Induced Automation: Evidence from Firm-level Patent Data

Antoine Dechezleprêtre David Hémous Morten Olsen
Carlo Zanella*

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Abstract

Do higher wages lead to more automation innovation? To answer this question, we first use the frequency of certain keywords in patent text to create a new measure of automation innovation in machinery. We show that our measure is correlated with a reduction in routine tasks in a cross-sectoral analysis in the US. Second, we combine macroeconomic data from 41 countries with geographical information on firms' patent history to build firm-specific measures of low- and high-skill wages. In firm-level panel regressions, we find that an increase in low-skill wages leads to more automation innovation with an elasticity of 2 to 5. Our analysis covers 58% of global international automation patents. Placebo regressions show that the effect is specific to automation innovations. Third, we focus on a specific labor market shock, the German Hartz reforms, and show that they reduced automation innovations by foreign firms relatively more exposed to Germany.

*Antoine Dechezleprêtre, OECD, David Hémous, University of Zurich, Morten Olsen, University of Copenhagen and Carlo Zanella, University of Zurich. David Hémous gratefully acknowledges the financial support of the European Commission under the ERC Starting Grant 805007 AUTOMATION. We thank Daron Acemoglu, Kirill Borusyak, Lorenzo Casaburi, Patrick Gaule, Michael McMahon, Pascual Restrepo, Joachim Voth and Fabrizio Zilibotti among others for helpful comments and suggestions. We also thank seminar and conference participants at the University of Zurich, Swiss Macro workshop, the University of Copenhagen, the TRISTAN workshop in Bayreuth, the University of Bath, London Business School, the NBER Macroeconomics Across Time and Space Conference, the NBER Summer Institute, the AlpMacro Conference, LMU, Oxford University, Helsinki Graduate School of Economics, TSE, Ecares, Collège de France, Berkeley, EIEF, EC-OECD and IMT Lucca. We thank Amedeo Andriollo, Jan Fasnacht, Selina Schön and Shi Suo for fantastic research assistance.

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1 Introduction

Do higher wages lead to more labor-saving innovations? And if so, by how much? Automation technologies progress rapidly and political campaigns are pushing for higher minimum wages. Therefore, answering these questions is of central importance, in particular because induced automation innovations may affect the long-term effects of these policies. To do so requires overcoming two challenges: identifying automation innovations and isolating exogenous variation in labor costs from the perspective of innovating firms. Accordingly, our paper makes two contributions: we develop a new measure of automation innovations based on patent data and we exploit firm-level variation to establish a causal effect of an increase in labor costs on automation innovations.

For our classification, we aim at identifying automation innovations that allow for the replacement of workers with machines in certain tasks. We focus on patents in machinery for which our identification strategy is ideally suited. Our classification follows a two-step procedure: we first classify technology categories (IPC and CPC codes) using patent text and then patents using their technology categories. This classification is transparent, covers a wide range of automation technologies, and can be built at a highly disaggregated sectoral level. We then reproduce the cross-sectoral analysis of Autor, Levy and Murnane (2003) but add a measure of the automation intensity of equipment. We find that in the United States, sectors that use automation-intensive equipment saw larger decreases in routine tasks.

A challenge for identification is that at the country level, technology and wages are co-determined. To find exogenous variation in labor costs, we exploit the fact that automation innovators are often equipment manufacturers which sell their machines to downstream firms in various countries. This is key for our identification strategy. Adapting the methodology of Aghion, Dechezleprêtre, Hémous, Martin and Van Reenen (2016, henceforth ADHMV), we construct a measure of firms' international exposure. We then compute weighted averages of low- and high-skill labor costs, specific to the innovating firms, using country-level data. These firm-specific labor costs (referred to as wages for simplicity) proxy for the average labor cost paid by the downstream firms of the innovating firms. As a result, an increase in the wage of a country—and with it local demand for automation technology—will affect innovating firms differently, allowing us to analyze their innovation response.

We carry out this empirical strategy as follows. We rely on the PATSTAT database, which contains close to the universe of patents. To proxy for firms' international exposure, we compute the geographical distribution of their machinery patents pre-sample. We conduct our main analysis over the sample period 1997-2011 and use wage data for 41 countries with automation patents for 3,341 firms. We restrict attention to biadic patents (that is patents applied for in at least two countries). The firms in our sample account for 58% of global automation innovations. We find a substantial effect of wages on automation innovations: higher low-skill wages lead to more automation innovations with an elasticity between 2 and 5 depending on specification. Higher high-skill wages tend to reduce automation, a finding in line with the capital-skill complementarity hypothesis (Krusell, Ohanian, Rios-Rull and Violante, 2000).

Further, we expand on the methodology of ADHMV by including country-year fixed effects for the innovator home country and sometimes excluding the home country from the wage variable. In these specifications, we identify the effect of wages on automation innovations by comparing how firms (say two German firms) respond to shocks on foreign wages (say US wages) depending on their market exposure. We also measure non-automation machinery innovations which we use as a placebo. Importantly, we find that our results are specific to automation innovations and do not extend to non-automation innovations in machinery.

In a second exercise, we focus on a specific labor market shock, namely the Hartz reforms in Germany in 2002-2004. The Hartz reforms are credited with increasing labor supply and reducing labor costs notably for low-skill workers, which should reduce automation innovations. We find that the Hartz reforms reduced the relative amount of automation innovation undertaken by foreign firms highly exposed to Germany, both in levels and relative to non-automation innovations in machinery.

The theoretical argument that higher wages should lead to more labor-saving technology adoption (e.g. Zeira, 1998) or innovation is well-understood. In Hémous and Olsen (forthcoming) and Acemoglu and Restrepo (2018a), wages affect the direction of innovation which can take the form of automation or the creation of new tasks.

There is a limited empirical literature looking at the effect of wages on technology adoption or innovation.[1] On adoption, a few papers show that labor market conditions affect labor-saving technology adoption in agriculture (Hornbeck and Naidu, 2014, and Clemens, Lewis and Postel, 2018), or manufacturing (Lewis, 2011). Lordan and Neumark

[1]In contrast, there is an extensive empirical literature on the effects of technology on wages and employment: see e.g. Autor et. al. (2003), Autor and Dorn (2013) or Gaggl and Wright (2017) for IT, Doms, Dunne and Totske (1997) for factory automation, Graetz and Michaels (2017) or Acemoglu and Restrepo (2020) for robots, Mann and Püttmann (2018), Bessen, Goos, Salomons and van den Berge (2019) and Aghion, Antonin, Bunin and Jaravel (2021) for broader measures of automation.

(2018) find that minimum wage hikes displace workers in automatable jobs and Fan, Hu and Tang (2020) that they lead to the adoption of industrial robots in Chinese firms. Unlike these papers, our focus is on *innovation* instead of *adoption*. This matters because the economic drivers of innovation may differ from those of adoption: innovation may respond differently to macroeconomic variables such as wages; and knowledge spillovers are likely to play a greater role.

On innovation, the literature is scarcer. Acemoglu and Restrepo (2018b) find a positive correlation in cross-country regressions between aging and patenting in robotics and numerical control (though their main focus is on adoption). Our paper differs in three ways: first, we build a broader measure of automation innovation in machinery; second, we are interested in the effect of all wage variations, not just those arising from demographic trends; and third and foremost, we conduct our analysis at the firm instead of the country-industry level. Danzer, Feuerbaum and Gaessler (2020) exploit German immigrant settlement policy to show that increases in labor supply discourage local automation innovation, while we exploit firm-level variation and focus on the effect of labor cost on global innovation.[2] Therefore our contribution is the first firm-level evidence on the effect of wages on automation *innovations*.[3]

A large literature shows that the direction of innovation is endogenous in other contexts (e.g. Acemoglu and Linn, 2004, and Popp, 2002). Here, we build on ADHMV, who use 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]

In contemporaneous work, Mann and Püttmann (2020) use machine-learning techniques to classify automation patents and Webb (2020) uses a dictionary approach similar to ours to identify robot, software and artificial intelligence patents and link them to occupations. We compare our approaches below.

Section 2 contains our first contribution: a classification of automation technologies.

[2] Relatedly, Andersson, Karadja and Prawitz (2020) look at the effect of emigration to the US in the 19^{th} century in Sweden and find that more exposed municipalities experienced an increase in innovation (but they do not identify automation innovations).

[3] Bena and Simintzi (2019) show 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. Process innovations and automation innovations are not the same: some process innovations reduce other costs than labor (say, materials costs) and many automation innovations are product innovations (a new industrial robot is a product innovation for its maker).

[4] Other papers have used ADHMV's methodology including Noailly and Smeets (2015) on innovation in electricity generation, Coelli, Moxnes and Ulltveit-Moe (2020) on the effect of trade policy on innovation and Aghion, Bénabou, Martin and Roulet (2020) on the role of environmental preferences and competition in innovation in the auto industry.

Section 3 introduces a simple model to motivate the analysis. Section 4 describes the data and our empirical strategy. Section 5 contains the results of the main analysis on the effect of wages on automation innovations. Section 6 discusses the event study of the Hartz reforms. Section 7 concludes. The Appendix provides additional robustness checks and details on our methodology.

2 Classifying Automation Patents

In this section, we describe the patent data and our method for classifying automation patents. We then show that our measure of automation predicts a decline in routine tasks (reproducing the analysis of Autor et. al., 2003).

2.1 Our approach to classify patents

Our goal is to identify automation innovations in machinery: that is innovations embedded in equipment goods, such as machine tools or robots, which allow for the replacement of workers in certain tasks. Non-automation innovations, in contrast, may improve energy efficiency, reduce the costs of producing certain machines or increase reliability.

We use two patent databases: the EP full-text database from 2018, which contains the full text of patent applications at the European Patent Office (EPO), and the World Patent Statistical Database (PATSTAT) from Autumn 2018 which contains the bibliographical information but not the text of close to the universe of patents.

In these datasets, the technological characteristics of patents are recorded in technological codes (notably CPC and IPC codes, henceforth C/IPC codes, explained in footnote 8 below). Certain types of technologies such as fossil fuel engines can readily be identified to existing groupings of C/IPC codes. Such a grouping does not exist for automation and we use text analysis to create one for patents in machinery.

We employ a dictionary method on patent data and proceed in four steps: i) We use the existing literature to identify keywords related to automation. ii) For each technology category (defined based on C/IPC codes), we compute the share of patents at the EPO, which contain one of our automation keywords. iii) We use this measure to classify technology categories as automation or not. iv) We then classify worldwide patents as automation if they belong to an automation technology category.

This strategy of first classifying technology categories and then patents has two advantages over classifying patents directly. First, it allows us to include patents without text from PATSTAT,[5] and other researchers can also use our technology category classification to classify patents without text and future patents. Second, the C/IPC codes are by themselves informative of the characteristics of an innovation including whether it relates to automation. While the particular wording of a patent is also a signal of these characteristics, patents are written in varying styles. The same innovation can often be described with or without using our keywords. Conversely, if a patent uses one of our keywords but does not belong to any C/IPC code where this is common, the inclusion of this keyword is frequently uninformative about the nature of the innovation. That is, the wording of a given patent is a weak signal of whether that patent corresponds to automation but the *combined* wording of many patents gives a strong signal of whether a technological code corresponds to automation. Hence, our strategy assumes that technology categories are a better signal of whether a patent is an automation patent or not than the presence of our keywords. Yet, as we do not know which technology categories correspond to automation, we use the text of a subset of patents to classify these first.[6]

Alternatively, we could have read and classified a subset of patents and then used machine-learning techniques to classify other patents or technology categories based on patent text. This is the procedure in Mann and Püttmann (2018), whose results we discuss in Section 2.3 and Appendix A.3. Relying on keywords instead of a training set of patents presents several advantages. First, manually classifying patents as automation is a difficult task which cannot be easily systematized and 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 and a machine-learning algorithm would require a very large training set. Third, by using a few keywords instead of a large training set, our approach is more transparent, easily replicable, and modifiable and, as researchers, we have fewer degrees of freedom since we pick most of our keywords from the literature.

[5] To give an idea of the increase in sample, over the period 1997-2011 there are 3.19 million patent families with patent applications in at least two offices (a condition we will impose in our main analysis). Among those only around $740,000$ have an EPO patent with a description in English.

[6] As a matter of fact, the World Intellectual Property Organization (WIPO) offers on its website a simple tool based on a similar principle: a search engine allows one to identify up to 5 IPC codes most likely to correspond to a set of keywords using the text of the patents in its database.

Table 1: Choice of automation keywords

Keywords	Comments	Source
Automat*	*Automation, automatization* *or automat* at least 5 times* or (automat* or autonomous) with (secondary words or *warehouse* or *operator* or arm or convey* or handling or inspect* or knitting or manipulat* or regulat* or sensor or storage or store or vehicle system or weaving or welding) in the same sentence at least twice	Own / Doms, Dunne and Troske (DDT) / Acemoglu and Restrepo (AR)
Robot*	Not surgical or medical	DDT and AR
Numerical Control	CNC or numeric* control* or (NC in the same sentence as secondary words)	DDT and AR
Computer-aided design and manufacturing	Computer-aided/-assisted/-supported in the same patent as secondary words CAD or (CAM and not "content addressable memory") in same sentence as secondary words	DDT
Flexible manufacturing		DDT
Programmable logic control	Programmable logic control or [PLC and not (powerline or "power line")]	DDT
3D printer	*"3D print*" or "additive manufacturing" or "additive layer manufacturing"*	Own
Labor	*Including laborious*	Own
Secondary words	*Machine or manufacturing or equipment or apparatus or* machining	

Notes: "In the same sentence as control words" refers to at least one control word. Keywords include i) natural adjacent words (i.e. numerical control includes NC, numerically controlled and numeric control), ii) British/American spelling (i.e. labour/labor) and iii) hyphenated adjectives (i.e. computer aided / computer-aided design). We added words in italics, the others come from AR or DDT. See Appendix for details.

2.2 Choosing automation keywords

To tie our hands, we choose most of our keywords from the automation technologies identified in Doms, Dunne and Troske (DDT, 1997) and Acemoglu and Restrepo (AR, 2018b) and complement with a few additional words as described below.[7] In fact, most of our search terms (for simplicity "keywords") correspond to the co-occurrence of several words in the same sentence or patent, or the repetition of these words a sufficient number of times. Table 1 describes the list of our search terms (together with their origin).

We have eight categories of keywords. Five of these, robot*, numerical control, computer-aided design and manufacturing, flexible manufacturing, and programmable logic control are automation technologies in DDT or AR. Simply applying these words may result in false positives. For instance "NC" can refer to either "numerical control" or "North Carolina". To address this issue, we require that these words are either in the same patent or in the same sentence as a list of secondary words, such as machinery or equipment, which indicate that the text describes a machine. Furthermore, we add "automation" and "automatization". The stem "automat*" gathers too many false positives such as "automatic transmission". We resolve this in two ways: either we restrict

[7]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 (2018b) include imports of automation technology and associate specific HS-categories from Comtrade with automation technology.

attention to patents where the frequency is 5 or more or we combine automat* with our secondary words or other words which largely come from technologies described in DDT or AR and often describe tasks (such as manipulat*, regulat* or inspect*). We count patents where automat* and one of these words appear in the same sentence at least twice. Finally, we add 3D printing, which was in its infancy when DDT was written, and "labor" which often indicates that an innovation reduces labor costs. The most important keywords are those associated with "automat*" (see Appendix A.2) and Section 5.6 shows that our main results are robust to only using those.

2.3 Automation technology categories

Defining machinery C/IPC codes. We base our classification on the set of EPO patent applications from 1978 till 2018 with a description in English (1,538,370 patent applications), which we denote Ω_{EPO}. To identify the technological characteristics of patent applications we use their C/IPC codes; each patent usually has several C/IPC codes and the C/IPC codes form a hierarchical classification system.[8] We define "technology categories" based on these codes and we use our keywords to classify technology categories as automation or not.

We take as a starting point technology categories defined as 6-digit C/IPC codes (e.g. B25J13). Because the co-occurrence of technological codes can also be informative about the characteristics of a patent, we extend the definition of technology categories to also include pairs of 4-digit C/IPC codes (e.g. B25J and A61F). Finally, inspired by Aschhoff et al. (2010), we also include the co-occurrence of 4-digit C/IPC codes with the 3 digit codes G05 or G06 (e.g. B25J together with G05 or G06) in the definition of technology categories. The code G05 corresponds to "controlling; regulating" and G06 to "computing; calculating; counting" and Aschhoff et al. (2010) use these combinations to identify advanced manufacturing technologies. We restrict attention to categories which contain at least 100 patents (we group 6-digit codes with the same 4-digit code and less than 100 patents in Ω_{EPO} in common artificial 6 digit codes).

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

Our keywords are best associated with automation in equipment and we accordingly restrict attention to C/IPC codes which belong to certain technological fields. There are 34 technological fields (see Figure A.1). We focus on "machine tools", "handling", "textile and paper machines" and "other special machines" with some adjustments, which we refer to as "machinery" patents (we use machinery and equipment interchangeably).[9] For pairs of 4 digit C/IPC codes or pairings of 4 digit C/IPC codes with G05 or G06 we classify them as belonging to machinery if at least a 4 digit code belongs to that field. This leaves us with 1009 6-digit codes, 1105 pairs of 4 digit codes and 25 groupings of 4 digit codes with G05/G06.

Defining automation C/IPC codes. A patent p is then associated with a set of machinery technology categories MT_p.[10] The combined set of machinery technology categories is $\mathcal{MT} = \cup_{p\in\Omega_{EPO}} MT_p$. A patent is also associated with a text T_p. For each keyword category (automat*, robot, CNC, etc.) we define functions $k^{automat*}(T_p)$, $k^{robot}(T_p)$, $k^{CNC}(T_p)$, etc. which take value 1 if one of the associated keywords is in the text and 0 otherwise. We define $k^{any}(T_p) = \max\{k^{automat*}(T_p), k^{robot}(T_p), k^{CNC}(T_p), ...\}$ which takes value 1 if any of the automation keywords are present. For all machinery technology category $t \in \mathcal{MT}$, we define the prevalence of automation keywords $s(t)$ as the share of patents containing at least one of our keywords:

$$s\left(t\right) = \frac{\sum_{p\in\Omega_{EPO}} 1_{t\in MT_p} k^{any}(T_p)}{\sum_{p\in\Omega_{EPO}} 1_{t\in MT_p}}.$$

We similarly define the prevalence of specific keyword categories. We show that these measures are positively correlated for the main keywords in Appendix A.2.

We manually checked the C/IPC codes extensively and sampled patents from each category to ensure that the procedure delivered reasonable results and adjusted the keywords accordingly. Yet, we never modified the classification after carrying out any

[9]We exclude F41 and F42 which correspond to weapons and ammunition and are in "other special machines". Drones and missiles show up (correctly) as a highly automated technology but do not fit our framework of labor-replacing technology in production. Moreover, 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 computer numerically controlled machine tool patents without C/IPC from the machine tools technological field; and the 6-digit code B62D65 which deals with engine manufacturing even though the rest of the B62D code deals with the vehicle parts themselves. We verify that these additional codes do not qualitatively affect our results.

[10]Technically, we use all C/IPC codes of the patent family associated with the EPO patent application p. See Section 2.4 for the definition of the patent family.

Table 2: Examples of 6-digit C/IPC codes in machinery

Code	Description	# patents	Any	Rank	Robot	Automat*	CNC	labor
		High prevalence						
B25J5	Manipulators mounted on wheels or on carriages	504	0.91	1	0.87	0.27	0.01	0.1
B25J9	Programme-controlled manipulators.	2809	0.86	4	0.79	0.29	0.07	0.08
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	0.06
A01J7	Accessories for milking machines or devices.	395	0.77	9	0.62	0.52	0	0.1
G05B19	Programme-control systems.	7133	0.7	16	0.22	0.39	0.25	0.08
B65G1	Storing articles, individually or in orderly arrangement, in warehouses or magazines	1064	0.58	29	0.18	0.46	0.01	0.11
		Low prevalence						
B23P6	Restoring or reconditioning objects.	613	0.26	266	0.07	0.06	0.05	0.09
A01B63	Lifting or adjusting devices or arrangements for agricultural machines or implements.	264	0.24	306	0.01	0.2	0	0.04
B66D3	Portable or mobile lifting or hauling appliances	215	0.13	677	0.02	0.07	0	0.06

Note: Prevalence of automation keywords for a few 6 digit C/IPC codes. ``Any'' is the share of patents with any of the keywords. ``Rank'' is the rank of the code among 1009 6-digit C/IPC codes in machinery with at least 100 patents. ``Robot'' , ``Automat*'', ``CNC'' and ``labor'' are the shares of patents with at least one keyword from these categories.

regressions.

Table 2 presents examples of 6-digit C/IPC codes in machinery with their prevalence of automation keywords $p(t)$ and their rank according to that measure. It also shows the prevalence of the most important subcategories (automat*, robots, CNC, and labor). C/IPC codes associated with robotics (B25J) have the highest prevalence numbers (91% for B25J5). 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. The last three C/IPC codes are examples with a low prevalence of automation keywords: machine-tools and processes for repairing or reconditioning objects (B23P6), devices typically mounted on tractors (A01B63), and lifting or hauling appliances such as hoists (B66D3), which do not replace workers in new tasks. The table also shows that the different sub-measures do not capture the same technologies: the robotic codes are ranked highly thanks to the prevalence of "robot" keyword, B23Q15 thanks to its CNC prevalence, and B65G1 thanks to its "automat*" prevalence.

Figure 1 gives the histogram of the prevalence of automation keywords for all C/IPC 6 digit codes in machinery. It shows that most C/IPC codes have a low prevalence of automation keywords but a few codes have a very high value. Appendix A.2 gives additional statistics on the prevalence measures.

We define automation technology categories as those with a prevalence measure above a threshold. As our baselines, we choose thresholds at the 90^{th} and 95^{th} percentiles of the distribution of the 6 digit code distribution (within machinery), which are given

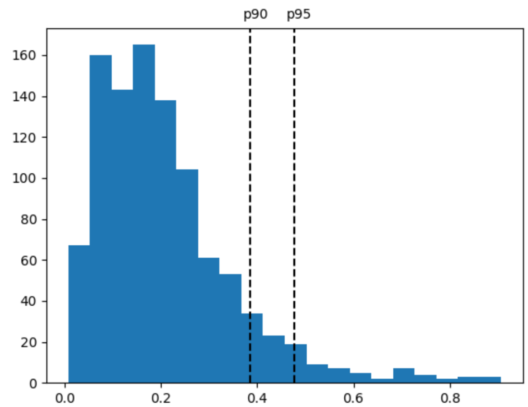


Figure 1: Prevalence of automation keywords for C/IPC 6 digit codes in machinery

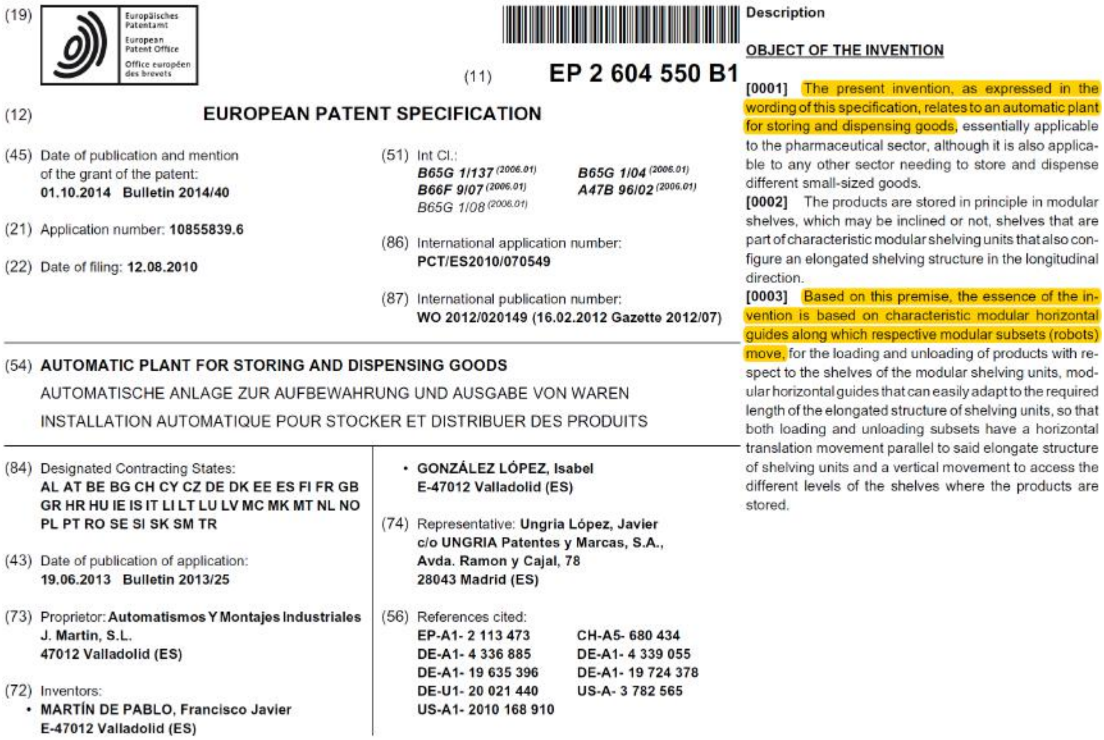
by 0.386 and 0.477, respectively.[11] Therefore, a technology category t belongs to the set of auto90 categories T^{90} if $s(t) > 0.386$ and to the set of auto95 category T^{95} if $s(t) > 0.477$. In Appendix A.2.3, we show that the technology categories with a high prevalence of automation keywords remain the same throughout the period considered. In particular, the correlation between the prevalence measures computed for the first half of the sample and the second half is 0.92.

2.4 Automation patents

We now proceed to classify automation patents. To do so, we use PATSTAT which contains bibliographical information for close to the universe of patents. 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 the first application (which we use as the year of an innovation), the patent offices where the patent is applied for, the identity of the applicants and the inventors, the number of citations received by the patent family and importantly the C/IPC codes associated with the innovation. From now on, we slightly abuse language and refer to a patent family as a patent.

We then define a patent family p in the PATSTAT dataset $\Omega_{PATSTAT}$ as an automa-

[11] Choosing different thresholds is easy and we investigate how robust our results are in Section 5.6.


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

(11) EP 2 604 550 B1

(12) EUROPEAN PATENT SPECIFICATION

(45) Date of publication and mention of the grant of the patent: 01.10.2014 Bulletin 2014/40

(21) Application number: 10855839.6

(22) Date of filing: 12.08.2010

(51) Int Cl.: B65G 1/137 (2006.01) B65G 1/04 (2006.01) B66F 9/07 (2006.01) A47B 96/02 (2006.01) B65G 1/08 (2006.01)

(86) International application number: PCT/ES2010/070549

(87) International publication number: WO 2012/020149 (16.02.2012 Gazette 2012/07)

(54) AUTOMATIC PLANT FOR STORING AND DISPENSING GOODS

AUTOMATISCHE ANLAGE ZUR AUFBEWAHRUNG UND AUSGABE VON WAREN

INSTALLATION AUTOMATIQUE POUR STOCKER ET DISTRIBUER DES PRODUITS

(84) Designated Contracting States: AL AT BE BG CH CY CZ DE DK EE ES FI FR GB GR HR HU IE IS IT LI LT LU LV MC MK MT NL NO PL PT RO SE SI SK SM TR

(43) Date of publication of application: 19.06.2013 Bulletin 2013/25

(73) Proprietor: Automatismos Y Montajes Industriales J. Martin, S.L. 47012 Valladolid (ES)

(72) Inventors:
- MARTÍN DE PABLO, Francisco Javier E-47012 Valladolid (ES)
- GONZÁLEZ LÓPEZ, Isabel E-47012 Valladolid (ES)

(74) Representative: Ungria López, Javier c/o UNGRIA Patentes y Marcas, S.A., Avda. Ramon y Cajal, 78 28043 Madrid (ES)

(56) References cited:

EP-A1- 2 113 473	CH-A5- 680 434
DE-A1- 4 336 885	DE-A1- 4 339 055
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.

