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

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Automation

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, drivers of investments in automated production capital, and productivity effects of automation is limited. This paper uses a new survey dataset combined with register data to examine these issues. The adoption of new technologies is slow, and almost half of Danish manufacturing firms relied greatly on manual production processes in 2010. Moreover, the manufacturing firms that are exposed to increasing international competition from China in their output markets invest more in automation than firms without intensifying competition. Finally, the manufacturing firms that invest in automated production processes improve productivity growth relative to the firms that do not invest in automated production processes. Omitted variable bias is considered carefully and it is argued that the two relationships of interest are most likely causal. However, due to the use of non-experimental data, we cannot claim that we have completely handled all the potential endogeneity problems.

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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We thank Ed Lazear, Kathryn Shaw, Chad Syverson, two anonymous referees, and the participants of several seminars for their useful comments. This paper is part of the AIM project that focuses on automation in Danish manufacturing firms. A main objective was to collect survey data on the automation of production. A survey was developed by researchers, consultants, engineers, and industry experts from Copenhagen Business School, the Danish Technological Institute, the University of Southern Denmark, Aalborg University, and Eltronic. Financial support from The Danish Industry Foundation is gratefully acknowledged. The Danish Industry Foundation had no involvement in this research.

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]

In this paper, we ask three questions. First, how widespread is the use 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. Second, has increasing international competition from China since its admission to the World Trade Organization (WTO) accelerated the adoption of automation technologies? This is a potential driver of automation investments for firms that are highly exposed to such competition. Third, what is the effect of automation on firm productivity? Even though we expect a positive relationship, a quantification is of high importance. Although automation is debated intensively in the literature, these three questions are not properly answered.

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, which enables us to study the three questions. 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 are automated; we label the latter measure the automation score. The survey was developed so that these two aspects could be measured.[2]

For the first question regarding the adoption of automation across manufacturing firms, we find that the use of automation is modest in many firms. In 2005, almost 40 percent of the firms' 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. Moreover, during the 5-year period under investigation, the adoption of automation mostly consists of incremental changes. These results lead us to conclude that the

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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 are 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.

adoption of automation technologies is limited and that many firms have not yet started the automation journey.

For the second question, 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 approximately 1.5 percentage points higher per year for the 75th percentile firm compared to the 25th ranked after Chinese export changes for the firms' main product.

For the third question regarding the effect of automation on firm productivity, we find that firms with increasing automation have higher productivity growth. Moving from the bottom to the top quartile of growth in automated capital is associated with an additional productivity growth rate of approximately 1.4 percentage points per year. Regarding the automation score, the same shift results in an increase of almost 1.7 percentage points of additional productivity growth.

Biased estimation results due to omitted variables is a concern because investments in automation are not randomly assigned across firms. This is especially the case for the analysis of productivity and automation. Among others, we do the following to mitigate this concern: We estimate long-differences models with firm fixed effects that handles time-invariant omitted variables. Moreover, using long-differences is one approach for addressing measurement errors. We also include time-varying measures of management practices, which could potentially constitute important omitted variables, in our analyses and find that our results are robust. These analyses indicate that the results for the second and third question are likely causal relationships. However, due to the use of non-experimental data, we cannot claim that we have completely handled all the potential endogeneity problems that can arise from simultaneity, measurement errors, and omitted variable bias.

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 productivity include Graetz and Michaels (2018) and Kromann, Malchow-Møller, Skaksen, and Sørensen (2014), 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 describes the production process and presents automation examples from firm visits. Moreover, the design of the survey is described. We present the empirical framework in Section 3. The empirical analyses are presented in Section 4 and Section 5 presents two robustness analyses. Section 6 discusses policy implications and concludes the paper. Sections 3 and 5 can be skipped without losing the main message of the paper.

2. THE IMPORTANCE OF CHARACTERIZING AUTOMATED CAPITAL

This section first reports on the observations from firm visits used to develop the questions on automation used in the survey. Second, we illustrate the structure of the survey, including information on how the automated capital and automation score are captured. 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 Section 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 automated capital and automation score increased in many firms over the 5-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 to 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 combing answers to this question with register data on investments in machinery and equipment, we can determine the investments in automated capital. With data on these investments, we construct automated capital stocks using the perpetuity investment method (PIM). The details are presented in the online Appendix B.

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?

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 are automated across the three stages.[3] 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).

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

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[3] 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.

processes continue to be largely manually operated. We also find high variation (not shown) in the automation score within narrowly defined manufacturing industries.

[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]

We close this subsection by concluding that there is high variation in automation across the surveyed firms, that automated capital and the automation score have increased over the 5-year period from 2005 to 2010, and that automation occurs in different stages of the production process. Overall, the results show that there is a wide range among Danish manufacturing firms in the automation of their production processes. Thus, there is considerable potential for firms to automate larger shares of their production processes. We perform an external validation of the collected survey data. We present the results in the online Appendix C.

2.4. Descriptive statistics

In this final sub-section, we present the descriptive statistics for the firms used in the empirical analyses. 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. Next, we present the descriptive statistics for the three automation questions separately. The table shows that the automation of manufacturing processes attains a value of 2.68 in 2005 and increases to 3.12 in 2010. Again, we see that firms have a relatively high degree of automation within this stage.

[TABLE Ia around here]

Next, we present the descriptive statistics for the additional variables used in the empirical analysis. The dependent variable and other explanatory variables used in the empirical analysis are the (log of) value added, (log of) automated capital, (log of) IT capital, (log of) non-IT, non-automated capital in a firm, (log of) employment, and skill share. Here, we present the (not log transformed) means and standard deviations. The result shows that, on average, the amount of non-IT, non-automated capital in a firm is approximately four times greater than the amount of automated capital. Non-IT, non-automated capital is approximately 10 times greater than IT capital. Moreover, value added 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-IT, non-automated capital do not decrease. The reason that IT capital falls relatively greatly is due to low investment levels and a large depreciation rate. A final observation is that the average firm in the sample is relatively small and has 111 employees. Just over 90 percent of the firms are small and medium enterprises (SMEs) with less than 250 employees.[4]

Table Ib presents the development in measures of international competition, measured by yearly changes in log points. The table shows that Chinese exports to the world, excluding Denmark, on average, increased by 0.29 log points per year for the four-digit product codes from 2001 to 2006. 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 4-year lag, as discussed in Section 4.1. 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).

[TABLE Ib around here]

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[4] In online Appendix G, 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 European Union members in 2000.

3. EMPIRICAL MODELLING

In this section, we present and discuss the main models that will be used for estimation in the empirical analyses. In broad terms, these models describe the relationship between Chinese exports and the accumulation of automated capital and the relationship between firm performance and automation.

3.1. Trade-induced Automation

We assume a linear relationship between the (log of) automated capital (k_{it}^{A}) and (log of) Chinese exports ($EX_{i,t}^{CHN}$) for firm i in year t. The hypothesis to be investigated is the trade-induced automation hypothesis that implies that the coefficient of $EX_{i,t}^{CHN}$ is positive and significantly different from zero. We also expect the hypothesis to hold after controlling for other inputs of production in the firm (W).

One concern when estimating the relationship between automated capital and Chinese exports is that the firms exposed to high competition from China may be of a different type than the 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. To address this problem that potentially leads to an omitted variable bias, we estimate a model with firm fixed effects (b_i) that eliminates this bias. In this way, we can include an intercept (or constant term) in the regression for each firm so that the starting level of the automated capital of each firm is held fixed in the regression, and the growth of automated capital within the firm that is driven by increasing Chinese exports can be estimated.

Another important problem in the estimation of the relationship between automated capital and Chinese exports 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, i.e., to use the change in variables over a 5-year period instead of using yearly observations, because the bias should be lower, as long differencing removes some of the noise by averaging temporary shocks; see Griliches and Hausman (1986). Therefore, we estimate the relationship in 5-year differences between 2005 and 2010. 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 a 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 and, therefore, to lay-off. The increasing competition from China lowers the demand for products that skilled workers helped produce. Due to the high training costs, the skilled workers stay 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 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 the 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.

3.2. Firm Performance and Automation

The relationship between firm performance and automated capital is estimated by using a Cobb-Douglas production function where the (log of) value added (y_{it}) is produced by three types of capital – (log of) automated capital (k_{it}^{A}); (log of) IT capital (k_{it}^{IT}); and (log of) non-automated, non-IT capital (k_{it}^{NA-NIT}) – and the (log of) labour input (l_{it}).

There is an extensive stream of recent literature that analyses the output and productivity 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 estimate a production function that includes both types of capital in addition to other inputs.

We build on the approach taken in the IT literature and estimate a production function that distinguishes between IT and non-IT capital. Furthermore, our dataset allows us to split non-IT capital into automated capital and other types of 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 productivity and the three types of capital. To the best of our knowledge, this study is the first to distinguish among IT capital, automated capital and non-IT, non-automated capital. In addition to automated capital, we assume that productivity is related to the automation score (AI_{it}).

As for the trade-induced automation hypothesis discussed above, we are concerned that firms may be of different types, where higher quality firms invest more heavily in automated capital, and that it may well be the better performance of these firms that makes them productive rather than investments in automated capital. To handle this potential problem, we estimate a model with firm fixed effects that eliminates this bias. Again, we measure the variables as 5-year differences, and we include a full set of industry dummies interacted with region dummies to absorb possible unobserved the trends that are correlated with value added and automation.

