Automation

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Summary

The automation of production processes is an important topic on the policy agenda in high-wage countries, and Denmark is no exception. However, the knowledge of the adoption of automation technologies across firms, of drivers of investments in automation, and on the association between automation and firm performance are limited. This paper uses a new survey to collect data on automation combined with register data to examine these issues. The variation in the adoption of automation technologies is high, the change in adoption over time is slow, and almost half of Danish manufacturing firms relied greatly on manual production processes in 2010. Increasing international competition from China is a driver for investments in automation, i.e., the manufacturing firms that are exposed to intensifying competition from China in their output markets invest more in automation than firms that are not exposed to this type of competition. We conduct external validation of the automation survey by examining the association between the automation measures and firm performance measures constructed from completely independent data sources. We find that the measures of automation are significantly associated with productivity and profitability.

JEL codes: F14, L2, O30, M2, O14

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Automation, Performance, and International Competition: A Firm-Level Comparison of Process Innovation

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1. INTRODUCTION

Increasing competition from low-wage countries has led many manufacturing firms to close or offshore parts of the production process. It has been argued that this may jeopardize continued welfare improvements. Helper, Krueger, and Wial (2012) argue that the (US) manufacturing sector is the major source of commercial innovation and is responsible for the lion's share of export earnings. The downsizing of the manufacturing sector is a cause for concern among policy makers in high-wage countries. They have been searching for clever ways to bring back manufacturing production and jobs. New technologies and automation are often considered possible solutions to the challenges.[1]

This paper presents empirical evidence for the adoption of automation technology across manufacturing firms using a firm sample with information on automation. Moreover, we find evidence of a driver of why some firms adopt automation technologies while others do not. Finally, we examine the association between automation and firm performance to ensure external validation of the automation survey that we develop.

There is almost no systematic empirical evidence for the potential economic effects of automation at the firm level. A deeper understanding requires firm data. We have gathered a new dataset that measures automation in Danish manufacturing firms. Based on observations from firm visits, two important measures that describe automation stand out. These are the stock of automated capital and the share of production processes that is automated. We label the latter measure the automation score and the purpose of this measure is to capture that automated capital can be used more or less efficient by the firms, depending on how well it is implemented and integrated into the manufacturing system. The survey was developed so that these two aspects could be measured.[2]

We start by examining the adoption of automation across manufacturing firms. Many industries are already using industrial robots, which is documented by data from the International Federation of Robotics, but information about the adoption of automation technologies across firms is not available. We find that the use of automation is modest in many firms. In 2005, almost 40 percent of the firms'

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[1] It is expected that many technological innovations that can potentially contribute to productivity will be developed in the future, see Council of Economic Advisers (2016). It is also expected to benefit activities outside manufacturing through servitization of products and closer connections to design and innovation, which allows for positive effects for the total economy, see Bruegel (2017).

[2] The motivation for including the automation score in the survey was that managers, supplier of automation equipment and industry experts claimed that the share of production processes that is automated is an important aspect of automation that is not necessarily captured by standard measures of capital. This claim is strongly supported in the empirical analyses of this paper.

investments in machinery and equipment targeted for automation were at approximately 10 percent or lower. In 2010, almost half of the firms still relied to a high extent on manual production processes. At the other end of the spectrum, there are firms that devote all their investments in machinery and equipment to automated capital and have high automation scores. During the five-year period under investigation, the adoption of automation mostly consists of incremental changes. These results lead us to conclude that there is high variation in the adoption of automation technologies across firms. This conclusion also holds within sub-industries, production methods and other groups of firms.

Given the variation in automation across firms, an immediate question is what drives investments in automation. Therefore, we turn to examining a potential driver of the adoption of the automation technologies. Specifically, we focus on increasing international competition from China since its admission to the World Trade Organization (WTO) and investigate whether this has accelerated the adoption of automation technologies. We refer to this as the trade-induced automation hypothesis. We find that increasing Chinese exports to the world drive investments in automated capital, which supports the hypothesis that firms intensively exposed to such exports, have a larger incentive to automate. The firms that specialize in product types in which Chinese exporters have a comparative advantage have an incentive to invest more in automation to withstand the increasing competition compared to firms that specialize in other products. The growth rate in automated capital is 2.16 percentage points higher per year for the 75th percentile firm compared to the 25th ranked after Chinese export changes for the firms' main product. We also investigate whether increasing Chinese exports to the world is related to the automation score. This turns out not to be the case, suggesting that Chinese export changes for the firms' main product only drive investments in automated capital but not how these investments are implemented in production.

Biased estimation results due to omitted variables are a concern. As long as the omitted factors that are correlated with automation are fixed over time at the firm level, we can handle these time-invariant variables using long-differences that sweep out firm fixed effects. Moreover, using long-differences is an approach for decreasing measurement error bias. In addition, we also include industry by region dummies to handle potential trends in automation measures. These analyses indicate that the result for the driver of automation is likely a causal relationship. However, we cannot claim that we have completely handled all the potential endogeneity problems that can arise from omitted variable bias.

Finally, we investigate whether the automation measures are significantly associated with alternative measures of firm performance. The analysis is a way to determine whether our survey contains important information on automation and not just white noise. We find that increasing use of automation is significantly associated with higher productivity growth and increases in profitability. The relationships are robust to a wide range of control variables including industry dummies interacted with region dummies, skill shares, and other production factors. These results offer some external validation of the automation survey. This approach follows Bloom and Van Reenen (2007) and Bloom et al (2019) that also apply the methodology on survey data. We do not give a causal interpretation to the results. Estimation of the causal effect of automation on firm performance is highly challenging and requires good instrumental variables, experimental data on automation, or other exogenous variation, which we do not have.

There is a small stream of existing literature on automation. Dunne (1994), Doms, Dunne, and Troske (1997), and Bartelsman, Leeuwen, and Nieuwenhuijsen (1998) focus on an earlier wave of automation during the 1980s and early 1990s. These papers mainly describe differences between plants or firms that adopt automation technologies and plants or firms that do not. Bartel, Ichniowski, and Shaw (2007) study a more recent period, namely, 1997-2002, but focus on one narrowly defined industry, i.e., valve manufacturing. Based on estimations of longitudinal models, investments in automation are found to improve the efficiency of production. Recent studies have mainly focused on the relation between automation and employment. The empirical papers that explore performance include Graetz and Michaels (2018) and Kromann, Malchow-Møller, Skaksen, and Sørensen (2019), and both papers conduct an industry-level analysis of productivity. They find that the industry-level adoption of industrial robots has raised productivity.

The rest of the paper is structured as follows. Section 2 presents empirical results for the adoption of automation technologies. Moreover, automation examples from firm visits are presented and the design of the survey is described. We present the empirical framework and results for the trade-induced automation hypothesis in Section 3. The external validation of the automation survey is studied in Section 4. Section 5 discusses policy implications and concludes the paper.

2. THE IMPORTANCE OF CHARACTERIZING AUTOMATED CAPITAL

This section first reports on the observations from firm visits used to develop the questions in the automation survey. Second, we illustrate the structure of the survey, including information on how the automated capital and automation score are measured. Third, an analysis of the distribution of automation across manufacturing firms is presented and, fourth, the descriptive statistics for the firms used in the empirical analysis of Sections 3 and 4 are presented. A description of the data collection process is included in the online Appendix A.

2.1. Examples of Automation from Firm Visits

Three main conclusions were drawn from the firm visits. First, there was great variation in the level of automation across firms. Second, the automation increased in many firms over the five-year period under investigation. Third, automation occurred in many different areas of the production process. Below, we illustrate these observations in more detail.

One of the most automated firms that was visited operated in the food industry. In 2005, this firm invested in a new production system that almost fully automated production. Hardly any workers were present on the factory floor except for machine operators who ensured that all machinery was running as required. In the warehouse, a worker still manually transported products using a forklift truck but with information from a software system on where to go and what to collect. In 2010, all investments in machinery and equipment were targeted for automation in this firm.

In contrast to the fully automated firm, the firm visited with the lowest level of automation was a firm that operated in the electrical and optical equipment industry. Similar to the above firm, this firm is large and exports many of its products. The run time, i.e., the time required to complete one item, was long. Between 1 and 3 weeks was required to produce a product, and production included approximately 270 production processes. Although the firm produced only approximately 250 items a day, 6,000 items were in process at all times. The production floor consisted of few machines and many workers performing manual tasks, such as sounding, testing and moving objects from one workstation to another. Very few investments in machinery and equipment were targeted for automation in 2010, although industry experts assessed that many of the production processes could easily be automated.

These two examples illustrate that there was great variation in the focus on and investments in automation across firms. In the remainder of this sub-section, we describe three automation projects that a small manufacturing firm in the chemical and pharmaceutical industry has implemented in its production. Because the firm tracked the run time before and after the processes were automated, an assessment of the effects on firm performance is included.

The first example is the phasing out of manual handling in the movement of semi-finished products between workstations. After the automation of this process, the handling is performed by machines that do not require manual monitoring and intervention. Before automation, employees had to handle the semi-finished products and move them between workstations. The outcome of this change in two production processes resulted in a reduction in the run time by factors of 4 and 8.

The second example is the automation of packaging products. Packaging products often involve folding boxes, loading products in boxes and some final controls. The firm invested in a machine that automatically places products in cardboard boxes. Moreover, the boxes are closed and sealed automatically without manual intervention. Before the installation of the new machine, workers manually placed products in boxes, closed them and sealed them. The investment in the packaging machine improved product quality by automatically weighing packages and improved the run time and inspection time, i.e., the time required to inspect a product, due to a change from two processes that were merged into one process.

The third example is related to the automation of a welding process in production. The firm installed a robot that automatically performs a welding process as opposed to the process being performed manually by a worker. Through this investment, the run time of the task was improved. Before the task was automated, 21 seconds were required to weld one product; after automation, the task was completed in 8 seconds.

We end this sub-section with a fourth and final example of inventory processes from another firm. In one of the most automated firms visited, the warehouse software system oversees the flow of all goods. Robots place and select orders of whole pallets and transport them out to trucks for delivery to customers. By automating the entire warehouse, the firm decreases the number of products that are damaged during storage and transportation, which increases the product quality delivered to customers. Simultaneously, workers are not used to select, palletize or ship, which reduces the number of employees required for inventory management. Unfortunately, we do not have data on the performance effects of this investment.

The examples illustrate that automation can take many forms, that many different production processes can be automated, and that automation can result in lower costs and stronger firm performance.

2.2. Structure of the Survey on Automation

Based on the observations from firm visits, two important aspects of automation should be included in the survey. The first aspect is automated capital. Production managers, engineers, and industry experts argued that automated capital constitutes a specific type of capital that is different from non-automated capital in the sense that it has a relatively larger effect on firm performance. To obtain a measure for automated capital, we needed to separate investments in machinery and equipment into automated and non-automated investments. Specifically, we formulated the following question for the survey:

What percentage of new capital investments in machinery and equipment is targeted at automation?

The respondent can choose among the following 5 ranges: 0-12 percent, 13-25 percent, 26-50 percent, 51-75 percent and 76-100 percent. The question is asked for the years 2005, 2007 and 2010. By combining answers to this question with register data on investments in machinery and equipment, we can determine the investments in automated capital. With data on investments, we construct automated capital stocks using the perpetuity investment method (PIM). The details are presented in the online Appendix B.[3]

The second aspect that we wanted to measure is the automation score that captures that automated capital can be used more or less efficient by the firms, depending on how well it is implemented and integrated into the manufacturing system. A measure of the automation score would optimally require information about all production processes in all firms. However, because the aim is to obtain data for a large number of firms across different manufacturing industries with different production processes, the compromise was to simplify production into three stages with multiple types of production processes in each stage, as illustrated in Figure I.

The first stage is manufacturing, processing and handling, in which all parts of the physical product are produced. The second stage is assembling and packing, in which all parts of the product are assembled into finished products and packed for customers. The third stage is inventory, which includes both raw materials and finished goods.

[FIGURE I around here]

Automation can be used for several purposes in production. The focus here is on *the share of the production processes performed automatically* instead of manually *within the stages of the production process*. This type of labour-saving automation is referred to by experts as mechanization, as seen in the following three survey questions applied:

- How mechanized are the manufacturing, processing and handling processes?
- How mechanized are the assembly and packaging processes?
- How mechanized are the inventory processes?

[3] A few firms did not answer the question for all three years. For these firms, the non-available value was replaced with the most recent answer. This change has implied that two of the firms, included in the estimation samples of Section 3 and 4, have a filled-in value for 2007.

The survey questions are scored from 1 to 5 with the following values 1: Only manual processes, 2: At least 1 process is automated, 3: A significant portion of processes are automated, 4: A predominant portion of the processes are automated, 5: All processes are automated. The automation score is measured as the average across the three questions in the firm and increases with the share of production processes that is automated across the three stages.[4] We are not aware of similar measures in the literature. However, the automation score parallels the scores on management practices developed by Bloom and Van Reenen (2007).[5]

2.3. Distribution of Automation

Below, we present the distribution of automation measures across firms. First, in Figure II, we present the distribution of the share of investments in machinery and equipment that is targeted at automated capital in firms for 2005 (dark grey) and 2010 (light grey). As Figure II shows, almost 40 percent of the firms targeted at most 12 percent of their investments at automation in 2005. This share decreased to less than 25 percent in 2010. At the other end of the spectrum, approximately one-fifth of the firms targeted more than half of their investments at automation in 2005; this share increased to more than 40 percent in 2010.

