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Contents

Foreword

Statistics Netherlands has a long tradition of analysing individual data of firms (kind-of-activity units, establishments and enterprises), going back even as far as the fifties, when productivity studies were published. In the last fifteen years the bureau has published many econometric analyses of individual firm data. A survey of several studies can be found in the 1992/3 issue of Netherlands Official Statistics. The present issue presents five recent Statistics Netherlands studies and a survey of the bureau’s work in this area. The first article, by Kees Zeelenberg and George van Leeuwen, gives a general survey of Statistics Netherlands studies. The second article, by Wim Koopman, describes the construction of a large database of individual firm data. The third contribution, by Aad Kleijweg and Henry Nieuwenhuijsen, analyses the dynamics of profits in Dutch manufacturing. The fourth article, by Eric Bartelsman, Henry Nieuwenhuijsen and George van Leeuwen, gives an analysis of the relation between advanced manufacturing technology and firm performance. Eric Bartelsman, Henry Nieuwenhuijsen, George van Leeuwen and Kees Zeelenberg, study the relation between R & D and productivity growth in the fifth article. The final contribution is by Martin Boon and investigates the effect of firm performance and technology on wages of individual employees.

Kees Zeelenberg

Micro-analysis of firm data

Kees Zeelenberg and George van Leeuwen

1. Introduction

In the previous decade interest has been growing among economic researchers for micro-economic data of firms (enterprises and establishments). Statistics Netherlands (CBS) collects and processes large quantities of such data. For instance detailed information on output, inputs, costs and revenue for a large number of firms are collected in the annual Production Surveys, while the Investment Surveys cover gross investment expenditure of the same respondents.

Increasingly, statistical bureaus have recognised the importance of firm micro-data, both for their own statistical analyses and for research. For example, linking data from several surveys enables the creation of new statistical products, and by combining data from the same survey across several years one can analyse the dynamics of firm behaviour.

In recent years we have also seen a growing interest in firm micro-data of firms by academic researchers. In the USA a lot of research has been carried out, using mainly data from the US Bureau of the Census. In the Netherlands the CBS has been carrying out major research projects since 1985, exploring individual firm data (see Huigen et al., 1992, for an overview of the first seven years). In other countries, such as Norway, Israel, France, Canada, and Finland, similar research projects are being carried out by the national statistical bureaus. At the international level, Eurostat has initiated the Enterprise Panels Project (EPP), which provides international coordination and discussion forums (EPP-conf., 1994).

Lastly, policy makers, too, are becoming more and more interested in analyses of firm micro-data of firms. For example, the 1994 G7 conference decided to ask the OECD to carry out some research projects on productivity and employment, one of which was to analyse micro-data of firms. Work on these projects and similar ones has been the subject of official conferences in Washington DC and Rotterdam.

Within several statistical bureaus this growing interest in micro-data of firms has led to the institution of separate units to create and maintain statistical databases with micro-data, carry out research, and provide facilities. Examples are the Center for Economic Studies (CES) at the US Bureau of the Census and the Centre for Research of Economic Survey Data (CERES) at Statistics Netherlands.

This article reviews these developments, their background, and examples. In section 2 we discuss the importance of micro-data for statistics and in section 3 their importance for economic research. Section 4 gives some examples of recent research at Statistics Netherlands. Section 5 describes how micro-economic databases are created at Statistics Netherlands, and section 6 how external researches can analyse these data. Section 7 gives some conclusions and looks at future developments.

2. Micro-data and statistics

There are three main reasons why micro-economic data are important for statistics. First, when micro-economic data are gathered they allow the creation of new statistical products by linking data from several surveys and/or from several years. By combining data from several surveys we can make all kinds of tables that cannot be made from the aggregated data of the surveys themselves; for example, by linking data from the R&D Survey and the Production Survey we can tabulate the relation between R&D and profits, or R&D and employment. A case in point is the recently published R&D Survey (CBS, 1995), where such a linked database was used to show that enterprises with R&D expenditure have a much higher profit margin than enterprises without R&D expenditure; this holds in particular for firms innovating new products, whereas firms innovating new production processes have a lower profit margin than firms without R&D expenditure.

Dynamic relationships can be identified and change statistics drawn up by combining data on several years. An example are the gross-flows statistics of the labour market, which show how many jobs have been created and how many destroyed. These statistics are computed from a micro-database of firms with data on several years (Davis and Haltiwanger, 1994). The results show that flows in the labour market are much larger than the net changes. Another example are dynamic effects of R&D: the R&D Survey shows that labour productivity grows more in enterprises with R&D expenditure than in those without; particularly for firms innovating new production processes, whereas firms innovating new products are comparable with firms without R&D expenditure.

Micro-economic data can also be useful for industrial and commodity classifications. We can much more easily investigate the consequences of alternative classifications or extrapolate new classifications backwards in time. We can also use statistical techniques or econometric analyses to devise new classifications. For example, at Statistics Netherlands a project is underway to investigate the possibilities of cluster analysis for making an industrial classification.

A second area where micro-data of firms are important is in the statistical production process. Inconsistencies and structural breaks can often be solved only by investigating the micro-data. An example is given by Van Leeuwen (1992), who compared investment in buildings according to the Investment Survey and the construction of buildings according to the Construction Survey. The differences between the two series appeared to be caused by differences in observation between the two surveys and could only be traced by comparing the observations of the same entities from the two surveys.

A third reason why micro-data are important is that scientific research can indicate problems in surveys. Apart from statisticians, researchers are the most important users of micro-data and they often use the data for a research question that has not been anticipated by the statistician. Problems they encounter in their research can provide indications for improvements of a survey. For example, in an analysis of an econometric model of the demand for energy, it was found that the yearly changes in the energy unit values showed a spread that was too large in comparison with the rate changes of public utilities (Kleijweg et al., 1989), resulting in major improvements in the Statistics Netherlands Energy Survey.

All these examples clearly show that micro-data are important because firms are heterogeneous: they differ in all respects and these differences can only be investigated with a database with as many firms as possible and with as many characteristics as possible of these firms.

3. Micro-data and economic research

In recent years the discipline of economics has increasingly come to recognise that many problems, including macro-economic ones, can only be investigated by using micro-economic data of firms (McGuckin, 1995). For example, in a survey article on unemployment, Bean (1994, p. 615-6) argues that not much can be learned from macro-data and that only micro-econometric studies can bring new insights into the determinants of wages and employment; and Nobel laureate Richard Coase also emphasised the relevance of micro-data of firms in his Nobel speech (Coase, 1994, p. 14). One important reason why micro-data are needed for the analysis of macro-economic problems is that many recent macro-economic theories do not start from the ’representative producer’, but from heterogeneous producers. Application and testing of these theories is not possible with aggregated data, but require micro-data.

Moreover, using micro-data has many practical advantages. In the first place, many explanatory variables in economic models, such as input prices, are exogenous at the micro level, whereas at the macro level there is often simultaneity between prices and quantities. For example, an increase in the demand for labour by an individual firm will have little effect on the wage rate, but an economy-wide increase will in general lead to a wage rise. A second advantage is that micro-data enable a disaggregation of the results, for example with respect to firm size or industry, whereas it is difficult to obtain sufficiently long time-series of meso-data. In this way the availability of time series data for individual firms can be used to test for differences in behaviour between groups of firms. Thirdly, estimation results based on aggregate time series may suffer from lack of precision because of the trendlike behaviour of most variables. Fourthly, panel data, constructed from the micro-databases, offer an opportunity to use the information on both the intertemporal dynamics (time-series dimension) and the unique features of individual firms (cross-section dimension of the data); this enables the researcher to test more complex models and to control for some sources of bias such as the effects of missing or unobservable time invariant variables.

However, micro-datasets also raise several problems related to data issues. For some variables there may be no appropriate observations at the micro level and for other variables measurement may deviate from theoretical constructs. Prices for inputs and outputs and data on the stock of physical capital are typical examples. For labour, materials, energy and output, some kind of implicit price measurement (unit values) is available from the Production Surveys. These measurements are fairly remote from the theoretically preferred price indices. Ignoring these errors in individual firm data will result in biased estimates and may lead to erroneous conclusions. As mentioned in section 2, measurement error is one area where economic research may have an impact on the production process of statistics. Another problem is that the data may not represent a random sample from the population due to attrition, resulting in selectivity bias. The various data problems can be solved by using information from other surveys, by using more restrictive models and by using standard econometric correction techniques.

4. Micro-data at Statistics Netherlands: organisational aspects

At Statistics Netherlands several divisions collect data on enterprises and establishments:

– the division of agriculture, industry and the environment collects data on output, value added, inputs, producer prices, energy, technology, the environment;
– the division of trade, transport and services collects data on output and value added, and financial data;
– the division of socio-economic statistics collects data on wages, employment, education.

Together the division of agriculture, industry and the environment and the R&D division have set up two units for micro-data of firms. The first – the Microlab – assembles databases from the separate surveys, links the firms from these databases and creates statistical products. The databases cover the years 1978–1993, until now only for the manufacturing industry. Recently, the Microlab has started to link these data to the data from the wages and employment surveys, so that a database with firms and employees within these firms can be created.

The other unit, the Centre for Research on Economic Survey Data (CERES), conducts research and provides facilities for external researchers. Previously the research focused on production structures; now it focuses on technology and productivity (see section 5). For the second task of CERES, providing facilities for external researchers, a separate computer network has been installed. External researchers wishing to analyse micro-data can hire the facilities; they also have to pay a fee for using the data. Strict security procedures ensure the protection of confidential data: only academic researchers have access to the data, external researchers have to sign a confidentiality form and are not allowed to take results outside the building, the report is thoroughly checked before it is to be published, and access to the CBS computer network is impossible from the separate network.

5. Research at Statistics Netherlands

In cooperation with Rotterdam University and the Economic Institute for Medium-sized and Small Businesses, Statistics Netherlands set up a research project on firm behaviour in 1985 (see Huigen et al., 1992). The project focused on the structure of production, in particular the aspects of energy and employment, and lasted until 1992. Several studies were carried out, concerning:

- energy demand
- the relation between firm size and firm growth
- the dynamics of employment
- the substitution between production factors
- the effect of sampling errors on estimation
- the appropriateness of firm-specific unit values.

For each study databases were constructed from several surveys and data problems had to be solved before the actual analysis could start.

In 1994 a new research project was started, in cooperation with the Free University of Amsterdam, focusing on technology and productivity. This project consisted of the following studies:

- productivity and downsizing
- productivity and new technology
- the return to R&D.

Again databases had to be constructed, in addition to the earlier ones.

The remainder of this section will discuss some of the data problems and the results of some of the studies. More information on the first research project can be found in Huigen et al., 1992 and in the papers mentioned in the references list at the end of this paper.

Data problems

Extensive data sets are needed for the estimation of models of firm behaviour. In order to make inferences about economies of scale and substitution between factors of production such models require data on prices and quantities for all factors of production and for gross output. The list of production factors includes material inputs, labour (preferably for different skill levels), capital and energy. Data on prices are required to decompose changes in values into changes in prices and changes in quantities, and are also important explanatory variables in models of firm behaviour. The yearly Production Surveys consist of data on costs of inputs and the value of sales and gross output together with corresponding quantities for material inputs. For several reasons the implicit price data of the Production Surveys could not be used straightforwardly.

Using data of the Production Surveys, unit values for intermediate inputs and gross output could have been calculated. To evaluate the implicit price data of the Production Surveys the available data on gross output for a small sector, i.e. the rubber processing industry, were investigated more closely (Huigen, 1989). The results clearly showed that unit values, not corrected for quality changes, are far inferior to the Laspeyres price indices compiled by the Department of Price Statistics for the sector as a whole. Therefore it was decided to use the sector price indices for material inputs and gross output instead of unit values at the firm level. These indices are available for approximately 70 branches of the manufacturing industry.

Data on total employment and total labour costs are available from the Production Surveys. Dividing the reported total wage bill (including social contributions paid by employers) by the number of employees, yields data on the implicit price (unit value) of labour. Total employment is used as a measure of labour input. These measures for labour input do not take into account the reduction in the weekly working hours in 1983 and 1984 and the steady increase in part-time work. Furthermore, there is a wide dispersion across firms in the average labour costs, probably reflecting differences in the composition of employment rather than true wage differences. In order to obtain more appropriate measures for labour input and labour costs, taking into account shortening of working hours and inter-firm differences in the composition of employment, Production Survey data were matched with Wage Survey data. The latter contain information on the composition of employment, working hours and wages. These data have been collected in yearly sample surveys from 1984 onwards. Constructing longitudinal data on labour costs and inputs for different types of labour proved to be very time consuming. Many difficulties had to be solved in order to be able to use the data from the Wage Surveys (Huigen et al., 1990a and 1990b). Lastly, it only appeared to be feasible to construct measures for labour inputs and labour costs for two broad categories (blue and white collar workers) and for a relatively short period comprising the years 1984–1987.

Attempts have been made to construct alternative measures for the stock of capital by using data on financial capital and data on investment in fixed assets. These attempts were not very successful either (Hommes and Van Leeuwen, 1987). It appeared to be impossible to integrate the information about the financial structure of enterprises and the firm data of the Production Surveys, mainly because of differences in definitions of the statistical units. A measure for capital costs was constructed using the Jorgenson formula for the implicit rental value of capital. Components of this measure are price indices for investment goods, the long term interest rate and tax parameters such as the corporate tax rate and investment subsidies. Price indices for investment goods were derived from capital stock deflators for 50 sectors of industry. These implicit deflators were computed with the aid of aggregated data on the composition of the capital stock in 1986.

Compared with the other production factors there were only minor data problems for energy. Data on quantities consumed and costs paid for natural gas and electricity were readily available from the Production Surveys. These have been used to compute unit values. Because of the homogeneous nature of both commodities unit values may serve as adequate price measures. In addition Divisia price indices were calculated for total energy. Data problems for energy were restricted to the elimination of outliers with the help of extraneous information on the structure of tariffs of natural gas and electricity supply. Furthermore many firms, especially small ones, did not report either the value or the volume of natural gas and electricity consumption, so that these firms had to be omitted in the analyses of energy demand at the firm level.

Energy demand

In the energy study the reaction of firms to the increases of energy prices was analysed by estimating a cost share equation for energy. We followed the standard neoclassical theory of the firm to derive the cost share equation, in which the cost share of energy is related to the level of gross output, the price of energy and the prices of other inputs. The equation contains firm-specific constants as well as time-specific industry constants. The first constants represent the effects on the cost share of energy of time-invariant missing or unobservable variables. The other group of constants represent the effects on the energy cost share of labour and capital prices. The equation was extended with three lagged energy prices in order to make inferences about the speed of adjustment.

The cost share equation was estimated for different partitions of the energy panel in order to investigate differences between groups of firms. Estimation results for different sectors of industry are presented in Kleijweg et al. (1989). In Table 1 the estimation results for the scale and long-run price elasticities for energy demand are presented for firms classified by energy intensity, investment/output ratio and number of employees. The scale and price elasticities measure the percentage change of energy consumption due to a one percent increase of output and energy prices respectively.

For total manufacturing the estimate for the scale elasticity of energy demand is 0.61 and for the price elasticity of energy demand –0.56. The corresponding standard deviations are 0.02 and 0.10. Thus, both the effects of output and energy prices are estimated with substantial precision. The result for the price elasticity clearly implies that energy consumption is considerably reduced when prices increase. It should be noted that the estimate of the price elasticity obtained with panel data is strikingly similar to the price elasticity –0.54 found by the Dutch Central Planning Bureau (CPB, 1984) in a study based on aggregate time series data. This indicates that most of the energy reduction takes place within existing firms, and should not be attributed to the changing composition of industries e.g. due to the birth and death of firms.

Table 1. Scale and energy-price elasticities

	Number	Scale	Own-price
Energy intensity			
< average	1,321	0.47	–0.80
		(0.01)	(0.04)
> average	322	0.67	–0.60
		(0.04)	(0.14)
Investment ratio			
< average	1,024	0.50	–0.45
		(0.03)	(0.13)
> average	619	0.71	–0.69
		(0.04)	(0.14)
Firm size			
Small firms	733	0.54	–0.48
(10–50 employees)		(0.04)	(0.16)
Medium-sized firms	364	0.70	–0.61
(51–100 employees)		(0.04)	(0.18)
Large firms	425	0.61	–0.68
(101–500 employees)		(0.04)	(0.15)
Very large firms	121	0.62	–0.95
(500 employees)		(0.11)	(0.43)

Table 1 shows that the scale elasticity is significantly higher for the energy-intensive firms than for the energy-extensive ones. The opposite applies to the price elasticity. This result may be explained by the fact that relatively energy-intensive firms use more of their energy consumption in the production process than energy-extensive ones. It is less easy to reduce this type of energy use than the energy consumption associated with heating and lighting buildings. Lastly the pattern observed for the partition according to the investment/output ratio supports the view that to some extent energy savings can only be realised by investing in more energy-extensive equipment.

The division by size shows that medium-sized firms have the highest and small firms the lowest scale elasticity. Furthermore the price elasticity increases monotonously (in absolute value) with firm size. Although the difference between the estimated price elasticities of small and very large firms is not significant this may indicate that large firms can reduce energy costs more than small firms. Large firms may have more know-how and experience so that they have more possibilities to save energy. In Kleijweg et al. (1990) it is shown that these differences in long-term price elasticities between size classes are related to differences in adjustment patterns. The immediate impact of a change in energy prices is almost the same for all size classes. For small firms this impact vanishes after two years. For other firms, however, it vanishes after three years (medium-sized firms) or even longer (large and very large firms).

The relationship between firm size and firm growth

The statement ’small firms grow faster than large ones, so growth of employment is due to small firms’ was investigated using employment data of 3,147 firms for the period 1972–1986. Following the approach of several earlier studies, such as Hall (1987), a simple regression model was specified for the relationship between firm growth and firm size. In this model the growth of employment in the years 1972–1986 was regressed on the natural logarithm of employment in 1972 using ordinary regression techniques. The results clearly point out that the estimated effect of size on growth was significantly negative, so that this result seems to corroborate the finding of other studies that small firms grow faster than large ones.