The main interest in this part of the study is the relationships between the (log of) value added (y_{it}) and (log of) automated capital (k_{it}^{A}) and between the (log of) value added (y_{it}) and the automation score (AI_{it}). 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 productivity is positively related to the share of automated production processes.

4. EMPIRICAL RESULTS

In this section, we present the main results of the analysis. Section 4.1 contains our results for trade-induced automation, whereas Section 4.2 presents our results on the relationship between productivity and automation.

It should be emphasized that omitted variable bias may still be an issue even though we apply models with firm fixed effects. This is the case if there are important omitted variables that change over time. Because of this, omitted variables that change over time will be discussed to some extent in the following empirical analyses. This is the case both for the trade-induced automation hypothesis and the analysis of productivity and automation.

4.1. Trade-induced Automation Hypothesis

The results of the trade-induced automation hypothesis are presented in Table II. In the first 4 columns, we estimate the relationship between automated capital and Chinese exports by using different additional explanatory variables (W). Finally, in columns 5 and 6, we estimate two equations similar to the regression in column 4 for different dependent variables, i.e., non-IT, non-automated capital and IT capital.

The trade-induced automation hypothesis states that the coefficient to $EX_{i,t}^{CHN}$ 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, $EX_{i,t}^{CHN}$. We use a lag of 4 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.

In column 1 of Table II, we include only Chinese exports and find a coefficient of 0.17, which is significant at the 5 percent level. 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 estimate long-difference models with firm fixed effects that eliminate time-invariant heterogeneity across firms. 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 measure similar to the measure that Bloom, Draca, and Van Reenen (2016) apply. 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.[5]

We also include 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 of) IT capital, (log of) non-IT, non-automated capital, (log of) employment, and skill share. The result is presented in column 4. Chinese exports remain positive and significant in the regression. The coefficient is equal to 0.129 and is significant at the 5 percent significance level.[6] Moving from the bottom to the top quartile of growth in Chinese exports is associated with a higher growth rate in automated capital of approximately 1.5 percentage points of additional growth per year.

[TABLE II around here]

Finally, columns 5 and 6 of Table II show that only automated capital is affected by Chinese exports. Neither IT capital nor non-IT, non-automated 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 on IT capital is that manufacturing firms have already to a great extent adopted IT by 2005.

We interpret the above result 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 not causal. 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".

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[5] We have also investigated if firms respond to Chinese exports by offshoring activities to low-wage countries. To do this, we ran regression 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.

[6] 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.

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, as mentioned in Section 3.1, 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 international competition.

4.2. Productivity and Automation

This section presents the results for productivity growth by using value added as an output measure. Specifically, we investigate the separate relationships between the two automation measures and firm performance. Aggregate capital consists of the following three types of capital: automated capital, IT capital, and non-IT, non-automated capital. The correlations between the 5 year log-changes of automated capital and non-IT, non-automated capital are relatively high and equal 0.47. This potentially leads to insignificant point estimates on automated capital and non-IT, non-automated capital when both are included due to multicollinearity. Motivated by this relatively high correlation, we include the three capital types in the regressions one at a time in columns 1-3 of Table III.

In column 1, we include automated capital. The point estimate equals 0.11 and is significant at the 1 percent level. In column 2, we include IT capital, which has a point estimate of 0.07 that is significant at the 5 percent level. In column 3, we include non-IT, non-automated capital as the capital measure. It is evident that this capital type has a positive point estimate of 0.06 that is significant at the 10 percent significance level. In summary, we conclude that the three capital types all enter with positive and significant point estimates when included one at a time.

In column 4, we include all three capital types together. Automated capital is positively and significantly correlated with the value added at the 1 percent level, IT capital is significant at the 10 percent level, whereas non-IT, non-automated capital is close to zero and insignificant. This result suggests that investments in automated capital have been an important growth driver. Moreover, even when we include three growth rates of different capital types, we obtain a positive coefficient for automated capital, which reflects that this capital type correlates significantly with firm performance even when including other capital types. The point estimate is the conditional correlation between changes in automated capital and changes in value added after controlling for other inputs. IT capital, on the other hand, loses some significance, whereas non-IT, non-automated capital loses all significance.[7]

It should also be mentioned that the point estimate for the effect of employment is 0.66, which is close to the share of labour costs of the value added and is consistent with the estimates found elsewhere in the literature; see, for example, Caroli and Van Reenen (2001).

Finally, in column 5, we add the automation score in addition to automated capital. Both measures of automation are positive and significantly different from zero, which supports the idea that both dimensions of automation increase firm performance and strongly supports the claim of production managers, suppliers of automation equipment and industry experts that the share of production processes that are automated is an important aspect.

[TABLE III around here]

Moving from the bottom to the top quartile of growth in automated capital is associated with an additional productivity growth rate of approximately 1.4 percentage points per year. Regarding the automation score, the same shift results in an increase of almost 1.7 percentage points of additional productivity growth.

The conclusion is not only that more automated capital adds more value than more IT capital, but also that, keeping fixed the amount of automated capital, having that automation of production processes increases productivity. The interpretation of this is that, the automation score is 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 productive.[8]

For the estimates presented in Table III, we are concerned with omitted variables that change over time. We are also concerned with two additional biases when estimating the production function. These are potentially simultaneity bias and bias related to firms that close down and exit the economy, which is labelled selection bias. Potential simultaneity of inputs lead to a positive correlation between the inputs and unobserved productivity shocks. Consequently, the coefficient of labour is positively biased. The selection bias arises from the relationship

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[7] We interpret the high significance of automated capital and lower significance of IT capital as a consequence of automated capital being a more important growth driver. However, 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 for IT capital and automated capital with high precision. That being said, it should be emphasized that both capital measures enter significantly in the regressions in Table III, at least at the 10 percent significance level.

[8] 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 regressions of Table III 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.

between productivity shocks and the probability of exit. If profitability is positively related to the capital stock, then a firm with a large capital stock is more likely to stay when a negative productivity shock is realized compared to a firm with a small capital stock, because firms with more capital expect greater profits in the future. The negative correlation between a capital stock and the probability of exit for a given productivity shock will result in point estimates for the capital variable that are biased downward. Also see the discussion in Olley and Pakes (1996). We expect this to be the case for all capital types, including also automated capital. We also expect the firm's profitability to be positively correlated with the automation score, such that a firm with a larger score is less likely to exit than a firm with a low score. In this sense, the point estimates for the automation variables will be underestimated.

In Section 5, we address omitted variables that change over time in a number of robustness analyses. We investigate simultaneity and selection in a broad sense using register data in online Appendix F. We have placed this discussion in the appendix because we expect that the biases of the automation variables are negative, implying that the obtained point estimates in Table III constitute the lower bounds of the true value.

5. ROBUSTNESS ANALYSES

In this section, we perform two robustness analyses. The first analysis is founded on the idea that important information related to management practices is omitted, see Section 5.1. In the second analysis, we study the relationship between alternative measures of efficiency and automation. We have collected data on many alternative measures of efficiency that permit the estimation of within-firm phase-specific models of the effects of automation, see Section 5.2. The strategy that we apply follows Bartel, Ichinowski and Shaw (2007).

5.1. Management Practices

We consider whether the obtained results for firm performance are biased by one specific omitted variable, namely, changing management practices in the production processes. The motivation for including management practice scores comes from a series of papers by Bloom and Van Reenen on this subject that conclude that good management practices improve productivity across firms, see, e.g., Bloom and Van Reenen (2007).

More specifically, we collected data on management practices in addition to the data on automation. These data address decentralization, human resource management, and performance tracking on the production floor. Management practice scores were constructed by following a similar method to the method used for the automation score by using 12 questions; for details, see the online Appendix D. The management practice scores are relevant for the factory floor and do not include management practices of firm support functions, such as, for example, sales offices.

In Table IV, the means and standard deviations are presented for the management practice scores for 2005 and 2010 and for the yearly change between these years. The table shows that the average yearly increase in the overall management practice score equals 0.10 and increases from a value of 2.41 in 2005 to 2.92 in 2010. Moreover, the scores for decentralization, human resource management, and performance tracking are presented. The table shows that these scores follow the same pattern, similar to the overall management practice score.

[TABLE IV around here]

The management practice scores are included in the production function, and the results are presented in Table V. All of the columns are similar to column 5 of Table III but include the management practice scores as additional explanatory variables.

In column 1, we include the overall management practice score in addition to the full set of explanatory variables. The coefficient of management practices attains a value of 0.08 at the 5 percent significance level. The automation score enters positively and is significant at the 5 percent level and the automated capital enters positively but is significant only at the 10 percent significance level.

[TABLE V around here]

Next, we divide management practice into 3 separate scores in the estimation. It is evident from columns 2 and 5 that the scores for decentralization are positively significant with a value of approximately 0.075. The other sub-scores are not significant.

The results presented in Tables V allow us to conclude that the automation score is not a proxy for management practices, which makes omitted variable bias less likely. This result indicates that both automation and management practices – particularly decentralization – have important roles to play in firm performance.