[FIGURE II around here]

Second, we turn to the automation score. Figure III shows the distribution of the automation score for 2005 (dark grey) and 2010 (light grey). The figure illustrates that there are firms whose production processes still largely depend on labour input to hold an object and/or a tool, and some firms exist whose production processes are very close to being fully automated. In 2010, 5 percent of Danish manufacturing firms relied only on manual processes, which was down from 11 percent in 2005, whereas even in 2010, only 2 percent of these firms were close to full automation. Overall, more firms have automated processes in 2010, but a large share of processes continue to be largely manually operated.

[4] Observations from firm visits suggest that production managers gave a rough estimate on how many employees that were replaced by automation in the different stages of production. In this sense, production managers weighted processes by number of full time employees. We did not observe any production managers that used production time or added value of processes as weights.

[5] We find that changes in the automation score is consistent with similar but less detailed survey data collected for the "Community Innovation Survey (CIS)" by Eurostat. We present the results in the online Appendix C.

[FIGURE III around here]

Figure IV presents the automation score in more detail and shows the three individual questions included in the automation score in 2005 and 2010. For all three questions, all five possible answers have been used. Stage 1 (manufacturing, processing and handling processes) is the most automated, with 73 percent (= 32 percent + 36 percent + 4 percent) of firms indicating that a significant portion of these processes are automated (a value of 3 or more) in 2010. This result contrasts with the result of stage 3 (inventory processes), in which only 20 percent (= 14 percent + 5 percent + 1 percent) of firms answered similarly in 2010. Finally, in stage 2 (assembly and packaging processes), 40 percent (= 20 percent + 17 percent + 3 percent) of firms had a significant share of processes automated in 2010. The figure also shows that firms have become more automated within the three stages from 2005 to 2010.

[FIGURE IV around here]

Finally, we present distributions for automation measures within sub-groups. We distinguish along the following dimensions: sub-industries of the manufacturing sector, different types of production, and firms with high and low export intensity. The results are presented in Figures V and VI. Figure V presents the distribution of the share of investments in machinery and equipment that is targeted at automated capital by sub-group for 2010 and Figure VI presents the distribution of the automation score by sub-groups for 2010. Types of production are measured in two ways. First, production is distinguished by batch and line production. Second, production is distinguished by customised products and standardised catalogue products, which follows Bartel, Ichniowski, and Shaw (2007). We find high variation in the two automation measures across firms within all sub-groups.

[FIGURE V and VI around here]

We close this subsection by concluding that there is high variation in automation across the surveyed firms, that automation has increased over the five-year period from 2005 to 2010, that automation occurs in different stages of the production process, and that there is also high variation in automation within more narrowly specified groups of firms. Overall, the results show that there is high variation across Danish manufacturing firms in the automation of their production processes.[6]

[6] In online Appendix G, the growth in the operational stock of robots is shown for Denmark, the EU, the US, and the World. In the applied period in the present analysis, Denmark has a similar growth rate in their operational stock

2.4. Descriptive statistics

In this final sub-section, we present the descriptive statistics for the firms used in the empirical analyses. The data is constructed from many different data sources. In addition to the automation survey collected by us, a survey on firm-level IT expenditures is used. The two surveys are merged with register data including data on financial account, information on foreign trade, and education level of employees. Finally, data from the UN COMTRADE database is added using product codes on the four digit level, which is merged with detailed sales information after product codes. More details on the data and the constructed variables are given in the online Appendix B.

Before we present the descriptive statistics, the sample selection should be described. The survey was voluntary to participate in, and the response rate was 41 percent, which is high by the standards of large-scale surveys that are not government mandated. There is no evidence that either the performance data or other observed firm characteristics differed systematically across participating firms and non-participating firms. Using a Probit model, the sample is shown to be a representative sample of the underlying population with no differences by industry, number of employees, performance measures, export intensity, and exposure to international competition. The results are available upon request. For more details on survey quality, sample selection and the estimation sample see online Appendix C.

Next, we describe the estimation sample. Table Ia presents the means and standard deviations of the automation variables and the other variables used in the analysis. The automation score is presented for 2005, 2010 and the average yearly change during the period. The table shows that the average yearly increase in the overall automation score equals 0.06 and increases from a value of 2.05 in 2005 to 2.37 in 2010. Thus, on average, at least one process is automated in the surveyed firms in 2005 and increases to slightly more in 2010. In the survey, we also ask questions about the expected values in 2015. The expected value of the automation score is 2.64 for this year, which implies that the trend between 2005 and 2010 is expected to continue from 2010 onward. We have also collected data on management practice scores; we provide a description in Section 4. For the management practice scores the average yearly increases equal 0.10 and increases from a value of 2.41 in 2005 to 2.92 in 2010.

[TABLE Ia around here]

of robots as the US and the growth rate is approaching that of EU. In the years after 2009 growth in the EU and Denmark is similar. The growth in the stock of robots is comparable across regions and therefore the present study might be relevant for many other countries.

Next, we present the descriptive statistics for the additional variables used in the empirical analysis. The variables in the empirical analysis are the log of labour productivity measured as value added per person engaged, profit-to-sales ratio, log of automated capital, log of IT capital, log of non-automated, non-IT capital, log of employment, and skill share as measured by the share of employees with 16 years of education or more. Here, we present the (not log transformed) means and standard deviations. The result shows that, on average, the amount of non-automated, non-IT capital in a firm is approximately four times greater than the amount of automated capital. Non-automated, non-IT capital is approximately 10 times greater than IT capital.[7] Moreover, value added, the profit-to-sales ratio and some inputs, on average, have negative growth from 2005 to 2010. This is partly a reflection of the financial crisis that hit Denmark in the summer of 2008; as such, 2005 is a pre-financial crisis boom year and 2010 is a post-financial crisis year. Although the financial crisis occurred during the period under investigation, the average log changes of the stocks of automated capital and non-automated, non-IT capital increase. Moreover, labour productivity also has a positive growth rate. A final observation is that the average firm in the sample is relatively small and has 111 employees in 2005. Just over 90 percent of the firms are small and medium-sized enterprises (SMEs) with less than 250 employees.[8]

Table Ib presents the development in measures of international competition, measured by yearly changes in log points. This data is applied in Section 3 on the trade-induced automation hypothesis. The table shows that Chinese exports to the world, excluding Denmark, on average, increased by 0.27 log points per year for the four-digit product codes from 2001 to 2006. It is also seen that the standard deviation equals 0.12, implying that there is high variability in the measure. The mean minus two standard deviations equal 0.03, whereas the mean plus two standard deviations equal 0.51. This implies that some firms are much more exposed to Chinese exports than other firms. In the following, we use Chinese exports and Chinese exports to the world, excluding Denmark, interchangeably. We measure exports from 2001 to 2006 because we find that automation is affected by a four-year lag, as discussed in Section

[7] To construct the three types of capital, we use accounting data on investments in machinery and equipment and industrial structures, our own-collected survey question on the share of investments in machinery and equipment targeted at automation, and survey data on IT-costs from Statistics Denmark. It turns out that the stock of non-automated, non-IT capital is negative for 28 firms in the data set. We attribute this to the uncertainty generated by using data from several sources. To deal with this problem, we simply use the measure of non-automated capital when the measure of non-automated, non-IT capital is negative. We have tried several alternative solutions to deal with this problem of negative capital stocks and the results presented in Sections 3 and 4 are robust across solutions.

[8] In online Appendix F, the structure of the Danish manufacturing sector is presented for 2005. The structure is described using value added and employment shares. Danish manufacturing is compared to manufacturing of the US-economy as well as manufacturing for the members of the European Union in 2000. Thereby, the Danish manufacturing industry can be considered to be a smaller version of the EU- and the US-economy.

3.2. It is evident that Chinese import penetration grows faster than for low-wage countries (incl. China) in general. This result is similar to the results reported elsewhere; see, for example, Bloom, Draca, and Van Reenen (2016). It is seen that we only have observations on international competition for 442 firms, whereas we have data for other variables for 474 firms. The reason for this drop of 32 firms is that we do not have information on sales broken-down after product codes for these firms.

[TABLE Ib around here]

3. TRADE-INDUCED AUTOMATION

We present and discuss the main model that will be used for estimation of the trade-induced automation hypothesis in Section 3.1. In broad terms, the model describes the relationship between Chinese exports and automation measures. In Section 3.2, we present the empirical evidence for the hypothesis.

3.1. Empirical Modelling

The relationship between automated capital and international competition is expressed as follows:

$$\Delta k_{ipjr}^{A} = a_0 + \theta_1 \Delta EX_{pjr}^{CHN} + \Delta W_{ijr}\theta + b_j \times d_r + u_{ipjr},$$

where Δk_{ipjr}^{A} is log change in automated capital in firm i with product p in industry j and region r. Δ refers to the change between 2005 and 2010. ΔEX_{pjr}^{CHN} is log change in a measure of international competition from China, and ΔW_{ijr} is a vector of changes in additional explanatory variables that includes other inputs of production. b_j and d_r are the industry and region dummies, respectively. u_{ipjr} is an error term. The hypothesis to be investigated is the trade-induced automation hypothesis that implies that the coefficient of ΔEX_{pjr}^{CHN} enters positively and significantly in the equation.

Firms exposed to high competition from China may be of a different type than firms that are not exposed to this high competition. For example, it may be that the firms that are exposed to such competition simply are higher quality firms that have perfected their production processes and can compete in the international market. If this is the case, it is incorrect to conclude that high Chinese exports lead to a high level of automated capital since it is rather a certain type of firm that can stand up to the competition from China. Having panel data allows us to address this problem that potentially leads to an omitted variable bias. We estimate a long-differences model that sweep out firm fixed effects, eliminating constant omitted variable bias. In this way, the growth of automated capital within the firm that is driven by increasing Chinese exports can be estimated.

We estimate the relationship in five-year differences between 2005 and 2010 to handle another challenge in the estimation of the relationship between automated capital and Chinese exports, which is classical measurement errors in the explanatory variables that will generate a bias towards zero for the estimates. One approach for addressing measurement errors is to use long-differences, because the bias decreases, as long-differencing removes some of the noise by averaging temporary shocks; see Griliches and Hausman (1986). Finally, we include a full set of industry dummies interacted with region dummies to control for unobserved trends that are correlated with automation and Chinese exports that could drive a positive correlation in the specification.

The empirical model is related to the theoretical model suggested by Bloom, Romer, Terry, and Van Reenen (2014) that propose a positive relationship between innovation and import competition. Specifically, the theoretical model explains why firms that are more exposed to competition from China have larger incentive to innovate after trade is liberalized. The mechanism is driven by "temporarily trapped factors", e.g., skilled workers that are expensive to train for the firm and, therefore, to fire because their firm-specific human capital is lost for the firm. The increasing competition from China lowers the demand for products that skilled workers produce. Due to the high training costs, the skilled workers keep their jobs in the firm, but their opportunity cost is reduced. Accordingly, the incentive for innovation in the firm increases after trade liberalization because the opportunity cost of skilled workers has gone down. Bloom, Draca, and Van Reenen (2016) establish empirical support for the model and investigate the effect of Chinese import competition on innovation across twelve European countries.

We also investigate the effects of international trade with China on innovation. Specifically, we study process innovation and use a measure of the accumulation of automated capital, which is a measure not captured by Bloom, Draca, and Van Reenen (2016). Moreover, we use the total exports from China to the world – excluding exports to Denmark – instead of the imports to Denmark from China as our main measure of international competition. There are two reasons for this choice. First, it is of interest to investigate whether import penetration into domestic markets or exports to international markets produce the incentive to innovate. In this respect, Denmark is a small and open economy that is greatly exposed to international competition on export markets. Exports in relation to GDP were greater than 50 percent in 2008 in Denmark. Additionally, approximately 85 percent of the firms in our sample are exporting firms. Therefore, it is reasonable to assume that increasing international competition from the products from China exported to the world markets has an effect on Danish manufacturing firms that specialize in the same products. A second reason for focusing on Chinese exports is that this measure is arguably exogenous to Danish manufacturing firms, which implies that we do not face simultaneity problems between growth in automated capital and growth in Chinese exports. The applied measure is product specific, is measured at the four-digit product level, and is matched to specific firms; see the online Appendix B for additional details.

In addition to using log change in automated capital as dependent variable, we also use the change in the automation score, i.e., ΔAS_{ipjr}. We do not necessarily expect that Chinese exports to the world is a driver for the automation score as the implementation of automation projects in firms are more likely related to knowledge, skills, and resources available for the firm when implementing the automation investments in production. This view is consistent with observations made during firm visits. Even though this is the case, we still investigate the relation between the automation score and Chinese exports for completeness.

