Automating Labor: Evidence from Firm-level Patent Data

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PRELIMINARY AND INCOMPLETE

Abstract

Do higher wages lead to more automation innovations? And if so, by how much? To answer this question, we build a firm-level panel dataset on automation innovation. We use the frequency of certain keywords in the text of patent data to identify automation patents in machinery. We validate our measure by showing that it is correlated with a reduction in routine tasks in a cross-sectoral analysis. We then use macroeconomic data on 40 countries and information on geographical patent history to build firm-specific measures of low-skill and high-skill wages. We find that an exogenous increase in low-skill wages leads to more automation innovations with an elasticity between 1 and 2.2. An increase in high-skill wages tends to reduce automation innovations. Placebo regressions show that the effect is specific to automation innovations.

JEL: O31, O33, J20

KEYWORDS: Automation, Innovation, Patents, Income Inequality

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1 Introduction

Do higher wages lead to more labor-saving innovations? And if so, by how much? At a time of fast technological progress in automation technologies such as robotics and AI and of political campaigns pushing for higher minimum wages, answering these questions is of central importance. Even more so because the endogeneity of automation innovations matters for the long-term effects of policy interventions (Hémous and Olsen, 2018). Yet, the literature on the effect of wages on labor-saving technological change is still limited. In fact the few existing papers (e.g. Lewis, 2011, Hornbeck and Naidu, 2014, or Acemoglu and Restrepo, 2018a) focus on the effect of labor costs on the *adoption* of automation technologies. Our paper is the first one to eDo higher wages lead to more automation innovations? And if so, by how much? To answer this question, we build a firm-level panel dataset on automation innovation. We use the frequency of certain keywords in the text of patent data to identify automation patents in machinery. We validate our measure by showing that it is correlated with a reduction in routine tasks in a cross-sectoral analysis. We then use macroeconomic data on 40 countries and information on geographical patent history to build firm-specific measures of low-skill and high-skill wages. We find that an exogenous increase in low-skill wages leads to more automation innovations with an elasticity between 1 and 2.2. An increase in high-skill wages tends to reduce automation innovations. Placebo regressions show that the effect is specific to automation innovations.stablish the causal effect of an increase in wages on automation *innovations*.

Answering this question requires overcoming two challenges: identifying automation innovations and finding a source of exogenous variation in wages from the perspective of innovating firms. To overcome the first challenge, we build a new method for classifying automation patents using the fact that patents are assigned to technological categories. We use the text of European Patent Office (EPO) patents and compute the frequency of certain keywords (such as "robot", "automation" or "computer numerical control") for each technological categories. Because our identification strategy is ideally suited for innovations in the equipment sector, we restrict attention to innovations in machinery. We define "automation technological categories" as technological categories where the frequency of use of the keywords is above a certain threshold. Finally, we identify as automation patents those which belong to automation technological categories. Our method presents at least two advantages: it is transparent and covers a wide range of innovations across several sectors compared with more narrow measures such as robots.

According to our laxer definition, the share of automation innovations among innovations in machinery has recently been increasing from 13% in 1999 to 21% in 2015. We use our measure in an exercise based on Autor, Levy and Murnane (2003). We find that in the United States, sectors where the share of automation patents filed in machinery was high, saw a decrease in routine tasks and an increase in the skill ratio. Our measure is uncorrelated with computerization, so that it captures similar trends but a different form of technological change.

At the country level, technology and wages are co-determined. Therefore, to isolate exogenous variation in wages, we exploit firm-level variations in the wages faced by the potential customers of innovating firms by exploiting variations in innovating firms' exposure to international markets. We expand on Aghion, Dechezleprêtre, Hémous, Martin and Van Reenen (2016, henceforth ADHMV)'s methodology and use the PATSTAT database, which contains close to the universe of patents. For each firm which undertakes automation innovations, we compute how much it has patented pre-sample in machinery in each country. We take this information as a proxy for the firm's international exposure and build firm-specific weighted averages of low- and high-skill wages using country-level data. These firm-specific wages proxy for the average wage paid by the customers of the firms. As a result, we identify the effect of an increase in wages on automation innovations, by comparing how much more automation innovations increase in, say, a German firm which has a high market exposure to the US relative to a German firm with a low exposure to the US when US low-skill wages increase.

We conduct our analysis over the sample period 1997-2011 and use wage data for 40 countries. We find a substantial effect of wages on automation innovations: higher low-skill wages lead to more automation innovations with an elasticity which we estimate between 1 and 2.2 depending on our specification. Higher high-skill wages, on the other hand, tend to reduce automation innovation with a smaller elasticity in line with the capital-skill complementarity hypothesis (Krusell, Ohanian, Rios-Rull and Violante, 2000). We look separately at the effect of low-skill wages in the largest market ("the domestic low-skill wage") and in the other markets ("the foreign low-skill wage") and find that the coefficients are similar. Moreover, we use the geographical localization of firms' inventors to compute the local knowledge stocks which firms are exposed to. We find strong evidence of local knowledge spillovers which suggest that the long-term effect of an increase in wages on automation innovations are larger than the short-term effect. Yet, we do not find evidence of path dependence at the firm level.

The theoretical argument that higher wages should lead to more labor-saving technology adoption or innovation dates back to Habakkuk (1962) and has been at the core of several theoretical papers (e.g. Zeira, 1998, Acemoglu, 2010). More recently, a small growth literature has emerged where endogenous innovation can take the form of either automation or another form of innovation (horizontal innovation) and where wages matter for the direction of innovation (Hémous and Olsen, 2018, Acemoglu and Restrepo, 2018b).

Yet, while there is an extensive literature on the effect of technological change on wages and employment,[1] the empirical literature on the reverse question is much more limited. A few papers show that labor market conditions affect technology adoption: Acemoglu and Finkelstein (2008) find that regulations which increase labor costs in hospitals lead to the adoption of labor-saving technologies; Lewis (2011) shows that low-skill immigration slows down the adoption of automation technology in manufacturing; Manuelli and Seshardi (2014) find that wages played a key role in the adoption of tractors; Hornbeck and Naidu (2014) find that the emigration of black workers from the American South favored the adoption of modern agricultural production techniques; Clemens, Lewis and Postel (2018) similarly find that the effect of limiting farm workers immigration on local wages and employment is consistent with the adoption of labor-saving technology; Lordan and Neumark (2018) find that minimum wage hikes displace workers in automatable jobs and Acemoglu and Restrepo (2018a) relate demographic trends with robot adoption. Our paper differs in at least two ways. First, our analysis is broader since it covers a range of automation technologies and 40 countries. Second, we focus on innovation instead of adoption,[2] which matters because the economic drivers of innovation may differ from those of adoption: it may be less responsive to macroeconomic variables such as wages and knowledge spillovers are likely to play a greater role. There is essentially no empirical literature on automation innovations: Alesina, Battisti and Zeira (2018) find in cross-country regressions that labor market regulations are correlated with innovation in low-skill intensive sectors, which is consistent with a model where innovation is labor-saving; and a recent working paper by Bena and Sim-

[1] See for instance Autor, Katz and Krueger (1998), Autor, Levy and Murnane (2003), Bartel, Ichniowski and Shaw (2007) or Autor and Dorn (2013) for IT, Doms, Dunne and Totske (1997) for factory automation, Graetz and Michaels (2017) or Acemoglu and Restrepo (2017) for robots, Mann and Püttmann (2018) for a broad measure of automation and Martinez (2018) or Aghion, Jones and Jones (2017) for the effect on factor shares.

[2] To be more precise, Acemoglu and Restrepo (2018a) also show some cross-country correlations between demographic trends and patents in robotics.

intzi (2019) shows that firms with a better access to the Chinese labor market decrease their share of process innovations after the 1999 U.S.-China trade agreement.[3]

This is perhaps surprising because a large literature shows that the direction of innovation is endogenous in other contexts: Acemoglu and Linn (2004) in the pharmaceutical industry; Hanlon (2015) in the 19th century cotton industry and several papers in the context of energy-saving or green innovations (Newell, Jaffe and Stavins, 1999, Popp, 2002 and Calel and Dechezleprêtre, 2016). Here, we build more specifically on the methodology of ADHMV, who build firm-level variations in gas prices to show that higher gas prices lead firms in the auto industry to engage more in clean and less in dirty innovations.[4]

Section 2 contains our first contribution: a classification of automation technologies and compares it with existing measures. Section 3 introduces a simple model to motivate the analysis. Section 4 describes our empirical strategy and the data we use. Section 5 contains the main results and Section 6 contains extensions and alternative specifications. Section 7 concludes. Appendix B provides details on our automation classification and additional robustness checks.

2 Identifying automation patents

In the following we describe the patent data that we use and how we identify patents as automation patents. Our approach proceeds in two steps: we first identify categories of automation technology and then automation patents as any patent belonging to an automation technology category. We then show how our measure of automation compares to previous measures of automation, notably using the framework of Autor, Levy and Murnane (2003).

[3] Process innovations and automation innovations are not the same: certain process innovations may involve reducing other costs than labor costs (for instance materials costs) and certain automation innovations can be product innovations (for instance a new industrial robot is a product innovation for its maker).

[4] Two other papers have used ADHMV's methodology: Noailly and Smeets (2015) use it to look at innovation in electricity generation and Coelli, Moxnes and Ulltveit-Moe (2018) use it to look at the effect of trade policy on innovation—as explained later in the text, we go further than these papers by looking separately at the effect of the domestic and foreign variables.

2.1 Patent data

We use two patent databases maintained by the European Patent Office (EPO). For most of our empirical analysis, we use the World Patent Statistical Database (PATSTAT) from 2018 which contains the bibliographical information of patents from most patent offices in the world, but not the text of individual patents. Since text analysis is essential to our approach, we supplement with the EP full-text database from 2018, which contains the full text of patent applications at the EPO. These are a subset of all of the patents from PATSTAT.

PATSTAT allows us to identify "patent families", a set of patent applications across different patent offices which represent the same innovation. For each patent family, we know the date of first application (which we use as the year of an innovation), the patent offices where the patent is applied for (which indicates its geographical breadth), the identity of the applicants and the inventors and the number of citations received by the patent family. In addition, to identify the technological characteristics of patents we use their IPC and their CPC codes (henceforth IPC/CPC codes).[5] Importantly each patent usually has several IPC/CPC codes. The IPC/CPC codes form a hierarchical classification systems. For certain research purposes patents can be readily identified as associated with a specific technology, say, green energy, using existing IPC/CPC groupings. Such a grouping does not exist for automation and it is our goal in the following to create it.

Our strategy to identify automation innovations relies on first identifying automation IPC/CPC codes (and combinations thereof) and then, using this information to identify automation patents. This allows us to include non-EPO patents in our analysis (since PATSTAT does not contain the text of those patents). In addition, technological codes by themselves are informative. Patents can be written in different styles, and often do not expand on the purpose of the invention. The particular wording of a patent is only a signal of its underlying characteristics, so that the same innovation could often be described with or without using our keywords. In other words, if a patent does not contain one of our keywords but belongs to an IPC/CPC code where patents most of the time do, there is a high likelihood that it is actually an automation patent (see examples in Figures 2a and 2b below). Conversely, if a patent uses one of our keywords but does

[5] The IPC is the International Patent Classification and the CPC the Cooperative Patent Classification used by the USPTO and the EPO. The CPC is an extension of the IPC and contains around 250,000 codes in its most disaggregated form.

not belong to any IPC/CPC codes where this is common, the inclusion of this keyword is frequently uninformative about the nature of the innovation.

2.2 Choosing automation keywords

In the following we explain how we choose our keywords associated with automation. We choose a few words, such as "automation", directly, but largely rely on the words used by Doms, Dunne and Troske (1997) and Acemoglu and Restrepo (2018) as well as combinations of those words.[6] Naturally, we seek to capture as many patents truly associated with automation as possible without too many false positives. Keywords can indicate that a patent corresponds to automation either directly or indirectly by referring to technologies associated with automation.

Keywords that directly indicate that a patent corresponds to automation innovation are "automation", "automatization", as well as words that describe the value of the innovation to reduce labor costs such as "laborious" or "labor". Words which contain the stem "automat" (denoted automat*) are often associated with automation patents as well, but by themselves gather too many false positives such as "automatic transmission". We resolve this in two ways: either by restricting attention to patents where the frequency is 5 or more or by combining automat* with other words. Our list of these words is based on the Survey of Manufacturing Technology (SMT) used in Doms et. al. (1997) (such as operator, handling, welding, sensor, etc) and the description of the HS-categories used by Acemoglu and Restrepo (2018) to denote imports of automation technology (including weaving and knitting and conveyors). We add "manufacturing", "machine" and "equipment" ourselves.[7] We count patents where automat* and one of these words appear in the same sentence at least twice.

Keywords that indirectly refer to automation by using technologies associated with automation are taken from Doms et al. (1997) and are: "robot", "numerical control", "computer aided design", "flexible manufacturing", and "programmable logic controllers" plus various extensions and conditions on those terms (see Appendix B.1 for details.) To this list we add 3D printing, which were in their infancy when the SMT was administered.

[6] Doms, Dunne and Troske (1997) measure automation using the Survey of Manufacturing Technology (SMT) from 1988 and 1993 conducted by the US Census. The survey asked firms about their use of certain automation and information technologies. Acemoglu and Restrepo (2018) include imports of automation technology and associate specific HS-categories from Comtrade with automation technology.

[7] The full list of words combined with automat* is: machine; manufacturing; machining; equipment; apparatus; operator; handling; "vehicle system"; welding; knitting; weaving; convey*; storage; store; regulat*; manipulat*; arm; sensor; inspect*; warehouse.

A natural alternative procedure would have been to read and classify a subset of patents and use machine learning techniques in order to classify patents (or technological categories) as automation or not, which is the procedure chosen by Mann and Püttmann (2018). We believe our approach has several advantages. First, we found that classifying patents as automation is a difficult task: often looking at a single patent in isolation is not enough, and one needs to look at several patents within the same technological grouping to find patterns suggesting that a patent is likely an automation patent. Therefore, the task of manually classifying patents cannot be easily outsourced. Second, patents are written in a technical language and do not primarily discuss the goal of an innovation, so that only a few words within the text are informative. Consequently, a machine-learning algorithm would require a large set of classified data to classify patents correctly. Third, once the classification is done it can easily be applied to patents for which researchers do not have text or on future patents. Fourth, our method is much more transparent and can easily be replicated or modified.

2.3 Defining automation technological categories and automation patents

As discussed above we do not associate a single patent with automation through the keywords, but instead a technological category consisting of many patents. These technological categories are defined as: 6-digit IPC/CPC codes, all pairs of 4-digit IPC/CPC codes and pairs combining the union of the 3 digit codes G05 and G06 with any 4-digit IPC/CPC codes (outside codes in G05, G06).[8] The code G05 corresponds to "controlling; regulating" and G06 to "computing; calculating; counting". Using combinations of G05 and G06 code with 4-digit IPC/CPC codes is inspired by Aschhoff et al. (2010) who use these codes to identify advanced manufacturing technologies. We restrict attention to categories which contain at least 100 patents to ensure that the prevalence of keywords measure is based on a sufficiently large number of patents.[9]

We then measure the prevalence of our keywords within technological categories for

[8]Technically, the structure of the IPC/CPC classification is as follows: IPC/CPC "classes" have 3 digit codes (for instance B25: "hand tools; portable power-driven tools; handles for hand implements; workshop equipment and manipulators"), "subclasses" have 4 digit codes (for instance B25J: "manipulators; chambers provided with manipulation devices") and main groups have 5 to 7 digit codes (for instance B25J 9: "programme-controlled manipulators"). In the following, we will abuse language and refer to classes, subclasses and main groups as 3 digit, 4 digit and 6 digit codes respectively.

