.07)	0.78*** (0.07)	0.94	144
20	Manufacture of chemicals and chemical products	0.13*** (0.03)	0.35*** (0.01)	0.47*** (0.02)	0.68*** (0.02)	0.60	2,678
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.23*** (0.07)	0.28*** (0.03)	0.68*** (0.05)	0.76*** (0.04)	0.91	385
22	Manufacture of rubber and plastic products	0.12*** (0.01)	0.25*** (0.01)	0.67*** (0.01)	0.80*** (0.01)	0.79	3,258
23	Manufacture of other non-metallic mineral products	0.10*** (0.03)	0.24*** (0.01)	0.52*** (0.02)	0.75*** (0.02)	0.63	1,804
24	Manufacture of basic metals	0.12*** (0.01)	0.24*** (0.01)	0.61*** (0.01)	0.78*** (0.01)	0.73	11,321
26	Manufacture of computers, electronic and optical products	0.08*** (0.02)	0.17*** (0.01)	0.72*** (0.02)	0.88*** (0.02)	0.80	2,119
27	Manufacture of electrical equipment	0.06** (0.03)	0.18*** (0.02)	0.61*** (0.02)	0.82*** (0.02)	0.67	997
28	Manufacture of machinery and equipment n.e.c.	0.09*** (0.01)	0.16*** (0.01)	0.68*** (0.02)	0.88*** (0.01)	0.77	5,061
29	Manufacture of motor vehicles, trailers and semi-trailers	0.16*** (0.02)	0.21*** (0.01)	0.74*** (0.02)	0.80*** (0.02)	0.89	1,036
30	Manufacture of other transport equipment	0.20*** (0.04)	0.21*** (0.02)	0.62*** (0.02)	0.87*** (0.02)	0.82	1,315
31	Manufacture of furniture	0.07*** (0.01)	0.35*** (0.01)	0.47*** (0.01)	0.63*** (0.01)	0.54	5,172
33	Repair and installation of machinery and equipment	0.10*** (0.01)	0.22*** (0.01)	0.71*** (0.02)	0.81*** (0.01)	0.80	3,274
	Unweighted average manufacturing industries	0.16	0.24	0.65	0.83	0.81	

Note: In this table, we report the input coefficients from production functions by two-digit manufacturing industries based on pooled data for the years 2009 to 2016. β_k and β_l represent coefficients of capital and labor, respectively. WDRG and OLS indicate the estimation methods are based on Wooldridge (2009) or OLS. RTS is the returns to scale, where we sum the coefficients of capital and labor. Obs is the number of observations for each industry in our sample. SBI is the industry code used by the Statistical office. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In Table 4.3, we compare productivity levels and mark-ups. We pool data for manufacturing firms included in the sourcing survey for 2011 and 2016. We have five different estimates of productivity: TFP by Wooldridge (2009) specifying a value-added production function with mark-up correction, TFP using OLS estimates from a gross output and a value-added production function and labor productivity, defined as gross output divided by employment or value-added divided by employment.

We report mark-ups estimated in four different ways: from the elasticities of TFP estimation by Wooldridge (2009) specifying a value-added production function, from elasticities of TFP estimation using OLS (value-added and gross output production function), and we report a Price-Cost Margin (PCM) that is directly observed from the data.[37] All mark-up estimates except for PCM follow the framework of De Loecker and Warzynski (2012).

The median mark-up is below one, suggesting firms' price below marginal costs. De Loecker and Warzynski (2012) point out that by relying on revenue but not quantity data, the level of the mark-up is affected while relative mark-ups will not be affected. The variation in the latter is used for our identification. The PCM is larger than one and appears more in line with expectations.

Table 4.3: Productivity and price mark-ups

	Interquartile range			
	25%	50%	75%	Obs
	(1)	(2)	(3)	(4)
TFP_WDRG_VA	10.896	11.506	12.159	612
TFP_OLS_VA	7.859	8.840	9.065	617
TFP_OLS_GO	3.015	3.678	4.131	617
LP_VA	10.924	11.221	11.579	623
LP_GO	12.088	12.453	12.947	629
Mark-up_WDRG_VA	0.624	0.815	1.027	612
Mark-up_OLS_VA	0.918	1.155	1.410	612
Mark-up_OLS_GO	0.830	0.977	1.130	617
PCM	1.041	1.138	1.284	629

Note: The quartiles are for the sample of manufacturing industries included in the sourcing surveys. We pool observations for 2011 and 2016. TFP and LP are total factor productivity and labor productivity respectively. WDRG and OLS indicate the estimate methods are based on Wooldridge (2009) or OLS. VA and GO indicate the setting of the estimate is based on a value-added or a gross output production function. Price mark-ups are estimated using the approach suggested by De Loecker and Warzynski (2012), except for PCM the price-cost margin which is directly observed from the data. TFP_WDRG is with mark-up correction. Estimates using the approach from Ackerberg et al. (2015) are reported in Appendix B.

[37]The price-cost margin is calculated as follows: PCM=revenue/(labor cost + intermediate input cost).

Table 4.4 shows the correlation between the various productivity and mark-up estimates. The Wooldridge (2009) TFP estimate is positively correlated with labor productivity. For mark-ups, we find that mark-ups based on coefficient estimates from a value-added production function using OLS and the Wooldridge (2009) approach are stronger correlated compared to those based on coefficients from gross output production functions.

Since the various estimates of productivity and price mark-ups are positively correlated, we do not expect substantial differences in the relation between productivity/mark-ups and function specialization, depending on the measure used. We will use the productivity and mark-up estimates based on the Wooldridge (2009) approach for value-added production function in our baseline analysis and use the other estimates to examine the sensitivity of the results.

Table 4.4: Correlation various estimates of productivity and mark-ups

	LP _GO	LP _VA	TFP _WDRG _VA
LP_GO	1.0000		
LP_VA	0.2300	1.0000	
TFP _WDRG_VA	0.5737	0.4811	1.0000

	Mark-up _OLS _VA	Mark-up _OLS _GO	Mark-up _WDRG _VA
Mark-up _OLS_VA	1.0000		
Mark-up _OLS_GO	0.2187	1.0000	
Mark-up _WDRG_VA	0.8653	0.1566	1.0000

Note: the sample of manufacturing industries included in the sourcing surveys. We pool observations for 2011 and 2016. TFP and LP are total factor productivity and labor productivity respectively. WDRG and OLS indicate the estimate methods are based on Wooldridge (2009) or OLS. VA and GO indicate the setting of the estimate is based on a value-added or a gross output production function. TFP_WDRG is with mark-up correction. Price mark-ups are estimated using the approach suggested by De Loecker and Warzynski (2012).

For the descriptive statistics presented in Table 4.5, we pool observations for manufacturing firms in the 2012 and 2017 surveys. The surveys provide information on the employment distribution across functions. Clearly, the majority of workers in manufacturing firms are involved in fabrication. The average employment share of fabrication is about 65 percent. Yet, we use relative employment shares, see equation 4.1, to determine the functional specialization of firms. The highest index across all possible activities is used to determine the functional specialization of the firm.