Figure 2: Example of an automation patent

tion innovation if it belongs to at least one automation technology category. That is p is an auto95 patent if $\exists t_p \in MT_p$ such that $t_p \in T^{95}$, and similarly for an auto90 patent. Note that close to 80% of automation patents are identified by their 6-digit codes alone (see Appendix A.2).

Figure 2 shows an automated storage cabinet patent. We classify it as automation because it contains the 6 digit code B65G 1 which has a high prevalence measure (0.58, see Table 2). This patent itself contains several keywords: a sentence with the words "automatic" and "storing," and another sentence with "robot". Appendix Figure A.2 shows an automation patent of a similar storage cabinet that belongs to the same C/IPC code but does not contain any keywords and still describes a labor-saving innovation. The supplemental material on our websites provides more examples.

Comparison with Mann and Püttmann (2018). Mann and Püttmann (2018) also classify patents as automation versus non-automation. Our approaches differ in three ways. First, they classify all patents while we focus on machinery. Second, they manually classify a training set and use machine learning to classify US patents in a given period, while we identify technology categories thanks to a dictionary method, so that we (or others) can classify any patent in machinery. Third, they define as automation "a device that carries out a process independently of human intervention", while we seek to identify innovations that replace workers in existing tasks. Therefore, they classify a number of patents related to elevators and printing machines as automation patents, which we do not (see Appendix A.3 where we compare the two approaches in details).[12]

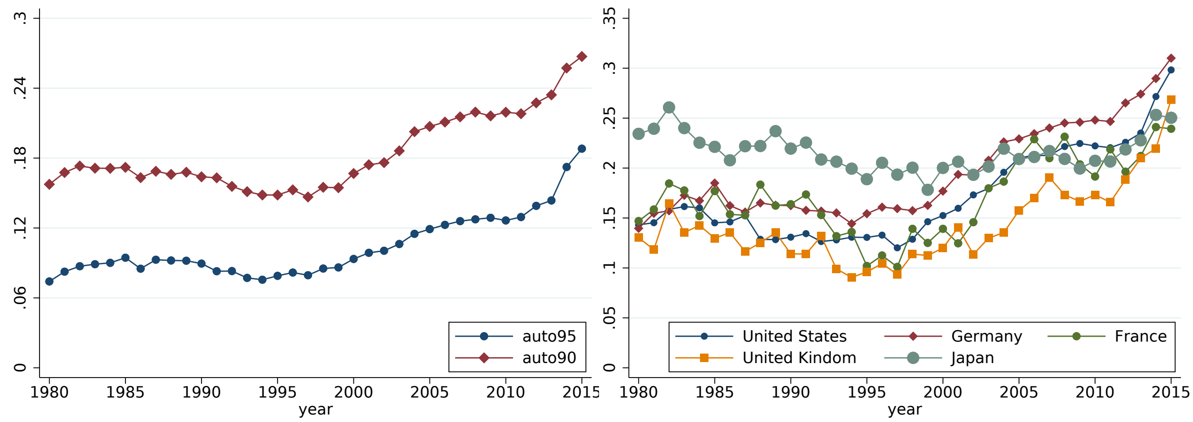
2.5 Trends in automation innovations

To restrict attention to innovations of a sufficient quality, we focus on patent families containing patent applications in at least two countries (referred to as biadic patents). Several studies (e.g. De Rassenfosse et al., 2013, and Dechezleprêtre, Ménière and Mohnen, 2017) have shown that such patents are of higher quality than others.[13] Focusing on biadic patents is also consistent with our empirical strategy which relies on firms' exposure to international markets.

Figure 3 plots the evolution of automation biadic patent families. Panel (a) shows that worldwide the share of automation patents in machinery slightly declined between the mid1980s (9.5% in 1985 for auto95) and the mid1990s (7.6% in 1994 for auto95) before increasing quickly (reaching 18.9% in 2015 for auto95 in 2015). Appendix Figure A.3 reports the raw numbers of auto90 and auto95 patents and their share out of total patents. Figure 3.b shows the trends for auto95 by applicant nationality. Japan's trend is distinct: the share of automation patents is initially higher, but declines in the 80s and 90s before picking up in the 2000s though slower than in the other countries. Germany has the highest automation share in 2015.

[12]Bessen and Hunt (2007) also use keywords to identify software patents. Webb (2020) focuses on matching three technologies (robotics, software and AI) to the occupations that they may replace. To identify the associated patents, he also uses keywords: he uses the algorithm of Bessen and Hunt (2007) for software patents, while robotics patents are defined as those with "robot" or "manipulat" in the title or abstract but exclude the CPC classes A61 or B01 (to avoid surgical robots). We instead focus on all automation innovation in machinery and since our classification is available at the C/IPC level, it can easily be used and extended by other researchers.

[13]We count applications and not granted patents because in certain patent offices, notably Japan, a patent is only formally granted if the applicants request an examination which they often only do when their rights are challenged. Further, biadic patents allow for better comparison across countries, since the same large innovation is typically covered by several small patents in certain offices like the JPO but only one broad patent in others like the USPTO. To restrict attention to patent families of even higher quality, we carry out robustness checks where we use patent citations.



(a) Share of automation patents in machinery worldwide.

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

Figure 3: Share of automation patents in machinery for biadic families

2.6 Automation and routine tasks

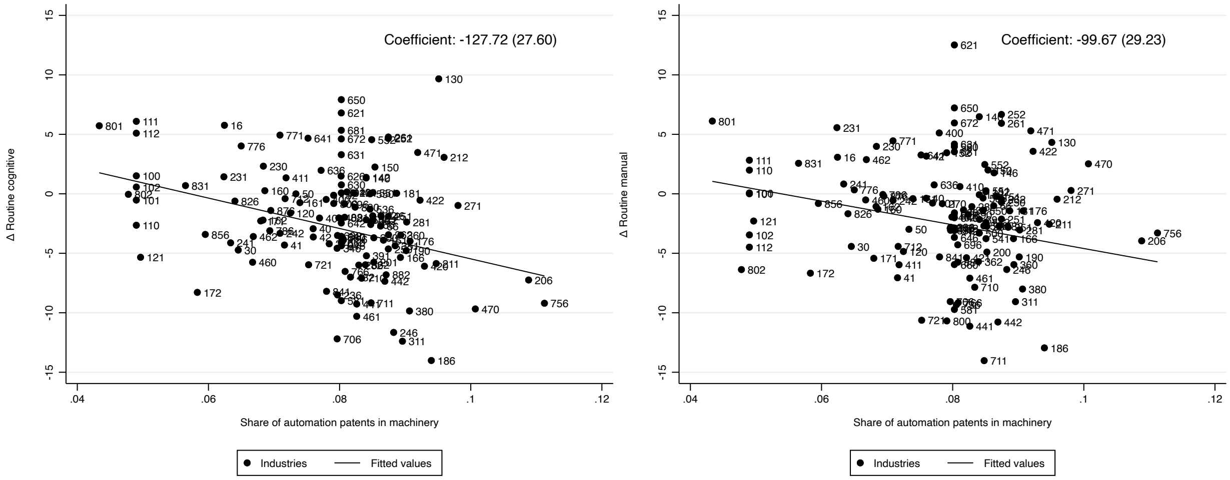
Autor et al. (2003) (henceforth ALM) show that computerization has been associated with a decrease in routine tasks at the industry level on U.S. data from 1960 to 1998. Here, we briefly analyze how our measure of automation relates to routinization, in part as a way to validate our measure of automation before focusing on our main topic: the effect of wages on induced automation innovation.

As ALM, we run industry level regressions of the type:

$$\Delta T_{jk\tau} = \beta_0 + \beta_C \Delta C_j + \beta_{aut} aut_{j\tau} + \varepsilon_{j\tau}. \tag{1}$$

$\Delta T_{jk\tau}$ represents the change in tasks of type k in industry j during period τ and ΔC_j is the measure of the change of computerization in sector j (it is computed over the years 1984-1997 and used for all time periods τ). $aut_{j\tau}$ is our patent-based measure of automation intensity in sector j, period τ. We do not first-difference this measure since patenting is already a measure of the flow of knowledge. We take our task measures directly from ALM, and therefore consider 5 types of tasks: nonroutine analytic, nonroutine interactive, routine cognitive, routine manual, and nonroutine manual. $\Delta T_{jk\tau}$ is measured as 10 times the annual within-industry change in task input measured in percentile of the 1960 task distribution.

To construct $aut_{j\tau}$, we allocate patents in machinery to their sector of use, focusing here on USPTO granted patents. Autor, Dorn, Hanson, Pisano and Shu (2020) match



(a) Change in routine cognitive tasks and automation intensity

(b) Change in routine manual tasks and automation intensity

Figure 4: 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 A.27

USPTO patents with firm-level data from Compustat and thereby provide detailed sectoral information for corporate patents. We use their data to create a (weighted) concordance table from C/IPC 4 digit codes to 4 digit SIC industries. This mapping can be used to allocate patents to sectors of invention. To get the sector of use, we then combine their mapping with the 1997 capital flow table from the BEA (the capital flow table is similar to an input output table but reports the flows in investment goods instead of intermediate inputs). For each sector j and period τ, we compute $aut_{j\tau}$ as the share of automation patents among machinery patents applied for during this period.

We consider 4 periods: 1970-1980, 1980-1990 and 1990-1998 and the joint time period 1980-1998. We restrict attention to sectors with at least 50 machinery patents over the period. This allows us to measure automation intensity for 124 sectors in 1980-1998. Our automation measure auto95 is only weakly correlated with computerization with a coefficient of 0.17 (and -0.19 when we weigh industries by employment). For further details on the data, see Appendix A.4.

Figure 4 provides simple scatter plots of the changes in routine tasks and the share of automation patents in machinery over the years 1980-1998, according to the auto95 definition. There is a clear relationship: sectors with a high share of automation patents experience a larger decline in routine cognitive and routine manual tasks. Given our focus on automation in machinery, a decline in routine cognitive tasks might seem surprising

Table 3: Correlation between changes in task intensity or 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 - 1980; n = 115						
Share of automation patents in machinery	-16.51	119.56**	-81.66*	-62.89	124.64***	1.49**
	(37.17)	(50.18)	(46.02)	(43.35)	(43.09)	(0.68)
Δ Computer use 1984 - 1997	6.38	10.17	-8.04	-7.33	-4.91	0.17*
	(4.98)	(6.72)	(6.16)	(5.80)	(5.77)	(0.09)
Intercept	0.90	-4.04	5.63	5.64	-6.53	-0.06
	(2.29)	(3.10)	(2.84)	(2.67)	(2.66)	(0.05)
R^2	0.02	0.06	0.04	0.03	0.08	0.06
Weighted mean Δ	1.22	4.27	-0.25	0.89	-0.79	0.05
Panel B: 1980 - 1990; n = 115						
Share of automation patents in machinery	88.81***	82.67**	-195.57***	-138.69***	35.49	1.89***
	(29.21)	(36.90)	(29.78)	(31.89)	(29.50)	(0.64)
Δ Computer use 1984 - 1997	18.84***	21.39***	-17.70***	-11.54*	-1.86	0.45***
	(5.56)	(7.02)	(5.67)	(6.07)	(5.61)	(0.12)
Intercept	-8.39	-5.64	16.62	11.53	-3.74	-0.16
	(2.71)	(3.42)	(2.76)	(2.96)	(2.73)	(0.06)
R^2	0.14	0.10	0.30	0.15	0.02	0.15
Weighted mean Δ	2.14	4.89	-2.01	-1.48	-1.33	0.07
Panel C: 1990 - 1998; n=115						
Share of automation patents in machinery	21.71	42.74	-77.53**	-99.72**	40.21	2.15***
	(31.82)	(36.19)	(36.65)	(38.65)	(26.37)	(0.76)
Δ Computer use 1984 - 1997	12.97**	16.30***	-16.91***	-29.51***	9.40**	0.59***
	(5.36)	(6.10)	(6.18)	(6.51)	(4.44)	(0.13)
Intercept	-1.63	-2.31	5.90	9.86	-5.28	-0.22
	(2.83)	(3.22)	(3.26)	(3.43)	(2.34)	(0.07)
R^2	0.05	0.06	0.08	0.17	0.05	0.20
Weighted mean Δ	2.54	4.10	-3.26	-3.43	-0.41	0.08

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 (highschool graduates, some college, 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

at first sight, yet in ALM, routine cognitive tasks are defined as the "adaptability to situations requiring the precise attainment of set limits tolerances or standards", which corresponds to the set of tasks that our automation machines may render superfluous. Metalworkers for instance are one of the occupations with the highest value. Further, note that several machines replace workers in tasks such as inspection and control (an example is given in Figure A.2).

Table 3 reports the results of regressions (1) 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 (in the 90s, the coefficient on routine manual tasks is not significant). For instance, Panel B indicates that a 1 pp increase in the share of automation patents is associated with a 2 and 1.4 centiles decrease in routine cognitive and manual tasks in the 80s. The standardized beta coefficients are larger than for computerization since they correspond to 2.7 and 1.9 centiles in routine cognitive and manual tasks versus 1.3 and 0.8 though the effect of computerization is larger in the 90s.[14] Column (6) looks at the change in the ratio of high-skill workers (defined as college graduates) over low-skill workers (defined as all other workers): we find that sectors with a higher share of automation innovation experience an increase in the skill ratio.

In Table 4 we separate the effect of using automation patents and inventing automation patents. We focus on the consolidated time period 1980-1998. Columns (1) and (4) reproduce the previous results for this time period (and contrary to Figure 4 control for computerization). In Columns (3) and (6), we add the share of automation patents in machinery where we allocate patents to the manufacturing sector (the inventing sector) instead of the using sector (i.e., we skip the capital flow table step when computing our automation variable at the sectoral level). We restrict attention to sectors where there are at least 50 machinery patents with both measures, which reduces the number of sectors. We also find a negative effect and the coefficient on the share of automation patents in the using sector is not too much altered relative to Columns (2) and (5) which carry our initial regression on the same set of sectors. Appendix A.4 includes additional robustness checks using biadic patents, auto90 patents, or an alternative concordance table between C/IPC codes and sectors by Lybbert and Zolas (2014). In all cases, we find a negative effect of the automation share on routine tasks.

[14] The employment-weighted standard deviation in the share of automation patents in the 80s for the included industry is 1.4% and the mean 7.8%, while the standard deviation for computerization is 0.07. Meanwhile routine tasks decline by 2 and 1.5 centiles on average for these sectors.

Table 4: Sector of use versus sector of manufacturing

Dependent variable	Δ Routine cognitive			Δ Routine manual		
	(1)	(2)	(3)	(4)	(5)	(6)
Automation share (using industry)	-146.44*** (26.72)	-179.22*** (34.33)	-154.22*** (33.70)	-120.22*** (28.18)	-84.40** (35.03)	-58.62* (34.34)
Automation share (manufacturing industry)			-25.85*** (8.29)			-26.65*** (8.44)
Δ Computer use 1984 - 1997	-17.70*** (4.74)	-19.02*** (5.93)	-19.28*** (5.65)	-19.43*** (5.00)	-28.15*** (6.05)	-28.42*** (5.76)
R^2	0.24	0.30	0.37	0.19	0.24	0.32
Observations	124	90	90	124	90	90

Standard errors are in parentheses. Each column presents a separate OLS regression of ten times the annual change in industry-level task input between 1980 and 1998 (measured in centiles of the 1960 task distribution) on the share of automation patents in machinery and the annual percentage point change in industry computer use during 1984 - 1997 and a constant. In columns (1) to (3) the dependent variable is the change in routine cognitive tasks and in columns (4) to (6) the change in routine manual tasks. Columns (2) and (5) restrict attention to the same industries as columns (3) and (6). The automation share measures correspond to the share of automation patents in machinery using different mappings between C/IPC codes and industries. "Using industry" allocates patents to their sector of use and "Manufacturing industry" to their sector of manufacturing following the method described in the paper. Automation patents are auto95 patents. Estimates are weighted by mean industry share of total employment in FTEs in 1980 and 1998. * p<0.1; ** p<0.05; *** p<0.01

To summarize, we have now classified machinery patents as automation or non-automation. This is a prerequisite for our main empirical exercise where we focus on the effect of an increase in labor costs on the innovations of equipment producers. Importantly, given a mapping between C/IPC codes and sectors, this classification also delivers a measure of automation at a more detailed sectoral level than alternatives such as robotization. And we have now shown that this measure is uncorrelated with computer use but is associated with a reduction in routine tasks at the sectoral level.

3 A Simple Model

Before carrying out our empirical analysis, we present a simple model to clarify our argument. The model is motivated by the business structure of the largest automation innovators. In 2018, Siemens, the biggest innovator in our sample, had 31% of its workforce but only 14% of its revenue in Germany. Its strongest growing division was the Digital Factory Division which provides a broad range of automation technology to manufacturers across the globe. The annual report (Siemens, 2018) describes how "The Digital Factory Division offers a comprehensive product portfolio and system solutions for automation technologies used in manufacturing industries, such as automation systems and software for factory automation, industrial controls and numerical control systems, motors, drives and inverters and integrated automation systems for machine tools and production machines...". Note that this sentence includes a lot of our keywords. The report is centrally interested in how "Changes in customer demand [for automation technology by downstream manufacturers] are strongly driven by macroeconomic cycles". Interestingly, the report never mentions "cost of labor" as a reason for automation, but instead uses a number of euphemisms such as "increase competitiveness", "enhance efficiency", "improve cost position" and "streamline production". Siemens further discusses how such macroeconomic trends affect its $R\&D$ decisions.

We incorporate these business features into a model built on Hémous and Olsen (forthcoming). A manufacturing good is produced with a continuum of intermediate inputs according to the Cobb-Douglas production function $Y = \exp\left(\int_0^1 \ln y\,(i)\,di\right)$, where $y(i)$ denotes the quantity of intermediate input i. The manufacturing good is the numéraire. 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:

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

$\gamma(i)$ is the productivity of low-skill workers, $\alpha(i)$ is an index which takes the value 0 for non-automated intermediates and 1 for automated intermediates and ν and β are 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, for each non-automated intermediate i, there is an innovator. The innovator creates a machine specific to intermediate i with probability λ if she spends $\theta\lambda^{\psi+1}Y/(\psi+1)$ units of the manufacturing good with $\psi > 0$.

For an automated intermediate input ($\alpha(i) = 1$), the downstream producer is indifferent between using low-skill workers or machines together with high-skill workers in production whenever $w_H^{\nu}p_x^{1-\nu} = w_L/\gamma(i)$. Therefore, the machine producer is in Bertrand competition with low-skill workers. As a machine costs 1, the machine producer charges a price $p_x(i) = \max\{(w_L/\gamma(i))^{\frac{1}{1-\nu}}\, w_H^{-\frac{\nu}{1-\nu}}, 1\}$ such that machines are used if $w_L/\gamma(i) > w_H^{\nu}$. Since the manufacturing good is produced according to a Cobb-Douglas production function, we get $p(i)y(i) = Y$ for all intermediates. We can then derive the profits of the machine producer as $\pi_i^A = \max\left(1 - (\gamma(i)/w_L)^{\frac{1}{1-\nu}}\, w_H^{\frac{\nu}{1-\nu}}, 0\right)\nu\beta Y$.

In turn, at the beginning of the period, the potential innovator solves $\max \lambda\pi_i^A - \theta\lambda^{\psi+1}Y/(\psi+1)$, giving the equilibrium innovation rate $\lambda = \left[\pi_i^A/(\theta Y)\right]^{1/\psi}$. As a result, the number of automation innovations is equal to:

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

This expression is increasing in the low-skill wage w_L and decreasing in the high-skill wage w_H with a magnitude which is larger for a lower ψ. Intuitively, the incentive to replace low-skill workers with machines (and high-skill workers) increases with low-skill wages, leading to a higher demand for machines. The reverse holds for high-skill wages. An upward shift in low-skill worker productivity, $\gamma(i)$, also reduces the number of automation innovations.

To contrast automation with other types of innovations, assume that the production of an intermediate takes place according to:

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

where m_i denotes non-automation "Hicks" machines with quality q_i. Hicks machines are also produced 1 for 1 with the final good. Each period one innovator may improve on the available quality of Hicks machines for intermediate i by a factor μ by investing in R&D. If she spends $\theta_m \lambda_m^{\psi+1} Y/(\psi+1)$ units of the final good, she is successful with probability λ_m. In that case, the innovator becomes the monopolistic provider of Hicks machine i under the pressure of a competitive fringe which has access to the previous technology, and the technology diffuses after one period. Otherwise, the good is produced competitively. The previous analysis on automation innovations remains identical. A successful Hicks innovator can charge a mark-up μ leading to profits $\pi_i^H = (1-\mu^{-1})\,\delta Y$. The innovation rate is then $\lambda_m = \left[(1-\mu^{-1})\,\delta/\theta_m\right]^{1/\psi}$, so that the number of Hicks innovations is a constant given by λ_m. In contrast to automation innovations, the number of non-automation innovations is independent of low- or high-skill wages.

4 Empirical Strategy and Data

We now take the predictions of our model to the data. In this section, we present the regression framework and the data construction. Section 5 will discuss results and identification assumptions.

4.1 Empirical strategy

As mentioned above, innovators in automation technologies are often large companies which sell their automation equipment internationally. Following the logic of our model, the incentives of the downstream producers to adopt automation technology is determined by wages in their local market. As a result, the decision of innovators to pursue automation research in the first place depends on the wages that their potential customers face in different countries.[15] To link patents with their owners, we use Orbis Intellectual Property.[16]

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

$$\begin{aligned} & PAT_{Aut,i,t} \\ = \quad & \exp\left(\begin{array}{c} \beta_{w_L} \ln w_{L,i,t-2} + \beta_{w_H} \ln w_{H,i,t-2} + \beta_X X_{i,t-2} + \beta_{Ka} \ln K_{Aut,i,t-2} \\ +\beta_{Ko} \ln K_{other,i,t-2} + \beta_{Sa} \ln SPILL_{Aut,i,t-2} + \beta_{So} \ln SPILL_{other,i,t-2} + \delta_i + \delta_{j,t} \end{array}\right) + \epsilon_{i,t}. \end{aligned} \tag{3}$$

$PAT_{Aut,i,t}$ denotes the number of biadic automation patent families by firm i for which the first application was filed for in year t. $w_{L,i,t-2}$ and $w_{H,i,t-2}$ denote the average low-skill and high-skill wages (more generally labor costs) faced by the customers of firm i at time $t-2$. We explain below how we proxy for them. Section 3 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 $\beta_{w_H} < 0$ since high-skill workers are complement to machines. $X_{i,t}$ represents a vector of additional controls (labor productivity, average GDP per capita, and GDP gap). Labor productivity captures technology or human capital shocks in the country where machines may be sold, GDP per capita similar shocks but also demand shocks and the GDP gap business cycles fluctuations and changes in demand.

[15] 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.

[16] Orbis IP matches global patent data with the companies identified in Orbis. For companies in the same business group, R&D decisions could happen at the group level, though treating a group as one agent is often too aggressive (as subsidiaries might be in different sectors). 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 and then merge firms with the same normalized name. All other firms are treated as separate entities. E.g., Siemens S.A., Siemens Ltd. or Belgian Siemens S.A. are merged, but Primetals Technologies Germany Gmbh which belongs to the same group remains a separate entity in our regressions.

Ideally, we would measure the cost of labor for automatable tasks or occupations (as identified by Webb, 2020, for instance) instead of low-skill and high-skill workers. Unfortunately, in the absence of good international occupational labor costs data, we cannot pursue this approach. Insofar as low-skill and middle-skill workers are those whose tasks have been more intensely automated, our low-skill wage measure can be used as a proxy for the cost of automatable tasks. This proxy will be particularly good if labor markets are flexible across occupations within education groups or if the labor shocks which move low-skill wages affect low-skill workers similarly across occupations. Otherwise, our use of a noisy measure should result in downward bias.

Following ADHMV, we include controls for knowledge stocks at the firm and country level. $K_{Aut,i,t-2}$ and $K_{other,i,t-2}$ denote the stocks of knowledge in automation and in other technologies of firm i at time $t-2$. 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 $t-2$ (we explain below how these are constructed). These controls ensure that we are not simply capturing the fact that some firms or countries are on different automation trends. δ_i are firm fixed effects. $\delta_{j,t}$ are industry-year fixed effects (in some specifications we only have year fixed effects). The industry j of a firm is the industry of manufacturing and corresponds to its 2 digit industry in Orbis. Appendix Table A.1 gives the distribution of firms and patents across the main industries in our sample. Finally, $\epsilon_{i,t}$ is an error term. 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—Section 5.6 considers alternative timing assumptions.[18] For estimation, we use the ppmlhdfe command from Correia, Guimaraes and Zylkin (2020), which allows us to run Poisson regression models with high-dimensional fixed effects.

[17] We use $\ln(1+K)$, a depreciation rate of 15% and a dummy for whether the knowledge stock is 0.

[18] To control for firm-level fixed effects, our baseline specification uses the Hausman, Hall and Griliches (1984, HHG) method which is the count data equivalent to the within-group estimator. Technically, this method is inconsistent with equation (3) as it requires strict exogeneity and hence prevents the lagged dependent variable from appearing on the right-hand side (which it does here to a limited extent through the knowledge stock $K_{Aut,i,t-2}$). Yet, we show in Section 5.6, that our coefficients of interest are unsurprisingly not affected by Nickell's bias by either removing the stock control or by implementing the Blundell, Griffith and Van Reenen (1999) method, which uses the pre-sample average of the dependent variable to proxy for the fixed effect, in line with the patent literature.

4.2 Macroeconomic data

Our macroeconomic variables come primarily from the 2013 release of the World Input Output Tables (WIOD, Timmer et al. 2015). The database contains information on hourly labor costs across groups of educational attainment (low-, middle- and high-skill workers) for the manufacturing sector from 1995 to 2009 for 40 countries including all major markets (US, Japan, all EU countries of 2009, China, India, Brazil, Russia, etc.). We get similar data from the Swiss Federal Statistical Office to add Switzerland, a large source of patents, to our analysis. For our baseline regressions, we focus on labor costs in manufacturing but check that our results are robust to using labor costs in the entire economy. Although our measures cover all labor costs, we refer to those as wages for simplicity. From the same dataset, we obtain measures of labor productivity (as value added divided by hours) and producer price indices (PPI for the whole economy and manufacturing). We obtain exchange rate and GDP data from UNSTAT and compute the GDP gap to control for business cycles.[19] All macroeconomic variables are deflated in the same way. In the baseline regression, we first deflate nominal values by the local PPI for manufacturing (indexed to 1995), and then convert everything into dollars using the average exchange rate for 1995 the starting year of our regressions. Appendix A.5 provides further details.

