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AUTOMATING LABOR: EVIDENCE FROM FIRM-LEVEL PATENT DATA

Antoine Dechezleprêtre, David Hémous, morten olsen and carlo Zanella

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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
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JEL Classification: O31, O33, J20

Keywords: automation, Innovation, patents, Income inequality

Antoine Dechezleprêtre - a.dechezlepretre@lse.ac.uk
OECD, LSE

David Hémous - david.hemous@econ.uzh.ch
University of Zurich and CEPR

morten olsen - mgo@econ.ku.dk
University of Copenhagen

carlo Zanella - carlo.zanella@econ.uzh.ch
University of Zurich

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Antoine Dechezleprêtre David Hémous Morten Olsen
Carlo Zanella*

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*Antoine Dechezleprêtre, Grantham Research Institute and Centre for Economic Performance, LSE and OECD, antoine.dechezlepretre@oecd.org. David Hémous, University of Zurich and CEPR, david.hemous@econ.uzh.ch, Morten Olsen, University of Copenhagen, mgo@econ.ku.dk. Carlo Zanella, University of Zurich, carlo.zanella@econ.uzh.ch. David Hémous gratefully acknowledges the financial support of the European Commission under the ERC Starting Grant 805007 AUTOMATION. We thank Daron Acemoglu, Lorenzo Casaburi, Patrick Gaule, Nir Jaimovich, Michael McMahon, Elias Papaioannou, Pascual Restrepo, Joachim Voth and Fabrizio Zilliboti 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 and Ecares. We thank Amedeo Andriollo, 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? At a time of fast technological progress in automation technologies and of political campaigns pushing for higher minimum wages, answering these questions is of central importance. Even more so because the endogeneity of automation innovations matters for the long-term effects of policy interventions (Hémous and Olsen, 2018). Yet, the literature on the effect of wages on labor-saving technological change remains limited. In fact, the few existing papers focus on the effect of labor costs on the *adoption* of automation technologies (e.g. Lewis, 2011, Hornbeck and Naidu, 2014, or Acemoglu and Restrepo, 2018a). Our paper is the first to establish a causal effect of an increase in labor costs on automation *innovations*.

Answering this question requires overcoming two challenges: identifying automation innovations and finding a source of exogenous variation in labor costs from the perspective of innovating firms.[1] To overcome the first challenge, we develop a new classification of automation patents using the existing assignment of patents to technological categories (IPC and CPC codes). We use the text of patents from the European Patent Office (EPO) and compute the frequency of certain keywords (such as "robot", "automation" or "computer numerical control") for each technological category. We restrict attention to innovations in equipment for which our identification strategy is ideally suited. We define "automation technological categories" as technological categories where the frequency of the keywords is above a certain threshold. Finally, we identify as automation patents all those which belong to automation technological categories (including non-EPO patents). Our method presents at least two advantages: it is transparent and covers a wide range of innovations across several sectors compared with more narrow measures such as the use of industrial robots. According to our stricter measure, the share of automation innovations among innovations in machinery has increased from 7.5% in 1994 to 18.9% in 2015. We conduct a validation exercise based on Autor, Levy and Murnane (2003). We find that in the United States, sectors where the share of automation patents filed in machinery was high, saw a decrease in routine tasks and an increase in the skill ratio.

At the country level, technology and wages are co-determined. Automation innova-

[1]From a theoretical standpoint we think of automation innovations as innovations which allow for the replacement of workers with machines in certain tasks. With a Cobb-Douglas aggregate production function, this corresponds to an increase in the factor share of capital (see Section 3 below).

tors are often equipment manufacturers which sell their machines to downstream firms in various countries. Therefore, to isolate exogenous variation in wages, we use innovating firms' exposure to international markets combined with the wages faced by their potential customers. We expand on the methodology of Aghion, Dechezleprêtre, Hémous, Martin and Van Reenen (2016, henceforth ADHMV) and use the PATSTAT database, which contains close to the universe of patents. We compute how much each firm has patented pre-sample in machinery in each country. We take this information as a proxy for the distribution of the firm's international exposure and build firm-specific weighted averages of low- and high-skill wages using country-level data. These firm-specific labor costs, which we refer to as wages for simplicity, proxy for the average labor cost paid by the downstream firms of the innovating firms. As a result, for, say, two German firms, we identify the effect of an increase in wages on automation innovations, by comparing how much more automation innovations increase for the firm which has the higher market exposure to the US when US low-skill wages increase.

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 find a substantial effect of wages on automation innovations: higher low-skill wages lead to more automation innovations with an elasticity between 2 and 4 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). Our results are robust to the inclusion of country-year fixed effects for the innovator home country and continue to hold when we focus on foreign wages. Moreover, we use the geographical localization of firms' inventors to compute the local knowledge stocks which firms are exposed to. We find strong evidence of local knowledge spillovers so that the long-term effects of an increase in wages on automation innovations are larger than the short-term effects. We run placebo regressions with low-automation patents in machinery for which we find no effect of low-skill wages.

Finally, we consider the Hartz reforms in Germany in 2002-2004, which aimed at increasing labor market flexibility. We conjecture that they lowered the effective cost of labor and therefore automation innovation. Indeed, while foreign firms most exposed to Germany were increasingly doing automation innovations relative to other innovations in machinery until the Hartz reforms, the trend sharply reversed thereafter.

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

There is an extensive empirical literature on the effects of technological change on wages and employment,[2] yet the literature on the reverse question is much more limited. A few papers show that labor market conditions affect labor-saving technology adoption in health care (Acemoglu and Finkelstein, 2008), agriculture (Manuelli and Seshardi, 2014, Hornbeck and Naidu, 2014, and Clemens, Lewis and Postel, 2018), and manufacturing (Lewis, 2011). Lordan and Neumark (2018) find that minimum wage hikes displace workers in automatable jobs. 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: it may be less responsive to macroeconomic variables such as wages; and knowledge spillovers are likely to play a greater role.

Acemoglu and Restrepo (2018a) focus on the effect of demographic trends on robot and automation technology adoption but also find a positive correlation in cross-country regressions between aging and patenting in robotics. Our paper differs in three ways: first, we focus on innovation; second, we are interested in the effect of all wage variations not just those arising from demographic trends; and third and most importantly, we conduct our analysis at the firm level instead of the country-industry. Further, Alesina, Battisti and Zeira (2018) find in cross-country regressions that labor market regulations are positively correlated with innovation in low-skill intensive sectors, which is consistent with our results on the Hartz reforms. Finally, a recent paper by Bena and Simintzi (2019) shows that firms with a better access to the Chinese labor market decrease their share of process innovations after the 1999 U.S.-China trade agreement.[3]

A large literature shows that the direction of innovation is endogenous in other contexts: Acemoglu and Linn (2004) in the pharmaceutical industry; Hanlon (2015) in the

[2]See Autor, Katz and Krueger (1998), Autor et. al. (2003), Bartel, Ichniowski and Shaw (2007), 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 (2017) for robots, Blanas, Gancia and Lee (2018) for different forms of capital, Mann and Püttmann (2018) or Bessen, Goos, Salomons and van den Berge (2019) for broader measures of automation and Aghion, Jones and Jones (2017), Martinez (2018) or Gaggl and Eden (2018) for the effect on factor shares (see Aghion, Bergeaud, Boppart, Klenow and Li, 2019, and Akcigit and Ates, 2019, for other factors behind the drop of the labor share).

[3]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).

19th century cotton industry and several papers in the context of energy-saving or green innovations (Newell, Jaffe and Stavins, 1999, Popp, 2002 and Calel and Dechezleprêtre, 2016). Here, we build more specifically on the methodology of ADHMV, who 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]

The use of text analysis using keywords has developed rapidly in economics since Gentzkow and Shapiro (2010). Mann and Püttman (2018) use machine-learning techniques to classify automation patents. We compare our approaches below.

Section 2 contains our first contribution: a classification of automation technologies, which we compare to existing measures. Section 3 introduces a simple model to motivate the analysis. Section 4 describes our empirical strategy and the data we use. Section 5 contains the 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. Appendix A and B provide additional robustness checks and details on our methodology.

2 Classifying automation patents

In the following we describe the patent data and our method for classifying automation patents. We then show how our measure of automation compares to previous measures of automation, notably the use of computers in the framework of Autor et. al. (2003). Our approach proceeds in three steps: i) We use the existing literature to identify keywords related to automation. ii) We use those keywords and the text of EPO patents to classify technological categories (based on the existing IPC and CPC codes) in machinery as automation or not. iii) We then classify worldwide patents as automation or not depending on whether they belong to an automation technology category.

2.1 Patent data

We use two patent databases maintained by the European Patent Office (EPO). For most of our empirical analysis, we use the World Patent Statistical Database (PATSTAT) from

[4]Three other papers have used ADHMV's methodology: Noailly and Smeets (2015) on innovation in electricity generation, Coelli, Moxnes and Ulltveit-Moe (2018) on the effect of trade policy on innovation and Aghion, Bénabou, Martin and Roulet (2019) on the role of environmental preferences and competition in innovation in the auto industry. As explained later in the text, we methodologically extend this work by separating the foreign variables.

Autumn 2018 which contains the bibliographical information of patents from 90 patent-issuing authorities (covering nearly all patents in the world) but not the text of individual patents. Since text analysis is essential to our approach, we supplement with the EP full-text database from 2018, which contains the full text of EPO patent applications (a subset of the patents from PATSTAT).

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

Our strategy to identify automation innovations relies on first identifying automation C/IPC codes (and combinations thereof) by computing the frequency of certain keywords in the text of patents belonging to those C/IPC codes. We then use this information to identify automation patents as those with automation C/IPC codes. This strategy has two advantages over classifying patents directly. First, it allows us to include non-EPO patents in our analysis, for which PATSTAT does not contain the text.[6] Second, technological codes by themselves are informative and one should think of the particular wording of a patent as a signal of its underlying characteristics. Patents are written in different styles, and often do not expand on the purpose of the invention, so that the same innovation can often be described with or without using our keywords. In other words, if a patent does not contain one of our keywords but belongs to a C/IPC code where patents most of the time do, there is a high likelihood that it is actually an automation patent (see examples in Figures 2a and 2b below). Conversely, if a patent uses one of our keywords but does not belong to any C/IPC codes where this is common, the inclusion

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

[6]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.

of this keyword is frequently uninformative about the nature of the innovation.[7]

Patents have been extensively used as a measure of innovative activity. They are a measure of the output of the innovation process, in contrast to indicators such as R&D expenditure. They are available for all firms and, as mentioned above, patent data provide detailed information including on the technology itself. Not all innovations are patented and inventors have alternative ways such as industrial secrecy or lead time to protect their intellectual assets. Yet, most economically significant inventions have been patented (Dernis and Guellec, 2001). Furthermore, Cohen, Nelson and Walsh et al. (2000) administered a survey to 1,478 R&D labs in the U.S. manufacturing sector, and found that the "Special Machinery Sector" (where many automation innovations originate) ranked third in terms of how effective patents are considered as a means of protection against imitation (after medical equipment and drugs).

2.2 Choosing automation keywords

In the following we explain how we choose our automation keywords. Most of them come from the automation technologies identified in Doms, Dunne and Troske (DDT, 1997) and Acemoglu and Restrepo (AR, 2018).[8] We complement this list as described below. Naturally, we seek to capture as many patents truly associated with automation as possible without too many false positives. Table 1 describes the list of keywords together with their origin (Appendix B.1 provides additional details).

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 keywords may result in false positives. For instance "NC" can refer to either "numeric control" or "North Carolina". To address this issue, we require that those keywords are either in the same patent or the same sentence as a list of secondary words which indicate that the text describes a machine. We add 3D printing, which was in its infancy when DDT was written. We also add "labor" which indicates that an innovation reduces labor costs.

We similarly add "automation" and "automatization". The stem "automat*" gather

[7]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.

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

Table 1: Choice of automation keywords

Key words	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 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	*Including 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.

too many false positives such as "automatic transmission". We resolve this in two ways: either by restricting attention to patents where the frequency is 5 or more or by combining automat* with other words which largely come from technologies described in DDT or AR (we count patents where automat* and one of these words appear in the same sentence at least twice). The most important keywords are those associated with "automat*" and "robot" followed by CNC, see Appendix B.1 for details.

An alternative procedure would have been to read and classify a subset of patents and use machine-learning techniques to classify patents (or technological categories) as automation or not. This is the procedure in Mann and Püttmann (2018). We believe our approach has several advantages. First, we find that classifying patents as automation is a difficult task: often looking at a single patent in isolation is not enough, and one needs to look at several patents within the same technological group to find patterns suggesting that a patent is likely an automation patent. Therefore, the task of manually classifying patents 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. Consequently, a machine-learning algorithm would require a large set of classified data to classify patents correctly. Third, once the classification is done it can easily be applied to patents without text and future patents. Fourth, our method is more transparent and can easily be replicated or modified.

2.3 Automation technological categories and patents

We use the keywords to associate technological categories, and not patents directly, to automation. These technological categories are defined as: 6-digit C/IPC codes, all pairs of 4-digit C/IPC codes and pairs combining the union of the 3 digit codes G05 and G06 with any 4-digit C/IPC codes (outside codes in G05, G06).[9] The code G05 corresponds to "controlling; regulating" and G06 to "computing; calculating; counting". Using combinations of G05 and G06 code with 4-digit C/IPC codes is inspired by Aschhoff et al. (2010) who use these codes to identify advanced manufacturing technologies. We restrict attention to categories which contain at least 100 patents.[10]

We then measure the prevalence of our keywords within technological categories for those patent applications from 1978 onward which contain a description in English (a total of 1,538,370 patent applications). In Appendix B.1.4, we verify that the choice of the starting year does not much affect our classification. Our classification scheme captures a broader set of automation technologies than what is relevant for our empirical analysis including Roombas and military drones. Therefore, we restrict attention to C/IPC codes which belong to technological fields associated with equipment. There are 34 technological fields (see Figure A.1) and 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).[11]

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

[10]We group 6-digit codes with less than 100 patents into codes at the 4-digit level.

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

This leaves us with 1009 6-digit C/IPC codes. For pairs of 4 digit IPC codes, we classify them as belonging to the machinery technological field when at least one of the 4 digit codes belongs to machinery. Similarly, the combinations of 4 digit IPC code and G05 or G06 belong to machinery if the 4 digit code belongs to that field.

We extensively checked the C/IPC codes and sampled patents from each category to ensure that the procedure delivered reasonable results. However, the validation exercises and the main empirical exercise where carried out after the classification was set.

Table 2 gives some examples of 6-digit C/IPC codes in machinery with the prevalence of automation keywords including their rank within machinery 6 digit codes with at least 100 patents. It also shows the prevalence of the most important subcategories (automat*, robots and CNC) in the patents linked to each C/IPC code. C/IPC codes associated with robotics (B25J) have the highest prevalence numbers with up to 91% patents in B25J5 which contain at least one of the keywords. Yet, there are also codes associated with machine tools other than robots at the top of the distribution such as B23Q15 and codes associated with devices used in the agricultural sector such as A01J7. B24B49 is a code close to the threshold we use to delimit automation patents. The last four C/IPC codes are examples with a low prevalence of automation keywords. The table also shows that the different sub-measures do not capture the same technologies: the robotic codes are ranked highly thanks to their share of patents with the word "robot", B23Q15 is high because a lot of patents contain words related to CNC, and B65G1, because a lot of patents contain words associated with automation directly.

Figure 1 gives the histograms of the prevalence of automation keywords for all C/IPC 6 digit codes (panel a) and C/IPC 6 digit codes in machinery (panel b). The histograms show that most C/IPC codes have a low prevalence of automation keywords and that the distribution is shifted to the right for machinery. Yet, a few codes have a high prevalence measure. Appendix B.1 gives additional statistics on the prevalence measures.

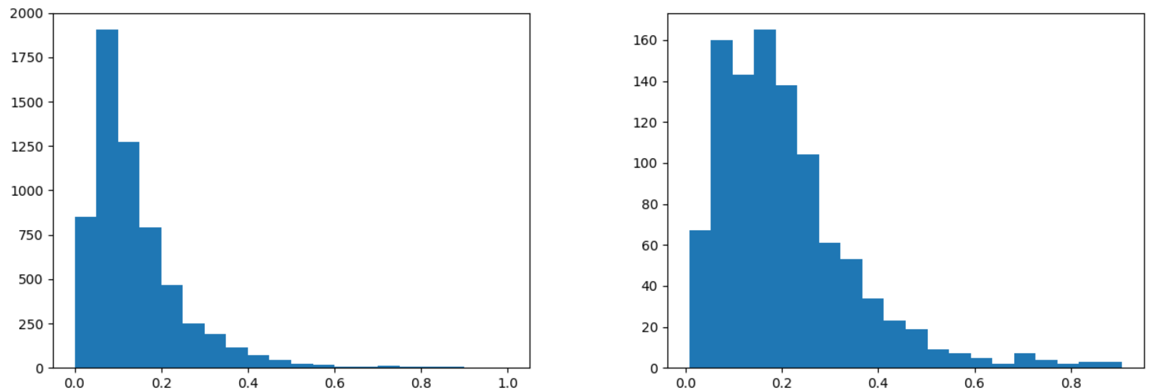
We define automation technological categories as those with a prevalence measure above some threshold. As our baseline, we choose thresholds at the 90^{th} and 95^{th} percentiles of the 6 digit code distribution within the machinery technological field, which are given by 0.386 and 0.477 respectively.[12] We then define a patent as an automation patent if it belongs to at least one automation technological group (that is a 6 digit code, a pair of 4 digit codes, or a combination of 4 digit code and G05/G06). Most automa-

of the B62D code is about the vehicle parts themselves.