Several extensions of the simple model have been specified in order to investigate whether the result could be reproduced when allowing for measurement errors in the employment variable or selectivity (Hommes and Van Leeuwen, 1988, and Huigen et al., 1991). The results of this sensitivity analysis show that measurement errors in the employment variable are positively correlated, but the influence of measurement errors on the relation between firm growth and firm size appears to be negligible. Furthermore it is shown that the effects of attrition are likely to be quite small as well.

We also investigated whether the negative relationship between firm growth and firm size may be attributed to the phenomenon of ’regression to the mean’, which may refer to a spurious negative correlation between firm growth and firm size in case of a time invariant size distributions of employment. To eliminate possible ’regression to the mean effects’ the orthogonal regression technique was applied (Huigen et al., 1991). The orthogonal regression estimates show that the influence of size on growth remains slightly negative, but the estimated coefficient of firm size is reduced by a factor 7 compared with earlier estimates and is hardly significant. This result indicates that when taking into account the possibility of regression to the mean the claim that ’small firms grow faster than large firms’ loses a lot of validity.

Technology and economic performance

A topic which has attracted much attention recently is the relationship between technology and the performance of economies. Part of the research effort in this field is initiated and coordinated by the OECD within the framework of its Technology-Economy Program. From the outset the research effort was macro oriented and it followed the generally accepted view that technology can be looked upon as a public commodity which may have substantial spillover effects to all parts of the economy. For instance, the R&D endeavours of private firms in specific sectors may also have substantial benefits for other economic agents, even on a worldwide scale. The mechanisms at work in transferring the benefits of technology and its impact on economic performance have been the subject of many studies.

Recently these studies have been supplemented with micro related analysis of the relationship between technology and economic performance. It is increasingly acknowledged that looking at the macro or meso level does not reveal all of the intricacies at work. For instance, in several micro studies it has been shown that the process of employment, output and productivity growth in manufacturing is far more complex than the picture which emerges from macro or meso level data, see e.g. Davis and Haltiwanger (1992), and Baily et al. (1995). These studies indicate that more attention should be paid to how productivity distributions of firms change over time and to the factors that determine the position of firms in the productivity distribution. Indeed, examining micro-level data may lead to an exposure of generally accepted views which originate in inferences drawn from the analysis of aggregated data. For instance, following the Davis and Haltiwanger line of research on firm-level data for the USA, it has also been established for the Netherlands that successful upsizing firms contributed relatively more to manufacturing productivity growth in the previous decade than downsizing firms (see Bartelsman e.a. 1995). This results contradicts the general belief that downsizing and productivity growth are inextricably linked.

The adoption of advanced manufacturing technology

We analysed the characteristics of firms which employ advanced manufacturing technology (AMT), explored the pattern of adoption of such technology and traced the effects of adoption on the evolution of employment and productivity. This study used linked firm-level data on production, factor inputs and on advanced manufacturing technology from three sources. Data on production and factor inputs were sourced from the yearly Production Surveys for 1985 and 1991. Data on the inputs of capital were derived from the Capital Stock Surveys. This is a rather unique dataset which contains data on stocks of capital by type of commodity and vintage for the same enterprise unit as observed in the Production Surveys. Both datasets were linked to the 1992 Survey of Advanced Manufacturing Technology (AMT), which contains data on the use of computer aided manufacturing, design and planning. We focused on the information pertaining to computer aided manufacturing equipment, because it is this technology which is most expected to lead to productivity improvements through streamlining of production processes and associated job losses.

It is found that the percentage of firms which employ advanced technology increases with higher labour productivity, higher export sales ratios and especially firm size. Corrected for interactions, however, only initial size and capital-labour ratios can predict adoption of AMT. Conditional on adoption of AMT it is found that the intensity of advanced technology inputs decreases with firm size and with labour productivity. Also, firms which employed AMT in 1992 show higher average growth rates of employment and of capital intensity. A most striking result of this study is that employment growth of AMT firms between 1985 an 1991 increased with the intensity of AMT application. Again this is contrary to the general belief that adoption of advanced technologies decreases employment opportunities.

R&D and productivity

In a second project we investigated whether firm performance and R&D are related. A considerable body of foreign literature suggests that the R&D productivity puzzle still remains unsolved. Contrary to the foreign situation there is very limited empirical evidence on the relationship between R&D and productivity for the Netherlands. The evidence which is available is almost exclusively based on macro data research. This situation is in sharp contrast with foreign research practice, where the mainstream of research pertaining to the relationship between R&D and productivity uses firm level data (see e.g. Mairesse and Sassenou, 1991, for a recent review of econometric studies of the R&D and productivity relation at the firm level).

For the Netherlands the investigation of the contribution of R&D to productivity growth raises considerable problems because of the very skew size distribution of R&D. It is well known that R&D expenditure of Dutch manufacturing is highly concentrated in five multinational companies. These companies spend a disproportional – albeit decreasing – part of their worldwide R&D in the Netherlands, whereas their production is largely located outside the Netherlands. The recent dramatic decrease of domestic R&D expenditure of these companies accounts for the negative performance of Dutch manufacturing R&D since 1989. Because of the dominance of these companies Dutch macro studies of the relationship between R&D and productivity growth are not very conclusive or even contradictory.

Apart from the distribution related problem these contradictory results may also be due to the more familiar aggregation problem inherent in the use of macro data. The latter problem can only be circumvented if firm level data are available. By linking files of the R&D surveys and data from the yearly Production Surveys, firm level data have recently become available. These data were used to estimate the relationship between R&D and productivity growth in a production function framework. Our primary objective was the estimation of private returns to R&D expenditure. We used data from the four-yearly extended R&D surveys for 1985, 1989 and 1993 to construct measures of the stock of R&D capital, which were included as a separate input in the production function.

Our data enable us to prevent biases by correcting for double counting of inputs, but on the other hand have the disadvantage of being selective. It is shown that the probability of exiting the sample is negatively related to the level of R&D intensity. This problem appeared to be exacerbated in the period 1989–1993, the years of declining R&D expenditure. In our estimation procedure we accounted for this selectivity problem by using a Tobit model. Furthermore we investigated the robustness of our results to different measures for the growth of the stock of R&D capital, by imposing non-negativity constraints on the growth of R&D capital and using different depreciation schedules.

After correcting for selectivity and heteroskedasticity we simultaneously obtain estimates for the elasticities of physical capital and R&D capital that are plausible and robust to our measures for the growth of R&D capital. In the R&D intensity approach we found an estimate for the gross marginal rate of return to R&D varying between 0.20 and 0.30. In the R&D knowledge stock approach – assuming that R&D expenditures are subject to deterioration – we found, for plausible values of the depreciation rate, an output elasticity for the R&D stock of approximately 0.10 and an estimate for ordinary capital close to 0.30. These results are very similar to the estimates of similar previous studies on firm-level data (e.g. Hall and Mairesse, 1995). This is surprising as the Hall and Mairesse estimates, for example, were derived from a panel with considerably more observations in the time dimension.

Conclusion

Many problems had to be solved before the micro-data of the Production Surveys could be used for analytical research purposes. Data on gross and net output, employment, total labour costs, energy costs and costs of material inputs were readily available to construct time series of sufficient length and for a sizeable number of firms. Constructing price data on the firm level, however, appeared to be very difficult. Data problems pertaining to prices were tackled by using micro-data from other statistics or, in the absence of sound alternatives, sector data. In general these problems could only be solved at the cost of substantial attrition, both in the firm and time dimension of the data, or (aggrevated) measurement errors.

Despite the data difficulties encountered it has been shown that satisfactory results could be obtained when applying estimation methods that take into account heterogeneity and measurement errors. The estimation results of the energy and employment studies clearly provide evidence for adjustment patterns that differ according to firm size.

6. Conclusion

Micro-data of establishments and enterprises are important for both statisticians and researchers. For the statistician they are important because they allow him to create new statistical products, to deal with inconsistencies and structural breaks, and to construct retrospective time series when new classifications are introduced. For researchers they are important because many economic questions can only be investigated with micro-data, because macro-economics is increasingly taking into account the heterogeneity of the underlying micro-data, because micro-data allow more disaggregation, and because micro-data better match the models of micro-economic theory. This article has elaborated these points and clearly shown that firms differ in many respects, i.e. they are heterogeneous. Therefore it is of the utmost importance to create databases with firms joined across surveys and across years. The article has also shown that several national and international statistical bureaus are responding to this growing need for micro-data; for example Statistics Netherlands has carried out several research projects concerning the structure of production and the effects of technology and has created separate units for the construction of micro-databases and research.

Future developments will take several directions. First, more data on the composition of the workforce within firms are needed. This will require linking data from several surveys, such as the Labour Force Survey, Wages Survey and the Production Survey (see Troske, 1995, for such a database for the USA). A database with a panel of firms and within each firm a panel of employees would be ideal for research purposes (Entorf and Kramarz, 1995). In the near future Statistics Netherlands will create a database with a panel of firms and within each firm a sample of its employees, with data on wages, education and other characteristics of the individual employees; the creation of a panel of employees within each firm will be the subject of a pilot project. Second, there will be a need for international comparisons (Doms et al., 1995.) and for the creation of a database of multinational firms, in which data from several countries are linked. Eurostat is already playing a role in these international developments. Third, there is a need for more financial data. The present databases are usually constructed from establishment data and focus on the structure of production. Because financial data are mostly on the enterprise level, the creation of a linked database requires the linking of establishments to enterprises. At Statistics Netherlands a project is being carried out in which this linking is done for the 100 largest enterprises.

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The Microlab: micro-data revived

Wim Koopman

The growing need for high quality statistical micro-data, both for purposes of analysis as well as to be able to make better and more extensive publications, has led Statistics Netherlands to aim at a substantial improvement of the coherence and quality of its micro-data on industry.

The need for micro-data

The process of making statistics is sometimes a somewhat introvert one. Each survey seems to focus mainly on one or a few particular objects of interest, and the connection with other surveys is usually considered to be less important. As a consequence data which in principle could tell us something about similar populations of enterprises, have to be retrieved from different statistical series, and it is difficult to compare them.

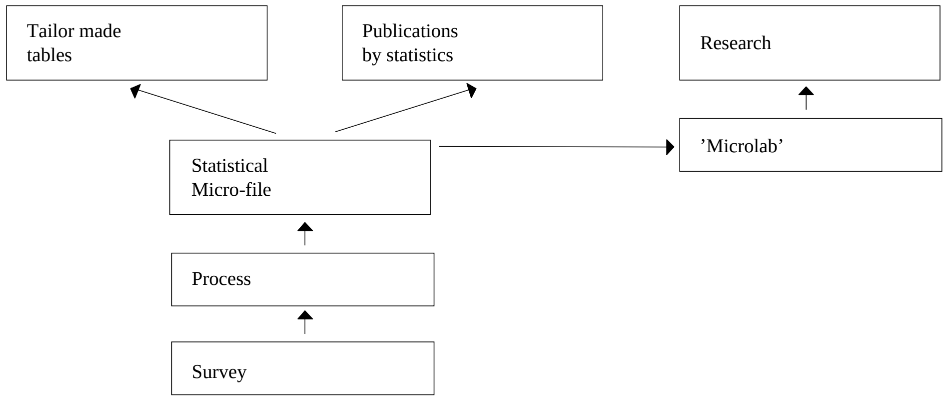
In view of the fact that in real life many collected data within the business statistics are interrelated, for instance, staff and production, rate of automation and productivity, innovation and employment and so on, we can only conclude that in this sense statistics can be improved. Also, the information on business dynamics is not used systematically, while it is essential for many kinds of analysis based on business statistics.

In order to meet the demand for such information, Statistics Netherlands is developing a Microlab, a unit in which analysts will be able to go beyond the individual surveys and relate micro-data from different surveys, and data from different statistical periods to each other.

Initial situation

As well as gradually becoming a tool for tailor-made statistics, statistical publications based on more than one survey, time series in new classifications and new indicators, the Microlab will give us more information on changes in enterprises. Research based on micro-data will be more valuable than ever before. All publication data will in future be derived from the Microlab and at aggregated levels be combined within the publication database StatLine.

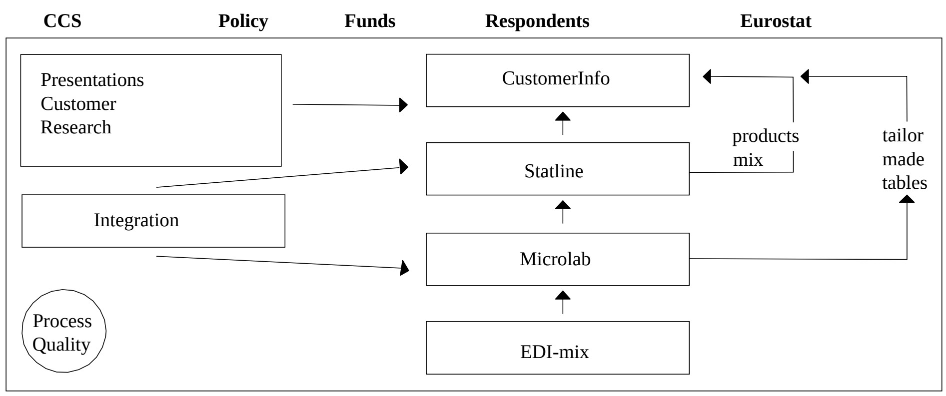
Figure 1



The intended situation

Statistics Netherlands has also developed plans to supply micro-data for external economics research, to be coordinated from its Centre for Research of Economic Survey Data (CERES). Unless legally forbidden, and with the consent of the respondents, our micro-data may be used by researchers outside Statistics Netherlands, although only under very strict conditions.

Figure 2



Levels of recording micro-data

Most of our business statistics are based on the concept 'kind of activity unit', as defined within the General Business Register. This kind of activity unit is an enterprise or part of an enterprise which independently engages in one, or predominantly one, kind of economic activity, without being geographically restricted, and for which data are available or can be meaningfully compiled to calculate the operating surplus. This is the lowest level at which data are available which can be used in a statistical sense. As a consequence this will also be the level at which information is recorded within the Microlab. For the sake of convenience the ’kind of activity unit’ will be referred to as ’enterprise’ in the remainder of this article, and the data on this level will be called ’micro-data’.

At a lower level we have data on the observation units. These may differ between surveys as they depend on the level of units on which our respondents are able to supply the data in question. Naturally data at this level have no specific meaning for purposes of economic research, and can only be of use to make aggregations to the level of the enterprise. At Statistics Netherlands considerable care is taken to make sure the data on observation units are always addable to data on enterprises, and will as a consequence be fully comparable at this level.

Micro-data

While up to now many of the micro-data were not or only poorly inter- related, the Microlab will pursue optimum linking. This will apply to linkage of statistical periods, as well as data from different surveys. In practice this means that links will be made between the data definitions used in different statistical periods. The same holds for enterprises. As in this method data are not brought together on a permanent basis, we have a set of unbalanced panels, derived from various surveys with information on the connection of the data-sets. This will give a great flexibility for research purposes. The Microlab will be able to supply balanced or unbalanced panels as required, thus serving research objectives as well as the needs of the statistical departments.

In order to use the Microlab to make publications, computer estimates will be made for missing data. Research is now being done to refine this imputation method and to improve the quality of micro-data for research purposes.

Depending on which survey the micro-data have been derived from, the database covers the years from 1972 up to the present. The recording of micro-data from the larger, mainly annual, surveys will be completed in the course of 1997, while quarterly and monthly surveys will follow within one year.

While in the future care will be taken to adjust the process in such a way that micro-data can be easily transferred to the Microlab, this year and next, work will be done to include a major part of our historical data too, mostly electronically stored data. Thus figures from as far back as 1972 for a few surveys, and the 1980s for most others will also be recorded in the Microlab. This work is carried out under the appropriate project name 'Save Our Data'. This has been proving to be a somewhat laborious task, as not all data have been kept in a well-documented and well-structured way. So in many cases this will come down to a painstaking process of bringing the micro-data back to life, in a manner of speaking. If lost, or no longer suitable documentation will have to be restored where possible. Sometimes the same holds for the data-files themselves. Due to many conversions in the course of time, some files are not readable at all, in others data have been lost or destroyed. Also there are sometimes doubts about the completeness of data-sets, and how links can be made to formerly published data.

Revision of the statistical process

If we are to achieve a smoothly operated, high quality Microlab, some parts of the statistical process will have to be adapted or revised in the near future. This revision project will define which mutual agreements and measurements are necessary, a process in which at least two major conditions have to be met:

1. a broad acceptance from the statisticians involved;
2. an relatively easy implementation of the revisions or adaptations in the statistical process.

Some relevant aspects in this respect are ownership and maintenance of the micro-data, data storage and documentation, relations between micro- data and publications, date and method of sampling.

Whereas rules concerning data storage and technical documentation, for example, record and file descriptions, can be easily made and agreed upon, purportual information on micro-data will be a different matter.

The way in which meta-data have to be structured may differ per kind of usage. Within the Microlab this is clearly the case, as it acts as a publishing tool and a coordination instrument as well as a database for research purposes.

Other developments at Statistics Netherlands also have to be taken in consideration: meta-systems are under development both for StatLine and EDI (Electronic Data Interchange). To make the most of Microlab the sampling methods have to be examined seriously to achieve a better coordination of methods, as well as coordination of the enterprises to be sampled in a given statistical period. Coordination in respect of updating or revising data-files and publications is also required.

We could consider including all the sometimes very complicated methodological information in the Microlab. However, as this methodology differs greatly between surveys and variables, it would make matters rather complicated if we had to use them every time we wanted to publish. Instead we shall make sure that in the future results on the level of the enterprise are also calculated within every survey; these results will then be recorded in the Microlab.

In addition we will have to make estimations for the non-sampled or non-responding enterprises, not only at an aggregate level, but also on the level of the enterprise. Having done all this, it will be easily possible to make many publication tables by a simple process of adding data together, without having to worry about methods used within the particular survey. Imputing data on an enterprise level gives rise to discussions on the desired refinement of the method used. Some people might feel there are possibilities for adding some quality to the micro-datasets with regard to usability or data analysis, and might therefore want to make weighted imputations using the same variables that have been used before to raise data to a higher level. We have not yet reached a decision in this respect.