5.2. Alternative Measures of Firm Performance

Although we have controlled for management practices in Table V, other unobserved shocks or management practices of other forms that are not included in our score may induce firms to introduce automation and to improve firm performance, thereby causing a bias in the automation coefficients. In this section, we apply several alternative dependent variables to measure firm performance to show that it is unlikely that omitted variables are driving our results in Table III. We focus, especially, on three production times that are related to three different phases of production. These are the early phase with the setup time as the efficiency measure, the intermediate phase with the run time, and the later phase with the inspection time.[9] This permits the estimation of within-firm phases-specific models of the effects of automation.

In addition to the three efficiency measures that apply to different phases of the production process, we use three internal measures of efficiency that are related to the full production process. These measures are the quantity produced per worker, the quality of the product, and the uptime, where uptime measures the share of time during which production is up and running.[10]

We present the annual growth rates in the alternative firm performance measures from 2005 to 2010 in Table VI. The table shows that the growth rates are in the range of 2 to 4 percent per year, with the run time, setup time, and inspection time being negative, as expected, and the quantity produced per worker, quality of the product, and uptime being positive. Moreover, the number of firms is reduced to 467 because 7 additional firms were excluded due to missing replies on the survey questions on the alternative efficiency measures.

[TABLE VI around here]

In Table VII, panel A, we include the change of automated capital as the only explanatory automation variable for the six alternative performance measures. We also include industry by region dummies.[11] As can be observed, the growing automated capital increases the quantity produced per worker with an effect that is significant at the 5 percent level. Moreover, the run time, setup time and inspection time all have negative but insignificant effects, whereas the quality of the product and uptime have positive but insignificant coefficients. Accordingly, these six performance measures change as expected with automation; however, the coefficients are insignificant except for the quantity produced per worker.

[TABLE VII around here]

In panel B, we include the change in the automation score in addition to the growth rate of automated capital. The growth rate of automated capital now becomes insignificant in the regression with the quantity produced per worker as the dependent variable with a significance level of 0.105. These results are broadly consistent with column 5 of Table III. In contrast, the change in the automation score is significant for most efficiency measures and has the expected sign. Especially, it is seen that setup time is reduced by automation. Reductions in setup time

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[9] Setup time is the time required to prepare a machine or system to be ready to run a job, run time is the time required to complete one item, and inspection time is the time required to inspect a product.

[10] For each of the five measures, the respondents were asked to indicate the level of improvement achieved from 2005 to 2007 and from 2007 to 2010. The following scale was adopted for each measure: 1=deterioration; 2=0-5 percent improvement; 3=5-10 percent improvement; 4=10-20 percent improvement; 5=20-30 percent improvement; and 6=more than 30 percent improvement. To calculate the performance improvement from 2005 to 2010, we multiplied the median percentage changes reported from 2005 to 2007 and from 2007 to 2010.

[11] For the sake of clarity, we do not include the inputs of other production factors, i.e., employment, skill share, IT capital, and non-IT, non-automated capital, as explanatory variables in the regressions. There are no important qualitative differences in the results when including them.

are important because they make it less costly to switch production from one product to another, which makes it easier to change to more customized production.[12]

To address the omitted variable explanation, we focus on the models for different phases of the production process. While we cannot rule out omitted variable interpretations, the results require that any omitted variable(s) must have certain characteristics besides a correlation with both automation and production times. An omitted variable must also vary over time within the firm and have different effects across phases of the production process, i.e., it should be correlated with the log-change in the automation score and with the change in run time and setup time, but not with the change in inspection time. If the firm efficiency in different phases of production is affected differently by automation, then it is difficult to imagine the unobserved shocks that would generate such effects.[13]

For a more detailed demonstration, in this section, we formulate three hypotheses based on observations from the firm visits. To address these, we apply, the scores for the three individual survey questions on automation. We start from the examples in Section 2.1 to formulate the hypotheses. First, in examples 1 and 3, the increased level of *automation in the manufacturing processing and handling processes* (AI_{it}^{MAN}) reduces the run time. Moreover, an increased level of AI_{it}^{MAN} is expected to improve not only the quantity produced per worker because fewer workers are required but also the product quality, because the robots perform the exact same movements each time. Assuming that this result holds across firms, our hypothesis is that a higher level of AI_{it}^{MAN} improves the quantity produced per worker, the run time and the product quality.

Second, in example 2 of Section 2.1, the increased level of *automation of the assembly and packaging processes* (AI_{it}^{ASS}) improves the run time, product quality and inspection time. If this result holds across firms, our hypothesis is that a higher level of AI_{it}^{ASS} involves a significantly positive coefficient for product quality and a significantly negative coefficient for the run time and inspection time. Moreover, Bartel, Ichinowski and Shaw (2007) argue that increased automation, measured by the number of CNC machines, reduces the setup time because automated equipment is expected to facilitate setting up machines for changes in products. If this result holds across industries, we expect a significantly negative coefficient on the setup time for higher levels of both AI_{it}^{MAN} and AI_{it}^{ASS}.

Third, in the last example of Section 2.1, the increased level of the *mechanization of the inventory processes (receiving, picking, palletizing, and shipping)* (AI_{it}^{INV}) improves the quality of the products that customers receive. However, neither the setup time nor the

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[12] In models with the change in the share of customized production out of total production as the dependent variable, we find the changes in the automation score and in the share of customized production are positively correlated. The results are available upon request. Bartel, Ichinowski and Shaw (2007) find similar results for batch processing in the US valve industry.

[13] An example of an omitted variable could be if *worker qualifications* improve near the time that the automation of manufacturing processes increase and these new *worker qualifications* affect the setup time, then this omitted factor can account for the observed effect of the *automation score* on the changes in setup time. However, the improved *worker qualifications* must somehow not be relevant to the changes in inspection time because the *automation score* does not have a significant effect on this variable.

inspection time are expected to be affected because they are not related to the inventory processes. Thus, the last hypothesis is that the coefficient of ΔAI_{it}^{INV} is significantly positive for product quality but insignificant for the inspection and setup times.

To summarize the three hypotheses, only two of the three types of automation are expected to affect setup time, and at least one of the types should not affect inspection time. If these hypotheses are supported, different types of automation have different effects across alternative efficiency measures. This will provide additional support for omitted variable(s) to be less likely using the same logic as above.

Panel C shows that the automation of manufacturing processes, AI_{it}^{MAN}, is important for the quantity produced per worker and the product quality. Moreover, the automation of assembly and packaging processes, AI_{it}^{ASS}, is important for the uptime. All other coefficients in Panel C are insignificant, which is largely a consequence of multicollinearity because the scores of the three individual survey questions are highly correlated, with correlation coefficients equal to 0.43 between the changes in AI_{it}^{MAN} and AI_{it}^{ASS}, 0.32 between the changes in AI_{it}^{MAN} and AI_{it}^{INV}, and 0.40 between the changes in AI_{it}^{ASS} and AI_{it}^{INV}.

Panel D, therefore, presents the results by including the three automation questions one at a time. By examining the three questions separately, the *automation in the manufacturing, processing and handling processes* improves the quantity produced per worker, the product quality and the setup time as expected. When examining the second question, the *automation of the assembly and packaging processes,* a significantly positive coefficient in the product quality regression and a significantly negative coefficient in the run time and setup time regressions are found. For the third question, the *automation of the inventory processes (receiving, picking, palletizing, and shipping)*, only product quality is affected significantly and positively. These results allow us to conclude that different types of automation have different effects across alternative performance measures.

The results presented in this section point to the fact that omitted factors must vary over time within firms, be something other than management practices, and should vary with some alternative efficiency measures but not with others. This result leads us to conclude that automation most likely has a causal effect on firm performance. In this sense, the results support an interpretation that is closer to a causal relationship.

6. 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. Even though automation has a positive effect on firm performance, the adoption of new technologies occurs at a slow pace in many firms. A first-order policy question arises from this study, which is as follows: why do firms not invest in automated capital when adoption results in higher productivity? This question is highly relevant for policy programmes that target automation.

The close collaboration with industry experts and production managers, during firm visits carries out during the development of the automation survey, suggested that the low use of automation is to some extent 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. Information barriers seemed to be present for a large part of the firms visited.

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 processes of production to automate. In this sense, information barriers seemed to 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.[14]

How should policy makers design programmes that focus on higher adoption rates of new technologies? One possibility is to focus on the financial support of investments in automated capital. This is expected to prompt firms that can pass information barriers to increase automation investments, which consist of firms that are already investing in automation or already have an automation plan; firms that do not invest because they evaluated their automation projects to have negative returns without a subsidy and positive returns with a subsidy; and firms that are unable to obtain funding. Another potential policy instrument is subsidies for consultancy to target the information barriers associated with automation that some firms cannot overcome without expert advice.

We discuss information barriers first. Regarding the need for advice, two cases are available from the Danish "Innovation voucher support program" that had the transfer of knowledge from research and technology organizations (RTOs) to SMEs as its main purpose.[15] One case from this programme describes a producer of custom-made driver's cabins that used a voucher for a feasibility study and the implementation of an IT system for 3D design. The firm had previously invested in another IT system, but this system was never used in production, mainly because it was not the best choice for the needs of the firm. Another firm – a coffin producer – wanted to implement a painting robot. The firm had already obtained sales offers from suppliers of robotics but was unable to understand the offers or their own needs. The firm used an innovation voucher for a feasibility study and to implement the painting robot in the production process. These two cases identify the importance of expert advice for feasibility studies and for the implementation of new technology.

