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Automation, Performance and International Competition: Firm-level Comparisons of Process Innovation

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Automation, Performance and International Competition: Firm-level Comparisons of Process Innovation*

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ABSTRACT

This paper presents new evidence on trade-induced automation in manufacturing firms using unique data combining a retrospective survey that we have assembled with register data for 2005-2010. In particular, we establish a causal effect where firms that have specialized in product types for which the Chinese exports to the world market has risen sharply invest more in automated capital compared to firms that have specialized in other product types. We also study the relationship between automation and firm performance and find that firms with high increases in scale and scope of automation have faster productivity growth than other firms. Moreover, automation improves the efficiency of all stages of the production process by reducing setup time, run time, and inspection time and increasing uptime and quantity produced per worker. The efficiency improvement varies by type of automation.

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1. Introduction

The main goal of this paper is to provide the first systematic evaluation of the effects of internationalization on automation as well as of the effects of automation on firm performance for a representative sample of manufacturing firms. For this purpose, we use a unique data set combining a retrospective survey that we have assembled with register data for 2005-2010. While the effects of IT investments – mainly measured as computers and computer-related investments – on productivity growth have been studied intensively and substantial gains from IT have been documented at the firm level (Bloom, Sadun, and Van Reenen, 2012 and Brynjolfsson and Hitt, 2000), studies on the effects of automated production capital are sparse. Despite intensive discussions of the potential impact of automation,[3] there is almost no systematic empirical evidence on its economic effects and none for a larger, representative sample of manufacturing firms.[4]

We investigate whether there is a positive and causal effect from increased international competition from China on investments in automated capital. Moreover, we investigate whether improvement in firm performance is positively associated with investments in automation. To perform the analysis we develop two dimensions of automated capital: One dimension is a measure of the *scale of automation*, which is simply a measure of the automated capital stock; the other dimension is a new indicator of the *scope of automation* of production capital that is measured by a series of survey questions focusing on different aspects of the production process that are aggregated into an overall automation index.

We find that firms that have specialized in product types for which the Chinese exports to the world market has risen sharply invest more in automated capital compared to firms that have specialized in other product types. We also find that firms with high increases in scale and scope of automation have faster productivity growth than other firms. It should be stressed that the applied productivity data, i.e., value added, employment, etc., stem from external data sources. Moreover, we find that increasing automation is associated with improvements in performance measures, such as setup times, run times, inspection times and uptime.

The assembled survey data on automation is applied to measure the extent, the variation, and the development of automation across firms and over time to understand the present state of automation. Our data reveal sizeable variation in automation level and adoption across manufacturing firms. Some firms are nearly fully automated, however, on average firms have relatively low automation levels. This leads us conclude that there is considerable potential to increase the extent of automation.[5]

The study contributes to the literature in a number ways. We investigate the effects of the automation of production processes on firm performance for a representative sample of manufacturing firms. To the

[3] Sometimes a "third industrial revolution" based on automated production processes is mentioned. See, e.g., the front page of The Economist on April 21st, 2012.

[4] For a study on the productivity effects of the increasing use of industrial robots at the industry level, see Kromann, Malchow-Møller, Skaksen, and Sørensen (2014).

[5] Moreover, we find that no firm in the sample has transitioned from using predominantly manual processes in production to becoming fully automated during the 5-year period under investigation. In other words, automation has taken place by incremental changes rather than in large steps.

best of our knowledge, this is the first study to consider this relationship for a representative sample of manufacturing firms. The only other paper that addresses automation and firm performance is Bartel, Ichinowski and Shaw (2007) who study a more narrow industry, namely, the U.S. valve industry.[6] We extend the production function by incorporating a third type of capital, namely, automation capital, in addition to IT-capital and non-IT and non-automated capital building on an approach taken in several studies for IT capital; see, for example, Bloom, Sadun, and Van Reenen (2012). We have also developed and introduced an automation index in the production function.[7] In addition, we show that international competition from China in product markets is an important driver of investments in automated capital. Other papers in this field show that firms innovate in response to import competition from low-wage countries; see, for example, Freeman and Kleiner (2005), Bugamelli, Schivardi and Zizza (2008), and Bloom, Draca, and Van Reenen (2015). None of these studies uses data on automation. Moreover, we find that in a small and open economy, exports to the world market rather than imports to the domestic market drive process innovations, in particular investments in automated capital in the present setting.

To perform this study, we have gathered a new and remarkable data set capturing measures of automation of production capital in Danish manufacturing firms. The most time-consuming aspect of this project has been the development of the retrospective survey. The data set constitutes one of the most – if not the most – comprehensive descriptions of the automation of production processes in manufacturing firms ever performed. Its construction consumed two years of intensive work. The survey allows us to develop measures of the two dimensions of automated capital discussed above.

In addition to the data collected on automation, we have collected data on management practices in production processes, i.e., the management practices used on the factory floor and not in other parts of the firm. The purpose of collecting these data is to eliminate the concern that any obtained relationship between automation and productivity is simply an artifact of omitted measures of managerial quality or management practice. Collection of this information is inspired by the work on management practices and firm performance by Bloom and Van Reenen (2007).

The data set also includes questions on production efficiency, including run time, inspection time, setup time, uptime, and quantity produced per worker. Moreover, we have enriched this innovative survey data set by merging information on value added, investments in machinery and equipment, sales at the product level, and education of employees using confidential register data from Statistics Denmark. In addition, we have merged data on Chinese exports at the product level into this data set using the UN Comtrade database. Finally, we have matched survey data on IT expenditures and innovation activities that originate from three Eurostat data sets.[8] These data sets are used to construct measures of IT capital at the firm level, and they provide data on activities addressing process and organizational innovation. The Eurostat surveys are especially important, as they enable us to perform external

[6] The advantage of this focus is that the authors can use specific technologies, such as CNN machines, that describe the applied technology. This strategy, however, was not possible in the present paper because the focus is much broader and covers the full manufacturing sector.

[7] Taken at face value a one standard deviation increase in the automation index implies an increase in TFP of 11 percent.

[8] These are the “Survey on ICT expenditures in enterprises”, “Community Innovation Survey” (CIS) and “Survey on ICT usage in enterprises”.

validation of the collected survey data on automation. Specifically, we are able to externally verify our survey data on automation and management practices.

The rest of the paper is structured as follows. In the next section, we present the theoretical and empirical framework in more detail. In Section 3, we present the data and descriptive statistics, whereas the empirical analysis is contained in Section 4. Section 5 presents a robustness analysis that includes an index of management practices as an additional explanatory variable. Section 6 discusses data collection, sample selection and external validation of the survey data. Section 7 concludes the paper.

2. Theoretical Model and Hypotheses for Automated Capital

In this section, we present and discuss the models that will be used for estimation in the empirical analyses. In broad terms, these models describe the relationship between international competition and the accumulation of automated capital as well as the relationship between firm performance and automation. Finally, we present a model for firm exit and automation.

2.1 Trade-induced Automation

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

$$k_{it}^{A} = a_{it} + \theta_1 EX_{i,t}^{CHN} + W\theta,$$

where $k_{it}^{A}$is log automated capital, $EX_{i,t}^{CHN}$ is a measure of international competition, and W is a vector of additional explanatory variables. More precisely, $EX_{i,t}^{CHN}$ is the logarithm of Chinese exports supplied to the world market, excluding exports to Denmark. The measure is firm specific because it is measured at the four-digit product level and matched to specific firms. The hypothesis to be investigated is the trade-induced technical change hypothesis implying that θ_1 is positive and significantly different from zero. We motivate this hypothesis in the following.

The above equation is related to Bloom, Romer, Terry and Van Reenen (2012), who develop a theoretical model that predicts a positive relationship between innovation and import competition, and Bloom, Draca and Van Reenen (2012), who establish empirical support for the model. Specifically, the theoretical model explains how international trade with China drives innovation5 in exposed firms. The model is based on factors of production that are costly to move between firms because of adjustment costs or sunk investments. These are referred to as “trapped factors”. Because trade with China reduces the relative profitability of producing low-tech products and because firms cannot easily reallocate labor and capital to other activities, the shadow cost of innovation has fallen. That is, Chinese trade reduces the opportunity cost of innovation by reducing the profitability of current low-tech products and freeing up inputs.

Bloom, Draca and Van Reenen (2015) empirically investigate the impact of Chinese import competition on innovation using indicators for patenting, IT, R&D, total factor productivity (TFP), and management practices across twelve European countries for the period 1996-2007. They establish that the absolute volume of innovation increases within the firms most affected by Chinese imports.

In the present analysis, we also investigate the impact of international trade with China on innovation. Specifically, we measure innovation as process innovation in terms of the accumulation of automated capital. In addition, we use total exports from China to the world economy – exclusive of exports to Denmark – instead of 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 produces the incentive to invest in innovation. In this respect, approximately 85 percent of the firms in our sample are exporters. Moreover, Chinese exports to the world market are arguably exogenous to Danish firms, implying that we estimate a causal relationship between total exports from China and investments in automated capital. The applied measure is discussed in more detail below.

We include firm fixed effects to allow a_{it} to vary systematically across firms due to, *e.g.*, different production technologies. Similarly, we include year fixed effects to allow a_{it} to vary systematically over time to capture investment trends that might be correlated with the development of automation. We therefore estimate the following empirical model:

$$k_{it}^{A} = a_0 + \theta_1 EX_{i,t}^{CHN} + W\theta + b_i + d_t + u_{it}, \qquad (1)$$

where b_i and d_t are the firm and year fixed effects, respectively.

2.2 Total Factor Productivity and Automation

The relationship between TFP and automation is:

$$y_{it} = tfp_{it} + \beta_1 l_{it} + \beta_2 k_{it}^{A} + \beta_3 k_{it}^{IT} + \beta_4 k_{it}^{NA-NIT} + X\gamma,$$

where y, l, and k refer to log value added, log employment, and log capital and X is a vector of additional explanatory variables. There are three types of capital: automated capital (k_{it}^{A}); IT capital (k_{it}^{IT}); and non-automated, non-IT capital (k_{it}^{NA-NIT}). Thus, tfp_{it} captures any differences in value added across firms and years that cannot be accounted for by the automated, IT, and non-automated, non-IT capital measures, labor inputs or other explanatory variables.

There is an extensive relatively recent literature analyzing the output and productivity effects of IT capital. 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. IT capital is usually determined by the accumulation of IT hardware; see, for example, Bloom, Sadun and Van Reenen (2012). A recent study by Cardona et al. (2013) that summarizes the findings of more recent empirical studies concludes that IT capital plays an important role in productivity statistics but that the evidence is most pronounced for the USA, while evidence for European countries is more ambiguous.

We build on the approach taken in this literature and estimate a production function that distinguishes between IT and non-IT capital to separate the effects of automation from any effects of IT capital. Automation is included in the non-IT capital measure, and our data set allows us to split non-IT capital into automated capital and other types of non-automated, non-IT capital. Therefore, we include three capital variables as regressors. We, thereby, investigate the relationship between labor productivity and the three types of capital. To the best of our knowledge, this is the first time that a study has distinguished between IT capital, automated capital and non-IT, non-automated capital.