Table 4.5 suggests 172 firms or 27.5 percent are specialized in R&D (172/623 * 100%). About one third have a relatively higher share of workers in fabrication, whereas the remaining 248 firms (39.7%) are specialized in marketing. The upstreamness and downstreamness of firms are calculated according to 4.2. Upstreamness values range from a minimum of 1.63 to a maximum of 3.56.[38]

Table 4.5 also reports two estimates of firm productivity and the price mark-up by De Loecker and Warzynski (2012). Labor productivity is real value-added divided by employment. TFP also accounts for capital inputs and is estimated econometrically using the approach suggested by Wooldridge (2009), with a price mark-up correction from De Loecker and Warzynski (2012), see section 4.3. Labor productivity and TFP are positively correlated. The average price mark-up is 0.9.

Table 4.5: Descriptive statistics

Variable	Obs.	Mean	Std. dev.	Min.	Max.
Specialization of firm in:					
R&D	623	0.28	0.45	0	1
Fabrication	623	0.33	0.47	0	1
Marketing	623	0.40	0.49	0	1
Upstreamness, U_k	623	2.55	0.62	1.63	3.56
Downstreamness, D_k	623	2.55	0.26	1.76	3.33
				Max - Min	
Labor productivity (in logs)	623	11.24	0.65	9.02	
Total factor productivity (in logs)	612	11.61	1.01	7.24	
Price mark-up	611	0.90	0.53	6.43	

Note: Descriptive statistics for manufacturing firms included in the surveys. See equation 4.1 for the measurement of a firm's functional specialization and equation 4.2 for calculation of firms' upstreamness and downstreamness. TFP is estimated using the Wooldridge (2009) approach specifying a Cobb-Douglas value-added production function and with mark-up correction. Labor productivity is real value-added divided by persons engaged. The price mark-up over marginal costs is estimated using the approach suggested by De Loecker and Warzynski (2012).

Table 4.6 compares functional specialization to the input-output based measure of upstreamness (U_k). The comparison is made for the sample of 623 manufacturing firms. The upstreamness measure U_k is continuous. To allow comparison, we group firms into terciles in the columns of Table 4.6. One third of firms with the highest (lowest) upstreamness measure U_k are considered more upstream (more downstream) and shown in the first (third) column.

If the upstreamness measure U_k aligns closely with the measure of functional specialization, most observations will be ordered along the main diagonal. This is not the case. There appears no relation between the upstreamness value U_k and the specialization of

[38]The minimum value corresponds with a firm that only exports products of the industry 'Manufacture of furniture; other manufacturing' for which we calculated an upstreamness value of 1.63 (see Appendix Table 4.A1). The maximum corresponds to a firm only exporting products related to the industry 'manufacture of basic metals'.

firms in R&D, fabrication, and marketing.[39] This provides suggestive evidence that input-output based measures of upstreamness do not relate to what firms do, which is tested more formally in the next section.

Table 4.6: Comparison between functional specialization and upstreamness

		Firm position based on the upstreamness measure U_k			
		More upstream	Middle	More downstream	**Sum**
Functional special-ization of firm in:	R&D	**9.5 (59)**	8.3 (52)	9.6 (60)	27.6 (171)
	Fabrication	10.8 (67)	**11.6 (72)**	10.6 (66)	32.6 (205)
	Marketing	13.2 (82)	13.5 (84)	**13.0 (81)**	39.9 (247)
	Sum	33.4 (208)	33.4 (208)	33.2 (207)	**100 (623)**

Note: The Percentage share of the number of firms in the total number of firms (number of firms in brackets). Manufacturing firms only. Firms are allocated to terciles in the columns using the upstreamness measure U_k. Shares may not sum due to rounding.

4.5 Results

This section examines the relation between functional specialization, measures of upstreamness, productivity, and mark-ups. We consider regression specifications that take the following form:

$$Y_{kst} = \alpha + \beta SI_{kst} + \gamma X_{kst} + \lambda_s + \lambda_t + \varepsilon_{kst} \tag{4.7}$$

where Y is either productivity or the price mark-up. The variable for functional specialization, SI, is a dummy variable. We include dummies for firms specialized in R&D and marketing and exclude the dummy for fabrication, so the β-coefficient estimates are relative to this excluded function. X includes a set of other variables such as upstreamness and control variables. Upstreamness is also a dummy variable based on the grouping of firms into terciles (see the previous section). The middle group is excluded in the regressions, so the coefficient estimates are obtained for firms that are more upstream or more downstream relative to the excluded group. The variables λ_s and λ_t are industry and time fixed-effects. We will also include a lagged productivity term in specification 4.7 in future research as the production function estimator assumes that productivity follows a first order Markov process.

[39]We also do not observe a relation between downstreamness (D_k) and functional specialization.

Section 4.5.1 presents the baseline results. Section 4.5.2 examines the robustness of the main results for including other explanatory variables.

4.5.1 Functional specialization, upstreamness, productivity, and mark-ups

Table 4.7 presents regression results using 4.7 with firm TFP as the dependent variable. Regression results in the first column only include dummies for the functional specialization of firms. Columns 2 and 3 add dummies for upstreamness and downstreamness respectively. In columns 4 and 5 the measures are included simultaneously.

Results in column 1 suggest firms specialized in R&D and marketing activities are associated with a significantly higher TFP level compared to firms specialized in fabrication. We observe a similar positive and significant relation if we consider real value added divided by employment (i.e. labor productivity).[40] The coefficient estimates suggest that on average, firms specialized in R&D have a 20 percent higher TFP level compared to firms that specialized in fabrication, which is the excluded dummy in the regressions. Firms that have relatively more workers involved in marketing are estimated to be 12 percent more productive on average. [41]

The higher productivity observed for firms specialized in R&D and marketing is consistent with findings in related literature. Innovation in products and processes often positively relates to productivity performance (see e.g. Raymond et al. 2015). One would therefore expect that firms specializing in R&D have higher TFP levels. Similarly, marketing may generate higher returns, for instance from nurturing brand names.

Our findings suggest that input-output based measures of upstreamness are not significantly related to firm TFP, see columns 2 and 3 in Table 4.7. That is, firms in the upper or lower tercile of the upstreamness measure (U_k) do not have a significantly higher productivity level (the middling tercile is the excluded dummy category). The downstreamness measure (D_k) also does not significantly relate to TFP. This is consistent with the findings by Chor et al. (2014) who calculate input-output based upstreamness and downstreamness measures for Chinese manufacturing firms and do not find a significant relation to productivity.

In columns 4 and 5 we include both measures of firm specialization simultaneously. Func-

[40] Results not shown but available upon request.

[41] We calculate the percentage impact of the dummy variable on TFP using Kennedy (1981). Assuming errors are normally distributed, we calculate $(exp(\beta - 0.5variance(\beta)) - 1) \times 100\%$, where the variance is the square of the standard error for the estimate of β.

tional specialization still significantly relates to productivity, and the implied relation with firm TFP is almost the same as in column 1. This suggests that input-output based upstreamness measures are largely orthogonal to functional specialization.