Another Danish policy programme that directly targets these two requirements is the Danish "Business Partnership for Advanced Production". This policy programme is still too new to be evaluated, as it only began to allocate funds in November 2016. However, many video cases

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[14] Complaints about limited access to funding may of course also reflect rational credit assessment.

[15] Similar voucher programmes have been implemented in many other countries over the past decade. These programmes were originally introduced in the Netherlands but quickly spread to many other European countries, such as Austria, Germany, Italy, Belgium and, more recently, in some states and provinces in North America.

exist for the firms that received funding for a feasibility study. The overall impression from these cases is that the managers and other key people at the firms are surprised by the suggested solutions that they had not seen themselves, which confirms that expert advice is important. It is also surprising, however, that firms do not finance such advice without public support. Some business executives state that it is uncertain whether they would have funded the preliminary project themselves without government-funded subsidies due to the ex-ante high uncertainty on the outcome of such a project. Thus, even though many firms experience ex-post positive returns on automation projects, they are not willing to finance the initial feasibility study themselves due to considerable own-perceived uncertainty about the outcome.

Regarding financial support, the U.S., for example, implemented tax incentives that encourage firms to replace ageing machines by installing robots and hastening automation. For the next five years, the revised tax code allows firms to immediately deduct the entire cost (compared with a depreciation scheme over many years) of equipment purchases from their taxable income. Such a policy will most likely have an impact on the firms that understand the potential of automation in their own production.

Whether one policy or the other policy is most effective policy for the adoption of new technologies is an important question that must be answered in the future. More research is needed to compare and contrast the outcomes of automation across countries.

We have only considered the effects of automation on firm performance. Brynjolfsson and McAfee (2014) and Frey and Osborne (2017) argue that, in the future, automation will likely replace many existing jobs. This is, of course, a very important topic. Borjas and Freeman (2019) and Acemoglu and Restrepo (2018) study the labour market effects of robots and find that the increasing use of industrial robots in an industry is associated with an important fall in employment and wages, especially for unskilled workers. At present, the number of robots per worker is too low to be a considerable determinant of employment and wage patterns. However, Borjas and Freeman (2019) conclude that in the future – over the next decade or so – this can turn out to be the case if the exponential growth of robots continues. This opens up important questions that we do not address in this paper, such as the following: Would it make sense to implement policies to slow down the rate of automation?[16] Would unskilled jobs be maintained in high wage countries if job automation limiting policies were employed or is job automation rather a consequence of increasing international competition from low-wage countries? The effects of automation on jobs and wages are still far from well-understood, but disruption of job markets from automation is an important issue and should be followed in the years to come.

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[16] A Pew Research Center survey for 10 advanced and emerging economies find that large majorities say that in the next 50 years robots and computers will probably or definitely do much of the work currently done by humans.

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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 index	2.05	0.77	2.37	0.84	0.06	0.09
Manufacturing processes, etc. (AI_{it}^{MAN})	2.68	1.00	3.12	0.99	0.09	0.14
Assembly and packaging processes (AI_{it}^{ASS})	1.96	1.05	2.28	1.21	0.06	0.12
Inventory processes (AI_{it}^{INV})	1.51	0.83	1.70	0.95	0.04	0.10
Value added	52.1	136.7	61.9	304.0	-0.02	0.11
Capital	62.7	211.0	59.4	189.6	0.01	0.10
Persons engaged	110.9	298.7	96.0	273.1	-0.04	0.09
Skills	0.10	0.11	0.11	0.11	0.00	0.01
Automated capital	11.2	56.9	11.0	49.4	0.05	0.17
IT capital	5.01	15.46	2.64	11.04	-0.12	0.15
Non-IT, non-automated capital	47.0	154.1	45.9	142.3	0.03	0.13
Number of firms	474		474		474	

Note: Upper part: The automation score is calculated as the mean across the 3 questions. Each question was answered on a scale from one to five for 2005 and 2010. The yearly changes are calculated as the change from 2005 to 2010 divided by 5 for each firm. Lower part: Persons engaged are measured in persons, and the value-added and capital are measured in millions of DDK according to 2005 prices. Yearly change is measured as the logarithm growth rate, i.e., *$log(x_t/x_{t-5})/5$.*

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

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

	Yearly growth rates	
	mean	s.d.
Chinese export	0.29	0.11
Chinese import penetration	0.36	0.35
Low-wage country import penetration	0.22	0.25
Number of firms	407	

Note: UN Comtrade data at the four-digit product level, Danish firm register data, Statistics Denmark. The yearly changes are measured as the logarithm growth rate, i.e.*,* $log(x_t/x_{t-5})/5$*. The period is 2001-2006. All numbers are unweighted.*

TABLE II: Automation and international competition – Various dependent variables. First difference estimation, 2005-2010

	(1) $\Delta\log(K_{it}^{A})$	(2) $\Delta\log(K_{it}^{A})$	(3) $\Delta\log(K_{it}^{A})$	(4) $\Delta\log(K_{it}^{A})$	(5) $\Delta\log(K_{it}^{NA-NIT})$	(6) $\Delta\log(K_{it}^{IT})$
Δlog of Chinese export	0.174**	0.217***	0.176**	0.129**	0.019	0.001
	(0.078)	(0.078)	(0.076)	(0.063)	(0.052)	(0.119)
Δlog of Chinese import penetration		-0.051				
		(0.033)				
Δlog of low-wage country import penetration			-0.006			
			(0.043)			
R-squared	0.211	0.220	0.211	0.444	0.456	0.179
Number of observations	407	407	407	407	407	407

*Note: The dependent variables are Δlog of automated capital in columns (1)-(4), Δlog of non-IT, non-automated capital in column (5), and Δlog of IT capital in column (6). We use OLS estimation on long differences of 5 years, 2005 to 2010. All regressions include a full set of industry by region dummies to control for industry trends that are allowed to vary across regions. There are 10 industries and 8 regions. The full set of explanatory variables in columns (4)-(6) includes capital measures other than those used as dependent variables, Δlog of employment, and Δ(skill share). See the main text and Table Ia for a description of the explanatory variables. All regressions are unweighted. The standard errors in brackets are clustered by the four-digit product code and 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 data from Statistics Denmark.

TABLE III: Productivity and automation – Dependent variable: Δlog of value added.
First difference estimation, 2005-2010

	(1)	(2)	(3)	(4)	(5)
Δ Automation score					0.124***
					(0.045)
Δlog of automated production capital	0.107***			0.096***	0.089**
	(0.035)			(0.036)	(0.034)
Δlog of IT capital		0.066**		0.052*	0.051*
		(0.031)		(0.031)	(0.030)
Δlog of non-IT, non-automated capital			0.064*	0.014	0.026
			(0.036)	(0.034)	(0.035)
Δlog of employment	0.665***	0.723***	0.714***	0.658***	0.667***
	(0.108)	(0.103)	(0.105)	(0.109)	(0.105)
Δ Skill share	0.707	0.816	0.715	0.716	0.706
	(0.527)	(0.560)	(0.565)	(0.530)	(0.507)
R-squared	0.458	0.446	0.444	0.462	0.471
Number of firms	474	474	474	474	474

*Note: The dependent variable is Δlog of value added. We use OLS estimation on long differences of 5 years, 2005 to 2010. Regressions include 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 regressions are unweighted. 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 data from Statistics Denmark.

TABLE IV: Management practices scores, yearly and yearly changes 2005-2010

	2005		2010		Yearly changes	
	mean	s.d.	Mean	s.d.	mean	s.d.
Management practices score	2.41	0.54	2.92	0.56	0.10	0.11
Decentralization	2.87	0.69	3.20	0.68	0.07	0.13
Human resource management	2.12	0.73	2.57	0.80	0.09	0.13
Performance tracking (KPI)	2.25	0.82	2.97	0.94	0.14	0.16
Number of firms	474		474		474	

Note: Yearly changes are measured as $(x_t - x_{t-5})/5$*. The period is 2005-2010. See the online Appendix E for details.*
Source: Authors' survey on automation in manufacturing.

TABLE V: Productivity, automation and management practices scores – Dependent variable: Δlog of value added. First difference estimation, 2005-2010.