Automation

Statistics Netherlands has just started creating an automated system for meta-information and data retrieval output. With the help of future Microlab users, prototypes will be tested and evaluated. The tools will be developed in Delphi under Windows95. The data themselves will be stored in an ORACLE database, together with all the necessary linkage information. Care will be taken to have the possibilities of exporting output data to all major statistical applications.

The dynamics of firm profits in manufacturing*

*Aad J.M. Kleijweg*** *and Henry R. Nieuwenhuijsen*

1. Introduction

During the eighties, the Netherlands did not excel in the domain of competition-related policy. For example, whereas it is prohibited in many countries, cartel formation was permitted and even registered by the Dutch government. Few people were concerned about the array of obstacles to free competition. The turning point came in the early nineties, when researchers and policymakers started attaching increasing importance to the dynamics of the Dutch economy [1)]. Since then the issue has enjoyed priority on the policy agenda, the dynamics in this case being associated with the adaptation capacity or the innovation intensity of the economy [2)].

At enterprise level, dynamics embraces the degree to which firms are inclined and able to enter or exit a market, to expand or abate, to modernise their production process or to modify their product range. At market level, dynamics is linked to the speed with which markets adapt, e.g. price adjustment in the event of excess capacity in a goods market or wage adjustment in the event of unemployment in the labour market. At neither level should there be any impediments to an adequate market mechanism.

Obviously, an economy should be sufficiently dynamic. Changes and innovations are required continuously if participants are to anticipate growth opportunities alertly. This view is also held by the government, which is of the opinion that welfare and employment may only be safeguarded in an economy able to adapt rapidly to changing circumstances, and where know-how intensive activities claim a crucial position [3)]. It is precisely the capacity to combine cost efficiency with continuous innovation that is deemed essential in the present international climate. Given that national policy-related reactions are materialising with increasing speed, a dynamic government is essential, too. Cost and benefits of (intended) policy measures, for instance, should be assessed quickly, after which an energetic government should arrive at decisions. From the policymakers' perspective, an assessment of the degree of competition is therefore very important, as it will provide an outline of the differences in competitive power between

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* Based on A.J.M. Kleijweg and H.R. Nieuwenhuijsen, *Winstpersistentie in de Nederlandse industrie, 1972–1991*, EIM, Zoetermeer, conducted on behalf of the Ministry of Economic Affairs.

** EIM Small Business Research and Consultancy.

sectors and countries, and will therefore serve as an adequate tool for implementing competition-related policy.

Various methods [4] may be employed to measure the level of competition; the one used here involves the direct assessment of permanent or temporary excess profits of firms. The underlying thought is that in the event of excess profits for one reason or the other (e.g. through sudden output rise), these will disappear faster with increasing intensity of competition. In a dynamic and competitive sector excess profits lead to a rapid entry of new firms or a direct expansion of activities by existing firms. Similarly, in the event of losses, loss-making firms will be forced to neutralise their losses as quickly as possible, since in the event of severe competition long-term losses cannot be compensated by long-term excess profits in the future. If these firms do not succeed in neutralising their losses they are doomed to terminate business operations.

The above method of assessing the degree of competition is elegant given that competition is not assessed at meso level on the basis of competition-associated indicators, but through direct measurement at firm level, i.e. the level at which decision-making is effected. Through measurement at firm level, this paper outlines the competitiveness of Dutch manufacturing by comparing it with the manufacturing industries in Canada, France, the United Kingdom, Japan, the United States, West Germany and Sweden. In addition several results for sectors in Dutch manufacturing are also presented.

2. The model

The model for persistence of profits as developed by Mueller and Geroski is used here [5]. In this model, competition is considered as a dynamic process of the creation of new products and processes. Within the model, the existence of permanent excess profits or the existence of short-term excess profits over a longer time span indicate imperfect competition. The model to be assessed reads [6]:

$$\pi_{it} = \alpha_i + \lambda_i \pi_{it-1},$$

where π_{it} denotes profits of firm i in year t.

Via parameter λ_i and constant value α_i, the profits of a firm in one year (π_{it}) depend on the profits generated in the previous year (π_{it-1}). Via $\pi_{it} = \pi_{it-1} = \pi_i^*$, it follows from the equation that the long-term equilibrium profit level π_i^* equals $\alpha_i/(1-\lambda_i)$. Departing from this long-term equilibrium profit level allows for an assessment as to whether *permanent excess profits* exist, while the time span of *short-term excess profits* is indicated by persistence of profits parameter λ_i.

In the event of perfect competition, the competition process assures (a) the non-existence of permanent excess profits, and (b) the rapid elimination of (short-run) excess profits. In the framework of our model, perfect competition entails equal long-term equilibrium profit levels, π_i^*, for all firms. None of the firms would manage to generate permanent excess profits; due to the competition, all firms have identical competitive profit levels. Moreover, in the event of perfect competition short-term excess profits are marked by a very brief duration (λ_i low). Given the high level of dynamics, any temporary advantage effected by one or several enterprises will be rapidly reproduced by other firms, thus causing the elimination of excess profits.

Profits are defined as the gross operating result divided by the production value. Henceforth the terms profits or level of profits indicate the profit ratio. Prior to assessment, profits will be corrected for business-cycle or other fluctuations which are equal for all firms. By effecting this correction (normalisation), the constant value α_i and the long-term equilibrium profit level π_i^* of a firm will be estimated as a deviation from the mean profit level. With respect to the interpretation of the model, the above implies that in the event of perfect competition long-term profits should rate zero for every firm. The mean profit level of all firms is perceived as a 'normal' compensation for entrepreneurial activity.

3. Estimation results for the Netherlands

The profit equation is estimated on the basis of time series of more than 2,000 industrial firms, covering the period 1978–1991 [7)]. It produces estimates of long-term profits and the persistence of profits parameter. Classified by initial profit levels, Table 1 outlines the results differentiated in six profit clusters. Each cluster has the same (or almost the same) number of firms, while initial profits equal normalised average profits generated in 1978 and 1979. Classification of the results by initial profit levels enables the identification of permanent excess profits, namely by comparing the estimated long-term profit level with the initial profit level.

Table 1 illustrates that in 1978 and 1979, the majority of profit-making firms generated profits exceeding the average of all enterprises by 12.5 percentage points. With 5.0 percentage points, the estimated long-term profit level of the former firms was also far above average. In view of mean profit levels of 9.6 percentage points in 1978–79 and 9.7 in the entire 1978–1991 period for all firms, these differences are substantial (approximately 50 per cent above average). The cluster generating the highest initial profits thus also commands a considerable lead in terms of generating the highest long-term profits. Although the cluster of firms generating the lowest initial profits is able to neutralise a substantial part of their 'profits deficit' of –10.9 percentage points below average, stranding at –3.7 percentage points below the –2.9 percentage points ’profits deficit’ of the cluster of firms ranking second as regards lowest initial profit level.

Table 1. Average estimated values for long-term profits and persistence of profits, clustered by initial profit level (1978–1991)*

Profit cluster	Initial profits**	Long-term profits	Persistence of profits
1	12.50	4.97	0.437
2	4.30	1.89	0.362
3	0.85	0.15	0.336
4	–1.97	–1.22	0.348
5	–4.82	–2.87	0.298
6	–10.87	–3.66	0.325
Total	0.00	–0.012	0.351

* Long-term and initial profits as a deviation from mean profits generated by all firms (in terms of percentage).
** Initial profits refer to mean profits generated in 1978 and 1979.

Given that the adopted cluster classification appears to be stable/persistent, we are inclined to conclude that the majority of firms generating the highest profits in 1978–79 will also be the ones generating the highest profits in the long run, and, reversely, that the majority of firms generating the lowest profits in 1978–79 will also be the ones generating the lowest profits in the long run. We observe that the discrepancy in initial profits generated by the first and the last cluster amounts to 23.4 percentage points, while this discrepancy is reduced to 8.6 percentage points with respect to long-term profits. We thus perceive a tendency for a mean profit level, but the competitive ’struggle’ is nevertheless far from producing equal profit levels.

The estimated values of the persistence of profits indicate the rapidity with which short-term excess profits disappear, ranging between 0.30 and 0.44 for the six profit clusters examined. The highest values (corresponding to the lowest rapidity of profit adjustment) is observed with firms generating the highest profit levels. This second assessment reveals that temporary excess profits disappear less rapidly in firms generating the highest profit levels than they do in firms generating less profits. The lowest values of persistence of profits is found for clusters of firms generating the lowest profit levels. Seemingly, it is essential that these firms rapidly diminish these ’lower-than-average’ profits.

The definition of profits, i.e. the gross operating result divided by the production value, includes depreciation, since depreciation is missing for a part of the 1978–1991 span. Therefore, capital intensity of firms may be of significance as regards classification in sub-clusters. A capital-intensive enterprise is likely to generate more profit (including depreciation and interest payments) than a capital-extensive enterprise, since the economic obsolescence of capital goods and interest cost of capital invested must be recovered.

To examine the impact of the above, the model was also estimated using depreciation data (for the years available) as an indicator for the use of capital. We have equated this indicator to the mean value of the quotient of depreciation and production value. Reassessment of the model with profit data corrected for depreciation at firm level produces identical results as regards long-term profits. Here too, classification based on initial profit levels (corrected for depreciation) is identical to decreasing long-term profits for the six clusters examined, while hardly any differences were found as regards profit levels.

Classification by sector (SIC 2-digit level) produces the results as illustrated in Table 2. The sectors are arranged according to level of long-term profits. The highest long-term profits are generated in the building materials, earthenware and glass industry (SIC 32), the paper and paper products industry (SIC 26) and the chemicals and chemical products industry (SIC 29). In these sectors, short-term excess profits are more persistent than in most other sectors.

Table 2. Long-term profits and persistence of profits; average at 2-digit level (1978–1991)*

SIC	Industry	Long-term profits**	Persistence of profits
32	Manufacture of building materials, earthenware and glass	4.1	0.44
26	Manufacture of paper and paper products	2.7	0.39
29	Manufacture of chemicals and chemical products	2.3	0.46
27	Printing and publishing	1.8	0.42
31	Manufacture of plastic and rubber products	1.3	0.40
36	Manufacture of electrical products	0.3	0.38
34	Manufacture of fabricated metal products	–0.1	0.31
35	Manufacture of machinery	–0.4	0.31
22	Manufacture of textile products	–0.9	0.33
20/21	Manufacture of food, beverages and tobacco	–1.0	0.37
37	Manufacture of transport equipment	–2.9	0.25
25	Manufacture of wood and wood products	–3.5	0.29
24	Manufacture of leather, footwear and other leather goods	–3.9	0.35
23	Manufacture of wearing apparel	–4.4	0.37

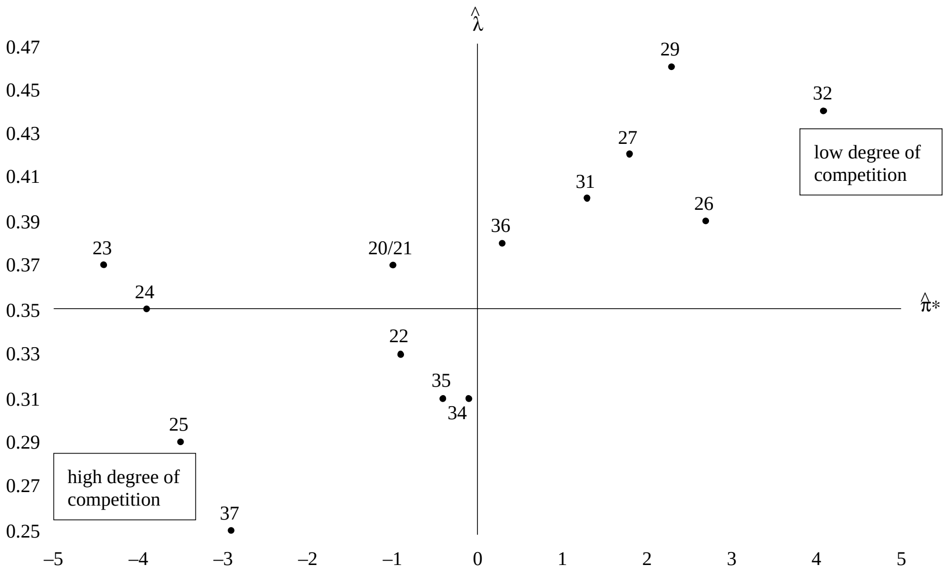
* Excluding petrochemical industry, manufacture of artificial and synthetic yarns and fibres, basic metal industry, precision and optical instruments industry and other industries (SIC 28, 30, 33, 38 and 39), due to data confidentiality or lacking years of observation.
** Long-term profits as a deviation from mean profits generated by all firms (in terms of percentage).

The lowest long-term profits are generated in the textile products industry (SIC 23), the leather, footwear and other leather goods industry (SIC 24), the wood and wood products industry (SIC 25) and the transport equipment industry (SIC 37). Short-term excess profits disappear rapidly in the transport equipment industry in particular and, to a lesser extent, in the wood and wood products industry.

Figure 1 illustrates the estimated values of the normalized long-term profits and of the persistence of profits. The axes are drawn at mean value while dots indicate the SIC 2-digit codes (see Table 2). An imaginary 'broad line' is clearly visible from the top right-hand corner (low degree of competition) to the bottom left-hand corner (high degree of competition). Short-term excess profits in a sector are thus more persistent with increasing degree of excess long-term profits.

Sectors marked by a high degree of competition are transport equipment and wood and wood products. Food, beverages and tobacco, electrical products, textile products (excluding clothes), metal products, and machinery rank at medium level.

Figure 1 Long-term profits ($\hat{\pi}^*$) and persistence of profits ($\hat{\lambda}$) at SBI 2-digit level



Sectors characterised by a low degree of competition are building materials, earthenware and glass, chemicals and chemical products, and paper and paper products. Entry thresholds in these latter sectors are presumably so high that profits do not tend towards more competitive levels.

4. International comparison

Are industrial profits more persistent in one country than in another? And if so where does the Netherlands rank? We shall try to answer this with the aid of the analysis for the Netherlands carried out in Section 3, and previous analyses by others for Canada, France, the United Kingdom, Japan, the United States, West Germany and Sweden [8)].

The definition of profits used in the Netherlands differs from those used in other countries, where profits are defined as interest plus after-tax profits divided by assets. As regards the level of profits (the numerator of the profits ratio employed), we rate – based on our exercises with the capital corrections – the approach of profitability as adequate. As regards scaling (the denominator of the profits ratio), we assume that the production value is a fair reflection of assets. Notwithstanding the controversial nature of this assumption, it is difficult in practice to obtain exact data on assets, as argued by Kessides [9)]. Another issue entails that the time span examined differs per country. A certain degree of caution thus seems to be required.

For every country, we have the classification of firms in six profit clusters based on initial profit levels, as outlined for the Netherlands in Table 1. Table 3 summarizes the country comparison. Column 1 presents the difference in long-term profits between the cluster with the highest versus the cluster with the lowest long-term profit levels, i.e. the range of long-term profit levels. Together with Canada, France and the United States (1950–72), the Netherlands belongs to the countries with the largest range of long-term profit levels. The ranges of the United Kingdom, Japan and West Germany are remarkably small. When also considering initial profit levels (column 2), we find that the difference between the highest versus the lowest cluster of initial profit levels is large in Canada, the Netherlands and Sweden, and to a lower extent in France, while that difference is small in Japan, the United States (1964–80) and West Germany.

Column 3 presents the persistence of profits indicating the rapidity in which short-term excess profits disappear. We observe two extreme values, i.e. a very slow adaptation (0.782) by Swedish manufacturing firms, and a very rapid adaptation (0.183) by American firms in the 1950–72 time span. For the Netherlands (0.351) the value is approximately equal to that of West Germany (0.366) and France (0.367). The value for Canada amounts to 0.299, while values for the United States (1964–80), the United Kingdom and Japan range from 0.465 to 0.491.

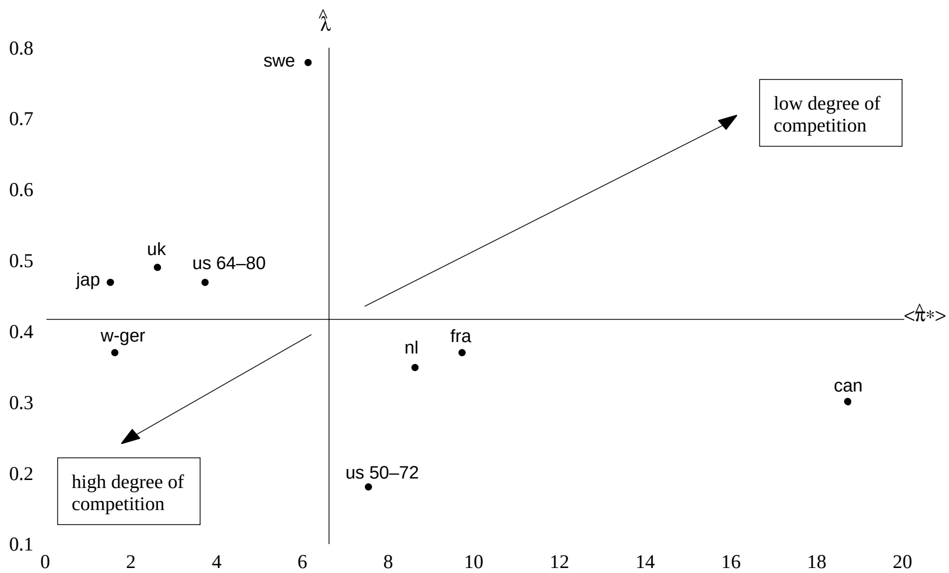
Large differences in long-term profit levels indicate the existence of permanent excess profits; a high value of the persistence of profits indicates the long-duration of short-term excess profits. Although the existence of permanent excess profits is more indicative of a lack in competition (surplus profits are not disappearing at all) than long-duration of temporary excess profits (these additional profits will disappear over time), both imply a low degree of competition. By way of illustration, the values are presented in Figure 2. The axes are drawn at the mean values of the range of long-term profits and the persistence of profits. Even when allowing for subtle distinctions, we arrive at the conclusion that the Netherlands scores moderately as regards the dynamics of profits. The equilibrium level of the profits tends towards a high level compared with most other countries.