[9]We group 6-digit codes with less than 100 patents in catch-all codes made at the 4-digit level.

patent applications from 1980 which contain a description in English (a total of 1,538,370 patent applications). We verify that the choice of the starting year does not much affect our classification in Appendix B.1. To select automation IPC/CPC codes, we further restrict attention to IPC/CPC codes which belong to technological fields which are associated with equipment. There are 34 technological fields (see Figure A.4) and we focus on "machine tools", "handling", "textile and paper machines" and "other special machines", which we refer to as the relevant technological fields or machinery patents.[10] For pairs of 4 digit IPC codes, we assume that they belong to the relevant technological field when at least one of the 4 digit code belongs to the relevant technological field. Similarly, the combinations of 4 digit IPC code and G05 or G06 belong to the relevant technological fields if the 4 digit code belongs to that group. We checked extensively the IPC/CPC codes and sampled patents from each category to ensure that the procedure delivered reasonable results.

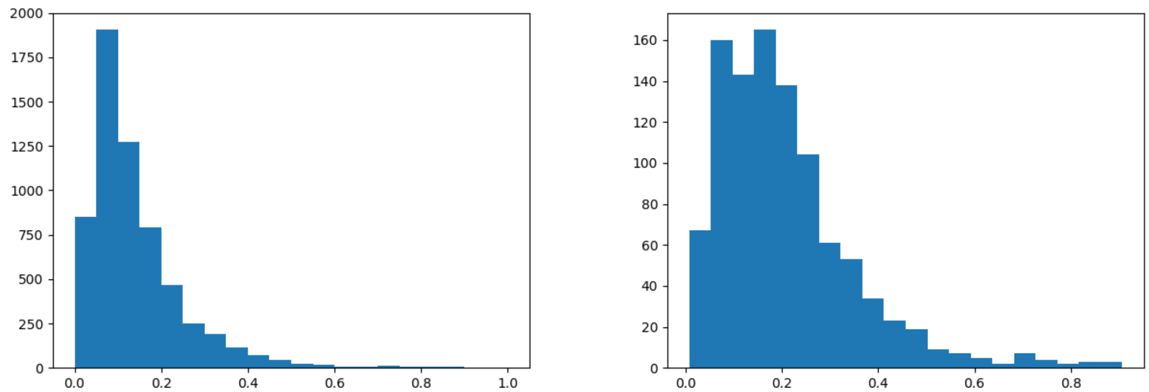
Table 1 give some examples of 6-digit IPC/CPC codes in machinery with the prevalence of automation keywords, their rank within machinery 6 digit codes with at least 100 patents but also the prevalence of the most important subcategories (automat*, robots and CNC). IPC/CPC codes associated with robotics (B25J) have the highest prevalence numbers with up to 91% patents in B25J5 which contain at least one of the keywords. Yet, there are also codes associated with machine tools at the top of the distribution such as B23Q15 and codes associated with devices used in the agricultural sector such as A01J7. B24B49 is a code close to the threshold we use to delimit automation patents (it is contained in the broader definition but not the stricter one). The last four IPC/CPC codes are examples with a low prevalence of automation keywords. The table also shows that the different sub-measures do not capture the same technologies: the robotic codes are ranked highly thanks to their share of patents with the word "robot", B23Q15 is high because a lot of patents contain words related to CNC, and B65G1, because a lot of patents contain words associated with automation directly.

Figure 1 gives the histograms of the prevalence of automation keywords for all IPC/CPC 6 digit codes (panel a) and IPC/CPC 6 digit codes in the "machinery" tech-

[10]In fact, we make some small modifications: We exclude F41 and F42 which correspond to weapons and ammunition and are in "other special machines". In addition, we include B42C which corresponds to machines for book production and B07C which corresponds to machines for postal sorting as both correspond to equipment technologies and contain 6-digit codes with a high prevalence of automation keywords; the 6-digit code G05B19 which corresponds to "programme-control systems" and contains a large number of NC and CNC (computer numerically controlled) machine tools which are not attributed IPC codes in the machine tools technological field; and the 6-digit code B62D65 which concerns engine manufacturing even though the rest of the B62D code is about the vehicle parts themselves.

Code	Description	Number of patents	All share	Rank (over 1009)	Robot share	Automat* share	CNC share
B25J5	Manipulators mounted on wheels or on carriages.	504	0.91	1	0.87	0.27	0.01
B25J19	Accessories fitted to manipulators, e.g. for monitoring or for viewing; safety devices combined with or specially adapted for use in connection with manipulators.	1001	0.89	2	0.85	0.22	0.04
B25J13	Controls for manipulators.	857	0.88	3	0.81	0.27	0.03
B25J9	Programme-controlled manipulators.	2809	0.86	4	0.79	0.29	0.07
B23Q15	Automatic control or regulation of feed movement, cutting velocity or position of tool or work.	591	0.79	7	0.09	0.36	0.65
A01J7	Accessories for milking machines or devices.	395	0.77	9	0.62	0.52	0
G05B19	Programme-control systems.	7133	0.70	16	0.22	0.39	0.25
B65G1	Storing articles, individually or in orderly arrangement, in warehouses or magazines.	1064	0.58	29	0.18	0.46	0.01
B24B49	Measuring or gauging equipment for controlling the feed movement of the grinding tool or work; Arrangements of indicating or measuring equipment, e.g. for indicating the start of the grinding operation.	608	0.42	75	0.12	0.18	0.19
B65H7	Controlling article feeding, separating, pile-advancing, or associated apparatus, to take account of incorrect feeding, absence of articles, or presence of faulty articles.	736	0.28	228	0.01	0.25	0.00
B23P6	Restoring or reconditioning objects.	613	0.26	266	0.07	0.06	0.05
A01B63	Lifting or adjusting devices or arrangements for agricultural machines or implements.	264	0.24	306	0.01	0.20	0
B66D3	Portable or mobile lifting or hauling appliances.	215	0.13	677	0.02	0.07	0.00

Table 1: Example of 6-digit IPC/CPC codes in relevant technological fields



(a) For all IPC/CPC 6 digit codes

(b) For IPC/CPC 6 digit codes in machinery with at least 100 patents

Figure 1: Histogram of the prevalence of automation keywords for IPC/CPC 6 digit codes

nological field. The histograms show that most IPC/CPC codes have a low prevalence of automation keywords and that the distribution is shifted to the right for the relevant technological fields. Yet, a few codes have a high prevalence measure. Appendix B.1 gives additional statistics on the prevalence measures.

Consequently, we define technological groups with a prevalence measure above some threshold. As our baseline we choose thresholds at the 90^{th} and 95^{th} percentiles of the 6 digit code distribution within the machinery technological field, which are given by 0.3864 and 0.4766 respectively. We then define a patent as an automation patent if it belongs to at least one automation technological group (that is a 6 digit code, a pair of 4 digit codes, or a combination of 4 digit code and G05/G06).[11] We refer to the two classifications as auto90 and auto95 depending on the threshold used.

Figure 2 shows two automation patents, both are automated storage cabinet and are counted as automation patents because they contain the IPC 6 digit code B65G 1. As described in Table 1, B65G 1 corresponds to devices for storing articles and has a high prevalence of automation keywords (0.58, which is above the 95^{th} percentile threshold). The patent of Figure 2a contains our keywords: a sentence with the words "automatic" and "storing," and another sentence with the word "robot." The description strongly suggests that this is indeed an automation patent. The patent of Figure 2b does not

[11]In practice, most automation patents in our dataset are automation patents because they belong to at least one 6 digit automation code—see Appendix B.1 for more details.

contain any of the keywords, but the description of the text still suggests a labor saving innovation.

2.4 Measuring innovation and trends in automation innovations

As already mentioned, an innovation in our empirical analysis corresponds to a patent family. To ensure that we only capture innovations of a sufficiently high quality, we restrict attention to patent families with patent applications in at least two countries, which we refer to as biadic patents.[12] Several studies have documented that patents filed in several countries are of higher quality (e.g. Harhoff, Scherer and Vopel, 2003, van Pottelsberghe de la Potterie and van Zeebroeck, 2008) and De Rassenfosse, Dernis, Guellec, Picci and van Pottelsberghe de la Potterie (2013) and Dechezleprêtre, Ménière and Mohnen (2017) show that biadic patents are already fundamentally different from patents applied to in only one office and a better innovation indicator. In addition, patents can be more or less broad across countries, for instance the same invention may be covered by two patents in Japan but only one in the US. By focusing on biadic patents, we only count such a case as one innovation.[13]

Figure 3 below shows the evolution of automation patents in the set of biadic patents. Panel (a) shows that worldwide, the share of automation patents declines in the 90s from 17% to 13% for the laxer auto90 measure and from 8.8% to 6.4% for the stricter auto95 measure before increasing quickly to reach 21%for auto90 and 10.6% for auto95 in 2015—Figure A.5 in the Appendix shows that automation patents in machinery represent between 1.9 and 3.6% of all patents with the auto90 definition. One interpretation is that globalization made cheap low-skill labor abroad available in the 90s and contributed to a temporary decline in automation, which has since reversed. Panel (b) computes the share of automation patents for the auto95 measure for biadic patents conditional on the patent being protected in certain countries. The graphs show that for UK, French, German and US patents, the decline of the 90s is less pronounced and the rise of the 2000s

[12] The original definition of biadic patents correspond to patents in at least 2 of the 3 main offices (EPO, USPTO and JPO), our definition is a generalization counting all patent offices. We check that our results are robust to the original definition of biadic in section 5.6.

[13] We count patent applications and not granted patents because in certain patent office, notably in Japan, a patent is only formally granted if the rights of the applicant are challenged. To restrict attention to patent families of even higher quality, we carry robustness checks where we use patent citations, or patents applied to more offices.

(19) Europäisches Patentamt / European Patent Office / Office européen des brevets

(11) **EP 2 604 550 B1**

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B65G 1/08 (2006.01)

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(54) **AUTOMATIC PLANT FOR STORING AND DISPENSING GOODS**

AUTOMATISCHE ANLAGE ZUR AUFBEWAHRUNG UND AUSGABE VON WAREN

INSTALLATION AUTOMATIQUE POUR STOCKER ET DISTRIBUER DES PRODUITS

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DE-A1- 19 635 396	**DE-A1- 19 724 378**
DE-U1- 20 021 440	**US-A- 3 782 565**
US-A1- 2010 168 910	

Description

OBJECT OF THE INVENTION

[0001] The present invention, as expressed in the wording of this specification, relates to an automatic plant for storing and dispensing goods, essentially applicable to the pharmaceutical sector, although it is also applicable to any other sector needing to store and dispense different small-sized goods.

[0002] The products are stored in principle in modular shelves, which may be inclined or not, shelves that are part of characteristic modular shelving units that also configure an elongated shelving structure in the longitudinal direction.

[0003] Based on this premise, the essence of the invention is based on characteristic modular horizontal guides along which respective modular subsets (robots) move, for the loading and unloading of products with respect to the shelves of the modular shelving units, modular horizontal guides that can easily adapt to the required length of the elongated structure of shelving units, so that both loading and unloading subsets have a horizontal translation movement parallel to said elongate structure of shelving units and a vertical movement to access the different levels of the shelves where the products are stored.

(a) Example with keywords

(19) Europäisches Patentamt / European Patent Office / Office européen des brevets

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(54) **STORAGE CABINET**

TECHNICAL FIELD

[0001] The present invention relates to a storage cabinet that stores contents (items) such as products and goods.

BACKGROUND ART

[0002] A storage cabinet is known that manages contents (items) by using radio frequency identification (RFID) technology. The patent literature 1 for example describes that scanning is performed in a cabinet for monitoring a product including a RF tag for the purpose of searching for an expired product or a product that have been manufactured in a recalled lot.

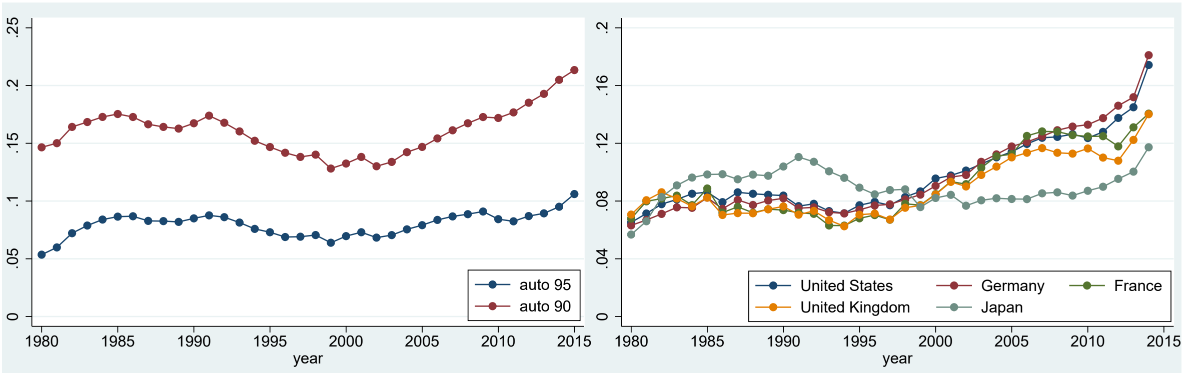
[0004] The conventional storage cabinet such as one described above may be able to perform scanning an item such as a product in the cabinet by using RFID technology; however, it is necessary for an operator to visually check an expired product or a product that have been manufactured in a recalled lot and remove them from the cabinet. Thus, there is a drawback in the conventional storage cabinet that, in a case in which many products are stored in the storage cabinet for example, the operator cannot immediately recognize whether all products to be removed have been actually retrieved from the storage cabinet.

[0005] Particularly, in a case in which the storage cabinet is not connected to a network, the operator cannot check whether all products to be removed have been actually retrieved from the storage cabinet.

[0006] In view of the above, one of the aspects of the present invention is to provide a storage cabinet from which one can surely retrieve a desired item.

(b) Example without keywords

Figure 2: Examples of automation patents from technological code B65G1, which are both automated storage cabinets.



(a) Share of automation patents in machinery worldwide. Automation technological categories are defined at the 90th percentile of the distribution of 6 digit IPC/CPC codes in machinery (for auto90) or the 95th percentile (auto95).

(b) Share of automation patents (auto95) in machinery conditional on the patent being protected in the designated countries.

Figure 3: Share of automation patents in machinery. Shares are computed for biadic patents.

is very stark. On the other hand, the decline of the 90s is more pronounced in Japan and the recent growth more timid there. As a result while the share of automation patents was the highest in Japan in the 80s and early 90s, it is now the lowest there. In the Appendix, Figure A.5 reports the share of automation patents in machinery according to the nationality of applicants, the trends are roughly similar but the share of Japanese patents remains higher (suggesting that the relative decline in the share of automation patents at the JPO is due to foreign firms). These country trends are similar with the auto90 measure.

2.5 Validating our automation measure

To validate our automation measure, we use it in the framework of Autor, Levy and Murnane (2003) (henceforth ALM), who show how computerization has been associated with a decrease in routine tasks at the industry level in a cross-section analysis on U.S. data from 1960 to 1998. Here, we provide a brief description of what we do, and we refer the reader to Appendix B.2 for details. To measure automation innovations at the sectoral level, we use USPTO patents which belong to the machinery technological field. We then allocate patents to sectors according to their 4-digit IPC/CPC codes (at the family level) using the concordance table provided by Lybbert and Zolas (2014). For each sector j and each period θ, we compute the share of automation patents among machinery patents applied for during this period. We denote this variable $aut_{j\theta}$. We then run regressions of the type:

$$\Delta T_{jk\theta} = \beta_0 + \beta_C \Delta C_j + \beta_{aut} aut_{jk\theta}, \tag{1}$$

where $\Delta T_{jk\theta}$ represents the change in tasks of type k in industry j during period θ and C_j is the measure of computerization in sector j (it is computed over the years 1984-1997 and used for all time periods θ). We take our tasks measures directly from ALM, and therefore consider 5 types of tasks: nonroutine analytic, nonroutine interactive, routine cognitive, routine manual and nonroutine manual. $\Delta T_{jk\theta}$ is measured as 10 times the annual within industry change in task input measured in percentile of the 1960 task distribution (as in ALM). We consider 3 time periods for which we can compute our automation intensity measure: 1970-1980, 1980-1990 and 1990-1998 (ALM also considers 1960-1970). The initial concordance mostly assigns codes to manufacturing sectors. As a result, we can measure automation intensity for between 67 and 69 sectors (depending on the time period) most of them in manufacturing (see full list in Table B.1). Our automation measures are strongly correlated with each other (the coefficient is 0.86) but not correlated with computerization (the coefficient is -0.04 for auto95 and -0.01 for auto90).