Table 4.7: Relation firm TFP and functional specialization

	(1)	(2)	(3)	(4)	(5)
Specialized in R&D	0.216***			0.219***	0.217***
	(0.072)			(0.073)	(0.073)
Specialized in Marketing	0.143**			0.146**	0.146**
	(0.066)			(0.067)	(0.066)
More upstream, U_k		-0.066		-0.054	
		(0.075)		(0.075)	
More downstream, U_k		0.090		0.106	
		(0.065)		(0.066)	
More upstream, D_k			-0.031		-0.043
			(0.066)		(0.067)
More downstream, D_k			9.85e-05		-0.004
			(0.076)		0.076)
Constant	11.65***	11.76***	11.73***	11.67***	11.65***
	(0.085)	(0.083)	(0.087)	(0090)	(0.090)
Observations	611	611	611	611	611
R^2	0.744	0.741	0.740	0.745	0.744

Note: Dependent variable is firm TFP estimated from a value added production function using the Wooldridge approach and adjusted for mark-ups, see section 4.3. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Industry and time dummies added in all regressions.

Next, we turn to examine the relation between functional specialization and mark-ups. Table 4.8 reports regressions with (the natural logarithm of) mark-ups as the dependent variable. These mark-ups are estimated following the approach suggested by De Loecker and Warzynski (2012), whereby a mark-up is obtained for a firm as the wedge between labor's expenditure share in revenue (directly observed in the data) and labor's output elasticity obtained by estimating the associated production function.

Scholars argue that the creation of intangibles may generate (temporary) market power (De Loecker and Eeckhout, 2017). For example, R&D may result in the development of new knowledge. Marketing may help establish brand names. This suggests a positive relation between mark-ups and functional specialization.

On the other hand, our descriptive analysis suggests that mark-ups are generally below one. The firms covered in the analysis might be more exposed to international competition due to the nature of products produced or function performed, which puts pressure not to charge prices above marginal costs. Indeed, the results in Table 4.8 suggest no significant relation between mark-ups and functional specialization. The absence of a significant relation is also found for alternative approaches to estimate the mark-up, including the PCM. If anything, our results suggest a negative relation between mark-ups and specialization, but this is at the border of common levels of statistical significance.[42]

Table 4.8: Relation between mark-ups and functional specialization

	(1)	(2)	(3)	(4)	(5)
Specialized in R&D	-0.065*			-0.063	-0.068*
	(0.039)			(0.040)	(0.039)
Specialized in Marketing	-0.048			-0.047	-0.057*
	(0.034)			(0.034)	(0.034)
More upstream, U_k		0.045		0.042	
		(0.038)		(0.039)	
More downstream, U_k		0.018		0.013	
		(0.037)		(0.038)	
More upstream, D_k			-0.019		-0.018
			(0.035)		(0.035)
More downstream, D_k			0.095**		0.099***
			(0.037)		(0.037)
Constant	-0.333***	-0.381***	-0.351***	-0.353***	-0.320***
	(0.041)	(0.041)	(0.040)	(0.047)	(0.043)
Observations	611	611	611	611	611
R^2	0.440	0.438	0.445	0.441	0.449

Note: Dependent variable is the (natural logarithm of the) mark-up using the labor elasticities from the value added production function estimates in the Wooldridge approach and the labor share, see section 4.3. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Industry and time dummies added in all regressions.

The survey also asks firms about the nature of their business. One possible response is that the firm indicates it 'does not produce goods, but contracts-out the production completely and has developed the goods or owns the intellectual property rights of the produced goods'. These are the so-called 'factory-less goods producing firms (FGPFs)'(Bernard and Fort, 2015). Classical examples are Apple, Nike and Reebok, which have contracted out all their fabrication activities. In the surveys, 32 out of 1,272 firms indicated being FGPFs. [43]

Table 4.9 examines all firms, both manufacturing and non-manufacturing, in the survey. Column 1 includes a dummy for FGPFs. We find a positive relation with TFP, but the result is not significant at conventional levels of significance. This might be due to the

[42]The results in Table 4.8 suggest a significant positive relation between mark-ups and more downstream firms for the measure D_k. This significant relation is not observed for other measures of the price mark-up and thus might be spurious.

[43]Note that we consider the full sample of 1,272 observations, since FGPFs are often not classified in manufacturing (Bernard et al. 2017). Out of the 32 FGPFs, 29 firms are identified as being specialized in either R&D or marketing using equation 4.1. This supports our approach.

limited number of observations for FGPFs. [44]

The other columns in Table 4.9 examine the relation between specialization and TFP for the full sample. As before, firms that have a relatively higher share of workers involved in R&D are significantly more productive. Using the coefficient estimate in column 2, firms specialized in R&D have a 16 percent higher TFP on average. [45]

Table 4.9: Factory-less goods producing firms and productivity

	(1)	(2)	(3)	(4)	(5)
Factory-less goods producing firm	0.148				
	(0.114)				
Specialized in R&D		0.170***			0.210***
		(0.045)			(0.050)
Specialized in Fabrication			-0.145**		
			(0.045)		
Specialized in Marketing				0.011	0.092*
				(0.048)	(0.054)
Constant	11.74***	11.70***	11.79***	11.74***	11.65***
	(0.078)	(0.077)	(0.077)	(0.082)	(0.083)
Observations	1,268	1,268	1,268	1,268	1,268
R^2	0.655	0.659	0.658	0.655	0.660

Note: Dependent variable is firm TFP estimated from a value added production function using the Wooldridge approach, with mark-up subtracted. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Industry and time dummies added in all regressions.

We also explored the relation between functional specialization and other measures of firm performance. The first column in Table 4.10 examines the relation between functional specialization and wages. These results suggest that specialization in R&D positively relates to wages. This finding is consistent with specialization requiring relatively more and better paid knowledge and innovation workers.

The second column considers the relation to the return on sales, measured as earnings before income and tax as a share in total turnover. Although we find a positive relation to functional specialization in R&D or marketing (as before, the excluded dummy is fabrication), these results are not significant. In column 3, we express earnings before income and tax as a share in value added. Again we observe a positive (but insignificant) relation to functional specialization in R&D or marketing. Moreover, three year moving averages for return on sales or value added also suggests a positive (and insignificant) relation.

[44] Results are also not significant if we consider labor productivity as the dependent variable.

[45] For the full sample, we also do not observe a significant relation between input-output based measures of upstreamness and firm TFP. Results not shown but available upon request.

The final columns in Table 4.10 examine the relation between intellectual property investment (column 4) and functional specialization. Also here, we do not observe a significant relation, but the coefficients suggest a positive relation for firms specialized in R&D or marketing.

Table 4.10: Relation other measures firm performance and functional specialization

	(1)	(2)	(3)	(4)
	Wages	RoS	RoVA	IP inv
Specialized in R&D	0.105***	0.051	3.230	0.015
	(0.035)	(0.033)	(3.032)	(0.012)
Specialized in Marketing	0.051*	0.016	2.082	0.012
	(0.031)	(0.021)	(1.933)	(0.013)
Constant	3.660***	0.053*	-0.119	0.041
	(0.038)	(0.028)	(0.419)	(0.027)
Observations	627	628	628	628
R^2	0.210	0.055	0.027	0.010

Note: Dependent variable is the average wage in logs (column 1); Return on Sales (column 2); Return on value added (column 3); and Intellectual Property investment as a share in value added (column 4). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Industry and time dummies added in all regressions.