In addition to automated capital, i.e., the scale of automation, we assume that value added is related to the scope of automation through an automation index, denoted by AI_{it}. The scope of automation is not necessarily properly captured when using capital stock because firms with similar extent of invest may integrate automated capital differently in their production processes. This variation depends – among other things – on experience with automation and the use of experts in the implementation of automation. Specifically, we assume that the automation index is related to *tfp* in the following way:

$$tfp_{it} = \beta_5 AI_{it} + a_{it},$$

where a_{it} reflects differences in *tfp* across firms and years that are not accounted for by differences in the scope of automation. Combining the two equations above and rearranging yields the following expression for log value added:

$$y_{it} = a_{it} + \beta_1 l_{it} + \beta_2 k_{it}^{A} + \beta_3 k_{it}^{IT} + \beta_4 k_{it}^{NA-NIT} + \beta_5 AI_{it} + X\gamma.$$

The main parameters of interest in this part of the study are β_2 and β_5. It is investigated to what extent automation capital influences value added and we hypothesize that β_2 is positive and significantly different from zero. In addition, we investigate the relationship between the automation index and TFP and hypothesize that β_5 is positive and significantly different from zero.

When estimating the above equation, we must put some restrictions on a_{it} to identify β_2 and β_5. Specifically, we apply $a_{it} = a_0 + b_i + d_t + u_{it}$. That is, we include firm fixed effects to allow a_{it} to vary systematically across firms due to, *e.g.*, different production technologies. Similarly, we include year fixed effects to allow a_{it} to vary over time to capture productivity trends that might be correlated with developments in automation. We therefore obtain the following empirical model:

$$y_{it} = a_0 + \beta_1 l_{it} + \beta_2 k_{it}^{A} + \beta_3 k_{it}^{IT} + \beta_4 k_{it}^{NA-NIT} + \beta_5 AI_{it} + X\gamma + b_i + d_t + u_{it}, \qquad (2)$$

where b_i and d_t are the firm and year fixed effects, respectively.

Still, if there are time-varying shocks to a_{it} that also affect the automation measures (which would be the case if productivity shocks drive investments in automation), the automation measures in (2) may be endogenous and, hence, cause the fixed effects estimators of β_2 and β_5 to be inconsistent. Therefore, we cannot claim a causal relationship between automation and *tfp*. To approach a causal effect between firm performance and automation, we turn our attention to alternative measures of firm performance.

2.3 Alternative Measures of Firm Performance and Automation

An important strength of our data set is that it permits empirical tests of the effects of investments in automation on firm performance. More precisely, we can estimate the relationships between various alternative firm performance measures and different aspects of automation. The strategy we apply follows Bartel, Ichinowski and Shaw (2007). If different aspects of firm performance are variously affected by different types of automation, then it is difficult to imagine a (productivity) shock that would generate such effects. In this sense, the results are closer to a causal relationship because different aspects of performance measures are influenced differently by alternative measures of automation.

In this part of the analysis, we test the hypothesis that increasing scope and scale of automation improve production process efficiency. Specifically, observations from firm visits imply that setup times, run times, and inspection times will decrease, whereas uptime and quantity produced per worker will increase after automated machines and equipment are adopted in these stages.

The applied estimation model is:

$$\binom{Percentage\ change}{in\ x} = \gamma_0 + \gamma_1 \Delta k_{it}^{A} + \gamma_2 \Delta AI_{it}^{M} + \gamma_3 \Delta AI_{it}^{PI} + \gamma_4 \Delta AI_{it}^{IC} + G\gamma + \varepsilon_{it}, \qquad (3)$$

where *x* refers to the five measures of firm performance mentioned above.[9] *G* is a vector of additional explanatory variables, and Δ indicates change in a variable. Moreover, AI_{it}^{M}, AI_{it}^{PI}, and AI_{it}^{IC} are three sub-indexes of the overall automation index, i.e., AI_{it}, measuring specific types of automation within mechanization and computerized optimization.

We expect that different types of automation have different effects on measures of firm performance. Thus, examining the three sub-indexes separately, we expect that increasing the level of *mechanization in all stages of the production process* will reduce required labor, as low-skilled jobs are replaced by automation-enhanced machinery that increases the quantity produced per worker. Furthermore, unscheduled downtime should be higher during start-up periods on lines with fewer computerized controls, see Ichniowski et al. (1997) that examine the steel industry. If this holds across industries, uptime increases as mechanization increases in all stages of the production process. In conclusion, our hypotheses are that growth in the ΔAI_{it}^{M} index involves a higher quantity produced per worker and improves uptime.

Examining the second sub-index (AI_{it}^{PI}), *mechanization of production processes between stages,* the three questions should affect different process performance measures depending on their relevance to the performance measure. For instance, mechanization of materials handling is expected to improve run time, whereas mechanization-enhanced changeover is expected to improve setup time, and mechanization-enhanced inspection of products is expected to improve inspection time. However, when combining the questions into an index, it is uncertain whether any of the improvements are strong enough to survive.

Examining the third sub-index (AI_{it}^{IC}), *IT used to optimize the production process,* we expect to see improved uptime, as IT is used to help firms observe, measure, document, track and manage performance accurately and transparently (see Aral, Brynjolfsson and Wu (2010)). Furthermore, we

[9] For each of the five measures, the respondents were asked to indicate the level of improvement achieved over four periods: 2003-2005, 2005-2007, 2007-2010, and 2010-2012. The following scale was adopted for each measure: 1=deterioration; 2=0-5% improvement; 3=5-10% improvement; 4=10-20% improvement; 5=20-30% improvement; 6=more than 30% improvement. To calculate performance improvements from 2005-2010, we multiplied the median percentage changes reported in the periods 2005-2007 and 2007-2010.

expect that the use of IT in the execution of production tasks will reduce run time and required labor, increasing the quantity produced per worker. In conclusion, the hypotheses to investigate are that growth in the IT to optimize production processes (ITOPP) index decreases run time and increases uptime and quantity produced per worker.

2.4 Firm Exit and Automation

A final issue that we wish to investigate is how automation affects firm exit. If firms improve their performance through investments in automation, we hypothesize that it is less likely that they will close down and exit the market:

$$exit_{it} = \zeta_0 + \zeta_1 k_{it}^{A} + Z\zeta + v_{it}, \quad (4)$$

where $exit_{it}$ is a dummy variable that is equal to 1 if a firm exits and 0 otherwise. Z is a vector of additional explanatory variables. The hypothesis to be investigated is that investments in automation imply that ζ_1 is negative and significantly different from zero.

3. Data

We use survey data on automation in Danish manufacturing firms that have been collected for the present analysis. The collected survey data set has been enriched by numerous additional data sets that were merged with the survey data using unique firm identifiers and commodity codes for firm production. We present a short description of the data collection process in Appendix A. The automation survey was collected for 567 manufacturing firms, or 21% of all manufacturing firms with more than 10 employees in 2005, that answered survey questions on automation, production process efficiency, management practices and more.

During data collection, we made a number of observations from visits to 16 firms that were used to improve data collection efforts. Specifically, production managers stated that the focus on automation was so strong that they were able to provide precise answers to retrospective questions. Therefore, it was decided to ask questions for the years 2005, 2007 and 2010, allowing us to evaluate self-reported changes in automation over the previous half-decade.[10] An important task of this paper is to provide external validation of the applied data set; consequently, we perform two sets of external validation. First, we present results that are based on survey data on automation and external data. An alternative interpretation of the results is that they establish whether the automation survey systematically captures meaningful content rather than mere statistical noise. Second, we investigate whether the collected measures are consistent with measures from other innovation surveys conducted by Eurostat. We return to the latter issue in Section 6.

[10] In other surveys, authors have 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; and Bloom et al. (2013) use the Management and Organizational Practices Survey (MOPS) from the US Census, where data on the management and organizational practices of US manufacturing firms are collected for 2005 and 2010.

The purpose of the present section is to describe the most important data sources used in the empirical analysis. Moreover, we discuss the construction of the dependent and explanatory variables included in the empirical analyses. These are measures of the automation of production processes, in both scale and scope; of Chinese exports and import penetration; and of firm performance.

3.1 Scale of Automation and other Capital Measures

Automated capital stock - Scale of automation

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

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

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

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

By using a combination of the collected survey data and accounting data on investments in machinery and equipment, it is possible to measure automated capital stocks for the majority of firms in the sample. Specifically, we use the following question from the survey:

> *What percentage of new capital investments in machinery and equipment is targeted for automation?*

The respondent can choose from among 5 ranges: 0-12%, 13-25%, 26-50%, 51-75% and 76-100%. The question is asked for the years 2005, 2007 and 2010. We use the answers to this question to determine investments in automated capital, which is used to determine the capital stocks. Specifically, we use the mid-range values of the firm responses. For 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 extrapolated. With information on the percentage of new capital investments targeted for automation and investments in machinery and equipment, automated capital is determined as follows:

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

where $I_{i,t}^{M\&E}$ is investments in machinery and equipment, and $s_{i,t}^{A}$ is the share of investments targeted for automation.

To construct the automated capital stock, we use investment data for the period 2001-2010. We measure $I_{i,0}^{A}$ as average investments over 2001, 2002 and 2003 because investment may fluctuate considerably from year to year. Moreover, we assume that δ^A= 20 percent and that g^A = 0 percent.[11] The requirement that investment data for a single firm must be available for a 10-year period implies that we lose nearly 100 firms, and only 476 of the 567 firms that responded to the survey are included in the analysis.

Other capital stocks

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

The measure of IT capital is constructed using survey data on IT spending ("IT spending in Danish Firms" from Statistics Denmark). The bookkeeping of IT costs involves either a full write-off of the expense in the year of purchase or activation on the balance sheet with depreciation rates below 100 percent. The survey asks firms to answer questions on the percentage of IT costs that have been depreciated in full at the year of investment and the percentage that has been activated on the balance sheet. We label the percentage of IT investments that is activated $s_{i,t}^{IT}$. In the construction of the IT capital measure, IT investments are depreciated by 36 percent, which follows Bloom, Sadun and Van Reenen (2012). The applied measure of IT capital is further described in Appendix E.

The measure of non-automated, non-IT capital is constructed using two types of investments from firm accounting data. These are the remaining investments in machinery and equipment that are not allocated to automated or IT capital:

$$I_{i,t}^{NA-NIT} = I_{i,t}^{M\&E} - I_{i,t}^{A} - s_{i,t}^{IT} I_{i,t}^{IT} = \left(1 - s_{i,t}^{A}\right) I_{i,t}^{M\&E} - s_{i,t}^{IT} I_{i,t}^{IT},$$

where $I_{i,t}^{NA-NIT}$ and $I_{i,t}^{IT}$ are investments in non-automated machinery and equipment and investments in IT capital, respectively. These investments are depreciated by 13 percent. In addition to $I_{i,t}^{NA-NIT}$, industrial structures are depreciated by 5 percent.