	(1)	(2)	(3)	(4)	(5)
Δ Management practices score	0.078**				
	(0.035)				
Δ Decentralization		0.076***			0.068**
		(0.029)			(0.032)
Δ Human resource management			0.017		-0.016
			(0.034)		(0.044)
Δ Key performance indicators				0.042	0.028
				(0.026)	(0.036)
Δ Automation score	0.093**	0.106**	0.118**	0.100**	0.098**
	(0.045)	(0.044)	(0.047)	(0.045)	(0.045)
Δlog of automated production capital	0.069*	0.077**	0.074**	0.068*	0.073**
	(0.036)	(0.036)	(0.036)	(0.037)	(0.037)
Δlog of IT capital	0.050*	0.048	0.052*	0.050*	0.047
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Δlog of non-IT, non-automated capital	0.028	0.021	0.027	0.032	0.025
	(0.035)	(0.036)	(0.035)	(0.035)	(0.036)
Δlog of employment	0.661***	0.662***	0.666***	0.663***	0.661***
	(0.105)	(0.105)	(0.105)	(0.105)	(0.105)
Δ Skill share	0.694	0.706	0.700	0.701	0.708
	(0.505)	(0.499)	(0.509)	(0.505)	(0.499)
R-squared	0.475	0.477	0.471	0.473	0.478
Number of firms	474	474	474	474	474

*Note: The dependent variable is Δlog of value added. We use OLS estimation on long differences of 5 years, 2005 to 2010. All regressions include 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 regressions are unweighted. 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 data from Statistics Denmark.

Table VI: Alternative measures of firm performance, yearly percentage change, 2005-2010

	mean	s.d.
Quantity produced per worker	0.024	0.019
Quality of product	0.027	0.022
Run time	-0.036	0.033
Setup time	-0.030	0.033
Inspection time	-0.021	0.035
Uptime, percent points	0.022	0.020
Number of firms	468	

Note: All changes are calculated as the yearly percentage change except for uptime in which the change is measured in percentage points.
Source: Authors' survey on automation in manufacturing.

TABLE VII Alternative firm performance – Various dependent variables, 2005-2010. First difference estimation

	Percentage change					
	Quantity produced per worker	**Quality of Product**	**Run time**	**Setup time**	**Inspection time**	**Uptime**
Number of observations	468	468	468	468	468	468
Panel A						
Δlog of automated capital	0.015*	0.010	-0.006	-0.003	-0.006	0.003
	(0.008)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)
R-squared	0.237	0.213	0.173	0.188	0.151	0.177
Panel B						
Δ Automation index	0.047***	0.050***	-0.028*	-0.039***	-0.018	0.044***
	(0.013)	(0.017)	(0.016)	(0.015)	(0.013)	(0.015)
Δlog of automated capital	0.009	0.003	-0.002	0.002	-0.004	-0.003
	(0.008)	(0.011)	(0.009)	(0.008)	(0.009)	(0.009)
R-squared	0.237	0.213	0.173	0.188	0.151	0.177
Panel C						
Δ Automation of:						
Manufacturing processes, etc. (AI_{it}^{MAN})	0.023**	0.021*	-0.008	-0.013	-0.008	0.013
	(0.010)	(0.013)	(0.010)	(0.010)	(0.009)	(0.009)
Assembly and packaging processes (AI_{it}^{ASS})	0.014	0.007	-0.015	-0.019	-0.012	0.026**
	(0.012)	(0.014)	(0.013)	(0.012)	(0.010)	(0.012)
Inventory processes (AI_{it}^{INV})	0.006	0.023	-0.002	-0.004	0.007	-0.000
	(0.014)	(0.016)	(0.017)	(0.014)	(0.011)	(0.013)
Δlog of automated capital	0.008	0.002	-0.002	0.002	-0.004	-0.002
	(0.008)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)
R-squared	0.239	0.214	0.174	0.189	0.153	0.180
Panel D (one by one estimation)						
Δ Automation of:						
Manufacturing processes, etc. (AI_{it}^{MAN})	0.029***	0.028**	-0.014	-0.020**	-0.011	0.023**
	(0.009)	(0.012)	(0.010)	(0.010)	(0.009)	(0.009)
Assembly and packaging processes (AI_{it}^{ASS})	0.026**	0.023*	-0.019*	-0.026**	-0.013	0.032***
	(0.010)	(0.013)	(0.012)	(0.011)	(0.009)	(0.011)
Inventory processes (AI_{it}^{INV})	0.021	0.034**	-0.012	-0.018	-0.001	0.017
	(0.013)	(0.015)	(0.015)	(0.012)	(0.009)	(0.013)

*Note: The dependent variables are the 5-year change, 2005 to 2010, quantity produced per worker, quality of product, run time, setup time, inspection time and uptime. We use OLS estimation on long differences of 5 years, 2005 to 2010. All regressions include 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. Moreover, all regressions include Δlog of employment, Δ skill share, Δlog of IT capital and Δlog of non-IT, non-automated capital as explanatory variables. All regressions are unweighted. 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 data from Statistics Denmark.

FIGURES

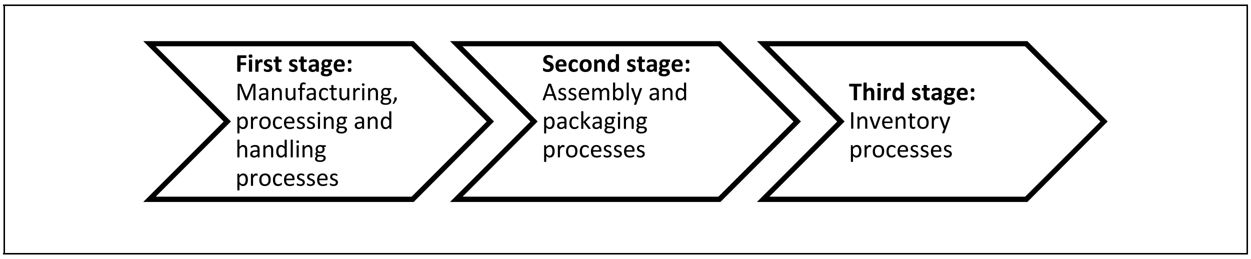

Figure I: Stages of production used in the automation score

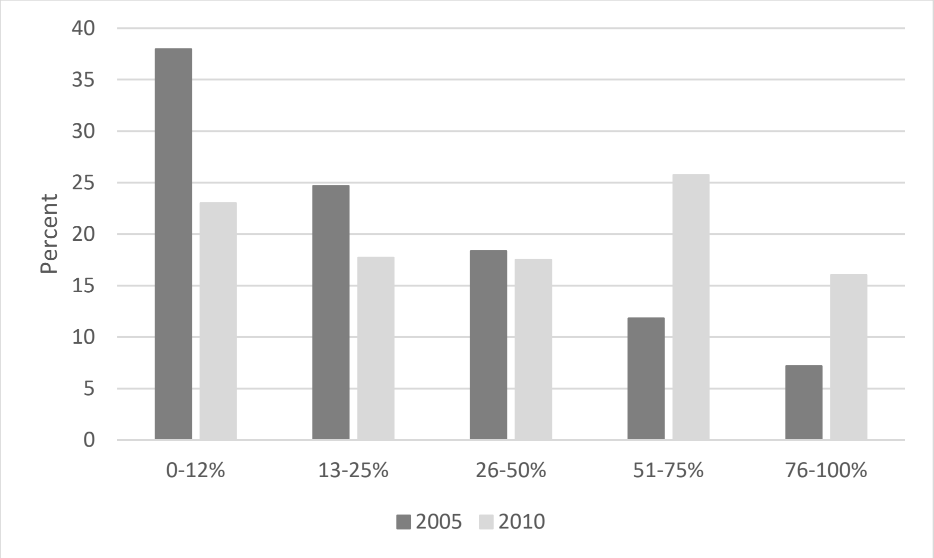

Figure II: Distribution of the percentage of new capital investments in machinery and equipment targeted at automation

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

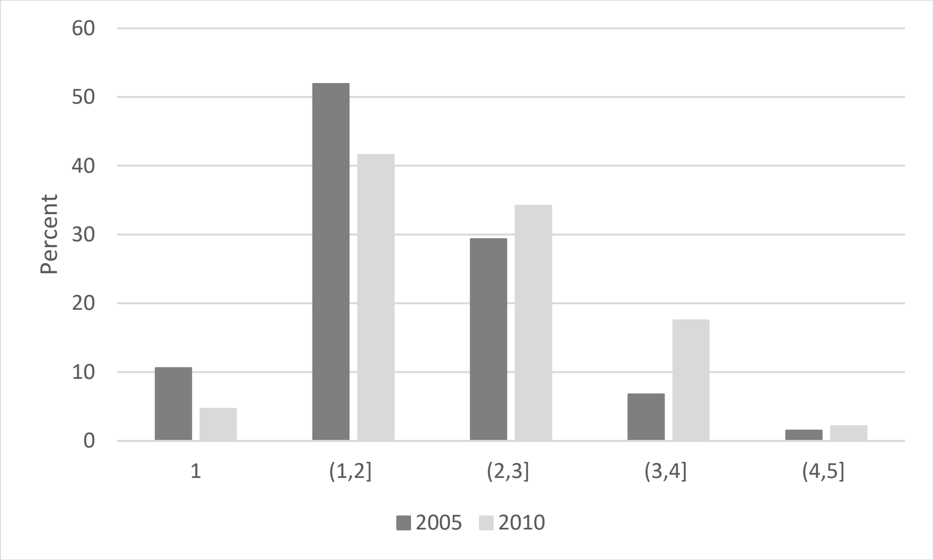

Figure III: Distribution of the automation score for 2005 and 2010

Note: Based on the 474 firms used in Section 4

Source: Authors' survey on automation in manufacturing.