In the data, low-skill workers are defined as those without a high-school diploma or equivalent and high-skill workers as those with at least a college degree. Middle- and low-skill wages are very highly correlated so one should interpret our low-skill wage variable as reflecting both.[20]

The countries with the highest low-skill wages in manufacturing in 2009 are Belgium, Sweden and Finland with \$41.9, \$42.2 and \$43.6 respectively and those with the lowest are India, Mexico and Bulgaria with \$0.28, \$0.61 and \$0.71, respectively. The corresponding number for the US is \$13.7. Table 5 summarizes these values and 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. Between 1995 and 2009, the skill premium in the United States rose from 2.46 to 3.02 while it slightly declined in Belgium from 1.56 to 1.46.

[19] We use a HP filter with a smoothing parameter of 6.25 on $\ln(GDP)$ to get the trend, and the GDP gap is measured as the difference between $\ln(GDP)$ and its trend.

[20] For our baseline sample of firms, included in Table 7 below, the correlation between low-skill and middle-skill wages is 0.94 controlling for firm and industry-year fixed effects versus 0.6 for low-skill and high-skill wages. See Appendix Table A.2.

Table 5: Low-skill wages and the skill premium in manufacturing for selected countries

Country	Low-skill wages (1995$)		High-skill wages (1995$)		Skill premium (HSW/LSW)	
	1995	2009	1995	2009	1995	2009
India	0.19	0.28	0.89	1.38	4.79	4.98
Mexico	0.89	0.61	3.46	2.56	3.90	4.21
Bulgaria	1.29	0.71	4.27	1.60	3.32	2.25
United States	11.57	13.67	28.42	41.23	2.46	3.02
Belgium	29.50	41.89	45.98	61.24	1.56	1.46
Sweden	19.92	42.16	34.44	55.92	1.73	1.33
Finland	23.41	43.63	28.10	63.71	1.20	1.46

Note: Wages data, taken from WIOD. The table shows manufacturing low-skill and high-skill wages (technically labor costs) deflated by (manufacturing) PPI and converted to USD using average 1995 exchange rates. Skill-premium is the ratio of high-skill to low-skill wages. The table shows the three countries with the lowest low-skill wages in 2009, the three with the highest and the US.

4.3 Computing firm's market-specific wages and spillovers

Ideally, we would measure the wages paid by the (actual and potential) customers of automation innovators. Since we do not observe them, we build a proxy which is a weighted average of country-level wages where the weights reflect the market exposure of innovators. We define the average low-skill wage faced by a firm's customers $w_{L,i,t}$ as

$$w_{L,i,t} \equiv \sum_c \omega_{i,c} w_{L,c,t}, \tag{4}$$

where $w_{L,c,t}$ is the low-skill wage in country c at time t and $\omega_{i,c}$ is the fixed weight of country c for firm i. We use the same approach to compute average high-skill wages, productivity or GDP per capita.

Firms have different exposure to different markets because of trade barriers, heterogeneous tastes of customers, or, if exporting involves sunk costs, various historical accidents. In reality, the exposure to different markets changes over time, probably in part in response to changes in wages. To ensure that weights are weakly exogenous, we keep them fixed and compute them pre-sample. As a result, we have a shift-share measure and our identification solely relies on how country-level shocks affect firms differently.[21] In fact, had we observed the wages of the customers of automation innovators, those would have suffered from reverse causality, and we would have used our measure as an instrument. Our regression should therefore be viewed as the reduced form of

[21] This approach is in line with our goal of identifying the exogenous effect of an increase in wages on innovation. Two distinct questions are how wage changes and firms' successful innovations affect their decision to enter new markets. Both are interesting but beyond the scope of this paper.

this instrumental approach. We discuss the recent literature on shift-share regressions in detail in Section 5.5.

To measure the weights in the absence of sales data, we use the firm's pre-sample history of patent filing as a proxy for its market exposure. This method follows and expands on that of ADHMV. A patent grants its holder the exclusive right to commercially exploit a technology in a specific country for a limited period of time and inventors must file a patent in each country where they wish to protect their technology. Patenting is costly: a firm needs to hire lawyers, possibly translators and pay filing costs. Further, the publication of a patent can increase vulnerability to imitation and inventors are therefore unlikely to apply for patent protection in a country unless they are relatively certain of the potential market value for the technology (Eaton and Kortum, 1996). Indeed, empirical evidence suggests that inventors do not patent widely and indiscriminately, with the average invention only patented in two countries (Dechezleprêtre et al., 2011).

We compute for each firm the fraction of its patents in machinery protected in each country c for which we have wage data, $\tilde{\omega}_{i,c}$, during the pre-sample period 1971-1994. We restrict attention to patent families with at least one citation (not counting self-citations) to exclude the lowest quality patents. See Appendix A.6 for details notably on EPO patents. Though patenting indicates whether the firm intends to sell in that market, the raw patent count does not reflect market size. Meanwhile a larger market attracts more firms so that the market size per firm will generally not grow 1 for 1 with country size. To account for this we weigh 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.[22] As a result, the weight of country c for firm i is given by:

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

We use 1971-1994 as a pre-sample period since PATSTAT's coverage improves significantly from the 70s and we prefer a long time period as our baseline measure. We show that our results are robust to alternative pre-sample periods and weighing schemes in Section 5.6.[23]

[22] Eaton, Kortum and Kramarz (2011) estimate the elasticity of French exports to GDP of the destination country to be 1 and the elasticity of the number of French exporters to be 0.65. This gives an elasticity of the average export by firm of 0.35. ADHMV use a power of 1 on GDP instead of 0.35.

[23] The weights are also stable over time. To show this, we compute alternative measure of low-skill wages using either patents from 1971-1984 or patents from 1985-1994 to build the weights. For the

Table 6: Descriptive statistics for firms in our baseline regression

Variable	Auto95		Auto90			Auto95	Auto90
Automation pantents	per year	1997-2011	per year	1997-2011	Weights		
Mean	0.78	11.65	0.92	13.79	Largest country	0.47	0.46
Standard deviation	3.97	52.60	4.71	62.55	Second largest	0.17	0.18
p50	0	2	0	2	US	0.21	0.21
p75	0	6	0	7	Japan	0.17	0.15
p90	1	19	2	22	Germany	0.2	0.21
p95	3	42	4	49	France	0.08	0.09
p99	13	184	15	216	UK	0.09	0.09
Number of firms	3341		4903				

ADHMV verify that a similar method accounts well for the sales distribution of major auto manufacturers. Coelli, Moxnes and Ulltveit-Moe (2020) carry out a more systematic exercise and verify such a method accounts well for aggregate bilateral trade flows and firm exports across 8 country groups in a representative panel of 15,000 firms from 7 European countries (regressing patent weights on sales weights gives a coefficient of 0.89 with a s.e. of 0.008). In supplemental material available on our web page, we also show that our patent weights correlate well with trade flows.

Given that knowledge spillovers have a geographical component, we use the location of firms' innovators to build a measure of the stock of knowledge to which a firm is exposed. We follow ADHMV and compute the stocks of automation patents and of other patents in each country. Then, for each firm, we build a weighted average of country-level knowledge stocks, where the weights correspond to the location of their innovators (obtained from PATSTAT) pre-sample in 1971-1994.[24]

4.4 Descriptive statistics

Our basic dataset consists of firms who have applied for at least one biadic automation patent between 1997 and 2011, who have at least one patent before 1995 which can be used to compute weights on geographical coverage and on the location of inventors, and who are not fully domestic (we exclude firms which have only patented in one country pre-sample but checked that our results are very similar if we include them). For the auto95 measure, this corresponds to $3,341$ firms, which are responsible for $35,803$ or 58% of the total number of biadic auto95 innovations.

firms in our baseline regression sample, the correlation between the two variables is 0.85.

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

Appendix Table A.3 shows that our sample of firms covers a very large share of worldwide automation innovations. First, Orbis' coverage is excellent: 93% of all biadic auto95 patent families in 1997-2011 can be assigned to a firm. Second, most heavy patenters had already patented in at least 2 countries pre-sample: the 3341 firms of our sample account for a disproportionate amount of biadic auto95 patent families, 58% of the sample. These biadic patent families themselves account for $179,007$ patent applications, 41.1% of all patent applications (the Table itself reports the total number of applications done by our firms).

Table 6 gives 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 filed 2 auto95 patent applications. The distribution is very skewed and the 99^{th} percentile firm in the sample has filed 184 auto95 patents. The largest country for a given firm has on average a weight of 0.47 (for auto95). To ensure that our results are not driven solely by the largest country, which we refer to as the "home country" of a firm, we will include in some regressions home country-year fixed effects. The second largest country has on average a weight of 0.17. The three countries with the largest weights on average are the United States, Germany, and Japan. Appendix Table A.4 lists the ten biggest automation innovators in our sample.

5 Global Wages and Induced Automation

We present our main results in three steps: First, our baseline regressions use the full variation of firm low-skill wages to estimate the effect of an increase in low-skill wages on automation innovations. Second, we use country-year fixed effects to isolate the contribution of foreign wages. Third, we contrast the results on automation innovations with those on other types of machinery innovations. The rest of the section discusses identification assumptions, robustness checks and additional results including on the minimum wage.

5.1 Baseline results

Table 7 presents the baseline results. The dependent variable is the number of auto95 biadic patent families dated in the year of the first application. We use the years 1997-2011 for the dependent variable and, due to the lag structure, 1995-2009 for the independent variables. Recall that skill-dependent wages are measured in the manufacturing sector and deflated by the PPI in that sector.

Table 7: Baseline regressions: effect of wages on automation innovations (auto95)

Dependent variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.21***	2.83***	1.80**	2.46***	2.32***	2.54***	2.90***	2.67***	3.59***
	(0.51)	(0.73)	(0.74)	(0.75)	(0.81)	(0.84)	(0.78)	(0.84)	(0.94)
High-skill wage		-0.92	-0.88	-1.56**	-1.73**	-1.43**	-2.22***	-2.61***	-1.52*
		(0.71)	(0.67)	(0.64)	(0.72)	(0.71)	(0.72)	(0.79)	(0.80)
Stock automation			-0.13**	-0.13***	-0.13***	-0.13***	-0.15***	-0.15***	-0.15***
			(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Stock other			0.63***	0.64***	0.64***	0.64***	0.65***	0.65***	0.65***
			(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
GDP gap				-3.30	-3.50	-3.00	-4.30*	-4.82*	-2.69
				(2.52)	(2.59)	(2.65)	(2.57)	(2.66)	(2.74)
Labor productivity					0.40			0.91	
					(0.92)			(0.92)	
GDP per capita						-0.31			-1.94
						(1.14)			(1.29)
Spillovers automation							0.60*	0.63**	0.76**
							(0.31)	(0.31)	(0.32)
Spillovers other							-0.27	-0.32	-0.41*
							(0.22)	(0.22)	(0.24)
Fixed effects	F+Y	F+Y	F+Y	F+IY	F+IY	F+IY	F+IY	F+IY	F+IY
Observations	50115	50115	50115	49174	49174	49174	49174	49174	49174
Firms	3341	3341	3341	3329	3329	3329	3329	3329	3329

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed effects regressions (HHG). All regressions include firm and year or year-industry fixed effects. 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. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Column (1) shows the results with only firm and year fixed effects. A higher low-skill manufacturing wage for the customers of an innovating firm predicts more automation innovation. The estimated coefficient is an elasticity so that an increase of 1% in the low-skill wage is associated with 2.2% more automation patents. Column (2) introduces high-skill wages as a control. In all specifications, high-skill wages have a negative (though not always significant) coefficient. Column (3) adds controls for the firm's stock of knowledge: a higher stock of automation knowledge predicts fewer automation innovations. Column (4) adds industry-year fixed effects and controls for the GDP gap. Columns (5) and (6) add controls for labor productivity in manufacturing and GDP per capita. None of these macroeconomic controls have consistent significant effects. Columns (7) to (9) repeat columns (4) to (6) but include knowledge spillovers and find that firms which are exposed to more knowledge in automation technologies innovate more in automation. In all specifications, the coefficient on low-skill wages is highly significant with elasticities between 1.8 and 2.9 for columns (1) to (8) and a larger elasticity of 3.6 in column (9). From column (4) onwards, we also control for industry-year fixed effects (where the industry is that of the innovating firm).

Our analysis focuses on innovation with a high automation content and reflects the behavior of firms that undertake automation innovations. As such these estimates do not directly reflect the average macro response of the economy to an increase in wages (see next section for a further discussion). By comparison, the elasticities of clean and dirty patents wrt. fuel price in ADHMV are slightly smaller (between 0.5 and 3).

In the baseline specification, we cluster at the firm-level to account for auto-correlation in errors. As firms in the same country might be affected by common shocks, we cluster standard errors at the home country (i.e., the country of largest weight) level in Appendix Table A.5. If anything, this tends to reduce the standard error on low-skill wages, a pattern that repeats itself throughout the specifications.[25]

5.2 Country-year Fixed Effects and Foreign wages

Country-level shocks which we have not controlled for may impact both wages and innovation, by affecting the cost of innovation or the demand for automation machines through other channels than wages. A tax reform in Germany, for instance, could affect both German low-skill wages and the incentive to innovate. Shocks that mainly affect firms through their home country can be captured through home country-year fixed effects in which case our estimation procedure relies on variation in foreign wages. Our identification assumption is then that foreign wages are exogenous to the automation innovation of the firm given our set of controls. We discuss a number of potential confounding factors below.

Country-year fixed effects. Columns (1) to (3) of Table 8 reproduce Columns (7) to (9) of Table 7 but add country-year fixed effects, where the country of a firm is still defined as the country with the largest weight (using the headquarters' location to define the home country gives similar results). We still obtain a positive effect of low-skill wages on automation innovations with similar elasticities (between 2.2 and 3.6).

Foreign wages. Columns (4) to (6) go further and only consider the foreign component of wages (and of the other macroeconomic variables). To do so, we decom-

[25] A potential explanation for the negatively correlated error terms is that a successful innovation by one firm reduces the innovation of its competitors as the market is already captured. In addition, standard errors may overstate confidence levels if the number of clusters is small or the size distribution of clusters is skewed. To address this, Appendix Table A.5 also includes p-values for low-skill wages using the BDM bootstrap-t approach of Cameron, Gelbach and Miller (2008). All coefficients remain strongly significant.

pose total low-skill wages $w_{L,i,t}$ into their home and foreign components as $w_{L,i,t} = \omega_{i,D} w_{L,D,t} + \omega_{i,F} w_{L,F,t}$, where $\omega_{i,D}$ is the home weight, $w_{L,D,t}$ the home wage, $\omega_{i,F} = 1 - \omega_{i,D}$ the foreign weight and $w_{L,F,t}$ the average foreign wage. We use the normalized foreign low-skill wage which is defined as $\frac{\omega_{i,F} w_{L,F,0}}{w_{L,i,0}} \log w_{L,F,t}$. The ratio $\frac{\omega_{i,F} w_{L,F,0}}{w_{L,i,0}}$ captures the fact that more internationally exposed firms are more affected by foreign wages and is computed at the beginning of the sample—though we obtain similar results when we use the average value over the whole sample. This specification ensures that our coefficient can be interpreted as an elasticity on total wages: Since $d \log w_{L,i,t} = \frac{\omega_{i,D} w_{L,D,0}}{w_{L,i,0}} d \log w_{L,D,t} + \frac{\omega_{i,F} w_{L,F,0}}{w_{L,i,0}} d \log w_{L,F,t}$, an increase in the normalized low-skill wage by 0.01 corresponds to an increase in total wages by 1% (recall that we have firm fixed effects). Normalized foreign high-skill wages, GDP per capita and labor productivity are defined similarly (as GDP gap is already an average of logs, we directly interact the foreign variables with $\omega_{i,F}$). Once again we find a positive effect of low-skill wages on automation innovation, with somewhat larger elasticities between 4.1 and 5.1. High-skill wages are the only other macro variable with a consistently significant effect, which is negative between -4.3 and -2.

In addition to the lag structure, country-year fixed effects are useful to address reverse causality: if a shock leads German firms to introduce more automation innovations, this will in turn lower German wages. Yet, these German automation innovations are less likely to have a strong effect on non-German wages. Our regressions show that including country-year fixed effects barely affects our coefficient of interest and focusing on foreign wages leads to larger coefficients.

Appendix Table A.6 reproduces the regressions of columns (7) to (9) in Table 7 and of Table 8 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, in line with auto95 being a stricter measure of automation. This also helps explain the magnitude of our elasticities in the previous tables: our analysis focuses on innovations with a high automation content (and therefore most likely to respond to an increase in wages) and one should not take our estimates directly to measure the average macro response of the economy to an increase in wages.

Skill premium and magnitude. In the previous regressions, the coefficients on low-skill and high-skill wages are of a similar magnitude but opposite signs suggesting that a driver of automation innovations is the skill premium. Table 9 directly regresses automation innovation on the log of the inverse of the skill premium. The coefficient on

Table 8: Country-year fixed effects

Dependent variable	Auto95					
	Domestic+Foreign			Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skill wage	2.21**	2.55**	3.56***	4.14***	5.08***	4.14**
	(0.99)	(1.13)	(1.24)	(1.31)	(1.54)	(1.77)
High-skill wage	-2.89***	-2.16**	-1.98*	-4.29***	-2.95**	-4.29***
	(0.94)	(1.05)	(1.05)	(1.29)	(1.46)	(1.39)
GDP gap	4.01	4.94	6.31	-0.72	1.29	-0.73
	(6.85)	(6.89)	(7.16)	(4.49)	(4.84)	(5.12)
Stock automation	-0.16***	-0.16***	-0.16***	-0.16***	-0.16***	-0.16***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Stock other	0.66***	0.66***	0.66***	0.65***	0.65***	0.65***
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Spillovers automation	1.39***	1.38***	1.37***	1.35***	1.32***	1.35***
	(0.47)	(0.47)	(0.47)	(0.46)	(0.46)	(0.47)
Spillovers other	-1.07***	-1.04***	-1.09***	-1.09***	-1.08***	-1.09***
	(0.36)	(0.37)	(0.36)	(0.35)	(0.35)	(0.35)
Labor productivity		-1.68			-2.15	
		(1.76)			(1.58)	
GDP per capita			-3.33*			0.00
			(1.88)			(2.07)
Fixed effects	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	48773	48773	48773	48773	48773	48773
Firms	3324	3324	3324	3324	3324	3324

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed effects regressions (HHG). All regressions include firm, industry-year, and country-year fixed effects. Columns (4) to (6) use normalized foreign macroeconomic variables. Normalized foreign low-skill wages are defined as the log of foreign low-skill wages interacted with a measure of the importance of foreign markets in the total wage. This measure is computed at the beginning of the sample period and equals the foreign weight times the foreign low-skill wage divided by total low-skill wages. Normalized foreign high-skill wages, labor productivity and GDP per capita are defined similarly. Normalized foreign GDP gap is the foreign GDP gap interacted with the foreign weight. See text for details. All regressions include dummies for no stock and no spillover. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 9: Skill premium

Dependent variable	Auto95								
	Domestic+Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill / High-skill wages	2.49***	2.64***	2.48***	2.56***	2.40***	2.65***	4.25***	4.11***	4.24***
	(0.69)	(0.69)	(0.68)	(0.87)	(0.86)	(0.87)	(1.25)	(1.22)	(1.24)
GDP gap	-4.59*	-4.86*	-4.57*	4.24	4.67	5.02	-0.76	-0.25	-0.57
	(2.55)	(2.57)	(2.57)	(6.77)	(6.71)	(6.83)	(4.50)	(4.56)	(4.60)
Labor productivity		0.96			-1.28			-0.43	
		(0.64)			(1.09)			(0.72)	
GDP per capita			-0.04			-1.71			-0.14
			(0.72)			(1.11)			(0.88)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	49174	49174	49174	48773	48773	48773	48773	48773	48773
Firms	3329	3329	3329	3324	3324	3324	3324	3324	3324

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). Columns (1)-(3) include firm and industry-year fixed effects. Columns (4)-(9) include firm, industry-year, and country-year fixed effects. Columns (7)-(9) compute the normalized foreign (log) inverse skill premium as the difference between the normalized (log) foreign low-skill wages and the normalized (log) foreign high-skill wages previously defined. In these columns, GDP gap, GDP per capita and labor productivity also correspond to their normalized foreign values. All regressions include dummies for no stock and no spillovers. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10: Non-automation innovations

Dependent variable	Placebo Machinery								
	Domestic+Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	0.51	0.68	1.73**	-0.07	-0.03	0.77	-0.64	-1.22	-0.80
	(0.60)	(0.69)	(0.69)	(0.80)	(0.91)	(0.95)	(1.19)	(1.29)	(1.23)
High-skill wage	-0.18	0.12	0.79	-0.27	-0.19	0.20	0.33	-0.39	0.24
	(0.71)	(0.65)	(0.75)	(0.97)	(0.91)	(1.02)	(1.18)	(1.30)	(1.33)
GDP gap	-3.39**	-3.04*	-0.07	-1.15	-1.06	0.31	-2.72	-3.87	-3.02
	(1.51)	(1.59)	(1.90)	(3.61)	(3.64)	(3.67)	(2.62)	(2.78)	(2.76)
Stock own	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Stock other	0.55***	0.55***	0.55***	0.56***	0.56***	0.56***	0.56***	0.57***	0.56***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Spillovers own	2.63***	2.66***	2.07***	1.39***	1.39***	1.33***	1.39***	1.35***	1.40***
	(0.40)	(0.41)	(0.45)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Spillovers other	-2.31***	-2.32***	-1.79***	-1.32**	-1.32**	-1.26**	-1.33**	-1.28**	-1.33**
	(0.46)	(0.46)	(0.49)	(0.54)	(0.54)	(0.54)	(0.53)	(0.54)	(0.53)
Labor productivity		-0.66			-0.17			1.18	
		(0.72)			(1.10)			(1.14)	
GDP per capita			-3.08***			-1.85			0.27
			(0.99)			(1.35)			(1.35)
Fixed effects	F+IY	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	114724	114724	114724	114478	114478	114478	114478	114478	114478
Firms	7696	7696	7696	7693	7693	7693	7693	7693	7693

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). Columns (1)-(3) include firm and industry-year fixed effects, while (4)-(9) include firm, industry-year, and country-year fixed effects. In Columns (7)–(9) the macroeconomic variables are the normalized foreign variables previously defined. Stock and spillover variables are calculated with respect to the dependent variable (placebo machinery). Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

the inverse skill premium is always of the same magnitude as that on low-skill wages in previous specifications and highly significant.

To illustrate the macroecomic magnitude of our coefficients and the effect of spillovers and stock variables, we run a simulation in Appendix A.7 where we uniformly and permanently decrease the global skill premium by 10%. This increases the share of automation innovations in machinery by 4.8 p.p. over 1997-2011, with 2.7 p.p. coming from the adjustment of stocks and spillovers. Combining this effect with the coefficients from Columns (1) and (4) in Table A.28, we find that, over a decade, such an increase would be associated with a decline in routine cognitive tasks of 7 centiles and a decline in routine manual tasks of 5.8 centiles (for comparison routine cognitive and manual tasks have declined at 4.8 and 2.4 centiles per decade).

5.3 Non-automation innovations

Is the effect of wages on automation innovations specific to automation or does it affect machinery patents in general? To answer this question, we now look at "placebo" regressions. Specifically, we consider the set of machinery patents and exclude any patent which has a technology category with a prevalence measure above the 60^{th} percentile of the distribution of C/IPC 6-digit codes in the machinery (0.2091). We refer to these as "placebo machinery" innovations. We recompute knowledge stocks and spillover variables for these innovations ("own") and for all innovations except those ("other"). Table 10 reports the results. Columns (1) to (3) correspond to the baseline regressions with firm and industry-year fixed effects. Low-skill wages only have a positive and significant effect in column (3), but even in that case the coefficient is statistically significantly smaller than with automation (and loses significance with other deflators). Columns (4) to (6) repeat the same regressions but add country-year fixed effects and columns (7) to (9) focus on foreign wages. Neither low-skill wages nor any other macroeconomic control variable has an effect on placebo machinery innovations. The sign of low-skill wages even flip in columns (7) to (9).[26] We view this exercise as validating both our empirical approach and our measure of automation.

5.4 Threats to identification

The previous results establish a correlation between the development of automation technology by a firm and the wages faced by its customers. This relationship is persistent and stable to the inclusion of a number of control variables. Adding country-year fixed effects controls for unobservable shocks to the home country and make it unlikely that reverse causality is the driver. We are interested in the causal effect of an increase in wages on the firm's propensity to introduce automation innovation (in our model, we would like to identify $\partial\lambda/\partial w_L$). Wages are an equilibrium outcome, but what matters for identification is that they are exogenous to the inventor. Changes to labor supply or labor costs in manufacturing arising from regulation, shifts in demand in other sectors or demographic changes present ideal variation from this perspective, as they are unlikely to affect firms' automation innovation decision through other channels than wages. Consequently, threats to identification arise from other foreign shocks which are correlated with wages and other drivers of automation. We now look at these in detail. In Section 6, we will focus on a specific labor-market shock namely the Hartz reforms in Germany.

Foreign demand shocks in manufacturing. The biggest threat to identification comes from foreign demand shocks in manufacturing which might drive both wages and

[26] Conditioning on the 60^{th} percentile is not important and we obtain similar results with machinery innovations excluding auto95 or auto90. Further, replacing low-skill and high-skill wages with the skill premium in these regressions gives insignificant coefficients. (Results not shown).

the demand for automation equipment. Some aspects of this have already been captured by the controls in Table 8 (GDP gap, GDP per capita, and labor productivity). We look at additional controls in Table 11 which contains country-year fixed effects (and looks at foreign variables only in Columns (5) to (10)). i) Columns (1) and (5) directly control for the share of the manufacturing sector in the economy, which is built analogously as our wage variable. ii) Conversely, increased offshoring in the foreign country might reduce both wages and the willingness to buy automation technology. We construct a measure of offshoring at the country-level based on the methodology of Timmer et al. (2014): the share of foreign value added in the gross value added in manufacturing. Then, as for other variables, we build the firm-specific value, and control for it in Columns (2) and (6). iii) In addition, the real interest rate covaries with the business cycle and is potentially an important determinant of the cost of purchasing equipment. Columns (3) and (7) control for the real yield on 10-year government bonds.[27] None of these control variables have a consistent effect on automation innovations and importantly they do not alter the wage coefficients significantly.

Low-skill labor productivity shocks. An additional concern might come from low-skill specific labor productivity shocks (captured by $\gamma(i)$ in Section 3) such as a change in low-skill human capital. Though we control for overall labor productivity, we cannot directly control for this. Yet, a positive shock to $\gamma(i)$ would be associated with higher wages and less automation innovation and would correspondingly bias our estimates downwards.

Innovation shocks. A recent period of higher than usual automation innovation might leave both wages and the incentive for further innovation low, creating a spurious positive correlation. To address this, we construct a measure of recent innovation in the same manner as we do for the low-skill wages: for each country we compute the number of automation innovations (from our set of firms or others) applied for in the last three years and then build firm-specific measures. We build a similar control for other innovations. The results in Columns (4) and (8) of Table 11 show that our results carry through (the low-skill wage coefficient in column (4) is just at the margin of significance).