3.2 Automation Index: Scope of Automation

In addition to the automated capital stock, we develop a new indicator – an automation index – that measures *the scope of automation of the production processes*. This implies that automation is measured by both the scope and the scale of automation. Based on firm visits and discussions with numerous production managers and engineers, it was decided to develop an automation index based on survey questions. The hypothesis behind an automation index in addition to the automated capital stock is that capital can be implemented, integrated and used in different ways on the factory floor, leading to varying firm performance. We are not aware of similar measures in the literature on automation.

[11] Deb and Deb (2010) state, "the approximated life span of a robot is between 5 and 8 years" (p. 461). A depreciation rate of 20 percent is considered a reasonable approximation for an 8-year life span. The value of g^A is fixed at 0. Estimations for capital stocks in manufacturing provided by Statistics Denmark reveal that the IT and the non-IT capital stocks hardly grew during the period 1975-2005 (see Statistics Denmark (NATP25V: Growth account after industry and type)); because the annual growth rates equal 0.25 percent and 0.36 percent, respectively, we assume that $g^A = 0$.

However, the automation index parallels the indexes on management practices developed by Bloom and Van Reenen (2007). Our automation index is based on 8 survey questions scored on a one to five scale using *z*-scores. Because this is not a standard method for measuring the scope of automation, we provide a detailed description of it below.

The scope of automation has previously been measured by the use of specific technologies (see, e.g., Bartel et al. (2007)). However, experience from several firm visits revealed that this type of measure is only valid if the firms analyzed have relatively homogenous production processes and if production managers are well informed about different types of technologies. For instance, visiting a firm in the food and drink industry after visiting several firms in the metals, machinery and equipment industry showed that these industries use different types of technologies.[12] Moreover, firm visits demonstrated that product managers were often unfamiliar with the technology terms used in other studies, such as Swamidass (2003).

The survey questions on the scope of automation were organized around three stages of the production process. The first stage is manufacturing, processing and handling, where all parts of the product are produced. The second stage is assembling and packing, where all parts are assembled into finished products and packed for customers. The third stage is inventory, which includes both raw materials and finished goods. The three stages are presented in Figure 1:

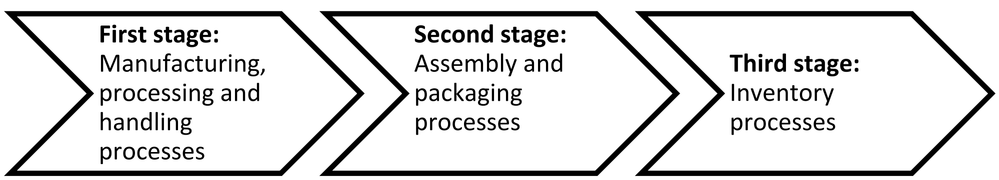

Figure 1: Stages of the production process used in the automation index

The survey questions were asked for two different types of automation. The first is the mechanization of production processes, which focuses on the proportion of the processes carried out mechanically rather than manually. In other words, this addresses the labor inputs in different stages of the production process. The survey asks six questions related to mechanization. The first three questions relate to *the share of production processes that are carried out mechanically* instead of manually *within stages of the production process*:

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

[12] Furthermore, the complexity of contemporary machinery makes it difficult to count specific types of technologies, as one machine bought today might perform the same tasks as three or more machines bought some years ago. Bartel et al. (2007) use exactly this variation as a measure of increases in computerization: "Managers stated that a decrease in the number of machines used to produce a given product would always reflect an increase in degree of computerization for newer versus older CNC machines and was also relatively simple for managers to identify. Thus, in empirical analyses in this study, we measure *improvements in CNC quality* by whether there was *a reduction in the number of CNC machines used to produce a given product* for CNC robots in the valve industry". However, it became clear from conversations with production managers that this was not a fruitful route to follow for a heterogeneous group of manufacturing firms.

- How mechanized are the inventory processes?

The other three questions addresses mechanization of the production processes *between stages*:

- How mechanized is the handling/feeding of components and raw materials into the manufacturing, processing, assembly, packaging and inventory processes?
- How mechanized are the changeover processes in the manufacturing, processing, assembling and packaging processes?
- How mechanized is the inspection of work pieces in the manufacturing, processing, assembling and packaging processes?

The second type of automation is the degree of computerization, which is related to the *share of production processes using IT systems* to optimize the use of equipment rather than relying on a team to select the next job and to consider process control. In other words, this is a measure of the reduction in manual intervention in execution and process control. This means, among other things, optimizing the utilization of machines and/or raw materials as well as optimizing the adjustment of machines in relation to wear and environmental factors. Two specific questions are asked:

- How automated is the execution (scheduling and start-up) of jobs run on the mechanized equipment?
- How automated is the process control (continuous correction of machine settings) of the mechanized processes?

The respondents answered the questions on a 5-point Likert scale, where 1 indicates that manual interference occurs in all processes and five indicates that all processes are fully mechanized. The respondent was asked to answer all of the questions for 2005, 2007, and 2010.

Based on these eight questions, we construct an automation index by calculating *z*-scores by normalizing to mean zero and standard deviation one. In the econometric specifications, we take the unweighted average across the eight *z*-scores, which are also normalized to mean zero and standard deviation one.

In addition to the aggregate index of automation, we also create some sub-automation indexes, specifically an index based on the mechanization of production processes within stages (MPPWSI), an index based on the mechanization of production processes between stages (MPPBSI), and an index based on the use o: IT to optimize the production processes index (ITOPP). All indexes are double normalized as in the aggregate automation index.

3.3 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 (2015) present data on the share of all imports into the EU and US from China and show that it has increased from approximately 5 percent in 2000 to approximately 11 percent in 2007. Chinese exports to world markets have increased considerably over time, which is evident from Figure 2.

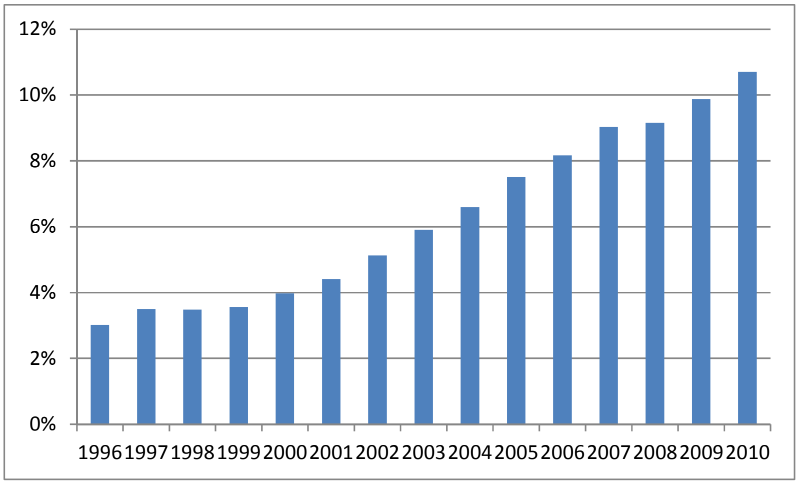

Figure 2: Share of world exports from China, 1996-2010
Source: UN Comtrade database

In the empirical analysis, we use data on exports from China to the world market from the UN Comtrade database. This is an international database of six-digit product-level information on all bilateral imports and exports between any given pair of countries. We aggregate from the six-digit product level to the four-digit product level.[13]

We focus on exports for two reasons. First, Denmark is a small, open economy that is greatly exposed to international trade and markets. One indication of this is that exports in relation to GDP were greater than 50 percent in 2008. Additionally, 85 percent of the firms in our sample are exporters. Therefore, it is reasonable to assume that increasing competition in (low-tech) products from low-wage countries exporting to world markets has an impact on Danish manufacturing firms specializing in the same products. A second reason for focusing on exports from China to the world markets is that this measure is exogenous to Danish manufacturing firms, implying that we are able to estimate the causal effect of increasing international competition from China on process innovation in the form of net investments in automated capital.

A potential concern in our empirical specification is that firms may shift out of the production of some products and into the production of others 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 export markets from China.

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

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

[13] This is an issue of market relevance and of 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 4-digit codes.

where $EX_{i,t}^{CHN}$ is Chinese exports to the world market of the product with the largest sales share of firm *i*. $EX_{p,t}^{CHN}$ is Chinese exports to the world market – excluding exports to Denmark – 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 Industrial Sales of Product Types from Statistics Denmark for $\gamma_{p,i,0}$. The measure is similar to a measure of import competition applied by Bernard, Jensen, and Schott (2006) and Bloom, Draca and Van Reenen (2015). However, they use a measure of import competition at the industry level, where firms are assigned to specific industries and not to the product with the largest sales share.

The causal relationship between k_{it}^{A} and $EX_{i,t}^{CHN}$ requires that the main driver behind Chinese world exports is not investments in automated capital but rather changes in China's comparative advantage or its accession to the World Trade Organization. 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.

From the Industrial Sales database, we observe total sales (domestic sales and exports) for each manufacturing firm by eight-digit product code, which we aggregate into the four-digit Harmonized System (HS) to match the aggregated trade data from the UN COMTRADE database. 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 threshold levels are not required to report to the Industrial Sales database, which implies that we lose many observations in the regression results presented below. Specifically, the regressions on automation capital and internationalization are based on 407 of the 567 firms in the automation survey.

3.4 Measures of Firm Performance

In this study of firm performance and automation, we apply value-added based performance measures that control for capital and labor inputs. Moreover, we apply the following internal measures of efficiency: quantity produced per worker, run time, setup time, inspection time, and uptime. The former type of measure originates from firm register data, whereas the latter is drawn from the survey fielded for this study.

3.5 Descriptive Statistics

In this section, we present the descriptive statistics for the data described above.

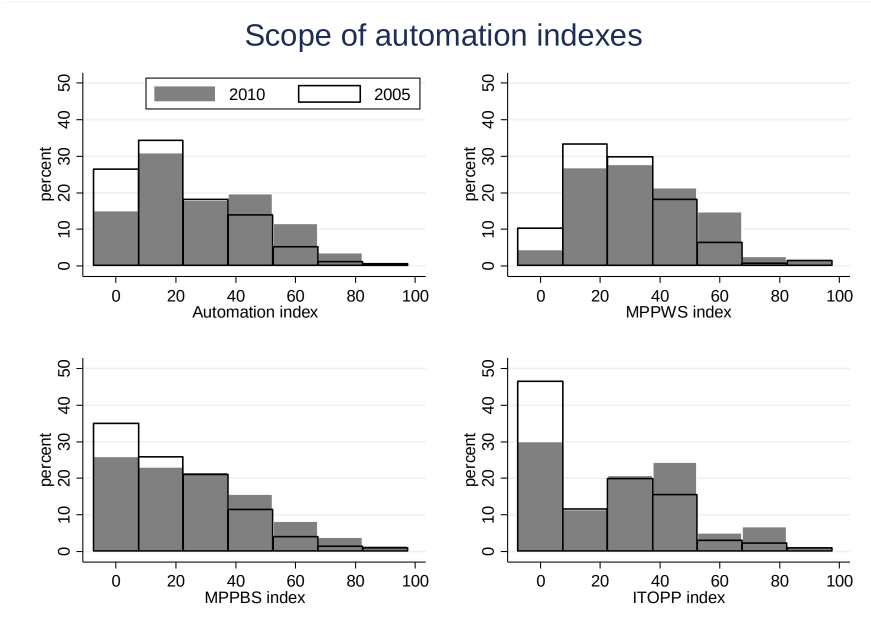

Figure 3: The distribution of the scope of automation indexes for 2005 and 2010

Figure 3 shows the distribution of the automation index and sub-automation indexes for 2005 (white) and 2010 (gray). For the overall automation index (top left corner), 0 indicates that firms still rely on labor inputs in each of the 8 production processes and 100 indicates that all 8 production processes are fully automated.