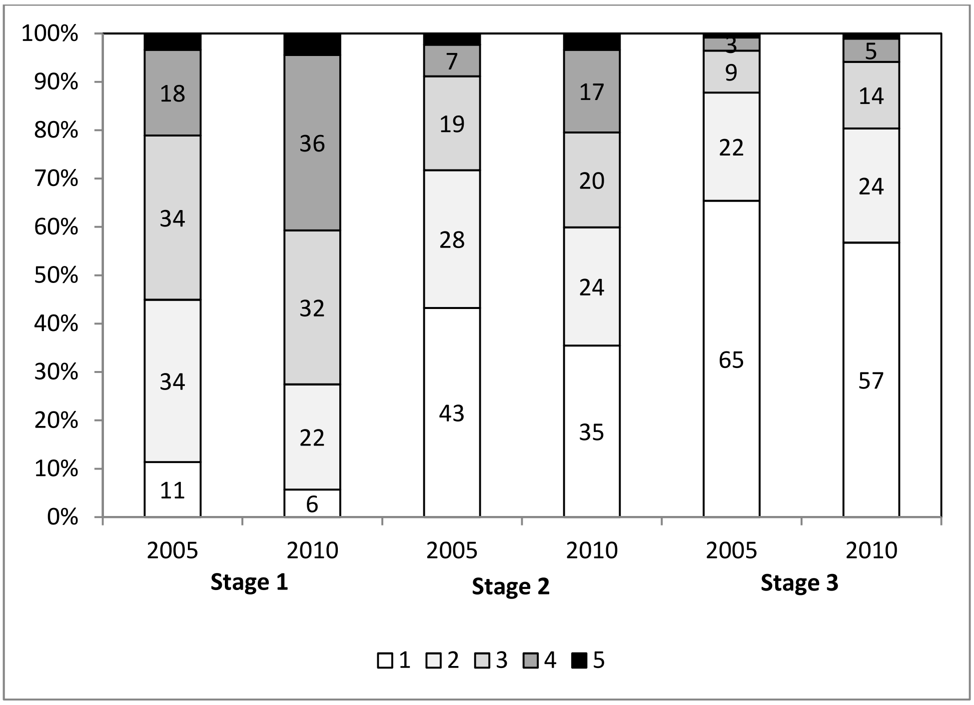

Figure IV: Distribution of the responses on the 5-point scale for three survey questions

Note: Based on the 474 firms used in Section 4. The survey questions are: stage 1: How mechanized are the manufacturing, processing and handling processes? (Manual ↔ Fully-mechanized processing/manufacturing). Stage 2: How mechanized are the assembly and packaging processes? (Manual ↔ Fully-mechanized assembly and packaging). Stage 3: How mechanized are the firm's inventory processes (receiving,, picking, palletizing, shipping)? (Manual ↔ Fully-mechanized inventories). The answer key for the three questions, were the following: 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.

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.

In addition, the firm visits showed that the explanations for the state of the machinery in the production process were much more accurate when providing 5 choices. However, most automated firms applied the scale very conservatively compared with the description of the automation degree, whereas the least automated companies applied it more progressively; this tendency made the inclusion of help text essential to obtain a comparable scale. This inclusion also further helped to address concerns regarding the inconsistent interpretation of categorical responses; see Bloom and van Reenen (2007), Manski (2004), and Bertrand and Mullainathan (2001).

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 12 broad sectors based on Statistics Denmark's 53 groupings:

- Food, beverages and tobacco
- Textile and leather

- Wood
- Paper and printing
- Chemical industry, Mineral oil refining
- Rubber and plastic products
- Stone, clay and glass
- Iron and metal
- Mechanical engineering
- Electronics
- Transport equipment
- Furniture and manufacturing

There are approximately 3,000 firms in the manufacturing sector with at least 10 employees. The goal was to obtain 500 completed surveys. In the empirical analysis of Section 5, we group the firms together in 10 industries instead of 12 due to a low number of firms in some industries.

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.

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[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 in the following years 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 3 CAPITAL VARIABLES: AUTOMATED, IT, AND NON-AUTOMATED, NON-IT CAPITAL

For this paper, we constructed a new and remarkable 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 and alternative performance measures. We have enriched this innovative 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 dependent and explanatory variables included in the empirical analyses. These variables are the capital measures, automation, Chinese exports and import penetration, and firm performance.

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 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.

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[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.

Firm-level financial accounts (FIRE): FIRE data include annual firm financial accounts between 1995 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 larger Table III firm sample, 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, as described below.

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. 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 46 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, which is calculated for automated capital.

The measure of IT capital is constructed by using the survey data on IT spending ("IT spending in Danish Firms" from Statistics Denmark). In the construction of the IT capital measure, IT investments are depreciated by 36 percent, which follows Bloom, Sadun and Van Reenen (2012).

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 or IT capital. These investments are depreciated by 13 percent. In addition, industrial structures are depreciated by 5 percent.

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]

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

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[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 first differences, this procedure has no implications for the obtained results, and the initial level of capital has therefore less importance.

[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.

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 67 observations in the regression results presented below. Specifically, the regressions on automation capital and internationalization are based on 407 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.

Measure of Firm Performance: We apply value-added-based performance measures that control for capital and labour inputs. The data originate from Danish registers.

APPENDIX C: EXTERNAL VALIDATION,SAMPLE SELECTION, AND ESTIMATION SAMPLE

C.1 External Validation of Survey

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 and 5 of the paper in which we find a strong association between the change in automation and management practices and value-added growth that originated 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, such as the “Community Innovation Survey (CIS)” and the “Surveys on ICT usage in enterprises”. 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, 298 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”. The same is true for ΔAI_{it}^{INV}, whereas ΔAI_{it}^{MAN} and ΔAI_{it}^{ASS} have positive but insignificant point estimates. However, the firms that respond “yes” to organizational innovation do not exhibit larger increases in the automation score or in the separate automation questions 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 and higher increases in the HRM score and the KPI score. In contrast, the firms that respond “yes” to having introduced new methods of organizing work responsibilities and decision making experience higher increases in the decentralization score. Thus, the changes in the scores for management practices 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 Data Collection and Sample Selection

The survey that we used to construct the automation capital, automation score, management practices score and alternative performance measures, 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. The only difference is that the responding firms are larger than the non-responding firms.

C.3 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 67 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 407 firms in the analysis on Automation and International competition. For more details see Table C4.

[TABLE C4 around here]

C.4 Survey Quality

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.

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 5 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 4 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 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 export supply to the world market have increased their automated capital stock more than the firms that are less exposed to increasing their export supply. 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.

E.2 Self-Selection Bias

To address the possibility that high-growth firms self-select into investments in automation, we re-estimate the regressions in Table III and Table V column 1, and we include the lagged growth rates of real value added in a first difference regression with 5-year differences between 2005 and 2010. In particular, we include the log changes from 2000 to 2005. This approach should permit the examination of the issue that high-growth firms potentially self-select into process innovation through automation in a manner that is not replicated by low-growth firms. The lagged growth rate is instrumented with the initial real value-added level measured in 2000; this approach is consistent with the approach of Caroli and Van Reenen (2001). The main result in our paper is unaffected by this specification. For instance, the point estimate of automated capital and the automation score in column 5 is significantly positive and has a similar magnitude to the result shown in Table III.

[TABLE E2 around here]

APPENDIX F: SELECTION AND SIMULTANEITY BIAS

The data used in this article is from a retrospective survey, which by design requires that firms have existed since 2005, see online Appendix C.2 above. This means that our results potentially suffer from survivorship bias. This sub-appendix examines the likely survivorship bias using register data that allow us to study both the surviving and dead firms.

First, we construct a graph that shows the number of Danish manufacturing firms to get an understand of the magnitude of exits of manufacturing firms in Denmark during 2005 to 2010. Second, we use register data to form a number of samples that enables us to evaluate the importance of selection bias due to firm exits. We can only make this assessment – in a broad sense – as we can only perform the analysis using aggregate capital; not automation capital measures that we use in the analyses in the paper.

Development of manufacturing firms in Denmark: Figure F1 shows the development in the number of employees and firms in the manufacturing industry from 2000 to 2016. Data is available from Statistics Denmark's website.[5] The

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[5] The data is from: GF1: General Enterprise Statistics By Industry (DB07 10- and 19-Grouping) and unit: www.statbank.dk/GF1. We would like to emphasis that the register data that we use includes exactly the same numbers of manufacturing firms as presented in the figure.

figure shows that the total number of manufacturing firm was equal to 16,636 in 2005 and to 15,718 in 2010 – implying that 5.5% of manufacturing firms on net went out of business.

[FIGURE F1 around here]

Estimation results – Samples, Simultaneity and Firm Exit: In our data collection strategy, we selected manufacturing firms that provided annual reports between 2008 and 2010 and that had 10 or more employees in 2005. It left us with 3057 firms in the population, presented in the first column in Table F1. We can also identify firm exist and entry. The number of manufacturing firms with more than 10 employees in 2005, that closed down before 2010 equals 345 firms, 277 firms entered after 2005, and finally 15 firms entered after 2005 and closed down before 2010. In total, the population of firms including exit and entry equals 3694 firms. The number of firms in 2005 equals 3057+345= 3402 and 3057+277= 3334 in 2010. In column 2, we present the balanced sample of 2939 firms that are in the registers in both 2005 and 2010. An important observation from the table is that the number of firm exits to the total number of firms in 2005 equals 10.6 percent (=(345+15)/(3057+345)).