[12]These thresholds are to some extent arbitrary but we do investigate how robust our results are and choosing different thresholds is easy.

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

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



(a) For all C/IPC 6 digit codes

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

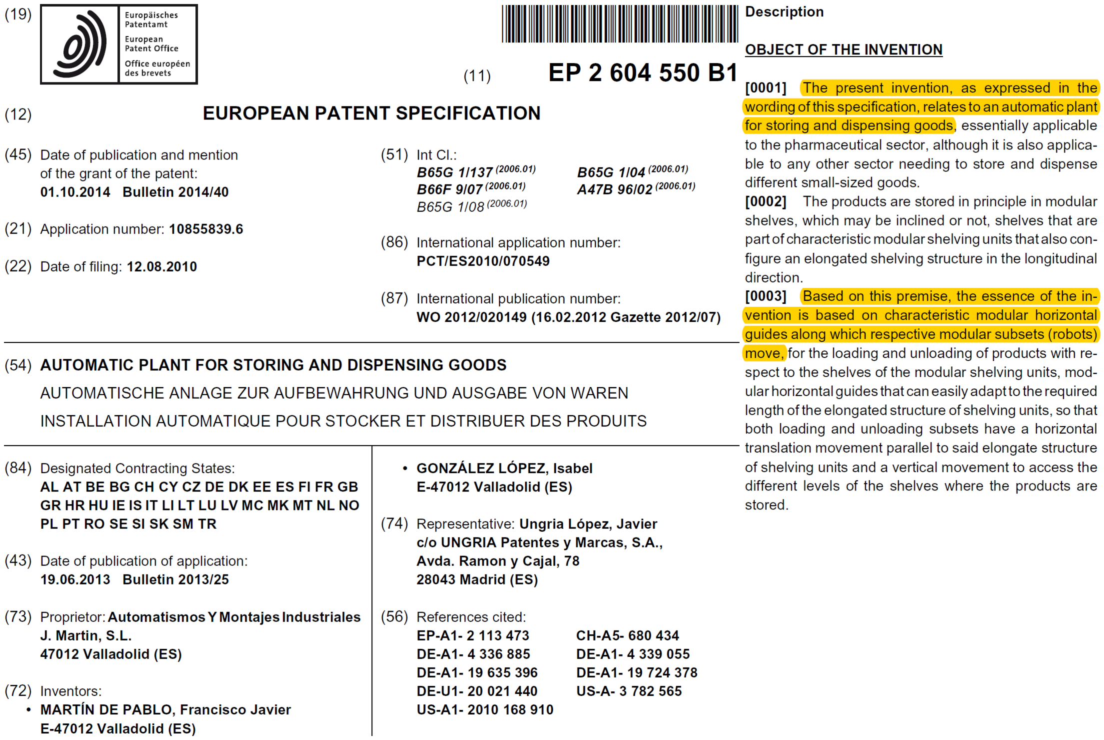
Figure 1: Histogram of the prevalence of automation keywords for C/IPC 6 digit codes

tion patents in our dataset are automation patents because they belong to at least one 6 digit automation code (see Appendix B.1). We refer to the two classifications as auto90 and auto95 depending on the threshold used. We can analogously define subcategories of automation patents such as robot90 using the single keyword robot and the same threshold as for auto90. By definition all robot90 patents are also auto90 patents.

Figure 2 shows two automation patents. Both are automated storage cabinets and are counted as automation patents because they contain the 6 digit code B65G 1. As described in Table 2, B65G 1 corresponds to devices for storing articles and has a high prevalence of automation keywords (0.58, which is above the 95^{th} percentile threshold). The patent of Figure 2a contains our keywords: a sentence with the words "automatic" and "storing," and another sentence with the word "robot." The description strongly suggests that this is indeed an automation patent. The patent of Figure 2b does not contain any of the keywords, but the description of the text still describes a labor-saving innovation. Appendix B.1.5 provides additional examples of patents.

2.4 Trends in automation innovations

To ensure that we only capture innovations of a sufficiently high quality, we restrict attention to patent families with patent applications in at least two countries in our main empirical analysis and for the trends depicted here. We refer to these as biadic patents. Several studies have documented that biadic patents are of higher quality



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(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

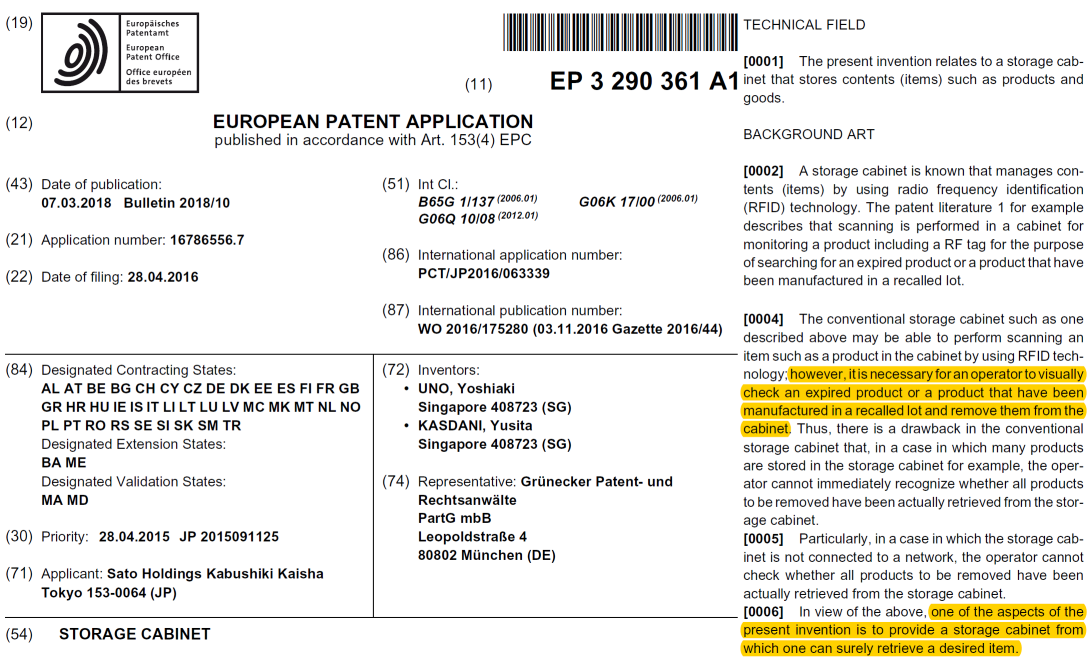
OBJECT OF THE INVENTION

[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.

(a) Example with keywords



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

(11) EP 3 290 361 A1

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(86) International application number: **PCT/JP2016/063339**

(87) International publication number: **WO 2016/175280 (03.11.2016 Gazette 2016/44)**

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Designated Extension States: **BA ME**
Designated Validation States: **MA MD**

(30) Priority: **28.04.2015 JP 2015091125**

(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.

(b) Example without keywords

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

and fundamentally different from patents applied for in only one office (e.g. Harhoff, Scherer and Vopel, 2003, van Pottelsberghe de la Potterie and van Zeebroeck, 2008, De Rassenfosse, Dernis, Guellec, Picci and van Pottelsberghe de la Potterie, 2013, and Dechezleprêtre, Ménière and Mohnen, 2017).[13]

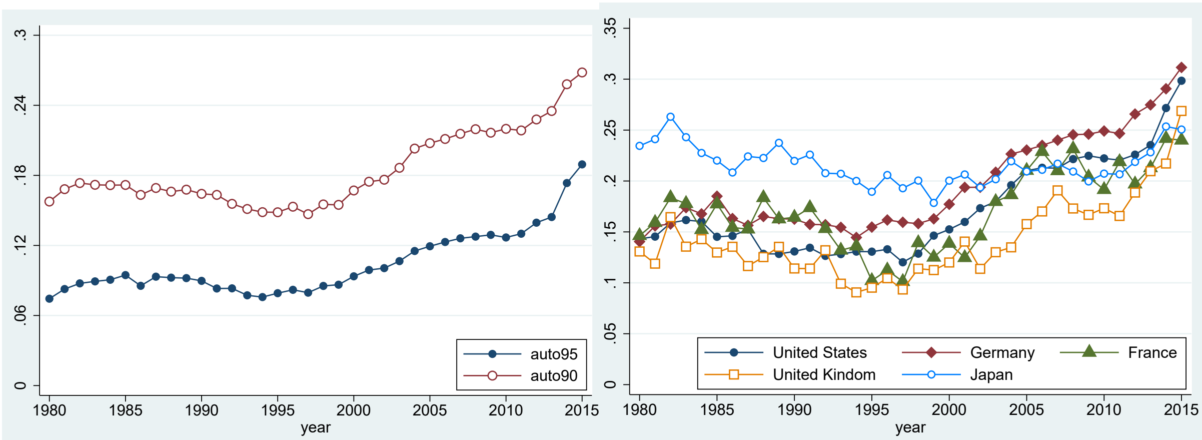
Figure 3 below shows the evolution of automation patent families in the set of biadic patents. Panel (a) shows that worldwide the share of automation patents in machinery declines between the mid1980s and the mid1990s from 17.4% in 1985 to 14.8% in 1994 for the laxer auto90 measure and from 9.5% to 7.6% for the stricter auto95 measure before increasing quickly to reach 26.8% for auto90 and 18.9% for auto95 in 2015—Figure A.2 in the Appendix shows that automation patents in machinery represent between 2.6% and 3.9% of all patents with the auto90 definition and it also reports the raw numbers of auto90 and auto95 patents. Panel (b) computes the share of automation patents in machinery for the auto95 measure for biadic patents by applicant's nationality. The graph shows a somewhat different trend for Japan compared to the US, the UK, France or Germany. The share of automation patents is initially much higher in Japan but declines in the 80s and 90s before picking up in the 2000s but slower than in the other countries. The share of automation patents in machinery is now the highest for German applicants. Appendix Figure A.3 reports the share of automation patents in machinery based on where the patent is protected. The trends are roughly similar but show less divergence between countries.

2.5 Automation patents and robots

Graetz and Michaels (2018) and Acemoglu and Restrepo (2017) use data on the stocks of industrial robots from the International Federation of Robotics (IFR) to measure automation. The data are available at the country and sector level.

We first compare our automation measure with robotization at the country level. To measure robotization in a given country, we follow Acemoglu and Restrepo (2017) and use the change in the stocks of industrial robots in between 1997 and 2011 divided by total employment in manufacturing in 1997 (employment data come from the OECD

[13]In addition, patents can be more or less broad across countries: for instance the same invention may be covered by two patents in Japan but only one in the US. By focusing on biadic patents, we only count such a case as one innovation. We count patent applications and not granted patents because in certain patent offices, notably in Japan, a patent is only formally granted if the rights of the applicant are challenged. To restrict attention to patent families of even higher quality, we carry out robustness checks where we use patent citations, or patents applied to more than two offices.



(a) Share of automation patents in machinery worldwide.

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

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

database). We measure automation at the country level as the shares of auto95 and auto90 patents in machinery among biadic patents applied for in each country over the years 1997-2011. Table 3 reports the correlation across 27 countries between the robotization measure and our measures. The correlation is quite high with a coefficient of 0.38 for the auto95 measure. When we correlate robotization with the shares of robotic patents in machinery we get a coefficient of 0.46 for robot80.

We then compare our two measures of automation at the sector level for the US and Germany. The IFR data contain consistent stocks of industrial robots for 17 sectors between 1997 and 2011 for Germany and between 2004 and 2011 for the US. We compute robotization in each sector by taking the difference between the stocks in the two years and dividing by employment in the first period.[14] We allocate patents to these sectors according to their (family-level) 4-digit C/IPC codes using a concordance table provided by Lybbert and Zolas (2014), and measure the share of auto95, auto90, robot90 and robot80 patents in machinery for each sector over the same time periods. Appendix Table A.1 reports shares of auto95 patents in machinery for patents granted at the USPTO, patents protected in Germany (i.e. granted German patents or granted EPO patents protected in Germany) and for all biadic patents across sectors. The shares of automation patents are very similar in the US, Germany and for the world. The three sectors with the highest shares for auto95 are always the automotive, "computer,

[14] The IFR sectoral data are available for the ISIC Rev 4 classification and aggregate robot stocks at the level of US, Canada and Mexico. We still use OECD data for employment.

Table 3: Correlations between our automation measures and robot intensity

	(1) Across Countries	(2) Across US Industries	(3) Across German Industries
Share of automation patents in machinery (auto95)	0.383	0.602	0.560
Share of automation patents in machinery (auto90)	0.377	0.483	0.426
Share of robot patents in machinery (robot90)	0.365	0.682	0.546
Share of robot patents in machinery (robot80)	0.461	0.740	0.780
Number of observations	27	17	17

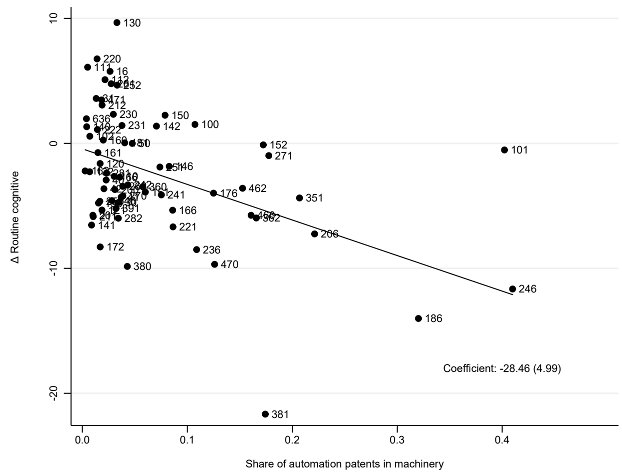
Note: This table reports correlations across countries or industries between shares of automation patents in machinery, robots patents in machinery and robot intensity. Robot intensity is measured as the difference between the stock of robots in 2011 and 1997 (columns 1 and 3) or 2004 (column 2) over employment in each country (column 1) or each sector (columns 2 and 3) in 1997 (columns 1 and 3) or 2004 (column 2). Shares of automation and robot patents are computed over the time period 1997-2011 for columns (1) and (3) and over 2004-2011 for column (2).

electronic, optical and electrical products" and "other transport equipment" industries. In addition, Table 3 reports correlations across sectors for these measures in the US and in Germany. We find higher levels of correlations with coefficients of 0.60 and 0.56 for both US and German industries with the auto95 measure. When we use our method to focus specifically on robotic patents, we find correlation coefficients up to 0.74 and 0.78 for the robot80 measure.

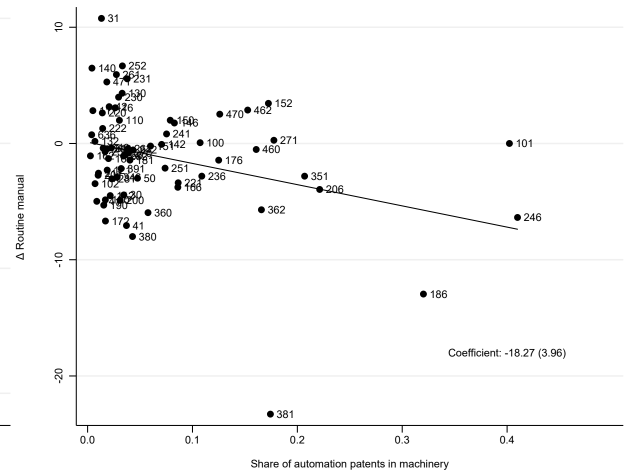
2.6 Validating our automation measure

To validate our automation measure, we use it in the framework of Autor et. al. (2003) (henceforth ALM), who show how computerization has been associated with a decrease in routine tasks at the industry level on U.S. data from 1960 to 1998. We provide a brief description of the exercise and refer the reader to Appendix B.2 for details. To measure automation innovations at the sectoral level, we use USPTO granted patents which belong to the machinery technological field. As before, we allocate patents to sectors according to their 4-digit C/IPC codes using another concordance table provided by Lybbert and Zolas (2014).[15] For each sector j and each period τ, we compute the share of automation patents among machinery patents applied for during this period.

[15] Lybbert and Zolas (2014) present several probabilistic concordance tables, which are based on matching industry descriptions with the title and the abstract of patents within an IPC code. This methodology cannot a priori distinguish between the sector of use of a patent and the industry of manufacture, we verify however on a few simple examples that within machinery, the classification seemed to assign patents to the sector of use (for instance textile machines are assigned to the textile industry not the equipment industry).



(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 B.4

Denoting this variable $aut_{j\tau}$, we run regressions of the type:

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

$\Delta T_{jk\tau}$ 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). We do not first difference our measure of automation because 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 (as in ALM). We consider 3 time periods for which we can compute our automation intensity measure: 1970-1980, 1980-1990 and 1990-1998 (ALM also considers 1960-1970), and the joint time period 1980-1998. We restrict attention to sectors with at least 50 machinery patents per decade. As a result, we can measure automation intensity for between 67 and 69 sectors most of them in manufacturing (see full list in Table B.4). Our automation measures, auto90 and auto95, are strongly correlated with each other (the coefficient is 0.86) but uncorrelated with computerization (the coefficient is 0.016 for auto95 and 0.05 for auto90).