The graph indicates that there are some firms whose production processes still fully depend on labor input to hold an object and/or a tool and some firms whose production processes are very close to being fully automated. Specifically, in 2010, 12% of Danish manufacturing firms relied on manual processes for the main production processes, down from 27% in 2005, while even in 2010, fewer than 1% of companies were close to full automation. Overall, more firms have automated processes in 2010, but there is still a large portion of processes that are mainly manually operated. Examining the three sub-indexes, the patterns parallel the overall index. In general, the production processes within stages are more likely to be automated than those between stages, and IT is least likely to be used to optimize these processes. In 2005, 47% of the firms used little IT to optimize processes; however, this improved to 30% by 2010.

Figure 4 shows the individual questions included in the automation index in 2010. For all eight questions, all five possible answers have been used. Stage 1 (manufacturing, processing and handling processes) is the most mechanized, and 74% of firms indicated that a significant portion of these processes are mechanized. This is in contrast to stage 3 (inventory processes, such as receiving, picking, palletizing, and shipping), where only 19 percent gave a similar answer. For the three questions related to processes between stages, even fewer firms have mechanized processes. Nearly 90% of firms answered that only a few of their inspection processes were mechanized; however, at least one firm answered that all of their processes were mechanized, indicating that this outcome is possible (at least in some of the industries) and that plenty of opportunities remain for firms to adopt automation. Finally, firm responses are on 3-5 of the Likert scale for one third of the firms for IT use in the form of execution and control.

Examining automation adoption from 2005 to 2010 in more detail (not shown), 25% of firms did not report any increase in automation. No firm appears to have transitioned from manual processes to fully automated production processes during this 5-year period. This finding suggests that automation in firms takes place as incremental change rather than as major changes. Generally, the data show a clear picture of firms being very slow to adopt automation even though the level in 2005 was not impressive. If this project had included only these data, we might have guessed that firms are not adopting automation because solutions are not available or are too expensive. However, many firm visits and discussions with industry experts have convinced us that one primary reason for the low level of automation and adoption is a lack of knowledge. Most of the firms in our studies are small and hence do not have the resources they need.

Overall, the descriptive statistics show that there is a wide range among Danish manufacturing firms in both the mechanization level of production processes and in the use of IT. Thus, there is considerable potential for firms to automate large portions of their production processes.

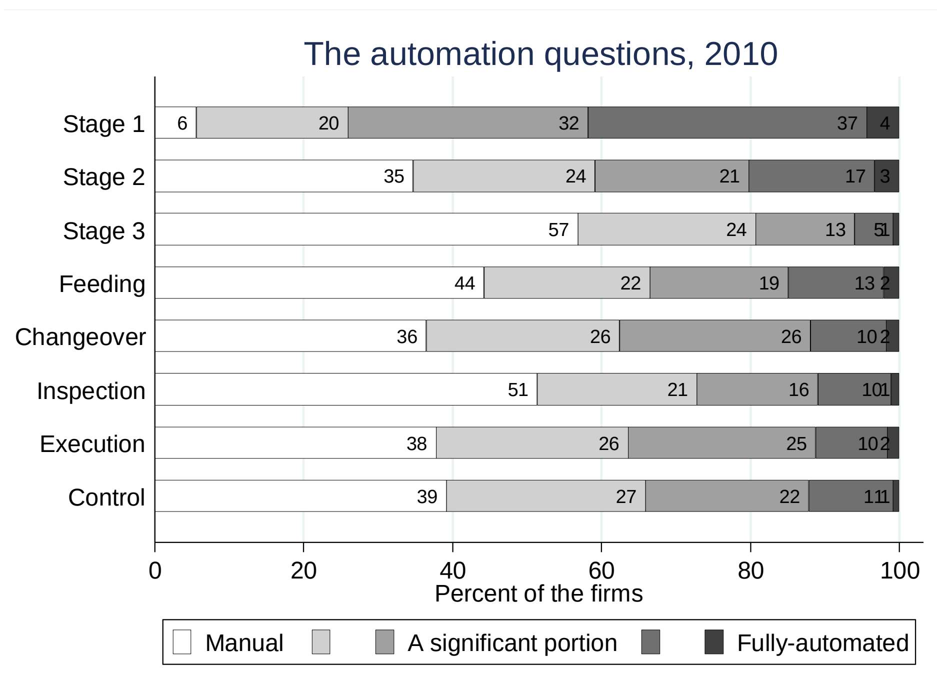

Figure 4: The distribution of responses on the 5-point Likert scale for eight automation questions

Next, we turn to descriptive statistics of other variables used in the analysis. In Table 1a, we present descriptive statistics for the dependent and explanatory variables used in the subsequent empirical analysis. Note that, on average, the amount of non-IT, non-automated capital in a firm is approximately four times larger than the amount of automated capital although automated capital is becoming gradually more important. Non-IT, non-automated capital is at least 10 times larger than IT-capital. Moreover, it is seen that all inputs on average fall over the period 2005-2010, except for automated capital that increases. That is, although the financial crisis raged during the period under investigation, the stock of automated capital increased on average. The reason that IT capital falls relatively much is due to low investments and a large depreciations rate.

Table 1a: Descriptive Statistics

	2005		2010		Change	
	mean	s.d.	mean	s.d.	mean	s.d.
Value added	54.21	137.95	63.27	303.60	9.50	235.70
Capital	62.74	207.94	60.69	187.97	-2.55	40.66
Persons engaged	115.28	301.01	98.72	273.78	-15.75	67.10
Automated capital	11.24	55.46	11.82	50.16	0.16	16.96
IT capital	4.49	15.25	2.39	10.93	-2.10	11.28
Non-IT, non-automated capital	47.36	152.70	46.58	140.61	-0.86	31.49
Number of firms	476		476		476	476

Note: Persons engaged are measured in persons, and value-added and capital are measured in millions of DDK of 2005-prices.
Source: Authors' survey on automation in manufacturing and register data from Statistics Denmark

It should be noted that mean value added increases and that the standard deviation quite a lot from 2005 to 2010. This change is driven by an outlier firm. Without this outlier the mean value does change much, whereas the mean change in value added is negative and around -1 million DKK.

Table 1b presents the development in measures of international competition measured by yearly changes in log points. It is seen that Chinese exports on average increased by 32 log points per year for four-digit product codes during the period 2002 to 2007. The reason that we measure exports over the period 2002-2007 is because we find that automation is affected by a 3 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 is similar to results reported elsewhere, see for example Bloom, Draca, and Van Reenen (2015).

Table 1b: International Competition, yearly change in log points, 2002-2007

	Δlog points	s.d.
Chinese export	31.84	16.73
Chinese import penetration	46.67	32.46
Low wage country import penetration	25.55	26.14
Number of firms	476	476

Note: UN Comtrade data at four-digit product level, Danish firm register data, Statistics data. The changes are measured time period is 2002-2007.

Table 1c presents the automation index for 2005, 2010 as well as the yearly change during the period. It is seen that the average yearly increase in the overall automation index equals 0.081, increasing from a value of -0.183 in 2005 to 0.215 in 2010.

Table 1c: Automation and Management Practices, yearly and yearly change 2005-2010

	2005	s.d.	2010	s.d.	Change	s.d.
Automation Index	-.183	.932	.215	1.059	.081	.106
Automation sub-indices:						
MPPWS index	-.175	.952	.208	1.044	.078	.114
MPPBS index	-.132	.936	.160	1.062	.059	.095
ITOPP index	-.185	.932	.210	1.056	.079	.124

MPPWS index: Mechanization of production processes within stages index. MPPBS index: Mechanization of production processes between stages index, ITOPP index: IT to optimize the production processes index.
Source: Authors' survey on automation in manufacturing.

Finally, we present the annual growth rates in the alternative firm performance measures during the period 2005-2010. It is seen that the growth rates are in the range of 2 and 4 percent per year.

Table 1d: Alternative measures of firm performance, yearly change, 2005-2010

	Change	s.d.
Quantity produced by worker, percent	3.51	2.62
Run time, percent	-4.22	2.83
Setup time, percent	-3.48	2.79
Inspection time, percent	-2.16	2.41
Uptime, percent points	3.08	2.92

Source: Authors' survey on automation in manufacturing

4. Results

In this section, we present the empirical findings. Section 4.1 contains our results for trade-induced automation based on the estimation of equation (1). Section 4.2 presents results on the relationship between productivity and automation based on equation (2), whereas the results for the relationships between alternative measures of firm performance and automation presented in Section 4.3 use equation (3). Finally, we estimate the relationship between firm exit and automation in Section 4.4 based on equation (4). The latter two sections are largely included to investigate whether the estimation results reported in Section 4.2 are influenced by omitted variable or survival biases.

4.1 Trade-induced Automation Hypothesis

The results for the trade-induced automation hypothesis are presented in the following. First, we estimate equation (1) for automated capital using different specifications of W, the vector of additional explanatory variables. Second, we estimate a number of equations similar to (1) for different dependent variables, i.e., non-IT, non-automated capital and IT capital. The results can be observed in Table 2.

The trade-induced technical automation hypothesis is that $\theta_1 > 0$. Note that we allow for a dynamic response in equation (1), depending on the lag of the measure of export supply. Our baseline results use a lag of 3 years. This implies that we study the impact on automated capital stock between 2005 and 2010 from changes in export supply from China during the period 2002 to 2007.

In column 1 of Table 2, we include only Chinese exports and find a coefficient of 0.091, significant at the 5 percent level. This result shows that firms that face a large increase in Chinese exports in their markets accumulate more automated capital than firms that are less exposed to increasing international competition. We interpret this result as follows: 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. The magnitude of the point estimate implies that an increase in Chinese exports of 10 log points increases automated capital by nearly one percent. The Chinese export supply has increased by 32 log points per year, which implies that the automated capital stock has increased by approximately 3 log points per year over the 5-year period.

In the following three columns, we include other measures of international competition in addition to the measure of Chinese exports. In column 2, we consider Chinese exports to Denmark in addition to Chinese exports to the world excluding Denmark. This measure expresses competition in the Danish domestic market from Chinese exporters, as reported by Chinese authorities. It is observed that Chinese exports to the world are driving the effect. Next, we use Danish imports from low-wage countries. Again, it is observed that Chinese exports to the world are driving the effect.

Finally, in column 4, we include an additional set of explanatory variables composed of other primary inputs of the firm. These include log IT capital, log non-IT, non-automated capital, log employment, and skill share. 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. It is observed that Chinese exports remain positive and significant in the regression.