By expanding the sample from the balanced sample to the full unbalanced sample, we would alleviate the bias by taking the exits into account – but we would not handle simultaneity. Here, we would have to rely on estimation methods that handles endogeneity of inputs directly such as Olley and Pakes (1996) – that takes selection and simultaneity into account. We follow their original paper – that focus on estimation of the production function in the Telecommunications Equipment Industry. Their main point of critique is when researchers use balanced panels when investigating production functions. Using such a strategy is especially problematic in the industry that Olley and Pakes is investigating because lots of exit and entry take place. Specifically, they find that moving from an unbalanced panel to a balanced panel implies that 65% of the observations in the unbalanced panel are dropped. They also find that the point estimates on capital and labor in a value added production function are quite different for the two samples. In Table F1, we see that only around 14 percent of the observations are dropped when moving from the unbalanced to the balnced sample in our data. This is an important difference between our analysis and that of Olley and Pakes.

An advantage of having access to full population register data is that we have access to value added, employment and aggregate capital as well as investment data for most firms in the samples. Therefore, we can estimate the production function using OLS, Fixed effects estimation and the method developed by Olley and Pakes on a number of samples of different size. The estimation methods are not perfect because we cannot include all capital types and the automation score at the same time. However, we can use them for the general case using two aggregate inputs, namely, total employment and total capital – or rather the bookvalue of fixed assets – measures that are available for the majority of firms in the samples.

Table F2 column 1-3 presents point estimates using the unbalanced sample; column 4-5 presents point estimates for the balanced sample, and column 6-7 presents point estimates for the sample used in the paper. The coefficients for both OLS and within are similar across the three samples. Moreover, the point estimates are of similar magnitude even when we handle simultaneity and selection using the Olley and Pakes method in column 3.

[TABLE F1 AND F2 around here]

In conclusion, about 10.6 percent of firms in our population went out of business between 2005 and 2010. Regression analysis across samples using aggregate capital – not different types of capital – shows that there is no indication of the results suffering from severe survivorship bias. Moreover, moving from the balanced sample to the unbalanced sample do not change point estimates as was the case in the study of Olley and Pakes (1996) for the narrowly defined industry that they investigated. Even though the results in Table F2 are strong, they only support our analysis in a broad sense and cannot be transferred directly to the analysis of the paper.

APPENDIX G: 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 G1 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 G1 AND G2 around here]

Figure G2 shows the structure of the Danish manufacturing sectors for 2005 using employment shares. The picture is similar to that using value added. In conclusion, you can ksort of say that the structure of the Danish manufacturing industry is just a smaller version of the EU-economy and the US-economy. Thus, the results might be relevant for many different countries

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APPENDIX TABLES AND FIGURES

TABLE C1: External validation of automation by using the Community Innovation Survey (CIS) – First Difference Estimation

	Δ Automation score	$\Delta\, AI_{it}^{MAN}$	$\Delta\, AI_{it}^{ASS}$	$\Delta\, AI_{it}^{INV}$
Process innovation	0.121**	0.133	0.107	0.123*
	(0.061)	(0.088)	(0.086)	(0.068)
Organizational innovation	0.003	0.010	-0.061	0.059
	(0.060)	(0.087)	(0.082)	(0.058)
R-squared	0.091	0.068	0.068	0.094
Number of observations	298	298	298	298

*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?" All regressions include 10 industry dummies. Moreover, all regressions include log(employment) and log(capital) as explanatory variables. 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 by using the Community Innovation Survey (CIS) – First Difference Estimation

	Δ Management practices	Δ Decentralization	Δ HRM	Δ KPI
Organizational innovation:				
Business practices	0.145**	0.015	0.195*	0.225***
	(0.068)	(0.118)	(0.115)	(0.079)
Organizing work responsibilities	0.078	0.212*	0.004	0.019
	(0.070)	(0.119)	(0.116)	(0.085)
R-squared	0.094	0.077	0.085	0.105
Number of observations	298	298	298	298

*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?" All regressions include 10 industry dummies. Moreover, all regressions include log(employment) and log(capital) as explanatory variables. 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	34
In registers in 2005 and 2010	539
Missing value added for 2005 and 2010	2
Missing employment for 2005 and 2010	3
Missing M&E capital (including automation capital)	46
Missing IT-capital	14
Sample of Table III of the paper	474
Missing product codes or information on product codes	67
Sample of Table II of the paper	407

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). First Difference Estimation, lagged export supply**

	(1)	(2)	(3)	(4)	(5)
Δlog of Chinese export supply 2005-2010	0.115 (0.104)				
Δlog of Chinese export supply 2004-2009		0.071 (0.067)			
Δlog of Chinese export supply 2003-2008			0.120 (0.071)		
Δlog of Chinese export supply 2002-2007				0.135* (0.074)	
Δlog of Chinese export supply 2001-2006					0.129** (0.063)
R-squared	0.303	0.441	0.445	0.446	0.4444
Number of firms	407	407	407	407	407

*Note: The dependent variable is the 5-year change, 2005 to 2010, log of automated capital. All regressions include a full set of explanatory variables that consist of the 5-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. See the main text and Table Ia for a description of the explanatory variables. The standard errors in brackets are clustered by the four-digit product code and 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 data from Statistics Denmark

TABLE E2: Productivity and automation – Dep. var.: Δ Log of value added. First Difference Estimation, 2005-2010

	(1)	(2)	(3)	(4)	(5)
Δlog of lag value added	0.112	0.180	0.169	0.181*	0.210*
	(0.096)	(0.115)	(0.111)	(0.107)	(0.114)
Δlog of employment	0.727***	0.740***	0.732***	0.675***	0.659***
	(0.112)	(0.109)	(0.111)	(0.113)	(0.112)
Δ Skill share	-0.054	-0.179	-0.261	-0.237	-0.224
	(0.358)	(0.384)	(0.370)	(0.352)	(0.363)
Δlog of IT capital		0.051*		0.037	0.034
		(0.033)		(0.030)	(0.031)
Δlog of automated capital	0.092***			0.095**	0.092**
	(0.033)			(0.037)	(0.037)
Δlog of non-IT capital					
Δlog of non-IT, non-automated capital			0.052	0.006	0.005
			(0.037)	(0.034)	(0.035)
SCOPE OF AUTOMATION AND MANAGEMENT					
Δ Automation score				0.112***	0.085*
				(0.042)	(0.044)
Δ Management practices score					0.073**
					(0.036)
R-squared	0.385	0.429	0.434	0.455	0.444
Number of firms	447	447	447	447	447

*Note: The dependent variable is Δlog of value added. We use OLS estimation on the long differences of 5 years, 2005 to 2010. Regressions (1) and (2) include region and industry dummies, whereas regressions (3)-(6) include 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. The standard errors in all columns are robust to heteroscedasticity and autocorrelation of an unknown form. Value added growth for 2000-2005 is instrumented by the value added in 2000. Column 6 includes the same variables as Table III column 1. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.*

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

TABLE F1: Balanced and Unbalanced Sample

	(1) Register Unbalanced	(2) Register balanced
Population	3057	
Exits	345	
Entry	277	
Entry and exits	15	
Number of firms	3694	2939
Number of firm x year observations	20284	17372

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

TABLE F2: Various estimation methods and samples – Dep. Var: log of value added, 2005-2010

			Unbalanced sample	Balanced sample		In paper	
	OLS	Within	Olley and Pakes	OLS	Within	OLS	Within
Log of employment	0.891	0.665	0.834	0.903	0.653	0.894	0.649
	(0.009)	(0.022)	(0.011)	(0.010)	(0.023)	(0.124)	(0.109)
Log of capital	0.139	0.107	0.112	0.130	0.090	0.123	0.096
	(0.006)	(0.008)	(0.008)	(0.006)	(0.007)	(0.016)	(0.027 A)
Number of firms	3650	3650	3617	2939	2939	474	474
Number of firm x year observations	19261	19261	16689	17372	17372	948	948

*Note: The dependent variable is log of (value added). We use OLS estimation in column 1, 4, and 6. In column 2 and 5 we use Fixed effect estimation and in column 3 Olley and Pakes estimation method is used. All regressions include a full set of industry-by-region dummies to control for the industry trends. 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 data from Statistics Denmark