4.5.2 Robustness analysis

Table 4.11 examines sensitivity of the results to controlling for other firm characteristics. A potential concern is that the baseline results on functional specialization are driven by confounding variables. There is a long list of variables that may relate to firm productivity such as investment in innovation or the firms' scope of activities (Syverson, 2011). As a result we cannot exclude the possibility of confounding variables, but we can examine whether the results are affected by control variables that are available in the dataset we constructed. [46]

In Table 4.11, we include the size of the firm approximated by the number of employees, investment in software and intellectual property as a share in firm value added, the age of the firm, and the trade share which is the log of gross exports plus imports divided by gross output. Firm size and engagement in international trade correlate positively with firm productivity. This correlation is widely documented and consistent with the model by Melitz (2003) where larger firms are more productive and more likely to trade. Investment in intellectual property relates positively to productivity as well. But for software

[46] The production statistics do not provide information on the educational attainment of the firm's workforce. Hence, we cannot include human capital as a control variable. Note that we observe a positive relation between specialization in R&D and wages, see Table 4.10.

investment we observe a significant negative relation. Investment in software typically requires company reorganization (Brynjolffson and Hitt, 2000). Therefore, productivity effects from software investment are likely better captured in studies that exploit the panel dimension of the data.[47]

The regressions reported in Table 4.11 are demanding as we include several control variables besides the year and industry fixed-effects that were also included before. Nevertheless, our findings suggest that the relation between functional specialization and productivity is still observed. R&D and marketing positively relate to higher TFP, although at the border of common levels of statistical significance.

In comparison to the baseline findings in Table 4.7, the coefficients in column 1 of Table 4.11 suggest that firms specialized in R&D have a 9 percent higher TFP level compared to firms that specialized in fabrication. Firms that have relatively more workers involved in sales and marketing are on average 8 percent more productive. As before, we do not observe a significant relation between firm productivity and input-output based upstreamness and downstreamness measures.[48]

[47]We also ran regressions whereby we used the three-year average software and intellectual property investment as a share in value added. This helps address the issue that investments are lumpy, i.e. typically investments are concentrated in a particular year with no investments for several years thereafter (Levinsohn and Petrin, 2003). Results are similar if we use a three-year average.

[48]The results reported in Table 4.11 are qualitatively similar if we use labor productivity instead of TFP as the dependent variable.

Table 4.11: Relation TFP and functional specialization, including control variables

	(1)	(2)	(3)	(4)	(5)
Specialized in R&D	0.113**			0.118*	0.111*
	(0.056)			(0.056)	(0.056)
Specialized in Marketing	0.098*			0.105**	0.094*
	(0.051)			(0.052)	(0.051)
More upstream, U_k		-0.009		-0.0001	
		(0.056)		(0.056)	
More downstream, U_k		0.129**		0.139**	
		(0.054)		(0.055)	
More upstream, D_k			0.065		0.057
			(0.056)		(0.056)
More downstream, D_k			0.012		0.057
			(0.061)		(0.056)
Employment (thousands)	0.380***	0.384***	0.381***	0.379***	0.376***
	(0.077)	(0.079)	(0.077)	(0.078)	(0.077)
Investment in intellectual	0.259***	0.269***	0.266***	0.263***	0.260***
property	(0.099)	(0.103)	(0.099)	(0.102)	(0.098)
Software investment	-2.247***	-2.225***	-2.220***	-2.253***	-2.247***
	(0.772)	(0.770)	(0.771)	(0.769)	(0.771)
Age of firm (year/1000)	0.976	0.916	0.889	0.934	0.917
	(1.04)	(1.04)	(1.05)	(1.03)	(1.05)
Trade share	0.048***	0.049***	0.051***	0.046**	0.048***
	(0.034)	(0.032)	(0.03)	(0.033)	(0.034)
Constant	11.12***	11.17***	11.17***	11.11***	11.12***
	(0.079)	(0.076)	(0.081)	(0.082)	(0.084)
Observations	611	611	611	611	611
R^2	0.764	0.764	0.762	0.766	0.764

Note: Dependent variable is firm TFP estimated from a value added production function using the Wooldridge approach and adjusted for mark-ups. Age of the firm refers to year of inception. Trade share is the log of gross exports plus imports divided by gross output. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Industry and time dummies added in all regressions.

4.6 Concluding remarks

This chapter proposed to measure functional specialization of firms and considered it as a determinant of productivity and mark-ups. Based on the firm's employment composition in business functions, we distinguished firms that are specialized in R&D, fabrication or marketing. Functional specialization aims to capture what firms do. It differs from upstreamness and downstreamness that measure where firms are positioned in the production line. The difference was confirmed by the empirical analysis, which indicated that functional specialization is not related to upstreamness. Moreover, we found that firms specialized in R&D and marketing are more productive compared to firms specialized in fabrication. Upstreamness and downstreamness do not significantly relate to firm productivity.

Our findings inform on an important debate. The decline of manufacturing employment shares and its implications for socio-economic outcomes such as wages and (un)employment are an important and often discussed issue in society. Recent work has documented that continuing firms may transition from manufacturing to services, and studied the implications for wages and employment conditional on the occupation of workers (Bernard et al. 2017). Ding et al. (2019) provide a model and empirical evidence whereby U.S. firms shift towards providing professional services as a response to international competition in physical inputs. The findings presented in this chapter suggest the shift away from physical production towards R&D and marketing positively relates to firm productivity.

Functional specialization can be measured for firms in countries that have administered the type of surveys used in this chapter. These include several European countries (Nielsen, 2018), but also the National Organizations Survey for the U.S. (Sturgeon et al. 2013), and the Survey of Innovation and Business Strategy for Canada. Alternatively, if information on the occupational composition of the firms' workforce is available, it can also be applied in situations where such surveys have not been held using the mapping between occupations and activities proposed in Timmer et al. (2019). This opens up further empirical research to study structural change within and across firms and their implications for socio-economic outcomes.

4.7 Appendix

Appendix A. Input-output based measures of upstreamness and downstreamness

In this appendix, we first outline a set of commonly used input-output based measures for up- and downstreamness. Second, we empirically implement the input-output based measures using world input-output tables.

Input-output based upstreamness and downstreamness measures: definition

To start the exposition, consider two accounting identities that form the basis for the input-output system.[49] First, gross output from each country ($i, j \in \{1, \ldots, N\}$) and good $s \in \{1, \ldots, S\}$ is used by final or intermediate purchasers, such that $y_i(s) = \sum_j f_{ij}(s) + \sum_j \sum_{s'} z_{ij}(s, s')$, where $y_i(s)$ is gross output of good s in country i, $f_{ij}(s)$ is the final output value of goods shipped from industry s in country i to country j, and $z_{ij}(s, s')$ are the values of intermediates from industry s in country i used by industry s' in country j.[50] Second, value added equals the value of gross output minus intermediate inputs: $v_i(s) = y_i(s) - \sum_j \sum_{s'} z_{ij}(s, s')$.