TABLE 2: Automation and international competition – Dependent variable: log(automated capital). Fixed effects estimation, 2005-2010

	(1)	(2)	(3)	(4)
Estimation method	FE	FE	FE	FE
Chinese export supply to World	0.091**	0.076*	0.084**	0.068**
	(0.037)	(0.039)	(0.039)	(0.029)
Chinese export supply to Denmark		0.012		
		(0.012)		
Low-wage country import penetration			0.007	
			(0.005)	
Full set of explanatory variables	No	No	No	Yes
R-squared	0.088	0.090	0.091	0.304
Number of observations	2356	2356	2353	2356
Number of groups	407	407	407	407
Smallest group size	2	2	2	2
Average group size	5.8	5.8	5.8	5.8
Largest group size	6	6	6	6

Note: The dependent variable in all columns is the log of automated capital. See the main text and Table 1a for a description of the explanatory variables. The period is 2005-2010. All regressions include area, industry and time dummies. The full set of explanatory variables includes log(IT capital), log(non-IT, non-automated capital), log(employment), and skill share. Standard errors in brackets are clustered by four-digit product code and are robust to heteroskedasticity and autocorrelation of unknown form. R-squared in fixed effects is the within R-squared. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

In Table 3, we present regressions similar to those in Table 2, column 4 using different lag lengths for export supply from China.

TABLE 3: **Automation and international competition - Dependent variable: log(automated production capital). Fixed effects estimation, lagged export supply**

	(1)	(2)	(3)	(4)	(5)
Estimation method	FE	FE	FE	FE	FE
Chinese export supply 2005-2010	0.03				
	(0.04)				
Chinese export supply 2004-2009		0.058			
		(0.05)			
Chinese export supply 2003-2008			0.071*		
			(0.04)		
Chinese export supply 2002-2007				0.068**	
				(0.03)	
Chinese export supply 2001-2006					0.048*
					(0.03)
R-squared within model	0.329	0.320	0.310	0.304	0.300
Number of observations	2393	2397	2383	2353	2313
Number of groups	406	407	407	407	407
Smallest group size	1	2	2	2	2
Largest group size	6	6	6	6	6

See notes to Table 2

It is observed that the Chinese export supply in 2003 and 2008 (2-year lag), in 2002 and 2007 (3-year lag) and in 2001 and 2006 (4-year lag) has a positive effect on automated capital stock, implying that firms specializing in product types that have experienced high increases in export supply to the world market have increased their automated capital stock more than firms that are less exposed to increasing export supply. For automation, therefore, the largest effects appear after three years, which is consistent with the idea that it takes some time to adjust to changing conditions for competition in the world market.

Last, Table 4 shows that automated capital is affected by Chinese export supply and the accumulation of IT capital is affected by Chinese exports to the world market. These results are consistent with the "trade induced technical change hypothesis" discussed in section 2.1. However, non-automated, non-IT capital is not influenced by increasing international competition.

TABLE 4: Automation and international competition – Various dependent variables. Fixed effects estimation

	$\log(K_{it}^{A})$	$\log(K_{it}^{NA-NIT})$	$\log(K_{it}^{IT})$
Chinese export supply	0.068**	-0.001	0.053*
	(0.029)	(0.017)	(0.031)
Full set of explanatory variables	Yes	Yes	Yes
R-squared within model	0.304	0.280	0.313
Number of observations	2356	2356	2383
Number of groups	407	407	407
Smallest group size	2	2	2
Average group size	5.8	5.8	5.9
Largest group size	6	6	6
Lag length	3	3	2

Note: The period is 2005-2010. All regressions include area and time dummies. The full set of explanatory variables includes log(automated capital), log(IT capital), log(non-IT, non-automated capital excl. structures), log(employment), and skill share, except the dependent variable. Standard errors in brackets are clustered at four-digit product codes and are robust to heteroskedasticity and autocorrelation of unknown form. R-squared in fixed effects is the within R-squared. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

4.2 Productivity and Automation

This section presents the empirical results based on productivity growth using value added as an output measure. Specifically, we investigate separate relationships between scale and scope of automation and firm performance.

Table 5 shows the coefficients from the estimated production functions with a focus on automated capital, other capital types, and measures of the scope of automation. The strategy is to first use an aggregate measure of capital that is later decomposed. Finally, we estimate equation (2) in columns 5 and 6, including the scope of automation. All regressions in Table 5 are estimated using fixed effects.

Table 5, column 1 presents the results when the aggregate capital stock, total employment, and skill share are used as explanatory variables. As expected from earlier studies, all three explanatory variables positively and significantly explain value added.

The point estimate for the effect of employment is 0.74, which is close to the share of labor costs of value added and consistent with estimates found elsewhere in the literature; see, for example, Caroli and Van Reenen (2001). The point estimate for aggregate capital is 0.11. These findings are again similar to existing results in the literature; see, e.g., Balsvik (2011). This result might, however, reflect sluggish adjustments in capital and noisy observed year-to-year changes; moreover, because identification in a fixed effects regression comes from changes over time, this might introduce an attenuation bias toward zero.

In column 2, we split aggregate capital into IT and non-IT capital, which is the division applied in the literature on IT capital and productivity. It is evident that IT capital is positively and significantly correlated with log value added, whereas non-IT capital is positively correlated but only significant at the 10 percent level. This result suggests that IT capital, i.e., computer hardware and software, is an important growth driver. The magnitude of the point estimate is is similar to those found for IT in Bloom, Sadun and Van Reenen (2012).

In columns 3 and 4, we further break-down non-IT capital into automated capital and non-IT, non-automated capital (incl. and excl. structures). It is observed that automated capital is positively and significantly correlated with value added, whereas non-IT, non-automated capital is now almost zero and insignificant. This result suggests that investments in automation capital have been an important growth driver during the period 2005-2010.[14]

Finally, in columns 5 and 6, we add our measures for the scope of automation in addition to the measure of scale of automation. In column 5, the aggregate index is added, whereas the three sub-indexes are added in column 6. Column 5 documents that both the scope and the scale of automation are positive and significant. This strongly supports the idea that both dimensions of automation increase firm performance, where the scale of automation influences labor productivity the scope of automation is positively associated with TFP. Taken at face value a one standard deviation increase in the automation index implies an increase in TFP of 11 percent.

In column 6, it is established that only the degree of computerization (ITOPP index) is positive and significant at the 10 percent level. The other two sub-indexes are insignificant. More generally, we cannot distinguish between types of automation due to multicollinearity, implying that none of the sub-indexes is significant at the 5 percent level; however, when including the sub-indexes separately, each has a positive, significant coefficient. This latter result makes sense if all three automation types improve performance in different parts of the production floor. If this were the case, we would expect that all three types would increase TFP but we could not distinguish the effects. We turn to this issue in Section 4.3, which considers a number of alternative performance measures.

[14] We have also estimated the production function allowing for endogenous factor inputs using the System GMM estimator of Blundell and Bond (1998, 2000). We find an automation coefficient of similar magnitude to the one reported in Table 5, column 3. The results are available upon request.

TABLE 5: Productivity and automation – Dependent variable: log(value added). Fixed effects estimation

	(1)	(2)	(3)	(4)	(5)	(6)
Log(employment)	0.754***	0.758***	0.740***	0.727***	0.647***	0.646***
	(0.086)	(0.086)	(0.085)	(0.089)	(0.087)	(0.087)
Skill share	0.541*	0.562*	0.540*	0.585*	0.628*	0.678*
	(0.302)	(0.302)	(0.298)	(0.304)	(0.357)	(0.362)
Log(capital)	0.107***					
	(0.032)					
Log(IT capital)		0.067***	0.058***	0.056***	0.053**	0.053**
		(0.019)	(0.019)	(0.020)	(0.026)	(0.026)
Log(automated capital)			0.069***	0.084***	0.059**	0.057**
			(0.024)	(0.028)	(0.028)	(0.028)
Log(non-IT capital)		0.045*				
		(0.025)				
Log(non-IT, non-automated capital incl. structures)			0.003		0.026	0.025
			(0.026)		(0.023)	(0.023)
log(non-IT, non-automated capital excl. structures)				-0.04		
				(0.036)		
log(structures)				0.03		
				(0.019)		
SCOPE OF AUTOMATION						
Automation index					0.105***	
					(0.035)	
MPPWS index						0.06
						(0.037)
MPPBS index						-0.02
						(0.044)
ITOPP index						0.069*
						(0.038)
R-squared within model	0.315	0.317	0.322	0.316	0.352	0.353
Number of observations	2853	2853	2853	2707	1413	1413
Number of groups	482	482	482	463	481	481
Smallest group size	1	1	1	1	1	1
Average group size	5.92	5.92	5.92	5.85	2.94	2.94
Largest group size	6	6	6	6	3	3

Note: The period is 2005-2010. All regressions include area and time dummies. Standard errors in all columns are robust to heteroskedasticity and autocorrelation of unknown form. MPPWS index: mechanization of production processes within stages index. MPPBS index: mechanization of production processes between stages index. ITOPP index: IT to optimize production processes index. R-squared in fixed effects is the within R-squared. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

It should be mentioned that the automation index is constructed using site- or plant-level information, whereas value added, skill share and employment, for example, are measured on 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 so our index will capture firm-wide effects.

We are concerned with the endogeneity of the applied automation measures in Table 5. In the next two sections, we will discuss two econometric challenges that may bias the estimates. These are omitted factors that may influence investment in both automation and firm performance, which will bias the automation coefficients, and survival selection bias.[15]

4.3 Alternative Performance Measures and Automation

As mentioned, we are concerned with the endogeneity of the applied automation measures. First, we are concerned about omitted factors that may influence both automation measures and firm performance; this will cause a bias in the automation coefficients. We therefore introduce a number of alternative performance measures at the site level in this section to investigate the relationship between performance and automation. Although we are not able to exclude the type of omitted variable interpretation described above, we argue that the results we establish make the omitted variable interpretation less likely. Additionally, in Section 5, we return to the issue of omitted factors and control for an important unobserved variable – changing management practices – using a management index collected through our survey to investigate the robustness of the results presented in Table 5.

The alternative performance measures used in this section are quantity produced per worker, run time, setup time, inspection time, and uptime. In panel A, we present estimation results for the first difference estimation of equation (3) for the relationships between alternative performance measures and automated capital. We also include inputs of other production factors, i.e., employment, skill share, IT capital, and non-IT, non-automated capital, as explanatory variables. It is observed that additional automated capital increases the quantity produced per worker and uptime, whereas run time, setup time and inspection time all decrease. In other words, all five performance measures change as expected with automation.

Next, we include the change in the automation index in addition to the growth rate of automated capital in Panel B. In other words, we include changes in both the scope and the scale of automation. It is observed that the growth rate of automated capital becomes insignificant except for the quantity produced per worker. On the contrary, the change in the automation index (scope) is significant and has the expected sign. Hence, the growth rate of the quantity produced per worker is positively affected by

[15] To address the potential selection problem that high-growth firms self-select into investments in automation, we included 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 for the 2000-2005 period. 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 rates are instrumented with the initial real value-added level measured in 2000; this approach is consistent with that of Caroli and Van Reenen (2001). The main result of the paper is unaffected by this specification. These results are available upon request.

both improving automation and the growth rate of automated capital. This parallels the finding in Table 5 that increasing both the scale and the scope of automation improves productivity.