Shocks to the inventing firm. Labor costs also affect the inventing firms through its production and R&D costs. Country-year fixed effects alleviate this concern as long as production and R&D are concentrated in the home country. For production costs, if a firm serves a foreign market through local production instead of exporting, higher

[27] We get data for 21 countries (AT AU BE CA CH DE DK ES FI FR GB GR IE IT JP KR LU NL PT SE US) from the IMF and the OECD and deflate nominal yields using the manufacturing PPI.

Table 11: Additional controls

Dependent variable	Auto95							
	Domestic+Foreign				Foreign			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	2.84**	2.97***	2.49**	2.01	4.58***	4.97***	5.06***	7.04***
	(1.41)	(1.15)	(1.14)	(1.24)	(1.75)	(1.50)	(1.53)	(1.72)
High-skill wage	-1.90	-1.46	-1.98*	-1.26	-3.24**	-3.02**	-2.79*	-3.97***
	(1.18)	(0.99)	(1.04)	(0.99)	(1.48)	(1.45)	(1.44)	(1.46)
GDP gap	4.30	5.04	5.83	7.02	2.88	1.99	2.07	3.21
	(6.78)	(6.87)	(6.98)	(6.78)	(5.32)	(5.27)	(4.82)	(4.93)
Labor productivity	-2.19	-2.69	-1.56	-2.45	-1.99	-1.71	-2.37	-5.14**
	(2.21)	(1.67)	(1.78)	(1.85)	(1.63)	(1.54)	(1.58)	(2.09)
Manufacturing share	3.69				-6.03			
	(9.34)				(8.72)			
Offshoring		10.33*				-1.93		
		(5.51)				(4.49)		
Long-term interest rate			0.09				-0.03	
			(0.11)				(0.06)	
Recent innovation own				-2.77**				1.24
				(1.27)				(0.92)
Recent innovation other				1.79**				-0.34
				(0.77)				(0.79)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	48773	48773	48467	48773	48773	48773	48356	48773
Firms	3324	3324	3299	3324	3324	3324	3294	3324

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). All columns include firm, industry-year, and country-year fixed effects. "Recent innovation own" denotes the log of a weighted average of automation innovations in the customer's countries in the last 3 years and "recent innovation other" the same value for all other innovations in these countries. In Columns (4) and (8), wages, GDP gap, labor productivity, and the long-term interest rate are recomputed using weights for the limited set of countries for which interest rates are available (see text). In columns (5)-(8) wages, GDP gap, and labor productivity correspond to their normalized foreign values as previously defined. Normalized foreign recent innovation is defined like the normalized foreign low-skill wages as the interaction between the foreign value and a measure of the importance of foreign markets in the total variable. This measure is computed at the beginning of the sample period and equals the foreign weight times the foreign recent innovation divided by total recent innovation. Normalized foreign manufacturing share, offshoring and long-term interest rates are defined similarly to the normalized foreign GDP gap as the interaction between their foreign component and the foreign weight. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

foreign low-skill wages in production would increase the price of machines and therefore bias our coefficient on low-skill wages toward 0. For R&D costs, we can address the potential issue by re-building our firm-specific macro variables using weights based on the location of inventors instead of patent offices. Appendix Table A.7 shows in horse-race regressions that the coefficient on the baseline low-skill wages remains positive and significant but the coefficient on low-skill wages weighted by inventor weights is small and insignificant. These regressions provide an additional placebo test as they treat firms with the same macroeconomic shocks but weigh them differently.

Placebo. Throughout, our coefficients on low-skill wages should be compared those from regressions with the placebo machinery innovations, which show persistently little effect from low-skill wages on innovation. Therefore, if our result on the effect of low-skill wages on automation innovations came from a bias, then that bias would have to be absent for other types of machinery innovations.

5.5 Shift Share

A recent literature addresses the identifying assumptions behind the shift-share set-up in linear regressions. In this respect, it is important for our identification strategy that the weights are pre-determined; that is firms do not choose where to patent based on their expectation of future wages. Appendix Table A.8 demonstrates that country-level growth rates in low- and high-skill wages between 1995 and 2000 have no predictive power on firm weights in 1995. Appendix Table A.9 shows that our results are robust to using weights computed only up to 1989 or to dropping the first 5 years of the regression.

We interpret our results through the lens of Borusyak, Hull and Jaravel (2018) who show, in the language of our setting, that the random assignment of wage shocks conditional on weights can be sufficient for identification. The inference is valid if either there is a large number of countries (such that the Herfindahl index of weights tends toward 0) affected by independent shocks (controlling for year and firm fixed effects); or the correlation of shocks within a country decays sufficiently rapidly that a large number of country-years is sufficient (see Appendix A2 in their paper).[28] They advise practitioners to use appropriate controls to capture omitted variables. We follow this approach by including a large set of controls and country-year fixed effects in our regressions. They recommend applying the standard error correction of Adão, Kolesár and Morales (2019).

Adão et. al. (2019) show that applications with the shift-share design often lead to an over-rejection of the null. In the language of our application, the problem arises when the residual errors of firms with similar country-distributions are correlated and it is not solved by standard clustering. They derive a formula for correcting standard errors in an OLS, which we cannot use directly since we employ a Poisson estimator. Deriving the corresponding correction for the Poisson estimator is beyond the scope of this paper. Instead, we implement a Monte Carlo simulation similar to theirs and show that we do not have the same problem of over-rejection.

Specifically, we replicate our main regressions of Columns (7) to (9) in Table 7 and of Table 8. For each firm, we keep the automation activity, the stocks of innovations, the spillover variables, as well as the distribution of country-weights based on actual data. For each country, we sample with replacement the entire path of macroeconomics variables (wages, labor productivity, GDP per capita, and GDP gap) from the existing set of all countries with 1000 draws. Table 12 reports the p-values of the coefficients on

[28] The Herfindahl index is 0.13 and 0.09 when only foreign weights are included. At the country-year level, the corresponding values are 0.009 and 0.006.

Table 12: Monte-Carlo simulations

Dependent variable	Auto95								
	Domestic+Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.90	2.67*	3.59**	2.21***	2.55***	3.56**	4.14**	5.08**	4.14***
	[0.105]	[0.072]	[0.015]	[0.006]	[0.003]	[0.019]	[0.018]	[0.023]	[0.000]
High-skill wage	-2.22**	-2.61	-1.52	-2.89***	-2.16*	-1.98**	-4.29*	-2.95**	-4.29
	[0.046]	[0.125]	[0.156]	[0.005]	[0.065]	[0.010]	[0.062]	[0.029]	[0.205]
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GDP gap	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labor productivity		Yes			Yes			Yes	
GDP per capita			Yes			Yes			Yes
Fixed effects	F+IY	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	49174	49174	49174	48773	48773	48773	48773	48773	48773
Firms	3329	3329	3329	3324	3324	3324	3324	3324	3324

Note: Marginal effects; P-values in brackets. The independent variables are lagged by two periods. Estimation is done by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(3) include firm and industry-year fixed effects. Columns (4)-(9) add country-year fixed effects. Columns (7)-(9) use the normalized foreign macro variables previously defined. All regressions include controls for stocks and spillovers. P-values are computed by sampling with replacement the entire path of macroeconomic variables for each firm with 1000 draws. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

low-skill wages and high-skill wages based on the simulated distribution of coefficients. The p-values are not markedly different than the ones obtained assuming the standard normal distribution. In particular, the coefficients of interest on low-skill wages are significant at least at the 10% level (except in column 1 with a p-value of 0.105) and at the 2.5% level when we focus on foreign wages. In the language of Adão et al. (2019) the set of controls soaks up most country-specific shocks affecting the outcome variable and, consequently, no shift-share structure is left in the regression residuals.[29]

Finally, Appendix Table A.11 checks that our results are not driven by a single country by sequentially excluding countries in our preferred set-up (with foreign wages and controlling for labor productivity). Excluding a country means that we treat it like the home country when computing normalized foreign wages. We also include the weight of the excluded country times a year dummy as a control. We successively remove the six largest countries by average weight (US, JP, DE, GB, FR, IT, and ES). The coefficient on low-skill wages always remains negative and significant.[30]

[29] Borusyak and Hull (2021) show that a regression based on a logged shift-share measure may be biased due to the non-linearity of the log function. They suggest a correction which removes this potential bias. We implement it in Appendix Table A.10 and the coefficients are very similar.

[30] Goldsmith-Pinkham, Sorking and Swift (2020) suggest carrying out a similar exercise by excluding countries with a large Rotemberg weight. Yet, this requires computing our macro-variables as weighted averages of log country-level variables instead of log of weighted averages of country-level variables. We checked that the six countries with the largest Rotemberg weights are the UK, FR, SE, DE, US, and BE. Our results are also robust to excluding Belgium and Sweden.

5.6 Additional Robustness Checks and Results

Timing. We look at alternative lags for the dependent variables in Appendix Table A.12 (we keep a lag of 2 for the stock variables, otherwise the dependent variable would be included in the RHS in the lead and contemporaneous cases). The largest coefficient on low-skill wages is obtained for a 2-year lag. It remains relatively stable without country-year fixed effects, while it is more clearly centered around lag 2 with country-year fixed effects.[31] Of course, innovators would not be interested in wages 2 years in the past per se, but only inasmuch as they are indicative of future wages. This is our interpretation throughout of our regressions, with the 2-year lag corresponding roughly to the time spent between an effect on R&D and the first results materialized by a patent application. In Appendix Table A.14, we compute predicted future wages at time $t-2$ based on an AR(1) process with country-specific trends and find similar results.

Innovation types. We look at other definitions or subcategories of automation innovations in Table 13 which reproduces regressions similar to Column (5) of Table 8 with foreign wages and controlling for labor productivity. Column (1) verifies that the results are not driven by the codes that we added to the definition of the machinery technological field listed in footnote 9 (though, we still exclude the weapons categories). Column (2) presents a laxer definition of automation using the 80^{th} percentile of the distribution of the C/IPC 6 digit codes. The effect of low-skill wages is still positive but smaller than for auto90 or auto95. Columns (3) and (4) show that the results are similar for Automat*90 and Automat*80 patents. Automat*90 patents are those which belong to technological categories with a frequency of only the "automat*" group of keywords above the threshold used to define auto90 and automat*80, robot90 or CNC90 are defined analogously. By definition automat*80 patents are all auto80 but 91.5% of them are also auto90. Column (5) and (6) shows that our results extend to robot90 and robot80 patents (which are also all auto95). The results differ for CNC patents in columns (7) and (8) perhaps because the sample size is much smaller.

Minimum wage. Given its policy relevance, we also look at the effect of minimum wages using data on 22 countries (instead of 41) in regressions where we replace low-skill wages with the minimum wage in Appendix Table A.15.[32] We find a positive effect of

[31] Appendix Table A.13 carries out placebo regressions where we regress automation innovation on 5, 10 or 15 year leads of wages. We do not find a significant effect of leading low-skill wages (except a negative effect in one column). As expected, given the large number of coefficients a few of the other coefficients are significant but never in a systematic way across specifications.

[32] We use data from the OECD. Importantly, not all countries have government-mandated minimum

Table 13: Innovation categories

Dependent variable	AutoX95	Auto80	Automat*90	Automat*80	Robot90	Robot80	CNC90	CNC80
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Foreign:								
Low-skill wage	5.22***	2.62**	6.90***	5.53***	5.83*	7.09***	-1.71	-1.15
	(1.59)	(1.29)	(2.13)	(1.94)	(3.23)	(2.49)	(4.01)	(3.10)
High-skill wage	-1.57	-1.82	-2.05	-1.96	-0.09	-3.27	5.02	0.89
	(1.60)	(1.33)	(1.92)	(1.77)	(2.91)	(2.32)	(5.40)	(3.59)
GDP gap	-0.07	1.01	7.76	3.90	4.83	0.21	-1.11	-0.03
	(4.50)	(3.03)	(5.08)	(4.64)	(8.19)	(6.77)	(11.20)	(9.34)
Labor productivity	-3.51**	-1.09	-5.16***	-4.12**	-6.71**	-5.10**	-3.20	-0.60
	(1.69)	(1.22)	(1.87)	(1.73)	(2.73)	(2.21)	(4.85)	(3.15)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	46980	96695	32738	48950	15927	23060	7609	13417
Firms	3224	6494	2264	3331	1156	1619	582	987

Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects, industry-year and country-year fixed effects. AutoX95 excludes the C/IPC codes which we added when defining the machinery technological field. Auto80 lowers the threshold to define automation innovation to the 80th percentile of the C/IPC 6 digit distribution. Automat*90 and Automat*80 only count words associated with automat. Robot90 and Robot80 only count words associated with robot. CNC90 and CNC80 words associated with CNC. 90 and 80 refer to the threshold used to delimit patents which is the 90th or the 80th percentile of the distribution of automation keywords for 6 digit C/IPC codes. The macroeconomic variables are the normalized foreign variables previously defined. Stocks and spillovers are computed with respect to the dependent variable. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

the minimum wage on automation innovations but the coefficients tend to be smaller in the foreign wage regressions and in one specification the coefficient is insignificant. Therefore low-skill wages are a better predictor of automation than the minimum wage. This is not surprising: first, the minimum wage only captures part of the labor costs, second, we focus on automation innovations that often happen in manufacturing where low-skill wages tend to be substantially above the minimum wage, and third, we lose nearly half of our countries. An analysis of automation in service industries might show a stronger relationship.

Long-difference. For most of our regressions, we follow the large patent literature and rely on the Poisson estimator, which best handles the count data nature of our dependent variable. In Appendix Table A.16, we conduct a long-difference estimation. To allow for zeros in the number of patents, we use the arcsinh transformation and we construct ten 5-year overlapping differences from our 15 years of data. Panel A focuses on firms which patented at least once over the time period considered (now 1995-2013), mirroring what a Poisson regression would do. We find a positive effect of low-skill wages and a negative effect of high-skill wages, although in some specifications the

wages and for some countries, we follow the literature and use sectorally bargained minimum wages. See details in Appendix A.5. We do not use the minimum wage as an instrument for low-skill wages because it would be inconsistent: if low-skill wages are endogenous, then high-skill wages are likely endogenous too so that we would need a second instrument.

positive effect of low-skill wage is non-significant (in unreported regressions we find that the inverse skill premium always has a positive and significant effect). The diminished significance of low-skill wages reflects the noisy behavior of one-time patenters: Panel B restricts attention to firms which have patented at least twice and recovers the same results as in our Poisson regressions: the change in low-skill wages has a large and significant positive effect on the change of automation innovations. These results suggest that automation responds to medium-run changes in wages.

Additional robustness checks. Appendix Table A.9 looks at alternatives to pre-multiplying our patents weights with $GDP^{0.35}$: with no multiplication, multiplying by GDP or by total payment to low-skill workers raised to the power of 0.35, $(w_L L)^{0.35}$, which may be a better measure of the potential market for technology designed to automate low-skill work. The table also shows that the results are robust to dropping the earlier years from the weights.

Our regressions include the stock of automation innovations and may suffer from Nickell's bias. Appendix Table A.17 removes this variable or uses the standard method of Blundell, Griffith and van Reenen (1999), which proxies for the fixed effect with the firm's pre-sample average of the dependent variable. We obtain very similar results.

Appendix Table A.18 investigates whether our results are robust when focusing on patents of higher quality and weighs patents by citations. We add to each patent the number of citations received within 5 years normalized by technological field and year of application. The results are weaker with total wages and country-year fixed effects but are very similar to the case without weighing patents in our preferred specification with foreign wages and country-year fixed effects.[33]

Appendix Table A.19 shows that our results (using foreign wages and country-year fixed effects) are robust to using different deflators, converting in USD every year or replacing manufacturing wages by total wages. Firms of different sizes may be on different trends in automation innovation. In Appendix Table A.20, we group firms into four bins according to their number of automation patents in 1995, allow for bin-year fixed effects and find similar results.

[33]This reflects in part that the number of citations is quite right-skewed. Once it is windsorized at the 99^{th} percentile, column (2) becomes significant at the 10^{th} percent level and the t-stats for columns (4) and (5) rise from 1 and 1.1 to 1.3 and 1.4.

6 Event study: the Hartz reforms in Germany

To look at a concrete case of a labor-market shock which affects labor costs, we now focus on a specific exogenous shock: the Hartz reforms. The Hartz reforms were a series of labor-market reforms in Germany first designed in 2002 and implemented between January 1st 2003 and January 1st 2005. These reforms were the major macroeconomic shock in Germany at the time. They aimed at reducing unemployment and increasing labor-market flexibility by reforming employment agencies to provide better job-search assistance, deregulating temporary work, offering wage subsidies for hard-to-place workers, reducing or removing social contributions on low-paid jobs, and reducing long-term unemployment benefits. The reforms have been widely credited with playing a major role in the remarkable performance of the German labor market since, in particular, for increasing labor supply and improving matching efficiency (see e.g. Krause and Uhlig, 2012). In line with the framework of Section 3, such reforms are predicted to reduce the incentive to automate low-skill labor by reducing labor costs (directly through social contribution and indirectly through an increase in labor supply) but also by allowing for more flexible contracts and reducing the expected cost of vacancies.

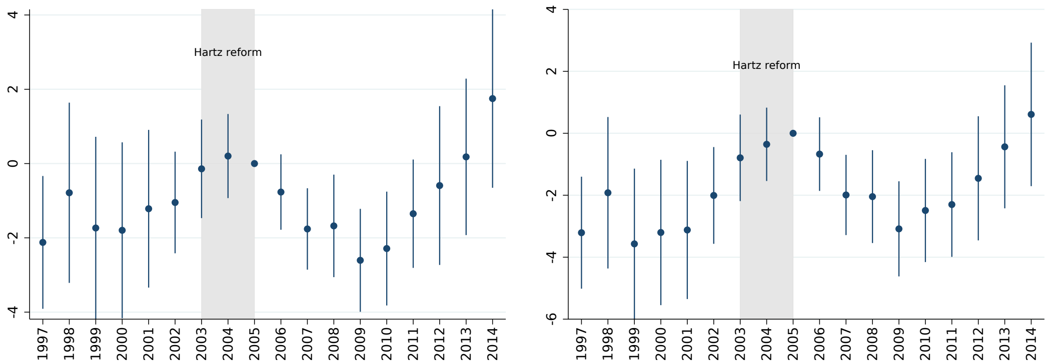
We use an analogous approach to before. We measure innovation and firm's exposure to international markets, but we exclude German firms as they are likely to have been affected by the Hartz reforms through other channels than the labor costs faced by their customers. We run the following regression, over the years 1997–2014:

$$PAT_{Aut,i,t} = \exp\left(\beta_{DE} \cdot \delta_t \omega_{i,DE} + \beta_{Ka} \ln K_{Aut,i,t-2} + \beta_{Ko} \ln K_{other,i,t-2} + \delta_i + \delta_{c,t}\right) + \epsilon_{i,t}.$$

We keep a 2-year lag to the innovation stocks. As before, $PAT_{Aut,i,t}$ is a count of automation patents, $K_{Aut,i,t-2}$ and $K_{other,i,t-2}$ represent firm knowledge stocks, δ_i a firm fixed effect and $\delta_{c,t}$ a country-year fixed effect. $\omega_{i,DE}$ is the fixed firm weight on Germany and δ_t is a set of year dummies (with 2005 as the excluded year). β_{DE} is the full vector of coefficients of interest which determines by how much more a firm exposed to Germany tends to do more automation patents in a given year relative to 2005.

As a preamble to this regression, Appendix Figure A.4 shows that the inverse skill-premium in Germany started to decline as soon as the Hartz reforms started being implemented in 2003 while it was flat beforehand. In contrast, there is no such trend for the rest-of-the-world.[34]

[34] The rest-of-the-world is defined from the prospect of the firms included in the regression as a



(a) Effect of German exposure on automation innovations

(b) Effect of German exposure on automation innovations relative to other machinery innovations.

Figure 5: Effect of German exposure on automation innovations. Panel (a) reports coefficients on the interaction between the German weight and a set of year fixed effects in a Poisson regression of auto95 innovations controlling for a full set of fixed effects and firm innovation stocks with 2153 firms. Panel (b) reports coefficients on the triple interaction between the German weight, a dummy for auto95 innovations and a set of year fixed effects in a Poisson regression of auto95 and other machinery innovations controlling for a full set of fixed effects, firm innovation stocks and the interaction between the German weight and a set of year fixed effects with 6452 firms.

Figure 5.a reports the results. The value of -2.3 in 2010 means that on average a firm with a German weight of 0.1 (the mean value is 0.106) had a 20% smaller increase in automation innovations between 2005 and 2010 than a firm with no German exposure.[35] From 2000 till 2004, firms highly exposed to Germany increased their propensity to introduce automation innovations. This is consistent with the view that German labor costs were rising at the time. This trend reversed between 2006 and 2009 and resumed from 2010. This is consistent with the Hartz reform increasing labor supply from 2003 onwards and therefore decreasing the incentive to introduce automation innovations from 2005. 2008 marks the beginning of the Great Recession which had a lower impact on German labor markets than in other countries potentially increasing the relative incentive to undertake automation innovations (with an effect 2 years later).

The previous figure clearly shows that the behavior of firms highly exposed to Germany differs over time from that of other firms. To show that the trends above are

weighted average of other countries using these firms' country weights (excluding Germany's). While, there is no aggregate trend, there are trends within countries.

[35]Between 2003 and 2008, the inverse skill-premium in Germany declined by 12% relative to the rest of the world. Using the elasticity of 2.5 of column (4) in Table 9, this would correspond to a decline in automation innovations of 30% between 2005 and 2010, which is similar but a little larger than the 20% that we observe directly here.

Table 14: Innovation and exposure to Germany

Dependent variables	Auto 95 and other + low auto		Auto95 and low auto	Auto95, low auto and other mach.
	(1)	(2)	(3)	(4)
Time trend × auto95 dummy × German exposure	0.60***	0.60***	0.63***	0.60***
	(0.23)	(0.21)	(0.23)	(0.21)
Time trend × auto95 dummy × post 2005 × German exposure	-1.20***	-1.20***	-1.26***	-1.19***
	(0.40)	(0.38)	(0.41)	(0.38)
Time trend × low auto dummy × German exposure				-0.03
				(0.12)
Time trend × low auto dummy × post 2005 × German exposure				0.06
				(0.18)
Year dummy × German exposure	Yes	Yes	Yes	Yes
Firm innovation stocks × innovation types	No	Yes	Yes	Yes
Firm-innovation types FE	Yes	Yes	Yes	Yes
Country-year-innovation types FE	Yes	Yes	Yes	Yes
Observations	77456	77456	62173	107284
Firms	5427	5427	4350	5427

Note: Marginal effects; Standard errors in parentheses. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions control for year dummies times the measure of German exposure, innovation stocks (and dummies for no stocks) times the innovation types, firm innovation types fixed effects and country year innovation types fixed effects. The innovation stocks are lagged by two periods. Innovation types are auto95 and all other machinery innovations (low auto and other machinery together) in columns (1)-(2), auto95 and low auto in column (3), and auto95, low auto and other machinery in column (4). German exposure is measured by the German weights in all regressions. Standard errors are clustered at the firm-level. * p < 0.1; ** p < 0.05; *** p < 0.01

specific to automation innovations, we run the following regression:

$$PAT_{k,i,t} = \exp\begin{pmatrix} \beta_{DE} \cdot \delta_t \omega_{i,DE} + \beta_{DE}^{aut} \cdot \delta_t \omega_{i,DE} 1_{k=aut} \\ +\beta_{Ka} \cdot \delta_k \ln K_{Aut,i,t-2} + \beta_{Ko} \cdot \delta_k \ln K_{other,i,t-2} + \delta_{k,i} + \delta_{k,c,t} \end{pmatrix} + \epsilon_{k,i,t}. \tag{5}$$

k denotes the type of an innovation which is either auto95 or another machinery innovation, $\delta_{k,i}$ represents a full set of innovation type firm fixed effects, $\delta_{k,c,t}$ innovation type country year fixed effects and $1_{k=aut}$ is a dummy for an auto95 innovation. Standard errors are clustered at the firm level. β_{DE}^{aut} is the vector of coefficients of interests. For each year, they measure how much exposure to Germany increases the relative propensity to introduce automation innovations instead of other forms of machinery innovations compared to 2005. Figure 5.b reports the results: the pattern is, if anything, more pronounced than in Figure 5.a.

To formally test that the Hartz reform created a trend break in the relative propensity of firms highly exposed to Germany to introduce automation innovation relative to other machinery innovation, we replace the full set of year fixed-effects δ_t in $\beta_{DE}^{aut} \cdot \delta_t \omega_{i,DE} 1_{k=aut}$ in equation (5) with a time trend $t - 2005$ and a time trend interacted with a post 2005 dummy $(t-2005)_{t>2005}$. We focus on the years 2000-2010 to have a panel centered on 2005 and avoid the effects of the Great Recession on innovation. This exercise is a triple difference with a continuous treatment (the exposure of each firm to Germany).

Table 14 reports the result. Column (2) corresponds exactly to equation (5): there is a significant time trend in the effect of German exposure on the relative propensity to carry automation innovation between 2000 and 2005, but this trend sharply reverses in the following five years. Column (1) omits the controls for the stock variables. Column (3) uses the low-automation innovations of Section 5.3 instead of all other machinery innovations. Finally, column (4) considers three types of innovations by separating non-auto95 machinery innovations into the low-automation innovations of the previous columns and the rest. In all cases, the trend break remains with a consistent magnitude. This exercise shows that, in line with our theory, the Hartz reforms reduced automation innovation of foreign firms highly exposed to Germany, both in absolute terms and relative to other types of machinery innovation.

7 Conclusion

In this paper, we identify automation patents and thereby provide a new measure of automation. Our measure is available at a highly disaggregated level and covers a broad range of technologies. Further, it predicts a decline in routine tasks across US sectors. We then use our classification to analyze the effect of labor market conditions on automation innovations in machinery. We first use global data and find that automation innovations are very responsive to changes in low-skill wages with elasticities between 2 and 5. We proceed to show that the German Hartz reforms led to a relative decrease in automation innovations by foreign firms with high exposure to Germany. Though using different variations in the data, both exercises emphasize that automation innovations are much more responsive to changes in labor market conditions than other innovations.

These results suggest that policies that increase labor costs for low-skill workers will lead to an increase in innovations that replace them. Therefore, with endogenous technological change, such policies are likely to be less costly for the economy in terms of overall welfare, but also to introduce additional negative effects for low-skill workers. Our paper provides a building block toward estimating by how much a policy-induced increase in low-skill wages would be undone in a couple of years through innovation.

Future research could adapt our classification method to automation patents beyond machinery. This would allow for an analysis of automation in the service industry or automation of high-skill tasks through Artificial Intelligence.

References

Acemoglu, D. and Linn, J. (2004). Market size in innovation: Theory and evidence from the pharmaceutical industry. *Quarterly Journal of Economics*, 119(3):1049–1090.

Acemoglu, D. and Restrepo, P. (2018a). The race between machine and man: Implications of technology for growth, factor shares and employment. *American Economic Review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2018b). Demographics and automation. NBER Working Paper 24421.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6):2188–2244.

Adão, R., Kolesár, M., and Morales, E. (2019). Shift-share designs: Theory and inference. *The Quarterly Journal of Economics*, 134(4):1949–2010.

Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2021). The labor and product market effects of machines and automation: Causal evidence from french firms and industries.