Table 3. Inter-country comparison of dynamics of profits

Country	Time span	Difference in long-term profits: highest versus lowest profit cluster* (1)	Difference in initial profits: highest versus lowest profit cluster (2)	Persistence of profits (3)
Japan	1964–82	1.5	7.0	0.47
West Germany	1961–82	1.6	8.3	0.37
United Kingdom	1951–77	2.6	13.1	0.49
United States	1964–80	3.7	9.4	0.47
Sweden	1957–85	6.1	20.0	0.78
United States	1950–72	7.5	10.2	0.18
Netherlands	1978–91	8.6	23.4	0.35
France**	1965–82	9.7	15.1	0.37
Canada**	1968–82	18.7	27.2	0.30

* Based on classification in six profit clusters arranged by initial profit level as a deviation from mean profits generated by all firms (in terms of percentage).
** Including mining and quarrying.

Figure 2 Range of long-term profit levels ($<\hat{\pi}^*>$) and persistence of profits ($\hat{\lambda}$)



5. Conclusion

In any dynamic economy where free competition is not hampered by an array of regulations and mutual agreements, firms are not likely to generate permanent excess profits. Besides, in a dynamic, competitive economy temporary deviations from the

’normal’ remuneration for entrepreneurial operations will be of a brief nature. Since in this study, the ’normal’ compensation for entrepreneurial activities is denoted by mean profits generated by industrial firms in a country, the analysis might underestimate excess profits of firms in a country on the basis of too high mean profits by all firms due to insufficient competition in that country. The results found may thus merely be of a more distinct nature.

In the present article, the dynamics of profits of Dutch manufacturing firms are compared with those of Canada, France, the United Kingdom, Japan, the United States, West Germany and Sweden. It was found that Dutch manufacturing business profits do not strongly tend towards a common long-term profit level. This implies the existence of permanent excess or below normal profitability. Compared with the average in other countries, temporary excess profits are slightly more short-lived in Dutch manufacturing firms. This international comparison produces the conclusion that Dutch manufacturing is not at the forefront as regards competitive ability. Lower prices and, thus, more output and employment seem viable possibilities. Thus resulting more vigorous competition may serve as an innovative impetus to stay ahead of competitors. Obviously, we do not intend to trivialise the fact that profits are required for investment and, thus, employment. Too high profits may, however, indicate distortions of competition and potentially related (cost) inefficiencies, lack of innovativeness [10)] and lack of activity.

From a sectoral point of view, the methodology presented here serves as a powerful auxiliary tool to trace sectors with an inadequate market mechanism. Measuring competition pressure at firm level – i.e. the level where competition is encountered – and subsequently aggregating these assessments to a level where markets are recognisable, produces a micro related quantification of the operation of markets. Combining the results obtained therefrom with other quantifications or qualitative information enables policymakers to draw up their action plan.

Notes

1) See among others A.L. Bovenberg, Overvloed en onbehagen (Abundance and malaise), Economische en Statistische Berichten (ESB), 11 November 1991, pp. 1 228–1 232; P.A.G. van Bergeijk and R.C.G. Haffner, Op zoek naar dynamiek (Looking for dynamics), ESB, 20 January 1993, pp. 52–56; A.R. Thurik, Is de Nederlandse industrie wel zo weinig dynamisch? (Is Dutch manufacturing that undynamic?), ESB, 28 April 1993, pp. 385–387; C. van Gent, Nederland: een geval apart! (The Netherlands: a special case!) ESB, 12 May 1993, pp. 442–443; B. van Ark, J. de Haan and R. Kouwenhoven, 1993, Het dynamische tekort van Nederland (The dynamic deficit of the Netherlands), ESB, 8 December 1993, pp. 1 131–1 134; A.R. Thurik, Dynamiek en kleinschaligheid (Dynamics and small business presence),

ESB, 24 August 1994, pp. 732–737; and G.B. Dijksterhuis, H.J. Heeres and A.J.M. Kleijweg, Indicatoren voor dynamiek (Dynamics indicators), ESB, 19 July 1995, pp. 652–657.

2) See among others Kleinschalig ondernemen 1993; dynamiek en ondernemersklimaat (Small-scale business 1993, dynamics and business climate), EIM, Zoetermeer, chapter 4.

3) Toets op het concurrentievermogen; executive summary, Ministry of Economic Affairs, The Hague, June 1995. The significance of know-how as regards business performance and growth is also proven at the micro level; see G. van Leeuwen and H.R. Nieuwenhuijsen, R&D-uitgaven en bedrijfsprestaties (R&D expenditure and company performance), in: Speur- en ontwikkelingswerk in Nederland, 1993, CBS, Voorburg, 1995, pp. 51–55 and E.J. Bartelsman, G. van Leeuwen, H.R. Nieuwenhuijsen and C. Zeelenberg, 'R&D and productivity growth; evidence from firm-level data for the Netherlands', this issue.

4) For an overview see Haffner, R.C.G., De meting van dynamiek: een onderzoek naar de marktwerking op goederen-markten in Nederland, (Measuring market dynamics: a survey for product markets in the Netherlands) Erasmus University Rotterdam and Ministry of Economic Affairs, The Hague, 1993; and A.R. Thurik, 1994, op. cit.

5) See D.C. Mueller, 1986, Profits in the long run, Cambridge University Press, Cambridge, 1986; and P.A. Geroski, Modelling persistent profitability, mimeo, University of Southampton, Southampton, 1987.

6) Entry of firms and the non-measurable threat thereof play an important role in the model. This entry (threat) also depends on market structure-related entry barriers. For a more in-depth explanation of the model, see A.J.M. Kleijweg and H.R. Nieuwenhuijsen, 1995, op. cit.; and A.J.M. Kleijweg, Persistence of profits and competitiveness in Dutch manufacturing, research report 9302/E, EIM, Zoetermeer.

7) In the computations we make use of business data as compiled by Statistics Netherlands in its Production Surveys. The annual data are linked for the period 1978–1991. The panel thus obtained comprises 2,085 time series of firms with 20 or more employees. For each firm, the model is estimated on the basis of 13 observations (14-year time series, while losing one observation due to a one-year time lag in the model).

8) These analyses can be find in D.C. Mueller (ed.), The dynamics of company profits; an international comparison, Cambridge University Press, Cambridge, 1990. For the inter-country comparison, see in particular the chapter by H. Odagiri and H. Yamawaki, The persistence of profits: international comparison, table 10.4, pp. 179–180.

[9] See I.N. Kessides, The persistence of profits in U.S. manufacturing industries, in: Dennis C. Mueller (ed.), The dynamics of company profits; an international comparison, Cambridge University Press, Cambridge, 1990, p. 68. For the Netherlands, testing on the basis of the company finance statistics (Statistiek financiën van ondernemingen) has proven that the results obtained hardly change when employing the definition of profits as used in other countries. These statistics allow for more definitions of profits than the production surveys, though they cover fewer firms and a shorter period of time.

[10] Illustrative in this context is that Dutch firms are not at the forefront in terms of R&D-related activities. See e.g. Kennis in beweging (Knowledge on the move), Ministry of Economic Affairs, Ministry of Education, Culture and Sciences and Ministry of Agriculture and Fisheries, The Hague, 1995, p. 17; and G. van Leeuwen and H.R. Nieuwenhuijsen, CBS-studie: R&D maakt bedrijven produktiever (Statistics Netherlands study: R&D makes companies more productive), NRC Handelsblad, 25 October 1995.

Advanced manufacturing technology and firm performance in the Netherlands

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1. Introduction

This article presents a summary of research on the characteristics of firms which use advanced manufacturing technology, the factors which contribute to adoption of this technology, and the effect of technology usage on firm performance and employment. This research corroborates findings from recent work in other countries on these relations in industrial firms or plants [1)].

Some of the findings from these studies are very similar to ours: penetration rates of advanced manufacturing technology (AMT) have been seen to increase with firm (or plant) size, with labour productivity, and with export share. Further, usage of advanced manufacturing technology is seen to be correlated with high labour productivity. Most of these studies show a positive correlation between usage of advanced technology and higher wages. In the Dutch data this relationship is not monotonic, but hump shaped. More disparate across countries are the effects of advanced technology usage on employment growth. In Italy, Norway, and Denmark, the results point towards employment declines, while for France, the United Kingdom and the United States employment growth is boosted by advanced technology usage. For the Netherlands, the data require more careful interpretation. Total employment for the firms which use AMT declines between 1985 and 1991, while it increases for the firms which do not. However, when the five largest firms are excluded, employment grows much more rapidly for AMT users than non- users. Further, the average growth rate of employment for AMT firms is higher than for non-AMT firms, and increases with the importance of AMT for production. The relationship between capital and AMT use is not well explored in studies from other countries. Using measured real gross capital stock for firms in the Netherlands, our study finds that firms with a high capital-labour ratio in 1985 were more likely to have adopted AMT by 1992, and that growth in the capital-labour ratio is much higher for AMT using firms than for non-users.

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One dimension of the links between AMT use and firm dynamics highlighted in the present article is the role of shifts in technology and market demand. AMT use is seen to be correlated with high growth in labour productivity. This could lead to declining employment, unless the firm's output grows rapidly enough to offset the reduced demand for employees per unit of output. This growth can occur through combinations of changing market share and changes in the size of the overall market. These interactions are studied using a framework developed by Baily et al. (1996) and applied to the case of the Netherlands by Bartelsman et al. (1995), where firms are split into groups of successful and unsuccessful upsizers and downsizers. It is found that AMT users are disproportionately represented among the successful upsizers.

Another feature of this study is that three concepts of AMT use are employed. The first is an indicator variable which shows whether or not a firm uses any advanced equipment. The second a subjective measure of the impact of equipment failure on a firm's production. And the third is an AMT intensity measure, which is related to the share of advanced equipment in productive inputs. We were able to construct the latter on the basis of firm level surveys of capital stock and various types of advanced equipment, such as CNCs or mini computers. Most other studies of manufacturing technology rely on a variable of the first type and cannot distinguish between firms on the basis of importance or intensity of the advanced equipment.

2. Data description and summary statistics

The data used in this study derive from linked surveys of firms in Dutch manufacturing. The main sources of data are the production survey of 1985 and 1991. These data are linked with information from the 1992 survey of advanced manufacturing technology (AMT), and data from the 1982–1993 capital stock surveys. Summary statistics of the data are given below, followed by a description of the methodology for creating capitals stock measures for all firms in the production survey, and for creation of a technology intensity measure based on information in the AMT survey.

The production surveys contain information on shipments, employment, materials and energy usage, inventory levels, exports, and capital consumption allowance. About 80 percent of the firms with more than 20 employees in the 1985 production survey were linked to the 1991 survey, based on firm code, name, industry and location. Real firm output was computed as shipments plus inventory changes deflated by 3-digit SIC prices with 1985 as base year. Materials use is also deflated at the 3- digit level.

Table 1. Summary Statistics, PS85, PS91, AMT92

	PS85-PS91	All	PS85-PS91-AMT92		
			AMT=0	AMT=1	AMT=1[f]
1991					
Firms	6,121	1,435	614	821	815
Output[a]	276	98	16	82	55
Value added[a]	61	32	3	20	13
Employment[b]	718	264	43	221	146
Wage[c]	62	63	56	65	61
Productivity[d]	384	371	363	373	377
K-L Ratio[e]	327	352	174	387	353
Avg. annual growth 1985–1991					
Output Growth	2.77	2.77	3.14	2.70	4.84
Value added Growth	–0.08	–0.67	–0.96	–0.63	1.53
Empl. Growth	0.96	–0.23	0.88	–0.44	2.06
Wage Growth	1.19	1.20	1.04	1.25	1.49
Prod. Growth	1.80	3.01	2.24	3.16	2.72
K-L Growth	5.96	6.30	2.51	6.78	6.85
TFP Growth	–1.76	–1.59	–2.80	–1.27	–1.31

[a] Millions, 1985 Guilders.
[b] Employees, thousands.
[c] Thousands, 1985 Guilders.
[d] Output per employee, thousands, 1985 Guilders.
[e] Gross capital stock per employee, thousands, 1985 Guilders.
[f] Excluding the top-five firms.

The rows of Table 1 provide summary statistics of the key variables, and the columns describe the samples from which they are derived. The linked PS85-PS91 panel contained 6,121 firms which existed in both 1985 and 1991. At these firms, output grew by 2.77 percent per year, employment increased by nearly 1 percent per year, and labour productivity increased by 1.80 percent per year. The last four columns present data for the panel on which most of the analysis was conducted, the linked PS85-PS91-AMT92 panel (hereafter referred to as the panel). The panel contains 1,435 firms which existed in both 1985 and 1991 and which responded to the 1992 AMT survey. Output growth was about the same as for the PS85-PS91 panel, but employment declined, resulting in labour productivity growth of about 3 percent per year. Larger firms are overrepresented in the panel, as are firms in the metal and electrical equipment sector, reflecting the design for the AMT survey and the sample selection from survival caused by linking the 1985 and 1991 production surveys.

The data for the panel are split into subsamples; those firms not using AMT, those using AMT, and those using AMT excluding the largest five firms. Even though productivity growth is higher for firms using AMT compared with those who do not, both output and employment growth are lower. This surprising result is endemic in aggregate statistics derived from a skewed size distribution of firms, such as in the Netherlands. The largest five firms comprised more than 10 percent of output and 12.5 percent of employment in all manufacturing in 1985. The last column shows the summary statistics excluding the five firms [2]. Excluding these five firms, employment growth for AMT firms in the panel is about 2 percent per year.

Rather striking are the results for changes in the capital-labour ratio. The last row of the table shows annual changes in this ratio of nearly 6 percent per year. Further, the growth rate is much higher for AMT firms than for the others, although this may partly reflect size and industry effects.

3. Capital stocks

The lack of firm or plant specific capital stocks has often been a serious problem with micro-level productivity studies. In our study, we have been able to create firm level (gross) capital stocks by combining measures for the larger firms from the capital stocks survey with information on capital consumption allowances (CCA) for all firms in the production statistics [3].

Since 1982, the capital stocks survey has annually measured historical and current value of gross capital stock by vintage and type, of companies with more than 100 employees. Every year firms in a selected group of industries are surveyed, covering all industries within a five-year period. The largest firms have a high probability of being resampled in a subsequent five-year period; so far, about 250 firms have been sampled more than once.

The capital stock variable is thus either measured directly, by aggregating over vintage and type for the firms in the capital stock survey, or by linking this information to the production survey to create an implied stock for the firms where stocks are not directly observed. The production survey includes a question on capital consumption allowances. The CCA is related to the size of the capital stock, but also reflects tax laws and state of the business cycle. The CCA for those firms which have a measured gross capital stock can be used to derive the implicit ’depreciation’ as the ratio between the CCA and the capital stock. By averaging the implied depreciation rate for firms within an industry for both 1985 and 1991, we can compute the real gross capital stock for those firms where the stock is not observed. Implicit in the methodology is the assumption that the vintage-type distribution of capital assets are the same for all firms within a specific industry in a specific year.

4. Advanced Manufacturing Technology survey

The AMT survey was conducted in 1992 among large firms. Within manufacturing, about 2,200 firms were linked to the 1991 production survey, and about 1,500 firms were found in the linked PS85-PS91 panel. The survey asked firms about use of computer aided manufacturing, design, and planning. However, the present article is limited to information on computer aided manufacturing equipment as it is this technology which is most thought to lead to labour productivity improvements through a streamlining of production processes with associated job losses.

The survey asks respondents to indicate whether they used any of a list of computer aided manufacturing process technologies, viz. CNC (computer numerical control), DNC (distributed numerical control), Pick and Place systems, robots, programmable logic controllers, and personal, mini and mainframe computers. For most of these technologies, firms were asked to indicate how many items of this type were in operation.

The results on AMT adoption are subject to some caveats. First, the date of adoption is not actually observed, only the fact that firms were using AMT in 1992. It is implicitly assumed that the firms did not yet use these technologies in 1985 and that it is reasonable to model the adoption decision using information from that year to predict AMT use in 1992.

Secondly, the use of AMT is a binary choice variable and does not provide information about the extent of application. Thus, if firm size were a good predictor of adoption, which it appears to be, this may reflect nothing more than the fact that large firms are likely to have at least one PC, for example. This problem plagues most other studies of AMT surveys, although Dunne (1991) created an index of intensity by summing the positive responses to binary questions on use of different technology. Using the Dutch data, two possibilities exist to correct for the problem.

One way is to construct an index of technology intensity which reflects the proportion of factor inputs belonging to the class of AMT equipment. The AMT survey contains counts of different types of equipment, such as CNCs or robots. In order to create an index of technology use, some weights are needed to aggregate the quantity responses. A simple approach is to regress these quantities on the firm’s real capital stock and use the estimated coefficients as weights. The regression provided estimates for the weights, interpretable as prices in 1985 guilders, which were of reasonable magnitude and reflected the importance of the various types of equipment.

Another possibility is to use the answer to a subjective survey question: ’What impact would failure of the above-mentioned equipment have on your production?’ The AMT intensity index mentioned above is highly correlated with the four possible answers to the subjective survey question.

5. Who uses AMT?

In the publication of results from the survey of manufacturing technology, Statistics Netherlands (1992) showed that adoption of AMT technology increases by firm size class. Further, the publication reported on variation of adoption by industrial classification, along with information on type of technology and investments and planned investments in 1992 and 1994. However, no further firm characteristics were included as queries in the survey. By linking the firm level statistics with data from the 1991 manufacturing survey, we are able to describe more completely the characteristics of the plants which employed advanced technology in 1992. Figure 1 presents penetration of technology (as a percentage of number of firms) by size, wage labour productivity, and export share.