Finally, to address the omitted variable interpretation, we divide the automation index into the three sub-indexes in Panel C. It is observed that improvements in the three types of process innovations and the growth rate of automated capital have different impacts on the five alternative performance measures.

The purpose of Panel C is to see whether different types of automation have different effects across alternative performance measures. If this is the case, we argue that it is more likely that we can rule out the omitted variable interpretation described above. If types of automation affect the alternative performance measures differently, an omitted variable interpretation requires certain characteristics in addition to a correlation between increasing automation and alternative performance measures. The estimated effects of changing automation pertain to three different stages of production within the same firm as well as to an internal productivity measure and to uptime. Thus, to account for the full set of automation coefficients, the factor omitted from the analysis that is correlated with both changing automation and improved performance must have different effects across stages within plants. For example, if management practices improve immediately before or after the point when automation is improved, then this omitted factor can account for the effect MPBBS index on inspection time. However, the improved management practice must somehow not be relevant to improving performance at the run and inspection stages because the improvements in the MPPBS index have no significant effect on either run times or setup times. A similar argument can be made for the ITOPP and run time.

In Section 2.3, we predicted that an increase in the MPPWS index and/or the ITOPP index would increase the quantity produced per worker and uptime, whereas we did not expect an increase in the MPPBS index to impact the alternative performance measures. Finally, an increase in the ITOPP index was also expected to decrease run time. Examining Panel C, the results are somewhat consistent with our hypotheses at a 5 percent significance level,[16] allowing us to conclude that different types of automation have different effects across alternative performance measures, making omitted variable bias less likely.

[16] The ITOPP index/uptime hypothesis is only significant at the 10 percent level and is therefore an exception.

TABLE 6: Alternative performance measures – Various dependent variables. First difference estimation

	Percentage change				
	Quantity produced per worker	Run time	Setup time	Inspection time	Uptime
Panel A					
Δlog(automated capital)	0.038***	-0.016*	-0.016*	-0.015*	0.022**
	(0.012)	(0.009)	(0.010)	(0.008)	(0.009)
R-squared	0.035	0.022	0.032	0.043	0.035
Panel B					
ΔAutomation index	0.096***	-0.074***	-0.058***	-0.037***	0.074***
	(0.017)	(0.013)	(0.013)	(0.012)	(0.014)
Δlog(automated capital)	0.023*	-0.002	-0.005	-0.009	0.01
	(0.012)	(0.009)	(0.010)	(0.008)	(0.009)
R-squared	0.117	0.094	0.077	0.068	0.102
Panel C					
ΔMPPWS index	0.046**	-0.018	-0.020	-0.005	0.036**
	(0.020)	(0.015)	(0.016)	(0.014)	(0.016)
ΔMPPBS index	0.002	-0.052	-0.079	-0.075*	0.062
	(0.066)	(0.050)	(0.050)	(0.044)	(0.052)
ΔITOPP index	0.050**	-0.046***	-0.021	-0.011	0.025*
	(0.020)	(0.014)	(0.013)	(0.011)	(0.013)
Δlog(automated capital)	0.023**	-0.001	-0.004	-0.009	0.009
	(0.012)	(0.009)	(0.010)	(0.008)	(0.009)
R-squared	0.114	0.102	0.084	0.071	0.105
Number of observations	451	453	453	451	453

Note: The period is 2005-2010. All regressions include area and industry dummies. Moreover, all regressions include log(employment), skill share, log(IT capital) and log(non-IT, non-automated capital incl. structures) as explanatory variables. Standard errors in all columns are robust to heteroskedasticity and autocorrelation of unknown form. MPPWS index: mechanization of production processes within stages index. MPPBS index: mechanization of production processes between stages index. ITOPP index: IT to optimize production processes index. R-squared in fixed effects is the within R-squared. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

4.4 Firm Exits and Automation

Our results may suffer from survival bias. This bias occurs if survival relates to productivity shocks, which also relate to the automation decision. The estimated effect of automation on firm performance could then be biased. To investigate whether this constitutes a potential problem, we estimate the probability of firm exits in the surveyed firms after the collection of survey data and until October 2014.

More precisely, the hypothesis under investigation is that firms that have a high stock of automated capital or that have invested intensively in automation are less likely to exit. In addition, it is hypothesized that firms that face severe international competition from China in their product market – as measured by Chinese exports at the product level – are more likely to exit.

In Table 7, results from the linear probability model, equation (4), are presented. We do not attribute a causal interpretation to the relationship between automated capital and firm exit. It is observed that firms that have had large changes in their log automated capital are less likely to exit. Moreover, it is observed that firms that specialize in products with high Chinese exports to the world market are more likely to exit.

As stated above, it is found that investments in automated capital are negatively correlated with firm exit, whereas the automation index does not correlate significantly with firm exit. In this sense, the coefficient of automation capital may be negatively biased in Table 5 because firms with low productivity growth and high investments in automation will remain in business and tolerate lower productivity growth. In this sense, the estimated coefficients for automated capital can be considered lower limits.

We have also included a number of additional explanatory variables measured at 2010 levels and as changes between 2005 and 2010. None of these additional variables contributes to the explanation of firm exit.

TABLE 7: Automation and international competition – Dependent variables: Dummy measuring firm exit after 2010. LPM estimation

	(1)	(2)	(3)	(4)	(5)
Δlog(automated capital)	-0.022**		-0.025**		-0.023*
	(0.01)		(0.011)		(0.012)
ΔAutomation index			0.005		-0.015
			(0.019		(0.024)
Δlog(IT capital)			0.012		0.015
			(0.018)		(0.017)
Δlog(non-IT, non-automated capital excl. structures)			0.007		0.005
			(0.013)		(0.014)
Chinese export supply		0.008**	0.008**	0.009**	0.010**
		(0.004)	(0.004)	(0.004)	(0.005)
Automation index				0.021*	0.024*
				(0.012)	(0.014)
log(automated capital)				-0.004	-0.002
				(0.007)	(0.007)
log(IT capital)				-0.005	-0.007
				(0.007)	(0.007)
log(non-IT, non-automated capital excl. structures)				0.001	0.003
				(0.008)	(0.008)
R-squared	0.063	0.059	0.07	0.072	0.083
Number of observations	411	411	411	411	411

Note: Changes are measured over the period 2005-2010. All regressions include area and industry dummies. Standard errors in all columns are robust to heteroskedasticity and autocorrelation of unknown form. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

5. Robustness – Management Practices.

To check robustness, we consider whether the obtained results for firm performance are a consequence of one specific omitted variable, namely, improved management practices in production processes. The motivation for including an index of management practices comes from a series of papers by Bloom and Van Reenen on this subject. Hence, what we have in mind is an omitted variable representing better management practices that both improve firm performance and increase the extent of automation. Therefore, one omitted variable interpretation of the results presented in Sections 4.2 and 4.3 is that some unobserved shock – changing management practice – provides incentives to introduce automation and improve productivity that would bias the automation coefficients.

Therefore, we have also collected data on management practices on the production floor in addition to the data collected on automation; for details, see the appendix. A management practice index was constructed following a similar method as that used for the automation index. The index on management practice was constructed using 25 questions about managerial practices used on the production floor, i.e., this measure does not address management of firm support functions, such as for example sales offices. These questions were largely inspired by Bloom and Van Reenen (2007). Thus, we collect data on several management practices, such as minimization of waste, decentralization, human resource management, total productive maintenance and total quality management.

In Table 8, the means and standard deviations are presented for the index of managerial quality for 2005 and 2010 as well as for the change between these years.

TABLE 8: Decentralization and Management Practice Index

	2005	s.d.	2010	s.d.	Change	s.d.
Management Practices	-.447	1.087	.471	.760	.184	.192

Note: See Appendix B for details.

This index is included in productivity equation (2) in Table 9 as well as in the first difference equations for alternative measures of firm performance in equation (3) in Table 10. In Table 9, column 1, the automation index is not included – only the index for management practice is included. In column 2, indexes for both management practice and automation are included. It is observed that the index for management practices is significant in column 1. However, when the automation index is included in the regression in column 2, the index for management practices becomes insignificant. This suggests that management practices on the production floor and the scope of automation are highly correlated but that automation adoption drives TFP. An alternative interpretation is that value added is a firm specific measure while management practices are site specific.[17] Of course, the automation index is also a site-specific measure. However, it seems likely that automation levels vary less across sites. Moreover, the measure for automated capital is constructed based on site- and firm-level information.

Table 10 presents the results when the index of management practice is included in equation (3). In Panel A, the automation index is not included but both indexes are included in Panel B. Unlike in Table 9, the index for management practice enters significantly for all alternative measures of firm performance in both Panels A and B, with the exception of uptime in Panel B. Moreover, it is observed that most of the coefficients of the automation measures in Table 5 are consistent when management practices are included. Thus, the results from Table 6, Panel B indicate consistent but slightly lower coefficients on the automation index.

[17] This is consistent with the quote in Ichniowski and Shaw (2013, p. 265): "The performance variable is rarely profits, because profits are measured at the level of the firm, and insider studies use samples below that level. Management practices are typically not the same across all workers in a firm. Production workers are not covered by the same practices as managers, and employees in one site may be covered by different practices than those at another site".

TABLE 9: Productivity, automation, and management practices – Dependent variable: log(value added). Fixed effects estimation

	(1)	(2)
Management practice index	0.042**	0.026
	(0.021)	(0.021)
Automation index		0.087**
		(0.035)
Log(automated capital)	0.064**	0.054*
	(0.029)	(0.029)
Log(IT capital)	0.050*	0.050*
	(0.026)	(0.026)
Log(non-IT, non-automated capital incl. structures)	0.022	0.023
	(0.024)	(0.023)
Skill share	0.488	0.486
	(0.347)	(0.347)
Log(employment)	0.665***	0.666***
	(0.083)	(0.082)
R-squared within model	0.35	0.354
Number of observations	1432	1430
Number of groups	483	482
Smallest group size	1	1
Average group size	3.0	3.0
Largest group size	3	3

Note: The years are 2005, 2007 and 2010. All regressions include area, industry, and time dummies. Moreover, all regressions include log(employment), skill share, log(IT capital) and log(non-IT, non-automated capital incl. structures) as explanatory variables. Standard errors in all columns are robust to heteroskedasticity and autocorrelation of unknown form. R-squared in fixed effects is the within R-squared. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively. The variable of management practice adoption is constructed in the same way as that for the automation index, using 25 questions on management practices.