Both accounting equations can be stacked to create a global input-output system. That is, consider a gross output vector $\mathbf{y}$ with block elements $\mathbf{y}_i$ of dimension $S \times 1$. Intermediate input flows are in a matrix $\mathbf{Z}$ with block elements $\mathbf{Z}_{ij}$ of dimension $S \times S$. Final goods flows are in a matrix $\mathbf{F}$ with dimension $NS \times N$ that has block elements $\mathbf{f}_{ij}$ of dimension $S \times 1$. And value added is in a vector $\mathbf{v}$ with $S \times 1$ dimensional block elements v_i. This can be used to define the global input-output matrix $\mathbf{A} = \mathbf{Z}\hat{\mathbf{y}}^{-1}$, with $\mathbf{A}_{ij} = \mathbf{Z}_{ij}\hat{\mathbf{y}}_j{}^{-1}$.[51] Rewriting the accounting identities in a global input-output system:

$$\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{F}\iota \tag{4.A1}$$

$$\mathbf{v}' = \mathbf{y}' - \iota'\mathbf{A}\hat{\mathbf{y}} = \mathbf{y}' - \iota'\hat{\mathbf{y}}\mathbf{B} \tag{4.A2}$$

where ι is a summation vector of appropriate dimension, and $\mathbf{B} = \hat{\mathbf{y}}^{-1}\mathbf{A}\hat{\mathbf{y}}$ measures the share of good s used by a downstream industry to produce s'. Equations 4.A1 and 4.A2

[49] We closely follow Johnson (2018) in the exposition of upstreamness and downstreamness measures. Note that these measures were initially developed by Dietzenbacher et al. (2005) to characterize 'distance' between industries, which they termed the average propagation length.

[50] In input-output analysis, industries are typically equated with products.

[51] A hat symbol 'ˆ' denotes a diagonal matrix with the vector along the diagonal.

can be re-written such that:

$$\mathbf{y} = [\mathbf{I}\text{-}\mathbf{A}]^{-1}\mathbf{f} = (\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \dots)\mathbf{f} \tag{4.A3}$$

$$\mathbf{y}' = \mathbf{v}'[\mathbf{I}\text{-}\mathbf{B}]^{-1} = \mathbf{v}'(\mathbf{I} + \mathbf{B} + \mathbf{B}^2 + \mathbf{B}^3 + \dots) \tag{4.A4}$$

Where $\mathbf{f} = \mathbf{F}\iota$. Note that $[\mathbf{I}\text{-}\mathbf{A}]^{-1}$ and $[\mathbf{I}\text{-}\mathbf{B}]^{-1}$, the Leontief inverse and the Ghosh inverse (Miller and Blair, 2009), are the geometric expansions that trace the stages in a global value chain. Equation 4.A3 shows that output is equal to the final good plus the value of intermediate inputs used to produce it, where $\mathbf{Af}$ are intermediate inputs directly used, $\mathbf{A}^2\mathbf{f}$ the intermediate inputs used to produce the intermediate inputs and so on. Similarly, in equation 4.A4, output is equal to direct value added from the sector from which the good originates plus value added from other sectors from which inputs where sourced further up the global value chain. So $\mathbf{v}'\mathbf{B}$ is one step back in the chain, $\mathbf{v}'\mathbf{B}^2$ is two steps back, and so on.

In this setup, a good that is used for final consumption or used as an input to produce a final good is more downstream. Likewise, a good is more upstream if it is used to produce intermediate inputs (that are used to produce intermediate inputs etcetera). Antràs and Chor (2013) count the number of steps away from final consumption and weight each stage by the output value. This results in the following upstreamness measure:

$$\mathbf{U} = 1\hat{\mathbf{y}}\mathbf{f} + 2\hat{\mathbf{y}}^{-1}\mathbf{A}\mathbf{f} + 3\hat{\mathbf{y}}^{-1}\mathbf{A}^2\mathbf{f} + \dots = \hat{\mathbf{y}}^{-1}[\mathbf{I}\text{-}\mathbf{A}]^{-2}\mathbf{f} \tag{4.A5}$$

It measures the average number of stages of production a good passes through before reaching the final consumer. Hence, this upstreamness measure is larger if a good is more upstream. For example, coltan is typically not used as a final product, but serves as an input for tantalum capacitors that are used in many electronic devices. By contrast, apparel is often sold to final consumers. Coltan would thus receive a higher upstreamness value than apparel.[52]

Fally (2012) developed an alternative measure of the position and length of global value chains. This measure counts the production stages for the production of a particular product backward:

[52] In the input-output literature $\mathbf{U}$ is known to measure the strength of total forward linkages in a production process. To see this, note that $\mathbf{U} = \hat{\mathbf{y}}^{-1}[\mathbf{I}\text{-}\mathbf{A}]^{-2}\mathbf{f} = \hat{\mathbf{y}}^{-1}[\mathbf{I}\text{-}\mathbf{A}]^{-1}\hat{\mathbf{y}}\iota = [\mathbf{I}\text{-}\mathbf{B}]^{-1}\iota$. So $\mathbf{U}$ is the row sum of the Ghosh inverse matrix (Miller and Blair, 2009).

$$\mathbf{D} = 1\mathbf{v}'\hat{\mathbf{y}}^{-1} + 2\mathbf{v}'\mathbf{B}\hat{\mathbf{y}}^{-1} + 3\mathbf{v}'\mathbf{B}^2\hat{\mathbf{y}}^{-1} + \cdots = \mathbf{v}'[\mathbf{I}\text{-}\mathbf{B}]^{-2}\hat{\mathbf{y}}^{-1} = \iota'[\mathbf{I}\text{-}\mathbf{A}]^{-1} \quad (4.\text{A6})$$

Thus, the length of an industry's value chain is equal to the column sum of the Leontief Inverse.[53] Fally (2012) shows $\mathbf{D}$ can be expressed as a weighted average of the number of stages required to produce good s in country i, weighted by how much each stage of production contributes to the final value of that good.

Using input-output tables, the upstreamness (U_s) and downstreamness (D_s) of a product can be measured. Typically, researchers have estimated these using national input-output tables.[54] This stands at odds with the 'global' in global value chains. That is, national input-output tables do not adequately reflect production networks fragmented across national borders. We therefore implement - upstreamness and downstreamness measures on the basis of world input-output tables (as e.g. in Fally and Hillberry, 2017 and Antràs and Chor, 2018).

Measuring upstream and downstreamness using World Input-Output Tables

We use the 2016 release of World Input-Output Tables (WIOTs), which provide tables for the period from 2000 to 2014 (Timmer et al. 2016). In essence, WIOTs are constructed by merging harmonized national input-output tables with international trade statistics. These tables provide information on input purchases, the parent (downstream) industry, as well as source country and industry. Total production and input purchases are disaggregated for 56 sectors of the economy.

The $\mathbf{U}_{is}$ and $\mathbf{D}_{is}$ statistics are calculated at the level of country-industry $(i; s)$ pairs. We focus on the length and position of industries for products that are finalized in the Netherlands. But we consider sensitivity of the results to alternative approaches such as a cross-country average measure of $\mathbf{U}_s$ and $\mathbf{D}_s$.