3.2. Empirical Results

The results of the trade-induced automation hypothesis are presented in Table II. In the first three columns, we estimate the relationship between automated capital and Chinese exports by using different additional explanatory variables (W_{ijr}). In the last three columns, we use different dependent variables. These are the automation score, non-automated, non-IT capital and IT capital.

The trade-induced automation hypothesis states that the coefficient to EX_{pjr}^{CHN} is positive and significantly different from zero. Note that we allow for a dynamic response, depending on the lag of the measure of Chinese exports, EX_{pjr}^{CHN}. We use a lag of four years, which implies that we study the change in automated capital between 2005 and 2010 from the changes in Chinese exports from 2001 to 2006. This period saw a considerable increase in exports from China to the world after China's admission to WTO in December 2001.

There are 189 different product types for the 442 firms used in the sample. One fourth of the firms are the only producer of a specific product in Denmark, for half of the firms three firms at most produce a product type, whereas three quarter of the firms seven firms at most produce a product type. 23 firms produce the product type with the highest number of firms producing it.

In column 1 of Table II, we include Chinese exports and an additional set of explanatory variables that comprise other factor inputs of the firm. The variables are included to investigate whether the relationship between automated capital and Chinese exports reflects a spurious relationship, for example, between internationalization and the employment of firms. These variables include log change of IT capital, log change of non-automated, non-IT capital, log change of employment, and the change in the skill share. Chinese exports enter positive and significant in the regression. The coefficient is equal to 0.145 and is significant at the 5 percent significance level.[9] Moving from the bottom to the top quartile of growth in Chinese exports is associated with a higher growth rate in automated capital of 2.16 percentage points of additional growth per year.

This result shows that the firms that face a large increase in Chinese exports in their markets accumulate more automated capital than the firms that are less exposed to increasing international competition. We interpret this result as follows: the firms that initially specialize in product types in which Chinese exporters have a comparative advantage have an incentive to invest more in process innovation to withstand the increasing international competition.

Chinese exports to the world are exogenous to the Danish manufacturing firms. Therefore, we are not concerned about simultaneity. Moreover, we eliminate time-invariant heterogeneity across firms by estimating long-differences models. However, omitted variable bias is still a concern if the important omitted variables are changing over time. In the next two columns, we include alternative measures of international competition in addition to the measure of Chinese exports to the world, excluding Denmark. The purpose is to investigate if the developments in alternative measures of international competition are correlated with the developments in both Chinese exports and automated capital. This could be imports to Denmark from China or from low-wage countries. For example, increasing imports could be correlated with increasing exports because both measures represent the general increase in international trade with China and, moreover, increasing imports could possibly also increase the incentive for manufacturing firms to raise investments in automated capital. In this case, our results could suffer from omitted variable bias, as it could potentially be imports from China to Denmark and not Chinese exports to the world that are important for investments in automated capital.

In column 2, we consider imports from China to Denmark in addition to Chinese exports to the world. It is seen that Chinese exports to the world are driving the effect. Next, we use Danish imports from low-wage countries in column 3, which is a

[9] We also estimated the relationship for different lag lengths for Chinese exports. Here, the increase in exports in the years after China became a member of WTO is most significant; see Table E1 in the online Appendix E.

measure similar to the measure that Bloom, Draca, and Van Reenen (2016) apply except that our measure is developed on the product code level not the industry level. Again, Chinese exports to the world are driving the effect on investments in automated capital. The point estimates of the other measures of international competition in columns 2 and 3 are close to zero and insignificant. The main result is, therefore, that the relevant measure of international competition for automated capital is Chinese exports to the world, excluding Denmark.[10]

[TABLE II around here]

Chinese export to the world may well have different impact on firms with low export intensity and firms with high export intensity because the former group of firms are less exposed to intensified competition from China on world markets. Therefore, we have run regressions where we distinguish between exporters and non-exporters. We find that for non-exporters, Chinese export to the world is not driving investments in automated capital. However, there is only 41 non-exporters in the sample implying that the low number of observations make it difficult to estimate an effect with high precision. Therefore, we also distinguish between firms with low export intensity (including non-exporters) and firms with high export intensity where the export intensity is defined as exports divided by sales. Defining the former group as firms with an export intensity below 0.10, we have 156 low export intensity firms. For this split-up, we find that the point estimate to Chinese exports is positive but insignificantly different from zero for firms with low export intensity, whereas it is positive and significantly different than zero for exporters with high export intensities. Even when we define the two groups using higher threshold levels for the export intensity – 0.20 or 0.30 resulting in 193 or 223 low export intensity firms, respectively – the point estimate is still lower for low export intensity firms and only significantly different from zero at the 10 percent level. (The results are not included but are available upon request).

In column 4 of Table II, we use the automation score – the other automation measure that we have collected data for – as dependent variable instead of automated capital. It is seen that this measure of automation is unrelated to increasing international competition from China. This result is consistent with the discussion of Section 3.1 that hypothesised that the automation score, which is a measure of how firms implement automation capital in production, is not (necessary) related to international competition.

[10] We have also investigated if firms respond to Chinese exports by offshoring activities to low-wage countries. To do this, we ran regressions similar to those of Table II but with log changes in offshoring measures as dependent variables. We find that changing offshoring is not related to changes in Chinese exports. In other words, Chinese exports are not a driver for offshoring in our sample. Results are available upon request.

Finally, columns 5 and 6 of Table II show that only automated capital is affected by Chinese exports. Neither IT capital nor non-automated, non-IT capital is influenced by increasing Chinese exports. The absence of an effect on IT capital is surprising because an effect on IT would be consistent with the "trade-induced technical change hypothesis" discussed in Section 3.1. A potential explanation for the absence of a significant effect on IT capital is that manufacturing firms have already to a great extent adopted IT by 2005.

We interpret the above result for automated capital and Chinese exports to be causal. The causal relationship requires that the main driver behind Chinese exports to the world is not investments in automated capital but rather changes in China's comparative advantage and its accession to the WTO. If, for example, a worldwide trend in automation is driving investments in both Danish and Chinese manufacturing firms and these investments in China are driving Chinese exports to the world market, then the estimated relationship is spurious. According to the International Federation of Robotics (2011), China had relatively few industrial robots in 2010: only 45,800 units out of a world stock of 1.1 million units. Because of the small number of robots in the Chinese economy, we do not consider a general automation trend to be a major problem. Moreover, China did not export robots in high volume, because, according to the International Federation of Robotics (2011), in reference to the year 2010, China "seems to lack a domestic robot manufacturer who can effectively compete with the quality of the foreign robot suppliers".

A comment should be made on the interpretation of causality from Chinese exports to the world and investments in automated capital. It is not possible for us to rule out the universe of potentially omitted variables and thereby omitted variable bias in the estimated coefficients. However, we have ruled out a set of important variables containing all time-invariant variables, alternative measures of international competition, and other production factors. Moreover, we include a full set of industry by region dummies. These dummies are included to absorb trends that differ across industry by region clusters, e.g., the development in wages in local labour markets or unobserved investment shocks that could drive a positive correlation in the specification. With these dummies included in the regressions, omitted variables that bias the results should be other than time-invariant variables, industry by region trends, other measures of production factors, and alternative measures of international competition.

4. VALIDATING THE AUTOMATION DATA

In section 2.3, we presented empirical evidence for high variations in the automation measures. An obvious question is whether the automation measures are associated to firm performance and therefore we investigate this relationship. We do not attribute a causal interpretation to the results. Instead, this analysis provides a method to determine whether our survey contains meaningful information for automation and not just white noise. This approach follows Bloom and Van Reenen (2007) and Bloom et al (2019) that apply the methodology on survey data on management practices.

4.1. Empirical Modelling

The relationship between value added and automated capital is given by a Cobb-Douglas production function. Taking logs and long-differences, the included variables are: Δy_{ijr} that is the log change of value added for firm i in industry j and region r, Δk_{ijr}^{A} that is log change of automated capital; Δk_{ijr}^{IT} that is log change of IT capital; Δk_{ijr}^{NA-NIT} that is log change of non-automated, non-IT capital, and Δl_{ijr} that is the log change of labour input. Δ refers to the change between 2005 and 2010. In addition to automated capital, we assume that value added is related to the automation score, ΔAS_{ijr}. We rewrite the equation to a measure of labour productivity because we prefer to use this measure in the empirical section. (This has no impact on the obtained point estimates). In sum, the equation used for estimation equals

$$\begin{aligned}\Delta y_{ijr} - \Delta l_{ijr} &= a_1 + \beta_1\left(\Delta k_{ijr}^{A} - \Delta l_{ijr}\right) + \beta_2\left(\Delta k_{ijr}^{IT} - \Delta l_{ijr}\right) \\ &+ \beta_3\left(\Delta k_{ijr}^{NA-NIT} - \Delta l_{ijr}\right) + (\beta_1 + \beta_2 + \beta_3 + \beta_4 - 1)\Delta l_{ijr} \\ &+ \beta_5 \Delta AS_{ijr} + \Delta X_{ijr}\gamma + c_j \times g_r + \nu_{ijr}\end{aligned}$$

where c_j and g_r are the industry and region dummies, respectively. ν_{ijr} is an error term. ΔX_{ijr} is a vector of changes in two additional explanatory variables that are explained in the following paragraph. The equation states that log changes in labour productivity is expressed as a function of growth in capital intensities of three capital types, log change in labour input, change in the automation score and changes in the two additional explanatory variables.

The first additional explanatory variable is the skill share measured as the share of employees with 16 years of education or more and the second is a management practice score. The skill share is included because more skills are expected to correlate positively with labour productivity. The management practice score is included to be able to eliminate the concern that the automation score is a proxy for management practices. The motivation for management practices to be important comes from Syverson (2011), Bloom et al (2019), and Bloom and Van Reenen (2007), who find and/or argue that management practices are considered an important driver for firm performance. We have collected data on management practices in addition to the data on automation. Management practice scores were constructed by following a similar method to the one used for the automation score; for details, see online Appendix D.

The main interest in this part of the study is the relationships between firm performance and automated capital and between firm performance and the automation score. We hypothesize that the relationships to both automated capital and the automation score are positive and significantly different from zero. The latter hypothesis suggests that firm performance is positively related to the share of automated production processes. We apply two alternative measures of performance; log change in labour productivity and the change in the profit-to-sales ratio.

There is an extensive stream of recent literature that analyses the performance effects of IT capital, such as the work of Bloom, Sadun and Van Reenen (2012). The approach taken in this literature has been to divide total capital into IT and non-IT types and to use measures of firm performance as dependent variables and both types of capital in addition to other inputs as explanatory variables. We build on the approach taken in the IT literature and distinguishes between IT and non-IT capital in the estimation of the above equation. Furthermore, our dataset allows us to split capital into automated capital, IT capital and non-automated, non-IT capital, which implies that the effects of automated capital are separated out from the effects of IT capital. We thereby investigate the relationship between firm performance and the three types of capital. To the best of our knowledge, this study is the first to distinguish among these three types of capital.

The equation used for estimation is formulated as a long-difference model, which implies that we sweep out firm fixed effects. We measure the variables as five-year differences, and we include a full set of industry dummies interacted with region dummies to absorb possible unobserved trends that are correlated with performance and automation.

4.2. Empirical Results

This section presents the results for the link between measures of firm performance and automation measures. Specifically, we investigate the separate relationships between the two automation measures and firm performance. In Table III, we present results for two dependent variables. These are measures of labour productivity and profitability.

In column 1, the dependent variable is labour productivity (measured as log change of (value added/labour)). Our main focus is on automated capital and the automation score. Both measures of automation are positive and significantly different from zero, which supports that the two measures contain meaningful information for automation rather than just white noise. That the automation score is positive and significant strongly supports the claim of production managers, suppliers of automation equipment and industry experts that the share of production processes that is automated is an important aspect of automation.

Specifically, the point estimate on automated capital equals 0.074 and the point estimate on the automation score equals 0.091. Both measures are significant at the 5 percent level. Furthermore, the automation score is interpreted as a measure of how successful the automation investment is implemented and integrated in the production process. According to this interpretation, projects that automate and integrate many production processes are especially associated with high firm performance.[11]

[TABLE III around here]

One challenge, when including three capital types is high correlations between the three types, e.g., the correlation coefficient between log changes in automated capital and non-automated, non-IT capital equals 0.47. This potentially leads to insignificant point estimates when all capital variables are included due to multicollinearity. When we include the three growth rates of different capital types, we obtain a positive coefficient for automated capital, which implies that this capital type correlates significantly with firm performance even when including other capital types. However, it is also seen that both IT capital and that non-automated, non-IT capital enter insignificantly in the estimation. When these two capital measures are included one at a time in the regression, they enter positively and significant.[12]

[11] There is an important caveat to this interpretation. Firms that automate many production processes may well invest in own produced automation capital. This was observed during firm visits. Such costs are not necessarily capitalized and therefore do not enter in the construction of automated capital stocks. Thereby, the book value of the automation investment is undervalued. If unreported automation investments are very important, the interpretation of the automation score could be that it corrects for mis-measured automated capital. We do not consider this mismeasurement of automated capital to be a severe problem because the point estimate is downward biased if measurement errors are important. When we including the automation score, we control (imperfectly) for measurement errors, however, we do not see an increase in the point estimate of automated capital in the regression as we would expect. Moreover, we use the log change in automated capital as explanatory variable, which implies that the measurement error – the share of automated capital that is capitalized – should vary over time within firms.