TABLE 10 Alternative firm performance measures – Various dependent variables. First difference estimation

	Percentage change				
	Quantity produced per worker	Run time	Setup time	Inspection time	Uptime
Panel A					
ΔManagement practice index	0.040***	-0.033***	-0.026***	-0.021***	0.026***
	(0.009)	(0.007)	(0.007)	(0.007)	(0.008)
Δlog(automated capital)	0.029**	-0.006	-0.008	-0.010	0.016
	(0.012)	(0.009)	(0.009)	(0.008)	(0.010)
R-squared	0.08	0.068	0.064	0.07	0.062
Panel B					
ΔManagement practice index	0.023***	-0.020***	-0.016**	-0.015**	0.012
	(0.010)	(0.007)	(0.008)	(0.007)	(0.008)
ΔAutomation index	0.080***	-0.061***	-0.047***	-0.027**	0.066***
	(0.019)	(0.015)	(0.014)	(0.013)	(0.015)
Δlog(automated capital)	0.020*	0.001	-0.002	-0.007	0.008
	(0.012)	(0.009)	(0.009)	(0.008)	(0.010)
R-squared	0.130	0.111	0.090	0.082	0.107
Panel C					
ΔManagement practice index	0.025**	-0.020***	-0.016**	-0.016**	0.013*
	(0.010)	(0.007)	(0.008)	(0.007)	(0.008)
ΔMPPWS index	0.038*	-0.016	-0.02	-0.001	0.033**
	(0.002)	(0.015)	(0.016)	(0.014)	(0.017)
ΔMPPBS index	-0.004	-0.029	-0.056	-0.069	0.056
	(0.069)	(0.049)	(0.047)	(0.043)	(0.053)
ΔITOPP index	0.042**	-0.042***	-0.018	-0.007	0.021
	(0.020)	(0.014)	(0.013)	(0.011)	(0.014)
Δlog(automated capital)	0.020*	0.001	0.001	-0.006	0.008
	(0.012)	(0.009)	(0.009)	(0.008)	(0.010)
R-squared	0.129	0.12	0.097	0.086	0.11
Number of observations	449	450	450	449	450

Note: The period is 2005-2010. All regressions include area and industry dummies. Moreover, all regressions include log(employment), skill share, log(IT capital) and log(non-IT, non-automated capital incl. structures) as explanatory variables. Standard errors in all columns are robust to heteroskedasticity and autocorrelation of unknown form. R-squared in fixed effects is the within R-squared. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively. The variable of management practice adoption is constructed in the same way as the automation index, using 25 questions on management practices.

6 External Validation and Sample Selection

6.1 External Validation of Survey

One important criticism of the survey data set for the automation of production processes and management practices is that the data for 2005, 2007 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 indexes for automation and management practices is large, so we cannot apply time-demeaned variation or long differences to the data set.

We argue that the collected survey data are of high quality for three reasons. First, during the 16 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 above in sections 4 and 5, in which we find a strong association between the change in automation and management practices and value added growth. 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", to which we now turn.

The CIS is collected each year by Statistics Denmark 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:*** *Did the firm introduce new or significant changes in methods for the production of goods or services over the past three years?*

We also use the following question on organizational innovation:

> ***Organizational Innovation:***
> - *Did the firm introduce new methods of organizing business processes or procedures during the past three years (such as quality management, performance management, knowledge management, lean, reorganization, supply chain management, etc.)?*
> - *Did the firm introduce new methods of organizing responsibilities or decision making over the past three years (such as decentralization, job rotation, teamwork, merger or division of departments, etc.)?*

We obtain data collected for four years of the CIS from 2007-2010, implying that we have answers to the questions covering the years 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 all of the largest firms answer every year, 80 percent of the second-largest firms, 60 percent of the third-largest firms, and so on. Of the firms we surveyed, 320 have also answered CIS surveys at least once during this period. For each question, we have constructed a dummy variable equal to 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 11, we investigate the relationship between the dummy-variables based on CIS and the changes in automation and management practice indexes from our survey.

TABLE 11: External validation using the Community Innovation Survey (CIS) – First difference estimation

	Δ(AI)	Δ(MPPWSI)	Δ(MPPBSI)	Δ(ITOPI)	Δ(MP)
Process innovation	0.150**	0.123	0.148**	0.137*	0.128
	(0.069)	(0.075)	(0.061)	(0.080)	(0.127)
Organizational innovation	0.009	0.023	0.007	-0.009	0.214*
	(0.067)	(0.072)	(0.060)	(0.078)	(0.123)
R-squared	0.142	0.105	0.124	0.118	0.078
Number of observations	299	300	300	299	297

Note: The period is 2005-2010. All regressions include area and industry dummies. Moreover, all regressions include log(employment), skill share, and log(capital) as explanatory variables. Standard errors in all columns are robust to heteroskedasticity and autocorrelation of unknown form. R-squared in fixed effects is the within R-squared. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

It is observed that firms that respond 'yes' to process innovation exhibit larger changes in the automation index during the periods 2005 and 2010 than do firms that respond 'no'. The same is true for physical integration and computerized integration and control, whereas the index for management practices is unaffected by process innovation. However, firms that respond 'yes' to organizational innovation exhibit larger increases in the index for management practices compared to firms that respond 'no'.

Next, we turn to external validation using the "Survey on ICT usage in enterprises". Specifically, we use the following question:

> *Has the firm within the last 2 years introduced new machinery or equipment that contains IT? Include both computers and other equipment that can process and exchange data digitally - including programmable microprocessor-controlled equipment.*

It is evident from Table 12 that firms that invest in machines and equipment containing IT have a higher increase in the index for computerized integration and control. The other sub-indexes of automation are not significantly correlated with the dummy variable.

TABLE 12: External validation using Eurostat "Surveys on ICT usage in enterprises" – First difference estimation

	Δ(AI)	Δ(MPPWSI)	Δ(MPPBSI)	Δ(ITOPI)
Investment in machines and equipment with IT	0.099	0.080	0.059	0.147**
	(0.072)	(0.080)	(0.063)	(0.071)
R-squared	0.086	0.068	0.068	0.096
Number of observations	319	320	320	319

Note: The period is 2005-2010. All regressions include area and industry dummies. Moreover, all regressions include log(employment), skill share, and log(capital) as explanatory variables. Standard errors in all columns are robust to heteroskedasticity and autocorrelation of unknown form. R-squared in fixed effects is the within R-squared. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

6.2 Data Collection and Sample Selection

This survey was voluntary, and the response rate is 41%, which is high by the standards of large-scale surveys that are not government mandated. In Table 14, the response rate and the reasons for refusal are shown. As observed from column 2 in the table, there were just over 3000 manufacturing firms in Denmark with more than 10 employees in 2005. Of those, 21% were included in our sample, which is a very high percentage for a survey.

TABLE 14: Response rate

	Population	**Adjusted population**	**Contacted firms**
*Number of manufacturing firms**	**3049**	**2705**	**1402**
Number of responding firms (100% completed)	**570**	**570**	**570**
Not contacted by the callers	**1303**	**1303**	
<u>Reasons for refusal:</u>			
No production in DK /outsourced	166		
Liquidation/insolvent	36		
Bought by another firm	1		
Wrong industry code, not a manufacturing firm	141		
Not relevant for the firm	126	126	126
By principle	51	51	51
Too complicated questionnaire	64	64	64
No time	336	336	336
Problems with anonymity	6	6	6
Not interested	77	77	77
Other reasons	172	172	172
Number of firms that refused to participate	**1176**	**832**	**832**
Response rate	**19%**	**21%**	**41%**

Note: *Manufacturing firms in Denmark with more than 10 employees in 2005

Comparing the participating firms with the non-participating firm 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 responding firms are larger compared to non-responding firms.

7 Discussion and Conclusion

This paper addresses three issues related to the automation of production processes in manufacturing firms. First, it examines the diffusion of automation in Danish manufacturing firms. Second, it investigates whether there is a positive and causal effect from increasing international competition from China on investments in automated capital in Danish manufacturing firms. Third, it investigates whether improvements in firm performance are positively associated with investments in automation.

For this paper, we have constructed a new and remarkable data set covering measures for the automation of production capital for firms in the Danish manufacturing industry. The data set constitutes one of the most – if not the most – comprehensive descriptions of automation technologies applied in manufacturing firms ever attempted. Its construction required two years of intensive work. First, we have collected new survey data on the characteristics of automated capital for 567 manufacturing firms with more than 10 employees in 2010, representing over 20% of the population of firms. These data include information on the scale and scope of automation. Moreover, we have enriched this innovative survey data set on automation with secondary data, such as value added, investments in machinery and equipment, exports and imports at the product level, total sales at the product level, education of employees, and other accounting data. In addition, we have merged data on Chinese exports by product code with the data set. These data originate from the UN Comtrade database.

Examining the level of automation in 2005 and the adoption rate up to 2010, we conclude that surprisingly many non-automated production processes persist in manufacturing firms. Furthermore, we clearly observe that firms adopt automated processes relatively slowly. This is the case even though the level in 2005 was not impressive.

An important result of this study is that firms that are exposed to relatively strong increases in international competition measured by exports from China to the world market tend to have large investments in automation. We argue that this effect is causal because the applied measure is increases in Chinese exports to the world market in the product type in which the firms initially specialized. Moreover, we consider a productivity measure based on value added and find that improved automation and increasing productivity are positively correlated. Hence, this result is consistent with the conclusion that automation improves productivity. This is the case for both scale and scope of automation where scale is measured using automated production capital and the scope of automation is measured by ab automation index. Automation capital is constructed using perpetual inventory method (PIM) combining survey data on automation with investment data on machinery and equipment. The automation index is based on eight survey questions focusing on different aspects of the production process.

Finally, we include an index of management practices from the production floor in the empirical analyses together with the measures of automation. This index of management practices is constructed from survey data. The motivation for including an index of management practices is that these are often found to be important drivers of firm performance; see, for example, Bloom and Van Reenen (2007). Therefore, management practices potentially represent an important omitted variable. We find that improved management practices are positively correlated with productivity growth even when automation measures are included. However, improved automation still enters positively and significantly in the explanation of productivity growth. The inclusion of management practices potentially addresses an important omitted variable. We are still unable to rule out the omitted variable interpretation but claim that this result makes the omitted variable interpretation even less likely.

An important strength is that the collected survey data are merged with very detailed external data sources, which enables us to perform external validation of the collected data using information from other sources. Specifically, we are able to externally verify our survey data on automation and management practices using the CIS and surveys on ICT usage in enterprises.

The broader implications of our findings are important: not only do they show that automation have a positive impact on firm performance but also that many firms currently underutilize automation. Small firms in particular can improve their level of automation to increase performance. During firm visits production managers often complained about limited access funding and advice for automation planning of the factory floor. Whether this reflects limited policy focus on investments in automation in Denmark is an open question. Related to this is the question whether automation-promoting policy programs could potentially constitute important drivers for investments in automation. Whether there are externalities that result in too little investments in automation is another question. These are all important questions that we leave it for future research.

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APPENDIX

A. Survey Data Collection

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

The development process

The AIM 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.[18] This was followed by workshops, discussions and visits to manufacturing firms; production managers for these firms were consulted. In general, product managers preferred a survey to a phone interview.[19] The comments provided from the workshops and visits were used to evaluate the firm information to be collected, which questions were relevant, and how questions should be asked as well as to decide how to collect the data.