Figure 4 first provides simple scatter plots of the changes in routine tasks and the share of automation patents in machinery (according to the auto95 definition) over the years 1980-1998.[16] Sectors with a high share of automation patents experience a decline in routine cognitive and routine manual tasks. Given our focus on automation in machinery a decline in routine cognitive tasks might seem surprising at first sight, but several machines replace workers for tasks such as inspection and control (such an example is given in Figure 2b).

Table 4, columns (1) to (5) report the results of regression (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. The coefficients of column (3) and (4) in panel B indicate that a 10 pp increase in the share of automation patents is associated with a 3 centiles and 2.2 centiles decrease in labor input of routine cognitive and manual tasks in the 80s. To interpret a 10 pp increase, note that the standard deviation in the share of automation patents in the 80s is 0.09 with a mean of 0.08. For comparison, the effect of a 1 standard deviation increase in computerization is associated with a decrease in routine cognitive tasks of 0.8 centiles and essentially no change in routine manual tasks (the effect is larger in the 90s). We obtain similar results when we restrict attention to biadic patents (as in our main regression exercise of section 5) or when we exclude the equipment sector, which could be contaminated if patents are assigned to the industry of manufacture instead of the sector of use (176 in the Census classification).

We also use the ratio of high-skill to low-skill workers (defined as college graduates over high-school dropouts and graduates) as our dependent variable in cross-section regressions similar to equation 1.[17] Column (6) of Table 4 shows that sectors with a higher automation share also experience a large increase in the ratio of high-skill to low-skill workers. Panel B suggests that a 10 pp increase in the share of automation patents is associated with an increase of 1.33 in that ratio in the 1980s.

In the Appendix, Table B.5 reproduces the same exercise for our laxer measure (auto90) and obtains similar results. Finally, Table B.6 reproduces the same analysis

[16] At this level of disaggregation, the five sectors with the highest share of automation patents are: scientific and controlling instruments, optical and health services (246), dairy products (101), electronic computing equipment, office and accounting machines (186), household appliances, radio, TV & communications equipment, electric machinery, equipment & supplies, n.e.c., not specified electrical machinery, equipment & supplies (206) and transport equipment (351).

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

Table 4: 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 - 80, n=67						
Share of automation patents in machinery	-1.29	5.42	-17.27***	-11.43**	-1.15	0.27***
	(5.10)	(6.27)	(6.59)	(5.59)	(7.46)	(0.07)
Δ Computer use 1984 - 1997	-6.86	-3.13	-19.51***	-3.46	14.87*	0.07
	(5.72)	(7.04)	(7.41)	(6.28)	(8.38)	(0.08)
Intercept	1.06	2.31**	3.07**	2.69***	-1.75	0.05***
	(0.95)	(1.17)	(1.23)	(1.04)	(1.39)	(0.01)
R^2	0.02	0.01	0.20	0.07	0.05	0.21
Weighted mean Δ	-0.05	2.17	-0.90	1.49	0.42	0.07
Panel B: 1980 - 90, n=67						
Share of automation patents in machinery	10.09	19.05**	-30.00***	-21.61***	16.78***	1.33***
	(7.14)	(8.12)	(6.76)	(5.42)	(6.04)	(0.23)
Δ Computer use 1984 - 1997	24.80**	22.21*	-13.24	-0.42	-6.49	0.29
	(10.43)	(11.85)	(9.87)	(7.91)	(8.82)	(0.33)
Intercept	-2.62	-0.65	2.15	1.20	-2.13	-0.04
	(1.70)	(1.93)	(1.61)	(1.29)	(1.44)	(0.05)
R^2	0.12	0.14	0.27	0.20	0.11	0.37
Weighted mean Δ	1.86	4.17	-2.22	-0.59	-1.74	0.11
Panel C: 1990 - 98, n=67						
Share of automation patents in machinery	11.06*	16.02*	-22.81***	-12.53**	6.66	0.77***
	(6.08)	(8.18)	(6.54)	(5.42)	(6.28)	(0.15)
Δ Computer use 1984 - 1997	26.77***	27.00**	-23.15**	-24.87***	7.48	0.66***
	(8.35)	(11.23)	(8.98)	(7.44)	(8.62)	(0.20)
Intercept	-2.36*	-1.43	1.72	2.27*	-2.40*	-0.06*
	(1.37)	(1.84)	(1.47)	(1.22)	(1.41)	(0.03)
R^2	0.19	0.15	0.25	0.23	0.03	0.41
Weighted mean Δ	2.45	3.79	-3.44	-2.36	-0.79	0.09

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

separately for each education category (as ALM) and shows that automation leads to a reduction of routine tasks and an increase in non-routine manual tasks for high-school graduates (but in line with column (6) of Table 4, a large share of the task changes at the industry level are explained by changes in educational composition - see Panel F).

Sectors of use versus manufacturing. As already mentioned, the concordance table from Lybbert and Zolas (2014) does not distinguish between sector of use (our focus here) and of manufacturing. We now present alternative ways to assign patents to sectors. First, we use a concordance table from Eurostat (van Looy, Vereyen and Schmoch, 2014) which maps IPC codes to 2 or 3 digit NACE rev 2 sectors according to the sector of the firm filing the patent, i.e. the sector of manufacturing. With this method, we can compute the share of automation patents for 58 sectors. Table 5 reports the results of regressions of the change in routine tasks on the share of automation patents for the consolidated period 1980-1998. Column (1) and (2) both use the Lybbert and Zolas (2014) concordance but column (2) restricts attention to the 58 sectors where we can compute the share of automation patents according to the industry of manufacturing. Column (3) uses the share of automation patents according to the manufacturing industry. The coefficient drops for routine cognitive tasks relative to column (2) and standard errors increase. We then combine the Eurostat concordance table with the industry of manufacturing with an input-output table to allocate patents according to their sector of use and compute the share of automation patents in that sector (see Appendix B.2). We can compute this statistic for 125 sectors and column (4) reports the results. Relative to our default measure we obtain larger coefficients. Finally in column (5) we carry out a horse-race regression between the sectors of use and of manufacturing measures. The results strongly support that it is the share of automation patents according to the sector of use which is associated with a decline in routine tasks.[18]

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

[18]The disadvantage of this method is that the Eurostat concordance table is more aggregated than the Lybbert and Zolas (2014) one and the mapping to the ALM sectors is less direct.

Table 5: Changes in routine task intensity and different measures of sectoral automation

Panel A: Δ Routine cognitive					
Automation share (Lybbert and Zolas)	-26.66*** (4.83)	-22.93*** (4.22)			
Automation share (manufacturing industry)			-14.79* (8.44)		17.06* (10.12)
Automation share (using industry)				-48.40*** (9.03)	-50.72*** (11.24)
Δ Computer use 1984 - 1997	-17.74** (6.79)	-12.71** (6.17)	-15.33** (7.42)	-12.06** (4.71)	-7.75 (6.60)
R^2	0.39	0.39	0.12	0.23	0.36
Observations	69	58	58	125	58
Panel B: Δ Routine manual					
Automation share (Lybbert and Zolas)	-17.09*** (3.90)	-15.47*** (3.53)			
Automation share (manufacturing industry)			-15.33** (6.48)		6.97 (8.02)
Automation share (using industry)				-18.04* (10.08)	-35.51*** (8.90)
Δ Computer use 1984 - 1997	-11.53** (5.48)	-13.47** (5.17)	-15.22*** (5.70)	-15.08*** (5.26)	-9.91* (5.23)
R^2	0.29	0.34	0.19	0.09	0.37
Observations	69	58	58	125	58

Standard errors are in parentheses. Each column of Panels A and B 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 as well as a constant. The automation share measures correspond to the share of automation patents in machinery (defined with the 95th percentile threshold) using different concordance tables. "Lybbert and Zolas" uses the same concordance table as in the body of the paper. "Manufacturing industry" uses a EUROSTAT concordance table between IPC codes and industry codes of innovating firms. "Using industry" uses the same concordance table combined with an input output table to get the industry of use. Columns (2), (3) and (5) restrict attention to sectors for which there are enough patents to compute the "Automation share (manufacturing industry)" measure. 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

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 in but only 14% of its revenues from Germany. During this year 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 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...". The report is centrally interested in how "Changes in customer demand [for automation technology by downstream manufacturers] are strongly driven by macroeconomic cycles" and discusses a number of such drivers including changes in cost of capital and political development towards trade protectionism.[19] Siemens further discusses how such macroeconomic trends affect its *R&D* decisions.

We incorporate these business features into a model built on the task framework of Acemoglu and Autor (2011) and more precisely on the growth model of Hémous and Olsen (2018). A manufacturing good is produced with a continuum of intermediate inputs according to the Cobb-Douglas production function:

$$Y = \exp\left(\int_0^1 \ln y\left(i\right) di\right), \tag{2}$$

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

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

$\gamma(i)$ is the productivity of low-skill workers and $\alpha(i)$ is an index which takes the value 0 for non-automated intermediates and 1 for automated intermediates. ν and β are

[19] Interestingly, the report never mentions "cost of labor" as a reason for automation, but instead used a number of euphemisms such as "increase competitiveness", "enhance efficiency", "improve cost position" and "stream line production".

fixed share parameters in $(0,1)$. Machines are specific to the intermediate input i. If a machine is invented, it is produced monopolistically, 1 for 1 with the final good so that the monopolist charges a price $p_x(i) \geq 1$.

At the beginning of the period, for each non-automated intermediate i, there is an innovator. The innovator creates a machine specific to intermediate i with probability λ if it spends $\theta\lambda^2 Y/2$ units of manufacturing good.

We solve the model in two steps, first we derive the profits realized by machine producers, second we solve for the innovation decision. 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:

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

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

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

In turn, at the beginning of the period, the potential innovator solves $\max \lambda\pi_i^A - \theta\lambda^2 Y/2$, giving the equilibrium innovation rate:

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

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

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

This expression is increasing in the low-skill wage w_L and decreasing in the high-skill wage w_H. 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.

More generally, the defining characteristic of automation is that it allows for the replacement of workers by machines in certain tasks. When intermediates have a unit-elasticity of substitution as in (2), the aggregate production function is Cobb-Douglas and automation corresponds to a change in factor shares. When intermediates have an elasticity of substitution lower than 1, the aggregate production function is CES and automation corresponds to a combination of labor-augmenting and capital-depleting technical changes (see Aghion et al., 2017).

4 Empirical Strategy and Data

4.1 Empirical strategy

We now take the predictions of our model to the data. As mentioned above, innovators in automation technologies are often large companies (e.g. Siemens) 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 such as Siemens to pursue automation research in the first place depends on the wages that their potential customers face in different countries.[20]

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

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

$PAT_{Aut,i,t}$ denotes the number of automation patents applied for by firm i in year t. $w_{L,i,t-2}$ and $w_{H,i,t-2}$ denote the average low-skill and high-skill wages (more generally

[20]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.

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 complements to machines. $X_{i,t}$ represents a vector of additional controls (average GDP per capita, GDP gap and labor productivity). Controlling for GDP per capita or labor productivity allows us to control for changes in productivity in the country where machines may be sold[21] and controlling for the GDP gap allows us to capture business cycle fluctuations and changes in demand.

$K_{Aut,i,t-2}$ 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.[22] $SPILL_{Aut,i,t-2}$ 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). δ_i and δ_t are firm and time fixed effects. Finally, $\epsilon_{i,t}$ is an error term assumed to be uncorrelated with the other right-hand side variables. The right-hand side variables are lagged by 2 years in the baseline regressions to reflect the delay between changes in R&D investments and patent applications—Section 5.4 considers alternative timing assumptions.[23]

4.2 Macroeconomic data

Our macroeconomic variables come primarily from the 2013 release of the World Input Output Tables, henceforth, WIOD (Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R. and de Vries, G. J., 2015). The database contains information on hourly labor costs across groups of educational attainment – low-skill, middle-skill and high-skill workers – for the manufacturing sector from 1995 to 2009 as well as value added and producer price indices. The dataset contains information on 40 countries, including all 27 EU

[21]GDP per capita could also capture non-homotheticity in preferences, for instance if higher quality goods or services are less automated.

[22]We use $\ln(1+K)$, a depreciation rate of 15% and add a dummy indicating whether the knowledge stock equals zero.

[23]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 through the knowledge stock $K_{Aut,i,t-2}$). Yet, the bias is small with large T, which is the case in our baseline regression (15 years). To address this issue we implement the Blundell, Griffith and Van Reenen (1999) method in Section 5.6, which uses the pre-sample average of the dependent variable to proxy for the fixed effect.

countries of 2009. We obtain 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 since our analysis in Section 2 showed that most of our patents (89% of biadic auto95 patents in 1997-2011) are associated with manufacturing, but we 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 from here on for simplicity. From the same dataset, we obtain measures of labor productivity (as value added divided by hours) and producer price indices (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.[24] Appendix B.3 provides additional details. All macroeconomic variables are deflated in the same way. In the baseline regression, we first deflate nominal values by the local producer price index for manufacturing (indexed to 1995), and then we convert everything into dollars using the average exchange rate for 1995 the starting year of our regressions.

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-skill wages and low-skill wages are very highly correlated so in practice one should interpret our low-skill wage variable as reflecting both low-skill and middle-skill.[25]

The countries with the highest low-skill wages in 2009 are Belgium, Sweden and Finland with \$41.9, \$42.2 and \$43.6 respectively (in 1995 dollars) 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 6 summarizes these values for these seven countries. It further shows that the ratio of high-skill to low-skill wages varies considerably across countries, even among those that have relatively similar low-skill wages. The skill-premium in the United States rose from 2.46 to 3.02 during this period while it slightly declined in Belgium from 1.56 to 1.46.

4.3 Computing firm's market-specific wages and spillovers

Ideally, we would like to measure the wages paid by the (actual and potential) customers of automation innovators. Since we do not observe these, we build a proxy which is a

[24]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.

[25]For our baseline sample of firms, included in Table 8 below, the correlation between low-skill and middle-skill wages is 0.94 controlling for firm and year fixed effects. It is only 0.6 for low-skill and high-skill wages. See Appendix Table A.2.

Table 6: Low-skill wages and the skill-premium in manufacturing sector for selected countries

Country	Low-skill wages (1995$)		Skill-premium (HS wages/LS wages)	
	1995	2009	1995	2009
India	0.19	0.28	4.79	4.98
Mexico	0.89	0.61	3.90	4.21
Bulgaria	1.29	0.71	3.32	2.25
USA	11.57	13.67	2.46	3.02
Belgium	29.50	41.89	1.56	1.46
Sweden	19.92	42.16	1.73	1.33
Finland	23.41	43.63	1.20	1.46

Note: Wages data, taken from the World Input Output Database. The table shows manufacturing low-skill wages (technically labor costs) deflated by (manufacturing) producer price index and converted to US dollars using average 1995 exchange rates. Skill-premium is the ratio of high-skill to low-skill wages (labor costs). The table shows the three countries with the lowest low-skill wages in 2009, the three with the highest and the United States.

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 firm customers' average high-skill wage, productivity or GDP per capita. Firms have different exposure to different markets because of trade barriers, heterogeneous tastes of customers, or various historical accidents if exporting involves sunk costs. This measure is a shift-share instrument (Bartik, 1991). The weights are computed pre-sample to ensure that they are weakly exogenous as patent location could be influenced by innovation shocks. Since the weights are fixed, our identification relies on how country-level shocks affect firms differently. 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 this instrumental approach. We discuss the recent literature on shift-share regressions in detail in Section 5.5.[26]

[26] As we keep the weights fixed we look at how wage changes in the countries where a firm already sells affect the firm's automation innovation. A different question would have been to analyze how wage

To measure the weights in the absence of sales data, we follow and expand on the methodology of Aghion et al. (2016, ADHMV). We use the firm's pre-sample history of patent filing as a proxy for its market exposure. 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 and possibly translators as well as pay the 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 (see Dechezleprêtre, Glachant, Hascic, Johnstone and Ménière, 2011).

We compute for each firm the fraction of its patents in machinery (not only automation) protected in each country c for which we have wage data, $\tilde{\omega}_{i,c}$, during the pre-sample period 1970-1994.[27] We only count patents in machinery because some of the biggest innovators in automation technologies are large firms (Sony, Siemens, etc.) which produce a wide array of products with different specialization patterns across industries. We restrict attention to patent families with at least one citation (not counting self-citations) to exclude the lowest quality patents. See Appendix B.4.1 for details.

Patenting indicates whether the firm intends to sell in that market. However, a patent in Belgium and one in the U.S. are unlikely to reflect the same market size. At the same time, 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.[28] As a result, the weight of country c for firm i is given by:

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

changes affect a firm's decision to enter a new market, this is beyond the scope of this paper.

[27] In Europe, firms can apply both at national patent offices and at the European Patent Office (EPO). In the latter case, firms still need to pay a fee for each country in which they want their patent to be protected. 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.

[28] 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.

We use alternative weighting schemes in Section 5.6.