[12] The loss of significance of IT capital could also be due to double counting of IT-investments in IT capital and in automated capital. This will be the case if firms report their IT-investments in both the IT-survey and in our own collected automation survey. Double counting of this type will increase the correlation between the log change in IT capital and automated capital, which makes it more difficult to estimate point estimates with high precision. That being said, it should be emphasized that both capital measures enter significantly in the regression at least at the 10 percent significance level when that automation score is not included in the regression.

In addition to the above-mentioned explanatory variables, we include the management practice score. The coefficient of this variable attains a value of 0.081 at the 5 percent significance level. This result indicates that the automation score is not just a proxy for management practices.

In column 2, the dependent variable is profitability (measured as the change in (profit/sales)). It is seen that changes in the automation score are positively associated with changes in profitability. I.e., successful implementation and integration of automation investments in the production process correlates with increases in profitability. It is also seen that changes in capital intensities are unassociated with changes in profitability. This is also found elsewhere, see Bloom and Van Reenen (2007).

In sum, we have shown that measures of firm performance are positively and significantly associated with automation. It is found that high investments in automated capital is positively associated with productivity growth. Moreover, it is found that increases in the automation score are positively associated with both productivity growth and changes in profitability. These results offer some external validation of the automation survey.

5. CONCLUSIONS

This paper has documented a new set of facts regarding automation in manufacturing firms using a combination of own collected survey data on automation and register data. We develop two measures of automation. These are the stock of automated capital and the automation score, i.e., the share of production processes that is automated.

The variation in automation across firms is high. A first-order policy question arises from this result, which is as follows: Is the absence of adoption of technology sub-optimal and consequently motivates policy intervention or is the absence of adoption optimal implying that firms do not automate because they are specialised in products where production should not be automated?

The close collaboration with industry experts and production managers, during firm visits carried out during the development of the automation survey, suggested that the low use of automation to some extent is due to a particular lack of the necessary skills and resources to investigate the firms' needs, possibilities for automation, and automation planning for the factory floor. The production managers were not unaware that automation technologies existed, but they were lacking knowledge or awareness regarding the specific technologies that they could invest in, on how to implement these, and on which production processes to automate. In this sense, information barriers may be an important market failure that potentially justifies policy intervention. Moreover, production managers often complained about limited access to funding, which also constitutes a potentially important market failure.[13]

We point to increasing international competition from China as a driver of automated capital and present empirical evidence for this to be the case. Increasing international competition from China can, however, not explain changes in the automation score. An important research issue for the future is drivers for the automation score answering the question why some firms have high automation scores while others have low scores.

We also show that measures of firm performance are positively and significantly associated with automation. This result offers some external validation of the automation survey. We do not attribute a causal interpretation to the results and consequently an important research issue for the future is to examine the causal effect of automation on firm performance.

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TABLES

TABLE Ia: Descriptive statistics, yearly and yearly change 2005-2010

	2005		2010		Yearly changes	
	mean	s.d.	mean	s.d.	mean	s.d.
Automation score	2.05	0.77	2.37	0.84	0.06	0.09
Management score	2.41	0.54	2.92	0.56	0.10	0.11
Labour productivity	0.45	0.18	0.50	0.40	0.01	0.10
Value added	52.1	136.7	60.5	296.8	-0.03[1]	0.11
Profits to sales ratio	0.05	0.11	0.02	0.11	-0.01	0.03
Capital	62.6	209.82	61.6	196.5	0.02[1]	0.10
Persons engaged	110.9	298.7	96.0	273.1	-0.04[1]	0.09
Skills	0.10	0.10	0.11	0.11	0.00	0.01
Automated capital	11.2	56.6	11.0	49.2	0.05[1]	0.17
IT capital	4.37	13.65	4.57	21.17	0.01[1]	0.16
Non-automated, non-IT capital	47.1	154.2	46.0	142.4	0.04[1]	0.13
Number of firms	474		474		474	

Note: 1) Yearly change is measured as the annual log change, i.e., $log(x_t/x_{t-5})/5$.

The automation score is a measure of the share of production processes that is automated. The management practice score measures the degree of delegation of power to production workers, the focus on human resource management, and the focus on performance management. Value added and capital are measured in millions of DKK in 2005 prices. Persons engaged are the number of persons employed. Labour productivity is defined as value added per person engaged. Skills measure the share of employees with 16 years of education or more. Profits to sales ratio is measured as EBIT (Earnings before interest and tax) to total sales. All changes are in five-year differences between 2005 and 2010.

Source: Authors' survey on automation in manufacturing and register data from Statistics Denmark

TABLE Ib: International competition, yearly change in log points, 2001-2006

	mean	s.d.
Chinese export	0.27	0.12
Chinese import penetration	0.31	0.31
Low-wage country import penetration	0.21	0.23
Number of firms	442	

Note: Chinese export is constructed using UN Comtrade data at the four-digit product level merged with Danish firm register data from Statistics Denmark. Chinese import penetration and low-wage country import penetration are constructed using data from the Danish foreign trade statistics merged with register data on product codes. There are 189 different product codes in the sample. For more details on the variables see online Appendix B3. Yearly change is measured as the annual log change, i.e., *$log(x_t/x_{t-5})/5$. All changes are in five-year differences between 2001 and 2006.*

Source: Authors' survey on automation in manufacturing, UN Comtrade data, and register data from Statistics Denmark

TABLE II: Automation and international competition – Various dependent variables. Five-year difference estimation (2005-2010)

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\log(K_{it}^{A})$	$\Delta\log(K_{it}^{A})$	$\Delta\log(K_{it}^{A})$	ΔAS_{ijr}	$\Delta\log(K_{it}^{NA-NIT})$	$\Delta\log(K_{it}^{IT})$
Δlog of Chinese export	0.145**	0.146**	0.145**	-0.008	0.012	-0.022
	(0.059)	(0.059)	(0.062)	(0.041)	(0.058)	(0.102)
Δlog of Chinese import penetration		-0.012				
		(0.023)				
Δlog of low-wage country import penetration			-0.002			
			(0.041)			
R-squared	0.450	0.450	0.450	0.186	0.391	0.183
Number of observations	442	442	442	442	442	442

*Note: *** denotes 1 percent significance, ** denotes 5 percent significance, and * denotes 10 percent significance. Estimation is by (unweighted) OLS with standard errors clustered by four-digit product code in parentheses. Standard errors are robust to heteroscedasticity and autocorrelation of unknown form. Regressions are performed on long-differences that sweep out firm fixed effects. The dependent variables are: Δlog of automated capital in columns (1)-(3), Δ automation score in column (4), Δlog of non-automated, non-IT capital in column (5), and Δlog of IT capital in column (6). The explanatory variables presented in the table are variables of international competition (log of Chinese export, log of Chinese import penetration, and log of low-wage country import penetration). All regressions include (i) a set of explanatory variables (not shown) including capital measures other than those used as dependent variables, Δlog of employment, and Δ skill share and (ii) a full set of industry by region dummies (10 industries and 8 regions). All changes are in five-year differences between 2005 and 2010, except for the three variables of international competition where the five-year differences are measured between 2001 and 2006. The measures of international competition are measured at the product level. There are 189 different product codes for the 442 firms.*

Source: Authors' survey on automation in manufacturing, UN Comtrade data, and register data from Statistics Denmark

TABLE III Firm performance and automation – Various dependent variables. Five-year difference estimation (2005-2010)

	Δlog of value added per employee	Δ Profit-to-sales ratio
Δ Automation score	0.091**	0.044***
	(0.044)	(0.015)
Δlog of automated production capital	0.074**	-0.003
	(0.036)	(0.011)
Δlog of automated IT capital	0.045	-0.001
	(0.028)	(0.008)
Δlog of non-automated, non-IT capital	0.015	-0.001
	(0.038)	(0.012)
Δlog of employment	-0.200*	-0.010
	(0.105)	(0.023)
Δ Skill share	0.792*	0.133
	(0.447)	(0.159)
Δ Management practices score	0.081**	0.020*
	(0.036)	(0.012)
R-squared	0.286	0.167
Number of observations	474	474

*Note: *** denotes 1 percent significance, ** denotes 5 percent significance, and * denotes 10 percent significance. Estimation is by (unweighted) OLS. Standard errors are robust to heteroscedasticity and autocorrelation of unknown form. Regressions are performed on long-differences that sweep out firm fixed effects. The dependent variables are: Δlog of value added per employee in column (1) and Δ Profit-to-sales ratio in column (2). All changes are in five-year differences between 2005 and 2010. Both regressions include a full set of industry by region dummies (10 industries and 8 regions).*

Source: Authors' survey on automation in manufacturing and register data from Statistics Denmark

FIGURES

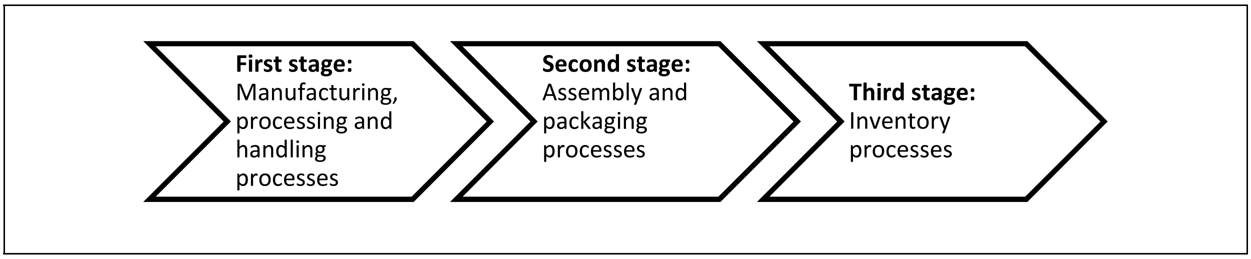

Figure I: Stages of production used in the automation index

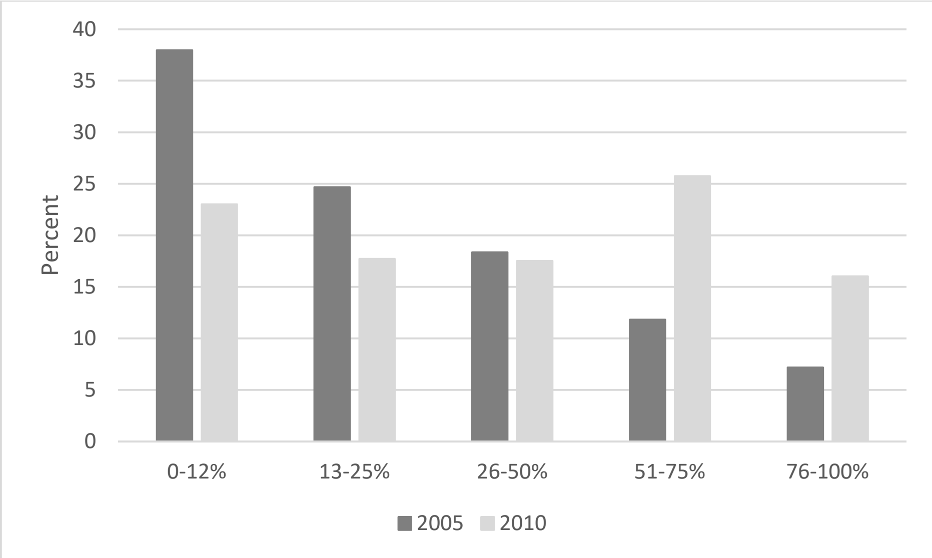

Figure II: Distribution of the percentage of new capital investments in machinery and equipment targeted at automation

Note: Based on 474 firms used in Section 4
Source: Authors' survey on automation in manufacturing

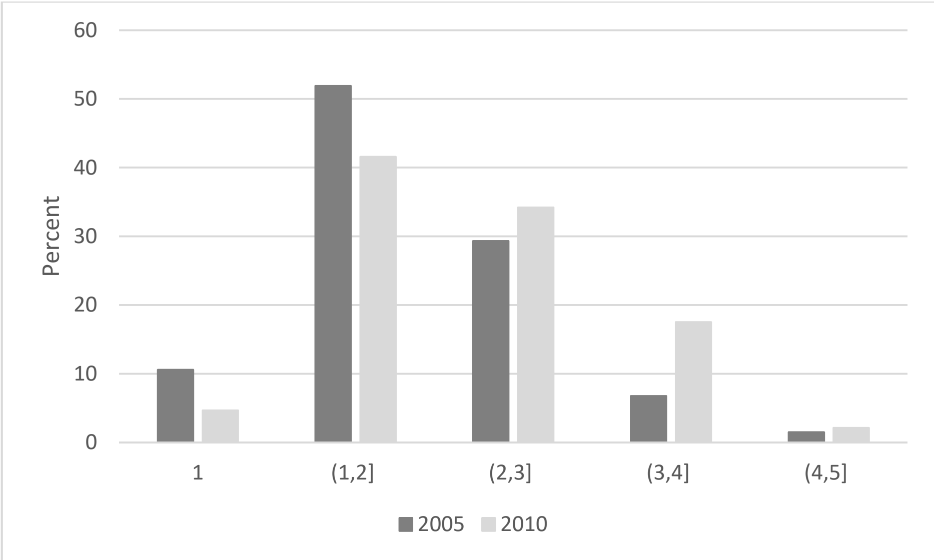

Figure III: Distribution of the scope of automation for 2005 and 2010

Note: Based on 474 firms used in Section 4
Source: Authors' survey on automation in manufacturing