Appendix Table 4.A1 shows upstreamness and downstreamness calculated according to equations 4.A5 and 4.A6 using the WIOT for 2014. Industries are ranked by their upstreamness in value chains from most upstream to least upstream.[55]

[53]The third equality follows from $\iota'\hat{\mathbf{y}} = \mathbf{v}'[\mathbf{I}\text{-}\mathbf{B}]^{-1}$ and $\hat{\mathbf{y}}[\mathbf{I}\text{-}\mathbf{B}]^{-1}\hat{\mathbf{y}}^{-1} = [\mathbf{I}\text{-}\mathbf{A}]^{-1}$. In the input-output literature this measure has commonly been used to measure total backward linkages.

[54]e.g. Fally (2012) and Antràs et al. (2012) use an input-output table for the US. Chor et al. (2014) use an input-output table for China.

[55]Two industries are not reported, for which no data for the Netherlands is provided in the WIOT, so in total 54 sectors are distinguished. Dutch industries which are not separately distinguished in the WIOTs are: Activities of households as employers (ISIC revision 4 code T), and Activities of extraterritorial organizations and bodies (ISIC revision 4 code U). Industries T and U are typically small industries and for the Netherlands included in 'other service activities' (ISIC revision 4 code R-S).

Typically, only values for manufacturing industries are reported (see e.g. Antràs et al. 2012; Fally, 2012). Instead, Appendix Table 4.A1 shows upstreamness for all 54 sectors of the economy, including services. The WIOTs distinguish two services sectors that are of interest here, namely 'Scientific research and development' (R&D sector) and 'Advertising and market research (Advertising sector). On the face of it, these two sectors might be considered to be upstream and downstream in global value chains, as e.g. in Rungi and Del Prete (2018).[56] Thus one might expect that the R&D sector will show up as being upstream based on estimates of $\mathbf{U}$ and $\mathbf{D}$, whereas the Advertising sector will be downstream based on $\mathbf{U}$ and $\mathbf{D}$.

An interesting finding that emerges from Appendix Table 4.A1 relates to the upstreamness, $\mathbf{U}_{is}$, of the R&D and Advertising sectors. We find that the R&D sector is one of the most downstream industries (the row is in italics in Appendix Table 4.A1). It is ranked 47 out of 54. The upstreamness measure $\mathbf{U}_{is}$ for the advertising sector suggests it is one of the most upstream industries (also in italics in Appendix Table 4.A1). It ranks 6 out of 54.

These findings are also observed for the downstreamness measure, $\mathbf{D}_{is}$. The R&D sector is an upstream activity in a global value chain, so we would expect it would be ranked among the least downstream industries as it stimulates little upstream intermediate demand. In fact, it ranks 39 out of 54. For example, it is ranked more downstream than manufacturers of furniture products (ranked 42). Advertising is a very downstream activity, but it ranks only 24 out of 54, appearing less downstream than basic metal products (ranked 7) and chemical products (ranked 3).

Does this finding hold more generally? First, we calculated $\mathbf{U}_{is}$ for the Netherlands in other years using the WIOTs that are available annually from 2000 to 2014. The R&D industry in the Netherlands has a similar value for $\mathbf{U}_{is}$ in the years from 2009 to 2014, ranking between 40 and 49 out of 54.[57] Advertising consistently ranks among the most upstream industries (ranking between 2 and 6 over the period from 2000 to 2014). Second, we calculated $\mathbf{U}_{is}$ for other country-industry pairs and calculated an unweighted average for each industry in the other 42 countries distinguished in the WIOTs. The R&D sector ranks between 38 and 49 out of 56 over the years from 2000 to 2014. The Advertising sector ranks between 12 and 19 out of 56 during these years. It suggests that the observations for the upstreamness and downstreamness of the R&D and advertising sectors hold more

[56]Antràs and Chor (2018) use the 2013 release of the WIOTs that do not distinguish R&D and advertising industries.

[57]In the years before 2009, we observe a much higher value for $\mathbf{U}_{is}$. It ranks between 5 and 8 out of 54 during the period from 2000 to 2008. This sudden change might be due to revisions in the data and appears specific to the Netherlands as they do not hold more generally. Due to the implementation of the new System of National Accounts, R&D is now considered an investment rather than intermediate input (UN et al. 2009).

broadly.[58]

[58]One may argue that industry classifications are too aggregated and create biases in computing $\mathbf{U}_{is}$ and $\mathbf{D}_{is}$ compared to what would be obtained with more disaggregated data. Fally (2012) examines the aggregation properties of indexes $\mathbf{U}$ and $\mathbf{D}$ and shows that aggregating industries does not substantially affect the average of $\mathbf{U}$ and $\mathbf{D}$ across industries.

Table 4.A1: Upstreamness and downstreamness, 2014

Code	Good/Industry s	$\mathbf{U}_{is}$	rank	$\mathbf{D}_{is}$	rank
B	Mining and quarrying	3.71	1	1.41	53
C24	Manufacture of basic metals	3.56	2	2.78	7
C20	Manufacture of chemicals and chemical products	3.55	3	2.99	3
C33	Repair and installation of machinery and equipment	3.50	4	2.40	21
E37-E39	Sewerage; waste collection and disposal activities	3.48	5	2.44	19
M73	*Advertising and market research*	3.46	6	2.19	24
M69_M70	Legal and accounting, head offices and consultancy activities	3.43	7	2.01	35
C17	Manufacture of paper and paper products	3.18	8	2.77	8
M74_M75	Other professional, scientific and technical activities	3.17	9	2.07	32
C18	Printing and reproduction of recorded media	3.15	10	2.44	20
K66	Activities auxiliary to financial services	3.14	11	1.62	50
C25	Manufacture of fabricated metal products	3.13	12	2.54	15
C23	Manufacture of other non-metallic mineral products	3.13	13	2.53	16
C19	Manufacture of coke and refined petroleum products	3.12	14	3.33	1
C16	Manufacture of wood and of products of wood	3.04	15	2.47	18
H53	Postal and courier activities	3.04	16	1.97	38
H52	Warehousing and support activities for transportation	3.04	17	2.00	36
C22	Manufacture of rubber and plastic products	3.02	18	2.58	14
K64	Financial service activities	3.01	19	1.57	52
J59_J60	Film production, publishing and broadcasting	2.98	20	2.04	34
N	Administrative and support service activities	2.95	21	1.73	47
D35	Electricity, gas, steam and air conditioning supply	2.89	22	2.32	23
H49	Land transport and transport via pipelines	2.83	23	2.17	27
J58	Publishing activities	2.80	24	2.09	31
H51	Air transport	2.74	25	2.85	4
C27	Manufacture of electrical equipment	2.72	26	2.35	22
H50	Water transport	2.71	27	2.62	10
G46	Wholesale trade, except of vehicles and motorcycles	2.62	28	1.88	43
J62_J63	Computer programming, consultancy and related activities	2.60	29	1.85	45
A01	Crop and animal production and related service activities	2.46	30	2.48	17
C28	Manufacture of machinery and equipment n.e.c.	2.39	31	2.59	12
G45	Trade and repair of motor vehicles and motorcycles	2.37	32	2.14	28
M71	Architectural and engineering activities;	2.36	33	1.93	40
F	Construction	2.33	34	2.59	13
J61	Telecommunications	2.29	35	2.17	26
C26	Manufacture of computer, electronic and optical products	2.29	36	3.09	2
C10-C12	Manufacture of food products, beverages and tobacco products	2.22	37	2.85	5
E36	Water collection, treatment and supply	2.11	38	1.76	46
A03	Fishing and aquaculture	2.07	39	2.06	33
C30	Manufacture of other transport equipment	1.96	40	2.82	6
C21	Manufacture of pharmaceutical products	1.92	41	2.10	30
C29	Manufacture of motor vehicles	1.90	42	2.76	9
K65	Insurance, and pension funding	1.86	43	1.93	41
A02	Forestry and logging	1.86	44	2.18	25
C13-C15	Manufacture of textiles, wearing apparel and leather products	1.79	45	2.59	11
L68	Real estate activities	1.74	46	1.98	37
M72	*Scientific research and development*	1.69	47	1.94	39
R_S	Other service activities	1.65	48	1.88	44
C31_C32	Manufacture of furniture; other manufacturing	1.63	49	1.91	42
I	Accommodation and food service activities	1.54	50	2.14	29
O84	Public administration and defense; social security	1.47	51	1.73	48
P85	Education	1.26	52	1.37	54
G47	Retail trade, except of motor vehicles and motorcycles	1.21	53	1.71	49
Q	Human health and social work activities	1.09	54	1.58	51