Aghion, P., Bénabou, R., Martin, R., and Roulet, A. (2020). Environmental preferences and technological choices: Is market competition clean or dirty? NBER wp 26921.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., and Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, 214(1):1–51.

Andersson, D., Karadja, M., and Prawitz, E. (2020). Mass migration and technological change.

Aschhoff, B., Crass, D., Cremers, K., Grimpe, C., Rammer, C., Brandes, F., Diaz-Lopez, F., Klein Woolthuis, R., Mayer, M., and Montalvo, C. (2010). European competitiveness in key enabling technologies. Technical report, Centre for European Economic Research (ZEW) and TNO.

Autor, D. and Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labor Market. *American Economic Review*, 103(5):1553–1597.

Autor, D., Dorn, D., Hanson, G., Pisano, G., and Shu, P. (2020). Foreign competition and domestic innovation: Evidence from u.s. patents. *American Economic Review: Insights*, 2(3):357–374.

Autor, D., Levy, F., and Murnane, R. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Bena, J. and Simintzi, E. (2019). Machines could not compete with Chinese labor: Evidence from U.S. firms' innovation. mimeo.

Bessen, J., Goos, M., Salomons, A., and van der Berge, W. (2019). Automatic reaction - what happens to workers at firms that automate ?

Bessen, J. and Hunt, R. (2007). An empirical look at software patents. *Journal of Economics and Management Strategy*, 16(1):157–189.

Blundell, R., Griffith, R., and Van Reenen, J. (1999). Market share, market value and innovation in a panel of British manufacturing firms. *The Review of Economic Studies*, 66(3):529–554.

Borusyak, K. and Hull, P. (2021). Non-random exposure to exogenous shocks: Theory and applications.

Borusyak, K., Hull, P., and Jaravel, X. (2018). Quasi-experimental shift-share research designs.

Cameron, A. C., Gelbach, J., and Miller, D. (2008). Boostrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, 90(3):414–427.

Clemens, M., Lewis, E., and Postel, H. (2018). Immigration restrictions as active labor market policy: Evidence from the Mexican bracero exclusion. *American Economic Review*, 108(6):1468–87.

Coelli, F., Moxnes, A., and Ulltveit-Moe, K. (2020). Better, faster, stronger: Global innovation and trade liberalization. *The Review of Economics and Statistics*.

Correia, S., Guimarães, P., and Zylkin, T. (2020). Fast poisson estimation with high-dimensional fixed effects. *The Stata Journal*, 20(1):95–115.

Danzer, A., Feuerbaum, C., and Gaessler, F. (2020). Labor supply and automation innovation. BGPE Discussion Paper No 198.

de Rassenfosse, G., Dernis, H., Guellec, D., Picci, L., and van Pottelsberghe de la Potterie, B. (2013). The worldwide count of priority patents: A new indicator of inventive activity. *Research Policy*, 42(3):720–737.

Dechezleprêtre, A., Glachant, M., Hascic, I., Johnstone, N., and Ménière, Y. (2011). Invention and transfer of climate change-mitigation technologies: a global analysis. *Review of Environmental Economics and Policy*, 5:109–130.

Dechezleprêtre, A., Ménière, Y., and Mohnen, M. (2017). International patent families: from application strategies to statistical indicators. *Scientometrics*, 111(2):793–828.

Doms, M., Dunne, T., and Troske, K. (1997). Workers, Wages, and Technology. *Quar-*

terly Journal of Economics, 112(1):253–290.

Eaton, J. and Kortum, S. (1996). Trade in ideas: patenting and productivity in the OECD. *Journal of International Economics*, 40:251–278.

Eaton, J., Kortum, S., and Kramarz, F. (2011). An anatomy of international trade: evidence from French firms. *Econometrica*, 79(5):1453–1498.

Fan, H., Hu, Y., and Tang, L. (2021). Labor costs and the adoption of robots in china. *Journal of Economic Behavior & Organization*, 186:608–631.

Gaggl, P. and Wright, G. (2017). A short-run view of what computers do: Evidence from a UK tax incentive. *American Economic Journal: Applied Economics*, 9(3):262–94.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *The American Economic Review*, 110(8):2586–2624.

Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5):753–768.

Hausman, J., Hall, B., and Griliches, Z. (1984). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica*, 52(4):909–938.

Hémous, D. and Olsen, M. (forthcoming). The rise of the machines: Automation, horizontal innovation and income inequality. *American Economic Journal: Macroeconomics*.

Hornbeck, R. and Naidu, S. (2014). When the levee breaks: Black migration and economic development in the American South. *American Economic Review*, 104(3):963–990.

Krause, M. and Uhlig, H. (2012). Transitions in the German labor market: Structure and crisis. *Journal of Monetary Economics*, 59(1):64–79.

Krusell, P., Ohanian, L., Ríos-Rull, J.-V., and Violante, G. (2000). Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica*, 68(5):1029–1053.

Lewis, E. (2011). Immigration, skill mix and capital skill complementarity. *Quarterly Journal of Economics*, 126 (2):1029–1069.

Lordan, G. and Neumark, D. (2018). People versus machines: The impact of minimum wages on automatable jobs. *Labour Economics*, 52(40-53).

Lybbert, T. and Zolas, N. (2014). Getting patents and economic data to speak to each other: An 'Algorithmic Links with Probabilities' approach for joint analyses of patenting and economic activity. *Research Policy*, 43:530–542.

Mann, K. and Puettmann, L. (2018). Benign effects of automation: New evidence from patent texts.

Noailly, J. and Smeets, R. (2015). Directing technical change from fossil-fuel to renewable energy innovation: An application using firm-level patent data. *Journal of Environmental Economics and Management*, 72:15–37.

Popp, D. (2002). Induced innovation and energy prices. *The American Economic Review*, 92(1):160–180.

Siemens (2018). Annual report. Technical report.

Timmer, M., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. J. (2015). An illustrated user guide to the world input-output database: the case of global automotive production. *Review of International Economics*, 23(3).

Timmer, M., Erumban, A. A., Los, B., Stehrer, R., and de Vries, G. (2014). Slicing up global value chains. *Journal of Economic Perspectives*, 28(2):99–118.

Webb, M. (2020). The impact of artificial intelligence on labor market.

Zeira, J. (1998). Workers, Machines, and Economic Growth. *Quarterly Journal of Economics*, 113(4):1091–1117.

A Online Appendix

A.1 Additional Figures and Tables

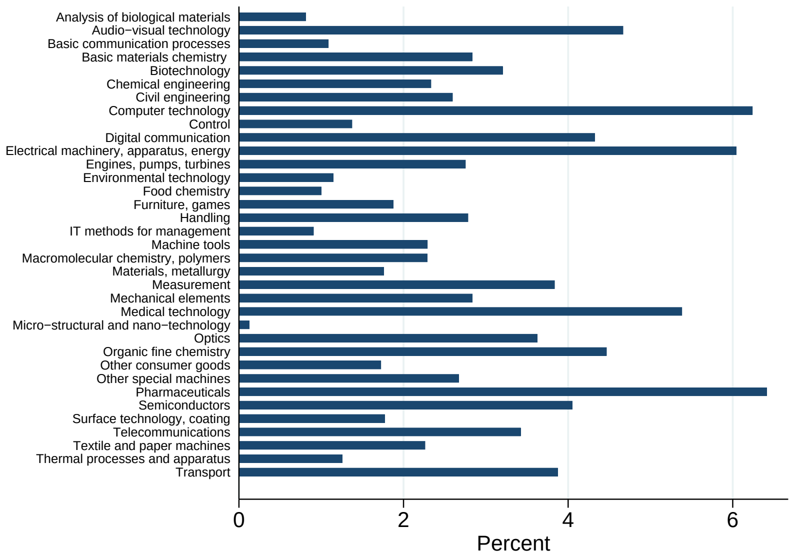
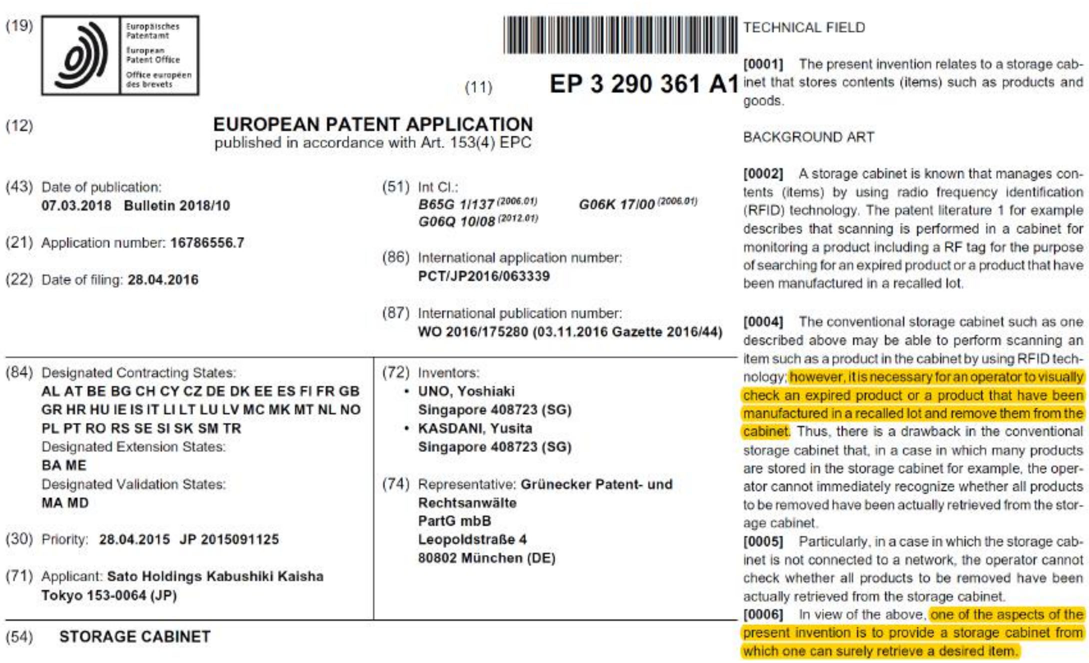


Figure A.1: Share of biadic patent applications in the different technical fields in 1997-2011



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(71) Applicant: **Sato Holdings Kabushiki Kaisha Tokyo 153-0064 (JP)**

(72) Inventors:
- **UNO, Yoshiaki Singapore 408723 (SG)**
- **KASDANI, Yusita Singapore 408723 (SG)**

(74) Representative: **Grünecker Patent- und Rechtsanwälte PartG mbB Leopoldstraße 4 80802 München (DE)**

(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

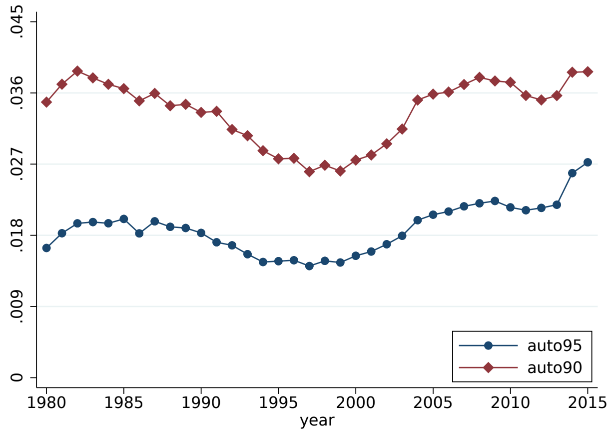
[0002] A storage cabinet is known that manages contents (items) by using radio frequency identification (RFID) technology. The patent literature 1 for example describes that scanning is performed in a cabinet for monitoring a product including a RF tag for the purpose of searching for an expired product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

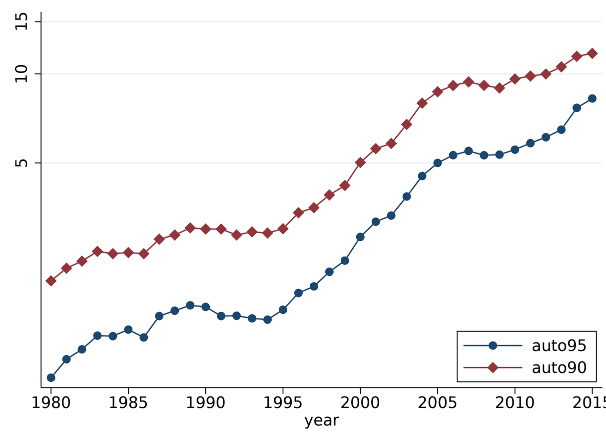
[0005] Particularly, in a case in which the storage cabinet is not connected to a network, the operator cannot check whether all products to be removed have been actually retrieved from the storage cabinet.

[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.

Figure A.2: Example of an automation patent without keywords



(a) Share of automation patents in machinery out of total patents according to the auto90 and auto95 definitions.



(b) Number of automation patents worldwide according to the auto90 and auto95 definitions

Figure A.3: Trends in automation (for biadic applications)

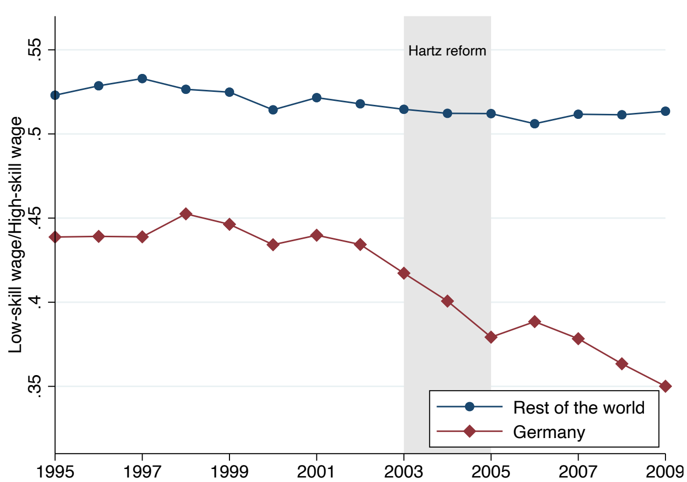


Figure A.4: Evolution of the inverse skill premium in Germany and the rest of the world. Note: the rest of the world series is computed as a weighted average using the weights (excluding Germany) of the firms included in the regression of Figure 5.a.

Table A.1: Industry of innovators

	Industry	Share auto95 (%)	Share firms (%)
20	Manufacture of chemicals and chemical products	2.18	3.45
25	Manufacture of fabricated metal products, except machinery and equipment	1.18	4.39
26	Manufacture of computer, electronic and optical products	22.83	7.42
27	Manufacture of electrical equipment	9.19	2.76
28	Manufacture of machinery and equipment n.e.c.	24.52	20.97
29	Manufacture of motor vehicles, trailers and semi-trailers	5.31	3.48
30	Manufacture of other transport equipment	4.5	1.2
46	Wholesale trade, except of motor vehicles and motorcycles	1.34	3.3
64	Financial service activities, except insurance and pension funding	1.75	0.96
72	Scientific research and development	2.04	2.37
	Other industries	13.23	27.15
	No information on industry	11.94	22.5

Notes: The table reports the industry of manufacturing of firms included in our baseline regression with industry-year fixed effects at the NACEv2 division level and the share of biadic auto95 families for each industry. Industries representing less than 1% of patents are summed up in the "Other industries" category.

Table A.2: Correlation matrix

	Low-skill wage	Middle-skill wage	High-skill wage	GDP gap	GDP per capita	Labor productivity
Low-skill wage	1.00					
Middle-skill wage	0.94	1.00				
High-skill wage	0.60	0.75	1.00			
GDP gap	-0.06	-0.05	-0.03	1.00		
GDP per capita	0.70	0.80	0.73	0.11	1.00	
Labor productivity	0.67	0.73	0.77	0.04	0.66	1.00

Note: Correlation of residuals for the auto95 sample controlling for firm and year-industry fixed effects.

Table A.3: Coverage of the regression sample

	Applications	Families	Biadic Families	Firms (with auto95 bia)
Patstat 1997-2011	435263	180805	61768	-
Matched with Orbis	349707	146169	57642	25126
Firms in sample	207894	88964	35803	3341

Note: This table reports summary statistics for the counts of auto95 patent families and patent applications in Patstat with no restriction, when we restrict to firms observed in Orbis and when we restrict to the firms included in our regression sample for the time period 1997-2011.

Table A.4: Top 10 auto95 innovators in our sample

Company	Number of biadic auto95 patents in 1997-2011
Siemens Aktiengesellschaft	1738
Honda Motor Co., Ltd.	810
Fanuc Co.	777
Samsung Electronics Co., Ltd.	706
Robert Bosch GmbH	655
Mitsubishi Electric Co.	652
Tokyo Electron, Ltd.	578
Murata Machinery, Ltd.	501
Kabushiki Kaisha Toshiba	473
General Electric Company	464

Table A.5: Baseline regressions for auto95 with country-level clustering

Dependent variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.21***	2.83***	1.80***	2.46***	2.32***	2.54***	2.90***	2.67***	3.59***
	(0.54)	(0.73)	(0.63)	(0.61)	(0.77)	(0.70)	(0.65)	(0.74)	(1.04)
	[0.000]	[0.000]	[0.004]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.001]
	{0.000}	{0.002}	{0.030}	{0.031}	{0.038}	{0.094}	{0.008}	{0.019}	{0.015}
High-skill wage		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GDP gap				Yes	Yes	Yes	Yes	Yes	Yes
Labor productivity					Yes			Yes	
GDP per capita						Yes			Yes
Stocks			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spillovers							Yes	Yes	Yes
Fixed effects	F+Y	F+Y	F+Y	F+IY	F+IY	F+IY	F+IY	F+IY	F+IY
Observations	50115	50115	50115	49174	49174	49174	49174	49174	49174
Firms	3341	3341	3341	3329	3329	3329	3329	3329	3329

Note: This table reproduces the baseline table but clusters standard errors at the country-level. [ ] brackets correspond to the p-value associated with estimated standard errors, { } brackets correspond to the p-values associated with the clustered standard errors following Cameron et. (2008). See text for details. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.6: Auto90 innovations

Dependent variable	Auto90								
	Domestic+Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.19***	1.95***	3.10***	1.57*	1.57*	2.61**	3.02***	3.49***	3.46**
	(0.65)	(0.67)	(0.77)	(0.81)	(0.87)	(1.03)	(1.12)	(1.30)	(1.42)
High-skill wage	-1.85***	-2.27***	-0.85	-1.78**	-1.76*	-1.09	-3.50***	-2.80**	-3.24***
	(0.59)	(0.65)	(0.65)	(0.80)	(0.91)	(0.85)	(1.14)	(1.30)	(1.22)
GDP gap	-3.85*	-4.41**	-1.53	4.47	4.49	6.23	-0.95	0.06	-0.09
	(2.10)	(2.14)	(2.25)	(5.20)	(5.29)	(5.37)	(3.25)	(3.52)	(3.66)
Labor productivity		0.95			-0.03			-1.11	
		(0.73)			(1.29)			(1.32)	
GDP per capita			-2.60**			-2.55*			-0.79
			(1.03)			(1.45)			(1.53)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	72721	72721	72721	72439	72439	72439	72439	72439	72439
Firms	4890	4890	4890	4887	4887	4887	4887	4887	4887

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). Columns (1)-(3) include firm and industry-year fixed effects, while (4)-(9) include firm, industry-year, and country-year fixed effects. In Columns (7)–(9) the macroeconomic variables are the normalized foreign variables previously defined. Stock and spillover variables are calculated with respect to the dependent variable (auto90). Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.7: Wages weighted by inventor weights

Dependent variable	Auto95								
	Domestic+Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.99***	2.39***	3.39***	2.15**	2.30**	3.44***	5.53***	6.39***	5.37***
	(0.87)	(0.92)	(1.08)	(1.03)	(1.17)	(1.32)	(1.63)	(1.81)	(2.08)
Low-skill wage (iw)	-0.22	0.12	0.10	-0.02	0.26	0.14	0.00	0.74	0.71
	(0.44)	(0.45)	(0.47)	(0.45)	(0.45)	(0.47)	(0.53)	(0.58)	(0.54)
High-skill wage	-2.59***	-3.45***	-2.04**	-3.02***	-2.60**	-2.15**	-5.15***	-4.53***	-5.66***
	(0.85)	(0.93)	(0.87)	(1.02)	(1.09)	(1.08)	(1.58)	(1.65)	(1.67)
High-skill wage (iw)	0.41	0.90**	0.58	0.18	0.60	0.24	-0.27	1.01*	0.21
	(0.39)	(0.43)	(0.40)	(0.37)	(0.41)	(0.39)	(0.47)	(0.52)	(0.51)
GDP gap	-8.38**	-9.83***	-6.89*	1.83	1.69	4.16	-2.28	-1.22	-3.06
	(3.67)	(3.66)	(3.85)	(6.02)	(5.97)	(6.28)	(4.26)	(4.27)	(4.72)
GDP gap (iw)	3.25	3.89	3.52	1.94	2.43	2.05	2.50	3.35*	3.89
	(2.51)	(2.41)	(2.64)	(2.68)	(2.49)	(2.83)	(2.29)	(1.86)	(2.38)
Labor productivity		2.10*			-0.91			-1.54	
		(1.12)			(1.75)			(1.62)	
Labor productivity (iw)		-1.14**			-1.02*			-2.08***	
		(0.54)			(0.54)			(0.65)	
GDP per capita			-1.27			-3.16*			0.81
			(1.43)			(1.86)			(2.29)
GDP per capita (iw)			-0.66			-0.29			-1.41**
			(0.59)			(0.63)			(0.61)
Stock automation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock other	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	48376	48376	48376	47977	47977	47977	36234	36234	36234
Firms	3274	3274	3274	3268	3268	3268	2480	2480	2480

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson fixed-effects regressions (HHG) in Columns (1), (3), and (5). In Columns (2), (4), and (6), estimation is done by Poisson regressions where the firm fixed effects are replaced by the pre-sample mean, following Blundell, Griffith and Van Reenen (1999, BGVR). All columns include industry-year fixed effects and Columns (3) to (6) include country-year fixed effects. In Columns (5) and (6) the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.8: Predicting weights using subsequent wages

	Panel A								
Dependent variable	$\omega_{i,c,1995}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$g_{LSW,2000}$	-0.14	-0.14	-0.27	-0.14	-0.14	-0.27	-0.12	-0.12	-0.13
	(0.12)	(0.12)	(0.28)	(0.12)	(0.12)	(0.28)	(0.12)	(0.12)	(0.29)
$g_{HSW,2000}$			0.13			0.13			0.01
			(0.24)			(0.24)			(0.27)
Firm fixed effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Clustering	C	C	C	F + C	F + C	F + C	C	C	C
Observations	136981	136981	136981	136981	136981	136981	136981	136981	136981
Firms	3341	3341	3341	3341	3341	3341	3341	3341	3341
	Panel B								
Dependent variable	$foreign\_\omega_{i,c,1995}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$g_{LSW,2000}$	-0.10	-0.10	-0.31	-0.10	-0.10	-0.31	-0.10	-0.10	-0.33
	(0.11)	(0.11)	(0.26)	(0.11)	(0.11)	(0.26)	(0.12)	(0.12)	(0.30)
$g_{HSW,2000}$			0.20			0.20			0.23
			(0.21)			(0.21)			(0.24)
Firm fixed effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Clustering	C	C	C	F + C	F + C	F + C	C	C	C
Observations	133640	133640	133640	133640	133640	133640	133640	133640	133640
Firms	3341	3341	3341	3341	3341	3341	3341	3341	3341

Note: OLS regressions of firm-level weights/foreign weights on country growth rates for low-skill and high-skill wages between 1995 and 2000. Columns (2), (3), (5), (6), (8) and (9) include firm fixed effects. Columns (7)-(9) weigh observations by the number of auto95 patents between 1997 and 2011. Standard errors are clustered at the country-level for columns (1)-(3), (7)-(9)and clustered at both the country and firm levels for (4)-(6). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.9: Alternative weights

Dependent variable	Auto95					
	1971–1989	1985–1994	start 2000	GDP^0	GDP^1	$(w_L \cdot L)^{0.35}$
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign:						
Low-skill wage	5.07***	4.98***	6.81***	4.12***	5.81***	5.11***
	(1.88)	(1.48)	(2.10)	(1.37)	(1.68)	(1.50)
High-skill wage	-3.41**	-1.51	-3.56*	-3.74***	-3.19**	-3.40**
	(1.66)	(1.52)	(2.03)	(1.32)	(1.62)	(1.32)
GDP gap	1.70	2.19	-0.47	-3.44	-1.83	-1.19
	(4.13)	(4.72)	(3.78)	(3.56)	(3.85)	(3.66)
Labor productivity	-2.03	-3.53**	-4.38**	-1.29	-1.59	-2.03
	(1.75)	(1.58)	(1.74)	(1.42)	(1.57)	(1.55)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	34710	44476	26577	48665	48802	48679
Firms	2386	3031	2695	3323	3322	3325

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, country-year and industry-year fixed effects. In column (1) firms' country weights for the macroeconomic variables are computed over the period 1971–1989; and over the period 1985–1994 for column (2). Columns (3) to (6) use the baseline pre-sample period of 1971–1994. Column (3) restricts the sample to the years 2000–2009. Column (4) does not adjust for GDP in the computation of the weights; Column (5) uses GDP instead of $GDP^{0.35}$ to adjust for country size and Column (6) replaces GDP with total low-skilled payment wL in the baseline formula. In all columns the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.10: Borusyak and Hull (2021)'s correction

Dependent variable	Auto95								
	Domestic+Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.21***	2.22***	3.69***	1.56*	2.22**	3.87***	5.17***	5.32***	3.91**
	(0.74)	(0.83)	(0.88)	(0.93)	(1.10)	(1.17)	(1.45)	(1.54)	(1.61)
High-skill wage	-2.19*	-2.17*	-0.90	-2.86***	-1.61	-1.61	-3.63***	-3.46***	-3.74***
	(0.66)	(0.72)	(0.73)	(0.90)	(0.97)	(0.99)	(1.19)	(1.51)	(1.20)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GDP gap	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labor productivity		Yes			Yes			Yes	
GDP per capita			Yes			Yes			Yes
Fixed effects	F+IY	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	49174	49174	49174	48773	48773	48773	48773	48773	48773
Firms	3329	3329	3329	3324	3324	3324	3324	3324	3324

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(3) include firm and industry-year fixed effects. Columns (4)-(9) add country-year fixed effects. Columns (7)-(9) use the normalized foreign macro variables previously defined. All regressions include controls for stocks and spillovers. The macroeconomic variables in log, low-skill wages, high-skill wages, GDP per capita and labor productivity are adjusted following the correction suggested in Borusyak and Hull (2021): we sample with replacement the entire path of macroeconomic variables for each firm with 250 draws, take the average value and subtract it from the original macroeconomic variable. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.11: Excluding one country at the time