ADHMV verify that a similar method accounts well for the sales distribution of major auto manufacturers. Coelli, Moxnes and Ulltveit-Moe (2016) carry out a more systematic exercise and verify that a similar method accounts well for 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 Appendix B.4.2, we similarly show that our patent weights correlate well with trade flows.[29]

Given that knowledge spillovers have a geographical component (Hall, Jaffe and Trajtenberg, 1993), we use the location of firm's innovators to build a measure of the stock of knowledge to which a firm is exposed. More specifically and similarly to ADHMV, we 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 pre-sample in 1970-1994.[30]

To link patents with their owners, we use Orbis Intellectual Property which links 40 million patents to companies available in the Orbis financial database. 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 (for instance because subsidiaries may 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 from the name and then merge firms with the same normalized name. All other firms are treated as separate entities.[31]

4.4 Descriptive statistics

Our basic dataset consists of applicants who have applied to at least one biadic automation patent between 1997 and 2011 (included), who have at least one patent prior to 1995 which can be used to compute weights, and who are not fully domestic (i.e. we exclude firms which have only patented in one country pre-sample). For the auto95 (resp. auto90) measure this corresponds to $3,341$ (resp. $4,905$) firms, which are responsible for

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

[30]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.

[31]For instance, 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.

Table 7: Descriptive statistics for firms in our baseline regression

Variable	Auto95		Auto90			Auto95	Auto90
Automation patents	per year	1997-2011	per year	1997-2011		weights	
Mean	0.7	11.22	0.84	13.24	Largest country	0.47	0.46
Standard deviation	3.46	48.71	4.04	56.76	Second largest	0.17	0.18
p50	0	2	0	3	US	0.21	0.21
p75	0.27	6	0.33	7	Japan	0.17	0.15
p90	1.4	19	1.6	22	Germany	0.2	0.21
p95	3	41	3.27	50	France	0.09	0.09
p99	12	173	13.73	194	UK	0.09	0.09
Number of firms	3341		4903				

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

35,803 (resp. 61,931), or 58% (resp. 58%) of the total number of biadic auto95 innovations. Table 7 gives some descriptive statistics on the number of automation patents per year and the country weights for the firms in our sample. Over the period 1997-2011, the median firm in the sample has filed 2 auto95 and 3 auto90 patent applications. The distribution is very skewed and the 99^{th} percentile firm in the sample has filed 194 automation patents for auto90 and 173 for auto95. 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 "domestic country" of a firm, we will include in some regressions domestic 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.3 gives the list of the ten biggest automation patenters in our sample.[32]

5 Main Empirical Results

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 contains additional results and robustness checks.

[32] For instance, for Siemens the countries with the largest weights are Germany (0.37), the USA (0.12), France (0.10), Japan (0.09) and the UK (0.07).

5.1 Baseline results

Our baseline results are contained in Table 8. The dependent variable is the number of biadic patents that qualify as automation when we use our stricter definition auto95. The regression uses the years 1997-2011 for the dependent variable and 1995-2009 for the independent variables. Skill-dependent wages are measured in the manufacturing sector and we deflate by the producer price index in the same sector.

Table 8: Baseline regressions: effect of wage on automation innovations (auto95)

Dependent variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.2000***	2.8254***	1.8160**	1.9058**	1.9992**	2.2954***	2.4627***	2.4266***	3.7365***
	(0.5123)	(0.7332)	(0.7421)	(0.7729)	(0.8223)	(0.8198)	(0.8351)	(0.8658)	(0.9116)
High-skill wage		-0.9210	-0.9009	-0.9695	-0.8698	-0.2971	-1.6180**	-1.6700*	-0.4838
		(0.7082)	(0.6715)	(0.6913)	(0.7511)	(0.6802)	(0.8033)	(0.8634)	(0.7650)
Stock automation			-0.1275***	-0.1269**	-0.1270**	-0.1239**	-0.1441***	-0.1443***	-0.1504***
			(0.0495)	(0.0496)	(0.0495)	(0.0495)	(0.0509)	(0.0510)	(0.0510)
Stock other			0.6311***	0.6296***	0.6309***	0.6260***	0.6408***	0.6407***	0.6489***
			(0.0579)	(0.0581)	(0.0581)	(0.0574)	(0.0600)	(0.0600)	(0.0595)
GDP gap				0.0210	0.0214	0.0179	0.0279*	0.0278*	0.0265*
				(0.0159)	(0.0157)	(0.0157)	(0.0158)	(0.0157)	(0.0156)
Labor productivity					-0.2551			0.1285	
					(0.8644)			(0.9199)	
GDP per capita						-1.5635*			-3.3618***
						(0.8765)			(0.8917)
Spillovers automation							0.5442*	0.5478*	0.8587***
							(0.3135)	(0.3151)	(0.3213)
Spillovers other							-0.3014	-0.3089	-0.5853**
							(0.2248)	(0.2315)	(0.2303)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	50115	50115	50115	50115	50115	50115	50115	50115	50115
Firms	3341	3341	3341	3341	3341	3341	3341	3341	3341

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

Column (1) shows that without any controls except 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 10% in the low-skill wage is associated with 22% more automation patents. Column (2) introduces high-skill wages as a control, which have a negative coefficients (though not always statistically significant). Column (3) adds control for the firm's stock of knowledge: a higher stock of automation knowledge reduces the amount of automation innovation, suggesting that firms do not become more specialized in automation technologies over time. Column (4) controls for the GDP gap, automation innovations appear to be mildly pro-cyclical with a small elasticity which is only significant at the 10% level in some specifications. Columns (5) and (6) add controls for labor productivity in manufacturing and GDP per capita. Labor productivity does not have a significant effect and GDP per capita has a negative effect, though its significance is not robust to the specifications to follow. 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 2.8 for columns (1) to (8) and a larger elasticity of 3.7 in column (9).

Firms in the same country could be affected by common shocks. We therefore cluster standard errors at the domestic country (i.e. the country of largest weight) level in Appendix Table A.4. If anything clustering at the country level tends to reduce the standard error on low-skill wages.[33]

Appendix Table A.5 repeats Table 8 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 Table 8: our analysis focuses on innovations with a high automation content (and therefore most likely to respond to an increase in wages) for firms which introduce at least one of those innovations.

5.2 Identification and foreign wages

Other country-level shocks which we have not controlled for may affect both innovation and wages. Insofar as firms are mainly affected by shocks in their domestic country, we can capture those through domestic country-year fixed effects. Country-year fixed effects would for instance control for a tax reform in Germany that would affect both the innovation incentives of Siemens and low-skill wages. They would also control for a technology shock that leads German firms to introduce more automation innovations and affect wages. Our identification assumption then becomes that foreign wages are exogenous to the automation innovation of the firm given our set of controls. One remaining concern would arise from shocks to the cost of innovation if firms innovate outside of their domestic country. We address this issue directly in section 5.6 by including wages weighted by the location of the firm's inventors.[34] Furthermore, in section 5.3

[33] 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.

[34] A related concern arises if a market is served through offshoring instead of exporting: the cost of machine production would then be correlated with foreign wages. Note, however, that higher foreign low-skill wages in production would increase the price of machines and therefore bias our coefficient on low-skill wages toward 0.

Table 9: Country-year fixed effects

Dependent variable	Auto95								
	Domestic + Foreign			Foreign					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.8852*	2.1429*	3.0411**	3.4891***	4.3023***	3.7989**	3.6420***	4.3362***	3.8663**
	(1.0367)	(1.1505)	(1.2232)	(1.2958)	(1.4482)	(1.6370)	(1.3146)	(1.4473)	(1.6288)
High-skill wage	-2.4820**	-1.9117*	-1.7526	-3.5161***	-2.4740*	-3.3526**	-3.7549***	-2.8325**	-3.6398***
	(1.0115)	(1.0157)	(1.1046)	(1.2515)	(1.4209)	(1.3633)	(1.2805)	(1.4364)	(1.3692)
GDP gap	0.0623*	0.0620*	0.0646*	0.0044	0.0016	0.0044	0.0031	0.0001	0.0031
	(0.0343)	(0.0342)	(0.0343)	(0.0492)	(0.0492)	(0.0492)	(0.0494)	(0.0494)	(0.0494)
Labor productivity		-1.2851			-1.7494			-1.5475	
		(1.6381)			(1.4131)			(1.3896)	
GDP per capita			-2.8260			-0.5289			-0.3829
			(2.0242)			(1.9347)			(1.8713)
Stock automation	-0.1511***	-0.1506***	-0.1541***	-0.1522***	-0.1523***	-0.1526***	-0.1530***	-0.1532***	-0.1533***
	(0.0528)	(0.0527)	(0.0523)	(0.0525)	(0.0523)	(0.0525)	(0.0524)	(0.0521)	(0.0524)
Stock other	0.6549***	0.6556***	0.6555***	0.6494***	0.6471***	0.6490***	0.6496***	0.6475***	0.6493***
	(0.0602)	(0.0602)	(0.0598)	(0.0602)	(0.0601)	(0.0600)	(0.0601)	(0.0601)	(0.0599)
Spillovers automation	1.4782***	1.4762***	1.4715***	1.4396***	1.4128***	1.4355***	1.4380***	1.4161***	1.4357***
	(0.4992)	(0.5000)	(0.4998)	(0.4872)	(0.4895)	(0.4899)	(0.4866)	(0.4896)	(0.4887)
Spillovers other	-1.2259***	-1.2020***	-1.2436***	-1.2377***	-1.2268***	-1.2436***	-1.2252***	-1.2141***	-1.2300***
	(0.3805)	(0.3820)	(0.3789)	(0.3748)	(0.3730)	(0.3716)	(0.3731)	(0.3725)	(0.3697)
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	50070	50070	50070	50070	50070	50070	50070	50070	50070
Firms	3338	3338	3338	3338	3338	3338	3338	3338	3338

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 and country-year fixed effects. All regressions include dummies for no stock and no spillover. In columns (4)-(6) foreign low-skill wages are interacted with the share of foreign low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. In columns (7)-(9), they are interacted with the average shares over the sample period instead. In columns (4)-(9), foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

we look at the effect of wages on low-automation machinery innovations and therefore any remaining bias would have to affect both types of machinery innovations differently.

Columns (1), (2) and (3) of Table 9 reproduce the columns (7), (8) and (9) of Table 8 but adding country-year fixed effects, where the country of a firm is still defined as the country with the largest weight. We still obtain a positive effect of low-skill wages on automation innovations with similar elasticities (between 1.8 and 3.0). Columns (4) to (9) go further and only consider the foreign component of wages (and of the other macroeconomic variables). In columns (4) to (9), the foreign low-skill wage variable is defined as the log of the weighted average of country-level wages excluding the domestic country multiplied by the share of foreign low-skill wages in total wages. This share is computed at the beginning of the sample for columns (4) to (6) and as the average value over the whole sample for columns (7) to (9). We pre-multiply the (log) foreign wage by this share to allow more internationally exposed firms to be more affected by foreign wages. This also ensures that the reported coefficient corresponds to an elasticity on total low-skill wages.[35] The foreign macroeconomic control variables are defined similarly.

[35] Denote $\omega_{i,D}$ the domestic weight and $\omega_{i,F} = 1 - \omega_{i,D}$ the total foreign weight with $w_{L,D,t}$ the wage in the domestic country and $w_{L,F,t}$ the average wage in the foreign country. Then we can decompose a

Once again we find a positive effect of low-skill wages on automation innovation, with slightly larger elasticities. Relative to Table 8, the main difference is that high-skill wages are now the macroeconomic control variable with the most explanatory power (neither labor productivity nor GDP per capita have a significant effect once high-skill wages are introduced). Clustering at the country-level (to account for correlation of errors across firms within a country over time) tends to reduce standard errors (Appendix Table A.6). For the auto90 measure, we obtain similar results with slightly smaller coefficients (Appendix Table A.7). Finally, we replace the country-year fixed effects with the interaction of country-year dummies with the domestic weight of each firm to allow for varying exposure to the domestic country across firms. Here as well, we obtain similar results although the magnitude of the coefficient on low-skill wages is a bit smaller (Appendix Table A.8).

Therefore, Table 9 establishes the effect of foreign downstream low-skill wages on automation innovations given a set of controls. Yet, low-skill wages are an equilibrium outcome and will move following demand shocks, labor supply shocks or labor productivity shocks. Demand shocks in manufacturing will affect low-skill wages but also other variables such as GDP per capita or high-skill wages which we control for.[36] General labor productivity shocks are controlled for by the labor productivity variable but we cannot directly control for low-skill specific labor productivity shocks. Note however that an increase in low-skill wages caused by a low-skill specific labor productivity shock (similar to $\gamma(i)$ in section 3) would be associated with less automation innovations. Labor market supply shocks for the downstream firms may originate from changes in labor market regulations, demographics or changes in low-skill labor demand from other sectors. Overall, our coefficient captures the average effect of an increase in foreign low-skill wages given our controls whatever the shock behind it and this effect should be compared to that on low-automation innovations below. Section 6 will focus on a specific

small change in $\log w_{L,i,t}$ as:

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

where $\omega_{i,D}w_{L,D,0}/w_{L,i,0}$ denotes the values around which the change is computed—which we take as the the value at the beginning of the period or the average value over the sample period. This shows that if $\frac{\omega_{i,F}w_{L,F,0}}{w_{L,i,0}}d\log w_{L,F,t}$ increases by 0.01 then $w_{L,i,t}$ increases by 1%. The same reasoning applies to high-skill wages or GDP per capita. In equation (3), GDP gap enters directly in levels as an average of logs so we directly interact the domestic and foreign variables with $\omega_{i,D}$ and $\omega_{i,F}$.

[36] In unreported regressions, we also controlled for the share of manufacturing in GDP which is insignificant and does not change the results.

Table 10: Non-automation innovations

Dependent Variable	Placebo Machinery								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	0.2962	0.5837	1.6587**	-0.0486	0.0964	0.6381	-0.7470	-1.0568	-0.9430
	(0.6209)	(0.7013)	(0.6573)	(0.8089)	(0.9245)	(0.9903)	(1.2590)	(1.4477)	(1.3045)
High-skill wage	-0.1907	0.3251	0.8911	-0.3499	-0.0648	0.0238	0.4969	0.1238	0.4016
	(0.6953)	(0.6428)	(0.7506)	(0.9539)	(0.9122)	(1.0053)	(1.3193)	(1.3073)	(1.4470)
GDP gap	-0.0307***	-0.0292***	-0.0292***	-0.0072	-0.0071	-0.0062	0.0117	0.0120	0.0114
	(0.0105)	(0.0103)	(0.0104)	(0.0188)	(0.0187)	(0.0188)	(0.0319)	(0.0319)	(0.0319)
Labor productivity		-1.1140			-0.6087			0.6174	
		(0.7467)			(1.1021)			(1.1452)	
GDP per capita			-3.4367***			-1.5038			0.3079
			(0.8242)			(1.3776)			(1.3051)
Stock own	0.0866**	0.0879**	0.0892**	0.0952**	0.0956**	0.0957**	0.0958**	0.0954**	0.0956**
	(0.0408)	(0.0411)	(0.0405)	(0.0405)	(0.0406)	(0.0404)	(0.0405)	(0.0406)	(0.0406)
Stock other	0.4797***	0.4811***	0.4758***	0.4854***	0.4861***	0.4847***	0.4862***	0.4871***	0.4866***
	(0.0464)	(0.0464)	(0.0463)	(0.0460)	(0.0459)	(0.0459)	(0.0448)	(0.0449)	(0.0449)
Spillovers own	2.6849***	2.7419***	1.9983***	1.1394***	1.1505***	1.0777**	1.1398***	1.1215**	1.1469***
	(0.4153)	(0.4163)	(0.4423)	(0.4410)	(0.4435)	(0.4411)	(0.4393)	(0.4428)	(0.4418)
Spillovers other	-2.4198***	-2.4342***	-1.8132***	-1.2443**	-1.2469**	-1.1918**	-1.2694**	-1.2450**	-1.2706**
	(0.5298)	(0.5348)	(0.5386)	(0.5052)	(0.5056)	(0.5047)	(0.4965)	(0.5008)	(0.4965)
Fixed effects	F + Y	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	115575	115575	115575	115515	115515	115515	115515	115515	115515
Firms	7705	7705	7705	7701	7701	7701	7701	7701	7701

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(3) include firm and year fixed effects, while (4)-(9) include firm and country-year fixed effects. Stock variables are calculated with respect to the dependent variable. In columns (7)-(9) foreign low-skill wages are interacted with the share of foreign low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. Foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

labor-market shock namely the Hartz reforms in Germany.

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" of the effect of wages on innovations with a low score on our automation metric. Specifically, we consider the set of machinery patents and exclude any patent which has a technological category with an automation score above a certain threshold. We fix that threshold at the 60^{th} percentile of the distribution of C/IPC 6 digit codes in the machinery technological fields (0.2091). We refer to these innovations as "placebo machinery" innovations and we recompute knowledge stocks and spillover variables for those 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 year fixed effects. Low-skill wages only have a positive and significant effect in column (3) when GDP per capita is included as a control variable, but even in that case the coefficient is statistically significantly smaller than with automation (1.66 versus 3.74 in column 9 of Table 8).[37] Columns (4) to (6) repeat the same regressions but add country-year fixed effects and columns (7) to (9) focus on foreign wages (here defined as in columns (4) to (6) of Table 9). 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).[38] We view this exercise as validating both our empirical approach and our measure of automation. In particular, if our result on the effect of low-skill wages on automation innovations came from a bias, than that bias would have to be absent for other types of machinery innovations.

5.4 Additional results

Skill premium. In some regressions, the coefficients on low-skill and high-skill wages in Table 9 are of a similar magnitude but opposite signs suggesting that a driver of automation innovations is the skill premium. Table 11 directly regresses automation innovation on the log of the ratio of low-skill to high-skill wages (the inverse of the skill premium) for firm fixed effects, country-year fixed effects and foreign wages with country-year fixed effects. The coefficient on the inverse skill premium is always of the same magnitude as that on low-skill wages and highly significant. On the other hand, replacing low-skill and high-skill wages with their ratio in the regressions with placebo machinery innovations of Table 10 gives insignificant coefficients.