Table 2, columns (1) to (5) reports the results for the auto95 measure. Columns (3) and (4) show that sectors with a high share of automation patents in machinery experienced a large reduction in both cognitive and manual routine tasks in each decade. The coefficients of column (3) and (4) in panel B indicate that a 10 pp increase in the share of automation patents is associated with a 3 centiles and 2.2 centiles annualized decrease in labor input of routine cognitive and manual tasks in the 1980s. To interpret a 10 pp increase, note that the standard deviation in the share of automation patents in the 1980s is 0.09, so that a 1 standard deviation increase in the automation share is associated with a decrease in routine cognitive and routine manual tasks of 2.7 and 1.9 centiles respectively. By comparison, the standard deviation of the computerization variable is 0.06, so that a 1 standard deviation in computerization is associated with a decrease in routine cognitive tasks of 0.8 centiles and essentially no change in routine manual tasks (the computerization variable has a larger effect in the 90s).[14]

Since we are interested in the effect of low- and high- skill wages on automation and do not measure the price of tasks directly, we also use the ratio of high-skill to low-

[14] The means of the share of automation in machinery are 0.06, 0.08 and 0.07 in the 70s, 80s and 90s, and the standard deviations are 0.07, 0.09 and 0.09 (with the 95th percentile threshold).

Table 2: Changes in task intensity and skill ratio across sectors and automation (auto95)

	(1) Δ Nonroutine analytic	(2) Δ Nonroutine interactive	(3) Δ Routine cognitive	(4) Δ Routine manual	(5) Δ Nonroutine manual	(6) Δ H/L
Panel A: 1970 - 80, n=67						
Share of automation patents in machinery	-1.29	5.42	-17.27***	-11.43**	-1.15	0.27***
	(5.10)	(6.27)	(6.59)	(5.59)	(7.46)	(0.07)
Δ Computer use 1984 - 1997	-6.86	-3.13	-19.51***	-3.46	14.87*	0.07
	(5.72)	(7.04)	(7.41)	(6.28)	(8.38)	(0.08)
Intercept	1.06	2.31**	3.07**	2.69***	-1.75	0.05***
	(0.95)	(1.17)	(1.23)	(1.04)	(1.39)	(0.01)
R^2	0.02	0.01	0.20	0.07	0.05	0.21
Weighted mean Δ	-0.05	2.17	-0.90	1.49	0.42	0.07
Panel B: 1980 - 90, n=67						
Share of automation patents in machinery	10.09	19.05**	-30.00***	-21.61***	16.78***	1.33***
	(7.14)	(8.12)	(6.76)	(5.42)	(6.04)	(0.23)
Δ Computer use 1984 - 1997	24.80**	22.21*	-13.24	-0.42	-6.49	0.29
	(10.43)	(11.85)	(9.87)	(7.91)	(8.82)	(0.33)
Intercept	-2.62	-0.65	2.15	1.20	-2.13	-0.04
	(1.70)	(1.93)	(1.61)	(1.29)	(1.44)	(0.05)
R^2	0.12	0.14	0.27	0.20	0.11	0.37
Weighted mean Δ	1.86	4.17	-2.22	-0.59	-1.74	0.11
Panel C: 1990 - 98, n=67						
Share of automation patents in machinery	11.06*	16.02*	-22.81***	-12.53**	6.66	0.77***
	(6.08)	(8.18)	(6.54)	(5.42)	(6.28)	(0.15)
Δ Computer use 1984 - 1997	26.77***	26.00**	-23.15**	-24.87***	7.48	0.66***
	(8.35)	(11.23)	(8.98)	(7.44)	(8.62)	(0.20)
Intercept	-2.36*	-1.43	1.72	2.27*	-2.40*	-0.06*
	(1.37)	(1.84)	(1.47)	(1.22)	(1.41)	(0.03)
R^2	0.19	0.15	0.25	0.23	0.03	0.41
Weighted mean Δ	2.45	3.79	-3.44	-2.36	-0.79	0.09

Standard errors are in parentheses. Colums (1) to (5) of Panels A to C each presents a separate OLS regression of ten times the annual change in industry-level task input between the endpoints of the indicated time interval (measured in centiles of the 1960 task distribution) on the share of automation patents in machinery (defined with the 95th percentile threshold) and the annual percentage point change in industry computer use during 1984 - 1997 as well as a constant. In Column (6), the dependent variable is the ratio of high-skill (college graduates) to low-skill (high-school graduates and dropouts) workers. Estimates are weighted by mean industry share of total employment in FTEs over the endpoints of the years used to form the dependent variable. * p<0.1; ** p<0.05; *** p<0.01

skill workers (defined as college graduates over high-school dropouts and high-school graduates) as our dependent variable in cross-section regressions similar to 1.[15] Column (6) of Table 2 shows that sectors with a higher automation share also experienced a large increase in the ratio of high-skill to low-skill workers. Panel B, for instance suggests that a 10 pp increase in the share of automation patents is associated with an increase of 1.33 in the ratio of high-skill to low-skill workers in the 1980s.

In the Appendix, Table B.2 reproduces the same exercise for our laxer measure (auto90) and obtains similar results. Figure B.3 provides scatter plots of the changes in routine tasks and the share of automation patents in machinery. Finally, Table B.3 reproduces the same analysis separately for each education category (as ALM) and shows that automation leads to a reduction of routine tasks and an increase in non-routine manual tasks for high-school graduates (but in line with column (6) of Table 2 a large share of the tasks changes at the industry level are explained by changes in educational composition).

Overall, these results suggest that our automation measure captures a form of skill-biased technical change, distinct from computerization and associated with a decrease in routine tasks by low-skill workers. We can therefore use it to analyze the effect of wages on automation innovation incentives.

3 A simple model

Before carrying our main empirical analysis, we now present a simple one period model to clarify our argument. A manufacturing good is produced with a continuum of intermediate inputs according to the Cobb-Douglas production function:

$$Y = \exp\left(\int_0^1 \ln y\left(i\right) di\right),$$

where $y(i)$ denotes the quantity of intermediate input i. The manufacturing good is the numeraire. Each intermediate input is produced competitively with high-skill labor ($h_{1,i}$ and potentially $h_{2,i}$), low-skill labor l_i and potentially machines x_i, according to the production function:

$$y_i = h_{1,i}^{1-\beta}\left(\gamma\left(i\right) l_i + \alpha\left(i\right) \nu^{\nu} (1-\nu)^{1-\nu} x_i^{\nu} h_{2,i}^{1-\nu}\right)^{\beta},$$

[15]The results are similar for the ratio of college graduates over high-school dropouts or college graduates and some college over high school graduates and dropouts.

where $\gamma(i)$ is the productivity of low-skill workers and $\alpha(i)$ is an index which takes the value 0 for non-automated intermediates and 1 for automated intermediates. ν and β are fixed share parameters in $(0,1)$. Machines are specific to the intermediate input i. If a machine is invented, it is produced monopolistically, 1 for 1 with the final good (so that the monopolist charges a price $p_x(i) \geq 1$.

At the beginning of the period, intermediate inputs are not automated, but for each intermediate i, there is an innovator. The innovator manages to create a machine specific to intermediate i with probability λ if she spends $\theta\lambda^2 Y/2$ units of manufacturing good, where θ is a productivity parameter.

We solve the model in two steps, first we derive the profits realized by machines producers, second we solve for the innovation decision. Consider an automated intermediate input (that is $\alpha(i) = 1$), then the intermediate input producer is indifferent using low-skill workers or machines together with high-skill workers in production whenever:

$$w_H^{\nu} p_x^{1-\nu} = w_L/\gamma(i).$$

As a result, the machine producer is in "Bertrand competition" with low-skill workers. Given that a machine costs 1, the machine producer will charge a price $p_x(i) = \max\left((w/\gamma(i))^{\frac{1}{1-\nu}} w_H^{-\frac{\nu}{1-\nu}}, 1\right)$, and the intermediate input producer will use low-skill workers whenever $w_L/\gamma(i) < w_H^{\nu}$ and machines otherwise. Therefore, the machine producer can charge a higher price when low-skill wages are lower but has to charge a lower price when high-skill wages are higher since high-skill workers and machines are complement. Using that the manufacturing good is produced according to a Cobb-Douglas production function, we have that $p(i)y(i) = Y$ for all intermediates. Therefore, we can derive the profits of the machine producer for intermediate i as:

$$\pi_i^A = \max\left(1 - \left(\frac{\gamma(i)}{w_L}\right)^{\frac{1}{1-\nu}} w_H^{\frac{\nu}{1-\nu}}, 0\right) \nu\beta Y.$$

In turn, at the beginning of the period, the potential innovator solves $\max \lambda\pi_i^A - \theta\frac{\lambda^2}{2}Y$, which gives the equilibrium innovation rate as:

$$\lambda = \frac{\nu\beta}{\theta} \max\left(1 - \left(\frac{\gamma(i)}{w_L}\right)^{\frac{1}{1-\nu}} w_H^{\frac{\nu}{1-\nu}}, 0\right).$$

As a result, the number of automation innovations is equal to:

$$Aut = \frac{\nu\beta}{\theta}\int_0^1 (1-\alpha(i)) \max\left(\left(1-\left(\frac{\gamma(i)}{w_L}\right)^{\frac{1}{1-\nu}} w_H^{\frac{\nu}{1-\nu}}\right),0\right) di.$$

This expression is increasing in the low-skill wage w_L and decreasing in the high-skill wage w_H, with a smaller elasticity in absolute value. Intuitively, the incentive to replace low-skill workers with machines (and high-skill workers) increases with low-skill wages and decreases with high-skill wages.

4 Empirical Strategy and Data

4.1 Empirical strategy

We now take the predictions of our model to the data, but to conduct our analysis at the firm level, we take advantage of the fact that many innovators sell to several countries. We take the model of section 3 as a starting point, but think of the producers—the target customers of the innovating firm's automation machines—as being located in different countries. The incentives of the producers to adopt automation technology is determined by wages and other macroeconomic variables in their local market. As a result, innovators' decision to pursue automation research in the first place depends on the wages that their potential customers face in different countries.[16] Hence our problem is similar to that of ADHMV and we follow a similar empirical approach.

In our baseline regression, we assume that a firm's innovation in automation is given by the following Poisson specification:

$$\begin{aligned} & PAT_{Aut,i,t} \quad (2) \\ = \; & \exp\left(\begin{array}{c} \beta_{w_L}\ln w_{L,i,t-2} + \beta_{w_H}\ln w_{H,i,t-2} + \beta_X X_{i,t-2} + \beta_{Ka}\ln K_{Aut,i,t-2} \\ +\beta_{Ko}\ln K_{other,i,t-2} + \beta_{Sa}\ln SPILL_{Aut,i,t-2} + \beta_{So}\ln SPILL_{other,i,t-2} + \delta_i + \delta_t \end{array}\right) + \epsilon_{i,t}. \end{aligned}$$

$PAT_{Aut,i,t}$ denotes the number of automation patents applied for by firm i in year t. $w_{L,i,t-2}$ and $w_{H,i,t-2}$ denote the average low-skill and high-skill wages faced by the customers of firm i at time $t-2$ (we explain below how we proxy for them). Section 3

[16]If the automation innovation is internal to the firm, then the argument follows if one interprets the innovator's customers as the different downstream production sites of the same firm.

predicts that $\beta_{w_L} > 0$: an increase in the average low-skill wage faced by the customers of firm i leads firm i to undertake more automation innovations. It also predicts that $\beta_{w_H} < 0$, an increase in the average high-skill wage faced by firm i's customers reduce the incentive to invest in automation technologies which are complementary to high-skill workers. $X_{i,t}$ represents a vector of additional controls (GDP per capita, GDP gap and labor productivity), which are built similarly to the wage variables. Controlling for GDP per capita or labor productivity allows us to control for changes in productivity in the country where machines are potentially sold and controlling for the GDP gap allows us to capture business cycle fluctuations and changes in demand. We include this control because the literature finds that innovation in general is affected by the business cycle (see for instance Aghion et al., 2010).

$K_{Aut,i,t-2}$ and $K_{other,i,t-2}$ denote the stocks of knowledge in automation and in other technologies of firm i at time 2. These knowledge stocks are computed using the perpetual inventory method.[17] $SPILL_{Aut,i,t-2}$ and $SPILL_{other,i,t-2}$ similarly denote the stocks of external knowledge (spillovers) in automation and in other technologies which firm i has access to at time 2 (we explain below how these are constructed). δ_i is a firm fixed effect and δ_t is a time fixed effect. Finally, $\epsilon_{i,t}$ is an error term, which, we assume, is uncorrelated with the other right-hand side variables. The right-hand side variables are lagged by 2 years in the baseline regressions to reflect the delay between changes in R&D investments and patent applications—we investigate the role of our timing assumption below.

To control for firm-level fixed effects, we use several econometric techniques. Our baseline specification uses the Hausman, Hall and Griliches (1984) method, denoted HHG, which is the count data equivalent to the within groups estimator. Technically, this method is inconsistent with equation (2) because it requires strict exogeneity and therefore prevents the lagged dependent variable from appearing on the right-hand side (which it does through the knowledge stock $K_{Aut,i,t-2}$). Yet, the bias is small with large T, which is the case in our baseline regression (14 years). Second, we use the Blundell, Griffith and Van Reenen (1999) method (henceforth BGVR), which proxies for the fixed effect by using the pre-sample average of the dependent variable.

[17]Specifically we use a depreciation rate of 15%. In addition, to deal with the log specification, we add two dummy indicator variables for when the knowledge stocks are zero.

Table 3: Low-skill wages and the skill-premium in manufacturing sector for selected countries

Country	Low-skill wages (2005$)		Skill-premium (HS wages / LS wages)	
	1995	2009	1995	2009
India	0.21	0.31	4.79	4.98
China	0.50	0.95	1.56	2.00
Mexico	1.50	1.03	3.90	4.20
USA	12.50	14.70	2.46	3.02
Finland	19.40	36.20	1.20	1.46
U.K.	19.70	34.40	1.97	2.07
Belgium	29.50	41.90	1.56	1.46

Note: Wages data, taken from the World Input Output Database, covering 40 countries. Table shows manufacturing low-skill wages deflated by (manufacturing) producer price index (indexed to 2005) and converted to US dollars using average 2005 exchange rates. Skill-premium is the ratio of high-skill to low-skill wages. Table shows the three countries with the lowest low-skill wages in 2009, the three with the highest and the United States.

4.2 Macroeconomic data

Our macroeconomic variables come primarily from the 2013 release of the World Input Output Tables, henceforth, WIOD (Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R. and de Vries, G. J., 2015). The database contains information on hourly labor costs across groups of educational attainment – low-skill, middle-skill and high-skill workers – for the manufacturing sector from 1995 to 2009 as well as value added and producer price indices. The dataset contains information on 40 countries, including all 27 EU countries of 2009. For each skill-group country pair we construct real hourly labor costs by dividing nominal labor costs by the producer price index for manufacturing (indexed to 2009). We convert everything into dollars using the average exchange rate for 2005. Although our measures cover all labor costs, we refer to those as wages from here on for simplicity. The countries with the highest low-skill wages in 2005 are Belgium, Finland and the U.K. with 41.9, 36.2 and 34.4 respectively (in 2005 dollars). The countries with the lowest high-skill wages in 2009 are India, China and Mexico with $0.31, $0.95 and $1.03, respectively. The corresponding number for the US is $14.7. Table 3 summarizes these values for these seven countries. It further shows that the ratio of high-skill to low-skill wages varies considerably across countries, even among those that have relatively similar low-skill wages. The skill-premium in the United States rose from 2.46 to 3.02 during this period while it slightly declined in Belgium from 1.56 to 1.46.