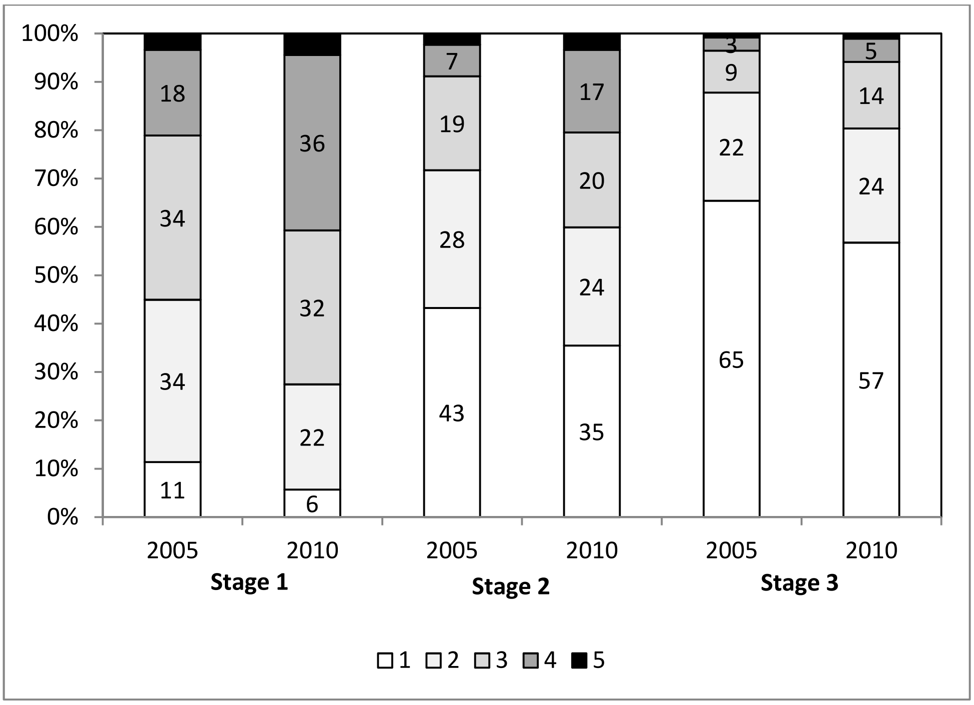

Figure IV: Distribution of the responses on the 5-point scale for three survey questions

Note: Based on 474 firms used in Section 4
Source: Authors' survey on automation in manufacturing

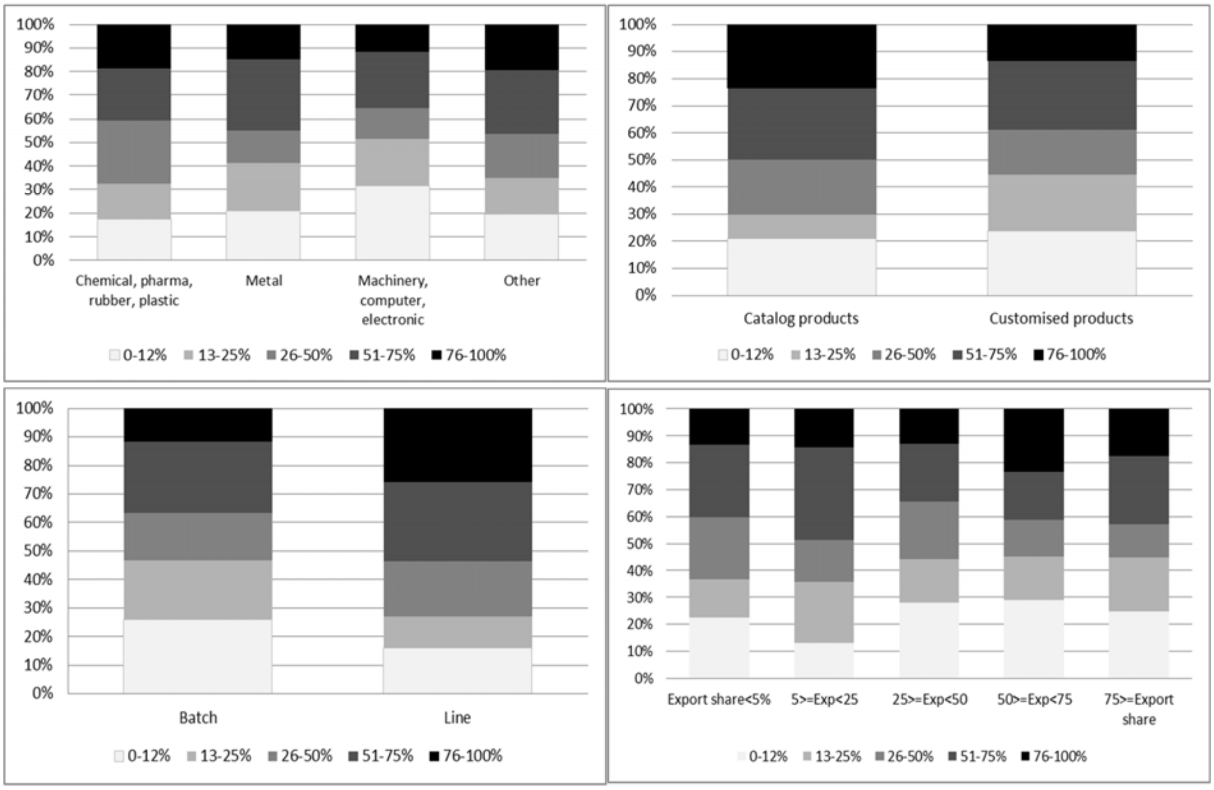

Figure V: Distribution of the percentage of investments in machinery and equipment targeted automation for 2010 across industry, production strategy, production layout, and export level.

Note: Based on 474 firms used in Section 4. Distribution for 4 aggregate industries (Top left). Distribution for two production strategies (Top right): ***Catalogue****: Firms that mainly produce products exactly as they are described in their catalogue.* ***Customised****: Firms that mainly produce products made to the customer's specification. Distribution for two production layouts (Bottom left):* ***Batch****: Firms that produce several products and equipment is therefore not positioned to produce a specific product, but more in groups depending on the type of process the equipment perform.* ***Line****: Firms that produce one or few products and therefore position the equipment in a line along which products are produced. Distribution for different export shares (export/sales) (Bottom right).*

Source: Authors' survey on automation in manufacturing

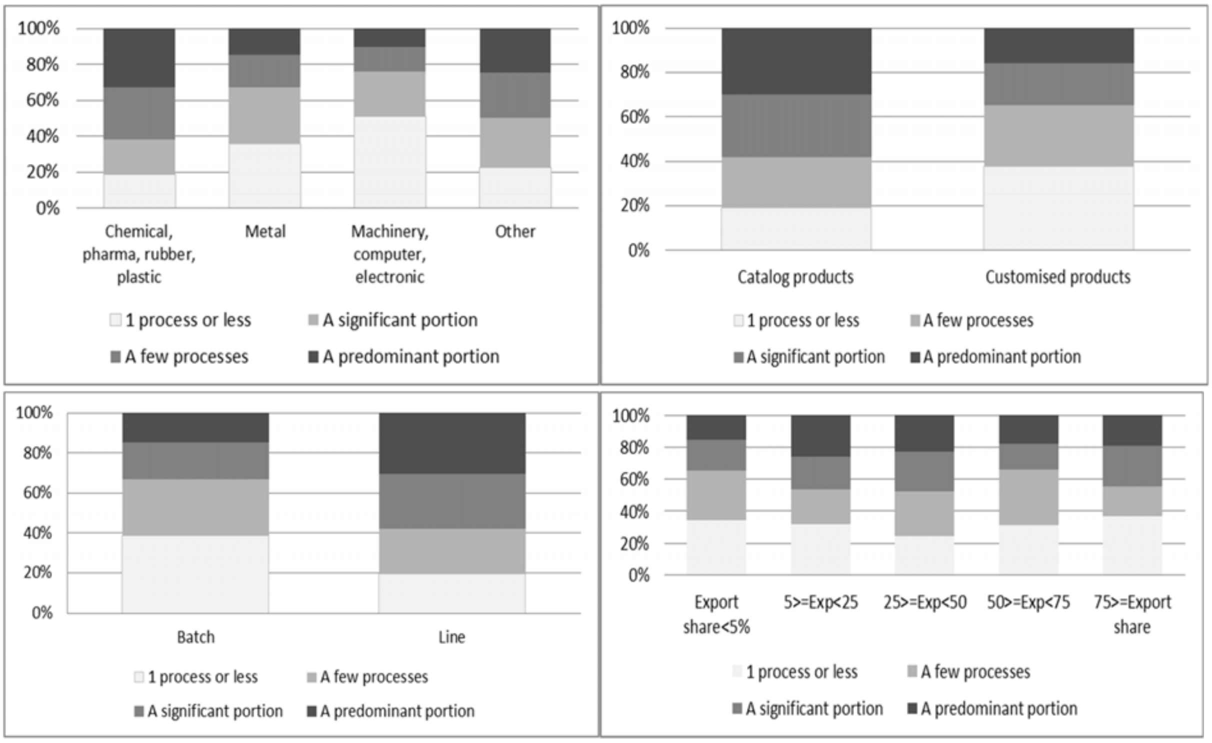

Figure VI: Distribution of the automation score for 2010 across industry, production strategy, production layout, and export level.

Note: Based on 474 firms used in Section 4. Distribution for 4 aggregate industries (Top left). Distribution for two production strategies (Top right): ***Catalogue****: Firms that mainly produce products exactly as they are described in their catalogue.* ***Customised****: Firms that mainly produce products made to the customer's specification. Distribution for two production layouts (Bottom left):* ***Batch****: Firms that produce several products and equipment is therefore not positioned to produce a specific product, but more in groups depending on the type of process the equipment perform.* ***Line****: Firms that produce one or few products and therefore position the equipment in a line along which products are produced. Distribution for different export shares (export/sales) (Bottom right).*

Source: Authors' survey on automation in manufacturing

Automation, Performance, and International Competition: A Firm-Level Comparison of Process Innovation

Online Appendix

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This online appendix contains detailed explanations of data creation and variable creation as well as additional empirical results referenced in the main text.

APPENDIX A: SURVEY DATA COLLECTION

This appendix describes the data collection process for the survey on automation in detail, including the process used to develop the final survey.

A.1 Development Process

The survey was developed by working closely with Danish manufacturing firms, engineers and industry experts. The iterations took over a year, beginning with a careful analysis of the advantages and disadvantages of previous studies of a similar nature, including Van Reenen and Bloom's work on management practices, technology, and organizational change. This process was followed by workshops, discussions and visits to manufacturing firms; production managers from these firms were consulted. In general, the production managers preferred a survey to a phone interview. The comments provided from the workshops and visits were used to evaluate the firm information to be collected, which questions were relevant, how questions should be asked, and how to collect the data.

The survey was revised several times after the firm visits and internal workshops. The final version of the survey was completed in early 2012, more than one year after we started, in connection with a pilot study of approximately 120 test firms. The pilot study was used to train the callers who would be used to call firms to introduce them to the project and to teach them how to recruit firms to participate in the electronic survey.

A.2 Findings from the Process

The dialogue with the production managers at the firm visits and workshops showed, among other things, that it is problematic to ask about the use of specific types of technology as was done in previous surveys (see, for example, Bartel, Ichinowski and Shaw (2007) and Swamidass (2003)) because applied technologies vary from one industry to another. Furthermore, it appeared that some respondents were not familiar with the definitions of commonly used technologies, such as warehouses and 3D CAD, and therefore answered incorrectly when asked about the technologies used. As a result, the questions concerning automation were changed so that they revealed the degree of automation rather than the application of specific types of machines/robots. The challenge was, nevertheless, to create questions that were relevant across different manufacturing industries.

A.3 Selection of the Sample

To identify the population of manufacturing firms for this survey, we used the information on firms' annual statements required by law and collected by a consultancy firm, Experian.

Population: All manufacturing firms in Denmark with more than 10 employees in 2005, i.e., the firms with a NACE industry code between 150,000 and 400,000. These firms can be divided into 1 broad sectors based on Statistics Denmark's 53 groupings:

- o Food, beverages and tobacco
- o Textile and leather
- o Wood, Paper, and printing

- Chemical industry, Mineral oil refining
- Rubber, plastic products, and non-metallic minerals
- Iron and metal
- Mechanical engineering
- Electronics
- Transport equipment
- Furniture and other manufacturing

There are approximately 3,000 firms in the manufacturing sector with at least 10 employees. The goal was to obtain 500 completed surveys.