Innovation types. Building on the previous results contrasting automation innovations and low-automation machinery innovations, we now look at subcategories of automation innovations and a laxer measure in Table 12, which reproduces column (8) of Table 8 for various types of innovations. Column (1) is essentially a robustness check which removes the codes that we added to the definition of the machinery technological field listed in footnote 11 (though, we continue to exclude the weapons categories). The results are similar to the baseline. Column (2) presents a laxer definition of automation using the 80^{th} percentile of the distribution of the C/IPC 6 digit codes. We still get a positive effect of low-skill wages though with a coefficient smaller than for either auto90 or auto95. Columns (3) to (8) look at subcategories of automation innovations.

[37]Further, this positive coefficient in the placebo regression is sensitive to specifications, and unlike for the regressions with automation, it loses significance with different deflators for wages (not shown).

[38]Conditioning on the 60^{th} percentile is not important and we obtain similar results with machinery innovations excluding auto95 or auto90.

Table 11: Skill premium

Dependent Variable	Auto95								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill/ High-skill wages	1.9423**	2.0420***	1.9008**	2.1995**	2.0520**	2.2870**	3.5089***	3.4205***	3.5012***
	(0.7552)	(0.7607)	(0.7478)	(0.9170)	(0.9049)	(0.9166)	(1.2083)	(1.1960)	(1.2021)
GDP gap	0.0263*	0.0268*	0.0251	0.0627*	0.0620*	0.0632*	0.0049	-0.0017	0.0030
	(0.0157)	(0.0157)	(0.0156)	(0.0343)	(0.0343)	(0.0344)	(0.0526)	(0.0496)	(0.0502)
Labor productivity		0.7026			-1.0613			-0.2814	
		(0.7035)			(1.1591)			(0.7369)	
GDP per capita			-0.6817			-1.5302			-0.1073
			(0.6943)			(1.2805)			(0.9038)
Stock own	-0.1448***	-0.1456***	-0.1466***	-0.1505***	-0.1507***	-0.1531***	-0.1522***	-0.1524***	-0.1523***
	(0.0509)	(0.0510)	(0.0511)	(0.0530)	(0.0528)	(0.0524)	(0.0526)	(0.0525)	(0.0525)
Stock other	0.6407***	0.6402***	0.6424***	0.6546***	0.6556***	0.6555***	0.6495***	0.6480***	0.6491***
	(0.0599)	(0.0601)	(0.0597)	(0.0603)	(0.0602)	(0.0600)	(0.0602)	(0.0602)	(0.0600)
Spillovers own	0.5783*	0.5783*	0.6625**	1.4755***	1.4769***	1.4766***	1.4397***	1.4346***	1.4386***
	(0.3153)	(0.3114)	(0.3340)	(0.4968)	(0.5004)	(0.5013)	(0.4868)	(0.4892)	(0.4888)
Spillovers other	-0.2349	-0.3132	-0.2543	-1.2535***	-1.2021***	-1.2160***	-1.2387***	-1.2253***	-1.2362***
	(0.2129)	(0.2328)	(0.2112)	(0.3717)	(0.3824)	(0.3807)	(0.3669)	(0.3755)	(0.3720)
Fixed effects	F + Y	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	50115	50115	50115	50070	50070	50070	50070	50070	50070
Firms	3341	3341	3341	3338	3338	3338	3338	3338	3338

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(3) include firm fixed effects and year dummies. Columns (4)-(9) include firm and country-year fixed effects. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Columns (7)-(9) use the log difference between foreign low-skill wages interacted with the share of foreign low-skill wages in total low-skill wages at the beginning of the sample and foreign high-skill wages similarly interacted; GDP gap, GDP per capita and VA per employee are also their interacted foreign components. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Robot90 and Robot80 were defined in Section 2.5. The other types of innovations are similarly defined: for instance, automat*90 covers patents which belong to technological categories with a frequency of the "automat*" keywords above the threshold used to define auto90. Columns (3) and (4) show that the results are similar for automat* patents (by definition automat*80 patents are all auto80 but 91.5% of them are also auto90). Column (6) shows that our results extend to robot80 patents (which are also all auto95) but not to robot90 maybe because the sample size is reduced. The sample size drops even more substantially for the CNC categories in columns (7) and (8), and consequently the coefficient on low-skill wages is very imprecisely estimated.

Timing. We look at alternative lags for the dependent variables in Table 13, though we keep a lag of 2 between patent applications and the patent stocks because otherwise the dependent variable would be included in the stock of automation when we consider contemporaneous regressions or leads. Column (4) reproduces our baseline results with a 2 year lag. Panel A shows that the largest coefficient on low-skill wages is obtained for a 2 year lag, but remains relatively stable between a 4 year lag and a 1 year lead. Both panels find an effect of low-skill wages more clearly centered around lag 2 (ADHMV also

Table 12: Innovation categories

Dependent Variable	AutoX95	Auto80	Automat*90	Automat*80	Robot90	Robot80	CNC90	CNC80
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	1.9759**	1.3013**	2.6151**	1.7535*	0.4046	2.3998*	-2.6476	-1.5273
	(0.9046)	(0.6373)	(1.1768)	(0.9657)	(1.6931)	(1.2440)	(2.0151)	(1.5877)
High-skill wage	-1.2113	-1.2776**	-0.9885	-0.9874	-0.8384	-2.0705*	2.0374	0.8833
	(0.9265)	(0.5754)	(1.0579)	(0.8395)	(1.6053)	(1.2334)	(1.8923)	(1.5580)
GDP gap	0.0370**	0.0047	0.0078	-0.0052	0.0345	0.0409	0.0317	0.0214
	(0.0186)	(0.0121)	(0.0214)	(0.0173)	(0.0365)	(0.0264)	(0.0411)	(0.0305)
Labor productivity	0.2216	0.8058	-0.9351	-0.2196	0.8059	0.7937	2.7221	1.9101
	(0.9431)	(0.6648)	(1.1098)	(0.9161)	(1.9404)	(1.3971)	(2.3494)	(2.1381)
Stock own	-0.1400**	0.0263	-0.1149*	-0.0861	-0.3029***	-0.1319*	-0.3043**	-0.2888***
	(0.0567)	(0.0374)	(0.0601)	(0.0525)	(0.0993)	(0.0790)	(0.1511)	(0.0999)
Stock other	0.6443***	0.5225***	0.6684***	0.6312***	0.8200***	0.6329***	0.5642***	0.6140***
	(0.0645)	(0.0460)	(0.0872)	(0.0737)	(0.1334)	(0.0994)	(0.1303)	(0.0961)
Spillovers own	0.7068*	0.9236*	0.3869	0.4415	0.2346	0.1891	0.7408**	0.4634*
	(0.4072)	(0.5235)	(0.4365)	(0.4719)	(0.5380)	(0.3489)	(0.3657)	(0.2727)
Spillovers other	-0.5863*	-0.6139	-0.3800	-0.3305	-0.0665	-0.2028	-1.5340***	-0.7109
	(0.3036)	(0.4435)	(0.2736)	(0.3469)	(0.3529)	(0.2887)	(0.5522)	(0.4478)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	48600	97635	34170	50220	17670	24645	8970	15000
Firms	3240	6509	2278	3348	1178	1643	598	1000

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

found that the largest coefficient for the effect of gas prices on innovations in the car industry was at a 2 year lag).[39]

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.10, we compute predicted future wages at time $t-2$ based on an AR(1) process with country-specific trends and find similar results.

Minimum wage. Given its policy relevance, we also look at the effect of minimum wages using data on 22 countries.[40] Importantly, we cannot use the minimum wage as an instrument for low-skill wages. Since high-skill wages have a significant effect, they should be included in regressions, and if low-skill wages should be instrumented so should

[39] Appendix Table A.9 carries out placebo regressions where we regress automation innovation on 10 or 15 year leads of wages. We do not find a significant effect of leading low-skill wages. As expected given the large number of coefficients a few of the other coefficients are significant.

[40] We use data from the OECD. Importantly, not all countries have government-mandated minimum wages, most notably Italy and, until 2015, Germany. For Germany, however, we follow Dolado, Kramarz, Machin, Manning, Margolis, Teulings, Saint-Paul and Keen (1996) and use the the collectively bargained minimum wages which in effect constitute law.

Table 13: Lags and leads

Dependent variable	Auto95							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lags (Leads)	-5	-4	-3	-2	-1	0	1	2
	Panel A: baseline							
Low-skill wage	1.4268*	2.0578**	1.9681**	2.4266***	2.0882**	2.0767**	2.2411***	1.4514*
	(0.8599)	(0.8328)	(0.8229)	(0.8658)	(0.8417)	(0.8331)	(0.8518)	(0.8251)
High-skill wage	-0.0640	-0.9379	-1.6808*	-1.6700*	-2.0273**	-2.5752***	-2.5365***	-2.7223***
	(0.9033)	(0.8937)	(0.9223)	(0.8634)	(0.7977)	(0.8281)	(0.7687)	(0.7828)
Labor productivity	0.1931	0.4055	1.1283	0.1285	0.0857	-0.0118	-0.2255	0.4201
	(1.1023)	(1.0789)	(1.0884)	(0.9199)	(0.7871)	(0.8022)	(0.8265)	(0.8912)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	47565	48240	49395	50115	50670	51315	52470	53940
Firms	3171	3216	3293	3341	3378	3421	3498	3596
	Panel B: country-year fixed effects							
Low-skill wage	0.9671	1.3572	1.5405	2.1429*	1.6930	1.2360	1.2538	0.1282
	(1.1012)	(1.1353)	(1.1175)	(1.1505)	(1.1222)	(1.1088)	(1.1409)	(1.0962)
High-skill wage	0.4539	-0.9749	-1.7245	-1.9117*	-2.0866**	-2.7165**	-2.1045**	-1.6862
	(1.3522)	(1.1490)	(1.0931)	(1.0157)	(1.0346)	(1.0935)	(1.0333)	(1.0682)
Labor productivity	-1.5193	-0.8311	-0.2556	-1.2851	-0.5775	0.3167	-0.1957	0.0676
	(1.8190)	(1.6338)	(1.5444)	(1.6381)	(1.6431)	(1.5761)	(1.6158)	(1.5974)
	Panel C: country-year fixed effects and foreign variables							
Low-skill wage	1.5679	2.5117*	3.1804**	4.3023***	3.0459**	1.6943	1.6996	0.4034
	(1.6579)	(1.4908)	(1.4684)	(1.4482)	(1.4516)	(1.5642)	(1.7055)	(1.7377)
High-skill wage	2.1192	-1.0194	-2.5135	-2.4740*	-3.2862**	-3.8818***	-3.3215**	-2.5666*
	(1.8327)	(1.6302)	(1.6445)	(1.4209)	(1.4238)	(1.4272)	(1.3771)	(1.4844)
Labor productivity	-2.3858	-0.9029	-0.7200	-1.7494	0.4010	1.8684	1.6417	1.6644
	(1.5235)	(1.5420)	(1.5937)	(1.4131)	(1.3247)	(1.4493)	(1.5255)	(1.6175)
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	47565	48240	49365	50070	50595	51255	52410	53895
Firms	3171	3216	3291	3338	3373	3417	3494	3593

Note: 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 coefficient. The independent variables (wages, VAemp and GDP gap) are lagged by the number of periods indicated in lag, except for the stock variables which are always lagged by 2 periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Panel A regressions contain firm and year fixed effects. Panel B and C regressions contain firm and country-year fixed effects. In Panel C regressions, wages are replaced with foreign wages interacted with the share of foreign wages in total wages at the beginning of the sample, and similarly for the other macro variables. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

high-skill wages. Therefore we would need a second instrument. We report the results of reduced form regressions where we replace low-skill wages with the minimum wage in Appendix Table A.11. We find a positive effect of the minimum wage on automation innovations though not significant in our regressions with country-year fixed effects. Clustering standard-errors at the country-level gives more significant coefficients (see Appendix Table A.12). The minimum wage is unlikely to be a strong predictor of automation in our analysis: first because it only captures part of the labor costs (contrary to our baseline measure), second because we focus on automation innovations that largely happen in manufacturing where wages for low-skill workers are often substantially higher, third we lose nearly half of our countries. An analysis on automation in service industries might show a stronger relationship.

5.5 Shift-share set-up

A recent literature addresses the identifying assumptions behind the shift-share set-up in linear regressions. In the language of our setting, Goldsmith-Pinkham, Sorkin and Swift (2019) show that the shift-share instrument is equivalent to a combination of weights time country-year dummies. Our coefficient would then capture the effect of low-skill wages on automation innovations if weights time country-year dummies only affect automation through the controls that we have included. In this interpretation, the exogeneity of the weights is important and we show below that our results are robust to using weights from an earlier period.

Borusyak, Hull and Jaravel (2018) show that country-time shocks can also be a source of identification in the shift-share setting. The inference is valid if either there is a large number of countries (such that the Herfindahl index 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-year is sufficient (see Appendix A2 in their paper).[41] 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 further recommend applying the standard error correction of Adão, Kolesár and Morales (2019).

Adão et. al. (2019) show theoretically and through Monte Carlo simulations that standard applications with the shift-share design often lead to an over-rejection of the

[41] 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.

null of no effect. In the language of our application, the problem arises when the standard errors of firms with similar country-distributions have correlated residual errors. Though this problem is related to the correlation of standard errors in clustered designs 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 similar Monte Carlo simulation and show that we do not have the same problem of over-rejection.

Specifically, we replicate the regressions of Columns (7) to (9) in Table 8, (1) to (6) in Table 9 and Table 11. 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 patents. 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 with 1000 draws. Table 11 reports the p-values of the coefficients on low-skill wages, high-skill wages or the inverse skill-premium 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 and the inverse skill premium are always significant at least at the 10% level (except in column 4 with a p-value of 0.11) and at the 1% 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.

5.6 Robustness checks

This section presents several robustness checks.

Controlling for the cost of innovation. Our measure of wages could still reflect the cost of innovation if innovation does not solely take place in the domestic country. To address this issue we re-build our firm-specific macroeconomic variable using the inventor weights of the firm instead of the patent weights. Table 15 reports the result. The baseline coefficient on low-skill wages remains positive and significant but the coefficient on low-skill wages weighted by inventor weights is small and insignificant. These regressions constitute a placebo test since they are treating firms with the same macroeconomic shocks but weighted differently.

Wages and deflators. Appendix Table A.13 shows that our results are robust to

Table 14: Monte-Carlo simulations

Dependent variable	Auto95								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: wages									
Low-skill wage	2.4627**	2.4266**	3.7365***	1.8852	2.1429*	3.0411**	3.4891***	4.3023***	3.7989***
	[0.025]	[0.029]	[0.001]	[0.111]	[0.097]	[0.019]	[0.005]	[0.005]	[0.0014]
High-skill wage	-1.6180	-1.6700	-0.4828	-2.4820***	-1.9117	-1.7526	-3.5161***	-2.4740*	-3.3526***
	[0.134]	[0.126]	[0.666]	[0.009]	[0.111]	[0.125]	[0.008]	[0.063]	[0.002]
GDP gap	Y	Y	Y	Y	Y	Y	Y	Y	Y
Labor productivity	N	Y	N	N	Y	N	N	Y	N
GDP per capita	N	N	Y	N	N	Y	N	N	Y
Control variables	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.
Fixed effects	F + Y	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Panel B: skill premium									
Low-skill/ High-skill wages	1.9423*	2.0420*	1.9000*	2.1995*	2.0520*	2.2870**	3.5089***	3.4205***	3.5000***
	[0.074]	[0.059]	[0.06]	[0.055]	[0.063]	[0.048]	[0.004]	[0.005]	[0.004]
GDP gap	Y	Y	Y	Y	Y	Y	Y	Y	Y
Labor productivity	N	Y	N	N	Y	N	N	Y	N
GDP per capita	N	N	Y	N	N	Y	N	N	Y
Control variables	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.	stocks + spill.
Fixed effects	F + Y	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY

Note:Marginal effects; P-values in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(3) include firm fixed effects and year dummies. Columns (4)-(9) include firm and country-year fixed effects. Columns (7)-(9) use the log foreign components of the macro variables interacted with the share of the foreign macro variable in the total macro variable at the beginning of the sample. 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.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 15: Wages weighted by inventor weights