4.3 Computing firm's market-specific wages and spillovers

To turn macroeconomic data such as wages and productivity which vary at the country level into data which vary at the firm level, we would like to take advantage of firms' different market exposure. That is we would like to write the average low-skill wage faced by a firm's customers $w_{L,i,t}$ as

$$w_{L,i,t} = \sum_c \omega_{i,c} w_{L,c,t}, \tag{3}$$

where $w_{L,c,t}$ is the low-skill wage in country c at time t and $\omega_{i,c}$ is the weight of country c for firm i. Firms may have different exposure to different markets because of trade barriers, heterogeneous tastes of customers, or various historical accidents if exporting involves sunk cost. In the absence of sales data for all firms involved in automation innovations, we expand on the ADHMV method, and we look at the firm's pre-sample history of patent filing.

When a firm applies for a patent, it applies for protection in a specific jurisdiction, and it has to pay a fixed cost whenever it wants to expand the geographic coverage of a patent. Therefore, whether a firm protects its innovations in a country or not reflects its intent to sell or license its technology in that country (see e.g. Eaton and Kortum, 1996). Taking this into account, we compute for each firm, the fraction of its patents in the relevant technological field of machinery (not only automation) protected in each country c, $\tilde{\omega}_{i,c}$ during a pre-sample period. We only count patents in the machinery because some of the biggest innovators in automation technologies are large firms (Sony, Siemens, etc...) which produce a wide array of products with different specialization patterns across industries. We restrict attention to patent families with at least one citation (not counting self-citations) to exclude the lowest quality patents.[18]

Patenting indicates whether the firm intends to sell in that market but each market will be of different sizes. A larger market is likely to host more firms so that the market size per firm will generally not grow 1 for 1 with size. To take this into account we weight each market c by $GDP_{0,c}^{0.35}$, where $GDP_{0,c}$ is the 5 year average GDP of country c at the end of the pre-sample period.[19] As a result, we get that the weight of country

[18] Including all patents generally increases the weight of the country with the most patents, in line with the finding that poor quality patents tend to be protected in fewer countries. However, further increasing the threshold from 1 to more citations does not significantly change the distribution of weights.

[19] Here we use Eaton et al. (2011) who estimate that the elasticity of French exports to the GDP of the destination country is 1 while the elasticity of the number of French exporters is 0.65, which gives

c for firm i is given by:

$$\omega_{i,c} = \frac{\tilde{\omega}_{i,c} GDP_{0,c}^{0.35}}{\sum\limits_{c'} \tilde{\omega}_{i,c'} GDP_{0,c'}^{0.35}}.$$

The weights are computed pre-sample to ensure that they are weakly exogenous as patent location could be influenced by shocks to innovation. We use patent data from 1997-2011, which allows us to include data from 40 countries, and the weights are computed over the pre-sample period 1970-1994. We use the same weights to compute firm customers' average high-skill wage, productivity or GDP per capita.

ADHMV verify that a similar method account well for the sales distribution of major auto manufacturers. Coelli, Moxnes and Ulltveit-Moe (2016) carry out a more systematic exercise and verify that a similar method accounts well for firm exports across 8 country groups in a representative panel of 15,000 firms from 7 European countries.[20]

We also follow ADHMV method to compute the spillover variables. Patent data report where inventors are located, combining this information across patents from the same firm, we obtain a measure of where a firm's research centers are located. As long as knowledge spillovers have a geographical component (as shown by Hall, Jaffe and Trajtenberg, 1993), we can use this information to build a measure of the stock of knowledge to which a firm is exposed. More specifically, we compute the stocks of automation patents in each country, the stock of other patents, and the geographical distribution of firms' research centers pre-sample in 1970-1994. Then, for each firm, we use those weights in order to build a weighted average of the knowledge stocks.[21]

To link patents with their owners, we use Orbis Intellectual Property, available under a commercial license, which links 40 million patents to companies available in the Orbis financial database. For each of these around 40 million patents, Orbis Intellectual Property provides a link to a (usually) unique firm identifier. A complication arises when such firms are members of a business group, in which case the R&D decision might happen at either the group or the subsidiary level. The corporate ownership data in Bureau van Dijk's Orbis allow to identify the global owner of every firm. Yet, treating all firms in a group as one agent deciding on innovation strategies is too aggressive in many cases

an elasticity of the average export by firm of 0.35. ADHMV use a power of 1 on GDP instead of 0.35. We use different values in robustness checks.

[20] There are three differences between our weights and those of these previous papers: we use the empirically founded exponent of 0.35 on GDP, we restrict attention to cited patent families and to patents in certain technological fields.

[21] The country stocks are built using the perpetual inventory method with a depreciation rate of 15%. We add dummy variables for when the spillover stocks are zero.

Table 4: Descriptive statistics

Variable	Auto90		Auto95	
Automation patents	per year	1997-2011	per year	1997-2011
Mean	0.69	11.02	0.60	9.63
Standard deviation	3.57	50.01	3.10	43.53
p50	0	2	0	2
p75	0	6	0	5
p90	1.33	17	1.2	15
p95	2.87	38	2.4	34
p99	11.47	159	10.13	141
Number of firms	6515		4323	

Note: Summary statistics for the firms used in our baseline regression.

since not all subsidiaries act jointly or are in the same sector. Therefore, for firms within the same business group, we normalize company names by removing non-firm specific words such as country names or legal entity types from the name and then merge firms with the same normalized name. All other firms are treated as separate entities.

4.4 Descriptive statistics

Our basic dataset consists of applicants who have applied to at least one biadic automation patents between 1997 and 2011 (included) and who have at least one patent prior to 1995 which can be used to compute weights. This corresponds to a set of 4323 firms when we consider the auto95 (using the 95th percentile cut-off for keywords) measure and 6515 firms for the auto90 (using the 90th percentile) measure.. Table 4 gives some descriptive statistics on the number of automation patents per year and the country weights for the firms in our sample. Over the period 1997-2011, the median firm in the sample has filed two automation patent applications (with either definition). The distribution is very skewed and the 99^{th} percentile firm in the sample has filed 159 automation patents for auto90 and 141 for auto95.

5 Main Empirical Results

5.1 Baseline results

Our baseline results are contained in Table 5. The dependent variable is the number of biadic patents that qualify as automation when we use a threshold of the 95th percentile for 6 digit IPC/CPC codes (auto95). The regression is carried over the years 1997-2011 for the dependent variable and 1995-2009 for the independent variables, a constraint imposed by the availability of wage data for a large number of countries. Skill-dependent wages are measured in the manufacturing sector and we deflate by the producer price index in the same sector.

Table 5: Baseline regressions: effect of wage on automation innovations (auto95)

Dependent variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.6329***	2.2244***	1.8081***	1.8224***	2.1059***	2.1728***	2.2607***	2.0408***	2.2607***
	(0.3363)	(0.5141)	(0.5032)	(0.5056)	(0.5049)	(0.5229)	(0.5414)	(0.5687)	(0.3357)
High-skill wage		-0.9256*	-1.0152**	-1.1610**	-1.3894***	-1.4557***	-1.3794***	-1.6030***	-1.3794***
		(0.5312)	(0.4669)	(0.4837)	(0.4879)	(0.4947)	(0.5110)	(0.4994)	(0.4307)
Stock automation			-0.1596***	-0.1609***	-0.1759***	-0.1748***	-0.1736***	-0.1761***	-0.1736***
			(0.0453)	(0.0453)	(0.0458)	(0.0462)	(0.0464)	(0.0464)	(0.0320)
Stock other			0.6506***	0.6497***	0.6566***	0.6567***	0.6577***	0.6560***	0.6577***
			(0.0489)	(0.0491)	(0.0506)	(0.0506)	(0.0505)	(0.0506)	(0.0314)
GDP gap				-3.8950*		-3.8791**	-2.8339	-4.1136**	-2.8339*
				(2.2398)		(1.8985)	(2.3664)	(1.9061)	(1.7047)
GDP per capita				0.4238			-0.6134		-0.6134
				(0.6544)			(0.8557)		(0.9014)
Spillovers automation					0.4930*	0.5256**	0.6284**	0.5308**	0.6284**
					(0.2530)	(0.2548)	(0.3123)	(0.2534)	(0.2459)
Spillovers other					-0.2604	-0.2839	-0.3336	-0.3051	-0.3336*
					(0.2066)	(0.2071)	(0.2106)	(0.2074)	(0.1842)
Labor productivity								0.4102	
								(0.6063)	
Observations	64845	64845	64845	64845	64845	64845	64845	64845	64845
Firms	4323	4323	4323	4323	4323	4323	4323	4323	4323

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Standard errors are clustered at the firm-level for columns (1)-(8) and at the country level for column (9). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Column (1) shows that without any controls, a higher (firm customer's) low-skill wage in manufacturing predicts more automation innovation. The estimated coefficient is an elasticity so that an increase of 10% in the low-skill wage is associated with 16.3% more automation patents. Column (2) introduces high-skill wages as a control. As predicted by the model, high-skill wages enter with a negative coefficient which is smaller in magnitude than the low-skill wage. Column (3) adds control for the firm's stock of knowledge: a higher stock of automation knowledge within the firm reduces the amount of automation innovation, suggesting that firms do not become more specialized in automation technologies over time. Column (4) controls for the GDP gap, automation innovations appear to be countercyclical, in line with Jaimovich and Siu (2012)'s observation that "routine jobs" are eliminated during recessions; and GDP per capita which is insignificant. Columns (5) and (7) repeat columns (3) and (4) but include knowledge spillovers: here, we find evidence of path dependence, firms which are exposed to more knowledge in automation technologies innovate more in automation (with an elasticity between 0.49 and 0.63 depending on specifications). Column (6) removes the GDP per capita control. Column (8) replaces GDP per capita with labor productivity (value added per hours worked in the manufacturing sector) as a control. Finally, Column (9) repeats column (7) but clusters standard errors at the country level instead of the firm level to capture correlated shocks at the country level. The coefficient on low-skill wages is always highly significant. Once high-skill wages are included as a control, it is also very consistent across specifications, with elasticities between 1.81 and 2.26. The coefficient on high-skill wages is negative, with an elasticity between -1.38 and -1.6 once spillovers are introduced.

Table 6: Baseline regressions: effect of wage on automation innovations (auto90)

Dependent variable	Auto90								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.4528***	2.0365***	1.4275***	1.4430***	1.7242***	1.7646***	1.8406***	1.6118***	1.8406***
	(0.3001)	(0.4369)	(0.4430)	(0.4515)	(0.4397)	(0.4459)	(0.4642)	(0.4670)	(0.3661)
High-skill wage		-0.8962**	-0.6574*	-0.6387*	-1.0517***	-1.1011***	-0.8961**	-1.3039***	-0.8961**
		(0.4258)	(0.3696)	(0.3883)	(0.3879)	(0.3910)	(0.4016)	(0.4065)	(0.4172)
Stock automation			-0.0896**	-0.0879**	-0.1014***	-0.1007***	-0.1003***	-0.1019***	-0.1003***
			(0.0370)	(0.0372)	(0.0366)	(0.0367)	(0.0369)	(0.0368)	(0.0362)
Stock other			0.5970***	0.5963***	0.6011***	0.6009***	0.6025***	0.6003***	0.6025***
			(0.0428)	(0.0428)	(0.0435)	(0.0435)	(0.0432)	(0.0435)	(0.0585)
GDP gap				-3.0549*		-4.0904**	-2.3914	-4.3637***	-2.3914**
				(1.8304)		(1.5943)	(1.8418)	(1.5844)	(1.1484)
GDP per capita				-0.1549			-1.0427*		-1.0427
				(0.5396)			(0.5958)		(0.6907)
Spillovers automation					0.8673**	0.9138***	1.1212***	0.9333***	1.1212***
					(0.3473)	(0.3507)	(0.3806)	(0.3484)	(0.2463)
Spillovers other					-0.5616**	-0.5979**	-0.7299**	-0.6360**	-0.7299***
					(0.2794)	(0.2807)	(0.2873)	(0.2805)	(0.1919)
Labor productivity								0.5181	
								(0.4584)	
Observations	97725	97725	97725	97725	97710	97710	97710	97710	97710
Firms	6515	6515	6515	6515	6514	6514	6514	6514	6514

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Standard errors are clustered at the firm-level for columns (1)-(8) and at the country level for column (9). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6 then repeats exactly Table 5 but for the auto90 measure of automation. The results are very similar but the coefficients on low-skill wages tend to be of a smaller magnitude: the elasticity is between 1.61 and 1.84 when spillovers are introduced versus 2.04 and 2.26 in the previous table. The magnitude of the coefficient on high-skill wages is also smaller. These results are in line with the idea that the auto95 measure is a stricter measure of automation.

5.2 Foreign versus domestic firms and wages

The key feature of our empirical approach is that by exploiting firm level variations instead of country-level variations, we can avoid issues of reverse causality: since each firm is small relative to a country, its own innovations should have little effect on the level of wages. This argument, however, requires that our firms are sufficiently diversified geographically (i.e. if all German firms only patent in Germany, then we are back to regressing country-level innovation on country-level macroeconomic variables). Therefore, in Table 7, we restrict attention to sufficiently multinational firms for the auto95 measure (the results are similar with auto90). Column (1) reproduces Column (6) of Table 5. Column (2) restricts attention to firms where the largest weight (the "domestic weight") is smaller than 0.9, Column (3), (4), (5) and (6) where it is smaller than 0.8, 0.7, 0.6 and 0.5 respectively. The coefficient on low-skill wages remains positive and significant in columns (2), (3) and (4) with a similar magnitude. As we further restrict the sample, the coefficient on low-skill wages declines and becomes insignificant. Column (7) carries the regressions for firms where the domestic weight is between 0.3 and 0.7 and here again we recover a significant coefficient with an elasticity close to the one in column (4). Therefore the non-significant coefficients of columns (5) and (6) are driven by the behavior of the most international firms which appears to be noisier.[22]

Table 7: Restricting on multinational firms

Dependent Variable	Auto95						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Domestic weight	all (100%)	< 90%	< 80%	< 70%	<60%	<50%	70%-30%
Low-skill wage	2.1728***	1.8408**	2.1559**	1.9698*	1.2568	0.4702	1.9523*
	(0.5229)	(0.8326)	(0.8626)	(1.0635)	(1.1560)	(1.4495)	(1.1771)
High-skill wage	-1.4557***	-0.7928	-0.8857	-0.8204	-0.6852	0.0176	-0.9269
	(0.4947)	(0.7120)	(0.7175)	(0.8475)	(0.9208)	(1.1601)	(0.9501)
GDP gap	-3.8791**	-5.4895**	-6.9538**	-2.6282	-2.9073	-5.1267	-0.3997
	(1.8985)	(2.7530)	(3.1956)	(3.8563)	(5.1079)	(6.9579)	(3.9897)
Stock automation	-0.1748***	-0.1846***	-0.2356***	-0.2190***	-0.2277***	-0.2127***	-0.1985***
	(0.0462)	(0.0547)	(0.0573)	(0.0626)	(0.0605)	(0.0689)	(0.0702)
Stock other	0.6567***	0.6821***	0.7469***	0.7301***	0.7387***	0.7557***	0.6598***
	(0.0506)	(0.0639)	(0.0656)	(0.0683)	(0.0738)	(0.0835)	(0.0676)
Spillovers automation	0.5256**	0.5985*	0.7751**	0.9272**	1.1499***	1.0586**	0.8149*
	(0.2548)	(0.3089)	(0.3171)	(0.3761)	(0.3615)	(0.4174)	(0.4324)
Spillovers other	-0.2839	-0.4228*	-0.6331***	-0.7536***	-0.9693***	-1.0152***	-0.6165**
	(0.2071)	(0.2251)	(0.2272)	(0.2651)	(0.2693)	(0.3204)	(0.2941)
Observations	64845	47670	44460	40680	35910	30345	26910
Firms	4323	3178	2964	2712	2394	2023	1794

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions include a dummy for no stock and no spillover. Column (1) contains all firms, (2) restricts attention to firm with a domestic weight below 90%, (3) below 80%, (4) below 70%, (5) below 60%, (6) below 50%, (7) between 70% and 30%. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

To further assess the role played by domestic versus foreign wages, we separate do-

[22] A possible explanation may be that those firms have a less consistent trade pattern, so that the presample weights may be a worse predictor of the wages of their potential customers, and following changes in wages across countries, they may react by changing their trade pattern instead of their innovation pattern.

mestic from foreign variables in Table 8. Domestic variables correspond to the country with the largest weight. Foreign variables correspond to the weighted average of country-level variables excluding the domestic country (the weights are re-normalized to still sum up to 1). Given that the domestic variables vary only at the country level, we systematically cluster at the country level for this table. Column (1) and (4) show the results for the auto95 and auto90 measures respectively: we find a significant effect of low-skill wages in the former case and a positive but non-significant effect in the second case. These coefficients are not really comparable to those of the baseline regressions though, because first, a 1% increase in either the domestic or foreign component of wages is not the same as a 1% increase in overall wages and second, firms vary in international exposure so an increase in foreign wages will not matter equally to all firms. To take this into account, in columns (3) and (6), we pre-multiply the log of domestic (or foreign) wages by the share of domestic (or foreign) wages in total wages averaged over the sample period. We do the same thing with GDP per capita and since the GDP gap variable is already in logs we simply interact the domestic (or foreign) GDP gap with the domestic (or foreign) weight.[23] As a result the coefficient on foreign low-skill wage can be interpreted as the elasticity of automation with respect to low-skill wages from a shock coming entirely through a change in the foreign component of low-skill wages. The coefficient on foreign low-skill wages is now of a magnitude closer to that in column 9 of Tables 5 and 6 but it is only significant in the auto95 case. In columns (2) and (5), the share of domestic (or foreign) wages is fixed at the beginning of the sample. The results are very similar.