A.4 Survey Collection

The data collection process was as follows:

- The firm was called to ensure that the correspondence targeted the appropriate person in the firm. If the person had no knowledge of the project, it was briefly described.
- An email with a link that corresponded to the survey was sent. The email also included a precise but brief presentation of the project and explained that by answering the survey, the firm would obtain access to an automation-benchmarking tool to compare their responses with the responses of other participating firms.
- The caller made another call to the firm if the survey was not completed. This process continued until the survey was completed or the firm refused to complete the survey.
- Several logic tests were performed before a completed survey was accepted. If the answers to the questions in the survey failed these tests, an engineer called the firm. Such a call occurred for approximately 28 percent of the surveys, and in 95 percent of these cases, the answers were subsequently corrected.

The firms were randomly assigned to one of 18 callers. The caller was aware of the name of the firm, but no financial information was shared in advance with the callers. The caller used the firms' websites to identify the relevant persons to contact. The callers were all students with experience from similar jobs, and all callers were assigned more than 50 firms. The performance of the callers was monitored as was their response rate and the number of times they had to contact the firms.[1] The callers received a flat rate of 125kr ($21) while they were learning about the project, including a firm visit. When calling, they received 75kr ($13) per hour and 500kr ($83) per completed survey.

[1] Bloom and van Reenen (2007) also use information on the completion process of the questionnaire, such as the number and type of prior contacts before obtaining the response, duration, local time of day, date and day of the week; these factors are not relevant here because the responder decides when to complete the questionnaire. The caller was trained on when to call and how much to push the production manager depending on the time and spirit of the respondent. However, the respondent could decide themselves when to complete the questionnaire and whether to complete it at once or spread it over more than one day.

A.5 Collection Period

The firms were contacted from March 2012 to August 2012. By October, 500 of the 567 fully completed surveys were completed. The remaining 67 were completed later as part of completing the survey collection process because it was decided that all firms that had been contacted should be treated similarly.

A.6 Sample period

During the firm visits, the production managers stated that the focus on automation was so strong that they could provide precise answers to retrospective questions. Therefore, it was decided to ask questions for the years 2005, 2007 and 2010, which allows us to evaluate the self-reported changes in automation over the previous half-decade. In other surveys, authors have also collected retrospective data. For example, Bartel, Ichinowski and Shaw (2007) collect information for 1997 and 2002 during the period from July 2002 to March 2003. Ichniowski, Shaw and Prennushi (1997) collect retrospective data on human resource management. Bloom et al. (2013) use the Management and Organizational Practices Survey (MOPS) from the US Census in which data on the management and organizational practices of US manufacturing firms are collected for 2005 and 2010. In addition, for some of the questions, we asked for the expectations in 2015.

APPENDIX B: DATA SOURCES AND THE CREATION OF VARIABLES

For this paper, we constructed a new dataset that includes measures for the automation of production capital for firms in the Danish manufacturing industry as explained in Appendix A. The dataset constitutes one of the most comprehensive descriptions ever assembled of the automation technologies applied in manufacturing firms.[2] In addition to automation, the collected data also include the measures of management practices used in production processes. We have enriched the survey dataset by merging information on the value added, investments in machinery and equipment, sales at the product level, and education of employees by using confidential register data from Statistics Denmark. Moreover, we have merged the data on Chinese exports at the product level by using the UN Comtrade database as well as IT expenditures and innovation activities that originate from two Eurostat datasets.

The purpose of this appendix is to describe the data sources and methodology used to construct the capital measure in the first subsection. In the second subsection, we discuss the construction of the capital measures and the automation score. In the third subsection we explain how Chinese exports, import penetration, and firm performance is constructed.

B.1 Data Sources

AIM dataset: The AIM data are collected by the authors. Question 8 of the survey asks about the percentage of investments in machinery and equipment that are targeted at automation; specifically, “What percentage of new capital investments in machinery and equipment is targeted at automation?” The question is asked for 2005, 2007 and 2010, and the respondent can choose from among 5 ranges, namely, 0-12

[2] Another important survey is the Manufacturing Technology Survey; a government survey run by the US Census Bureau in the United States. (https://www.census.gov/econ/overview/ma0700.html). The survey is collected for a large representative sample of manufacturing firms on their use of automation technologies. The first wave of the survey was conducted in 1988 and the last wave of that survey was in 1993.

percent, 13-25 percent, 26-50 percent, 51-75 percent and 76-100 percent. We ask this question to divide machinery and equipment investments into automated production capital and non-automated production capital. These two types of investments are used to determine the stocks of automated and non-automated production capital.

Firm-level financial accounts (FIRE): FIRE data include annual firm financial accounts between 2000 and 2010. Data include detailed income statements, balance sheets and investments in real capital. We use machinery and equipment investments to determine the automated and non-automated capital stocks.

Financial account data originate from different sources collected by Statistics Denmark, such as annual reports submitted by firms and self-reported tax information. For some firms, not all account information is available. For these firms, Statistics Denmark constructs the missing account data. Thus, the samples of firms that we apply have shares of interpolated values. For the sample of firms in Table II, which we follow for 10 years, 5.9 percent of the 4,080 firm-year observations are interpolated, but the majority of firms have only up to 2 years of interpolated values. This information is revealing because we use automation capital as a dependent variable in Table II. For the firm sample used in Table III, 6.7 percent of the firms have interpolated values. However, the majority of firms again have interpolated values for less than 3 years. Notably, the AIM dataset is site- or plant-level information, whereas the value added, skill share and employment, for example, are measured at the firm level. However, the majority of firms in Denmark only have one plant/establishment. For the remaining firms, we assume that automation is relatively homogeneous across plants and that our index will therefore capture firm-wide effects.

In addition, we have information on the "expenses for the purchase of small inventory/equipment with a short life". This entry is often used for IT expenditures. We use the variation in this entry to complete the missing values in the IT data.

Firm-level IT expenditures (FITE): FITE survey data are collected by Statistics Denmark from 2003 to 2010. For FITE, questions are asked about the expenditures for acquisitions in the 7-9 ICT capital categories, including hardware and software. In addition, the survey provides information on the shares of IT expenditures activated during the year and are thereby depreciated over a period longer than one year. This information enables us to divide non-automated machinery and equipment investments into IT investments and other non-automated machinery and equipment investments. There is a 100 percent sampling frame for the businesses with 100 or more employees and a stratified random sample of the firms with fewer than 100 employees. The sample covers 371 of the 567 firms included in the AIM dataset.

B.2 Estimation of IT, Automated and Non-automated Capital Stocks

Scale of Automation: To determine the automated capital stock, we apply the Perpetual Inventory Method (PIM). Assuming a constant depreciation rate, the method states the following:

$$K_{i,t}^{A} = I_{i,t}^{A} + (1 - \delta^{A})K_{i,t-1}^{A},$$

where K^A denotes the automated capital stock, I^A denotes the investments in automated machinery and equipment, and δ^A is a constant depreciation rate. *i* and *t* denote the firm and time, respectively.

A key challenge in applying PIM is the estimation of the initial capital stock. We follow the method proposed by Hall and Mairesse (1995) and applied by Hempell (2005). Under the assumption that investment expenditures on capital goods have grown at a similar and constant average rate g^A in the past in all firms, the PIM equation for the initial state can be rewritten as follows:

$$K_{i,0}^A = I_{i,0}^A / (\delta^A + g^A).$$

By using a combination of the collected survey data and accounting data on investments in machinery and equipment, the automated capital stocks for the majority of firms in the sample can be measured. We use the question on the percentage of new capital investments in machinery and equipment that is targeted at automation presented in Section 2 of the paper. Specifically, we use the mid-range values of the firm responses. For the years prior to 2005, we assume that the percentage focused on automated capital equals the 2005 share. For 2006, 2008 and 2009, the shares are interpolated. With information on the percentage of new capital investments that is targeted at automation, $s_{i,t}^A$, and the investments in machinery and equipment, $I_{i,t}^{M\&E}$, automated capital is determined as follows:

$$I_{i,t}^A = s_{i,t}^A I_{i,t}^{M\&E}.$$

To construct the automated capital stock, we use investment data from 2001 to 2010. We measure $I_{i,0}^A$ as the average investments over 2001, 2002 and 2003 because investments can fluctuate considerably from year to year. Moreover, we assume that δ^A=20 percent and that g^A =0 percent.[3] The requirement that the investment data for a single firm must be available for a 10-year period implies that we lose 48 firms in the analysis. The investment data are randomly missing across firm size, industry, labour, skills, and value added, which allows us to draw general conclusions.

Other capital stocks: In addition to the automated capital stock described above, we develop measures of two additional capital stocks. These stocks are the IT capital stock (K^{IT}) and the non-automated, non-IT capital stock (K^{NA-NIT}) in which the IT capital stock measure refers to the accumulation of hardware, other IT equipment, and software assets. Both capital stocks are calculated with PIM as was the case for automated capital.

The measure of IT capital is constructed by using the survey data on IT spending, see the above section B.1. In the construction of the IT capital measure, IT investments are depreciated by 31.5 percent, which follows EUKLEMS.

The measure of non-IT, non-automated capital is constructed with two types of investments from the firms' accounting data. These types are the remaining investments in machinery and equipment that are not allocated to automated capital or IT capital. These investments are depreciated by 13 percent. In addition, industrial structures are depreciated by 5 percent.

[3] Deb and Deb (2010) state that "The approximated life span of a robot is between 5 and 8 years" (p. 461). A depreciation rate of 20 percent is considered to be a reasonable approximation for an 8-year life span. The value of the growth rates of capital are fixed to zero for simplicity. Since we are using five-year differences, this procedure has no implications for the obtained results, and the initial level of capital has therefore less importance.

Automation score: We develop an automation score that measures how successful the automation investment is implemented and integrated in the production process, as explained in Section 2.[4]

B.3 Other variables

Chinese Exports: International competition from low-wage countries has increased dramatically over the last decade. Chinese imports have increased particularly dramatically. For example, Bloom, Draca, and Van Reenen (2016) present data on the share of all imports into the EU and US from China; these data show that the share increased from approximately 5 percent in 2000 to approximately 11 percent in 2007. Chinese exports to the world market have also increased considerably over time, which is evident from Figure B1. The figure shows that the share of world exports increased from approximately 3 percent in 1996 to almost 11 percent in 2010. The vast part of the increase has occurred since 2001, the year that China became a member of the World Trade Organization (WTO).

[FIGURE B1 around here]

In the empirical analysis, we use the data on Chinese exports to the world market excluding Denmark from the UN COMTRADE database. This international database contains six-digit product-level information on all bilateral imports and exports between any given pair of countries. We aggregate from the six-digit product level to the four-digit product level. This issue relates to market relevance and how specifically a product should be defined to capture the relevant international competition measure for the individual firm. There are approximately 1,250 different product types when applying the 4-digit codes.

A potential concern in our empirical specification is that firms might shift out of the production of some products and into the production of other products in reaction to increasing international competition. Thus, we use the pre-sample specialization patterns of firms, i.e., the 2005 specialization pattern, to calculate the relevant measure of international competition in the export markets from China.

Chinese exports is an aggregate measure of the exports of Chinese-produced product types exported to the world market. This measure includes all exports to the world, excluding exports to Denmark. We create a measure defined as follows:

$$EX_{i,t}^{CHN} = EX_{p,t}^{CHN} \text{ with } p\ max(\gamma_{1,i.0}, \dots, \gamma_{p,i.0}, \dots, \gamma_{P,i.0}),$$

where $EX_{i,t}^{CHN}$ is the Chinese exports to the world market of the product – excluding exports to Denmark – with the largest sales share of firm *i*. $EX_{p,t}^{CHN}$ is the Chinese exports to the world market of product p at time t, and $\gamma_{p,i,0}$ is the product p sales share of firm *i* at time 0, i.e., the pre-sample sales share. The calculation of Chinese exports is based on UN COMTRADE data for $EX_{p,t}^{CHN}$ and on the Industrial Sales of Product Types from Statistics Denmark for $\gamma_{p,i,0}$. Because the firm identifier in the Industrial Sales database is the same as other firm-level identifiers, we can match the sales data to the firm statistics. Firms with employment levels or sales below the threshold levels are not required to report to the Industrial Sales database, which implies that we lose 32 observations in the regression results presented below. Specifically,

[4] We have also constructed an automation score by calculating the z-scores - normalizing to a mean of zero and a standard deviation of one. The established results in the paper are robust to this choice.

the regressions on automation capital and internationalization are based on 442 of the 474 firms in the estimation dataset. The information is randomly missing across skills, valued added, and capital stock, but firms with fewer than 10 employees in 2010 are underrepresented, as are firms in the food and metal industries.

The measure is similar to the measure of import competition applied by Bernard, Jensen, and Schott (2006) and Bloom, Draca, and Van Reenen (2016). However, they use a measure of import competition at the industry level in which firms are assigned to specific industries and not to the product with the largest sales share in the firm.