Dependent Variable	Auto95								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.6194***	2.4897***	3.7088***	1.9136*	2.0761*	2.9547**	4.7342***	5.6526***	5.0494**
	(0.9119)	(0.9549)	(1.0503)	(1.0705)	(1.1954)	(1.3173)	(1.5977)	(1.7376)	(1.9638)
Low-skill wage (iw)	-0.2924	-0.1985	-0.0762	-0.1439	0.0552	0.0944	-0.1005	0.6363	0.4886
	(0.4461)	(0.4668)	(0.4805)	(0.4747)	(0.4794)	(0.4754)	(0.5772)	(0.6011)	(0.5562)
High-skill wage	-1.9307**	-2.1087**	-0.8557	-2.5728**	-2.2029**	-1.9204*	-4.0721***	-3.4857**	-4.2454**
	(0.9171)	(1.0032)	(0.8490)	(1.0770)	(1.0546)	(1.1427)	(1.5497)	(1.6359)	(1.6521)
High-skill wage (iw)	0.3960	0.5295	0.4991	0.1804	0.4874	0.2735	-0.2895	0.7720*	0.0817
	(0.3397)	(0.3869)	(0.3370)	(0.3249)	(0.3727)	(0.3451)	(0.4384)	(0.4655)	(0.4573)
GDP gap	0.0364	0.0366	0.0314	0.0616*	0.0616*	0.0630*	-0.0077	-0.0166	-0.0080
	(0.0229)	(0.0227)	(0.0231)	(0.0362)	(0.0362)	(0.0361)	(0.0567)	(0.0565)	(0.0565)
GDP gap (iw)	-0.0076	-0.0083	-0.0050	0.0003	-0.0017	0.0022	0.0186	0.0126	0.0208
	(0.0123)	(0.0121)	(0.0124)	(0.0122)	(0.0120)	(0.0125)	(0.0152)	(0.0153)	(0.0153)
Labor productivity		0.4313			-0.8383			-1.5747	
		(1.1116)			(1.6547)			(1.5093)	
Labor productivity (iw)		-0.3065			-0.7076			-1.8365***	
		(0.5374)			(0.5066)			(0.6146)	
GDP per capita			-3.0004***			-2.4889			-0.1854
			(0.9236)			(1.9888)			(2.1553)
GDP per capita (iw)			-0.4388			-0.4514			-1.1406**
			(0.5746)			(0.6508)			(0.5649)
Control variables	stock + spill	stock + spill	stock + spill	stock + spill	stock + spill	stock + spill	stock + spill	stock + spill	stock + spill
Fixed Effects	F + Y	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	49305	49305	49305	49245	49245	49245	37395	37395	37395
Firms	3287	3287	3287	3283	3283	3283	2493	2493	2493

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(3) include firm and year fixed effects, while (4)-(9) include firm and country-year fixed effects. Stock variables are calculated with respect to the dependent variable. In columns (7)-(9) foreign low-skill wages are interacted with the share of foreign low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and labor productivity. Foreign GDP gap is interacted with the foreign weight. In columns (1)-(6), there is no such interactions. All regressions with patent-weighted low-skill wage variable include a corresponding inventor-weighted low-skill wage variable, similarly for high-skill wage, GDP gap, GDP per capita and labor productivity. All inventor-weighted variables are denoted by (iw) after their names. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

deflating our macroeconomic variables differently: by converting to USD in a different year (columns 1 and 2), every year (columns 3 and 4) or using the local GDP deflator instead of the local PPI in manufacturing (columns 5 and 6). Further, we look at total wages instead of manufacturing wages either with our baseline deflator (columns 7 and 8) or converting every year (columns 9 and 10). Our results remain largely robust but with smaller coefficients when converting to USD every year (which increases the correlation of our macroeconomic variables).

Weights. We investigate alternative weights in Appendix Table A.14. Columns (1) and (2) drop the 5 most recent years in computing the weights. Despite a substantially lower number of firms, the effect of low-skill wages on automation innovation is still positive. This regression addresses the potential concern that our weights could be endogenous because firms which already intend to do automation innovations may decide to locate in places where they forecast an increase in low-skill wages: it is hard to see how firms' location decisions before 1989 could reflect increases in wages from 1995 onward.[42] In columns (3) and (4), we compute the patent weights over a more recent period (1985-1994) and obtain the same results. Columns (5) to (10) keep the patent weights as in our baseline analysis but instead of multiplying them by $GDP_c^{0.35}$, they do not multiply them (columns 5 and 6), multiply them by GDP (7 and 8) or by the total value of low-skill employment to the power 0.35 ($(w_L L)^{0.35}$: this may be a better measure of the potential market for technology designed to automate low-skill work). We obtain similar results.

Quality. Appendix Table A.15 investigates whether our results are robust when focusing on patents of higher quality. We look at patents which have been applied for at 2 of the 3 main patent offices (EU, Japan and US), or at these 3 offices (triadic patents). These give similar results. We also restrict attention to biadic patents with at least one citation within 5 years and weigh patents by citations.[43] This weakens the results somewhat perhaps because whereas the decision to innovate is a choice variable of the firm the eventual quality of the innovation is largely random.

Nickell's bias. Our regressions include the stock of automation innovations and

[42]The same concern can be addressed by keeping our baseline weights but dropping the first few years. See Appendix Table A.15 which reproduces Table 8 but only from 2000. Though the standard errors are bigger, the results are essentially the same.

[43]We add to each patent the number of citations received within 5 years normalized by technological field and year of application, similarly to Kogan, Papanikolaou, Seru and Stoffman (2017), who find a positive correlation between patent value and citations. Abrams, Akcigit and Grennan (2018) find an inverted U relationship between patent value and citations.

therefore may suffer from Nickell's bias. Appendix Table A.16 removes the stock of automation innovations or uses Blundell, Griffith and van Rennen (1999)'s method, which proxies for the fixed effect with the firm's pre-sample average of the dependent variable. We obtain very similar results.

Industry-year fixed effects. Appendix Table A.18 introduces industry-year fixed effects where the industry of a firm corresponds to its 2 digit industry in Orbis. The results are very similar.

5.7 Macroeconomic interpretation of the regression coefficients

To better understand the magnitude of our coefficients and the effect of spillovers and stock variables, we run a simulation where we uniformly and permanently decrease the skill-premium by 10% between 1995 and 2009 in all countries and use our regression results to re-compute the share of automation innovations in machinery. Importantly, we stress that one *must not* interpret the result of this simulation as predictive in part because a change in innovation should in turn affect the skill premium. Nevertheless, our analysis could be used to calibrate any model which predicts that the direction of innovation reacts to changes in the skill premium. We focus on changes in the skill-premium (instead of low-skill wages) because a change in the skill premium is easier to interpret than a change in low-skill wages keeping high-skill wages constant.

Specifically, we simulate the regression results of Appendix Table A.19. There, we regress both auto95 innovations and all machinery innovations except auto95 on the inverse of the skill premium, the GDP gap, stock and spillover variables and firm and country-year fixed effects. We consider separately the stocks and spillovers of auto95 innovations, machinery except auto95 innovations and all other innovations.[44]

Figure 5 reports the results averaged over 500 simulations (using the median gives similar results).[45] 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 2.39 of auto95 innovations with respect to the inverse skill premium (with an elasticity of -0.09 for other machinery

[44]The regression further includes the squares of the spillover variables. The linear setting of the baseline regressions features coefficients greater than 1 which leads to explosive behavior. This does not materially affect the coefficients on the inverse skill premium.

[45]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.

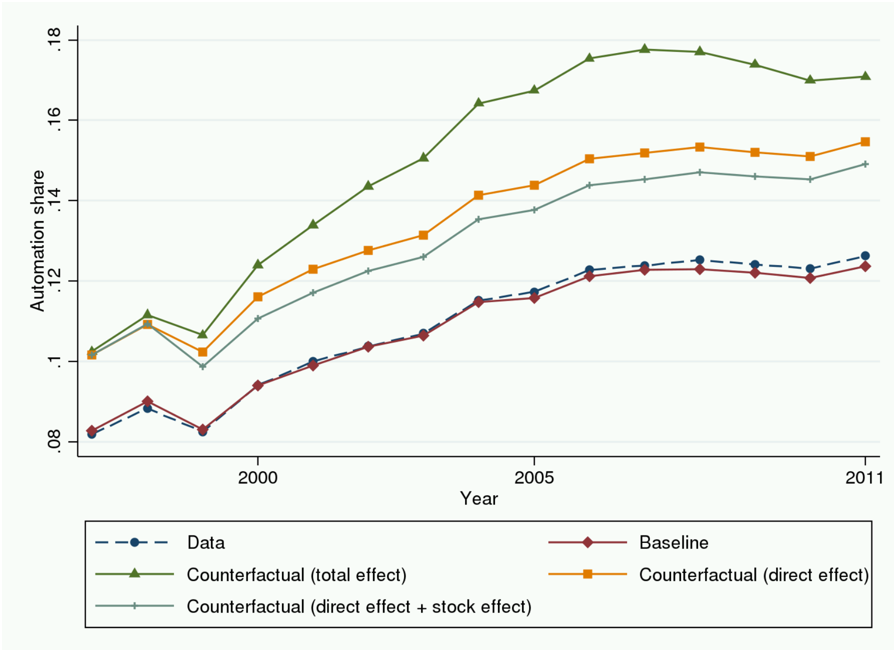


Figure 5: Simulating the impact of a permanent and global 10% decrease in the skill premium on the share of automation innovations in machinery.

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. The overall effect of an increase in low-skill wages involves the impact of knowledge spillovers. This is captured by the gap between the baseline curve and the counterfactual one.[46] 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 4.6 p.p. from 11% to 15.6%. This is 2 p.p. more than the direct effect. This 4.6 p.p. increase can be compared to the 4.4 p.p. increase in the data over the same time period.

To further interpret the 4.6 p.p increase, we use the results of Section 2.6. Using the coefficients from Column (1) in Table 5 (which gives the correlation between tasks changes and the share of automation innovation in 1980-1998), we see that, over a decade, such an increase would be associated with a decline in routine cognitive tasks of

[46]We recompute the spillover variables for the auto95 innovations and other machinery innovations but keep non-machinery innovations constant here. Further, when we recompute spillovers we need to allocate innovations to specific countries. Since the data series is only one possible realization, it differs slightly from the average baseline, which is why the two curves are not identical. Appendix B.5 explains in details how we update the spillover variables.

1.2 centiles and a decline in routine manual tasks of 0.8 centiles. Over this time period, routine cognitive tasks decline at 4.8 centiles per decade and routine manual tasks at 2.4 centiles per decade. Although one should not interpret these numbers as causal, they indicate that the effect of the skill premium on automation innovations that we have found is economically significant.

6 Event study: the Hartz reforms in Germany

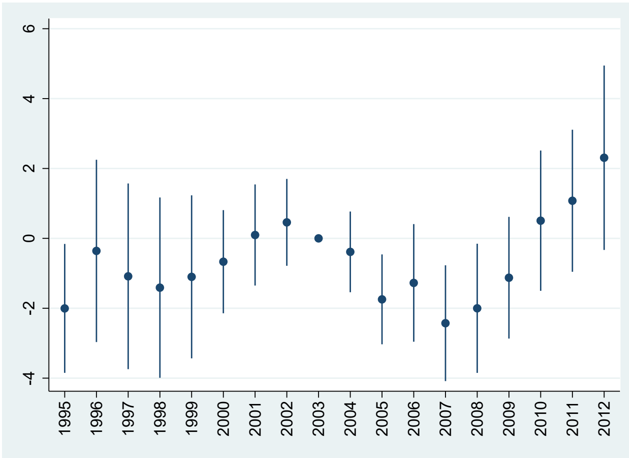
We now use the Hartz reform as an event study to complement our main analysis. The Hartz reforms were a series of labor-market reforms in Germany designed from 2002 onward and implemented between January 1st 2003 and January 1st 2005. The reforms aimed at reducing unemployment and increasing labor-market 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 (see Jacobi and Kluve, 2007). 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 Krause and Uhlig, 2012, Krebs and Scheffel, 2013 and 2017, or Burda and Seele, 2016). Such reforms should 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 start from the same database linking firms and patents as in our main empirical analysis of Section 5, using the same weights to measure firms' exposure to different countries and focusing on biadic patent applications as a measure of innovation. We still define the country of a firm as the country of largest weight, and restrict attention to firms from the countries with the highest average exposure to Germany (Austria, France, Italy, Japan, the Netherlands, Spain, Switzerland, the UK and the US).

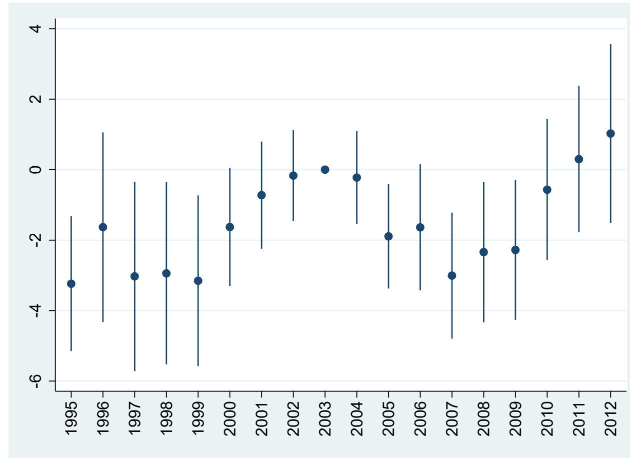
We run the following regression, over the years 1995-2012, maintaining a 2-year lag:

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

As before $PAT_{Aut,i,t+2}$ is a count of automation patents, $K_{Aut,i,t}$ and $K_{other,i,t}$ represent firm knowledge stocks, δ_i a firm fixed effect and $\delta_{c,t}$ a country-year fixed effect. $\omega_{i,DE}$ is



(a) Effect of German exposure on automation innovations



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

Figure 6: 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.

the fixed firm weight on Germany, δ_t is a set of year dummies (with 2003 as the excluded year) and β_{DE} is the full vector of coefficients of interest. β_{DE} determines by how much more a firm exposed to Germany tends to do more automation patents in a given year relative to 2005 (with the 2 year lag). Figure 6.a reports the results. The value of -2 in 2008 indicates that on average a firm with a German weight of 0.1 (the mean value is 0.106) did 20% less automation innovations in 2010 than in 2005 (recall the 2 year lag) compared to a firm with no German exposure. The figure suggests that from 2000 until 2004 firms highly exposed to Germany increased their propensity to introduce automation innovations. This trend reversed between 2006 and 2009 and resumed from 2010. This is consistent with the Hartz reform increasing labor supply from 2002-2004, and therefore decreasing the incentive to introduce automation innovations 2 years later. 2008 marks the beginning of the Great Recession which had a lower impact on German labor markets than in other countries, so that German labor markets remained relatively tight, potentially increasing the incentive to undertake automation innovations.

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 specific to automation innovations, we run the following regression:

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

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 (given the 2 year lag with the excluded year, 2003). Figure 6.b reports the results: the pattern is even more pronounced than in Figure 6.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 $t - 2003$ and a time trend interacted with a post 2003 dummy $(t - 2003)1_{t>2003}$. We focus on the years 1998-2008 to have a panel centered on 2003 and avoid the Great Recession. Table 16 reports the result. Column (2) corresponds exactly to the specification we discussed: it shows a significant time trend in the effect of German exposure on the relative propensity to carry automation innovation two years later between 1998 and 2003, but this trend sharply reverses in the following 5 years. Column (1) runs the same regression but omits the controls for the stock variables. To test whether the break in time trends is associated with a shift in levels, Column (3) adds a control for the triple interaction of the German weight, a dummy for automation innovations and a dummy for post-2003. The coefficient is insignificant. Column (4) replaces the German weight by a dummy indicating that the firm is in the top quartile of exposure to Germany among innovating firms: the results are of similar magnitude as the 75^{th} percentile of German weight is 0.16. Column (5) uses the low-automation innovations of section 5.3 instead of all other machinery innovations. The results are similar. Finally, column (6) considers three types of innovations by separating non-auto95 machinery innovations into the low-automation innovations of the previous columns and the rest. Overall, this exercise suggests that the Hartz reforms reduced the propensity of foreign firms highly exposed to Germany to introduce automation innovations.

Table 16: Innovation and exposure to Germany

Dependent variables	Auto95 and low auto + other mach.				Auto95 and low auto	Auto95, low auto and other mach.
	(1)	(2)	(3)	(4)	(5)	(6)
time trend*dummy auto95*German exposure	0.6309**	0.6245***	0.7726*	0.0929**	0.6486***	0.6523***
	(0.2502)	(0.2296)	(0.3957)	(0.0366)	(0.2464)	(0.2322)
time trend*dummy auto95*post_2003*German exposure	-1.2330***	-1.2322***	-1.3229**	-0.1810**	-1.2500***	-1.2826***
	(0.4473)	(0.4291)	(0.5273)	(0.0766)	(0.4605)	(0.4300)
dummy auto95*post_2003*German exposure			-0.7289			
			(1.0856)			
time trend*dummy low auto*German exposure						0.0081
						(0.1278)
time trend*dummy low auto*post_2003*German exposure						-0.0386
						(0.1835)
year dummy* German exposure	Y	Y	Y	Y	Y	Y
firm innovation stocks* innovation types	N	Y	Y	Y	Y	Y
firm* innovation types fixed effects	Y	Y	Y	Y	Y	Y
country* year* innovation types fixed effects	Y	Y	Y	Y	Y	Y
Observations	75116	75116	75116	75116	60365	104002
Firms	5245	5245	5245	5245	4209	5245

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 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. Innovation types are auto95 and all other machinery innovations (low auto and other machinery together) in columns (1) to (4), auto95 and low auto in column (5), and auto95, low auto and other machinery in column (6). German exposure is measured by the German weights in all regressions except for column (4) where it is replaced by a dummy signaling that the firm is in the top quartile of Germany exposed firms. Standard errors are clustered at the firm-level.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

7 Conclusion

In this paper, we have used patent text data to identify patents which correspond to automation innovations and provide a new measure of automation. Across sectors, our measure is uncorrelated with computerization but positively correlated with robotization. We also find that our measure is associated with a decline in routine tasks across US sectors. We then use our classification to analyze for the first time the effect of wages on automation innovations in machinery. We find that automation innovations are very responsive to changes in low-skill wages with elasticities estimated between 2 and 4. This result does not extend to other innovations in machinery. Furthermore, we show that the Hartz reforms in Germany were associated with a relative increase in automation innovations by foreign firms with a high exposure to Germany.