[23]Since our regressions include firm fixed effects, the coefficient in front of $\log w_{L,i,t}$ in (2) corresponds to the effect of a change in $\log w_{L,i,t}$ on automation innovations. Denote $\omega_{i,D}$ the domestic weight and $\omega_{i,F} = 1 - \omega_{i,D}$ the total foreign weight with $w_{L,D,t}$ the wage in the domestic country and $w_{L,F,t}$ the average wage in the foreign country. Then we can decompose a small change in $\log w_{L,i,t}$ as:

$$d \log w_{L,i,t} = d \log \left(\omega_{i,D} w_{L,D,t} + \omega_{i,F} w_{L,F,t}\right) = \frac{\omega_{i,D} w_{L,D,0}}{w_{L,i,0}} d \log w_{L,D,t} + \frac{\omega_{i,F} w_{L,F,0}}{w_{L,i,0}} d \log w_{L,F,t}$$

where $\omega_{i,D} w_{L,D,0}/w_{L,i,0}$ denotes the values around which the change is computed—which we take as the average value over the sample period or the value at the beginning of the period. This shows that if $\frac{\omega_{i,F} w_{L,F,0}}{w_{L,i,0}} d \log w_{L,F,t}$ increases by 0.01 then $w_{L,i,t}$ increases by 1%. The same reasoning applies to high-skill wages or GDP per capita. In (2), GDP gap enters directly in levels as an average of logs so we directly interact the domestic and foreign variables with $\omega_{i,D}$ and $\omega_{i,F}$.

Table 8: Separating domestic and foreign variables

Dependent variable	Auto95			Auto90		
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Low-skill wage	1.6035***	3.1167***	3.1416***	1.1727***	2.1766***	2.3232***
	(0.2409)	(0.3863)	(0.3762)	(0.2706)	(0.5242)	(0.5175)
Foreign Low-skill wage	0.9413**	1.6473*	1.7323*	0.6237	1.4191	1.5079
	(0.4428)	(0.9881)	(0.9798)	(0.4793)	(1.0964)	(1.0565)
Domestic High-skill wage	-0.6814***	-1.6779**	-1.5802**	-0.5472*	-1.0204*	-1.1113**
	(0.2292)	(0.7961)	(0.7704)	(0.2984)	(0.5937)	(0.5553)
Foreign High-skill wage	-0.9958	-1.0067	-1.1805	-0.5636	-0.8075	-0.9260
	(0.8532)	(0.9227)	(0.8469)	(0.7625)	(1.0807)	(1.0045)
Domestic GDP gap	-0.1097	-2.1162	-1.7671	-1.0121	-1.7032	-1.7645
	(0.6047)	(2.5420)	(2.4605)	(0.7161)	(2.2561)	(2.2712)
Foreign GDP gap	-1.9222	5.2820**	5.4363**	-0.7061	4.2047	4.2659
	(3.1672)	(2.4856)	(2.4213)	(1.7024)	(2.6275)	(2.6575)
Domestic GDP per capita	-1.1872**	-1.5208	-1.6642*	-0.9786**	-1.5229	-1.4590
	(0.4735)	(1.0012)	(0.9474)	(0.4919)	(0.9665)	(0.9232)
Foreign GDP per capita	-0.6297	-2.9469***	-2.9139***	-0.2487	-3.0092***	-2.9803***
	(1.4455)	(1.0567)	(0.9570)	(1.0471)	(0.5490)	(0.5862)
Stock automation	-0.1541***	-0.1534***	-0.1551***	-0.0529	-0.0574**	-0.0588**
	(0.0381)	(0.0353)	(0.0353)	(0.0342)	(0.0291)	(0.0291)
Stock other	0.6508***	0.6413***	0.6412***	0.5827***	0.5755***	0.5751***
	(0.0480)	(0.0542)	(0.0539)	(0.0707)	(0.0772)	(0.0770)
Spillovers automation	0.8699***	1.2876***	1.2605***	1.2287***	1.5698***	1.5630***
	(0.2853)	(0.2490)	(0.2545)	(0.2540)	(0.1660)	(0.1596)
Spillovers other	-0.5635**	-0.8701***	-0.8480***	-0.9431***	-1.2362***	-1.2349***
	(0.2807)	(0.1963)	(0.2021)	(0.2939)	(0.1738)	(0.1871)
Observations	50025	50025	50025	73395	73395	73395
Firms	3335	3335	3335	4893	4893	4893

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables include a dummy for no stock and no spillover. In columns (2) and (5) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages and GDP per capita. In columns (3) and (6), they are interacted with the average shares over the sample period instead. In columns (2), (3), (5) and (6), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. Standard errors are clustered at the country-level * p < 0:1; ** p < 0:05; *** p < 0:01

Table 9: Alternative estimators

Dependent Variable	Auto95				Auto90			
	(1) Poisson	(2) ZI Poisson	(3) Neg Bi	(4) ZI Neg Bi	(5) Poisson	(6) ZI Poisson	(7) Neg Bi	(8) ZI Neg Bi
Low-skill wage	1.6085***	1.4610***	0.8518***	0.9538***	1.2614***	1.3168***	0.6102**	0.6727***
	(0.3520)	(0.3560)	(0.3181)	(0.3192)	(0.2845)	(0.2886)	(0.2411)	(0.2420)
High-skill wage	-0.5302	-0.5622	-0.3182	-0.3855	-0.2388	-0.4622*	0.0583	0.0040
	(0.3464)	(0.3529)	(0.2886)	(0.2888)	(0.2601)	(0.2670)	(0.2180)	(0.2181)
GDP gap	-5.6892**	-5.1981**	-4.2473**	-4.2617**	-4.8190***	-4.3705**	-5.1212***	-5.0264***
	(2.3188)	(2.3352)	(2.0795)	(2.0376)	(1.8297)	(1.8457)	(1.5985)	(1.5805)
Stock automation	1.1431***	0.9004***	1.1541***	0.9641***	1.1692***	0.9353***	1.2025***	1.0303***
	(0.0133)	(0.0144)	(0.0147)	(0.0163)	(0.0125)	(0.0132)	(0.0128)	(0.0146)
Stock other	0.1100***	0.0849***	0.1528***	0.1371***	0.1046***	0.0886***	0.1532***	0.1407***
	(0.0077)	(0.0077)	(0.0063)	(0.0064)	(0.0059)	(0.0059)	(0.0050)	(0.0050)
Spillovers automation	0.0375	0.0190	0.1545***	0.1298***	0.1081***	0.0657	0.1437***	0.1302***
	(0.0450)	(0.0463)	(0.0436)	(0.0425)	(0.0393)	(0.0418)	(0.0364)	(0.0357)
Spillovers other	0.0124	-0.0010	-0.1300***	-0.1034**	-0.0733*	-0.0514	-0.1192***	-0.1057***
	(0.0456)	(0.0469)	(0.0439)	(0.0429)	(0.0384)	(0.0413)	(0.0355)	(0.0349)
Observations	64845	64845	64845	64845	97710	97710	97710	97710
Firms	4323	4323	4323	4323	6514	6514	6514	6514

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. All Estimations are BGVR. Columns (1) and (5) show the estimates of Poisson, Columns (2) and (6) Zero-Inflated Poisson, Columns (3) and (7) Negative Binomial, Columns (4) and (8) Zero-Inflated Negative Binomial. All regressions include firm fixed effects and year dummies. All regressions include a dummy for no stock and no spillover. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

5.3 Different estimators and country-year fixed effects

Table 9 reproduces the baseline regression of column (6) in Table 5 for different estimators for the auto95 and auto90 measures. Columns (1) and (5) use the BGVR method to proxy for firm fixed effects. This has the advantage of addressing Nickell's bias (though the inclusion of the stock of automation variable did not materially affect our results in Table 5), but the disadvantage of not controlling well for firm's heterogeneity if firms' pre-sample average of the dependent variable is a poor proxy for firm's future patenting activity. We find a positive effect of low-skill wages with elasticities of 1.6 for auto95 and 1.3 for auto90, the coefficient on the high-skill wage is negative nearly significant at 10% for auto95 and not significant for auto90. Columns (2) to (4) and (6) to (8), also use the BGVR method but change the estimator to Zero-Inflated Poisson, Negative Binomial and Zero-Inflated Negative Binomial, the results on low-skill wages stay similar (with smaller coefficients for the negative binomial regressions).

The BGVR method allows us to introduce country-year fixed effects. We do so in Table 10, where the country of a firm is still defined as the country with the largest weight. This allows us to fully address the issue that the domestic component of wages may be endogenous to firms' behavior (Table 8 does not fully address the issue because if domestic wages are endogenous, they would be a bad control). Columns (1) and (4)

Table 10: Country-year fixed effects

Dependent variable	Auto95			Auto90		
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skill wage	1.7718***			1.4633***		
	(0.4661)			(0.3779)		
Foreign low-skill wage		3.5296***	3.2784***		1.9838***	1.7355**
		(0.8956)	(0.8608)		(0.7475)	(0.7220)
High-skill wage	-1.5385***			-1.0635***		
	(0.4657)			(0.3823)		
Foreign high-skill wage		-2.8185***	-2.6335***		-1.6570**	-1.4671*
		(0.8856)	(0.8561)		(0.7920)	(0.7686)
GDP gap	0.7801			0.0749		
	(4.7075)			(3.6713)		
Foreign GDP gap		0.2910	0.3056		-0.1523	-0.1109
		(4.7918)	(4.8020)		(4.1079)	(4.1197)
Stock automation	1.1825***	1.1840***	1.1841***	1.1657***	1.1714***	1.1710***
	(0.0143)	(0.0154)	(0.0154)	(0.0124)	(0.0133)	(0.0134)
Stock other	0.1003***	0.0920***	0.0917***	0.1028***	0.0940***	0.0938***
	(0.0074)	(0.0078)	(0.0078)	(0.0059)	(0.0062)	(0.0062)
Spillovers automation	0.0012	-0.0448	-0.0409	0.0323	-0.0008	0.0002
	(0.0504)	(0.0527)	(0.0524)	(0.0432)	(0.0453)	(0.0451)
Spillovers other	0.0419	0.0881	0.0846	0.0077	0.0394	0.0384
	(0.0527)	(0.0556)	(0.0553)	(0.0435)	(0.0454)	(0.0452)
Observations	64845	50025	50025	97710	73395	73395
Firms	4323	3335	3335	6514	4893	4893

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by BGVR Poisson regressions. All regressions include country-year dummies. All regressions with stock variables include a dummy for no stock and no spillover. In columns (2) and (5) foreign low-skill wages are interacted with the share of foreign low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages and GDP per capita. In columns (3) and (6), they are interacted with the average shares over the sample period instead. In columns (2), (3), (5) and (6), foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the firm-level * p < 0:1; ** p < 0:05; *** p < 0:01

reproduce our baseline regressions with total wages for the auto95 and auto90 measures. We find positive and significant effects for low-skill wages with magnitudes similar to those in Tables 5, 6 and 9, the coefficient on high-skill wages is also significant and negative. In the other columns we isolate the foreign component of wages (or the GDP gap) as we did Table 8. The foreign wages are pre-multiplied by the share of foreign wages in total wages computed at the beginning of the sample (columns (2) and (5)) or averaged over the sample (columns (3) and (6)). Low-skill wages have a positive and significant coefficient with elasticities of 3.5 and 3.3 for the auto95 measure and 2 and 1.7 for the auto90 measure. Table A.15 in the Appendix reproduces this Table but with standard errors clustered at the country level. The results are very similar.

5.4 Non-automation innovations

In contrast with our baseline result, we now look at the effect of wages on innovations that score lower on our automation metric. To find non-automation patents (or more

Table 11: Non-automation innovations

Dependent Variable	Placebo Pharma		Placebo Chemistry		Placebo Machinery			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	-0.2312	-0.1384	-0.0663	0.1988	0.6091	0.6718	0.3534	0.5942
	(0.7932)	(0.7943)	(0.6707)	(0.6148)	(0.4207)	(0.4231)	(0.5843)	(0.5949)
High-skill wage	1.0371	1.4451*	0.3344	0.9683*	-0.4274	-0.1100	0.3070	0.6743
	(0.7285)	(0.7836)	(0.5825)	(0.5679)	(0.4293)	(0.4480)	(0.5994)	(0.6380)
GDP gap	-4.7732**	-2.1480	-2.5938	1.1431	-1.3796	0.5604	-6.4535***	-1.1372
	(2.1242)	(2.2471)	(1.8288)	(1.7038)	(1.2385)	(1.4474)	(1.6663)	(2.2951)
GDP per capita		-1.8040*		-2.0323**		-1.3922**		-3.0917***
		(0.9600)		(0.8906)		(0.5885)		(1.0967)
Stock own	0.4669***	0.4697***	0.2993***	0.3082***	0.0550	0.0568	0.0325	0.0380
	(0.0558)	(0.0558)	(0.0476)	(0.0466)	(0.0398)	(0.0391)	(0.0457)	(0.0456)
Stock other	0.1295**	0.1353**	0.2856***	0.2867***	0.4848***	0.4852***	0.4897***	0.4891***
	(0.0627)	(0.0631)	(0.0481)	(0.0478)	(0.0430)	(0.0429)	(0.0504)	(0.0504)
Spillovers own	-0.6814**	-0.7405**	1.0873***	0.9920***	2.5132***	2.1191***	2.5214***	1.8569***
	(0.3059)	(0.3086)	(0.3789)	(0.3659)	(0.3614)	(0.3863)	(0.4258)	(0.4604)
Spillovers other	1.1699***	1.2204***	-0.3170	-0.1748	-2.0696***	-1.6143***	-2.3173***	-1.5852***
	(0.3243)	(0.3239)	(0.3463)	(0.3430)	(0.4437)	(0.4918)	(0.5372)	(0.5769)
Observations	31980	31980	69720	69720	158955	158955	97174	97174
Firms	2132	2132	4648	4648	10597	10597	6941	6941

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions include a dummy for no stock and no spillover. Stock and Spillovers variables are estimated according to the referred dependent variable. Columns (7) and (8) restrict attention to firm with a domestic weight below 90%. Standard errors are clustered at the firm-level. *p < 0:1; **p < 0:05; ***p < 0:01

accurately, low-automation patents), we look at innovations in certain technological fields, and we exclude patents which have a technological category in that field (defined as in section 2.3) with a prevalence of automation keywords measure above a certain threshold. We choose as a threshold the 60^{th} percentile of the distribution of IPC/CPC 6 digit codes in the machinery technological fields (0.2091). We then carry out the same exercise as before.[24] Table 11 reports regressions results for placebos computed in the technological field of pharmacy (columns (1) and (2)), those of chemistry (columns (3) and (4), corresponding to the technical fields of organic and macro chemistry) and machinery (columns (5) to (8)). Columns (1) to (4) show that low-skill wages do not have an effect on placebo innovations in pharmaceuticals and chemistry. In column (5) and (6), the effect of low-skill wages on low-automation innovation in machinery is much smaller than for the auto90 and auto95 measures and is below conventional levels of significance. In addition the coefficients become smaller and far from significant when we restrict attention to firms with a domestic weight below 0.9 (columns (7) and (8)).