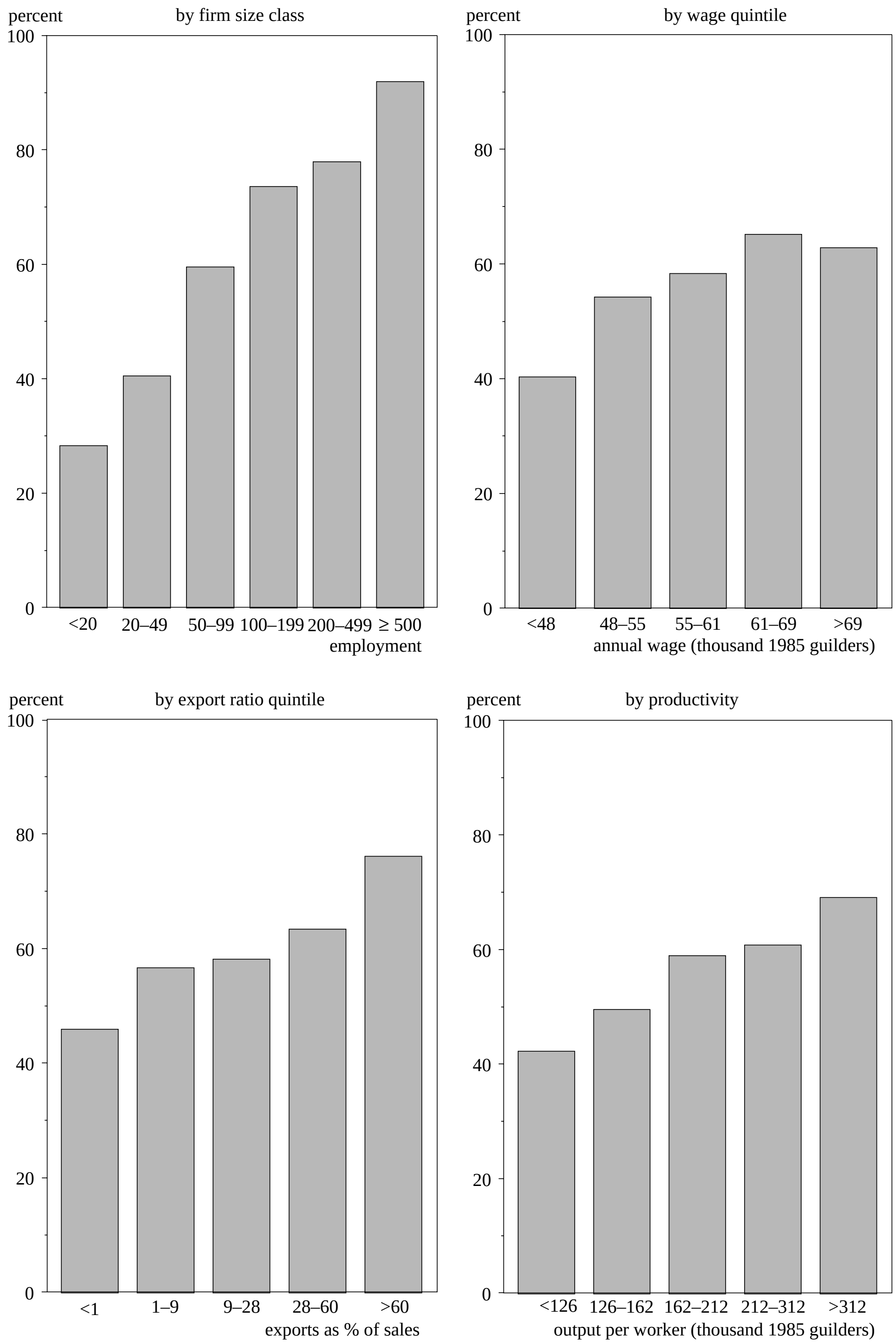
As illustrated, the percentage of firms employing such technology increases rapidly with firm size, to more than 92 percent for firms with more than 500 employees. (Size is measured by total employment and disaggregated by size class definitions of Statistics Netherlands.) This result, however, highlights the shortcoming of this approach. Whether or not a firm uses AMT is not an indicator of intensity of use of such equipment, so that even if the pattern of (unobserved) intensity across size class were uniform, one would still expect to see rising adoption probabilities with firm size. The following section gives evidence on the variables correlated with AMT intensity, conditional on having adopted some technology.

The percentage of firms using AMT increases in the low wage quintiles but flattens out and decreases in the highest quintile. (Wages are measured by total 1991 payroll divided by employment – in thousands per worker, deflated by CPI, 1985=100 – and split by quintiles of workers.) As seen, the cross-sectional distribution of average firm wages is rather narrow in the Netherlands, with the median worker in the lowest quintile earning about 55 percent of the median worker in the top quintile.

The ratio of exports to sales of firms with AMT is also higher than those without, and penetration is seen to increase with this ratio. (The export ratio shows nominal exports as a percentage of sales, split by quintile of sales.) Lastly, penetration of AMT increases with output per employee (measured in thousands of 1985 guilders of gross production per worker, split by quintiles of employees).

However, consistent with results in other countries, we find significant interactions between these characteristics. For example, our sample shows AMT adoption increasing

Figure 1   CAM penetration by 1991 firm characteristic



with size, as well as a considerable size-wage premium. As such, the bivariate plots show little about the role of the characteristics in adoption of advanced technology. Further, it should be emphasised that the results in this section are merely correlations between AMT use and nearly contemporaneous firm characteristics. For example, wages and AMT use are endogenous variables, and causality may, in principle, go in either direction. High wages may push firms to adopt labour-saving technologies, or in any case, to increase the capital-labour ratio. On the other hand, AMT use may lead to higher wages, either through rent sharing or through upgrading of the workforce. This is discussed further below.

6. Adoption of AMT and 1985 firm characteristics

Our data do not distinguish the date on which AMT was adopted. It seems safe to assume that firms using AMT in 1992 most likely had it in 1991. It is further assumed that these technologies had not been adopted in 1985, so that one can consider the 1985 firm characteristics as exogenous to the adoption decision.

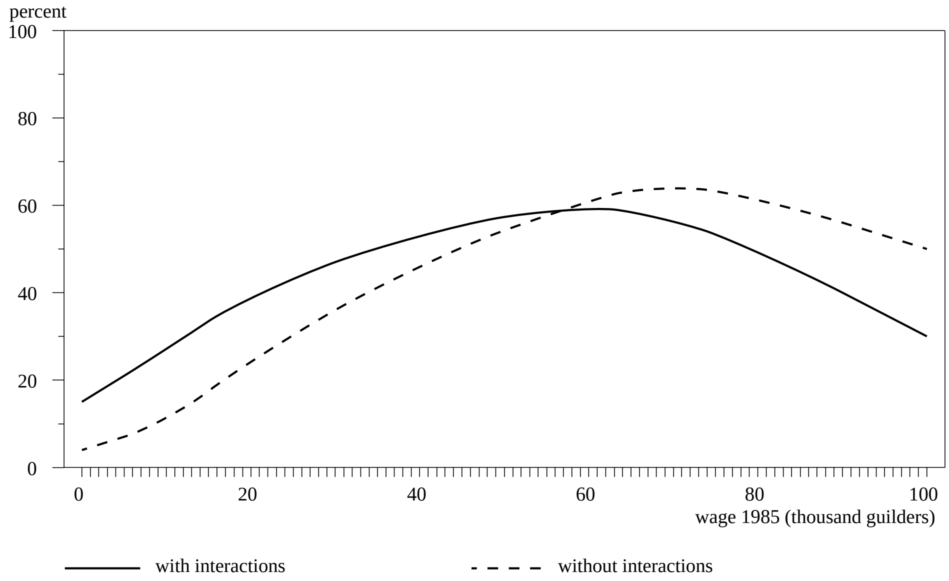
A probit model was used to explain the adoption probability of AMT, using size and industry dummies, as well as 1985 observations on wages, labour productivity, TFP, capital-labour ratio, export share of output, and interactions of wages with size. The probit analysis showed that the capital-labour ratio, export ratio, wage, and wage squared have a significant effect. When the dummies are included the wage and export ratio effects decline as does their significance. The size dummies are highly significant and show the adoption probability rising sharply with size. By industry, higher adoption probabilities are found in the food and beverage industry (the omitted category) and in the machinery industry. When wages are interacted with size, significant positive wages effects occur for the smallest firms, but a negative effect for the largest ones.

Figure 2 shows the adoption probability by wage as a result of a probit regression with only wage and wage squared as explanatory variables (the dotted line) and the results from a probit with size dummies, industry dummies, the capital-labour ratio and the export share, along with wage and wage squared as explanatory variables (the solid line). As can be seen, the wage effect peaks earlier once the other covariates are taken into account.

7. Employment and productivity dynamics

The next investigations concern the employment and productivity movements between 1985 and 1991 for plants using AMT in 1992. It is implicitly assumed that the adoption

Figure 2 AMT adaption probabilities



of technology took place early enough to have an impact on firm dynamics in this period. The effects of the binary choice variable, the AMT use index, and the AMT impact variable on firm dynamics will all be evaluated.

As described earlier employment growth did not rise more rapidly at AMT using firms than at non-AMT users. However, this is no longer true when the largest five firms are excluded: employment growth is 1.5 percentage points per year higher for AMT users. Table 1 also shows that labour productivity grew by about 0.5 percentage point faster for AMT users than non-users, while TFP dropped by nearly 1.5 percentage points for AMT users.

Instead of relying on aggregates of the balanced sample, with or without the largest five firms, the effect of AMT usage on average changes in employment was estimated by regressing changes in employment on an AMT dummy, lagged wage, lagged productivity, wage change, productivity change, and size and industry dummies. It was found that AMT use leads to higher employment growth at the firm level, while high wage growth is correlated with employment declines. Further, the larger the impact of AMT use on production, which is the subjective effect on a firm's production in the case of failure of the AMT equipment, the higher the positive employment effect. However, it is seen that even though AMT use increases employment growth, the intensity of use does not strengthen this effect.

On average, the intensity variable is not seen to have much effect on employment growth, conditional on adoption. The insignificant effect could be the result of two opposing effects. On the one hand, the intensity is driven by the technology which is necessary to produce the types of goods which demanded in the marketplace. The job losses caused by more efficient production at the ’successful’ companies which rely heavily on AMT are compensated by job gains through increases in market share. This is explored further below.

Table 2 shows the relationship between changes in employment and productivity for AMT users and non-users, as well as for different categories of AMT impact and intensity. The second and third columns of the table show the changes in labour productivity and employment, respectively. The last four columns show the share of total employment for each row in four groups of firms split by changes in employment and productivity [4]. The first group contains firms where both employment and labour productivity increased between 1985 and 1991, the second group contains firms with declining employment and increasing productivity, in the third group, both employment and productivity decline, while in the last group employment increased while productivity declined.

Table 2. Employment and productivity Changes, by Quadrant, 85–91

Category	$\triangle \Pi$ [1]	$\triangle E$ [2]	Quad I	Quad II	Quad III	Quad IV [3]
All Plants	2.58	1.77	41.31	26.51	6.66	25.53
AMT Usage						
AMT=0	2.22	0.87	37.39	29.21	6.54	26.86
AMT=1	2.69	2.04	42.51	25.67	6.69	25.12
AMT Impact						
Nil	2.68	1.18	31.41	38.78	4.41	25.40
Marginal	1.82	1.26	44.32	21.62	8.22	25.85
Significant	2.77	2.27	40.89	28.53	6.05	24.53
Complete	2.51	3.38	52.87	18.26	5.05	23.82
AMT Intensity						
1st Quintile	2.71	1.37	35.02	28.95	6.58	29.45
2nd Quintile	4.38	2.30	49.84	29.75	5.17	15.24
3rd Quintile	2.80	0.03	61.14	21.43	17.42	0.00
4th Quintile	2.32	2.00	46.23	23.98	10.27	19.52
Top Quintile	2.14	2.66	43.92	21.60	5.08	29.40

I: $\triangle \Pi$, $\triangle E>$; II: $\triangle \Pi>0$, $\triangle E<0$;
III: $\triangle \Pi<0$, $\triangle E<0$; IV: $\triangle \Pi<0$, $\triangle E>0$

1) Within-group aggregate labour productivity growth. (percent, annual average).
2) Within-group aggregate employment growth. (percent, annual average).
3) Percent of total employment in each Quadrant.

Employment and productivity growth is higher for AMT users, and the percentage of employment in the first group, the ’successful upsizers’, was higher for users of AMT equipment. Employment growth increases for AMT users as the impact of the technology on production increases. Also, the proportion of successful upsizers is larger for firms reporting complete production stoppage due to equipment failure, than for the firms which report little or no effect. The intensity measure, on the other hand, shows no clear pattern for employment and productivity growth or for assignment to quadrants.

8. Conclusions

The investigation into the role played by AMT in the Dutch manufacturing industry found that the probability that a firm used AMT equipment increased with firm size and the capital-labour ratio. Conditional on AMT use, the intensity of use increased with the capital-labour ratio, but declined with the level of labour productivity. Further, the intensity declined with firm size, even after correcting for possible sample selection bias.

The effects of AMT on company performance are more complex. Firms which use AMT have higher employment growth on average, and as a group have higher employment growth than non-users when the largest five firms are excluded. Conditional on adoption, the employment impact increases with the subjective importance of the AMT impact, but does not vary with AMT intensity. Labour productivity growth increases by about half a percentage point more per year for the AMT using firms than for the others, but on average, the AMT effect is insignificant. Mostly, it is the increase in the capital-labour ratio which is seen to improve labour productivity.

Notes

1) The research summarised here, as well as some of the following papers, were presented at the OECD-NRC conference on the Effects of Technology and Innovation, May 1995, Washington DC, and will appear in a conference volume. Contributions from other countries include Baldwin and Johnson (1994), Regev (1995), Entorf and Kramarz (1995), Vivarelli et al. (1995), and Nyholm (1995).

2) Not all five firms reduced their employment over this period, but for disclosure reasons, we exclude the top five.

3) Regev (1995) makes use of a related methodology to combine data from a capital stock survey to firm specific information on depreciation in order to create capital stocks.

4) These groups were used by Baily et al. (1995) to describe successful and unsuccessful upsizers and downsizers. For the Netherlands, this analysis was replicated by Bartelsman et al. (1995).

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R&D and productivity growth: evidence from firm-level data for the Netherlands

Eric Bartelsman[*], George van Leeuwen, Henry Nieuwenhuijsen and Kees Zeelenberg

1. Introduction

This article presents evidence on the links between R&D and productivity for manufacturing firms in the Netherlands. The study provides estimates of the output elasticity of the R&D stock and of the private rate of return to R&D. The article applies the methodology used by Hall and Mairesse (1995) to a panel dataset of R&D performing firms in the Netherlands, with some minor modifications. First, a correction for sample selection bias is used in an attempt to adjust the results for possible bias arising when the basic methodology is applied to the R&D survey for the Netherlands. Next, more complete adjustment is made to the resource input data to correct for the 'double counting' of R&D inputs. Lastly, an attempt is made to correct for heteroskedasticity in the error term of the basic model. The study makes use of linked files of the R&D surveys and the annual production statistics collected by Statistics Netherlands for the years 1985, 1989, and 1993.

Most previous work on the link between R&D and productivity in the Netherlands has been based on aggregate or industry data. Den Butter and Wollmer (1992) report a significantly negative estimate for private returns to R&D, whereas the cross-country study of Coe and Helpman (1993) shows a positive contribution of private R&D to total factor productivity growth for the Netherlands. These inconclusive results are a likely reason that Verspagen (1995) omits the Netherlands from his broad-based survey article on R&D and productivity growth. The ambiguous estimates probably derive from the very skewed distribution of firm size and R&D expenditure in the Netherlands. R&D expenditure in Dutch manufacturing is highly concentrated in five multinational companies. These companies spend a disproportionate – albeit decreasing – part of their worldwide R&D in the Netherlands, whereas their production is to a large extent located outside the Netherlands. The recent dramatic decrease of domestic R&D expenditure of these companies can be held responsible for the decline in aggregate manufacturing R&D from 1989 onwards.

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The use of micro-data enables us to estimate the effect of R&D on productivity growth free from aggregation bias. However, the use of firm-level data does not solve all econometric problems. Measurement errors, simultaneity and selectivity can continue to cloud results (see e.g. Grilliches and Mairesse, 1995). The data allow robustness checks of the results with respect to measurement of capital stocks, double counting of R&D inputs, creation of initial R&D knowledge stocks, and different measures of output. We correct for simultaneity bias by estimating a production function in 'long-difference' form and by using a partial TFP approach. Selectivity may be a problem in our sample: indeed the probability of exiting the sample is negatively related to the level of R&D intensity. The problem appears to be more severe in the period 1989–1993, when R&D expenditure was declining, on average. In our estimation procedure an attempt is made to correct for the selectivity problem by using a Tobit model.

Our findings are very similar to the results recently published by Hall and Mairesse (1995). It is found that the elasticity for the stock of R&D capital is about 0.06 for gross output and 0.08 for value added and the private gross rate of return to R&D varies between 12 percent for gross output and about 30 percent for value added. Because the Hall and Mairesse estimates were derived from a panel with considerably more observations in the time dimension, this is a surprising result.

2. The data

The dataset used in this study contains linked firm-level information from the annual production surveys and the extended R&D surveys of 1985, 1989 and 1993, conducted by Statistics Netherlands [1)]. The production surveys provide data for each firm on sales, gross output, value added, payroll, number of employees, materials, electricity use and capital consumption allowances (depreciation costs). The R&D surveys give information on R&D full-time equivalents and other staff, and expenditure on in-house R&D and outsourced R&D. The R&D expenditure is further disaggregated into staff costs, material costs and R&D plant and equipment investments. Other disaggregations split expenditure by type of research (basic and applied) and by process and product research.

A distinct advantage of this dataset is that the R&D expenditures can be separated from the other operating expenses of the firm, avoiding the biases in estimation caused by 'double counting' resource inputs (see Schankerman, 1981). In the production function estimations, material and labour input variables can be adjusted for the amounts used in R&D endeavour. This adjustment is not attempted for the capital input because the R&D investments account for only 10 percent of total R&D expenditure and we have only two observations of R&D expenditure for each panel (1985–1989 and 1989–1993). So the best we can do is to solve the double counting problem for 90 percent.

The nominal variables in the dataset are all deflated into constant 1985 guilders. Output and materials are deflated by applying 3-digit SIC [2)] product and material prices to all firms within the corresponding industry. R&D expenditure is deflated by a Divisia index of changes in wages of R&D staff and material prices. The price changes for R&D staff were computed for industry groups as the change in average hourly compensation for R&D employees between 1985 and 1989 and between 1989 and 1993 [3)]. Using firm-specific labour and material expenditure shares, the appropriate wage change was averaged with the material price change to construct R&D expenditure deflators.