Dependent Variable	Auto95							
Excl. country	None	US	DE	JP	GB	FR	IT	ES
Average weight		0.21	0.20	0.17	0.09	0.09	0.03	0.03
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Foreign:								
Low-skill wage	5.08***	5.41***	3.60***	3.43***	4.78***	3.60**	5.20***	4.84***
	(1.54)	(1.68)	(1.37)	(1.33)	(1.33)	(1.48)	(1.45)	(1.51)
High-skill wage	-2.95**	-2.74*	-1.72	-1.57	-0.82	-2.31*	-4.62**	-2.51*
	(1.46)	(1.46)	(1.26)	(1.29)	(1.34)	(1.33)	(1.90)	(1.48)
GDP gap	1.29	0.73	2.62	1.59	1.99	0.97	1.19	1.05
	(4.84)	(5.14)	(5.58)	(3.88)	(4.85)	(5.02)	(5.13)	(4.90)
Labor productivity	-2.15	-3.39**	-2.26	-1.43	-3.24**	-1.49	-0.73	-2.35
	(1.58)	(1.67)	(1.39)	(1.48)	(1.58)	(1.48)	(1.63)	(1.56)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+CY+IY	F+CY+IY	F+CY+IY	F+CY+IY	F+CY+IY	F+CY+IY	F+CY+IY	F+CY+IY
Control		$\omega_c * Y$	$\omega_c * Y$	$\omega_c * Y$	$\omega_c * Y$	$\omega_c * Y$	$\omega_c * Y$	$\omega_c * Y$
Observations	48773	47997	48319	48594	48391	48713	48638	48702
Firms	3324	3270	3291	3312	3299	3320	3315	3319

Notes: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions effects (HHG). All columns include firm, industry-year and country-year fixed effects. In Column (0), the macroeconomic variables are the normalized foreign variables previously defined. Columns (1) to (7) further exclude the country in the column header in addition to the domestic country when computing the normalized foreign macroeconomic variables. Columns (1) to (7) also control for the weight of the header-country times year dummies. The average weight is the average country weight for firms in the sample of Column (0). Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.12: Lags and leads

Dependent variable	Auto95							
Lags (Leads)	-5	-4	-3	-2	-1	0	1	2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	2.08***	2.53***	2.66***	2.67***	2.34***	2.60***	2.45***	1.48*
	(0.76)	(0.78)	(0.81)	(0.84)	(0.83)	(0.82)	(0.84)	(0.82)
High-skill wage	-1.23*	-2.16***	-3.04***	-2.61***	-2.75***	-3.12***	-2.94***	-2.80***
	(0.74)	(0.76)	(0.78)	(0.79)	(0.76)	(0.81)	(0.76)	(0.72)
Labor productivity	1.17	1.46*	2.11**	0.91	0.54	0.11	0.03	0.51
	(0.81)	(0.84)	(0.88)	(0.92)	(0.89)	(0.91)	(0.93)	(0.92)
Fixed effects	F+IY	F+IY	F+IY	F+IY	F+IY	F+IY	F+IY	F+IY
Observations	46783	47422	48514	49174	49657	50216	51262	52659
Firms	3156	3202	3279	3329	3368	3412	3490	3587
	Panel B: country-year fixed effects							
Low-skill wage	1.81*	1.89*	2.15*	2.55**	2.27**	2.04*	1.85	0.88
	(1.03)	(1.10)	(1.10)	(1.13)	(1.13)	(1.12)	(1.15)	(1.10)
High-skill wage	-0.05	-1.32	-1.98*	-2.16**	-2.51**	-3.17***	-2.95***	-2.19**
	(1.20)	(1.12)	(1.03)	(1.05)	(1.15)	(1.15)	(1.06)	(1.07)
Labor productivity	-1.91	-1.03	-0.70	-1.68	-0.92	-0.17	0.13	-0.13
	(1.65)	(1.58)	(1.58)	(1.76)	(1.85)	(1.75)	(1.69)	(1.57)
	Panel C: country-year fixed effects and foreign variables							
Low-skill wage	2.41	3.04**	4.05***	5.08***	3.82**	2.80*	2.55	1.62
	(1.50)	(1.52)	(1.55)	(1.54)	(1.55)	(1.65)	(1.76)	(1.77)
High-skill wage	0.41	-2.12	-3.30**	-2.95**	-4.08***	-5.03***	-5.07***	-3.71**
	(1.53)	(1.50)	(1.48)	(1.46)	(1.56)	(1.56)	(1.52)	(1.58)
Labor productivity	-1.77	-0.61	-0.92	-2.15	0.35	2.07	2.57	1.78
	(1.64)	(1.65)	(1.61)	(1.58)	(1.60)	(1.71)	(1.76)	(1.78)
Fixed effects	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	46461	47136	48172	48773	49236	49810	50857	52253
Firms	3156	3202	3277	3324	3361	3406	3484	3584

Marginal effects; Standard errors in parentheses. Each panel represents a different regression. All regressions contain controls for GDP gap, stocks and spillovers, for which we do not report the coefficients. The independent variables (wages, labor productivity, GDP gap and spillovers) are lagged by the number of periods indicated in lag, except for the stock variables which are always lagged by 2 periods. Estimation is done by conditional Poisson regressions fixed-effects (HHG). Panel A regressions contain firm and industry-year fixed effects. Panels B and C add country-year fixed effects. In Panel C the macroeconomic variables are their foreign normalized values previously definted. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.13: Placebo regressions: long leads

Dependent variable	Auto95								
	Domestic+Foreign						Foreign		
	$t+5$	$t+10$	$t+15$	$t+5$	$t+10$	$t+15$	$t+5$	$t+10$	$t+15$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	-0.34	-1.77	-1.39	-0.41	-1.35	-1.71**	0.65	2.44	0.81
	(0.79)	(1.08)	(1.13)	(0.66)	(0.83)	(0.78)	(1.32)	(1.78)	(1.95)
High-skill wage	1.83**	0.53	-0.64	0.12	0.68	-0.33	2.62**	-1.36	-1.67
	(0.89)	(1.54)	(1.27)	(0.58)	(0.89)	(0.81)	(1.19)	(2.03)	(2.03)
GDP gap	-0.91	3.36	3.24	-4.01	-0.34	7.88***	2.05	7.82*	5.61
	(8.66)	(6.29)	(5.70)	(3.17)	(2.64)	(3.04)	(4.14)	(4.41)	(4.12)
Labor productivity	-1.04	1.27	-0.38	0.61	-0.07	-0.57	-2.33*	-4.24***	-2.51
	(1.14)	(1.91)	(1.73)	(0.77)	(0.94)	(0.96)	(1.29)	(1.47)	(1.54)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	51124	59393	62059	51506	59917	62670	51124	59393	62059
Firms	3850	4177	4284	3859	4183	4290	3850	4177	4284

Note: Marginal effects; Standard errors in parentheses. The independent variables are led by 5 periods (Columns (1), (4) and (5)) 10 periods (Columns (2), (5) and (8)) or 15 periods (Columns (3), (6) and (9)), except the stock variables which are lagged b two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). Columns (1)-(3) include firm and industry year fixed effects, while (4)-(9) include firm, industry-year, and country-year fixed effects. In Columns (7)–(9), the macroeconomi variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p <$ 0.05; *** $p < 0.01$

Table A.14: Predicted wages

Dependent variable	Auto95								
	Domestic+Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.38***	1.77**	2.40***	1.60*	1.47	1.61*	3.79***	4.03***	3.78***
	(0.80)	(0.81)	(0.81)	(0.92)	(1.01)	(0.93)	(1.28)	(1.37)	(1.29)
High-skill wage	-2.77***	-4.79***	-2.81***	-3.38***	-3.78***	-3.39***	-4.35***	-3.79**	-4.34***
	(0.81)	(1.08)	(0.82)	(1.01)	(1.38)	(1.02)	(1.31)	(1.52)	(1.32)
GDP gap	-4.90*	-4.23*	-4.95*	4.10	4.09	4.11	-0.86	-0.36	-0.81
	(2.56)	(2.51)	(2.56)	(6.78)	(6.79)	(6.78)	(4.45)	(4.51)	(4.49)
Labor productivity		2.92***			0.59			-0.92	
		(0.95)			(1.54)			(1.48)	
GDP per capita			0.12			0.02			-0.02
			(0.10)			(0.12)			(0.14)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	49174	49174	49174	48773	48773	48773	48773	48773	48773
Firms	3329	3329	3329	3324	3324	3324	3324	3324	3324

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). We estimate for each country an AR(1) process with time trends for wages, labor productivity, and GDP per capita. We then use the estimated process to predict with the information available at time t-2 the average values between the years t+2 and t+7, which are in turn the independent variables in these regressions. Columns (1)-(3) include firm and industry-year fixed effects, while (4)-(9) include firm, industry-year, and country-year fixed effects. In Columns (7)–(9) the macroeconomic variables are the normalized foreign variables previously defined. Stock and spillover variables are calculated with respect to the dependent variable. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.15: Minimum wage

Dependent variable	Auto95								
	Domestic+Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Minimum wage	2.10***	1.85***	2.11***	1.79**	1.92**	1.92*	2.15*	2.20*	0.92
	(0.62)	(0.63)	(0.78)	(0.88)	(0.92)	(1.04)	(1.17)	(1.24)	(1.38)
High-skill wage	-1.88***	-2.50***	-1.86**	-3.69***	-3.17***	-3.46**	-3.35**	-3.19*	-5.35***
	(0.66)	(0.79)	(0.82)	(1.01)	(1.22)	(1.40)	(1.36)	(1.84)	(1.85)
GDP gap	-2.99	-3.89	-2.96	7.05	7.72	7.55	2.79	2.97	-2.52
	(2.46)	(2.55)	(2.74)	(6.42)	(6.50)	(7.00)	(4.72)	(5.21)	(6.10)
Labor productivity		1.22			-0.94			-0.20	
		(0.79)			(1.48)			(1.62)	
GDP per capita			-0.04			-0.47			4.11*
			(1.22)			(1.98)			(2.49)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	49129	49129	49129	48757	48757	48757	47577	47577	47577
Firms	3326	3326	3326	3322	3322	3322	3237	3237	3237

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed effects regressions (HHG). Columns (1)-(3) include firm and year-industry fixed effects, while (4)-(9) include firm, year-industry, and country-year fixed effects. In Columns (7)–(9) the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.16: Five-year difference estimation

Dependent Variable	Δ Arcsinhauto95								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Firms which patented at least once in 1995-2013								
Δ Low-skill wage	0.94***	0.91***	0.98***	0.70**	0.59	0.49	1.10**	0.74	0.46
	(0.27)	(0.29)	(0.32)	(0.34)	(0.37)	(0.43)	(0.49)	(0.56)	(0.61)
Δ High-skill wage	-0.95***	-1.00***	-0.91***	-0.99***	-1.21***	-1.14***	-1.20**	-1.62***	-1.60***
	(0.25)	(0.28)	(0.28)	(0.35)	(0.40)	(0.38)	(0.51)	(0.58)	(0.54)
Δ GDP gap	-1.45	-1.55	-1.38	-0.19	-0.50	-0.36	-0.41	-1.27	-1.80
	(1.07)	(1.07)	(1.15)	(2.18)	(2.19)	(2.22)	(1.42)	(1.65)	(1.74)
Δ Labor productivity		0.12			0.50			0.75	
		(0.39)			(0.59)			(0.56)	
Δ GDP per capita			-0.10			0.54			1.22*
			(0.44)			(0.60)			(0.66)
Fixed effects	IY	IY	IY	CY + IY	CY + IY	CY + IY	CY + IY	CY + IY	CY + IY
Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35310	35310	35310	35280	35280	35280	35280	35280	35280
Firms	3531	3531	3531	3528	3528	3528	3528	3528	3528
	Panel B: Firms which patented at least twice in 1995-2013								
Δ Low-skill wage	1.87***	1.86***	1.87***	1.42***	1.40**	1.26*	2.43***	1.96**	1.74*
	(0.43)	(0.47)	(0.53)	(0.54)	(0.60)	(0.70)	(0.76)	(0.88)	(0.96)
Δ High-skill wage	-1.74***	-1.75***	-1.74***	-1.88***	-1.92***	-2.00***	-2.36***	-2.91***	-2.79***
	(0.39)	(0.44)	(0.45)	(0.56)	(0.64)	(0.61)	(0.77)	(0.89)	(0.84)
Δ GDP gap	-2.38	-2.39	-2.37	-2.06	-2.11	-2.19	-0.81	-1.92	-2.29
	(1.46)	(1.47)	(1.60)	(3.20)	(3.24)	(3.28)	(2.09)	(2.46)	(2.61)
Δ Labor productivity		0.02			0.09			0.96	
		(0.60)			(0.94)			(0.89)	
Δ GDP per capita			-0.01			0.42			1.28
			(0.71)			(0.98)			(1.06)
Fixed effects	IY	IY	IY	CY + IY	CY + IY	CY + IY	CY + IY	CY + IY	CY + IY
Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22650	22650	22650	22630	22630	22630	22630	22630	22630
Firms	2265	2265	2265	2263	2263	2263	2263	2263	2263

Note: Marginal effects; Standard errors in parentheses. Estimation is done by OLS. $t = 2000 - 2009$: The dependent variable is the difference between the arcsinh of the sum of yearly auto95 patents in t to $t+4$ and the arcsinh of the sum of yearly auto95 patents in $t-5$ to $t-1$. Columns (1)-(3) include industry-year fixed effect, while (4)-(9) include industry-year and country-year fixed effects. In Columns (7) to (9) the macroeconomic variables are the normalized foreign variables previously defined. All the independent variables are the sum of yearly counterparts from $t-4$ to t. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.17: Addressing Nickell's bias

Dependent variable	Auto95					
	Domestic+Foreign				Foreign	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skill wage	2.64***	2.41***	2.67**	2.85***	4.71***	4.09***
	(0.79)	(0.83)	(1.05)	(1.08)	(1.42)	(1.39)
High-skill wage	-2.46***	-0.81	-2.30**	-1.26	-2.78**	-1.55
	(0.77)	(0.79)	(0.99)	(1.00)	(1.39)	(1.50)
GDP gap	-4.71*	-2.66	4.51	8.28	0.73	1.20
	(2.73)	(3.52)	(7.05)	(7.72)	(4.92)	(5.47)
Labor productivity	0.81	0.09	-1.32	-1.90	-1.66	-1.53
	(0.90)	(1.04)	(1.67)	(1.53)	(1.48)	(1.52)
Stock automation	No	Yes	No	Yes	No	Yes
Stock other	Yes	Yes	Yes	Yes	Yes	Yes
Spillovers	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Estimator	HHG	BGVR	HHG	BGVR	HHG	BGVR
Observations	49174	49174	48773	48787	48773	48787
Firms	3329	3329	3324	3326	3324	3326

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG) in columns (1), (3), and (5). In columns (2), (4), and (6), estimation is done by Poisson regressions where the firm fixed effects are replaced by the pre-sample mean, following Blundell, Griffith and Van Reenen (1999, BGVR). Columns (1) and (2) include year-industry fixed effects and columns (3) to (6) include year-industry and country-year fixed effects. In Columns (5) and (6) the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.18: Citations-weighted patents

Dependent variable	Citations-weighted auto95								
	Domestic+Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.06**	1.79	3.28***	1.28	1.62	3.53**	3.39**	4.16**	3.80*
	(1.00)	(1.10)	(1.14)	(1.22)	(1.45)	(1.50)	(1.72)	(1.87)	(2.21)
High-skill wage	-2.38**	-2.88***	-0.97	-3.26**	-2.41*	-1.71	-4.00**	-3.02	-3.77**
	(0.96)	(0.99)	(1.07)	(1.27)	(1.30)	(1.40)	(1.64)	(1.89)	(1.76)
GDP gap	-3.80	-4.47	-0.74	0.53	1.75	4.62	-0.69	1.01	0.11
	(3.15)	(3.36)	(3.26)	(7.80)	(7.97)	(7.98)	(5.06)	(5.47)	(5.71)
Labor productivity		1.15			-1.90			-1.63	
		(1.23)			(2.29)			(1.80)	
GDP per capita			-3.54**			-5.60**			-0.71
			(1.63)			(2.35)			(2.61)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes			
Fixed effects	F+IY	F+IY	F+IY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	49174	49174	49174	48773	48773	48773	48773	48773	48773
Firms	3329	3329	3329	3324	3324	3324	3324	3324	3324

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). Patents are citations-weighted: we add to each patent the number of citations received within 5 years normalized by technological field and year of application. Columns (1)-(3) include firm and industry-year fixed effects, while (4)-(9) include firm, industry-year, and country-year fixed effects. In Columns (7)–(9) the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.19: Wages and deflators

Dependent variable	Auto95				
Sector	Manufacturing			Total	
Deflator	Manufacturing PPI, conversion in 2005	US manufacturing PPI, conversion every year	GDP deflator, conversion in 1995	Manufacturing PPI, conversion in 1995	US manufacturing PPI, conversion every year
	(1)	(2)	(3)	(4)	(5)
Foreign:					
Low-skill wage	5.00***	4.24***	4.88**	5.23*	4.75**
	(1.51)	(1.41)	(1.93)	(2.80)	(2.03)
High-skill wage	-2.68*	-3.60**	-2.58*	-2.58	-3.43
	(1.38)	(1.42)	(1.48)	(2.27)	(2.23)
GDP gap	1.53	0.49	1.40	0.15	-0.52
	(4.78)	(4.82)	(4.84)	(4.42)	(4.55)
Labor productivity	-2.40	-1.10	-2.32	-2.85	-2.24
	(1.51)	(1.56)	(1.62)	(3.06)	(2.90)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY	F+IY+CY
Observations	48773	48773	48773	48773	48773
Firms	3324	3324	3324	3324	3324

Note: All regressions include firm fixed effects, industry-year fixed effects and country-year fixed effects. Columns (1) to (3) use manufacturing wages and Columns (4) and (5) on total wages. In Column (1), macroeconomic variables are deflated with the local manufacturing PPI and converted to USD in 2005. In Columns (2) and (5) they are converted to USD every year and deflated with the US manufacturing PPI. In Column (3), macroeconomic variables are deflated with the local GDP deflator and converted to USD in 1995. In Column (4), macroeconomic variables are deflated with the local manufacturing PPI and converted to USD in 1995. In all columns, the macroeconomic variables are the normalized foreign variables previously defined. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.20: Firm bin size - year fixed effects

Dependent Variable	Auto95								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	3.03***	2.78***	3.56***	2.31**	2.70**	3.57***	4.34***	5.51***	4.36**
	(0.79)	(0.84)	(0.95)	(0.98)	(1.12)	(1.24)	(1.31)	(1.54)	(1.77)
High-skill wage	-2.29***	-2.70***	-1.77**	-2.85***	-2.01*	-2.02*	-4.52***	-2.87*	-4.50***
	(0.71)	(0.77)	(0.79)	(0.94)	(1.07)	(1.04)	(1.32)	(1.47)	(1.40)
GDP gap	-3.32	-3.89	-2.11	3.95	5.01	6.11	-0.68	1.78	-0.63
	(2.67)	(2.78)	(2.83)	(6.76)	(6.80)	(7.06)	(4.54)	(4.81)	(5.15)
Labor productivity		0.99			-1.92			-2.67*	
		(0.90)			(1.77)			(1.62)	
GDP per capita			-1.46			-3.09			-0.04
			(1.30)			(1.90)			(2.06)
Stocks / Spillovers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	F+IY	F+IY	F+IY	F+IY	F+IY	F+IY	F+IY	F+IY	F+IY
	BY	BY	BY	BY	BY	BY	BY+CY	BY+CY	BY+CY
Observations	49935	49935	49935	49890	49890	49890	49890	49890	49890
Firms	3329	3329	3329	3326	3326	3326	3326	3326	3326

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is done by conditional Poisson fixed-effects regressions (HHG). Firms are classified into five bins by the stock of total patents in 1995 with 25th, 50th, 75th and 95th percentiles as four thresholds. Columns (1)-(3) include firm, indsutry-year (IY) and bin-year (BY) fixed effects, while (4)-(9) include firm, indsutry-year, bin-year and country-year fixed effects. In Columns (7) to (9) the macroeconomic variables are the normalized foreign variables previously defined. Foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

A.2 Details on the classification of automation patents

We derived the exact list of keywords in Table 1 after experimenting extensively with variations around them and looking at the resulting classification of technology categories and the associated patents. 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 count all laser patents as they are not all related to automation—but we obtain patents related to automation using laser technologies thanks to our other keywords. Furthermore, the Y section of the CPC classification is organized differently from the rest and is only designed to provide additional information. As a result, we ignore Y codes throughout.

Table A.21: Summary statistics on the prevalence of keywords

	IPC/CPC 6 digit					IPC4 + (G05 or G06)					IPC4 pairs				
Share	all	robot	automat*	CNC	labor	all	robot	automat*	CNC	labor	all	robot	automat*	CNC	labor
Mean	20.9	4.3	11.2	2.4	5.9	53.2	15.4	32.4	11.2	9.5	18.5	4.5	8.8	1.8	5.4
S. d.	14.4	8.4	9.5	5.8	3.7	19.3	17.7	11	16.5	3.8	16.3	10	9.9	4.7	3.8
p25	10.5	0.8	4.2	0	3.3	40	6.7	26.6	0.8	2.6	7.7	0.6	2.5	0	2.6
p50	18	2	8.7	0.4	5.3	54.3	10	31.9	3	4.6	13.6	1.8	5.2	0.4	4.6
p75	26.6	4.5	15.3	1.8	7.7	63.8	16	40.3	15.5	7.3	23	4.2	10.7	1.4	7.3
p90	38.7	9.1	24.3	6.1	10.4	77.9	36.4	43.3	38.2	10.4	36.8	8.9	21.7	4.4	10.4
p95	47.7	13.7	29.4	12.7	12.7	85.6	44.3	45.2	55.3	12.3	51.8	14.5	31	7.7	12.3
p99	75	35.8	43.8	33.1	17.9	90.1	82.9	59.9	56.6	17.9	84.5	60	45.3	23.1	17.9

Note: This table computes summary statistics on the share of patents with any automation keywords, robot keywords, automat* keywords, CNC keywords or labor keywords for each type of technological categories (6 digit codes, pairs of 4 digit codes and combinations of ipc4 codes with G05 or G06) within machinery with at least 100 patents.

A.2.1 Statistics on the classification

Table A.21 gives summary statistics on the prevalence of automation keywords across technology categories in machinery, $p(t)$, as well as the prevalence of the 4 main subgroups of keywords: automat*, robot, numerical control (CNC) and labor. The 95^{th} and 90^{th} percentile for the prevalence of automation keywords for 6-digit codes in machinery define the thresholds used to categorize auto95 and auto90 patents. The distributions are quite similar for the C/IPC 6 digit codes and for pairs of IPC 4 digit codes (see also the histograms below). As expected, the distributions are significantly shifted to the right for combinations of C/IPC 4-digit codes with G05 or G06. All prevalence measures are right-skewed particularly for 6-digit codes and 4-digit pairs, and even more for the robot and CNC patents. The automat* keywords are also more common as the prevalence of automat* is significantly higher than for the other keywords. Yet, the difference narrows somewhat in the right tail: the 95^{th} percentile for 6 digit codes is 29.4%

for automat* and 13.7% and 12.7% for robot and CNC. In fact, the thresholds (5 and 2) used in the definition of the automat* keywords were chosen so that the distributions of the prevalence measures are somewhat comparable. The right tails of the distribution are similar for the prevalence of the robot and CNC keywords.

Table A.22: Correlation between the main prevalence measures

Keywords	Automat	Robot	CNC	Labor
Automat	1.000			
Robot	0.383	1.000		
CNC	0.215	0.206	1.000	
Labor	0.391	0.225	0.090	1.000

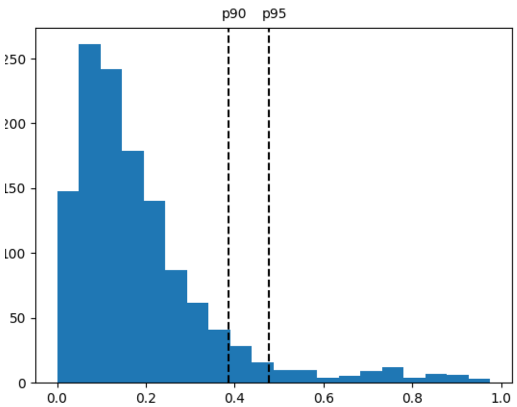
Note: Correlation between the prevalence of the main keywords, computed for C/IPC 6-digit codes.

Table A.22 shows the correlation between the prevalence of the 4 mains keyword categories (automat*, robot, CNC and labour) for 6 digit C/IPC codes. These measures are positively correlated with a coefficient above 0.2 in all cases except CNC and labour. The broadest category, automat*, is the one with the highest correlation coefficients.

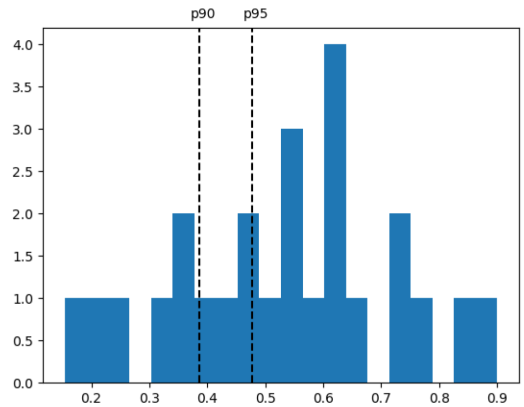
Figure A.5.a gives the histograms of the prevalence of automation keywords for machinery technology categories which are pairs of C/IPC 4-digit codes. The histograms are very similar to those of C/IPC 6 digit codes in Figure 1. Figure A.5.b shows the histograms for all combinations of machinery C/IPC 4-digit codes with G05 or G06. The distribution is considerably shifted to the right, in line with expectations since G05 proxies for control and G06 for algorithmic, two set of technologies which have been used heavily in automation. There are, however, many fewer combination of these types, and accordingly fewer patents can be characterized as automation innovations this way.

A.2.2 How are auto90 and auto95 patents identified?

Given that our classification procedure is relatively complex, we assess here which features dominate. To do so, we focus on the set of $15,212,134$ biadic patent applications in 1997-2011 (corresponding to the $3,187,536$ patent families which have patent applications in at least two countries), since this corresponds to the set on which we run our main regressions. There are $310,458$ auto95 patent applications corresponding to $61,768$ patent families (and similarly $541,693$ auto90 patent applications corresponding to $107,237$ patent families). Table A.23.a gives the share of biadic patents which are identified through a C/IPC 6 digit code, a pair of 4-digit codes or a combination of 4-digit code with G05/G06 (the shares sum up to more than 100% since patents may be



(a) For all pairs of C/IPC 4 digit codes within machinery with 100 patents



(b) For combinations of IPC4 in machinery with G05 G06 and at least 100 patents

Figure A.5: Histograms of the prevalence of automation keywords. The p90 and p95 lines are those of the 6 digit distribution and mark the thresholds used to define auto90 and auto95 technological categories.

identified as automation innovations in several ways). 6-digit codes are the most relevant since they identify close to 80% of either auto90 or auto95 patents alone.

Similarly, one may wonder which keywords are the most important in identifying automation patents. To assess that, we define robot95 patents as patents which contain a technology category with a prevalence of "robot" keywords above the threshold used to define auto95 (namely 0.4766), therefore those patents are a subset of the auto95 patents. We define CNC85, automat*95, robot90, CNC90, automat*90, robot80, CNC80 and automat*80 similarly. The other keywords are much less common. Table A.23.b reports the share of auto95, auto90 and auto80 patents which belong to each subcategory. "Automat*" is the most important keyword since 72% of auto95 patents are also automat*80 patents. "Robot" matters as well with 33.6% of auto95 patents which are robot80 and 17.7% which are even robot95 (more than automat*95). CNC does not matter much: only 13% of auto95 patents are CNC80.