[24] In particular, we recompute knowledge stocks and spillover variables for the placebo innovations and we recompute weights for all firms for the technological fields associated with each regression.

Table 12: Lags and leads

Dependent variable	Auto95							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lags (Leads)	-5	-4	-3	-2	-1	0	1	2
Low-skill wage	1.1712**	1.6327***	1.8693***	2.1728***	1.9810***	1.9811***	1.4830***	0.9023
	(0.5333)	(0.4869)	(0.4837)	(0.5229)	(0.5512)	(0.5746)	(0.5472)	(0.5677)
High-skill wage	0.0386	-0.7443	-1.1434**	-1.4557***	-1.7288***	-2.2426***	-2.0029***	-1.8096***
	(0.4912)	(0.4737)	(0.4835)	(0.4947)	(0.4895)	(0.5586)	(0.5176)	(0.5385)
GDP gap	-2.8726	-1.6974	-1.3977	-3.8791**	-2.4716	0.9948	3.2157	0.1748
	(1.7565)	(1.7570)	(1.7233)	(1.8985)	(2.4320)	(2.0456)	(2.2744)	(2.1317)
Stock Automation	-0.1545***	-0.1814***	-0.1792***	-0.1748***	-0.1778***	-0.1821***	-0.1538***	-0.1442***
	(0.0483)	(0.0456)	(0.0452)	(0.0462)	(0.0464)	(0.0461)	(0.0456)	(0.0464)
Stock other	0.6559***	0.6377***	0.6376***	0.6567***	0.6479***	0.6659***	0.6586***	0.6769***
	(0.0545)	(0.0519)	(0.0503)	(0.0506)	(0.0503)	(0.0500)	(0.0483)	(0.0471)
Spillovers automation	-0.0786	0.1416	0.3104	0.5256**	0.7620***	1.0501***	1.0089***	0.9578***
	(0.2832)	(0.2646)	(0.2487)	(0.2548)	(0.2501)	(0.2698)	(0.2760)	(0.3023)
Spillovers other	0.1353	0.0701	-0.0385	-0.2839	-0.3343	-0.5068**	-0.3900	-0.3073
	(0.2598)	(0.2353)	(0.2164)	(0.2071)	(0.2084)	(0.2310)	(0.2398)	(0.2574)
Observations	61575	62655	64035	64845	65700	66315	68370	70170
Firms	4105	4177	4269	4323	4380	4421	4558	4678

Note: Marginal effects; Standard errors in parentheses. The independent variables (wages, GDP and GDP gap) are lagged by the number of periods indicated in lag, except for the stock variables which are always lagged by 2 periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions include a dummy for no stock and no spillover. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

5.5 Timing

Our baseline regressions assume a lag of 2 years between wages and patent applications. We look at alternative lags in Table 12—we keep a lag of 2 between patent applications and the stocks of patents from the firm because otherwise the dependent variable would be included in the stock of automation when we consider contemporaneous regressions or leads. Column (4) reproduces the baseline result of Column (6) of Table 5 and corresponds to a 2 year lag between patent applications and the independent variables. The regressions show that the largest coefficient is obtained for a 2 year lag, but remains relatively stable between a 4 year lag and a 1 year lead, which suggests that our effect is identified by long-term trends in wages instead of short-run fluctuations. At a 5 year lag, the coefficient is still significant but smaller, and with a 2 year lead, the coefficient on low-skill wages is not significant.

5.6 Robustness checks

This section presents several robustness checks.

Skill premium. Low-skill and high-skill wages are correlated, therefore one might worry that our regressions are affected by multicollinearity issues—although controlling for firm fixed effects, year fixed effects and the stocks and spillovers variables, the correlation coefficient is 0.85 and drops to 0.69 after controlling for GDP per capita for

Table 13: Skill premium

Dependent variable	Auto95			Auto90		
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skill / High-skill wage	1.7315***	1.7962***	1.7964***	1.3553***	1.3999***	1.3602***
	(0.3434)	(0.3797)	(0.3832)	(0.4155)	(0.4282)	(0.4020)
GDP gap		-3.8695**	-3.7045**		-4.1325***	-3.3022***
		(1.7607)	(1.8359)		(1.3006)	(0.8898)
GDP per capita			-0.0972			-0.5181
			(1.0136)			(0.7415)
Stock automation	-0.1767***	-0.1758***	-0.1756***	-0.1024***	-0.1017***	-0.1017***
	(0.0319)	(0.0324)	(0.0324)	(0.0369)	(0.0369)	(0.0369)
Stock other	0.6547***	0.6547***	0.6548***	0.5991***	0.5990***	0.5994***
	(0.0316)	(0.0315)	(0.0313)	(0.0579)	(0.0579)	(0.0576)
Spillovers own	0.5150***	0.5471***	0.5642**	0.9008***	0.9469***	1.0572***
	(0.1975)	(0.1818)	(0.2645)	(0.2628)	(0.2515)	(0.2677)
Spillovers other	-0.1932	-0.2162	-0.2216	-0.5077*	-0.5447**	-0.5989***
	(0.2199)	(0.2135)	(0.2050)	(0.2609)	(0.2505)	(0.2200)
Observations	64845	64845	64845	97710	97710	97710
Firms	4323	4323	4323	6514	6514	6514

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions include a dummy for no stock and no spillover. Standard errors are clustered at the country-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

the auto95 sample (and 0.84 and 0.69 for the auto90 sample). To deal with this issue, Table 13 regresses automation innovation on the log of the ratio of low-skill to high-skill wages (the inverse of the skill premium) for both classifications. Unsurprisingly given the results of Table 5, we obtain a positive and significant coefficient with an elasticity of 1.8 for auto95 with both controls included and 1.4 for auto90. It is worth mentioning that regressing our non-automation innovation in machinery measure (from Table 11) on the ratio of low-skill to high-skill wages gives an insignificant coefficient.

Other robustness checks. Appendix A contains additional robustness checks. Table A.16 investigates whether our results are robust when focusing on patents of higher quality. We look at patents which have been applied for at 2 of the 3 main patent offices (EU, Japan and US), or at triadic patents which have been applied for at the 3 offices. Triadic patents are generally considered to be patents of very high quality. The results are similar to our baseline.

6 Alternative specifications

6.1 Middle skill wages

Table 14 adds middle-skill wages to the regressions with the auto95 measure. We regress automation innovations on middle-skill wages, combined with low-skill, high-skill or both

Table 14: Including middle-skill wages

Dependent Variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	3.9849***		3.2275***	4.0403***		3.2278***	3.9803***		3.2091***
	(1.1539)		(1.1044)	(1.1599)		(1.0996)	(1.2006)		(1.1080)
Middle-skill wage	-3.1868***	2.2234***	-1.5571	-3.2287***	2.3155***	-1.4689	-2.9902**	2.4337***	-1.3337
	(1.2063)	(0.6192)	(1.3069)	(1.2021)	(0.6404)	(1.2914)	(1.2867)	(0.6645)	(1.3101)
High-skill wage		-1.5914***	-1.0437*		-1.6777***	-1.1272**		-1.6343***	-1.0884*
		(0.5704)	(0.5516)		(0.5819)	(0.5588)		(0.5967)	(0.5609)
GDP gap				-3.3298*	-3.7728**	-3.7909**	-2.2430	-2.7860	-2.8677
				(1.9593)	(1.9038)	(1.9307)	(2.3536)	(2.3908)	(2.3573)
GDP per capita							-0.6595	-0.5805	-0.5488
							(0.9660)	(0.9192)	(0.8697)
Stock automation	-0.1743***	-0.1698***	-0.1777***	-0.1731***	-0.1685***	-0.1767***	-0.1718***	-0.1671***	-0.1754***
	(0.0457)	(0.0458)	(0.0457)	(0.0462)	(0.0463)	(0.0460)	(0.0464)	(0.0465)	(0.0462)
Stock other	0.6583***	0.6527***	0.6580***	0.6582***	0.6525***	0.6580***	0.6592***	0.6534***	0.6588***
	(0.0505)	(0.0503)	(0.0507)	(0.0505)	(0.0503)	(0.0507)	(0.0504)	(0.0501)	(0.0506)
Spillovers automation	0.4587*	0.4154*	0.5159**	0.4811*	0.4460*	0.5461**	0.5918*	0.5420*	0.6361**
	(0.2524)	(0.2523)	(0.2551)	(0.2529)	(0.2537)	(0.2565)	(0.3120)	(0.3157)	(0.3113)
Spillovers other	-0.3196	-0.1623	-0.2959	-0.3396	-0.1830	-0.3168	-0.3881*	-0.2280	-0.3581*
	(0.2124)	(0.2038)	(0.2126)	(0.2127)	(0.2038)	(0.2128)	(0.2111)	(0.2080)	(0.2135)
Observations	64845	64845	64845	64845	64845	64845	64845	64845	64845
Firms	4323	4323	4323	4323	4323	4323	4323	4323	4323

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables include a dummy for no stock and no spillover. Standard errors are clustered at the country-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

wages. First, low-skill wages always enter with a positive and very significant coefficient between 3.2 and 4.0 (higher therefore than in regressions which do not include middle-skill wages). Middle-skill wages appear negatively when low-skill wages are present but positively otherwise (because low-skill wages are an omitted variable). Columns (3), (6) and (9) which contain the three wages are particularly instructive, they show that higher low-skill wages lead to more automation innovations and higher high-skill wages to less automation innovations. The effect of middle-skill wages is less clear: the coefficient is negative but not significant, therefore our measure of automation in machinery seems to capture technologies which are strong substitute for low-skill but not middle-skill workers. Note that middle-skill wages are very strongly correlated with low- and high-skill wages: controlling for firm and year fixed effects, plus the stock and spillover variables, the correlation coefficients are 0.95 and 0.96, and they drop to 0.9 and 0.9 when controlling for GDP per capita. The results are similar with the auto90 measure except that the coefficient on middle-skill wages becomes significant when the two other wages are included (see Table A.17 in the Appendix).

7 Conclusion

In this paper, we have used patent text data to identify patents which correspond to automation innovations. We use this classification to analyze for the first time the effect of wages on automation innovations in machinery. We find that automation innovations are very responsive to changes in low-skill wages as we estimate an elasticity of automation innovation with respect to low-skill wages typically between 1 and 2.

These results suggest that policies which increase labor costs for low-skill workers will lead to an increase in innovations which aim at saving on low-skill workers. Therefore, with endogenous technological change, such policies are likely to be less costly for the economy in terms of overall welfare, but they introduce additional negative effects for low-skill workers. By how much then would an exogenous increase in low-skill wage be undone in a couple of years through innovation? Answering this question requires finding the effect of an increase in automation patents on low-skill wages. This is the next step of our research agenda.

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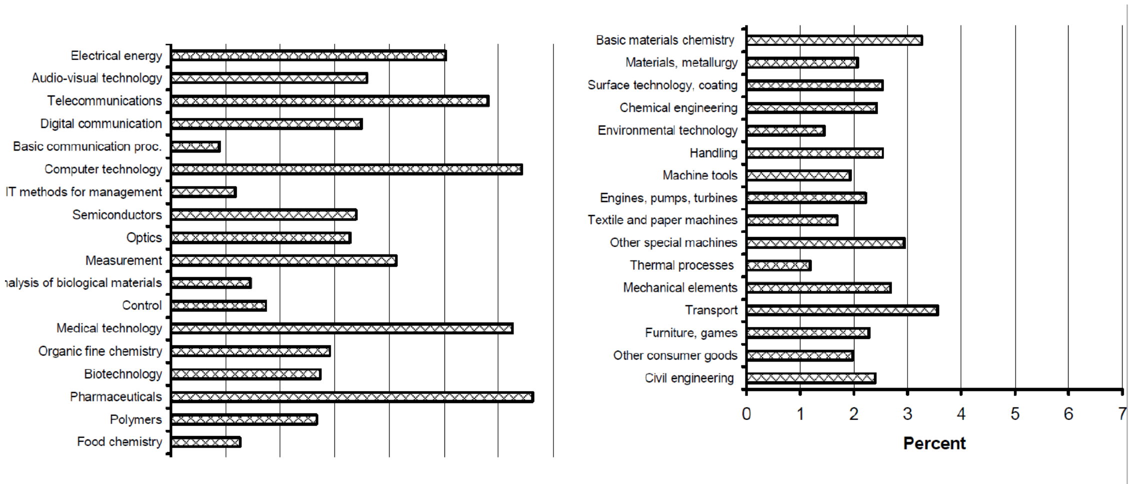
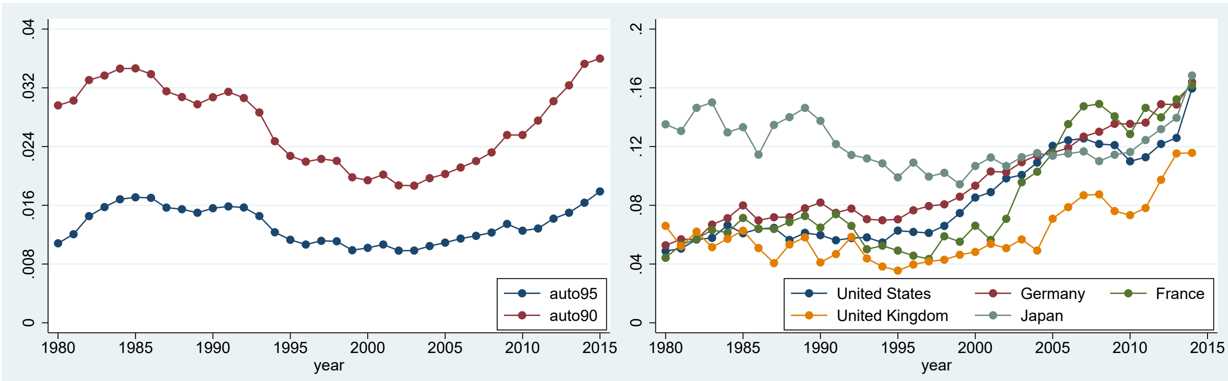


Figure A.4: Technological fields in 2005

A Appendix Figures and Tables



(a) Share of automation patents in machinery worldwide. Automation technological categories are defined at the 90th percentile of the distribution of 6 digit IPC/CPC codes in machinery (for auto90) or the 95th percentile (auto95).