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

Future research could also 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

Abrams, D., Akcigit, U., and Grennan, J. (2018). Patent value and citations: Creative destruction or strategic disruption? NBER Working Paper 19647.

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. *Handbook of Labor Economics*, 4(B).

Acemoglu, D. and Finkelstein, A. (2008). Input and technology choices in regulated industries: Evidence from the health care sector. *Journal of Political Economy*, 116(5):837–880.

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. (2017). Robots and jobs: Evidence from US labor markets. NBER Working Paper 23285.

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

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

Acemoglu, D. U. (2010). When Does Labor Scarcity Encourage Innovation? *Journal of Political Economy*, 118(6):1037–1078.

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., Bénabou, R., Martin, R., and Roulet, A. (2019a). Environmental preferences and technological choices: Is market competition clean or dirty?

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P., and Li, H. (2019b). A theory of falling growth and rising rents.

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.

Aghion, P., Jones, B., and Jones, C. (2017). Artificial intelligence and economic growth. NBER Working Paper 23928.

Akicigit, U. and Ates, S. (2019). Ten facts on declining business dynamism and lessons from endogenous growth theory. NBER working paper 25755.

Alesina, A., Battisti, M., and Zeira, J. (2018). Technology and labor regulations: theory and evidence. *Journal of Economic Growth*, 23(1):41–78.

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., Katz, L., and Krueger, A. (1998). Computing Inequality: Have Computers Changed the Labor Market? *Quarterly Journal of Economics*, 113(4):1169–1213.

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.

Bartel, A., Ichniowski, C., and Shaw, K. (2007). How Does Information Technology Really Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement and Worker Skills. *Quarterly Journal of Economics*, 122(4):1721–1758.

Bartik, T. (1991). *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute.

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

Bessen, J. (2016). How computer automation affects occpations: Technology, jobs and skills.

Blanas, S., Gancia, G., and Lee, S. Y. (2018). Who is afraid of machines?

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

Burda, M. and Seele, S. (2016). No role for the Hartz reforms? Demand and supply factors in the German labor market, 1993-2014. SFB 649 Discussion Paper 2016-010.

Calel, R. and Dechezleprêtre, A. (2016). Environmental policy and directed technical change: Evidence from the European carbon market. *The Review of Economics and Statistics*, 98(1).

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. (2016). Better, faster, stronger: Global innovation and trade liberalization. NBER Working Paper 22647.

Cohen, W., Nelson, R., and Walsh, J. (2000). Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent or not. NBER Working Paper 7552.

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.

Dernis, H. and Guellec, D. (2001). Using patent counts for cross-country comparisons of technology output. *STI-Science Technology Industry Review*, 27:129–146.

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).

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).

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

Gaggl, P. and Eden, M. (2018). On the welfare implications of automation. *Review of Economic Dynamics*, 29:15–43.

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.

Gentzkow, M. and Shapiro, J. (2010). What drives media slant? evidence from U.S. daily newspapers. *Econometrica*, 78(1):35–71.

Goldsmit-Pinkham, P., Sorkin, I., and Switf, H. (2019). Bartik instruments: What, when, why, and how.

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

Habakkuk, J. (1962). *American and British Technology in the Nineteenth Century*. Cambridge University Press.

Hanlon, W. (2015). Necessity is the mother of invention: Input supplies and directed technical change. *Econometrica*, 83(1):67–100.

Harhoff, D., Scherer, F., and Vopel, K. (2003). Citations, family size, opposition and the value of patent rights. *Research Policy*, 32:1343–1363.

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. (2018). The rise of the machines: Automation, horizontal innovation and income inequality. CEPR dp 10244.

Henderson, R., Jaffe, A., and Trajtenberg, M. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108(3):578–98.

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.

Jacobi, L. and Kluve, J. (2007). Before and after the Hartz reforms: The performance of active labour market policy in Germany. *Journal for Labour Market Research*, 40(1):45–64.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2):665–712.

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

Krebs, T. and Scheffel, M. (2013). Macroeconomic evaluation of labor market reform in Germany. *IMF Economic Review*, 61(4).

Krebs, T. and Scheffel, M. (2017). Labor market institutions and the cost of recessions. IMF working paper WP/17/97.

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.

Manuelli, R. and Seshadri, A. (2014). Frictionless technology diffusion: The case of tractors. *American Economic Review*, 104(4):1368–1391.

Martinez, J. (2018). Automation, growth and factor shares. mimeo.

Newell, R. G., Jaffe, A. B., and Stavins, R. N. (1999). The induced innovation hypothesis and energy-saving technological change. *The Quarterly Journal of Economics*, 114(3):941–975.

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.

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).

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

van Pottelsberghe de la Potterie, B. and van Zeebroeck, N. (2008). A brief history of space and time: The scope-year index as a patent value indicator based on families and renewals. *Scientometrics*, 75(2):319–338.

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

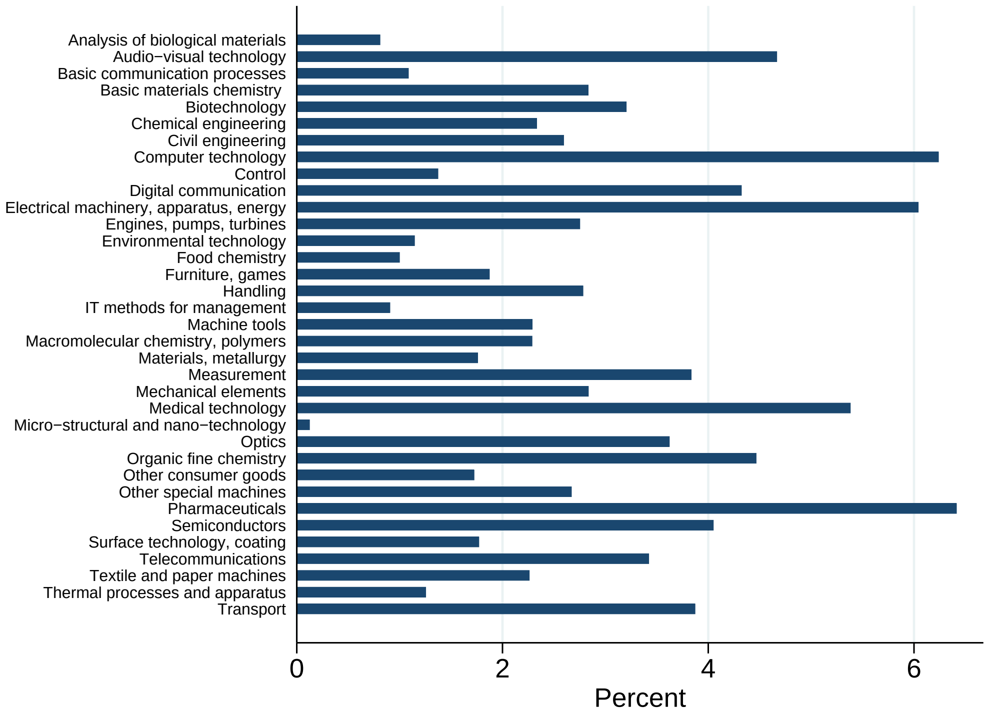
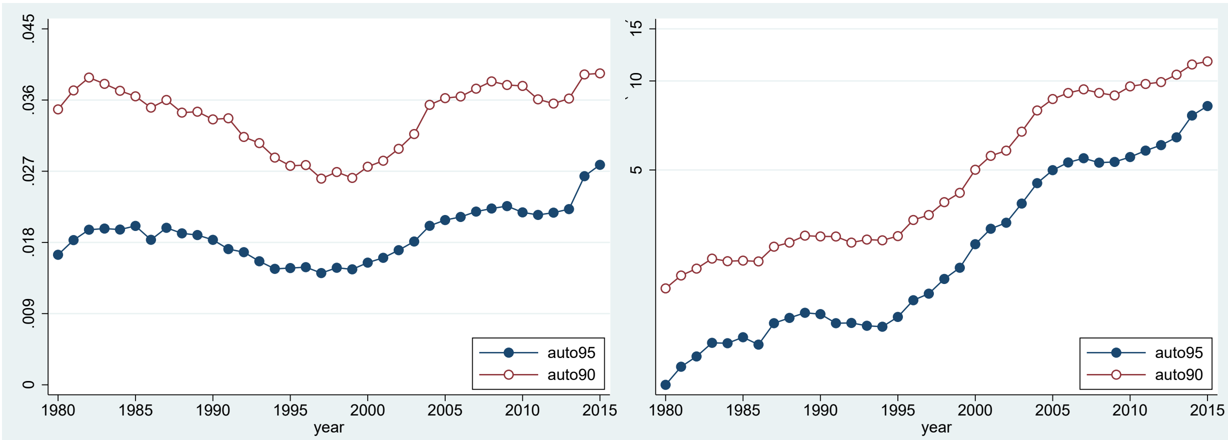


Figure A.1: Share of biadic patent applications in the different technical fields in 1997-2011

A Appendix Figures and Tables



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

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

Figure A.2: Trends in automation (for biadic applications)

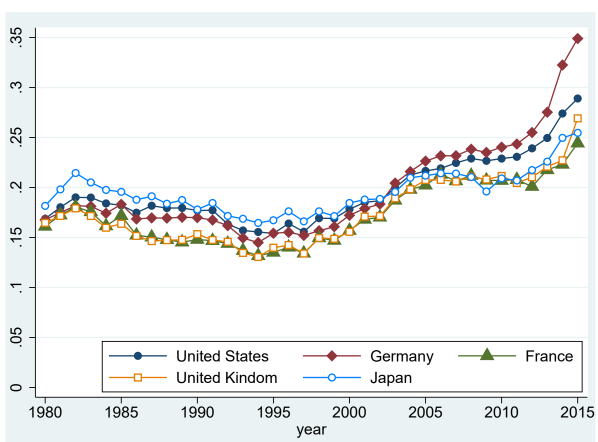


Figure A.3: Share of automation patents (auto95) in machinery conditional on the patent being protected in the designated countries.

Table A.1: Share of automation patents in machinery across sectors

ISIC Rev. 4	Title	Share of automation patents in machinery 1997 - 2011 (in %)					
		Germany		United States		All Countries	
		auto95	auto90	auto95	auto90	auto95	auto90
A	Agriculture, forestry and fishing	5.7	12.4	6.4	14.8	6.8	13.8
B	Mining and quarrying	10.0	17.6	9.9	18.2	9.8	17.2
10-12	Food, beverages and tobacco products	4.6	12.9	5.6	15.2	5.0	12.6
13-15	Textiles, wearing apparel, leather and related products	3.9	9.0	4.7	11.4	4.2	10.3
16	Wood and products of wood and cork	4.3	9.3	4.7	11.9	4.9	10.9
17-18	Paper, paper products and printing	2.6	6.8	2.8	7.5	2.8	7.6
19-22	Coke, chemicals, pharmaceuticals, rubber and plastic products	2.9	6.9	3.8	8.2	3.0	7.0
23	Other non-metallic mineral products	6.1	11.7	6.7	13.9	5.9	12.0
24	Basic metals	10.8	26.0	12.4	29.4	11.1	27.0
25	Fabricated metal products	7.7	22.3	8.8	24.3	8.4	23.7
26-27	Computer, electronic, optical and electrical products	30.7	39.4	30.1	40.1	29.4	39.1
28	Machinery and equipment n.e.c.	17.4	30.5	18.1	30.7	18.8	31.5
29	Motor vehicles, trailers and semi-trailers	32.6	36.8	30.0	35.7	31.9	36.8
30	Other transport equipment	24.5	29.3	22.8	29.1	26.1	31.9
91	All other manufacturing branches	15.7	23.2	18.7	27.9	18.9	27.7
D-E	Electricity, gas and water supply	6.6	13.2	8.2	16.5	7.9	14.7
F	Construction	7.7	11.7	9.4	15.5	8.4	13.3

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	.	.	.	.	.
Middle-skill wage	0.9401	1	.	.	.	.
High-skill wage	0.6009	0.7469	1		.	.
GDP gap	-0.0660	-0.0239	0.0482	1		.
GDP per capita	0.6972	0.7974	0.7277	-0.0117	1	.
Labor productivity	0.6678	0.7340	0.7724	0.1980	0.6519	1

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

Table A.3: 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.4: Baseline regressions for auto95 with country-level clustering

Dependent variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.2000***	2.8254***	1.8160***	1.9058***	1.9992**	2.2954***	2.4627***	2.4266***	3.7365***
	(0.5464)	(0.7421)	(0.6310)	(0.6863)	(0.9001)	(0.5383)	(0.7170)	(0.8727)	(0.6582)
High-skill wage		-0.9210	-0.9009**	-0.9695***	-0.8698	-0.2971	-1.6180***	-1.6700**	-0.4838*
		(0.6234)	(0.3519)	(0.3701)	(0.7025)	(0.2972)	(0.4701)	(0.7968)	(0.2831)
Stock automation			-0.1275***	-0.1269***	-0.1270***	-0.1239***	-0.1441***	-0.1443***	-0.1504***
			(0.0336)	(0.0339)	(0.0335)	(0.0355)	(0.0358)	(0.0365)	(0.0389)
Stock other			0.6311***	0.6296***	0.6309***	0.6260***	0.6408***	0.6407***	0.6489***
			(0.0495)	(0.0506)	(0.0483)	(0.0518)	(0.0493)	(0.0492)	(0.0501)
GDP gap				0.0210***	0.0214**	0.0179**	0.0279***	0.0278***	0.0265***
				(0.0081)	(0.0088)	(0.0074)	(0.0091)	(0.0096)	(0.0076)
Labor productivity					-0.2551			0.1285	
					(1.0309)			(0.9693)	
GDP per capita						-1.5635*			-3.3618***
						(0.8207)			(0.8952)
Spillovers automation							0.5442***	0.5478***	0.8587***
							(0.1831)	(0.1931)	(0.1270)
Spillovers other							-0.3014	-0.3089	-0.5853***
							(0.2573)	(0.2395)	(0.1790)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	50115	50115	50115	50115	50115	50115	50115	50115	50115
Firms	3341	3341	3341	3341	3341	3341	3341	3341	3341

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

Table A.5: Baseline regressions: effect of wages on automation innovations (auto90)

Dependent variable	Auto90								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.7307***	2.4414***	1.3357**	1.3715**	1.4738**	1.8797***	1.9059***	1.8309***	3.1623***
	(0.4953)	(0.6610)	(0.6363)	(0.6610)	(0.6778)	(0.7051)	(0.6883)	(0.7008)	(0.7486)
High-skill wage		-1.0613*	-0.7746	-0.8019	-0.6844	0.0911	-1.4074**	-1.5340**	-0.0865
		(0.5844)	(0.5311)	(0.5480)	(0.6068)	(0.5491)	(0.6296)	(0.6850)	(0.6114)
Stock automation			-0.0347	-0.0345	-0.0348	-0.0328	-0.0475	-0.0479	-0.0538
			(0.0405)	(0.0405)	(0.0404)	(0.0406)	(0.0403)	(0.0403)	(0.0403)
Stock other			0.5682***	0.5676***	0.5690***	0.5611***	0.5773***	0.5770***	0.5814***
			(0.0496)	(0.0497)	(0.0495)	(0.0495)	(0.0508)	(0.0508)	(0.0504)
GDP gap				0.0081	0.0085	0.0038	0.0152	0.0151	0.0127
				(0.0137)	(0.0134)	(0.0135)	(0.0133)	(0.0133)	(0.0132)
Labor productivity					-0.2904			0.2911	
					(0.7011)			(0.7224)	
GDP per capita						-2.0568***			-3.5341***
						(0.7380)			(0.7721)
Spillovers automation							0.8903**	0.9102**	1.2870***
							(0.4162)	(0.4190)	(0.4170)
Spillovers other							-0.6079**	-0.6342**	-1.0159***
							(0.3050)	(0.3140)	(0.3174)
Fixed Effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	73545	73545	73545	73545	73545	73545	73545	73545	73545
Firms	4903	4903	4903	4903	4903	4903	4903	4903	4903