We also include Chinese import penetration and import penetration from low wage countries in some of the regressions. Chinese import penetration is an aggregate measure of the import of Chinese-produced product types exported to Denmark. The calculation of the Chinese import penetration is based on trade data available through Statistics Denmark and merged on the existing data using the product code at the four digit level with the largest sales share in 2005 for each firm.

Low-wage country import penetration is constructed similar to Chinese import penetration. We split the countries accordant to 2005 GNI per capita, calculated using the World Bank Atlas Method.

Measure of Firm Performance: We apply two measures of firm performance, labour productivity, which is constructed as log of (value-added/labor) and profit-to-sales ratio. Both originate from Danish registers.

APPENDIX C: SURVEY QUALITY, SAMPLE SELECTION, AND ESTIMATION SAMPLE

C.1 Quality of Survey Questions

One important criticism of the survey dataset for the automation of production processes and management practices is that the data for 2005 and 2010 are collected at the same point in time. A relevant critique is therefore that the data quality is low and that the measurement error in the observed changes in the scores for automation and management practices is large; therefore, we cannot apply long differences to the dataset.

We argue that the collected survey data are of high quality for three reasons. First, during the 20 firm visits, production managers consistently stated that there is so much focus on automation and management practices that they could provide high-quality retrospective answers. Second, considerable external validation of the survey data is shown in the analysis presented in sections 4 of the paper in which we find a strong association between the change in the automation score and the management practice score and labour productivity growth and the change in profit-to-sales ratio that both originate from a different data source. Third, we show that the changes in automation and management practices are consistent with similar – but less detailed – survey data collected for previous years in the "Community Innovation Survey (CIS)". We turn to this issue now.

The CIS is collected each year by Statistics Denmark by using a rotating panel. We consider the questions on process and organizational innovations to externally validate our survey questions on automation and management practices. Specifically, we use the following question on process innovation:

Process Innovation: *In the past three years, did your enterprise introduce new or significantly improved methods for the production of goods or services?*

We also use the following question on organizational innovation:

Organizational Innovation: *In the past three years, did your enterprise introduce*

- *New business practices for organizing procedures (e.g., supply chain management, business reengineering, knowledge management, lean production, or quality management)?*
- *New methods of organizing work responsibilities and decision making (e.g., first use of a new system of employee responsibilities, teamwork, decentralization, integration or de-integration of departments, or education/training systems)?*

We use four years of the CIS data, 2007-2010, which implies that we have answers to the questions that include 2005-2010. Because the CIS is a rotating panel, the same firms do not answer the survey every year. The sample is stratified such that the largest firms answer every year, 80 percent of the second-largest firms answer every year, 60 percent of the third-largest firms answer every year, etc. Of the firms that we surveyed, 290 have also answered CIS surveys at least once during this period. For each question, we constructed a dummy variable equalling one if the firm answered “yes” to a question at least one time during the four rounds of the survey and 0 otherwise.

In Table C1, we investigate the relationship between the dummy variables based on CIS and the changes in automation from our survey.

[TABLE C1 around here]

The firms that respond “yes” to process innovation exhibit larger changes in the automation score from 2005 to 2010 than the firms that respond “no”. However, the firms that respond “yes” to organizational innovation do not exhibit larger increases in the automation score compared with the firms that respond “no”.

We ran similar regressions for management practices, which are presented in Table C2. We present the results with two dummies for organizational innovation, namely, one for each of the two questions reproduced above. Moreover, we excluded the dummy for process innovation because this dummy enters insignificantly in the regressions when included.

[TABLE C2 around here]

Table C2 shows that the firms that respond “yes” to having introduced new business practices also experienced a higher increase in the management practice score. Thus, the changes in the score for management practices and automation are consistent with the cruder variables on process and organizational innovation from Eurostat CIS, which provides additional external validation of the collected survey data.

C.2 Internal Validation of Survey

When using a survey, it is always important to ensure high-quality responses. We ensured the quality of the survey in two ways. First, in the process of constructing the survey, we visited companies, and following a tour of the shop floor, we monitored the respondents who completed the survey to ensure that the scales were used in agreement with our intention. Early in the process, we performed a similar exercise and then reformulated and added examples and information to the questions to eliminate ambiguities. Second, internal validation was considered during the data collection phase. Additional questions were built into the survey to allow for a test for consistency to be performed on the electronic data immediately after a survey was finalized. This test for consistency accomplishes two goals. First, it should ensure that the questions were understood as intended. Second, the validation ensures that the firms did not complete the survey randomly. The responses that failed the consistency test gave rise to the companies being contacted again and interviewed concerning their manufacturing system by industry experts. These experts also reviewed a group of apparent outliers, which consisted of medium to large firms that reported surprisingly low automation levels and a set of companies that reported the highest automation levels. Eight apparent outlier firms were re-contacted to confirm the answers that they had provided.

C.3 Data Collection and Sample Selection

The survey that we used to construct the automation capital, automation score, and management practices score, was voluntary to participate in, and the response rate was 41 percent, which is high by the standards of large-scale surveys that are not government mandated. In Table C3, the response rate and the reasons for refusal are shown. As seen in column 1, there were just over 3,000 manufacturing firms in Denmark that provided annual reports between 2008 and 2010 and had more than 10 employees in 2005. Of these firms, 21 percent were included in our sample, which is a very high percentage for a survey.

[TABLE C3 around here]

After comparing the participating firms with the non-participating firms by using a Probit model (results not shown), there is no evidence that either the performance data or other observed firm characteristics differed systematically across the groups.

C.4 Sample used in the paper

In this sub-appendix we clarify the number of observations dropped due to missing information in the other data sources used. Of the survey sample of 576 manufacturing firms, 573 firms are found in the register data. We lose 99 firms because we do not have complete data for value added, employment, and capital variables to include in the analysis. This leaves us with 474 firms in the analysis of productivity and automation. We lose an additional 32 firms in the analysis of automation and Chinese exports due to missing information on product codes. This is firms with employment levels or sales below the threshold levels that are not required to report to the Industrial Sales database, This leaves us with 442 firms in the analysis on Automation and International competition. For more details see Table C4.

[TABLE C4 around here]

APPENDIX D: MANAGEMENT PRACTICE SCORE

Because the general attitude among both researchers and managers is that success in implementing complex technologies requires changes to the entire organization, information related to automation and to the management practices on the production floor was needed.

To investigate the distribution of management practices across industries and firms, we constructed a management practice score. This appendix presents the questions included in the score. The survey questions can be grouped into "decentralization of decisions in the production process" (Decentralization – DEC), "human resource management of production workers" (Human Resource Management – HRM), and "performance management" (Key Performance Indicators – KPI) categories. The management practice score used in Section 4 is constructed as an unweighted mean of the firm responses. The questions are inspired by the series of papers by Bloom and van Reenen.

Decentralization (DEC): DEC is related to the delegation of power to production workers. The four questions asked about DEC are the following:

1. Who (what) decides the speed of work in production?
2. Who (what) decides the timing of production tasks (scheduling)?
3. To what extent is the work assigned to autonomous groups rather than to individuals working independently?
4. Who generally decides how tasks are to be performed (*e.g.*, concerning process improvements or machine choices)?

Each question is answered on a scale from 1 to 5, which differs depending on the wording of the question.

Human resource management (HRM): HRM relates to the investment in and development of employees to ensure that workers have the required knowledge and are motivated and empowered to perform their jobs. The following four questions are asked about HRM:

1. Does the workplace have a systematic approach for identifying efficient production workers who achieve results?
2. Does the workplace have a systematic approach for identifying inefficient and ineffective production workers who do not achieve results?
3. What actions are taken to address inefficient production workers?
4. What proportion of production employee wages are performance-based?

Each question is answered on a scale from 1 to 5, which differs depending on the wording of the question.

Performance management (KPI): KPI is related to the evaluation of production processes. The following four questions are asked:

1. How many key performance indicators are used for managing daily production?
2. How often are the key performance indicators measured or computed?
3. What is the communication process for daily production key indicators?
4. Are there any actions for following up on daily production key indicators?

Each question is answered on a scale from 1 to 5, which differs depending on the wording of the question.

APPENDIX E: ADDITIONAL EMPIRICAL RESULTS

E.1 Lagged Chinese Exports and Automation

In Table E1, we present regressions similar to the regressions in Table II column 1 by using different lag lengths for Chinese exports to the world market excluding Denmark.

[TABLE E1 around here]

The table shows that the Chinese exports from 2003 to 2008 (2-year lag), from 2002 to 2007 (3-year lag) and from 2001 to 2006 (4-year lag) has a positive effect on automated capital stock. Thus, the firms that specialize in product types that have experienced high increases in Chinese export to the world market have increased their automated capital stock more than the firms that are less exposed to increasing Chinese export. For automation, therefore, the largest effects appear after four years, which indicates that some time is required to adjust to the changing conditions of competition in the world market.

APPENDIX F: THE DANISH MANUFACTURING SECTOR COMPARED TO EU AND THE US

To give the reader a better understanding of the structure of the Danish manufacturing sector this sub-appendix shows the distributions of the manufacturing sector for Denmark, the US and EU using value added and employment. This hopefully help readers to see that the findings are not only relevant for Denmark, but for many other countries also.

Figure F1 shows the structure of the Danish manufacturing sectors for 2005 measured using value added shares. Denmark is compared to the US-economy as well as the group of countries from the European Union that was members in 2000. This group contains the following countries: Austria, Belgium, Spain, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Sweden and the United Kingdom.

Overall the figure shows that the structure of the Danish manufacturing sector is relatively similar to that of the US-economy and EU structure with a few deviations. The most important deviations are for the food industry and the transportation industry. The share of value added is much larger for the food industry than it is in the US and EU and much smaller for the transportation industry.

[FIGURE F1 AND F2 around here]

Figure F2 shows the structure of the Danish manufacturing sectors for 2005 using employment shares. The picture is similar to that using value added. In conclusion, the structure of the Danish manufacturing industry is in many ways just a smaller version of the EU-economy and the US-economy. Thus, the results presented in the present study are assessed to be relevant for many other countries

APPENDIX G: THE DANISH AUTOMATION STOCK COMPARED TO EU, THE US AND THE WORLD

To give the reader a better picture of the use of automation in Denmark this sub-appendix shows the development in the robot stock for Denmark, the EU, the US and the World in general. The purpose is to show that the findings are not only relevant for Denmark, but for many other countries as well. The data is from IFR – International Federation of Robotics.

[FIGURE G1 around here]

Figure G1 shows the operational stock of robots for the manufacturing sector.[5] We have normalized the robot stock to take the value 1 in 2015 to be able to compare the development more easily. The operational stock of robots is in 2003 similar for Denmark and the World measured relative to the stock in 2015. Between 2003 and 2008 the growth in the stock is somewhat larger for Denmark at the same level as the US, approaching the level of the overall stock in the EU. After 2008 Denmark follow the same pattern as the EU. Therefore, we can conclude that the development in the robot stock in Denmark is of similar magnitude to that of the EU and the US. Thus, the results presented in the present study are assessed to be relevant for many other countries

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[5] IFR uses the definition of a "manipulating industrial robot" given by the ISO 8373 standard from the International Organization for Standardization. This standard defines an industrial robot as: *"An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications"* (International Federation of Robotics 2011, p. 6). IFR collects their data from the producers of robots. They provide data both on shipments/sales of robots to industries in different countries, and on the operating stock of robots in different countries. In calculating the operating stock, it is assumed that the average operating service life of an industrial robot is 12 years.