The capital input measure required to estimate the production functions is proxied by the consumption allowances, available in the production statistics. This financial measure is related to the capital stock but does not directly reflect the capital service flow. Tax laws, vintage and type distribution of the assets, and cyclical capital utilisation all cause differences between the depreciation data and the desired measure of capital real capital input. When the production function is estimated in first difference form, changes in the capital inputs are proxied by changes in electricity use. This measure should correct for fluctuations in capital utilisation, but may misrepresent the growth of capital inputs if firms adopt energy saving technologies. Given the fall of electricity prices in the period of observation, it is unlikely that large scale substitution between energy and capital has taken place.

Tables 1A, 1B and 2 give some summary statistics for the linked datasets. In table 1A descriptive statistics for three cross-sections of linked data are presented. In total 382, 436 and 347 R&D firms could be linked to the production statistics of 1985, 1989 and 1993 respectively. These firms contribute to between 90 and 95 percent of Dutch manufacturing R&D. The major R&D performing firms are included in all years, ensuring that coverage remains high. The top five firms alone account for approximately 70%, 65% and 60% of manufacturing R&D in 1985, 1989 and 1993 respectively. Smaller firms – as measured by their contribution to manufacturing R&D – have a higher probability of exiting the panel due to incidental R&D performance. In fact the four-yearly extended R&D surveys reflect to some extent a rotating design, because small firms have higher probability to be replaced by other firms. Firms may also exit the sample owing to merging or liquidation. Because of the considerable drop out of the smaller R&D performing firms no attempt was made to construct a panel over the full period of three years. Instead two different panels are used in the estimation procedures, labelled PS-RD8589 and PS-RD8993. The nature of the balanced panels may introduce a selectivity bias in the estimated R&D coefficients. An attempt is made to correct for this problem by including a selectivity equation in the models.

Table 1A. Summary Statistics for yearly cross-sections

Year	1985		1989		1993	
	Mean	Q1–Q3[a]	Mean	Q1–Q3	Mean	Q1–Q3
Number of employees	757	100–430	686	102–368	619	85–317
Gross output[b]	252	22–128	226	21–131	232	20–102
Value added[b]	71	8– 35	66	7– 36	68	6– 31
Capital per employee[c]	10	5– 13	13	6– 16	16	7– 19
Labour productivity[d]	87	60– 96	92	59– 06	94	57–107
R&D to sales ratio (%)	2.0	0.3–2.7	2.4	0.5–2.9	2.7	0.6–3.1
Number of observations	382		436		347	

[a] IQ: inter-quartile range: first and third quartile boundary;
[b] In million guilders of 1985;
[c] Depreciation charges per employee in thousand guilders;
[d] Value added per employee in 1985 prices in thousand guilders.

Table 1B. Summary Statistics for balanced data

Period	1985–1989[a]				1989–1993[a]			
Year	1985		1989		1989		1993	
	Mean	Q1–Q3[b]	Mean	Q1–Q3	Mean	Q1–Q3	Mean	Q1–Q3
Number of employees	1,169	124–581	1,158	146–589	1,347	119–589	1,084	119–480
Gross output	380	32–167	393	38–190	414	30–165	348	31–195
Value added	110	10– 55	119	12– 54	133	10– 49	111	9– 63
Capital per employee	11	5– 14	15	7– 17	13	6– 17	16	8– 20
Labour productivity	92	66– 99	106	65–116	103	73–115	114	70–129
R&D to sales ratio (%)	2.6	0.4–3.3	2.7	0.6–3.1	3.1	0.7–3.6	3.4	0.8–4.0

[a] Number of observations for 1985–1989: 209, for 1989–1993: 159. All amounts in constant 1985 guilders;
[b] IQ: inter-quartile range: first and third quartile boundary.

Table 2. Growth in balanced panels[a]

Period	1985–1989[b]					1989–1993[b]				
	Mean	Median	Q1–Q3[c]	Min	Max	Mean	Median	Q1–Q3	Min	Max
Employment	0.2	1.4	–2.6– 4.9	–45	24	–0.5	–0.7	–2.8– 2.5	–23	26
Labour productivity	2.0	1.5	–2.3 –6.8	–65	64	0.5	–0.2	–5.1– 5.5	–36	33
Total factor productivity	0.6	0.1	–1.3– 2.1	–10	26	0.2	–0.2	–1.9– 2.3	–7	11
R&D capital δ [d] = 0.05	6.3	5.0	3.7– 7.6	–4	48	5.8	4.4	2.7– 7.3	–3	56
R&D capital δ = 0.15	6.9	5.0	2.8– 9.5	–13	61	5.7	4.0	0.7– 9.2	12	71
R&D capital δ = 0.25	7.0	5.0	1.9–11.0	–24	69	5.4	3.7	1.1–10.6	–21	79
R&D expenditures	4.7	3.4	–2.6–14.0	–100	90	1.2	0.9	–8.8–13.3	–90	101

[a] Average growth (%) per year (in constant 1985 prices);
[b] Number of observations for 1985 1989: 209, for 1989 1993: 159;
[c] IQ: interquartile-range: boundary of the first and third quartile;
[d] δ = depreciation rate.

As can be seen from the means and inter-quartile ranges for the balanced panels (table 1B) and the 1985 cross-section, as presented in table 1A, the datasets consist of relatively large firms. Average firm size in the panel is much larger than the average firm size for total manufacturing for two reasons: the R&D survey only covers firms with more than 50 employees and the probability of performing own R&D increases with firm size. Further, the size distributions within our dataset are very skew, with means for employment, gross output and value added substantially larger than the third quartile. The distribution of R&D expenditure is even more skew than for output and employment. For example the average R&D-sales ratios presented in tables 1A and 1B are unweighted averages. On a weighted base these ratios are considerably larger: respectively 4.6%, 6.6% and 6.7% for 1985, 1989 and 1993. This reflects the dominance of the 'top five' enterprises, which spend a disproportionately large share of their worldwide R&D in the Netherlands compared with the domestic share of their production. The extreme size of these enterprises together with their inordinate share of R&D indicates why estimates of the return from R&D from industry-level data reveal little about the effects of R&D for the average firm [4)]. Idiosyncratic movements in their research expenditure, such as moving research labs overseas, may greatly affect the aggregate R&D measure, while not affecting domestic production.

From table 1B it can also be inferred that the two periods are rather different. Employment, gross output and value added dropped significantly in the second period. The turn of the business cycle is more manifest in our dataset because of the impact of the chemical industry. Chemical firms are overrepresented in our R&D panels. Due to severe price competition gross output and value added of relatively few but very large firms producing basic chemicals show a dramatic decrease in the period 1989–1993. Together with the downsizing of other large R&D performing companies this explains the picture of aggregate R&D in the second period. A better impression of the dynamics can be obtained by looking at the distribution of growth rates in both periods. From table 2 it can be inferred that the distributions for R&D expenditure and productivity growth rates are shifted to the left in 1989–1993. Average labour productivity growth dropped from 2.0 in 1985–1989 to 0.5 in 1989–1993. Similar patterns are observed for the decreases of total factor productivity and R&D expenditure. We also have listed growth rates for R&D capital using different depreciation rates (δ). As can be seen the different depreciation assumptions have a substantial impact on the shape of the R&D capital growth rates distributions, but the means and medians remain relatively stable between the alternatives presented.

3. Methodology

The empirical framework for this article will be a production function with R&D knowledge stock, or R&D intensity, as an additional input. This is a commonly used specification to estimate the effects of R&D on productivity (see e.g. Mairesse and Sassenou, 1991). Starting point is the Cobb-Douglas production function:

$$(1) \qquad q_{it} = \alpha_{it} + \gamma k_{it} + \Sigma_j \beta_j x_{jit} + \varepsilon_{it}$$

where q_{it} is the log of real production of firm i in year t, α_{it} is a firm and time specific indicator of the level of technology, k_{it} is the (log of) R&D stock of knowledge and the x's are the (log) traditional factor inputs belonging to set S, and ε is a normally distributed error term with mean zero and variance σ^2. The summation in (1) runs over factor inputs, $j \in S$. If production is measured by value added then S = {C, L}, capital and labour, and if it is measured by real gross output then the input set is augmented by materials: S = {C, L, M}. The β's and γ are output elasticity parameters to be estimated. In its present form, equation (1) is not identified and further assumptions regarding the disembodied technology parameter α_{it}, are needed. For example, if $\alpha_{it} = \alpha_i + \lambda t$, and if a full panel of firm data over time were available, then a fixed effect estimator of differenced data, a 'within' estimator, would provide consistent estimates of the output elasticities.

Given that data are only available for 1985, 1989 and 1993, 'within' estimation is not possible. The first possibility is to estimate the elasticities from equation (1) under the assumption that there is a different constant term in each year ($\alpha_{it} = \lambda_t$). The restriction that the output elasticities are constant over time can also be dropped. The resulting estimation procedure is then equivalent to estimating a separate cross-sectional equation for 1985, 1989 and 1993. Using the matched panel, firm-level fixed effects of the form $\alpha_{it} = \alpha_i + \lambda t$ cannot be estimated from (1), but can be eliminated by estimating the production function in 'long-difference' form. Taking 'long-differences' has the additional advantage that it preserves more variance for the identification of the parameters than other data transformations (see Griliches and Mairesse, 1995, pp 13). The long difference form is

$$(2) \qquad \Delta_4\, q_{it} = \lambda + \gamma\Delta_4\, k_{it} + \Sigma\beta_j\Delta_4 x_{jit} + \mu_{it}$$

where $\Delta_4 z_{it} = z_{i,89} - z_{i,85}$ or $z_{i,93} - z_{i,89}$ and μ_{it} is a newly defined disturbance term ($= \Delta_4\varepsilon_{it}$). Equation (2) is used in various forms to get estimates of the output elasticities. A number of alternatives will be discussed in section 4. The issue of how to measure the relevant R&D variable is explained below.

R&D knowledge stock

Two related methods have been widely used to assess the effects of R&D on productivity. The first assumes that R&D expenditure accumulates into a stock of knowledge, similar to the formation of capital through investment. This assumption implies that past R&D continues to have spillover effects on production in the present, although the effect may diminish over time through depreciation. In estimating this specification, it is assumed that all firms have the same output elasticity of the knowledge stock. The alternative specification assumes that there is no depreciation of the knowledge stock, and in estimating assumes that the rate of return to the R&D knowledge stock is the same for all firms.

The first method calculates the R&D stock using the perpetual inventory method (PIM):

(3) $K_{it} = R_{it} + (1-\delta)K_{it-1}$

where K_{it} is the R&D knowledge stock of firm i in year t, R_{it} represents real R&D expenditures and δ is the rate of depreciation. The depreciation is supposed to reflect, for example, the obsolescence of ideas and the reduced profitability of old products as new ones are created. The magnitude of the depreciation rate is usually chosen in the 15 to 20 percent range (see e.g. Hall and Mairesse, 1995).

Two problems arise in implementing this method with the available data: R&D expenditure is observed only in 1985, 1989 and 1993, and no initial R&D knowledge stock measure is available. Real R&D expenditure for the intervening years is interpolated using the observed growth rate for each firm. Initial stocks of knowledge, $K_{i,85}$ for the first wave and $K_{i,89}$ for the second wave, are created by assuming a pre-sample R&D expenditure growth rate, g, constant across firms. Then, following Hall and Mairesse (1995), the initial knowledge stock can be written as:

(4) $$K_{i0} = \frac{R_{i0}}{(g+\delta)}$$

Combining this expression into the PIM framework yields the knowledge stock growth equation:

(5) $$\Delta_4 k_i = 1\text{n}\left(\frac{(1-\delta)^4}{(g+\delta)} + \sum_{s=1}^{4}(1+r_i)^s(1-\delta)^{4-s}\right) + 1\text{n}(g+\delta)$$

with r_i the growth rate of real R&D expenditure for firm i in the period 1985–1989 or 1989–1993. A range of parameter values for g and δ will be used in order to assess the sensitivity of the estimated R&D elasticities to different assumptions pertaining to depreciation and initial stocks.

R&D intensity

The alternative method for estimating the effect of R&D on productivity is the intensity method, where the rate of return to R&D is assumed to be constant across firms. Assuming no depreciation (δ = 0), the change in the R&D knowledge stock can be written as:

$$(6) \qquad \Delta_4 K_{it} = \sum_{s=1}^{4} R_{io}(1 + r_i)^s.$$

Using the fact that the marginal product of the R&D stock, ρ, is equal to its output elasticity times the ratio of output to the R&D stock:

$$(7) \qquad \rho \equiv \frac{\partial Q_{it}}{\partial Q_{it}} = \gamma \frac{Q_{it}}{K_{it}},$$

Now we can rewrite equation (2) as:

$$(8) \qquad \Delta_4 q_{it} = \lambda + \gamma \frac{Q_{i0}}{K_{i0}} \frac{\Delta_4 K_{it}}{Q_{i0}} + \sum_{j \in s} \beta_j x_{jit} + \mu_{it} = \lambda + \rho \frac{\Delta_4 K_{it}}{Q_{i0}} + \sum_{j \in s} \beta_j x_{jit} + \mu_{it}.$$

In this specification, the R&D intensity variable is computed as the sum of R&D expenditure from 1986 to 1989 and from 1990 to 1993 divided by output in 1985 and 1989 respectively. The interpretation of ρ is that of the marginal product of a unit of knowledge stock, which in the absence of depreciation, is the amount by which output increases with an increase in real R&D expenditure. Although being a different model than (2) we also estimated equation (8) for two reasons: its ease of interpretation and because this specification has been frequently applied in related empirical research.

4. Estimation of R&D contribution

Cross-sectional estimates

As a starting point estimates are presented for the output elasticities using a log-linear Cobb-Douglas production function with R&D capital (equation 1). In this level specification R&D-capital is proportional to the R&D expenditures (see equation 4). Both gross output and value added are used as output measures and estimates are presented for specifications with and without the adjustment for ’double-counting’, the latter with labour and material inputs containing non-R&D inputs, and value added measured as gross output minus non-R&D materials. In estimating, all R&D firms that could be linked to the production surveys in either year are used and sectoral dummy intercepts are included.

Table 3A. Cross-sectional estimates 'log-level' specification not adjusted for double-counting

Dependent variable	Gross output			Value added		
Year	1985	1989	1993	1985	1989	1993
Coefficient of						
Labour	.136	.145	.189	.570	.626	.755
	(.013)	(.014)	(.019)	(.036)	(.042)	(.067)
Material inputs	.769	.750	.727			
	(.010)	(.010)	(.013)			
Capital	.080	.103	.085	.365	.352	.253
	(.009)	(.010)	(.013)	(.025)	(.031)	(.049)
R&D	.009	.003	.012	.041	.026	.035
	(.006)	(.005)	(.006)	(.018)	(.018)	(.026)
SIC dummies[a]	yes	yes	yes	yes	yes	yes
N of observations	382	436	347	382	436	347
R^2	.992	.990	.990	.911	.882	.826

[a] SIC-dummies for four groups: [1] food, beverages and tobacco, [2] petroleum, chemical industry and allied, [3] metal industries and [4] other industries (textiles, wearing apparel, paper and paper products and manufacture of building materials).

The sectoral dummies distinguish between four sectors: 1) food, beverages and tobacco, 2) petroleum, chemical industry and allied, 3) metal industries and 4) other industries (textiles, wearing apparel, paper and paper products and manufacture of building materials). These groups will be used throughout.

In estimating the production function in log-levels with panel data, much of the identification comes from cross sectional variation. Biases in coefficient estimates may arise owing to fixed effects or endogeneity of inputs, i.e., better firms have elevated outputs and inputs. Even so, the estimates presented in Table 3A for the traditional factor elasticities are close to the corresponding factor shares as these should be under the maintained hypothesis of perfect competition. Further the elasticities add up to about unity in most cases and constant returns to scale cannot be rejected [5]. Contrary to the results for traditional factor inputs, the estimate for the R&D elasticity does not differ significantly from zero in the majority of cases. However, the adjustment for 'double counting' (see Table 3B) produces some important differences. When the traditional inputs are adjusted for double counting, the R&D elasticities become significant. This result confirms predictions by Schankerman (1981) that double counting factor inputs gives lower estimates of R&D output elasticities. The interpretation for this, on the assumption that the estimates are accurate, is that total returns to R&D are significantly positive, but R&D did not provide increases in output above and beyond that predicted by the traditional factors, i.e. no excess returns.

Table 3B Cross-sectional estimates 'log-level' specification adjusted for double-counting

Dependent variable	Gross output			Value added		
Year	1985	1989	1993	1985	1989	1993
Coefficient of						
Labour	.134	.142	.174	.552	.602	.700
	(.012)	(.013)	(.013)	(.035)	(.039)	(.063)
Material inputs	.763	.740	.723			
	(.010)	(.010)	(.013)			
Capital	.081	.105	.090	.362	.347	.269
	(.010)	(.010)	(.013)	(.025)	(.030)	(.048)
R&D	.018	.015	.024	.068	.059	.076
	(.006)	(.005)	(.006)	(.017)	(.017)	(.025)
SIC dummies[a]	yes	yes	yes	yes	yes	yes
N of observations	382	436	347	382	436	347
R^2	.992	.990	.990	.914	.889	.833

a) SIC-dummies for four groups: 1) food, beverages and tobacco, 2) petroleum, chemical industry and allied, 3) metal industries and 4) other industries (textiles, wearing apparel, paper and paper products and manufacture of building materials).

'Long difference' estimates

A disadvantage of estimating 'log-level' specifications is that they have not been controlled for fixed effects. If these effects are correlated with other explanatory variables, then the cross-sectional estimates are not consistent. This problem can be solved by using differenced series. However, by differencing the data measurements errors are exacerbated. This pitfall can be circumvented by estimating 'long difference' equations, which relate growth of output to growth of factor inputs over some years. The introduction of the time dimension may, however, worsen the simultaneity problem. Before treating this issue further, we first present several variants of 'long-difference' growth equations.