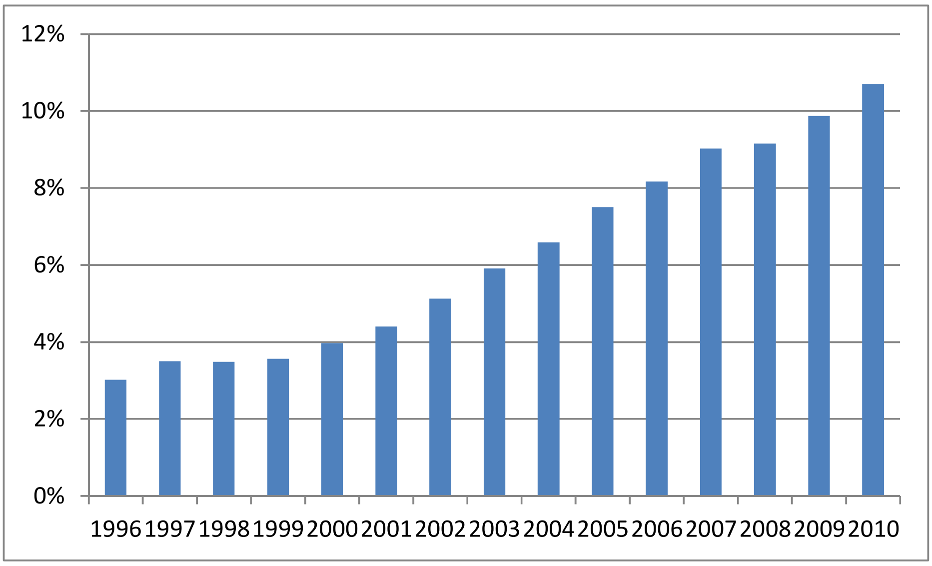

FIGURE B1: Share of world exports from China, 1996-2010
Source: UN Comtrade database

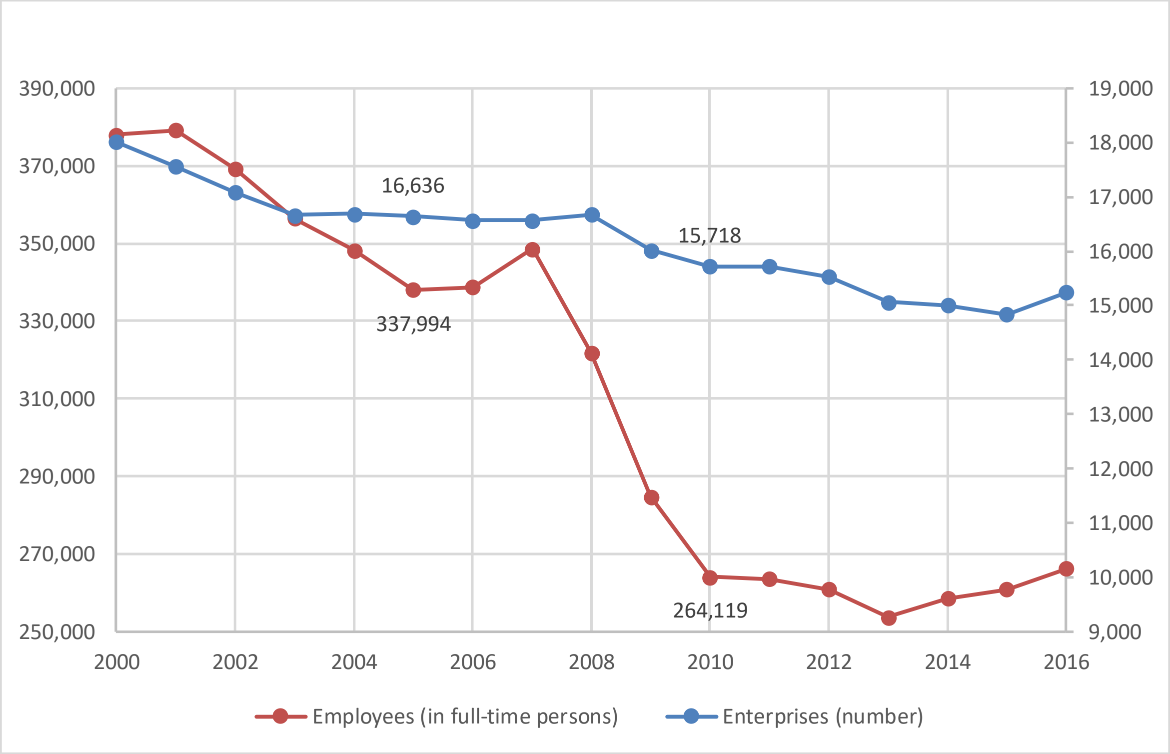

FIGURE F1: Danish manufacturing firms and employment over time
Note: From 2008 a new data source for the calculation of full-time employees is used. As a consequence, there is a databreak in the number of full-time employees from 2007 to 2008.
Source: Statistics Denmark: www.statbank.dk/GF1

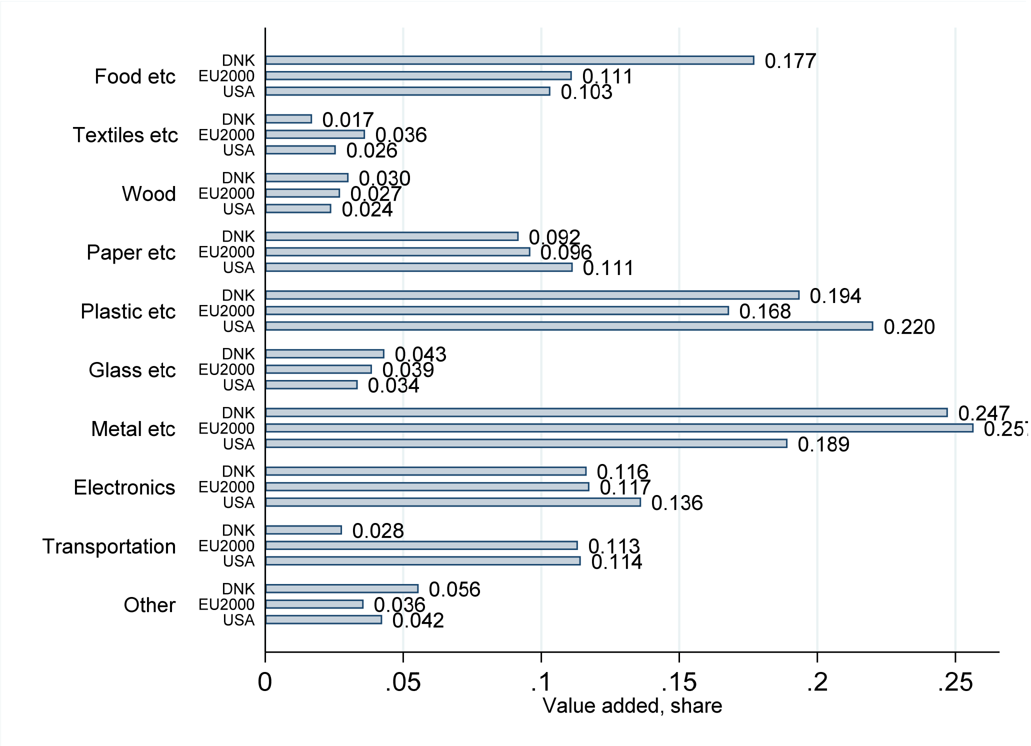

Figure G1: Value added across industries and country groups in 2005.

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..

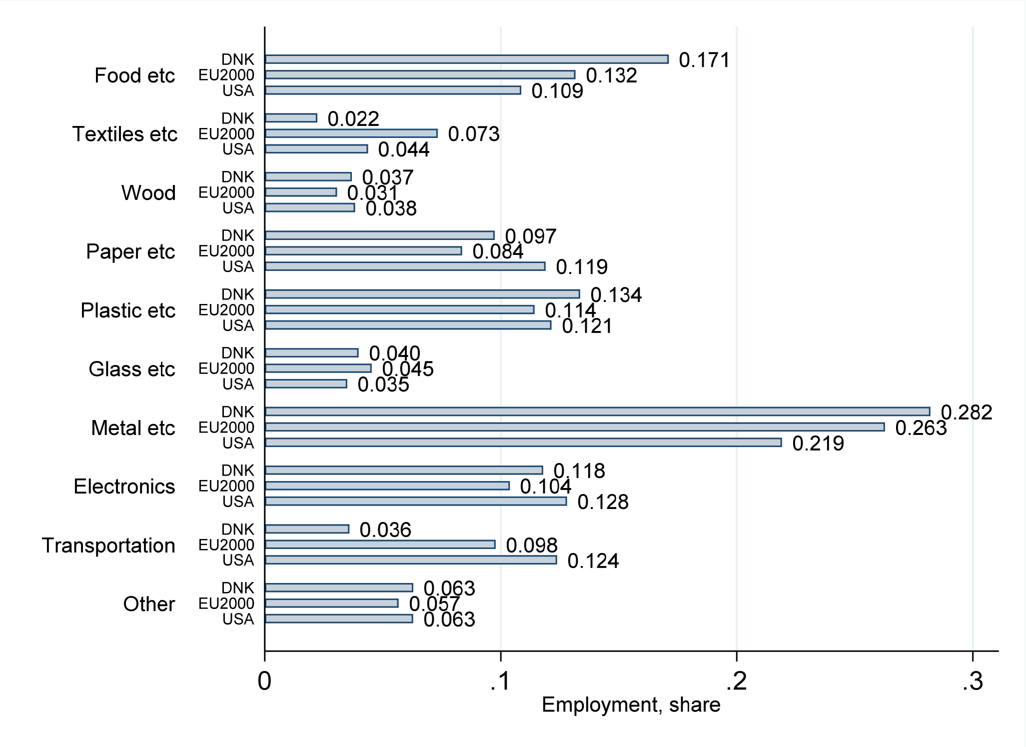

Figure G2: Hours worked by person engaged across industries and country groups in 2005.

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.