(b) Share of automation patents (auto95) in machinery conditional by the nationality of applicants.

Figure A.5: Share of automation patents (for biadic patents).

Table A.15: Country-year fixed effects

Dependent variable	Auto95			Auto90		
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skill wage	1.7718***			1.4633***		
	(0.4697)			(0.4892)		
Foreign low-skill wage		3.5296***	3.2784***		1.9838***	1.7355**
		(0.5586)	(0.4499)		(0.7074)	(0.7252)
High-skill wage	-1.5385**			-1.0635*		
	(0.7501)			(0.6068)		
Foreign high-skill wage		-2.8185***	-2.6335***		-1.6570*	-1.4671*
		(0.5630)	(0.5430)		(0.8752)	(0.8886)
GDP gap	0.7801			0.0749		
	(2.5883)			(3.2654)		
Foreign GDP gap		0.2910	0.3056		-0.1523	-0.1109
		(5.1144)	(5.0935)		(3.9844)	(3.9599)
Stock automation	1.1825***	1.1840***	1.1841***	1.1657***	1.1714***	1.1710***
	(0.0103)	(0.0059)	(0.0059)	(0.0169)	(0.0298)	(0.0303)
Stock other	0.1003***	0.0920***	0.0917***	0.1028***	0.0940***	0.0938***
	(0.0159)	(0.0169)	(0.0163)	(0.0130)	(0.0123)	(0.0120)
Spillovers automation	0.0012	-0.0448	-0.0409	0.0323	-0.0008	0.0002
	(0.0923)	(0.0761)	(0.0781)	(0.0748)	(0.0551)	(0.0563)
Spillovers other	0.0419	0.0881	0.0846	0.0077	0.0394	0.0384
	(0.0737)	(0.0620)	(0.0640)	(0.0693)	(0.0568)	(0.0586)
Observations	64845	50025	50025	97710	73395	73395
Firms	4323	3335	3335	6514	4893	4893

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by BGVR Poisson regressions. All regressions include country-year dummies. All regressions with stock variables include a dummy for no stock and no spillover. In columns (2) and (5) foreign low-skill wages are interacted with the share of foreign low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages and GDP per capita. In columns (3) and (6), they are interacted with the average shares over the sample period instead. In columns (2), (3), (5) and (6), foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the country-level * p < 0:1; ** p < 0:05; *** p < 0:01

Table A.16: Other innovation indicators

Dependent Variable	Auto95				Auto90			
	Biadic (US, JP, EU)		Triadic		Biadic (US, JP, EU)		Triadic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	1.8574***	1.8479***	2.1177**	2.0080**	1.6460***	1.5640**	1.7247**	1.6118**
	(0.6903)	(0.6844)	(0.9180)	(0.9277)	(0.6239)	(0.6152)	(0.7856)	(0.7872)
High-skill wage	-1.4357**	-0.8827	-2.0390**	-1.1414	-1.1733**	-0.5892	-1.5555**	-0.8430
	(0.6372)	(0.6329)	(0.9379)	(0.9188)	(0.5222)	(0.5147)	(0.7311)	(0.7395)
GDP gap	-3.9765*	-1.0072	-13.3860***	-8.3251**	-3.3403*	-0.5206	-10.0603***	-6.0539*
	(2.3487)	(2.5753)	(3.9369)	(4.2402)	(1.9751)	(2.1922)	(2.9136)	(3.3147)
GDP per capita		-2.1119**		-3.5100**		-1.9317***		-2.6313**
		(0.9200)		(1.4179)		(0.6970)		(1.0510)
Stock automation	-0.2159***	-0.2193***	-0.4261***	-0.4367***	-0.1496***	-0.1538***	-0.2497***	-0.2600***
	(0.0552)	(0.0555)	(0.0721)	(0.0723)	(0.0432)	(0.0430)	(0.0542)	(0.0540)
Stock other	0.6791***	0.6845***	0.7093***	0.7138***	0.6414***	0.6450***	0.6409***	0.6452***
	(0.0577)	(0.0575)	(0.0786)	(0.0785)	(0.0521)	(0.0519)	(0.0615)	(0.0615)
Spillovers automation	0.5108	0.8674**	0.9510*	1.0923**	0.8066*	1.1148**	0.9081*	0.9041*
	(0.3669)	(0.4294)	(0.5200)	(0.5216)	(0.4525)	(0.4597)	(0.5144)	(0.5059)
Spillovers other	-0.5266**	-0.6288***	-0.3856	-0.6728	-0.6844**	-0.8768***	-0.3417	-0.4893
	(0.2413)	(0.2433)	(0.4519)	(0.4903)	(0.2773)	(0.2836)	(0.4783)	(0.4874)
Observations	50370	50370	31635	31635	74655	74655	47040	47040
Firms	3358	3358	2109	2109	4977	4977	3136	3136

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions include a dummy for no stock and no spillover. Column (1)-(2) and (5)-(6) consider biadic patents in at least two countries among US, JP, EU. Column (3)-(4) and (7)-(8) consider triadic patents. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.17: Including middle-skill wages

Dependent Variable	Auto90								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	3.6406***		3.2072***	3.6751***		3.1959***	3.4011***		3.0289***
	(0.8780)		(0.8365)	(0.8825)		(0.8348)	(0.9109)		(0.8454)
Middle-skill wage	-3.0155***	1.6967***	-2.0731**	-3.0480***	1.7562***	-2.0038**	-2.4914***	1.9070***	-1.6742*
	(0.9129)	(0.5486)	(0.9955)	(0.9125)	(0.5554)	(0.9857)	(0.9500)	(0.5780)	(0.9899)
High-skill wage		-1.1348**	-0.5898		-1.1985***	-0.6529		-1.0345**	-0.5406
		(0.4600)	(0.4377)		(0.4648)	(0.4402)		(0.4784)	(0.4418)
GDP gap				-3.7921**	-4.0274**	-3.9954**	-2.1942	-2.2473	-2.4907
				(1.6010)	(1.5879)	(1.6011)	(1.8279)	(1.8573)	(1.8329)
GDP per capita							-1.0208	-1.0965*	-0.9381
							(0.6306)	(0.6418)	(0.6010)
Stock automation	-0.1022***	-0.0975***	-0.1035***	-0.1014***	-0.0967***	-0.1028***	-0.1009***	-0.0961***	-0.1021***
	(0.0364)	(0.0366)	(0.0365)	(0.0366)	(0.0368)	(0.0366)	(0.0368)	(0.0371)	(0.0368)
Stock other	0.6031***	0.5990***	0.6024***	0.6030***	0.5987***	0.6022***	0.6043***	0.6004***	0.6035***
	(0.0433)	(0.0436)	(0.0434)	(0.0433)	(0.0436)	(0.0434)	(0.0431)	(0.0433)	(0.0432)
Spillovers automation	0.8576**	0.7648**	0.9095***	0.8935**	0.8100**	0.9530***	1.0999***	1.0295***	1.1327***
	(0.3448)	(0.3475)	(0.3487)	(0.3475)	(0.3509)	(0.3520)	(0.3767)	(0.3824)	(0.3796)
Spillovers other	-0.6141**	-0.4425	-0.6200**	-0.6450**	-0.4770*	-0.6532**	-0.7648***	-0.6171**	-0.7621***
	(0.2855)	(0.2761)	(0.2842)	(0.2869)	(0.2772)	(0.2855)	(0.2897)	(0.2840)	(0.2895)
Observations	97710	97710	97710	97710	97710	97710	97710	97710	97710
Firms	6514	6514	6514	6514	6514	6514	6514	6514	6514

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables include a dummy for no stock and no spillover. Standard errors are clustered at the country-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

B Appendix

B.1 Details on the classification of automation patents

B.1.1 List of keywords

For each technological category, we compute the following share of patents:[25]

1. Automat* patents. Share of patents which contain the words:

   (a) *Automation* or *automatization;*

   (b) or *automat** at least 5 times;

   (c) or (*automat** or *autonomous*) in the same sentence as (*machine* or *manufacturing* or *machining* or *equipment* or *apparatus* or *operator* or *handling* or *"vehicle system"* or *welding* or *knitting* or *weaving* or *convey** or *storage* or *store* or *regulat** or *manipulat** or *arm* or *sensor* or *inspect** or *warehouse*) at least twice.

2. Labor patents. Share of patents which contain the words: *laborious*, *labourious,* *labor* or *labour.*

3. Robot patents. Share of patents which contain the word *robot** but not (*surgical* or *medical*).

4. Numerical control patents. Share of patents which contain the words:

   (a) *CNC* or "*numerically controlled*" or "*numeric control*" or "*numerical control*" or the same terms but with hyphens;

   (b) or *NC* in the same sentence with (*machine* or *manufacturing* or *machining* or *equipment* or *apparatus*).

5. Computer aided design and manufacturing patents. Share of patents which contain the words:

   (a) "*computer aided*", "*computer assisted*" or "*computer supported*" or the same terms with hyphens) in the same patent with (*machine* or *manufacturing* or *machining* or *equipment* or *apparatus*);

[25] x* indicates any word which starts with x, for instance automat* corresponds to the words automatic, automatically, automate, automates, etc...

   (b) or (*CAD* or (*CAM* and not "*content addressable memory*")) in the same sentence with (*machine* or *manufacturing* or *machining* or *equipment* or *apparatus*).

6. Flexible manufacturing. Share of patents which contain the words: "*flexible manufacturing*".

7. PLC patents. Share of patents which contain the words: "*programmable logic controller*" or (*PLC* and not (*powerline* or "*power line*")).

8. 3D printing patents. Share of patents which contain the words: "*3D print**" or "*additive manufacturing*" or "*additive layer manufacturing*".

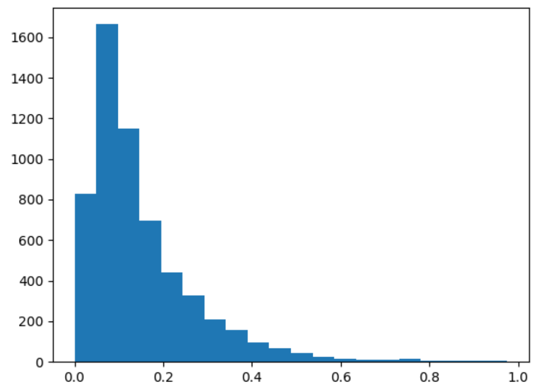
9. Automation patents. Share of patents which satisfy any of the previous criteria.

We derived this exact list after experiencing extensively with variations around those words and looking at the resulting classification of technological codes and the associated patents. For instance, the thresholds (5 and 2) used in the definition of the share of automat* patents where chosen so that the distribution of the share of automat* patents is comparable to the distribution of the share of numerical control patents across technological codes. Similarly, requiring that *NC* be in the same sentence as words such as *machine*, ensures that *NC* is short fort numerical control instead of North Carolina.

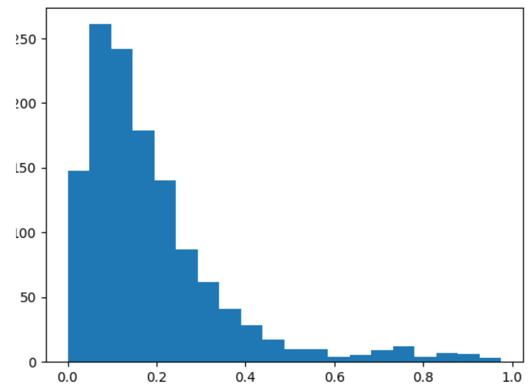
Relative to the original list of technologies given in the SMT, we did not include keywords related to information network, as these seem less related to the automation of the production process and the patents containing words such as "local area network" do not appear related to automation. We also did not directly count all laser related technologies as not all of these are related to automation—but we obtain patent related to automation using laser technologies thanks to our other keywords.

B.1.2 Statistics on the classification

Figure B.1 gives the histograms of the prevalence of automation keywords for all pairs of IPC/CPC 4 digit codes (panel a) and all pairs with at least one member in the the relevant technological fields (panel b). The histograms are very similar to those of IPC/CPC 6 digit codes in Figure 1. Figure B.2 shows the histograms for all combinations of IPC 4 digit codes with G05 or G06 (panel a), or when the IPC 4 code is in the relevant technological field (panel b). Both distributions are considerably shifted to the right, in line with expectations since G05 proxies for control and G06 for algorithmic, two



(a) For all pairs of IPC/CPC 4 digit codes



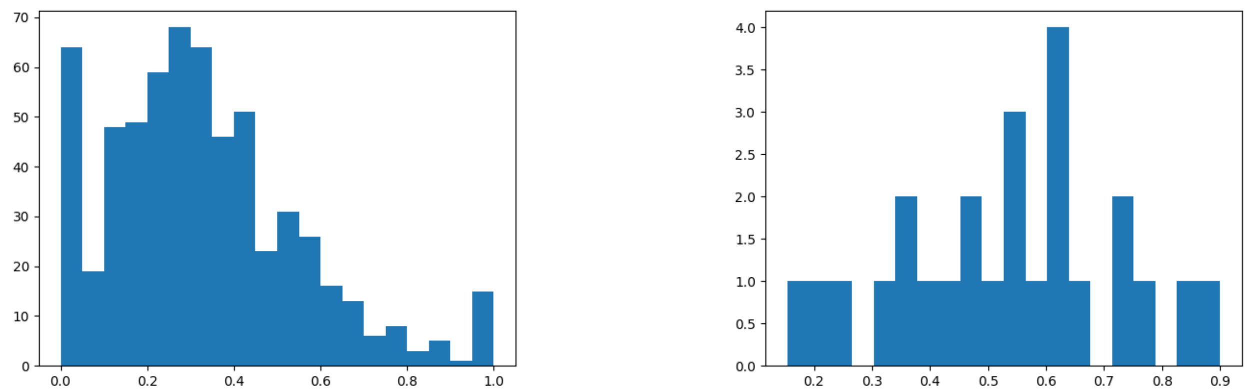
(b) For all pairs of IPC/CPC 4 digit codes within chinery with 100 patents

Figure B.1: Histogram of the prevalence of automation keywords for IPC/CPC pairs of 4 digit codes

set of technologies which have been used heavily in automation. There are, however, much fewer combination of these types (in part because all histograms only consider groups with at least 100 patents), and accordingly few patents can be characterized as automation innovations this way.

B.2 Redoing ALM

In this Appendix, we provide details on the analysis conducted in section 2.5. We use granted patents at the USPTO between 1970 and 1998. To assign patents to sectors, we first use Lybbert and Zolas (2014) who provide a concordance table between IPC codes at the 4 digit level and NAICS 1997 6 digits industry codes (mostly in manufacturing). The concordance table is probabilistic (so that each code is associated with a sector with a certain probability). In this exercise we are interested in matching patents with a sector of use and not the inventing sector (which is what is provided by the Eurostat concordance table for instance). The Lybbert and Zolas concordance tables are derived by matching patents texts with industry descriptions, and as such they cannot *a priori* distinguish between sector of use and industry of manufacturing. We checked, however, that patents associated with "textile and paper machines" for instance are associated with the textile



(a) For all combinations of IPC4 with G05 G06

(b) For combinations of IPC4 in machinery with G06 and at least 100 patents

Figure B.2: Histogram of the prevalence of automation keywords for combinations of IPC 4 digit codes with G05 G06

and paper sectors and not with the equipment sector (as is the case with the Eurostat concordance table). We attribute patents to sectors fractionally in function of their IPC codes. To assign patents to the consistent Census industry codes used by ALM, we first use a Census concordance table (https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html) to go from NAICS 1997 to Census industry codes 1990, then we use the concordance table of ALM to get to the consistent Census industry codes of ALM. Finally, for each sector and each time period, we compute the sums of automation patents and machinery patents and take the ratio to be our measure of automation intensity. We exclude sectors with less than 50 machinery patents (which is why the number of sectors varies across time periods). We are left with 66 to 68 sectors, with only 7 of them not in manufacturing.