R&D knowledge stock approach

Estimates for the 'long difference' equations are presented in Table 4. All firms for which two adjacent observations were available in the four-yearly R&D surveys are included. The growth of the R&D knowledge stock is calculated according to (5), using a pre-sample R&D growth of 5% and a depreciation rate of 15%. Estimates are presented for the two panels separately and for the pooled data. In the pooled estimates an extra dummy intercept is included. This time dummy represents a mixture of time and population effects. The data are adjusted for double-counted R&D inputs. Further, we distinguish between estimates for the gross output and the value added specification.

Table 4. Estimates R&D contribution for 'long-difference' specifications

Dependent variable	Gross output			Value added		
Year	85–89	89–93	Pooled	85–89	89–93	Pooled
Coefficient of						
Labour	.196	.222	.205	.780	.700	.752
	(.037)	(.052)	(.030)	(.125)	(.139)	(.092)
Material inputs	.718	.689	.705			
	(.025)	(.032)	(.019)			
Capital	.024	.031	.030	.083	.105	.095
	(.019)	(.027)	(.015)	(.069)	(.083)	(.052)
R&D capital	.074	.028	.051	.247	.104	.179
	(.023)	(.026)	(.017)	(.083)	(.080)	(.057)
Period dummy			.123			–.764
SIC dummies	yes	yes	yes	yes	yes	yes
N of observations	209	159	368	209	159	368
R^2	.903	.867	.890	.329	.227	.299

The results show two major differences from the 'log-level' specifications of Tables 3A and 3B. First, the output elasticities for labour increase at the expense of the capital output elasticities. With the exception of the pooled estimates the capital elasticity even becomes insignificant. Secondly, the elasticity of the R&D knowledge stock is more than doubled when one controls for 'permanent' differences across firms. The results suggest that both the traditional and the R&D capital variable are strongly correlated with firm effects. Further, Table 4 shows that the estimates for R&D stock elasticities for 1989–1993 are insignificant.

R&D intensity approach

Next estimates are made of the rate of return to R&D under the assumption of zero depreciation of the R&D knowledge stock and a marginal rate of return to R&D common to all firms. Here, as mentioned above, we replace $\Delta_4 k_i$ by the appropriate R&D intensity by estimating equation (8). The coefficient of the R&D intensity variable can be interpreted as the gross marginal private rate of return to R&D. The results are presented in Table 5. As can be seen from a comparison with Table 4, imposing the constraint $\delta = 0$ has only minor effects on the pattern of parameter estimates for the traditional inputs. According to these estimates the gross rate of return to R&D is insignificantly different from zero in the gross output specification and about 20 percent in the value added specification. The 1989–1993 period has a lower rate of return than the earlier period, although the differences are not statistically significant.

Table 5. Estimates R&D intensity equations

Dependent variable	Gross output			Value added		
Year	85–89	89–93	Pooled	85–89	89–93	Pooled
Coefficient of						
Labour	.216	.223	.215	.838	.677	.771
	(.038)	(.052)	(.030)	(.124)	(.139)	(.091)
Material inputs	.719	.693	.707			
	(.027)	(.032)	(.020)			
Capital	.024	.032	.030	.069	.101	.085
	(.020)	(.027)	(.015)	(.069)	(.083)	(.052)
R&D intensity	.052	–.004	.030	.218	.173	.192
	(.061)	(.079)	(.048)	(.085)	(.082)	(.059)
Period dummy			.083			–1.032
			(.032)			(1.088)
SIC dummies	yes	yes	yes	yes	yes	yes
N of observations	209	159	368	209	159	368
R^2	.898	.866	.990	.321	.241	.301

5. Robustness tests

A striking difference between the estimates for the ’log-level’ specifications of table 3B and the estimates for the ’long-difference’ equations (Table 4) is that the coefficients for the R&D variables are higher in the ’long difference’ estimates than in the ’log-level’ estimates, whereas the opposite applies to the elasticity estimates for the traditional inputs. There are several possible candidates for explaining the observed change in the patterns of the parameter estimates when switching from the cross-sectional to the time series dimension of the data. Plausible candidates are the measurement related issues such as the assumptions underlying the construction of the R&D knowledge stocks and the selectivity of the R&D data set. Furthermore, our data show heteroskedasticity in the error terms related to the R&D variables used in the equations. Also the simultaneity problem may be more manifest when estimating ’long difference’ equations. In this section we pay attention to the robustness of the results, to the assumptions underlying the calculation of the growth of the R&D knowledge stock variable, to selectivity and to the problems of heteroskedasticity and simultaneity. We first discuss the way in which several sources of biases were dealt with and lastly we present the results of the robustness tests, focusing on the estimates of the R&D variables and the elasticity of traditional capital inputs.

Depreciation and pre-sample growth for the R&D knowledge stock

With respect to the measurement related problems we first look at the construction of the R&D knowledge stock. A robustness test was performed by applying various assumptions for the depreciation parameter and the R&D pre-sample growth rate. The results of similar previous studies suggest that the estimates for the output elasticities of the R&D stock are rather robust to different assumptions concerning the rate of depreciation, δ. However, these results are based on balanced firm-level time series data with longer R&D histories. Given that the construction of data on the growth of the R&D stock – in essence – rests on only two observations for R&D expenditure, the elasticities presented in Tables 3 to 5 may be dependent on the choice of δ and the pre-sample growth g in formula 5. For this reason equation (2) is re-estimated using three alternative assumptions for δ (0.10, 0.15 and 0.20) and three assumptions for pre-sample R&D growth, g (0.03, 0.05, 0.07). The results of this robustness test show that the R&D output elasticities only slightly decline with increasing δ and with increasing g. Overall, the output elasticities seem to be rather robust to different assumptions with respect δ and g. For this reason and for reasons of space we shall not present the estimates for this robustness test (see Bartelsman et al. (1996) for more details).

Selectivity

In section 2 it was shown that in constructing the panel data, sample attrition was a possible cause of selectivity biases in regression results. Some elements of selectivity are inherent in the use of the R&D surveys, because the probability of exit decreases with the R&D intensity, which is our variable of interest. For this reason, the estimated R&D contribution to productivity growth could be biased. Selectivity can be taken into account by extending our models with a selection equation which models the probability of continuing in the sample. Several approaches are possible to capture the effects of selectivity. We could follow Heckman’s two-step method by including a correction term in the regression equations. A more efficient estimate can be obtained with the so-called Tobit model. Assuming that the probability of being selected in the sample depends on the level of the R&D intensity in the first year, the Tobit model reads as:

(9A) $\Delta_4 q_{it} = \lambda + \gamma \Delta_4 k_{it} + \Sigma_{j\in s} \beta_j \Delta_4 x_{jit} + \mu_{it}$

or

$$\Delta_4 q_{it} = \lambda + \rho \frac{\Delta_4 K_{it}}{Q_{i0}} + \sum_{j\in s} \beta_j \Delta_4 x_{jit} + \mu_{it} \qquad \text{if } D = 1$$

(9B) $\Delta_4\, q_{it}$ not observed if $D = 0$,

with selection equations

(10A) $D = 1 \quad \text{if} \quad c + \alpha \frac{R_{i0}}{Q_{i0}} + \eta_{it} > 0$

(10B) $D = 0 \quad \text{if} \quad c + \alpha \frac{R_{i0}}{Q_{i0}} + \eta_{it} \leq 0$,

where $\frac{R_{i0}}{Q_{i0}}$ is the R&D intensity in the starting year, c a constant term and η_{it} a Gaussian disturbance term.

In using the Tobit model the number of observations differ from those given for the matching specifications in tables 4 and 5, because firms which are in production survey samples but not in the R&D dataset in the end year are also included in the analysis.

Heteroskedasticty and simultaneity

Other possible biases in the 'long difference' estimates can arise due to heteroskedasticity and simultaneity. Indeed, the Goldfeld-Quandt test for heteroskedasticity indicates a significantly higher residual variance for firms with the lowest growth rates in the R&D stock than for firms with the highest growth rates[6)]. In the robustness tests we corrected for heteroskedasticity by applying weighted least squares with weights equal to the square root of the R&D variables. The possible biases due to simultaneity caused by the producers' joint decisions on inputs and outputs was investigated by using the Partial Total Productivity (labelled P-TFP) form for the productivity equation (see Bartelsman et al. (1996) for a detailed explanation of this approach).

Results of the robustness tests

The results for the different robustness tests applied to the pooled data are presented in Tables 6 and 7. Table 6 gives the elasticity estimates for R&D and traditional capital for the specifications with the growth of the R&D knowledge stock as the explanatory R&D variable. Table 7 gives the same estimates for the R&D intensity specifications, using the pooled results of Table 5 as a reference. The base case of Table 6 is represented by the pooled estimates of Table 4. WLS estimates are not given for the gross output specification because the relevant Goldfeld-Quandt statistics did not indicate heteroskedasticity for this specification.

Table 6. Robustness tests R&D stock approach on pooled data

Dependent variable	Gross output		Value added	
Coefficient of	R&D capital	Ordinary Capital	R&D capital	Ordinary Capital
Base LD	.051 (0.17)	.030 (0.15)	.179 (0.57)	.095 (0.52)
Selectivity LD	.061 (.022)	.038 (0.17)	.226 (.080)	.095 (.045)
Simultaneity LD	x	x	.190 (.064)	.098 (.043)
Heteroskedasticity LD	x	x	.070 (.039)	.269 (.054)
Heteroskedasticity + Simultaneity LD	x	x	.077 (.039)	.304 (.045)

Further P-TFP estimates are not presented for the gross output specification because the P-TFP approach starts from a value added specification.

Two conclusion can be drawn from Table 6. First when relating output growth to the growth of the R&D knowledge stock, the selectivity and the simultaneity bias seem to be rather small. Correcting for selectivity raises the R&D output elasticity for both specifications, but the difference compared with the base case is statistically insignificant. Secondly, simultaneity seems not to be an important source of bias for this specification either: the elasticity estimate for the P-TFP variant also does not differ very much from the base case estimate. However, correcting for heteroskedasticity makes quite a difference. Applying WLS reduces the estimates of the R&D capital elasticities and also restores the pattern of the two capital elasticity estimates found for the 'log-level' specifications of Table 3B, with the elasticity of the traditional capital input higher than that for the R&D capital input.

Lastly, Table 7 presents the results of the robustness test for the estimates of the rates of return to R&D, with the base case represented by the estimates of Table 5. Again the comparisons aim at assessing the importance of biases due to selectivity (both for the gross output and value added specifications) and heteroskedasticity (for the value added specification) [7)]. However, the pattern of results differ from that presented in Table 6. Selectivity seems to be an equally important bias as heteroskedasticity. Modelling the presence in the sample being dependent on the level of R&D doubles the rate of return for the gross output specification and also increases the rate of return to R&D in case of the value added specification by more than ten percent. The latter result is also obtained after correcting the base case estimates for heteroskedasticity in the R&D intensity measure, leading to an estimate for the gross rate of return to R&D close to 0.30.

Table 7 Robustness tests R&D intensity approach on pooled data

Dependent variable	Gross output		Value added	
Coefficient of	R/Q	Ordinary Capital	R/Y	Ordinary Capital
Base LD	.030 (0.48)	.030 (0.15)	.192 (0.59)	.085 (0.52)
Selectivity LD	.124 (.058)	.025 (0.17)	.314 (.078)	.085 (.060)
Heteroskedasticity LD	x	x	.348 (.154)	.276 (.041)

6. Summary and conclusions

In a first attempt to estimate the contribution of R&D to productivity growth using firm-level data for the Netherlands, several variants of production functions with R&D as a separate input have been analysed. The main objective was to estimate the private returns to R&D and output elasticities of the stock of R&D knowledge capital. The data derive from the four-yearly extended R&D surveys for 1985, 1989 and 1993. These surveys were linked to the production surveys. In using firm-level data it became possible to circumvent the specific problems which arise when using aggregated R&D data for the Dutch manufacturing industry. These problems are related to the very skew distribution of manufacturing R&D due to the dominance of few multinational enterprises. The variants of the basic R&D augmented production functions were made along different dimensions. First corrections were made for double- counting of R&D inputs. This correction increased the R&D output elasticity estimate for the 'log-level' value added specification by about 5 percentage points. Next 'long-difference' estimates were presented, both for output elasticities and rates of return to R&D. The 'long-difference' specifications correct for biases from firm fixed effects. Subsequently, the 'long-difference' specifications of the R&D augmented production function were used as a base case to assess the importance of other sources of biases in the R&D estimates. The R&D elasticities appeared to be relatively insensitive to different assumptions concerning the depreciation rate and pre-sample growth in R&D expenditure and also to simultaneity due to the joint decision on inputs and outputs. Selectivity appeared to be an important source of bias for the estimation of the gross rate of return to R&D, but not so when estimating elasticities of R&D capital. In both cases heteroskedasticity of the error terms related to the R&D measures seems to be an equally important source of bias. Cutting through all the specifications the output elasticity for R&D capital is about 6 percent for gross output and about 8 percent for value added, while the private rate of return to R&D varies between 12 percent for gross output and 30 percent for value added.

Notes

1) R&D surveys were also conducted for the intervening years, but only for the largest R&D performing firms. The 1985, 1989 and 1993 surveys are more representative, and provide a more adequate sample size after linking with the production statistics.

2) SIC: Standard Industrial Classification of Statistics Netherlands; the 3-digit-level allocates industrial firms to 122 groups.

3) The industry groups are: food, beverages and tobacco (SIC 20,21), chemical industry and allied (SIC 28–31), metal industry (SIC 33–38) and other manufacturing (SIC 22–27, 32 and 39).

4) For instance in 1989 the 'top five' firms had 15 percent of their employees working in R&D but their labour productivity was about the same as the rest of the firms in the panel.

5) At the 90% significance level the hypothesis of constant returns to scale is rejected in favour of slightly increasing returns to scale for the 1993 value added specifications.

6) The Goldfeld-Quandt test statistics is computed based on residual variances for the first and forth quartiles of firms for the distribution of the R&D stock growth. For instance for $\delta = 0.15$ the test statistics were 3.151 for 1985–1989 at a critical value of 1.60.

7) The Goldfeld-Quandt test also indicates that heteroskedasticity is absent for the gross output R&D intensity specification. Furthermore simultaneity appears to be an insignificant source of bias for the value added specification, also when using the R&D intensity measure as the explanatory R&D variable.

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Effects of firm performance and technology on wages: evidence from cross-sectional matched worker-firm data*

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1. Introduction

According to neoclassical competitive theory there are no wage differentials between employees with comparable skills and working under similar conditions. In fact, however, there are systematic differences in wages across industries or firms (enterprises and establishments) which cannot be explained on the basis of observed worker and job characteristics (such as age, education and shift work). Empirical evidence for the above is established by several studies, like Krueger and Summers (1988) for the US and Hartog et al. (1994) for the Netherlands.

Alternative theories, among which the efficiency wage theory and the insider-outsider theory, have proposed possible explanations for the persistent wage differentials between industries or firms. In view of the important role of trade unions in the Netherlands at wage formation, we consider the insider-outsider theory. This theory emphasizes that workers (insiders) have more bargaining power in wage negotiations than the unemployed (outsiders). This difference in bargaining power is due to different levels of knowledge and skills. In particular workers of technologically advanced firms possess strategically important knowledge, such as know-how gained at an R&D department or by experience with computer-based production processes. Because of the constant threat for the firm that employees go over – with their knowledge – to a competitor, they have considerable bargaining power. Given this power, insiders are able to obtain a share of the revenue of a firm in addition to the reservation wage of outsiders. If this bargaining model is correct, the wage rate at firm-level depends on the performance, the technology-intensity and the number of insiders in the firm.

Determining the empirical relevance of alternative models of wage determination is quite important, since the non-competitive models generate implications with respect to issues such as unemployment and industrial policy. An increase in the wage above the

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competitive wage by insider power of unions, could under certain circumstances lead to a reduction of employment of outsiders. One may consider the research on persistent wage differences across firms as an attempt to test indirectly the validity of the competitive model of wage determination against the insider-outsider theory.

In trying to explain why non-competitive wage differentials exist, various studies have examined the effect of an employee's industry or firm on wages. Most empirical work relies either on worker surveys with little information about employers or on firm surveys with little information about workers. Only a few studies used detailed information at micro-level on both employer and worker characteristics to analyze the effect of technology use and profitability on wages. In this paper we examine the wage differences across firms in the Dutch manufacturing industry. To study the effect of technology and performance on wages, we shall use a cross-sectional database that matches data on individual workers and on their employers from two years. This dataset contains information on earnings, personal and job characteristics, firm-level productivity, R&D expenditure and manufacturing technology use for individual workers.

The remainder of this article is organised as follows. Section 2 reviews previous studies of the impact of firm performance and technology on wages. Before the estimation results of the wage regressions are described in section 4, section 3 describes the data used in the study. Section 5 concludes and suggests topics for further research.

2. Previous studies

Previous studies examining the relationship between wages and firm (or industry) characteristics fall into three categories. The first group consists of studies attempting to relate firm attributes and average worker characteristics to a measure of firm average wages. Adopting a log-linear wage function derived from human capital theory:

$$(1) \qquad \ln w_j = \Sigma_m ß_m x_{jm} + \Sigma_n \gamma_n z_{jn} + \varepsilon_j,$$

where $\ln w_j$ is the (log) average hourly wage paid to workers in firm j, x_{jm} is a set of average characteristics (m=1,...,M) of workers in firm j, z_{jn} is a set of firm characteristics (n=1,...,N), $ß_m$ and γ_n are parameters and ε_j is a normally distributed error term.

Another group of studies uses individual data on wages and personal characteristics, and augments the set of explanatory variables of (log) wage functions with average firm attributes. The specification is thus:

$$(2) \qquad \ln w_{ij} = \Sigma_m ß_m x_{im} + \Sigma_n \gamma_n z_{jn} + \varepsilon_{ij},$$

where lnw_{ij} is the (log) hourly wage of worker i in firm j, x_{im} is a set of worker i characteristics and ε_{ij} is a normally distributed error term. The problem with this approach is that the inclusion of aggregate data in a micro specification can lead to some bias in the estimated parameters.