Table A.23: Identification of automation technology categories

(a) Type of C/IPC codes identifying auto90 and auto95 patents

Ipc codes / Patents	Auto90	Auto95
Matches ipc6	78.2%	78.7%
Matches ipc4 pair	17.3%	24.3%
Matches ipc4 - G05/G06 combination	47.7%	47.8%

Note: Share of innovations classified as automation innovation through ipc6 codes, ipc4 pairs or ipc4 - G05/G06 pairs. Statistics computed on biadic patents from 1997-2011.

(b) Auto patents and subcategories of automation innovations

Sources / Patents	Auto80	Auto90	Auto95
Auto80	100.0%	100.0%	100.0%
Automat*80	36.2%	53.1%	72.1%
CNC80	5.0%	8.0%	13.2%
Robot80	12.0%	19.2%	33.6%
Auto90	62.4%	100.0%	100.0%
Automat*90	21.6%	34.6%	56.0%
CNC90	2.2%	3.6%	6.3%
Robot90	7.8%	12.5%	21.8%
Auto95	35.8%	57.3%	100.0%
Automat*95	4.4%	7.1%	12.4%
CNC95	1.6%	2.5%	4.4%
Robot95	6.3%	10.2%	17.7%

Note: Share of auto95 (auto90 and auto80, respectively) innovations which are also classified as automat*80/90/95, CNC80/90/95, and robot80/90/95 innovations. Statistics computed on biadic patents from 1997-2011.

Table A.24: Correlation between the prevalence of automation keywords for different periods

	Prevalence of automation keywords using patents during the period:			
	1978-2017	1997-2011	1978-1997	1998-2017
1978-2017	1	.	.	.
1997-2011	0.9863	1	.	.
1978-1997	0.9693	0.9321	1	.
1998-2017	0.9885	0.992	0.9241	1

Notes: Correlation matrix for the prevalence of automation keywords by C/IPC 6-digit codes in machinery using EPO patents over different time periods. We exclude catch-all categories made at the 4-digit level.

A.2.3 Stability of the classification

To assess the stability of our classification, we redo exactly the same exercise but instead of using EPO patents from 1978 to 2017, we restrict attention to EPO patents from the first half of the sample (1978-1997), the second half (1998-2017) or the period of our main regression analysis (1997-2011). There is a modest increase in the share of patents with automation keywords within each technology category. At the C/IPC 6-digit level in machinery, the share of patents with an automation keyword increases on average from 0.19 in the first half of the sample to 0.21 in the second half. Nevertheless, the ranking of codes is remarkably stable as shown in Table A.24which reports the correlations of the prevalence measures for the different time periods.

Table A.25: Confusion table for different classification periods

Confusion Matrix		Auto95 based on the 1998-1997 classification		Auto95 based on the 1998-2017 classification		Auto95 based on the 1997-2011 classification		Total
		Yes	No	Yes	No	Yes	No	
Auto95 based on	Yes	240,194	70,264	280,047	30,411	262,972	47,486	310,458
the 1978-2017	No	53,137	14,848,539	25,186	14,876,490	26,368	14,875,308	14,901,676
classification	Total	293,331	14,918,803	305,233	14,906,901	289,340	14,922,794	15,212,134

Notes: The statistics are always computed on patents from 1997-2011.

Further, focusing on the same set of biadic patent applications in 1997-2011, Table A.25 shows confusion tables on the classification of patents as auto95 according to each of the classification period. Regardless of the time period used the number of automation patents stays roughly constant. In particular, 85% of the baseline auto95 patents are still auto95 if we run the classification over the years 1997-2011. This common set of patents then represent 91% of all biadic patents classified as auto95 patents when using the period 1997-2011 instead of the full sample.

A.3 Comparison with Mann and Puettmann (2020)

We considered the machinery (according to our definition) of Mann and Puettmann (2020, henceforth MP) and them as auto95 or not (at the family level). We have a lower share of automation patents (18.5% for auto90 and 10% for auto90) than MP who have 30.8%. 70% of our auto95 patents are classified as automation patents by MP (to analyze this number, it is useful to note that their algorithm has a 17% false negative error rate on the training set), while we classify 22.7% of their automation patents as auto95. Therefore, our measure of automation is generally stricter than theirs although it is not a perfect subset.

To facilitate comparison, we computed the share of automation patents at the C/IPC 60digit level according to their classification and compare this number with our measure of the prevalence of automation keywords. The correlation between these two measures is high (at 0.58). Figure A.6 shows the histograms of the two distributions. Our prevalence measure is more skewed and has a fatter tail (with a kurtosis of 7 versus 3.5), as such it more clearly identifies a set of outliers among 6-digit C/IPC codes.

We compute the difference between our prevalence measure and their share of automation patents and look at the codes with the highest and lowest values (focusing on codes with at least 100 patents in both their dataset and our EPO dataset). Table A.26 lists the 6 codes with the largest positive difference (among auto95 codes) and the 6 codes with the largest (in absolute value) negative difference (among non-auto90 codes).

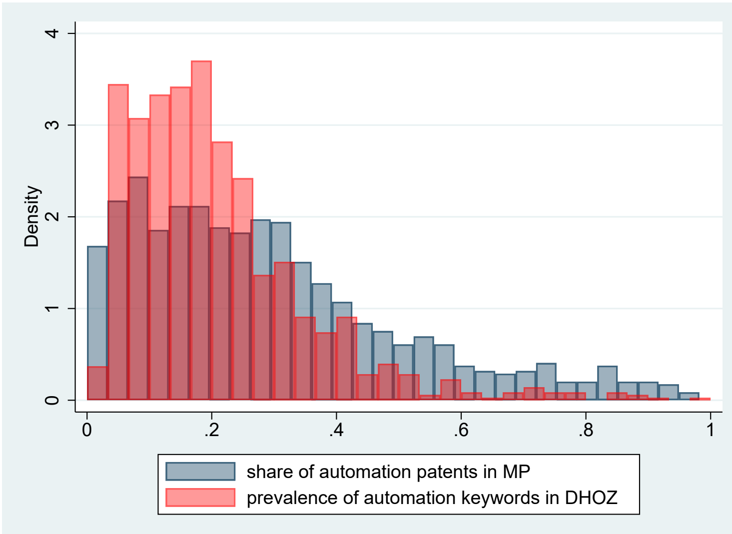


Figure A.6: Histograms of the share of automation patents in MP and of the prevalence of automation keywords in this paper at the 6 digit level in machinery.

3 of the codes with a high difference belong to the manipulator subclass (B25J), they correspond to joints (B25J17), gripping heads (B25J15) and accessories of manipulators (B25J19). MP classify a large share of these patents as automation but our prevalence number is even higher. In their definition of automation patents, MP specify that they exclude innovations which only refer to parts of a machine. This accounts for some of the patents in these codes that they do not classify as automation. D01H9 corresponds to "arrangements for replacing or removing bobbins, cores, receptacles, or completed packages at paying-out or take-up stations" for textile machines. The share of automation patents in MP is low at 0.38, however their "raw share" (computed before they exclude certain patents) is quite high at 0.71. The excluded patents are not chemical or pharmaceutical patents (as emphasized in the paper), but belong to the "other" technological field (according to the Hall-Jaffe-Trajtenberg classification). The same situation occurs for B65B2210 (which is about packaging machines) where their raw automation score is actually at 0.63 and the patents excluded by MP are not chemical. B23P23 is a machine tool subclass (specifically "Machines or arrangements of machines for performing specified combinations of different metal-working operations not covered by a single other subclass") which often involves CNC technologies.

The non-auto90 codes where MP find a high share of automation patents but for which we have a comparatively low prevalence measure are easily identifiable. Among the top 6, half are in the subclass B66B which corresponds to elevators and the other

Table A.26: Outliers 6-digit C/IPC codes in the comparison between our measure and MP's measure

C/IPC 6 digit code	Simplified description	Prevalence of automation keywords (DHOZ)	Share of automation patents (MP)
	Positive outliers (among auto95 codes)		
B25J17	Manipulators (joints)	0.84	0.54
D01H9	Textile machines (arrangements for replacing or removing various elements)	0.62	0.38
B65B2210	Specific aspects of packaging machines	0.48	0.25
B25J15	Manipulators (gripping heads)	0.71	0.50
B23P23	Metal working machines (specified combinations n.e.c)	0.67	0.46
B25J19	Manipulators (accessories)	0.89	0.69
	Negative outliers (among non-auto 90 codes)		
B66B2201	Control systems of elevators	0.19	0.97
B66B3	Elevators (signalling and indicating device applications)	0.19	0.92
B41J23	Typerwriters / printing machines (power drive)	0.08	0.82
B66B1	Elevators (control systems)	0.16	0.89
B41J19	Typerwriters / printing machines (characters and line spacing mechanisms)	0.14	0.84
B41J5	Typerwriters / printing machines (controlling character selection)	0.21	0.91

Note: This table lists the 6 auto95 codes with the largest positive difference between the prevalence of automation keywords in our data and the share of automation patents according to MP in their data; and the 6 non-auto90 codes with the largest negative difference between the two measures. We restrict attention to codes with at least 100 patents in both datasets.

half are in the subclass B41J which corresponds to typewriters and printing machines. In fact, the first 34 6-digit C/IPC codes belong to either B66B, B41J or the subclass B65H which is about handling thin or filamentary material and also involves patents associated with printing machines. It is not surprising that our classifications differ for these types of innovation, since they do correspond to processes perform independently of human action (in line with MP's criterion); yet elevators and printers do not (or at least no longer) replace humans in existing tasks.

A.4 Redoing ALM

We detail how we build the variables used in Section 2.6 and provide further results.

A.4.1 Data for the ALM exercise

Except for the automation measures, we take the variables directly 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 1% 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 concert 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 starts in 1970 and drops a few sectors but we keep the original ALM measure to facilitate comparison. As in ALM, the dependent variable in Table 3 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 change per decade in the percentage of industry workers using a computer at their jobs between 1984 and 1997 (estimated from the October Current Population Survey supplements). For all regressions, observations are weighed by the employment share in each sector.

To map patents to sectors we proceed in 4 steps. First, we build a mapping between C/IPC 4 digit codes and the SIC sector that holds the patent (inventing sector). To do that, we use Autor et al. (2020) who match 72% of domestic USPTO corporate patents to firms in Compustat. This allows us to assign a 4-digit SIC sector to this subset of patents. We match the USPTO patents to our patent family data from PATSTAT, which we use to get the full set of C/IPC codes of the family. We then restrict attention to granted patents in machinery applied for in the period 1976-2010. Each patent family for which we have a sector creates a link between its C/IPC codes and that sector. We weigh that link inversely to the number of 6-digit C/IPC codes in the patent. Counting these connections allows us to build a weighted concordance table between 656 4-digit C/IPC codes and 397 SIC codes (at different levels of aggregation), where the industries refer to the industry of invention / manufacturing.

Second, to obtain the sector of use we rely on the 1997 "investment by using industries" table from the BEA (at the most disaggregated level, 180 commodities for 123 industries) which gives the flows of investment from commodities to industry available at www.bea.gov/industry/capital-flow-data. Beforehand, we assign commodities to industries using the 1997 make table at the detailed level from the BEA (available at www.bea.gov/industry/historical-benchmark-input-output-tables) which gives the commodities produced by each industry.[36] We dropped commodities associated with the

[36]Since our industries are in SIC 1987, we use concordance tables from the IO industries to NAICS 1997 provided by the BEA and then the weighed concordance table between NAICS 1997 and SIC 1987 from David Dorn's website https://www.ddorn.net/data.htm which we complete with a concordance ta-

Table A.27: Sectors with the highest and lowest shares of automation patents

ind6090	Title	Auto95	ind6090	Title	Auto95
	Sectors with the highest share of automated patents in machinery			*Sectors with the lowest share of automated patents in machinery*	
756	Automotive services and repair shops	0.111	801	Bowling alleys, billiard and pool parlors	0.043
206	Household appliances; Radio, TV & communications equipment; Electric machinery, equipment & supplies; Not specified electrical machinery, equipment & supplies	0.109	802	Misc. entertainment and recreation services	0.048
			100	Meat products	0.049
			101	Dairy products	0.049
470	Water supply and irrigation	0.101	102	Canned and preserved fuits and vegetables	0.049
271	Iron and stell foundaries	0.098	110	Gain mill products	0.049
212	Misc. plastic products	0.096	111	Bakery products	0.049
130	Tobacco manufactures	0.095	112	Sugar and confectionary products	0.049

Auto95 is the share of automation patents in machinery (95th threshold) in 1980-1998.

construction sector which are structures. Combining the two BEA tables, we obtain an investment flow table at the industry level. We combine that table with the C/IPC to industry of manufacturing table previously derived to get an C/IPC to industry of use table mapping 656 4-digit C/IPC codes into 966 SIC industries.

Third, we allocate patent families fractionally to their C/IPC 4-digit codes and use the previous table to assign them to an industry of use in the SIC classification (having restricted attention to the C/IPC codes which appear in the table). Fourth, we use a concordance table from the US Census Bureau from SIC industries to the Census industries from 1990 (ind90) given by Scopp (2003) and ALM concordance table from ind90 to consistent Census industries (ind6090) in order to allocate patents to their industry of use in ALM's classification.

Finally, for each sector and 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 (so that the number of sectors varies across time periods). Table A.27 shows the sectors with the highest and lowest shares of automation patents in machinery.

To compute the share of automation patents in machinery according to the industry of manufacturing / invention, we proceed as above but skip step 3 with the investment flow table. Once patents are assigned to a SIC industry of manufacturing, we use the same concordance tables to assign patents to an ind6090 industry of manufacturing.

Finally, in robustness checks, we also use an alternative mapping from patents to sectors based on Lybbert and Zolas (2014) who provide a concordance table between IPC codes at the 4-digit level and NAICS 1997 6-digit industry codes. The concordance table is probabilistic (so that each code is associated with a sector with a cer-

ble from the Census available here (www.census.gov/eos/www/naics/concordances/concordances.html). To generate weights in the mapping between IO industries and NAICS 1997 and to disaggregate the NAICS industries from the capital flow table, we use CBP data from 1998 (https://www.census.gov/data/datasets/1998/econ/cbp/1998-cpb.html).

Table A.28: Changes in routine task intensity and different measures of sectoral automation

Dependent variable	Δ Routine cognitive			Δ Routine manual		
	Biadic	Auto90	Lybbert and Zolas	Biadic	Auto90	Lybbert and Zolas
	(1)	(2)	(3)	(4)	(5)	(6)
Automation share	-127.97***	-75.32***	-26.66***	-97.85***	-53.91***	-17.09***
	(26.33)	(14.58)	(4.83)	(27.70)	(15.56)	(3.90)
Δ Computer use 1984 - 1997	-20.39***	-17.77***	-17.74**	-21.36***	-18.97***	-11.53**
	(5.08)	(4.81)	(6.79)	(5.37)	(5.13)	(5.48)
R^2	0.21	0.22	0.39	0.02	0.15	0.29
Observations	118	124	69	118	124	69

Standard errors are in parentheses. Each column presents a separate OLS regression of ten times the annual change in industry-level task input between 1980 and 1998 (measured in centiles of the 1960 task distribution) on the share of automation patents in machinery and the annual percentage point change in industry computer use during 1984 - 1997 and a constant. In columns (1) to (3) the dependent variable is the change in routine cognitive tasks and in columns (4) to (6) the change in routine manual tasks. The automation share measures correspond to the share of automation patents in machinery. "Biadic" uses only biadic auto95 patents, "Auto90" defines automation patents as auto90 patents. In both cases, patents are allocated to their sector of use. "Lybbert and Zolas'' uses auto95 patents and allocates patents using a concordance table between C/IPC codes and industries from Lybbert and Zolas (2014). Estimates are weighted by mean industry share of total employment in FTEs in 1980 and 1998. * p<0.1; ** p<0.05; *** p<0.01

tain probability). The Lybbert and Zolas concordance tables are derived by matching patent 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 and paper sectors and not with the equipment sector. In addition, it has the advantage of providing a much more direct mapping between C/IPC codes and industries. We attribute patents to sectors fractionally in function of their C/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, and then again use ALM concordance table.

A.4.2 Additional results

We carry a number of robustness checks in Table A.28 for the consolidated time period 1980-1998. In Columns (1) and (4), we compute the share of automation patents using only granted USPTO patents which are also biadic (again restricting attention to sectors with at least 50 machinery biadic patents). The results are very similar. In Columns (2) and (5), we use the share of auto90 patents in machinery to measure automation in the sector of use. The results are similar but with smaller coefficients than in the regressions using auto95. In Columns (3) and (6), we instead map patents to sectors based on a concordance table from Lybbert and Zolas (2014) between 4 digit C/IPC codes and sectors. This method has the advantage of mapping more directly patents to sectors but cannot distinguish between manufacturing and using sectors. We still find that sectors with a high share of automation patents experienced a decline in routine tasks. The coefficients are smaller, but given larger standard deviations, the standardized coefficients are similar.

A.5 Macroeconomic variables

Our main source of macroeconomic variables is the *World Input Output Database (WIOD)* from Timmer et al. (2015) which contains information on hourly wages (low-skill, middle-skill and high-skill) for the manufacturing sector and the total economy from 1995 to 2009 for 40 countries. It further contains information on GDP deflators and PPIs both for manufacturing and for the whole economy. They employ the ISCED skill-classification, where category 1+2 denote low-skill (no high-school diploma in the US) 3+4 denote middle-skill (high-school but not completed college) and 5+6 denotes high-skill (college and above). Switzerland is not included in the WIOD database and we add data on skill-dependent wages, productivity growth and price deflators using data obtained directly from *Federal Statistical Office of Switzerland.*

We supplement this data with data from *UNSTAT* on exchange rates and GDP (and add Taiwan from the *Taiwanese Statistical office*). We calculate the GDP gap as the deviations of log GDP from HP-filtered log GDP using a smoothing parameter of 6.25. To compute the offshoring variable we follow Timmer et al. (2014) and compute the share of foreign value added in manufacturing from the WIOD 2013 (except for Switzerland where we use the 2016 release and assign to the years 1995-1999 the same value as in 2000). For the nominal interest rate, we use the yield on 10-year government bonds with data from the OECD for AT AU BE CA CH DE DK ES FI FR GB IE IT JP NL PT SE US and from the IMF for KR GR LU.

The primary data source for the hourly minimum wage data is *OECD Statistics.*[37] For

[37] Not all countries have government-imposed hourly minimum wages. Spain, for instance, had a monthly minimum wage of 728 euros in 2009. To convert this into hourly wage we note that Spain has 14 "monthly" payments a year. Further, workers have 6 weeks off and the standard work week is 38 hours. Consequently we calculate the hourly minimum wages as monthly minimum wage$\times 14/\left[(52-6)\times 38\right]$, which in 2009 is 5.83 euros per hour. We perform similar calculations, depending on individual work conditions, for other countries with minimum wages that are not stated per hour: Belgium, Brazil, Israel, Mexico, Netherlands, Poland and Portugal.

the US, we use data from FRED for state minimum wages and calculate the nation-level minimum wage as the weighed average of the state-by-state maximum of state minimum and federal minimum wages, where the weight is the manufacturing employment in a given state. Further, the UK did not have an official minimum wage until 1999. Before 1993, wage councils set minimum wages in various industries (see Dickens, Machin and Manning, 1999). We compute an employment-weighed industry average across manufacturing industries and use the 1993 nominal value for the four years in our sample (1995-1998) with no minimum wage. Finally, Germany did not have a minimum wage during the time period we study. Instead, we follow Dolado et al. (1996) and use the collectively bargained minimum wages in manufacturing which effectively constitute law once they have been implemented. These data come from personal correspondence with Sabine Lenz at the *Statistical Agency of Germany.*

A.6 Firm-level patent weights

We give further details on the firm level patent weights. As mentioned in the text, we only count patents in machinery because some of the biggest innovators in automation technologies are large firms which produce a wide array of products with different specialization patterns across industries. Further, we exclude firms which have more than half of their patents in countries for which we do not have wage information.

In Europe, firms can apply both at national patent offices and at the EPO, in which case they still need to pay a fee for each country where they seek protection. We count a patent as being protected in a given European country if it is applied for either directly in the national office or through the EPO. In addition, we take the following steps in order to deal with EP patents. We assign EP patents to countries when they enter into the national phase. A firm's untransferred EP patents are assigned using information on where that firm previously transferred its EP patents. If a firm does not have any already transferred EP patents, we assign the patent based on a firm's direct patenting history in EPO countries. Untransferred EP patents that are still left are assigned to countries based on the EPO-wide distribution of transfers. We also drop a firm if more than half of its patents are EP patents assigned using the EPO-wide distribution.

Finally, as mentioned in the text we only count patents in families with at least one (non self-) citation. 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.

A.7 Macroeconomic interpretation of the regression coefficients

In this section, we analyze the economic magnitude of our regression coefficients by combining them with the results of Section 2.6 on the effect of automation on routine tasks. Two issues prevent us from simply directly multiplying coefficients: First, our regressions control for the stock of knowledge of firms and the knowledge spillovers that they are potentially subject to, which will both change as a change in wages affect (all) firms' innovation decisions. Second, in Section 2.6, we looked at the effect over a decade of changes in the share of automation patents over total machinery patents.

Therefore, we run a simulation where we consider a uniform and permanent decrease in the skill premium by 10% between 1995 and 2009 in all countries. We use our regression results to recompute the share of automation innovations in machinery over that period. Importantly, we stress that one *must not* interpret the result of this simulation as predictive notably because a change in innovation should in turn affect the skill premium. Yet, our analysis could be used to calibrate a model which predicts that the direction of innovation reacts to changes in the skill premium. We focus on a changes in the skill premium as it is easier to interpret than a change in low-skill wages keeping high-skill wages constant.

Specifically, we simulate the regression results reported in Figure A.7. Given our goal of computing changes in the share of automation innovations in machinery, this regression differs slightly from the ones in the paper. We regress both auto95 innovations and all other machinery innovations on the inverse of the skill premium, the GDP gap, stock and spillover variables and firm and industry-year fixed effects and we consider separately the stocks and spillovers of auto95 innovations, all other machinery innovations and all other innovations.

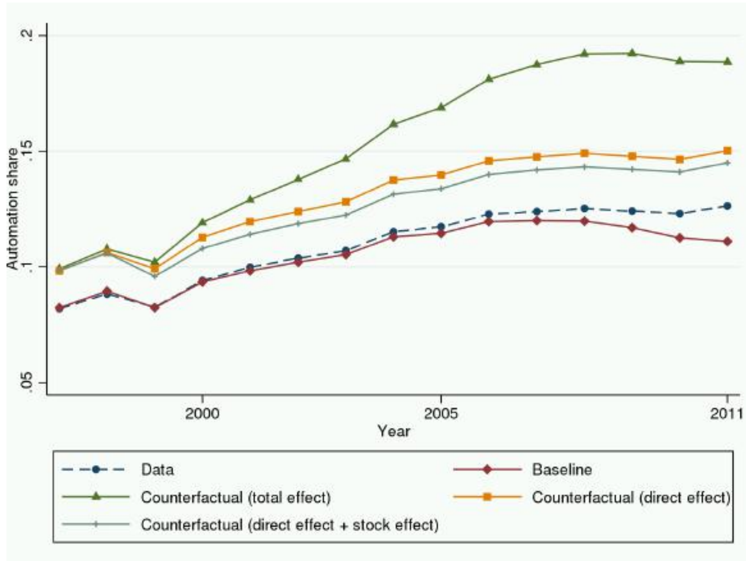
Figure A.7 reports the results averaged over 500 simulations (using the median gives similar results).[38] We first compute the direct effect of a decrease in the skill premium (keeping stocks and spillover variables constant) on the share of automation innovations in machinery. This is captured by the gap between the data curve and the counterfactual (direct effect) curve. This gap reflects the elasticity of 2.38 of auto95 innovations with respect to the inverse skill premium (with an elasticity of 0.25 for other machinery

[38]The figure reports the share of automation patents for the firms in our regression sample. This differs from Figure 3 since the latter reports the share of automation patents for all firms.

Dependent variable	Auto95	Mach.\auto95
	(1)	(2)
Low-skill / High-skill wages	2.38***	0.25
	(0.67)	(0.51)
GDP gap	-4.80*	-2.96**
	(2.64)	(1.36)
Stock automation	-0.16***	0.14***
	(0.05)	(0.03)
Stock mach.\auto95	0.35***	0.26***
	(0.06)	(0.03)
Stock other	0.35***	0.26***
	(0.06)	(0.04)
Spillovers automation	1.04***	-0.13
	(0.36)	(0.21)
Spillovers mach.\auto95	1.14*	2.25***
	(0.60)	(0.38)
Spillovers other	-1.68**	-1.92***
	(0.73)	(0.49)
Fixed effects	F+IY	F+IY
Observations	49174	154965
Firms	3329	10367

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

(a) Supporting regression



(b) Simulation result

Figure A.7: Simulation of a permanent and global 10% decrease in the skill premium on the share of automation innovations in machinery

innovations). Taking into account the response of firms' own innovation stocks slightly decreases the effect of low-skill wages reflecting the negative effect of the automation stock on auto95 innovations and its positive effect on other machinery innovations.

We then assess the importance of knowledge spillovers by recomputing the spillover variables for the auto95 innovations and other machinery innovations (but not the non-machinery innovations). This involves two complications. First, our model only applies to the number of innovations and not their location. To allocate innovations to countries, we assign the simulated innovations proportionally to the firm's inventor weights (used to construct the spillover variables). Second, firms in our sample account for only 58% of all biadic innovations in 1997-2011. We assume that the other firms respond similarly so that when we assign simulated innovations to countries, we increase innovations by out-of-sample firms to keep the ratio of in-sample to out-of-sample innovations constant.

The overall effect of an increase in the inverse skill premium is then captured by the gap between the baseline curve and the counterfactual one. The baseline curve and the data series differ because the baseline is an average while the data series is only one possible realization. Knowledge spillovers increase the overall elasticity of the share of automation patents with respect to low-skill wages. The average share of automation innovations in machinery between 1997 and 2011 increases by 4.8 p.p. from 10.5% to 15.3%. This is 2.7 p.p. more than the direct effect. This 4.8 p.p. increase can be compared to the 4.4 p.p. increase in the data over the same time period. As mentioned in Section 5.2, one can then combine these effects with the results of Section 2.6, and obtain that this 4.8 p.p. increase in the share of automation innovation would be associated with a decline in routine cognitive tasks of 7 centiles and a decline in routine manual tasks of 5.8 centiles. Though one should not interpret these numbers as causal, they indicate that the effect of the skill premium on automation innovations is economically significant.

Online Appendix References

Dolado, J., Kramarz, F., Machin, S., Manning, A., Margolis, D., and Teulings, C. (1996). The Economic Impact of Minimum Wages in Europe. *Economic Policy* 11 (23).

Dickens, R., Machin, S., and Manning, A. (1999). The Effects of Minimum Wages on Employment: Theory and Evidence from Britain. *Journal of Labor Economics,* 17 (1).

Lybbert, T. and Zolas, N. (2014). Getting patents and economic data to speak to each other: An 'Algorithmic Links with Probabilities' approach for joint analyses of patenting and economic activity. *Research Policy,* 43: 530-542.

Scopp, T. (2003). The relationship between the 1990 Census and Census 2000 Industry and Occupation Classification Systems. US Census Bureau.