The other variables are directly taken from ALM. We refer the reader to that paper for a detailed explanation. The task measures are computed using the 1977 *Dictionary of Occupational Titles* (DOT) which measure the tasks content of occupations. Occupations are then matched to industries using the Census Integrated Public Micro Samples one percent extracts for 1960, 1970 and 1980 (IPUMS) and the CPS Merged Outgoing Rotation Group files for 1980, 1990 and 1998 (MORG). The task change measure at the industry level reflects changes in occupations holding the task content of each occupation constant, which ALM refer to as the extensive margin. Since tasks measures do not have a natural scale, ALM converted them into percentile values corresponding to their rank in the 1960 distribution of tasks across sectors, so that the employment-weighted means of all tasks measure across sectors in 1960 is 50. Our analysis only uses manufacturing sectors and starts in 1970 but we kept the original ALM measure to facilitate comparison. As in ALM, the dependent variable in Table 2 corresponds to 10 times the annualized change in industry's tasks inputs to favor comparison across periods of different lengths. Computerization ΔC_j is measured as the annual change in the percentage of industry workers using a computer at their jobs between 1984 and 1997 (estimated from the October Current Population Survey supplements), multiplied by 10 to ensure that all variables are over the same time length. For all regressions, observations are weighted by the employment share in each sector. In Table 2, the ratio of high-skill to low-skill workers are measured as the ratio of college graduates (and more than college) to high-school dropouts and graduates, taken from ALM—knowing that their data in turn come from IPUMS and MORG.

Table B.2 reproduces Table 2 but with the laxer auto90 measure. The results are very similar—the only difference is that the coefficient on routine manual tasks is not significant at the usual levels in the 90s.[26]

Figure B.3 provides scatter plots of the changes in routine tasks and the share of automation patents in machinery (according to the auto95 definition) over the years 1980-1998. Tasks changes are still measured as 10 times the annual change in centiles of the 1960 distribution between 1980 and 1998. The share of automation patents is computed as an average over those years. The list of sectors plotted (which are also the sectors in the regressions) is given in Table B.1.

Table B.3 reproduces the Table 5 of ALM by carrying the analysis of Table 2 for each education groups over the time period 1980-1998 with the auto95 measure (the results are very similar with auto90). The table shows that automation reduces the amount of routine tasks undertaken by high-school dropouts and high-school graduates. Following ALM, Panel F computes the average effect of automation in tasks changes (from Panel A) and how much of this average effect can be explained by changes within educational groups (from Panels B to E). We find that changes within educational categories explain a significant share of the overall reduction in routine tasks but changes in educational composition also play a role, in line with Colmun 6 of Table 2. In contrast, ALM found

[26]To interpret the effect of the automation variable, note that the means are 0.13, 0.15 and 0.14 in the 70s, 80s and 90s, and the standard deviations are 0.10, 0.12 and 0.11 with the auto90 definition.

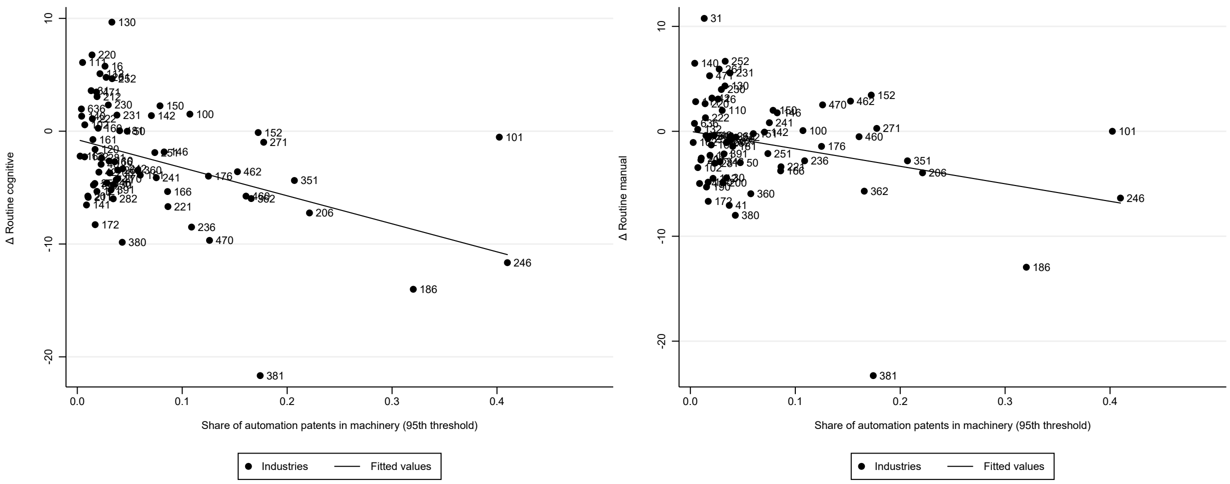
ind6090	Title	ind6090	Title
16	Ag production crops & livestock; Ag services; Horticultural services	201	Misc. petroleum and coal products
		206	Household appliances; Radio, TV & communications equipment; Electric machinery, equipment & supplies, n.e.c., not specified electrical machinery, equipment & supplies
30	Forestry		
31	Fishing, hunting and trapping		
40	Metal mining		
41	Coal mining		
42	Crude petroleum and natural gas extraction	211	Other rubber products, and plastics footwear and belting + tires & inner tubes
50	Nonmetallic mining & quarrying, except fuel		
66	Construction	212	Misc. plastic products
100	Meat products	220	Leather tanning and finishing
101	Dairy products	221	Footwear, except rubber and plastic
102	Canned and preserved fuits and vegetables	222	Leather products, except footwear
110	Gain mill products	230	Logging
111	Bakery products	231	Sawmills, planning mills, and millwork
112	Sugar and confectionary products	236	Railroad locomotives & equipment; Cycles & misc transporation equipment; Wood buildings & mobile homes
120	Beverage industries		
121	Misc. food preparations, kindred products		
130	Tobacco manufactures	241	Misc. wood products
132	Knitting mills	242	Furniture and fixtures
140	Dyeing and finishing textiles, except wool and knit goods	246	Scientific and controlling instruments; Opcial and health service supplies
141	Floor coverings, except hard surfaces	250	Glass products
142	Yarn, thread, and fabric mills	251	Cement, concrete, gypsum & plaster products
146	Primary aluminum and other primary metal industries	252	Structural clay products
		261	Pottery and related products
150	Misc. textile mill products	262	Misc. nonmetallic mineral & stone products
151	Apparel and accessories, except knit	270	Blast furnaces, steelworks, rolling and finishing mills
152	Misc. fabricated textile products	271	Iron and stell foundaries
160	Pulp, paper, and paperboard mills	281	Cutlery, handtools, and other hardware
161	Misc. paper and pulp products	282	Fabricated structural metal products
162	Paperboard containers and boxes	346	Plastics, synthetics & resins; Soaps & cosmetics; Agricultural chemicals; Industrial & miscellaneous chemicals
166	Screw machine products; Metal forgings & stampings; Misc. fabricated metal products		
172	Printing, publishing, and allied industries except newspapers	351	Transporation equipment
		360	Ship and boat building and repairing
176	Engine and turbines; Construction & material handling machines; Metalworking machinery; Machinery, except electrical, n.e.c.; Not specified machinery	362	Guided missiles, space vehicles, and parts,
		380	Photographic equipment and supplies
		381	Watches, clocks, and clockwork operated
		391	Misc. manufacturing industries and toys,
181	Drugs	460	Electric light and power
186	Electronic computing equipment; Office and accounting machines	462	Eletric and gas, and other combinations
		470	Water supply and irrigation
190	Paints, varnishes, and related products	471	Sanitary services
200	Petroleum refining	636	Grocery stores; Retail bakeries; Food stores, n.e.c.

Table B.1: List of sectors in the ALM regressions

Table B.2: Changes in task intensity and skill ratio across sectors and automation (auto90)

	(1) Δ Nonroutine analytic	(2) Δ Nonroutine interactive	(3) Δ Routine cognitive	(4) Δ Routine manual	(5) Δ Nonroutine manual	(6) Δ H/L
Panel A: 1970 - 80, n=67						
Share of automation patents in machinery	0.78	3.58	-17.72***	-10.55***	-0.84	0.11**
	(3.48)	(4.28)	(4.19)	(3.71)	(5.09)	(0.05)
Δ Computer use 1984 - 1997	-7.16	-2.99	-18.92***	-3.26	14.86*	0.08
	(5.71)	(7.03)	(6.88)	(6.09)	(8.36)	(0.09)
Intercept	0.93	2.14*	4.32***	3.39***	-1.71	0.04***
	(1.00)	(1.23)	(1.21)	(1.07)	(1.47)	(0.02)
R^2	0.02	0.01	0.31	0.12	0.05	0.08
Weighted mean Δ	-0.05	2.17	-0.90	1.49	0.42	0.07
Panel B: 1980 - 90, n=67						
Share of automation patents in machinery	8.94*	13.25**	-25.33***	-13.78***	9.70**	0.73***
	(5.39)	(6.20)	(4.94)	(4.26)	(4.70)	(0.19)
Δ Computer use 1984 - 1997	24.76**	22.96*	-13.42	-1.55	-5.38	0.39
	(10.34)	(11.90)	(9.48)	(8.17)	(9.02)	(0.37)
Intercept	-3.15*	-1.22	3.56**	1.70	-2.40	-0.06
	(1.77)	(2.03)	(1.62)	(1.40)	(1.54)	(0.06)
R^2	0.13	0.13	0.32	0.14	0.06	0.21
Weighted mean Δ	1.86	4.17	-2.22	-0.59	-1.74	0.11
Panel C: 1990 - 98, n=67						
Share of automation patents in machinery	9.20**	10.64*	-13.40***	-6.22	3.91	0.42***
	(4.56)	(6.20)	(5.11)	(4.18)	(4.75)	(0.12)
Δ Computer use 1984 - 1997	27.30***	28.17**	-25.09***	-26.11***	8.05	0.73
	(8.27)	(11.25)	(9.27)	(7.58)	(8.61)	(0.22)
Intercept	-2.93**	-1.94	2.23	2.41*	-2.55*	-0.08**
	(1.44)	(1.96)	(1.61)	(1.32)	(1.50)	(0.04)
R^2	0.20	0.14	0.20	0.19	0.03	0.29
Weighted mean Δ	2.45	3.79	-3.44	-2.36	-0.79	0.09

Standard errors are in parentheses. Colums (1) to (5) of Panels A to C each presents a separate OLS regression of ten times the annual change in industry-level task input between the endpoints of the indicated time interval (measured in centiles of the 1960 task distribution) on the share of automation patents in machinery (defined with the 90th percentile threshold) and the annual percentage point change in industry computer use during 1984 - 1997 as well as a constant. In Column (6), the dependent variable is the ratio of high-skill (college graduates) to low-skill (high-school graduates and dropouts) workers. Estimates are weighted by mean industry share of total employment in FTEs over the endpoints of the years used to form the dependent variable. * p<0.1; ** p<0.05; *** p<0.01



(a) Change in routine cognitive tasks and automation intensity

(b) Change in routine manual tasks and automation intensity

Figure B.3: Scatter plots of routine tasks changes and automation intensity (auto 95) in 1980-1998 in the United States. The list of sectors is given in Table B.1

that nearly all of the decline in routine tasks due to computerization came from within educational group changes.

Table B.3: Changes in task intensity and skill ratio across sectors and automation (auto95) by skill groups

	(1) Δ Nonroutine analytic	(2) Δ Nonroutine interactive	(3) Δ Routine cognitive	(4) Δ Routine manual	(5) Δ Nonroutine manual
Panel A: Aggregated within-industry change					
Share of automation patents in machinery	9.53**	17.97***	-26.66***	-17.09***	12.57***
	(4.53)	(5.39)	(4.83)	(3.90)	(4.30)
Δ Computer use 1984 - 1997	24.91***	23.81***	-17.75***	-11.53**	0.47
	(6.36)	(7.56)	(6.79)	(5.48)	(6.03)
Intercept	-2.36**	-1.01	2.05*	1.73*	-2.37**
	(1.03)	(1.22)	(1.10)	(0.89)	(0.98)
R^2	0.26	0.27	0.39	0.29	0.12
Weighted mean Δ	2.05	3.88	-2.62	-1.29	-1.34
Panel B: Within industry: High school dropouts					
Share of automation patents in machinery	2.41	13.61	-26.19***	-5.80	4.56
	(7.89)	(10.85)	(6.94)	(6.22)	(6.35)
Δ Computer use 1984 - 1997	11.70	18.08	15.84	8.68	-9.95
	(11.08)	(15.24)	(9.74)	(8.73)	(8.91)
Intercept	-4.47**	-8.45***	0.87	0.55	1.16
	(1.79)	(2.47)	(1.58)	(1.41)	(1.44)
R^2	0.02	0.05	0.19	0.02	0.02
Weighted mean Δ	-2.56	-4.73	1.20	1.39	0.04
Panel C: Within industry: High school graduates					
Share of automation patents in machinery	-7.08	6.50	-26.09***	-13.43***	9.62*
	(5.47)	(7.05)	(5.64)	(4.25)	(5.37)
Δ Computer use 1984 - 1997	9.30	-0.76	-14.39*	-2.86	6.71
	(7.69)	(9.90)	(7.92)	(5.96)	(7.54)
Intercept	-2.86**	2.19	2.25*	0.00	-1.43
	(1.24)	(1.60)	(1.28)	(0.97)	(1.22)
R^2	0.04	0.01	0.30	0.14	0.06
Weighted mean Δ	-2.03	2.57	-1.88	-1.45	0.30
Panel D: Within industry: Some College					
Share of automation patents in machinery	-11.94	-7.49	-4.92	-5.92	12.48*
	(8.04)	(7.31)	(6.01)	(5.72)	(6.56)
Δ Computer use 1984 - 1997	7.05	13.85	-14.68*	-14.11*	9.14
	(11.29)	(10.26)	(8.44)	(8.03)	(9.20)
Intercept	-1.10	0.31	0.38	2.21*	-2.74*
	(1.83)	(1.66)	(1.37)	(1.30)	(1.49)
R^2	0.04	0.04	0.06	0.07	0.07
Weighted mean Δ	-0.97	1.78	-2.17	-0.33	-0.43
Panel E: Within industry: College graduates					
Share of automation patents in machinery	-6.54	-7.28**	-11.58*	-7.70	16.00***
	(4.25)	(3.59)	(6.48)	(7.74)	(6.03)
Δ Computer use 1984 - 1997	14.44**	9.29*	-5.55	-7.69	11.14
	(6.00)	(5.06)	(9.14)	(10.91)	(8.50)
Intercept	-0.94	0.17	-1.22	-0.14	-5.35***
	(0.97)	(0.82)	(1.48)	(1.77)	(1.38)
R^2	0.01	0.09	0.06	0.03	0.14
Weighted mean Δ	0.69	0.99	-2.93	-1.86	-2.40
Panel F: Decomposition of automation effects into within and between education group					
Explained task Δ	0.73	1.38	-2.04	-1.31	0.96
Within educ groups (%)	-64.01	15.75	72.28	54.60	80.78
Between educ groups (%)	164.01	84.25	27.72	45.40	19.22

n in Panels A-D is 69 and in Panel E it is 68 consitent CIC industries. Standard errors are in parentheses. Each column of panels A - E presents a separate OLS regression of ten times the annual change in industry-level task input for the relevant education group (measured in centiles of the 1960 task distribution) during 1980 - 1998 on the the share of automation patents in machinery (defined with the 95th percentile threshold) and the annual percentage point change in industry computer use during 1984 - 1997 as well as a constant. Estimates are weighted by mean industry share of total employment (in FTEs) in 1980 and 1998. The 'explained' component in Panel F is the within-industry change in the task measure predicted by the share of automation patents in regression models in Panel A. * p<0.1; ** p<0.05; *** p<0.01