A third group proceeds in two steps and offers a possible solution to the aggregation problem. In the first step an individual wage equation is estimated with firm characteristics z_{jn} replaced by firm dummies α_j. In the second step these firm dummies α_j are regressed on firm characteristics z_{jn}. This two-step regression has the following form:

(3a) $lnw_{ij} = \Sigma_m ß_m x_{im} + \alpha_j + \mu_{ij}$,

(3b) $\alpha_j = \Sigma_n \gamma_n z_{jn} + \mu_j$,

where μ_{ij} and μ_j are normally distributed error terms.

A large part of the research on the relationship between wages and firm characteristics is concerned with the effect of firm performance (that is profitability and productivity). Dickens and Katz (1987) give a review of early studies. Recent studies that adopted a bargaining or insider-outsider model are Nickell and Wadhwani (1990), Holmlund and Zetterberg (1991), Nickell and Kong (1992), Nickell et al. (1994), Lever and Van Werkhoven (1995) and Johansen (1996). These studies were based on industry-level or firm-level data for different countries and used a wage equation including value added per employee (the inside factor) and the aggregated wage rate (the outside factor) as explanatory variables. The overall conclusion was that inside factors, measured by labour productivity, have a significant positive effect on wages. Hildreth (1995) investigated not only whether employers share rents with their workers but also which shocks create rent-sharing. Using British matched worker-firm data he found large rent-sharing effects for workers whose employers have invested in new process technology.

There is a growing body of empirical evidence on the role of technological change in influencing wage inequality. Brouwer and Kleinknecht (1994) have tested the prediction that technology-intensive firms try to prevent their workers from quitting by paying higher wages. After controlling for the influence of worker education, age and sex, they found that high-technology firms pay high wages. This study used Dutch firm-level data on R&D activities (measured by the percentage of R&D staff in total employment). Other empirical studies which used R&D activities as a proxy for technological change are Tan and Batra (1995) and Vainiomaki and Laaksonen (1995). The former used data for individual firms in Taiwan, Mexico and Colombia to show that employer investments in R&D and training lead to large wage premiums for skilled workers but not for unskilled workers (after controlling for firm characteristics). Vainiomaki and

Laaksonen found no straightforward connection between the (average) wages of Finnish manufacturing firms and the technological level (measured by R&D expenditures) of their industries. The wage equations estimated in the last two studies did not include controls for characteristics of the workforce in the firms.

Another measure of the technological position of a firm is the use of computer-based machines such as CNC (computer numerical control), DNC (distributed numerical control), robots, (personal) computers and computer aided design. The following two studies applied this technology measure. Dunne and Schmitz (1995) found that firms that use the most advanced technology pay the highest wages. They used linked firm-level US data. No controls for worker quality were included in this study. Using matched worker-firm data Doms et al. (1995) found similar correlations between advanced technological use by employers and wages, though the size of the wage premium was substantially diminished after controlling for worker characteristics (such as education, occupation, age and sex). Their results were based on two approaches: one-step regression (1) using firm data and two-step regression (3a,b) using matched worker-firm data. Krueger (1993) explored the impact of the ’computer revolution’ on the wage structure using worker-level data. He showed that US employees are rewarded more highly if they use computers at work. Computer-use included programming, word processing, computer-aided design etc. In this study controls for the effect of worker education, age, sex, race and occupation were included.

One problem with cross-sectional estimates is that they could be biased because of unobservable worker or firm fixed effects (such as inborn worker skills). Panel data offer the opportunity to control for the biasing effects of unobservable time invariant variables. Entorf and Kramarz (1995) studied the impact of both use of and experience with computer-based technology on wages. This analysis was based on cross- sections as well as panels, which matched French data on individuals and on their firms. The range of technology covered was larger than the computer-based technology investigated in Doms et al. (1995) and Krueger (1993). The French data also included advanced office technologies. The wage regressions were controlled for worker education, experience, occupation, sex, full-time/part-time, firm size and profits. Results based on individual panel data differ from what emerged from the cross-sectional estimates. After the elimination of the individual effects the technology use by workers no longer had a significant influence on wages. This could be explained by the fact that higher average wages at the firm level for technologically advanced firms are related to higher unobserved quality of the workers.

Some studies assume that all explanatory variables in the wage regressions are strictly exogenous. This may be questionable with firm-level variables like technology. Chenells and Van Reenen (1995) implemented a two-stage least squares (2SLS) model to deal with the simultaneous determination of technology (with R&D intensity and number of patents as instruments) and wages. They used UK firm-level data and defined technology as a dummy variable for whether there has been an advanced technical change in the firm. The human capital controls were relatively crude. Controlling for the endogeneity bias led to the conclusion that the introduction of new technologies does not cause higher wages and that high wages appear to give firms greater incentives to introduce new technologies.

3. Data description and summary statistics

The data used in this study concern cross-sectional information on individual workers and their firms in Dutch manufacturing for the years 1985 and 1989 [1)]. The worker-firm data were created at Statistics Netherlands (CBS) by linking micro-data from the wages survey (WS), the production survey (PS), the R&D survey (RDS) and the manufacturing technology survey (MTS).

The annual wages survey provides data on the structure of earnings in firms with employees. Data from the survey is broken down by employee characteristics like age, education and sex, and job characteristics like the working hours arrangement (regular, irregular or shift work). The survey has a two-stage sample design. First the CBS takes a stratified sample of firms and then each sampled firm takes a simple random sample of its employees. For each sampled employee, his employer provides data on, among other things, gross weekly wages (excluding overtime and holiday pay). The gross weekly wages are transformed into gross hourly wages using information on weekly working hours. Only in the years 1985 and 1989 were firms asked about their workers' level of education.

In the annual production survey firms in the manufacturing industry are asked for detailed information on inputs and outputs. Among other things this information contains sales, gross output, value added, wage bill, number of employees, materials and electricity use. From these survey data we calculated a measure for labour productivity as gross value added (at factor costs) per employee. The measure for profitability equals gross value added (at factor costs) minus wage bill divided by number of employees. Up to 1987 all firms with 10 or more employees were observed and smaller firms were excluded. Since 1987 all firms with 20 or more employees are surveyed, while a sample is drawn from the firms with fewer than 20 employees.

The yearly R&D Survey provides insight into the size and the structure of R&D activities in the Netherlands. In the years 1985 and 1989 an extended R&D Survey was held among all firms with 50 or more employees. From these surveys data is available on R&D full-time equivalents and other staff and expenditure on in-house (or own) R&D and outsourced R&D. The R&D expenditure is further disaggregated by type of cost (staff costs, costs of materials used and R&D equipment investments), by type of research (basic and applied) and by object of research (process and product innovation). We used (total) own R&D expenditure per employee (henceforth called ’R&D intensity’) as a measure of the technological status of a firm.

The four-yearly manufacturing technology survey asks firms to indicate whether they used any of a list of computer aided manufacturing (CAM), design (CAD) and production planning (CAPP). However, here we focus on the information pertaining to CAM equipment, as in general it is this technology which results in labour productivity improvements. The CAM technologies include CNC, DNC and robots. The MTS was conducted in 1985 and 1989 among firms with five or more employees. As firms were only requested to state how many pieces of each type of CAM technology were in operation in the 1989 survey, we have created a measure of technology by summing the positive responses to binary questions on use of three different types of CAM technologies. This measure is henceforth denoted by ’use of CAM equipment’.

We analysed the effects of firm performance and technology on individual wages by means of a log-linear regression model which relates the logarithm of gross hourly wages to employee, job and firm characteristics (see equation (2)). Appendix A contains a description of the regressors used in the analysis. We refrained from the use of profitability in the wage model, because this variable is highly correlated with labour productivity. Further we added as regressor the sector of economic activity (according to the 2-digit level of the CBS Standard Industrial Classification) to capture the influence of other firm-specific variables like capital intensity. For most regressors a set of dummy variables is created by treating each category of the regressor in question as a separate variable. To avoid multicollinearity it is necessary to exclude one of the dummies (marked with an asterisk in appendix A) for each explanatory variable. We took no account of the interaction effects between the regressors in the wage equation. Addition of interaction terms would lead to a large increase in the number of dummies and with that to inaccurate estimates of regression parameters. Further it is assumed that all explanatory variables in the wage regression are strictly exogenous, so that the model can be estimated unbiasedly by ordinary least squares (OLS).

Our cross-sectional dataset is the result of linking micro-data from several surveys. We examined how representative the linked datasets are by comparing with the original datasets. It appears that firms in the linked datasets are larger than in the original samples. We also find that a large portion of firms in the linked datasets are in the chemical and petroleum industry, while other manufacturing sectors account for a smaller portion. The comparison of datasets shows that workers in the original sample and in the linked samples are fairly similar. One exception is the mean hourly wage: workers in the linked dataset earn higher wages than the workers in the original dataset. There is much empirical evidence that large employers pay their workers more than small employers (see for instance Brown and Medoff, 1989). The fact that our linked samples contain larger firms implies that our linked samples will also contain higher wage workers. Therefore, we have to take into account that the regression estimates based on linked data may be subject to some sample selectivity bias.

4. Empirical results

Appendix B shows the estimation results from the log-linear wage regressions based on different datasets for the years 1985 and 1989. In the appendices the OLS estimates of the regression parameters along with their statistical significance levels are given. These parameters represent approximately the proportional change in the hourly wage resulting from a change in one of the explanatory variables (given the effect of the other included variables). There are four columns with estimates, consisting of a cross classification of year (1985/1989) and type of technology (R&D/CAM). Note that we have used different datasets for the estimation with the R&D variable and for the estimation with the CAM variables: respectively the linked WS-PS-RDS dataset and the linked WS-PS-MTS data set. More detailed results are given in Boon (1996).

The adjusted multiple correlation coefficient (R^2) of the regression model including both employee, job and firm variables are about 55 per cent, so that 55 per cent of the variation in the log hourly wages is explained by the model. The omission of the firm characteristics from the wage equation that contains all variables decreases the R^2 by about 3 per cent (see Boon, 1996). So the overall contribution of firm variables is rather small. The firm variables have less sizable effects on the wages than the employee and job variables. Note that the sample size of the data sets ranges from 675 to 1,992 employees.

First, we consider effects of employee and job characteristics. Most variables have a statistically significant effect (at the 95 per cent level) on (log) wages. For the standard human capital variables age, sex and education we find the usual theoretical effects in the (log) wage regressions. The wage a worker earns increases as he or she becomes older, and a woman earns ceteris paribus about 10 per cent less than a man. Higher educated workers receive higher wages than workers with a lower education. Further, full-time workers are better rewarded per hour than part-timers or flexible labour forces, and irregular or shift work pays better than regular work.

Next, we look at the wage effect of labour productivity, activity sector, and firm size. Firm labour productivity has a statistically significant (at the 95 per cent level), though limited in size, effect on worker reward. This effect is quite stable across time. Increasing the value added per employee with 1,000 Dutch guilders results in a hourly wage rise of 0.05–0.10 per cent in the years concerned. It appears from our dataset that a correlation exists between labour productivity on the one hand and working hours arrangement, firm size and activity sector on the other. Excluding the latter three variables from the wage regression appeared to lead to a minor increase in the productivity effect (see Boon, 1996). It can be concluded from the empirical estimates based on our matched worker-firm data that the wage rate in the Dutch manufacturing industry is to a small extent determined by firm productivity.

With respect to firm size we see the result that workers in large firms are rewarded with higher wages. The effect of the sector of economic activity is harder to determine because of the relatively high standard errors (not shown here) of the coefficient estimates. The average worker wage is relatively low in the textile, apparel and leather industries.

Lastly, we examine how worker wages vary with the technology use of their firm. As already mentioned this study uses two measures of the technological status of a firm: internal R&D expenditure per employee and number of CAM technologies applied. The OLS estimates based on linked WS-PS-RDS data show that the size of internal firm R&D activities has a statistically significant (at the 95 per cent level) but limited effect on the hourly wage. Increasing the own R&D expenditure per employee by 1,000 guilders results in a wage rise of 0.01–0.07 per cent. Thus, R&D intensive firms pay higher wages. In our dataset we do not find a strong correlation between R&D intensity and other included variables (such as education). This means that the R&D effect on wages does not increase after excluding other variables in the model.

We analyse the influence of firm use of CAM technologies on worker rewards. The regression results based on matched WS-PS-MTS data show that there is no statistically significant CAM technology effect on wage rates. It is possible that the insignificant CAM coefficient is caused by correlation between CAM use and other included variables. Evidence of multicollinearity can be found by deleting some variables, like labour productivity, firm size and sector of economic activity, from the wage equation. From the estimation of this restricted equation (not shown here) it can be derived that this does not lead to a large improvement of the significance of the CAM effect. From our results we can conclude that no clear relation exists between worker wages and firm use of CAM equipment.

5. Conclusions and further research

The present article investigates the impact of firm performance and technology use on worker wages in the Netherlands manufacturing industry for the years 1985 and 1989. Our empirical analysis uses cross-sectional worker-firm data which are created by linking Statistics Netherlands surveys on wages, production, R&D and manufacturing technology.

The estimation results show that firms that have a higher R&D intensity or that have a higher labour productivity pay their workers significantly higher wages. We controlled adequately for the influence of worker quality. Further we found that the use of manufacturing technology has no significant influence on the wages of workers. Firm characteristics play a less important role at the wage formation than employee and job characteristics like age, education and job level. The level of R&D has a small significant effect on wages, while the use of CAM-technology appeared to have a slight effect. The results presented here for the Netherlands can be seen as providing weak support for the insider-outsider model of wage determination and not as a structural test of this model. This means that wage differences caused by insider power do not play a substantial role in Dutch manufacturing firms. In other words, the Dutch labour market behaves reasonably in accordance with competitive theory.

Finally, we would like to point out some limitations of the results presented. In the wage model we included aggregate data (firm level) as well as micro-data (worker level). OLS estimates of the wage regression parameters may be biased because of this aggregation problem.

There are more larger firms in the linked dataset than in the original sample. Thus, the estimated regression coefficients of the wage equations may be subject to some sample selectivity bias.

It is assumed that all explanatory variables in the wage regressions are strictly exogenous. This may be questionable with firm-level variables such as technology and productivity. Unfortunately we lack instruments to take endogeneity into account by econometric methods.

The wage regression estimates are based on cross-sectional data and may be biased by neglect of unobservable worker or firm effects. However, in defence of our analysis, a number of variables are used here that are often subsumed into the fixed effects component.

Only panel data of workers and their firms would enable us to deal more satisfactorily with the problems of fixed effects. The Dutch socio- economic panel survey offers good possibilities for further research, because in this annual survey a panel of individuals are asked for their demographic, geographic, labour and income data. By linking this panel worker survey with cross-sectional (worker-)firm surveys such as the wages survey and the production survey we can create a promising research database.

Appendix A. Description of variables used in the analysis

Variable	Definition
Employee characteristics	
age	≤19 years
	20–24 years
	25–29 years*
	30–34 years
	35–49 years
	≥50 years
sex	man*
	woman
level of education	primary education
	advanced primary education
	intermediate education*
	higher vocational education
	university education
	unknown
Job characteristics	
employment contract	full-time*
	part-time/flexible
working hours arrangement	regular*
	irregular/shift work
Firm characteristics	
sector of economic activity	food, beverages, tobacco*
	textile, apparel, leather
	paper, printing
	chemical and petroleum
	metal, electrical engineering
	other manufacturing
firm size	≤99 employees
	100–499 employees*
	≥500 employees
labour productivity	gross value added per employee
R&D intensity	own R&D expenditure per employee
use of CAM equipment	none*
	1 type
	2 types
	3 types

* Included in the constant term of the wage regression.

Appendix B. **OLS regression estimates**

Variable		WS-PS-RDS		WS-PS-MTS	
		1985	1989	1985	1989
intercept		2.7643*	2.8999*	2.8645*	2.9116*
age	≤19 years	–0.4317*	–0.5254*	–0.6437*	–0.6898*
	20–24 years	–0.1076*	–0.1091*	–0.1262*	–0.1356*
	25–29 years	0	0	0	0
	30–34 years	0.1595*	0.1511*	0.1380*	0.0863*
	35–49 years	0.3004*	0.3030*	0.2381*	0.2561*
	≥50 years	0.3789*	0.3540*	0.2793*	0.2638*
sex	man	0	0	0	0
	woman	–0.0895*	–0.1077*	–0.1390*	–0.1358*
level of education	primary education	–0.2665*	–0.2444*	–0.2747*	–0.2132*
	advanced primary education	–0.1030*	–0.1023*	–0.1421*	–0.1097*
	intermediate education	0	0	0	0
	higher vocational education	0.2301*	0.2693*	0.2454*	0.2972*
	university education	0.4441*	0.4280*	0.3142*	0.3231*
	unknown	–0.0722	–0.0520*	–0.0212	–0.0480*
employment contract	full-time	0	0	0	0
	part-time/flexible	–0.1401*	–0.0255	–0.0190	–0.0616#
working hours arrangement	regular	0	0	0	0
	irregular/shift work	0.1113*	0.0819*	0.0688*	0.0747*
firm size	≤99 employees	–0.0307	–0.0529	–0.0650*	–0.0571*
	100–499 employees	0	0	0	0
	≥500 employees	0.0150	0.0310*	0.0238	0.0526*
sector of economic activity	food, beverages, tobacco	0	0	0	0
	textile, apparel, leather	–0.1052	–0.0868*	–0.1013*	–0.0548*
	paper, printing	0.0453	0.0396	0.0232	0.0526*
	chemical and petroleum	–0.0194	–0.0119	0.0376	–0.0066
	metal, electrical engineering	–0.0431	–0.0394*	–0.0431#	–0.0202
	other manufacturing	–0.0407	–0.0426	–0.0486	–0.0610*
labour productivity		0.0010*	0.0005*	0.0007*	0.0006*
R&D intensity		0.0007*	0.0001*		
use of CAM equipment	none			0	0
	1 type			0.0121	–0.0003
	2 types			–0.0033	–0.0119
	3 types			0.0783	–0.0263
adjusted R^2		0.550	0.523	0.552	0.584
sample size (employees)		675	1,992	982	1,749

* significantly different from zero at the 95% level.
\# significantly different from zero at the 90% level.

Note

[1] We could not create a panel of individual workers, because in our data set there were no variables available which uniquely identify each worker in the course of time.

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