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

Findings from the process

Dialogue with product managers at 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 some 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 gave incorrect answers when asked about the technologies used. As a result, questions regarding 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, firm visits showed that 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 to the description of the automation degree, while the least automated companies applied it more progressively; this tendency made the inclusion of help text essential to obtain a comparable scale. This also further helped to address concerns about inconsistent

[18] The first draft of the survey was based on other projects from other countries - including Van Reenen and Bloom's work on management practices, technology, and organizational change. In addition, the survey took inspiration from surveys by Statistics Canada, the European IMSS (International Manufacturing Strategy Survey) and studies undertaken in the U.S. by researchers such as Kathryn Shaw.

[19] This allows a survey format that prevents the respondent's answer from being affected by the way the question was asked, which is a tendency documented in the psychology literature.

interpretation of categorical responses, see Bloom and van Reenen (2007), Manski (2004), and Bertrand and Mullainathan (2001).

Selection of the sample

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

Population: All manufacturing firms in Denmark with more than 10 employees in 2005, i.e., firms with a NACE industry code between 150,000 and 400,000. These 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 questionnaires.

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 the corresponding link to the AIM questionnaire 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 to those 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. This happened for approximately 28% of the questionnaires, and in 95% of those cases, answers were subsequently corrected.

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 firm 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 firms.[20] The callers received a flat rate of 125kr ($21) while they were learning about the project, including a firm visit. While calling, they received 75kr ($13) per hour and 500kr ($83) per completed survey.

Collection period

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, as it had been decided that all firms that had been contacted should be treated in a similar way.

B. Management Practice Index

As 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 as well as to management practices on the production floor was needed.

To investigate the distribution of management practices across industries and firms, we have constructed a management practice index. This appendix presents the questions included in the index. The survey questions can be grouped into "waste minimization in the production process" (Just-in-time - JIT), "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 index used in Section 5 is constructed using z-scores for the waste minimization, decentralization, human resource management, and performance management indexes. The questions are inspired by the series of papers by Bloom and van Reenen.

Minimization of waste (JIT)

JIT is related to the flow of goods from suppliers through the firm and to the final customer, where waste is reduced, if not eliminated, in all non value-added items such as waiting, moving and storing. In addition, JIT refers to the optimal utilization of employee capabilities. The following nine questions about JIT were asked:

1. To what extent is production built on this principle: The products are pulled through to completion with a strong focus on minimizing all forms of waste?
2. Minimizing defects in production (including material waste and disposal of raw materials or work-in-progress)?
3. Minimizing the overproduction of goods in the production process?
4. Minimizing the inventory of unfinished goods?

[20] 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 are not relevant here as 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 as well as whether to complete it at once or spread it over a couple of days.

5. Eliminating processes that do not add value for customers or employees (for example, removing problems instead of using inspection or reprocessing)?
6. Rationalizing worker movement?
7. Reducing transport and goods handling?
8. Minimizing waiting time for other processes?
9. Optimally using employee talents and knowledge sharing?

Each question is answered on a scale from 1 to 5, where 1 indicates that the firm has no focus on minimizing the specific type of waste in the production process referred to in the question and five indicates that there is a strong focus on minimizing the specific type of waste. The first question is a control and is not part of the score.

Decentralization (DEC)

DEC is related to the delegation of power to production workers. The eight questions asked about DEC are the following:

1. To what extent are decisions about daily operations the responsibility of production employees (rather than that of the factory manager or similar employee)?
2. Strong focus on improving product and process quality in the workplace: To what extent are employees responsible for the quality of the products and processes they work with?
3. Which employees are involved in problem solving?
4. Who is responsible for taking action?
5. Who (what) decides the speed of work in production?
6. Who (what) decides the timing of production tasks (scheduling)?
7. To what extent is the work assigned to autonomous groups rather than to individuals working independently?
8. Who generally decides how tasks are to be performed (regarding process improvements, machine choices, etc.)?

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 do their jobs.

The following three 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 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 five questions are asked about KPI:

1. How many key indicators are used to manage daily production?
2. How often are these key indicators computed?
3. Are key indicators and general business goals integrated?
4. What is the communication process for daily production key indicators?
5. Are daily production key indicators followed up on?

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

C. Automated capital, IT capital, and non-automated, non-IT capital

In the paper, three types of capital are used in the analysis of productivity and automation. The purpose of this appendix is to describe the data sources and methodology used to construct the capital measure, which is the Perpetual Inventory Method (PIM).

Data sources

AIM data set: The AIM data are collected by the authors. Question 8 of the survey asks about the percentage of investments in machinery and equipment targeted for automation, specifically "What percentage of new capital investments in machinery and equipment is targeted for automation?" The question is asked for 2005, 2007 and 2010, and the respondent can choose from among 5 ranges: 0-12%, 13-25%, 26-50%, 51-75% and 76-100%. We ask this question to divide machinery and equipment investments into automated production capital and non-automated production capital. These two types of investments are used to determine the stocks of automated and non-automated production capital.

Firm-level financial accounts (FIRE): FIRE data include annual firm financial accounts between 1995 and 2010. Data include detailed income statements and balance sheets as well as investments in real capital. We use machinery and equipment investments to determine automated and non-automated capital stocks. In addition, we have information on "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 missing values in the IT data, as described below.

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

Estimation of IT, automated and non-automated capital stocks

To estimate the three capital stocks, we apply the PIM. Assuming constant depreciation rates, the method states:

$$K_{i,r,t} = I_{i,r,t} + (1 - \delta_r) K_{i,r,t-1},$$

where K denotes capital stock, I denotes investments or gross fixed capital formation of capital type *r*, and δ is a constant depreciation rate. *i*, *r*, and *t* denote firm, capital type and time, respectively.

A key challenge in applying the PIM is the estimation of the initial capital stocks. We use the following method proposed by Hall and Mairesse (1995) and applied by Hempel (2005). Under the assumption that investment expenditures on capital good *r* have grown at a similar and constant average rate g_r in the past in manufacturing, the PIM equation can be rewritten as:

$$K_{i,r,t} = I_{i,r,1} / (\delta_r + g_r).$$

In the regressions in the paper, we include only firms that are in the FIRE data from 2001 to 2010. We measure $I_{i,r,1}$ as the average investments over 2001, 2002 and 2003 because investments may fluctuate quite dramatically from year to year.

Investments are deflated using economy-wide deflators, which follows Bloom, Sadun, and Van Reenen (2012). IT investments are deflated using the IT deflator from the Danish EUKLEMS database, see Van Ark et al. (2008), which is based on the harmonized hedonic price index. In the baseline estimations, we apply the production price index for both investments in automated capital and investments in non-automated capital.

Capital is depreciated at constant depreciation rates. IT capital is depreciated using a depreciation rate of 36 percent, which follows Bloom, Sadun, and Van Reenen (2012). Automated capital is depreciated using a depreciation rate of 20 percent, whereas non-automated capital is depreciated using a depreciation rate of 13 percent. The motivation for these depreciation rates is that the usual overall depreciation rate for machinery and equipment capital is 15 percent; see Fraumani (1997). Because the average overall share of automated capital equals one-fifth the weighted average of the two types of capital, this results in a depreciation rate of approximately 13 percent. Moreover, as Deb and Deb (2010) state, “the approximated life span of a robot is between 5 and 8 years” (p. 461). A depreciation rate of 20 percent is considered a reasonable approximation for an 8-year life span.

The values of g_r are fixed at 0 for all three capital types. Estimations for capital stocks in manufacturing provided by Statistics Denmark reveal that that the IT and non-IT capital stocks have hardly grown during the period 1975-2005 (see Statistics Denmark, NATP25V: Growth account after industry and type). Because the respective annual growth rates equal 0.25 percent and 0.36 percent, we assume that $g_{IT}=g_A=g_{NA\text{-}NIT}=0$.

We use expenditures for hardware, software, system software, and other IT equipment to construct IT capital. The construction of IT capital stock is based on the additional assumption that IT expenditures constitute a constant share of "expenses for the purchase of small inventory/equipment with a short life". Based on this assumption, we construct IT investments for years with missing observations from FITE data using the average ratio between IT expenditures and "expenses for the purchase of small inventory/equipment with a short life" in the sample multiplied by the firm-specific "expenses for the purchase of small inventory/equipment with a short life".

D. Additional Issues

In this appendix, we discuss a number of additional issues: firm size and other within-firm effects.

Table D1 divides the sample into firms that employ fewer than 50 people and those that employ 50 or more. The reason for dividing the sample into these groups is founded in the hypothesis that the scale of automation is relatively more important for small firms than for large firms. We expect that larger firms have invested in automated capital to a larger extent than smaller firms in 2005 because they began the transition toward automated production earlier. However, it should still be possible for larger firms to make improvements in the scope of automation as technology improves.

The results obtained after dividing the sample by firm size are presented in Table D1. Column 1 presents firms that employ fewer than 50 workers. It is evident that both the scope and the scale of automation are positively and significantly associated with value added. By contrast, column 2 reveals that larger firms benefit from an increasing scope of automation but not from an increasing scale of automation. The finding indicates that smaller firms will benefit from both dimensions of automation, whereas larger firms will benefit from greater scope of automation only.

The table also presents results for other dependent variables. These are (i) the share of orders designed or developed for customers and (ii) the share of production that is batch or flow production.

The share of orders designed or developed for customers is found to be positively correlated with the scope of automation in column 3. This is consistent with the findings in Bartel, Ichniowski, and Shaw (2007).

The share of production that is batch production is found to positively correlate with the scope of automation, whereas the flow production is found to positively correlate with the scale of automation.

TABLE D1: Productivity and automation. Fixed effects estimation

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Value added Small	Value added Large	Customized	Flow1	Batch3
Automation index	0.090*	0.086**	2.638**	0.076	0.124***
	(0.055)	(0.040)	(1.03)	(0.056)	(0.046)
Log(automated production capital)	0.095***	-0.045	(0.45)	0.122**	0.035
	(0.036)	(0.044)	(0.54)	(0.057)	(0.032)
Log(IT capital)	0.052	0.031	0.56	0.023	0.074**
	(0.038)	(0.029)	(0.48)	(0.049)	(0.030)
Log(non-IT, non-automated capital incl. structures)	0.022	0	0.41	0.039	0.031
	(0.025)	(0.050)	(0.34)	(0.065)	(0.022)
Skill share	0.268	0.321	0.61	0.183	0.194
	(0.346)	(0.937)	(3.90)	(0.939)	(0.332)
Log(employment)	0.611***	0.929***	1.00	0.730***	0.675***
	(0.111)	(0.104)	(0.74)	(0.127)	(0.115)
R-squared within model	0.347	0.436	0.04	0.298	0.418
Number of observations	887	550	1432	401	929
Number of groups	298	186	482	136	312
Smallest group size	1	1	1	1	1
Average group size	2.98	2.96	2.97	2.95	2.98
Largest group size	3	3	3	3	3

Note: The years were 2005, 2007 and 2010. All regressions include area, industry, and time dummies. Moreover, all regressions include log(employment), skill share, log(IT capital) and log(non-IT, non-automated capital incl. structures) as explanatory variables. Standard errors in all columns are robust to heteroskedasticity and autocorrelation of unknown form. R-squared in fixed effects is the within R-squared. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.