APPENDIX TABLES AND FIGURES

TABLE C1: External validation of automation using the Community Innovation Survey (CIS) – Five-year difference estimation

	Δ Automation score
Process innovation	0.132**
	(0.063)
Organizational innovation	-0.017
	(0.061)
R-squared	0.026
Number of observations	290

*Note: The period is 2005-2010. Process innovation is a dummy variable equal to one if the firm responds "yes" to "In the past three years, did your enterprise introduce new or significantly improved methods for production of goods or services?" Organizational innovation is a dummy variable equal to one if the firm responds "yes" to "In the past three years, did your enterprise introduce new business practices for organizing procedures?" or to "In the past three years, did your enterprise introduce new methods of organizing work responsibilities and decision making?". The regression includes log(employment) and log(capital) as additional explanatory variables (not shown). The standard errors in all columns are robust to heteroscedasticity and autocorrelation of an unknown form. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.*
Source: Authors' survey on automation in manufacturing and register and survey data from Statistics Denmark

TABLE C2: External validation of management practices using the Community Innovation Survey (CIS) – Five-year difference estimation

	Δ Management practices
<u>Organizational innovation:</u>	
Business practices	0.157**
	(0.078)
Organizing work responsibilities	0.050
	(0.080)
R-squared	0.106
Number of observations	290

*Note: The period is 2005-2010. Business processes is a dummy variable equal to one if the firm responds "yes" to ""In the past three years, did your enterprise introduce new business practices for organizing procedures?" Organizing work responsibilities is a dummy variable equal to one if the firm responds "yes" to "In the past three years, did your enterprise introduce new methods of organizing work responsibilities and decision making?" The regression includes log(employment) and log(capital) as additional explanatory variables (not shown). The standard errors in all columns are robust to heteroscedasticity and autocorrelation of an unknown form. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.*
Source: Authors' survey on automation in manufacturing and register and survey data from Statistics Denmark

TABLE C3: Response rate

	Population	Adjusted population	Contacted firms
*Number of manufacturing firms**	**3,057**	**2,713**	**1,409**
Number of responding firms (100% completed)	**576**	**576**	**576**
Not contacted by the callers	**1,304**	**1,304**	
Reasons for refusal:			
No production in DK /outsourced	166		
Liquidation/insolvent	36		
Bought by another firm	1		
Wrong industry code, not a manufacturing firm	141		
Adjusted population	**2,713**		
Not relevant to the firm	126	126	126
By principle	51	51	51
Too complicated survey	64	64	64
No time	336	336	336
Problems with anonymity	6	6	6
Not interested	77	77	77
Other reasons	173	173	173
Number of firms that refused to participate	**1,177**	**833**	**833**
Response rate	**19%**	**21%**	**41%**

*Note: * Manufacturing firms in Denmark with more than 10 employees in 2005*
Source: Authors' survey on automation in manufacturing and register data from Statistics Denmark

Table C4: Firms that complete the survey, but have other missing information:

Number of responding firms (100% completed)	576
Not in registers	3
In registers	573
Not in registers in 2005 or 2010	29
In registers in 2005 and 2010	544
Missing value added for 2005 and 2010	2
Missing employment for 2005 and 2010	5
Missing M&E capital (including automation capital)	48
Missing IT-capital	15
Sample of Table III of the paper	474
Missing product codes or information on product codes	32
Sample of Table II of the paper	442

Source: Authors' survey on automation in manufacturing and register data from Statistics Denmark

TABLE E1: **Automation and international competition – Dependent variable: log(automated production capital).**
Five-year difference estimation, lagged Chinese export

	(1)	(2)	(3)	(4)	(5)
Δlog of Chinese export 2005-2010	0.095				
	(0.075)				
Δlog of Chinese export 2004-2009		0.101			
		(0.066)			
Δlog of Chinese export 2003-2008			0.109*		
			(0.059)		
Δlog of Chinese export 2002-2007				0.130**	
				(0.063)	
Δlog of Chinese export 2001-2006					0.145**
					(0.059)
R-squared	0.445	0.447	0.449	0.450	0.450
Number of firms	442	442	442	442	442

*Note: Estimation is by (unweighted) OLS with standard errors clustered by the four-digit product code in parentheses. Standard errors are robust to heteroscedasticity and autocorrelation of unknown form. Regressions are performed on long differences that sweep out firm fixed effects. The dependent variable is the five-year change log of automated capital. The explanatory variables presented in the table is the change in the log of Chinese export. All regressions include a full set of explanatory variables that consist of the five-year change in the log of IT capital, log of non-IT, non-automated capital, log of employment and skill share as well as a full set of industry-by-region dummies to control for the industry trends that are allowed to vary across regions. There are 10 industries and 8 regions. All changes are in five-year differences between 2005 and 2010, except for the log of Chinese export where the five-year differences are presented in the table. The measures of international competition are measured at the product level. There are 189 different product codes for the 442 firms. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.*
Source: Authors' survey on automation in manufacturing, UN Comtrade data, and register data from Statistics Denmark

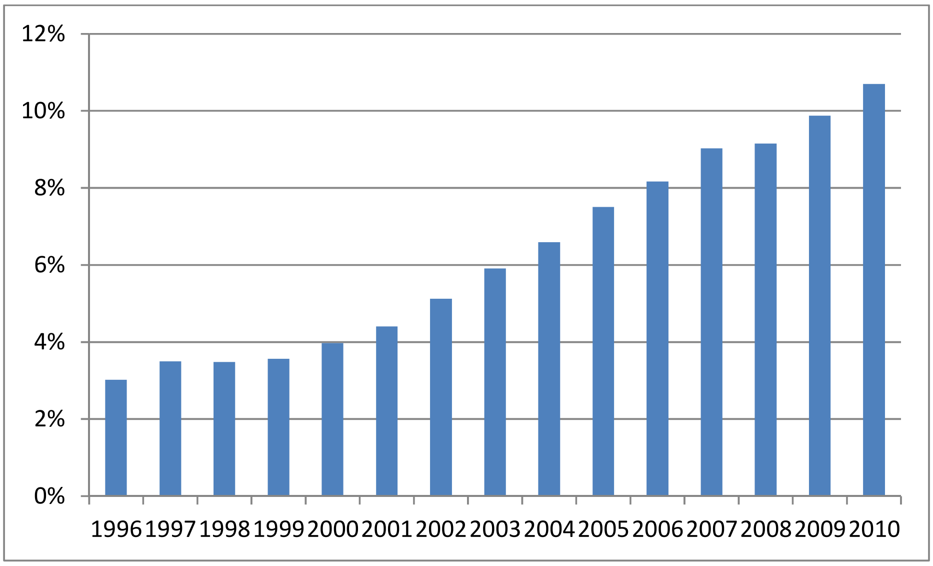

FIGURE B1: Share of world exports from China, 1996-2010
Source: UN Comtrade database

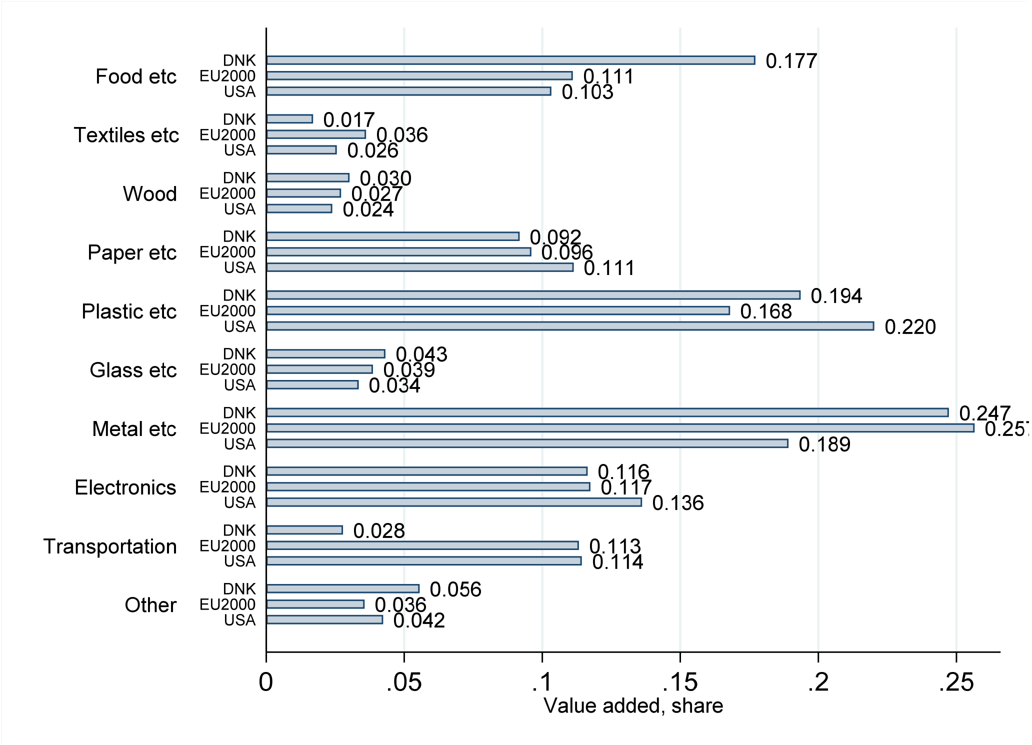

Figure F1: Value added across industries and country groups in 2005.

Note: DNK: Denmark; EU2000: Austria, Belgium, Spain, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Sweden and the United Kingdom (members of the European Union in 2000).

Source: EUKLEMS data. EUKLEMS (2009) database, contains industry-level measures of output, inputs, productivity and worker quality for 25 European countries, Japan and the USA for the period 1970-2007. O'Mahony and Timmer (2009) provide a description of the EUKLEMS data.

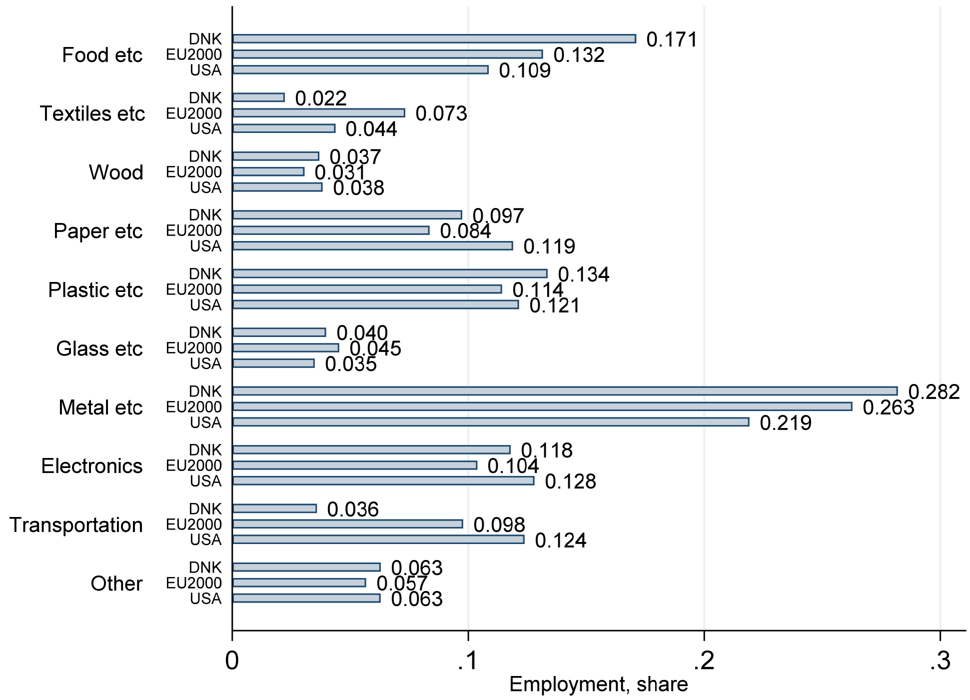

Figure F2: Hours worked by person engaged across industries and country groups in 2005.

Note: DNK: Denmark; EU2000: Austria, Belgium, Spain, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Sweden and the United Kingdom (members of the European Union in 2000).

Source: EUKLEMS data. EUKLEMS (2009) database, contains industry-level measures of output, inputs, productivity and worker quality for 25 European countries, Japan and the USA for the period 1970-2007. O'Mahony and Timmer (2009) provide a description of the EUKLEMS data.

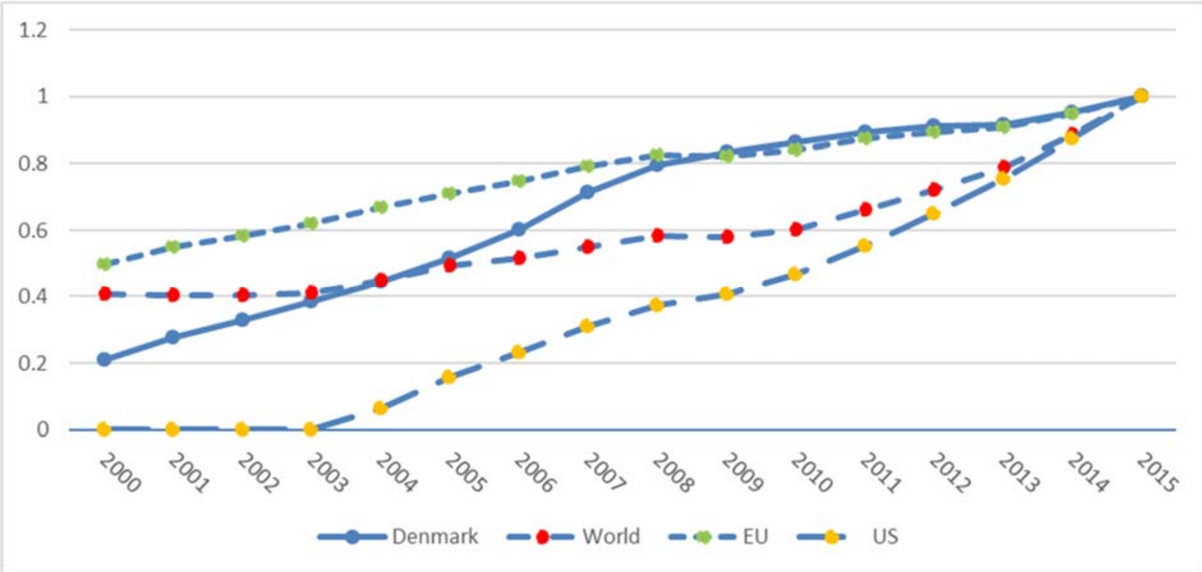

Figure G1: Operational stock of robots for the manufacturing sector across time for Denmark, EU, the US, and the World

Note: The stock of robots is calculated relative to 2015 for each region.

Source: International Federation of Robotics data.