Note: Upstreamness, U_{is}, according to equation 4.A5. Downstreamness, D_{is}, according to equation 4.A6. Industry codes are the ISIC revision 4. Country-industry pairs for the Netherlands are reported. *Source:* World Input-Output Tables, 2016 release.

Appendix B. TFP estimation with intermediate inputs as flexible production factor

Considering the argument of the less flexible labor market situation in the Netherlands, we incorporate an alternative setting to estimate the output elasticity of factor inputs, TFP and mark-ups. Specifically, we consider labor as dynamic input that also enters the state space as of capital. In the Netherlands, the use of intermediate inputs is likely to be more flexible than labor. Therefore, we consider intermediate input as the flexible input in the production function. In order to estimate mark-up of firms, we need to estimate the output elasticity of the flexible input. This means that it is necessary to be able to estimate the coefficient of intermediate inputs using our production function. We consider a gross output production function:

$$go_{kst} = \beta_0 + \beta_1 Capital_{kst} + \beta_2 Labor_{kst} + \beta_3 Intermediates_{kst} + \omega_{kst} + \varepsilon_{kst} \tag{4.B1}$$

Compared with equation 4.3, the gross output setting of equation 4.B1 has gross output on the left hand side and includes intermediate inputs on the right hand side. We follow Ackerberg et al. (2015) to estimate β_1, β_2 and β_3 in the second stage of the control function approach, so that our estimation does not suffer from the functional dependence problem. However, as discussed in Ackerberg et al. (2015), a gross output setting has difficulty in the identification of the coefficients of labor and material separately, as the two variables are often correlated. Therefore, there is a tradeoff in the gross output setting between being able to estimate production function and calculate mark-up on a more flexible input-material, and the capability to identify the coefficient of intermediate inputs (De Loecker and Warzynski, 2012). However, according to Van Heuvelen et al. (2019), in the Netherlands, labor is considered to be semi-fixed and intermediate inputs flexible, so it indicates that there is less of an issue concerning identification. On the other hand, Ackerberg et al. (2015) suggest to solve this identification problem by using lagged input prices as instruments. We try to run two analyses, one without lagged wage as instrument and the other using lagged wages as instrument when estimating the production function. We estimate the production function (B1) using Ackerberg et al. (2015) approach with GMM and bootstrap standard errors.[59]

In a gross output setting, the way to estimate mark-up is similar to that in value added setting (see main text):

[59]We set the iteration to a maximum of 100 to make the time to run the program reasonable and possible. This, however, may come at the cost of lowering accuracy of the estimation results.

$$\mu_{kst} = \frac{P_{kst}}{MC_{kst}} = \frac{Intermediates\_Elasticity_{kst}}{Intermediates\_Share_{kst}} \tag{4.B2}$$

Table 4.B1: Productivity, mark-up levels

	Interquartile range			
	25%	50%	75%	Obs
	(1)	(2)	(3)	(4)
TFP_ACF_GO	3.971	7.325	8.585	617
TFP_ACF_GO_IV	5.380	8.591	11.643	617

Note: The quartiles for levels are for the manufacturing industries included in the sourcing surveys, where we pool observations for 2011 and 2016. TFP is total factor productivity. ACF indicates the estimation method is based on Ackerberg et al. (2015). GO indicates the setting of the estimate is based on gross output. IV indicates that the ACF method uses wage as instrument variable.

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6 Dutch Summary

Globalisering, de toenemende interactie tussen landen, is een verschijnsel dat diepgaand onderzocht en besproken is. De grensoverschrijdende onderlinge economische verbanden zijn de afgelopen decennia sterk toegenomen en hebben geleid tot het ontstaan van mondiale waardeketens (Global Value Chains, GVC's). GVC's hebben betrekking op productieprocessen die opgesplitst zijn over landsgrenzen heen. Deze opsplitsing, zo wordt betoogd, is in gang gezet door opener economisch beleid, verlaging van transportkosten en, met name, lagere communicatie- en coördinatiekosten (Baldwin, 2016). Dit heeft geresulteerd in een snelle uitbreiding van de internationale handel in intermediaire producten en stromen van ondersteunende zakelijke diensten, zoals backofficediensten en diensten na verkoop. Deze verplaatsing van bedrijfsfuncties en productiefases naar het buitenland wordt ook wel 'offshoring' genoemd (Baldwin, 2006). Globalisering in de vorm van offshoring is nauw verbonden met functionele specialisatie, en samen hebben ze grote economische consequenties zoals de onshore vraag naar arbeid en bedrijfsproductiviteit.

In dit proefschrift gaan we uit van enkele belangrijke onderzoeksvragen, zoals wat de consequenties zijn van de totstandkoming en ontwikkeling van GVC's voor de verschillende aspecten van de omvang en groei van inkomen, werkgelegenheid, handel en productiviteit. Tot voor kort waren onderzoekers door de beperkte beschikbaarheid van gegevens slecht toegerust voor het bestuderen van GVC's. Bestaande gegevens en tools zijn georganiseerd rondom producten en bedrijfstakken. Ze meten de door de industrie van een land toegevoegde waarde in waardeketens. Maar dit geeft geen informatie over specifieke activiteiten die worden verricht, zoals montage-, productontwerp- of marketingactiviteiten (Timmer e.a. 2019). De definitie van een GVC legt duidelijk de nadruk op de noodzaak om bedrijfsprocessen en -activiteiten te bestuderen. De bijdrage van dit proefschrift is de mogelijkheid om de activiteiten die binnen GVC's worden verricht, te meten en te analyseren aan de hand van een veelheid van gegevens en kwantitatieve benaderingen. Dat gebeurt op macroniveau (de industrie van een land), op regionaal niveau en op microniveau (bedrijf).