B Supplemental material

B.1 Additional examples

We provide a few additional examples of automation and non-automation patents. Figure B.1 shows the example of a robot with a patent containing the IPC code B25J9. The patent describes a multi-axis robot with a plurality of tools which can change the working range of each arm. This essentially increases the flexibility of the robot. Figure B.2 shows an automation innovation used in the dairy industry. The patent contains the code A01J7 which is a high automation code (see Table 2). It describes a system involving a robotic arm to disinfect the teats of cows after milking. The patent argues that this reduces the need for human labor and therefore saves costs. Figure B.3 describes an automated machining device, yet another example of a high automation innovation, which contains the code B23Q15 (a high automation code described in Table 2). The devices features a built-in compensation system to correct for errors thereby reducing the need for a "labor-intensive adjustment process". Figure B.4 describes another high automation patent belonging to the same IPC code as well as to G05B19. This is also a machining device. The patent explains that innovations in machining have aimed at making the process as automated as possible by involving some feedback mechanism (as in the previous older patent). This invention aims at better predicting the machining requirements in the first place.

In contrast Figure B.5 describes a low automation innovation in machinery (none of the codes are above the 90th percentile in the 6 digit C/IPC distribution). The innovation relates to a "conveying belt assembly for a printing device"', which is about the circulation of paper in the printing machine. This innovation does not directly involve automation. Similarly Figure B.6 describes a winch to raise and lower people, another low-automation innovation in machinery. This innovation seems rather low-skill labor complementary as its goal is to enable workers to move in a plurality of directions. Finally Figure B.7 describes a harvester (which also counts as a machinery innovation since the code A01B63 belongs to other special machinery). This is also a low-automation innovation as its goal is to ensure that the harvester can both operate in the field and travel on roads.

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(71) Applicant: **SONY CORPORATION**
7-35, Kitashinagawa 6-chome Shinagawa-ku Tokyo(JP)

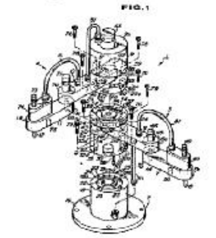
(72) Inventor: **Kakinuma, Takekazu**
c/o Sony Corporation 7-35 Kitashinagawa 6-chome
Shinagawa-ku Tokyo(JP)

(74) Representative: **Ayers, Martyn Lewis Stanley et al**
J.A. KEMP & CO. 14 South Square Gray's Inn London, WC1R 5EU(GB)

(54) **Multi-axis type robot.**

(57) A multi-axis robot includes a stationary base (2) and one or more detachable arm units (3, 4). Each of the detachable arm unit comprises a pivotal base (5, 9) detachably mounted on the stationary base, and a first arm (6, 10) pivotably supported on the pivotal base, a second arm (7, 11) pivotably supported on a free end of the first arm, and a tool mounting shaft (8, 12) supported on a free end of the second arm The angular orientation of the arm units with respec to the stationary base and to each other may b optimally adjusted, so as to select suitable workin ranges for each of the arm units and define coop erative working ranges for a plurality of arm units.

FIG.1



EP 0 380 206 A1

The present invention relates generally to a multi-axis type robot which includes at least one arm unit have a plurality of pivotal axes. More specifically, the invention relates to a multi-axis type robot which has at least one arm unit comprising a pivotal base or shoulder member, a first pivotal arm pivotably supported on the shoulder member, and a second pivotal arm pivotably supported on the first pivotal arm at a free end thereof.

In recent years, various industrial robots have been used for processing various materials, such as the manufacturing of parts, or the assembling of apparatus. One of such industrial robot is a multi-axis type robot which includes an arm unit having a plurality of pivotal axes. Such a robot is basically

In addition, although a multi-axis robot can be compact, it is difficult to pre-mount a plurality of tools on the robot. Therefore, there are disadvantages in that the tool mounted on the robot must be changed whenever a line operation is altered, reducing operation efficiency.

In order to overcome the aforementioned disadvantages, there has been proposed an improved, multi-arm type, multi-axis robot on which a plurality of tools can be mounted and which can selectively or simultaneously drive the tools. This robot generally comprises an essentially cylindrical stationary base, and two arm units pivotably supported on the stationary base. Utilising such a robot, the overall length of an assembly line can be reduced. However, since the respective arms are mounted on the stationary base at predetermined positions, the working range of each arm is fixed, meaning that the cooperative working range of the arms is fixed. Therefore, when the working range of any of the arms or the cooperative working range between the arms needs to be changed in order to facilitate a change in line operation, another robot must be arranged on the line.

It is therefore a principal object of the present invention to eliminate the aforementioned disadvantages and to provide a multi-axis robot which can optionally alter the working ranges of its arms and thereby, its cooperative working range.

Figure B.1: Example of a high automation patent: an industrial robot

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(71) Applicant: **Technologies Holdings Corporation**
Houston, TX 77019 (US)

(72) Inventors:
- **HOFMAN, Henk**
NL-8531 PC Lemmer (NL)
- **VAN DER SLUIS, Peter, William**
8271 PP IJsselmuiden (NL)
- **GROENSMA, Yep**
8441 CA Ca Heerenveen (NL)

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(74) Representative: **Moore, Derek**
Jensen & Son
366-368 Old Street
London EC1V 9LT (GB)

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(54) **METHOD AND AUTOMATED SYSTEM FOR APPLYING DISINFECTANT TO THE TEATS OF DAIRY LIVESTOCK**

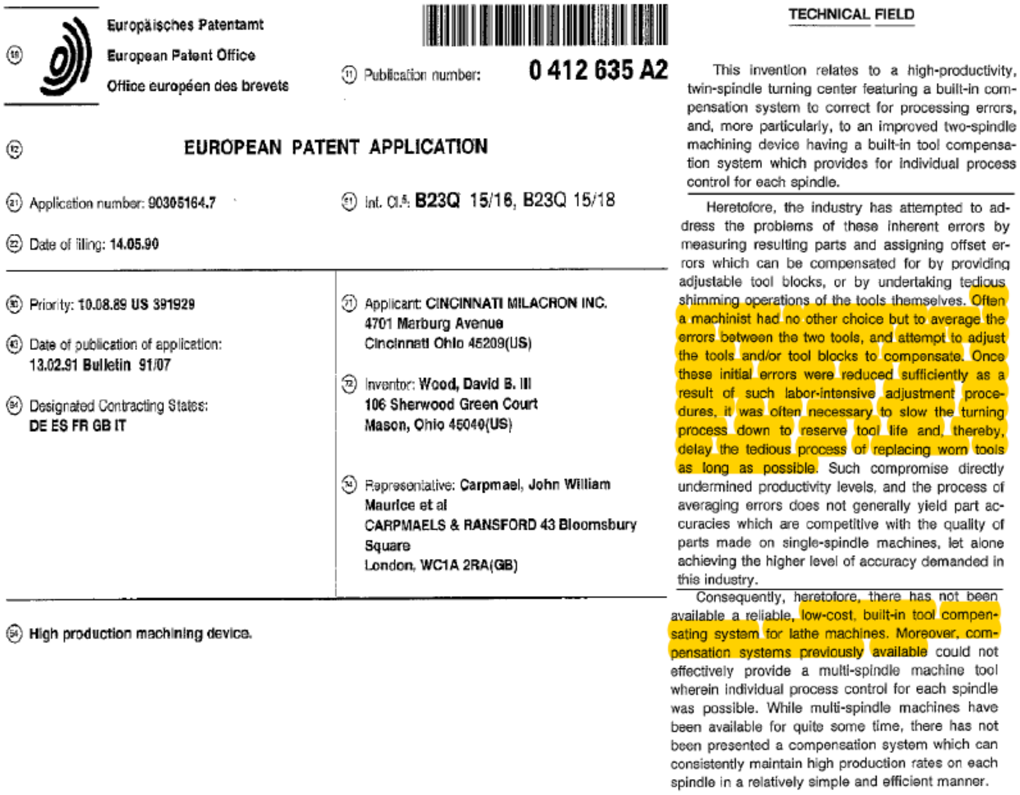
SUMMARY OF THE INVENTION

[0003] According to embodiments of the present disclosure, disadvantages and problems associated with previous systems supporting dairy milking operations may be reduced or eliminated.

[0004] In certain embodiments, a system for applying disinfectant to the teats of a dairy livestock includes a carriage mounted on a track, the carriage operable to translate laterally along the track. The system further includes a robotic arm including a first member pivotally attached to the carriage such that the first member may rotate about a point of attachment to the carriage, a second member pivotally attached to the first member such that the second member may rotate about a point of attachment to the first member, and a spray tool member pivotally attached to the second member such that the spray tool member may rotate about a point of attachment to the second member. The system further includes a controller operable to cause at least a portion of the robotic arm to extend between the hind legs of a dairy livestock such that a spray tool of the spray tool member is located at a spray position from which the spray tool may discharge an amount of disinfectant to the teats of the dairy livestock.

[0005] Particular embodiments of the present disclosure may provide one or more technical advantages. For example, certain embodiments of the present disclosure may provide an automated system for applying disinfectant to the teats of dairy livestock. Additionally, certain embodiments of the present disclosure may minimize overspray, thereby reducing the volume of the disinfectant needed. By reducing the need for human labor and reducing the volume of disinfectant used, certain embodiments of the present disclosure may reduce the cost associated with applying disinfectant to the teats of dairy livestock in certain dairy milking operations. Furthermore, the use of the automated system of the present disclosure in conjunction with a rotary milking platform may increase the throughput of the milking platform, thereby increasing the overall milk production of the milking platform.

Figure B.2: Example of a high automation patent: a milking robot



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(11) Publication number: **0 412 635 A2**

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DE ES FR GB IT

(71) Applicant: **CINCINNATI MILACRON INC.**
4701 Marburg Avenue
Cincinnati Ohio 45209(US)

(72) Inventor: **Wood, David B. III**
106 Sherwood Green Court
Mason, Ohio 45040(US)

(74) Representative: **Carpmael, John William Maurice et al**
CARPMAELS & RANSFORD 43 Bloomsbury Square
London, WC1A 2RA(GB)

(54) **High production machining device.**

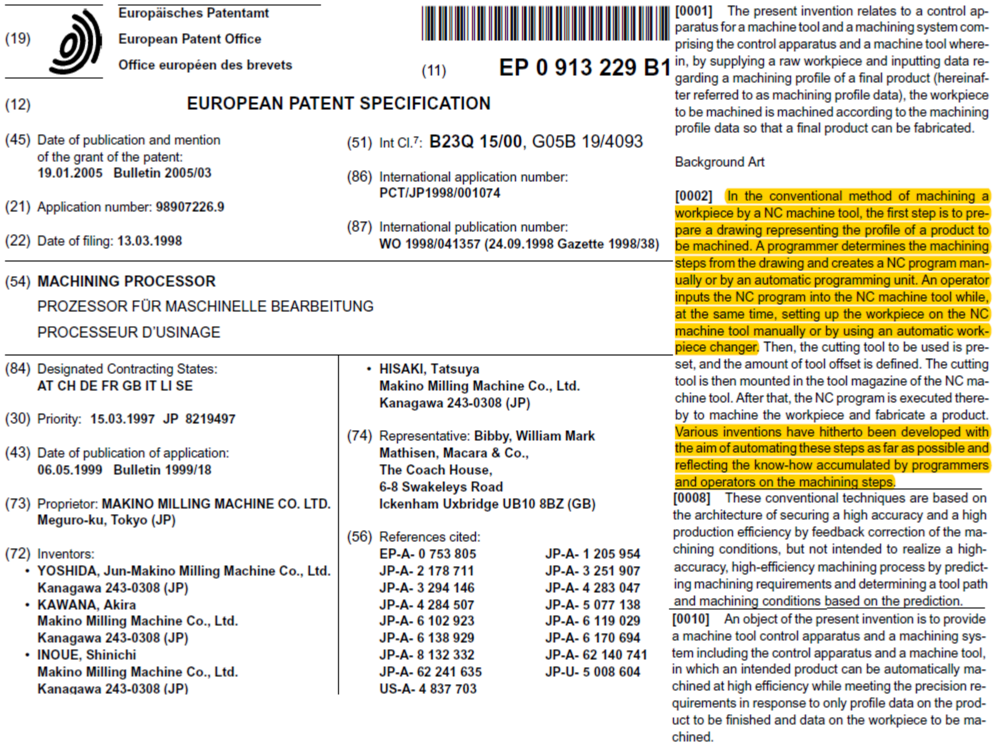
TECHNICAL FIELD

This invention relates to a high-productivity, twin-spindle turning center featuring a built-in compensation system to correct for processing errors, and, more particularly, to an improved two-spindle machining device having a built-in tool compensation system which provides for individual process control for each spindle.

Heretofore, the industry has attempted to address the problems of these inherent errors by measuring resulting parts and assigning offset errors which can be compensated for by providing adjustable tool blocks, or by undertaking tedious shimming operations of the tools themselves. Often a machinist had no other choice but to average the errors between the two tools, and attempt to adjust the tools and/or tool blocks to compensate. Once these initial errors were reduced sufficiently as a result of such labor-intensive adjustment procedures, it was often necessary to slow the turning process down to reserve tool life and, thereby, delay the tedious process of replacing worn tools as long as possible. Such compromise directly undermined productivity levels, and the process of averaging errors does not generally yield part accuracies which are competitive with the quality of parts made on single-spindle machines, let alone achieving the higher level of accuracy demanded in this industry.

Consequently, heretofore, there has not been available a reliable, low-cost, built-in tool compensating system for lathe machines. Moreover, compensation systems previously available could not effectively provide a multi-spindle machine tool wherein individual process control for each spindle was possible. While multi-spindle machines have been available for quite some time, there has not been presented a compensation system which can consistently maintain high production rates on each spindle in a relatively simple and efficient manner.

Figure B.3: Example of a high automation patent: an automated machining device



(19) Europäisches Patentamt
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(11) **EP 0 913 229 B1**

(12) **EUROPEAN PATENT SPECIFICATION**

(45) Date of publication and mention of the grant of the patent:
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(86) International application number:
PCT/JP1998/001074

(87) International publication number:
WO 1998/041357 (24.09.1998 Gazette 1998/38)

(54) **MACHINING PROCESSOR**
PROZESSOR FÜR MASCHINELLE BEARBEITUNG
PROCESSEUR D'USINAGE

(84) Designated Contracting States:
AT CH DE FR GB IT LI SE

(30) Priority: **15.03.1997 JP 8219497**

(43) Date of publication of application:
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(73) Proprietor: **MAKINO MILLING MACHINE CO. LTD.**
Meguro-ku, Tokyo (JP)

(72) Inventors:
- **YOSHIDA, Jun-Makino Milling Machine Co., Ltd.**
Kanagawa 243-0308 (JP)
- **KAWANA, Akira**
Makino Milling Machine Co., Ltd.
Kanagawa 243-0308 (JP)
- **INOUE, Shinichi**
Makino Milling Machine Co., Ltd.
Kanagawa 243-0308 (JP)
- **HISAKI, Tatsuya**
Makino Milling Machine Co., Ltd.
Kanagawa 243-0308 (JP)

(74) Representative: **Bibby, William Mark**
Mathisen, Macara & Co.,
The Coach House,
6-8 Swakeleys Road
Ickenham Uxbridge UB10 8BZ (GB)

(56) References cited:

EP-A- 0 753 805	JP-A- 1 205 954
JP-A- 2 178 711	JP-A- 3 251 907
JP-A- 3 294 146	JP-A- 4 283 047
JP-A- 4 284 507	JP-A- 5 077 138
JP-A- 6 102 923	JP-A- 6 119 029
JP-A- 6 138 929	JP-A- 6 170 694
JP-A- 8 132 332	JP-A- 62 140 741
JP-A- 62 241 635	JP-U- 5 008 604
US-A- 4 837 703	

[0001] The present invention relates to a control apparatus for a machine tool and a machining system comprising the control apparatus and a machine tool wherein, by supplying a raw workpiece and inputting data regarding a machining profile of a final product (hereinafter referred to as machining profile data), the workpiece to be machined is machined according to the machining profile data so that a final product can be fabricated.

Background Art

[0002] In the conventional method of machining a workpiece by a NC machine tool, the first step is to prepare a drawing representing the profile of a product to be machined. A programmer determines the machining steps from the drawing and creates a NC program manually or by an automatic programming unit. An operator inputs the NC program into the NC machine tool while, at the same time, setting up the workpiece on the NC machine tool manually or by using an automatic workpiece changer. Then, the cutting tool to be used is preset, and the amount of tool offset is defined. The cutting tool is then mounted in the tool magazine of the NC machine tool. After that, the NC program is executed thereby to machine the workpiece and fabricate a product. Various inventions have hitherto been developed with the aim of automating these steps as far as possible and reflecting the know-how accumulated by programmers and operators on the machining steps.

[0008] These conventional techniques are based on the architecture of securing a high accuracy and a high production efficiency by feedback correction of the machining conditions, but not intended to realize a high-accuracy, high-efficiency machining process by predicting machining requirements and determining a tool path and machining conditions based on the prediction.

[0010] An object of the present invention is to provide a machine tool control apparatus and a machining system including the control apparatus and a machine tool, in which an intended product can be automatically machined at high efficiency while meeting the precision requirements in response to only profile data on the product to be finished and data on the workpiece to be machined.

Figure B.4: Example of a high automation patent: another automated machining device

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Designated Validation States:
MA

(30) Priority: **26.08.2014 EP 14182318**

(71) Applicant: **OCE-Technologies B.V.**
5914 CA Venlo (NL)

(72) Inventor: **ALBERS, Antonius G.H.**
5914 CA Venlo (NL)

(74) Representative: **Cornelissen, Leandra**
Océ-Technologies B.V.
Corporate Patents
P.O. Box 101
5900 MA Venlo (NL)

(54) **CONVEYING BELT ASSEMBLY FOR A PRINTING DEVICE**

Description

[0001] The present invention relates to a conveying belt assembly for a printing device, a method for controlling the position of an endless conveyor belt, and the use of a conveying belt assembly.

[0002] In printing devices conveying belts are used to transport a sheet of paper through the printing device. The sheet of paper transported through the printing device requires high accuracy in control of its position.

[0003] The present invention has as its object to provide a conveying belt assembly for a printing device, which conveying belt assembly allows very accurate control of the position of the conveyor belt or its conveying part.

Figure B.5: Example of a low automation patent: a printer

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(71) Applicant: ERGOLET A/S
4220 Korsor (DK)

(72) Inventor: Hjort, Mogens
4220 Korsor (DK)

(74) Representative:
van Walstijn, Bartholomeus Gerard G.
Walstijn Intellectual Property ApS
Parkovsvej 3
2820 Gentofte (DK)

(54) A winch for raising and lowering persons

[0001] The present invention relates to a winch for raising and lowering persons, comprising a housing provided with a first attachment member, a first opening formed in the housing substantially opposite to the first attachment member, an electric motor coupled to the input of a reduction gearing, a reel component coupled to the output of the reduction gearing, and a flexible elongated traction member connected to the reel component for winding and unwinding the traction member for raising and lowering a person. Further, the invention relates to the use of a winch according to the invention as a ceiling lift. The invention also relates to a ceiling lift assembly, comprising an overhead rail with at least one carriage guided therein, the carriage being provided with an attachment member, a winch provided with at least one attachment member on the winch housing and the winch comprising a flexible elongated traction member with an attachment member on its free end and a spreader bar with an attachment member.

[0004] Against this background, it is an object of the present invention to provide a winch of the kind referred to initially, which overcomes or at least reduces the above mentioned problems by allowing it to operate in a plurality of orientations. This object is achieved in accordance with claim 1 by providing a winch of said kind with the housing having a second opening so that the traction member can be guided through the first opening or through the second opening.

[0005] Thus, it becomes possible to operate the winch in more orientations.

Figure B.6: Example of a low automation patent: a winch

(19) Europäisches Patentamt
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(71) Applicant: Frans Vervaet B.V.
4521 PE Biervliet (NL)

(72) Inventors:
- Vervaet, Edwin Joseph Germain
4521 PT Biervliet (NL)
- Poppe, Bertus Marinus
4365 NG Meliskerke (NL)
- Vervaet, Robin Richard
4521 PE Biervliet (NL)

(74) Representative: Eveleens Maarse, Pieter
Arnold & Siedsma,
Advocaten en Octrooigemachtigden,
Sweelinckplein 1
2517 GK Den Haag (NL)

(54) Harvester

Description

[0001] The invention relates to an agricultural machine provided with at least one pair of wheels and at least one wheel for performing operations on the land.

[0002] Such agricultural machines are generally known.

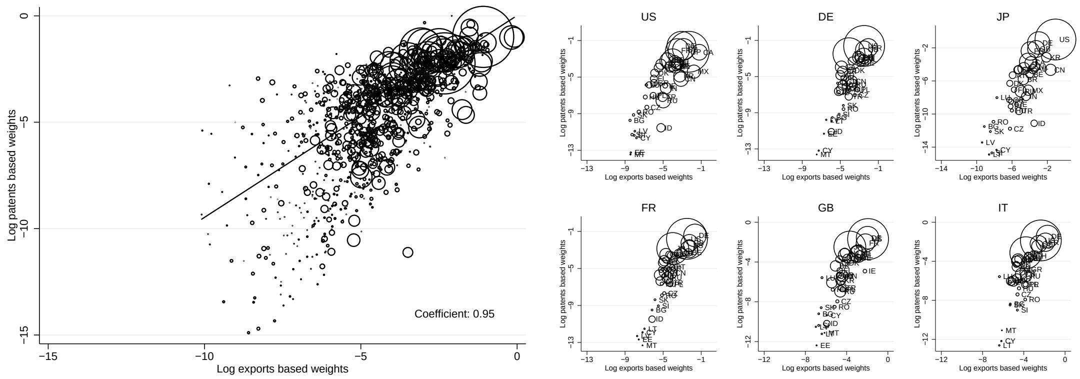
[0003] In order to perform operations on the land, it is important for stability that the wheels are placed far apart, while for travel without performing operations it is important that the wheels are placed closer together to improve the quality of travel.

[0004] The object of the invention is to provide a machine which can meet both requirements.

Figure B.7: Example of a low automation patent: a harvester

B.2 Validating our weights approach

We compare our firm-level weights to bilateral trade flows and show that they are strongly correlated. The first step is to compute patent-based weights at the country level. For this exercise (and this exercise only), we define the home country d of a firm based on the location of its headquarters (according to the country code of its



(a) All countries

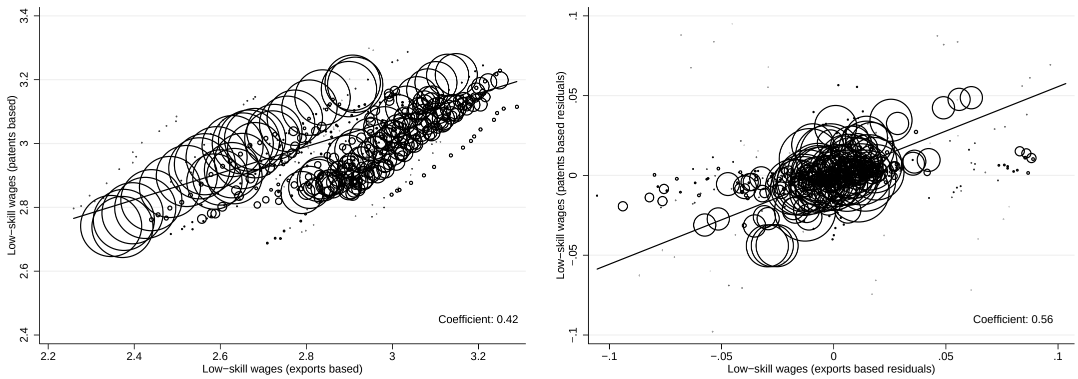
(b) Trade from the 6 largest countries

Figure B.8: Bilateral patent flows and trade flows in machinery. Panel (a) plots log patent based weights, which are a weighted average of the destination country's weights in the (foreign) patent portfolio of firms from the origin country, against export shares in machinery over the years 1995-2009. The size of each circle represents the product of the GDP of both countries, which is used as a weight in the regression. Panel (b) focuses on the weights from the listed countries and observations are weighted by the GDP of the partner country.

identifier in the Orbis database—for firms which we merged, we keep the country code of the largest entity by biadic machinery patents in 1997-2011). We compute the foreign weights for each firm i by excluding the home country. Therefore the foreign weight for country $c \neq d$ for firm i is given by $\omega_{i,c}/(1-\omega_{i,d})$ (recall that these weights are computed based on patenting from 1971 to 1994). We then build the foreign patent-based weight in country c for country d as a weighted average of the foreign weights in country c of the firms from country d (each firm is weighted according to the number of machinery biadic patents in 1997-2011).

The second step is to build similar weights based on exports. To do that, we collect sectoral bilateral trade flow from UN Comtrade data between between 1995 and 2009 for 40 countries (Taiwan is not included in the data). To obtain trade flows in machinery, we use the Eurostat concordance table between 4 digit IPC codes and 2 or 3 digits NACE Rev 2 codes (van Looy, Vereyen, and Schmoch, 2014), this concordance table matches IPC codes to the industry of manufacturing. The concordance table assigns a unique industry to each IPC code. Then, for each industry, we compute the share of biadic patents over the period 1995-2009 which are in machinery according to our definition.[39] This gives us a machinery weight for each industry code and each country.

[39]To do that we use a fractional approach: each patent is allocated NACE sectoral weights (and machinery weights) depending on the share of IPC codes associated with a NACE sector or machinery.



(a) Low-skill wages.

(b) Residualized low-skill wages

Figure B.9: Foreign low-skill wages for each country computed either with patent-based weights or with trade-based weights. Wages are computed for the years 1995-2009. Panel (a) plots log foreign low-skill wages using either patent-based weights or trade-based weights. Panel (b) plots the residuals of foreign wages according to both methods controlling for country and year fixed effects. Observations are weighted by the number of biadic machinery patents by firms from the the country over the years 1997-2011.

We then multiply sectoral trade flows (after having aggregated the original data to the NACE Rev 2 codes used in the concordance table) by this weight to get bilateral trade in machinery. We then compute the export share in machinery across destinations. We compute trade based weights for each year in 1995-2009 and take the average (there are a few missing observations for 1995).

Figure B.8 plots the patent-based weights against the trade-based weights. Panel (b) focuses on a few origin countries while Panel (a) plots all countries together. We find a strong correlation between the two measures with a regression coefficient of 0.94 (when observations are weighted by the trade flow in 1996).

Figure B.9 goes further and compares low-skill wages computed with either sets of weights. For each country, we compute "foreign low-skill wages" as a weighted average of foreign wages where the weights are either the patent-based weights or the trade-based weights derived above. Foreign wages are deflated with the local PPI and converted in USD in 1995 as in our main analysis. Panel (a) then reports foreign log low-skill wages according to both types of weights in 1995-2009 and finds that they are strongly correlated. Panel (b) reports the same foreign log low-skill wages but taking away country and year fixed effects. The regression coefficient is 0.56, when observations are weighed by the number of machinery patents in the country between 1997 and 2011.

Overall, this exercise shows that there is tight relationship between our patent-based weights and (future) trade flows, suggesting that we can use these patent-based weights as proxies for firms' markets exposure.

References

van Looy, B., Vereyen, C., and Schmoch, U. (2014). Patent Statistics: Concordance IPC V8 - NACE REV.2. Eurostat.