In hoofdstuk 2 wordt het macro-economische verband onderzocht tussen offshoring en de functionele structuur van de vraag naar arbeid in geavanceerde economieën. In dit hoofdstuk wordt een analyse gegeven op het niveau van de industrie van een land. We maken gebruik van de door Timmer e.a. (2019) samengestelde bedrijfsfunctiegegevens. Aan de hand van de World Input- Output Database onderscheiden we twee soorten offshoring:

die van de tussenfase en die van de eindfase. Op basis van een translog cost function komen we tot een stelsel van vergelijkingen met betrekking tot de kostenaandelen van verschillende bedrijfsfuncties, die we vervolgens relateren aan offshoring-indicatoren en een reeks structurele variabelen, zoals de verhouding tussen ICT-kapitaal en opbrengst. De parameters van het stelsel berekenen we op basis van de Seemingly Unrelated Regression (SUR) techniek. We zijn een van de eersten die onderzoeken wat het verband is tussen de verschillende vormen van offshoring en de functionele specialisatie van de vraag naar arbeid in geavanceerde economieën. Onze bijdrage aan de bestaande literatuur is dat arbeid per bedrijfstak, aan de hand van de unieke bedrijfsfunctiedata, verder gedifferentieerd kan worden naar bedrijfsfunctiegroepen. Dit sluit aan bij het argument van Brown (2008) dat binnen elk bedrijf, ongeacht de bedrijfstak waartoe het behoort, bedrijfsfuncties worden gehanteerd en geordend. We kunnen dus zowel binnen bedrijfstakken als tussen bedrijfstakken onderling patronen van verticale specialisatie waarnemen. Nog belangrijker is dat we, doordat we beschikken over informatie over de functionele structuur van de vraag naar arbeid, meteen inzicht kunnen krijgen in het meest relevante aspect van arbeid binnen GVC's, namelijk de activiteiten die worden verricht. We zien dat offshoring van de eindfase significant negatief gerelateerd is aan het aandeel in de productiekosten, wat suggereert dat het verplaatsen van de montage-eindfase naar het buitenland de vraag naar onshore productiewerknemers doet afnemen. Offshoring van de tussenfase is, daarentegen, significant positief gecorreleerd met het kostenaandeel van R&D-activiteiten, maar negatief gecorreleerd met het kostenaandeel van management. Offshoring van de tussenfase is niet significant gerelateerd aan het kostenaandeel van productie- of marketingactiviteiten. Daarnaast zien we dat offshoring naar verschillende bestemmingen meestal wisselende, en soms zelfs tegengestelde, effecten heeft op de onshore functievraag. Zo is offshoring van de tussenfase significant positief gerelateerd aan het kostenaandeel van de onshore productie als de bestemming een land met een hoog inkomen is, maar het tegenovergestelde is het geval als de bestemming een ontwikkelingsland is. Offshoring van de eindfase is, ongeacht de bestemming, negatief gecorreleerd met de onshore vraag naar productieactiviteit. We concluderen daarom dat het effect van offshoring op de onshore functionele vraag naar arbeid in belangrijke mate afhangt van de productiefase die wordt ge-offshored en van de bestemming van de offshoring.

Hoofdstuk 3 bevat een analyse op regionaal niveau, waarbij we de functionele specialisatie in Nederlandse regio's bestuderen en onderzoeken welke rol offshoring daarin speelt. Aangezien het potentieel voor productiviteitsgroei verschillend is per bedrijfsfunctie, is het bijhouden van patronen en trends op het gebied van functionele specialisatie belangrijk om meer inzicht te krijgen in de plaats van regio's in de waardeketen en het ontwikkelingspotentieel (Timmer e.a. 2019). We maken gebruik van onderzoek van het Centraal Bureau voor de Statistiek, dat informatie geeft over offshoring ten aanzien van verschillende bedrijfsfuncties. Door informatie uit die onderzoeken te combineren met gegevens van de regionale bedrijfsgegevensbank, kunnen we per regio meten in hoeverre verschillende bedrijfsfuncties blootstaan aan offshoring. Daarnaast maken we gebruik van de werkgelegenheidsgegevens van de Enquête Beroepsbevolking om per regio de functionele structuur van de vraag naar arbeid te meten. Daardoor kunnen we belangrijke patronen en trends van regionale functiespecialisatie in Nederland aan het licht brengen. Daarnaast brengen we per regio in Nederland blootstelling aan functionele offshoring in verband met de functionele vraag naar arbeid. Onze beschrijvende analyse suggereert het volgende. Ten eerste verandert de functionele samenstelling van de Nederlandse beroepsbevolking langzaam, waarbij die verandering duidelijk beweegt van productie- en administratieve activiteiten richting kennisintensieve activiteiten zoals R&D en technologieontwikkeling, verkoop en marketing en beheer. Ten tweede zijn kennisintensieve activiteiten in vergelijking met andere activiteiten meer regionaal geconcentreerd. Deze concentratie van kennisintensieve activiteiten in bepaalde Nederlandse regio's heeft een stabiel verloop. Ten derde is er wat betreft specialisatie in bedrijfsfuncties sprake van grote verschillen tussen regio's. Onze empirische bevindingen geven aan dat offshoring niet significant gerelateerd is aan functionele specialisatiepatronen in de regio's. Alleen voor administratieve en backofficefuncties vinden we een (lichte) statistisch significante positieve relatie tussen offshoring en een afgenomen vraag naar arbeid. Investeringen in R&D en informatie- en communicatietechnologieën zijn significant gerelateerd aan een afname van productiebanen.

Hoofdstuk 4 is gebaseerd op gegevens op bedrijfsniveau; we bestuderen functionele specialisatie en de relatie daarvan met de productiviteitsprestaties van bedrijven in Nederland. In dit hoofdstuk meten we de functionele specialisatie van bedrijven op drie brede terreinen: fabricage, R&D en marketing. We maken met name gebruik van een op de Balassa-index gelijkende indicator van specialisatie waarin het werkgelegenheidsaandeel van het bedrijf in een bedrijfsfunctie wordt vergeleken met het gemiddelde werkgelegenheidsaandeel van die activiteit in alle bedrijven tezamen. Bedrijven zijn in een bepaalde functie gespecialiseerd als ze beschikken over een relatief hoger aandeel werknemers in die functie. Vervolgens relateren we die functionele specialisatie-index aan de TFP van bedrijven, die wordt berekend door middel van de Wooldridge-benadering (2009). Door gebruik te maken van unieke gegevens en door een nieuwe functionele specialisatie-index te introduceren, kunnen we de relatie onderzoeken tussen de functionele specialisatie van bedrijven en hun productiviteitsprestaties. We zien dat bedrijven die gespecialiseerd zijn in R&D en marketing significant productiever zijn dan bedrijven die gespecialiseerd zijn in productie. Deze bevindingen blijven robuust wanneer gecontroleerd wordt op andere mogelijk bepalende factoren voor productiviteit. Dit resultaat suggereert dat R&D en het opbouwen van merknamen leiden tot hogere opbrengsten dan fabricagee (Mudambi, 2008;

Park e.a. 2013). We nemen geen significant verband waar tussen functionele specialisatie en prijsopslagen. De bedrijven die deel uitmaken van de analyse, hebben vanwege de aard van de gemaakte producten of uitgevoerde functies mogelijk te maken met meer internationale concurrentie, zodat deze bedrijven het moeilijk krijgen als ze prijzen vragen die boven de marginale kosten liggen.