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

Table A.6: Country-year fixed effects and country-level clustering

Dependent variable	Auto95								
	Domestic + Foreign			Foreign					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.8852**	2.1429***	3.0411***	3.4891***	4.3023**	3.7989**	3.6420***	4.3362**	3.8663**
	(0.8028)	(0.7524)	(1.1398)	(1.2222)	(1.9288)	(1.6359)	(1.3319)	(2.0053)	(1.5920)
High-skill wage	-2.4820***	-1.9117	-1.7526***	-3.5161**	-2.4740**	-3.3526***	-3.7549**	-2.8325***	-3.6398***
	(0.7416)	(1.3292)	(0.3511)	(1.5767)	(1.0274)	(1.2889)	(1.5240)	(0.9297)	(1.2942)
GDP gap	0.0623***	0.0620**	0.0646***	0.0044	0.0016	0.0044	0.0031	0.0001	0.0031
	(0.0239)	(0.0242)	(0.0216)	(0.0445)	(0.0397)	(0.0439)	(0.0456)	(0.0407)	(0.0452)
Labor productivity		-1.2851			-1.7494			-1.5475	
		(1.2933)			(1.6920)			(1.6342)	
GDP per capita			-2.8260			-0.5289			-0.3829
			(1.7682)			(1.3544)			(1.2045)
Stock automation	-0.1511***	-0.1506***	-0.1541***	-0.1522***	-0.1523***	-0.1526***	-0.1530***	-0.1532***	-0.1533***
	(0.0383)	(0.0382)	(0.0401)	(0.0371)	(0.0370)	(0.0373)	(0.0370)	(0.0370)	(0.0371)
Stock other	0.6549***	0.6556***	0.6555***	0.6494***	0.6471***	0.6490***	0.6496***	0.6475***	0.6493***
	(0.0532)	(0.0530)	(0.0543)	(0.0559)	(0.0570)	(0.0563)	(0.0555)	(0.0567)	(0.0559)
Spillovers automation	1.4782***	1.4762***	1.4715***	1.4396***	1.4128***	1.4355***	1.4380***	1.4161***	1.4357***
	(0.1276)	(0.1317)	(0.1188)	(0.1230)	(0.1585)	(0.1243)	(0.1243)	(0.1574)	(0.1254)
Spillovers other	-1.2259***	-1.2020***	-1.2436***	-1.2377***	-1.2268***	-1.2436***	-1.2252***	-1.2141***	-1.2300***
	(0.1690)	(0.1690)	(0.1633)	(0.1997)	(0.2111)	(0.1934)	(0.2002)	(0.2126)	(0.1941)
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	50070	50070	50070	50070	50070	50070	50070	50070	50070
Firms	3338	3338	3338	3338	3338	3338	3338	3338	3338

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 and country-year fixed effects. All regressions with stock variables include a dummy for no stock and no spillover. In columns (4)-(6) foreign low-skill wages are interacted with the share of foreign low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. In columns (7)-(9), they are interacted with the average shares over the sample period instead. In columns (4)-(9), foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the country-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.7: Country-year fixed effects and auto90

Dependent variable	Auto90								
	Domestic + Foreign			Foreign					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.3896*	1.4107	2.2798**	2.6344**	3.1221**	3.2536**	2.7215**	3.1094**	3.2428**
	(0.8386)	(0.8937)	(1.0390)	(1.1574)	(1.3170)	(1.3955)	(1.1927)	(1.3384)	(1.4122)
High-skill wage	-1.5576*	-1.5109	-1.0014	-3.0164**	-2.3531*	-2.6864**	-3.1666**	-2.6147*	-2.8915**
	(0.8304)	(0.9212)	(0.8793)	(1.2101)	(1.3149)	(1.2787)	(1.2485)	(1.3342)	(1.2984)
GDP gap	0.0387	0.0387	0.0405	-0.0044	-0.0060	-0.0042	-0.0053	-0.0070	-0.0053
	(0.0270)	(0.0270)	(0.0269)	(0.0361)	(0.0361)	(0.0360)	(0.0361)	(0.0362)	(0.0361)
Labor productivity		-0.1045			-1.0847			-0.8988	
		(1.1919)			(1.2059)			(1.1768)	
GDP per capita			-2.1599			-1.0595			-0.8978
			(1.4800)			(1.4139)			(1.3541)
Stock automation	-0.0537	-0.0536	-0.0556	-0.0572	-0.0576	-0.0577	-0.0577	-0.0580	-0.0581
	(0.0405)	(0.0406)	(0.0404)	(0.0405)	(0.0405)	(0.0405)	(0.0405)	(0.0404)	(0.0405)
Stock other	0.5846***	0.5847***	0.5845***	0.5802***	0.5794***	0.5792***	0.5802***	0.5796***	0.5795***
	(0.0510)	(0.0509)	(0.0508)	(0.0508)	(0.0507)	(0.0506)	(0.0508)	(0.0507)	(0.0506)
Spillovers automation	1.7794***	1.7789***	1.7682***	1.7676***	1.7438***	1.7562***	1.7652***	1.7459***	1.7563***
	(0.5417)	(0.5421)	(0.5434)	(0.5367)	(0.5388)	(0.5381)	(0.5357)	(0.5388)	(0.5370)
Spillovers other	-1.5492***	-1.5469***	-1.5563***	-1.5439***	-1.5316***	-1.5527***	-1.5350***	-1.5238***	-1.5431***
	(0.4359)	(0.4375)	(0.4366)	(0.4321)	(0.4320)	(0.4315)	(0.4305)	(0.4314)	(0.4298)
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	73485	73485	73485	73485	73485	73485	73485	73485	73485
Firms	4899	4899	4899	4899	4899	4899	4899	4899	4899

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 and country-year fixed effects. All regressions with stock variables include a dummy for no stock and no spillover. In columns (4)-(6) foreign low-skill wages are interacted with the share of foreign low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. In columns (7)-(9), they are interacted with the average shares over the sample period instead. In columns (4)-(9), foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.8: Country-year dummies interacted with the domestic weight

Dependent variable	Auto95								
	Domestic + Foreign			Foreign					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.8108	2.3860*	2.2889*	2.0881*	2.6237**	2.9819**	2.1664*	2.6391**	2.9695**
	(1.1242)	(1.2486)	(1.3755)	(1.1178)	(1.2557)	(1.3805)	(1.1418)	(1.2624)	(1.3847)
High-skill wage	-2.7802**	-2.0793*	-2.5647**	-2.7271**	-2.1941*	-2.3615**	-2.9054**	-2.4236*	-2.5943**
	(1.1391)	(1.2117)	(1.1867)	(1.1229)	(1.2359)	(1.1984)	(1.1471)	(1.2481)	(1.2101)
GDP gap	0.0053	-0.0020	0.0021	0.0086	0.0037	0.0046	0.0075	0.0028	0.0039
	(0.0436)	(0.0444)	(0.0445)	(0.0440)	(0.0448)	(0.0445)	(0.0441)	(0.0449)	(0.0447)
Labor productivity		-1.2255			-0.9968			-0.9151	
		(0.9351)			(0.9758)			(0.9585)	
GDP per capita			-0.7515			-1.3618			-1.2168
			(1.2918)			(1.3924)			(1.3560)
Stock automation	-0.1531***	-0.1525***	-0.1531***	-0.1518***	-0.1514***	-0.1523***	-0.1519***	-0.1515***	-0.1525***
	(0.0523)	(0.0521)	(0.0522)	(0.0522)	(0.0520)	(0.0521)	(0.0522)	(0.0520)	(0.0520)
Stock other	0.6433***	0.6417***	0.6429***	0.6420***	0.6407***	0.6412***	0.6422***	0.6409***	0.6415***
	(0.0605)	(0.0603)	(0.0603)	(0.0607)	(0.0606)	(0.0603)	(0.0607)	(0.0606)	(0.0603)
Spillovers automation	1.1705***	1.2209***	1.2079***	1.0883**	1.1219***	1.1442***	1.1121***	1.1484***	1.1663***
	(0.4154)	(0.4139)	(0.4199)	(0.4241)	(0.4227)	(0.4283)	(0.4191)	(0.4183)	(0.4241)
Spillovers other	-0.9536***	-0.9457***	-0.9736***	-0.9431***	-0.9441***	-0.9801***	-0.9379***	-0.9386***	-0.9719***
	(0.3302)	(0.3305)	(0.3319)	(0.3315)	(0.3310)	(0.3333)	(0.3315)	(0.3315)	(0.3335)
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	50085	50085	50085	50085	50085	50085	50085	50085	50085
Firms	3339	3339	3339	3339	3339	3339	3339	3339	3339

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 and country-year fixed effects. Country-year fixed effects are interacting with the countries' weights. All regressions with stock variables include a dummy for no stock and no spillover. In columns (4)-(6) foreign low-skill wages are interacted with the share of foreign low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. In columns (7)-(9), they are interacted with the average shares over the sample period instead. In columns (4)-(9), foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.9: Placebo regressions: long leads

Panel A: Independent variables are lagged by 10 years.

Dependent Variable	Auto95					
	Domestic + Foreign			Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skill wage	-0.6971	-1.3102	-2.2759	1.4820	2.4995	0.9875
	(1.3783)	(1.2749)	(1.6483)	(2.0809)	(2.2640)	(2.2871)
High-skill wage	0.7190	-0.5961	-0.3672	-4.0906	-2.3516	-4.4106*
	(1.3025)	(1.7655)	(1.3453)	(2.5322)	(2.5102)	(2.6414)
GDP gap	0.0407	0.0427	0.0385	0.0529	0.0481	0.0532
	(0.0374)	(0.0376)	(0.0377)	(0.0559)	(0.0555)	(0.0559)
Labor productivity		3.0468			-2.6255	
		(1.9773)			(1.6419)	
GDP per capita			3.9620**			0.9242
			(1.9791)			(1.9811)
Control variables	stock + spill	stock + spill	stock + spill	stock + spill	stock + spill	stock + spill
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	61170	61170	61170	61170	61170	61170
Firms	4187	4187	4187	4187	4187	4187

Panel B: Independent variables are lagged by 15 years.

Dependent Variable	Auto95					
	Domestic + Foreign			Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skill wage	-0.6407	-0.7833	-1.1595	0.4649	1.2613	0.5584
	(1.0666)	(1.1196)	(1.5609)	(1.7477)	(1.9794)	(2.3955)
High-skill wage	-1.0255	-1.3071	-1.4130	-3.1632	-1.8177	-3.1003*
	(1.2360)	(1.3377)	(1.1015)	(1.9781)	(1.9220)	(1.7537)
GDP gap	0.0003	0.0006	-0.0006	0.0167	0.0121	0.0165
	(0.0320)	(0.0320)	(0.0320)	(0.0551)	(0.0547)	(0.0546)
Labor productivity		0.6899			-2.0360	
		(1.8157)			(1.4866)	
GDP per capita			1.3848			-0.1780
			(2.4752)			(2.0382)
Control variables	stock + spill	stock + spill	stock + spill	stock + spill	stock + spill	stock + spill
Fixed effects	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	63903	63903	63903	63903	63903	63903
Firms	4298	4298	4298	4298	4298	4298

Note: Marginal effects; Standard errors in parentheses.Estimation is by conditional Poisson regressions fixed-effects (HHG). All columns include firm and country-year fixed effects. All regressions include stock and spillover variables as controls. Stock variables are calculated with respect to the dependent variable. In columns (4)-(6) foreign low-skill wages are interacted with the share of foreign low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. Foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.10: Predicted wages

Dependent Variable	Auto95							
	joint ρ, average		joint ρ, t+4		separate ρ, average		separate ρ, t+4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	1.6899**	1.4813*	1.7039**	1.4899*	1.7557**	1.4318*	1.7803**	1.4313*
	(0.8152)	(0.8080)	(0.8167)	(0.8107)	(0.8286)	(0.8087)	(0.8314)	(0.8137)
High-skill wage	-1.7960**	-2.9855**	-1.7638**	-2.8597*	-1.7838**	-2.7068**	-1.7874**	-2.7378**
	(0.8440)	(1.5046)	(0.8440)	(1.4860)	(0.8196)	(1.2652)	(0.8283)	(1.2776)
GDP gap	0.0162	0.0161	0.0164	0.0163	0.0144	0.0119	0.0144	0.0117
	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0142)	(0.0139)	(0.0142)	(0.0139)
Labor productivity		1.7353		1.6234		1.4848		1.5467
		(1.7310)		(1.7208)		(1.1824)		(1.2247)
Stock automation	-0.1433***	-0.1451***	-0.1430***	-0.1446***	-0.1433***	-0.1451***	-0.1431***	-0.1450***
	(0.0509)	(0.0514)	(0.0509)	(0.0514)	(0.0509)	(0.0517)	(0.0510)	(0.0517)
Stock other	0.6408***	0.6380***	0.6407***	0.6379***	0.6405***	0.6371***	0.6405***	0.6371***
	(0.0601)	(0.0603)	(0.0601)	(0.0603)	(0.0602)	(0.0604)	(0.0601)	(0.0604)
Spillovers automation	0.4847	0.6321*	0.4848	0.6209*	0.5049*	0.7348**	0.5097*	0.7364**
	(0.3045)	(0.3449)	(0.3049)	(0.3445)	(0.3036)	(0.3702)	(0.3044)	(0.3679)
Spillovers other	-0.1628	-0.3290	-0.1674	-0.3214	-0.1842	-0.4488	-0.1899	-0.4498
	(0.2276)	(0.2877)	(0.2278)	(0.2866)	(0.2281)	(0.3182)	(0.2282)	(0.3152)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	50115	50115	50115	50115	50115	50115	50115	50115
Firms	3341	3341	3341	3341	3341	3341	3341	3341

Note: Marginal effects; Standard errors in parentheses. Estimation is by conditional Poisson regressions fixed-effects (HHG). The wage variables and labor productivity are predicted at time t-2. Columns (1) to (4) predict wages and labor productivity with an AR(1) process with country-specific trends and with the same auto-regression coefficient across countries. Columns (5) to (8) use different auto-regression coefficients across countries. In columns (1), (2), (5) and (6) the wages and labor productivity are the average of the predicted values between years t+2 and t+7. In columns (3), (4), (7) and (8), they are the predicted values for year t+4. 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. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.11: Minimum wage

Dependent Variable	Auto95								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Minimum wage	1.5230**	1.5171**	2.2977***	1.4636	1.5601	1.3912	1.8773	1.8401	0.9621
	(0.6865)	(0.6628)	(0.7425)	(0.9127)	(0.9566)	(1.0076)	(1.2125)	(1.2411)	(1.3409)
High-skill wage	-1.2239*	-1.2358	-0.0468	-3.0712***	-2.6564**	-3.2042**	-2.8017**	-2.9368	-4.2497**
	(0.7166)	(0.8701)	(0.7673)	(1.0907)	(1.1667)	(1.4214)	(1.4072)	(1.8000)	(1.7559)
GDP gap	0.0235	0.0235	0.0226	0.0562	0.0563	0.0560	-0.0232	-0.0232	-0.0184
	(0.0151)	(0.0150)	(0.0150)	(0.0347)	(0.0347)	(0.0347)	(0.0513)	(0.0514)	(0.0517)
Labor productivity		0.0246			-0.7554			0.1730	
		(0.9249)			(1.4016)			(1.4426)	
GDP per capita			-2.2653**			0.2730			2.9814
			(0.9798)			(1.9656)			(2.1494)
Stock own	-0.1445***	-0.1446***	-0.1472***	-0.1548***	-0.1544***	-0.1546***	-0.1563***	-0.1564***	-0.1568***
	(0.0513)	(0.0513)	(0.0517)	(0.0522)	(0.0523)	(0.0522)	(0.0530)	(0.0531)	(0.0527)
Stock other	0.6374***	0.6374***	0.6407***	0.6569***	0.6572***	0.6571***	0.6549***	0.6552***	0.6594***
	(0.0596)	(0.0596)	(0.0593)	(0.0597)	(0.0597)	(0.0595)	(0.0607)	(0.0607)	(0.0605)
Spillovers own	0.6456*	0.6462*	0.8154**	1.4309***	1.4270***	1.4308***	1.4198***	1.4215***	1.4172***
	(0.3363)	(0.3397)	(0.3367)	(0.4958)	(0.4967)	(0.4953)	(0.4939)	(0.4966)	(0.4893)
Spillovers other	-0.3546	-0.3559	-0.5197**	-1.1991***	-1.1837***	-1.1971***	-1.2744***	-1.2764***	-1.2597***
	(0.2408)	(0.2535)	(0.2430)	(0.3854)	(0.3864)	(0.3836)	(0.3795)	(0.3821)	(0.3745)
Fixed effects	F + Y	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	50070	50070	50070	50040	50040	50040	48765	48765	48765
Firms	3338	3338	3338	3336	3336	3336	3251	3251	3251

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(3) include firm and year fixed effects, while (4)-(9) include firm and country-year fixed effects. Stock variables are calculated with respect to the dependent variable. In columns (7)-(9) foreign minimum wages are interacted with the share of foreign minimum wages in total minimum wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. Foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.12: Minimum wage with country level clustering

Dependent Variable	Auto95								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Minimum wage	1.5230**	1.5171***	2.2977**	1.4636**	1.5601***	1.3912	1.8773***	1.8401***	0.9621
	(0.5926)	(0.4580)	(0.9024)	(0.6148)	(0.4905)	(1.1772)	(0.4685)	(0.6459)	(0.9948)
High-skill wage	-1.2239**	-1.2358	-0.0468	-3.0712***	-2.6564**	-3.2042***	-2.8017***	-2.9368***	-4.2497***
	(0.5538)	(1.0144)	(0.6842)	(0.5048)	(1.2687)	(0.9645)	(1.0073)	(0.8003)	(1.4124)
GDP gap	0.0235***	0.0235***	0.0226***	0.0562***	0.0563***	0.0560***	-0.0232	-0.0232	-0.0184
	(0.0046)	(0.0047)	(0.0046)	(0.0209)	(0.0210)	(0.0214)	(0.0246)	(0.0245)	(0.0237)
Labor productivity		0.0246			-0.7554			0.1730	
		(0.9997)			(1.4283)			(1.3091)	
GDP per capita			-2.2653			0.2730			2.9814
			(1.4038)			(2.5259)			(2.5884)
Stock own	-0.1445***	-0.1446***	-0.1472***	-0.1548***	-0.1544***	-0.1546***	-0.1563***	-0.1564***	-0.1568***
	(0.0385)	(0.0390)	(0.0397)	(0.0403)	(0.0400)	(0.0404)	(0.0392)	(0.0402)	(0.0375)
Stock other	0.6374***	0.6374***	0.6407***	0.6569***	0.6572***	0.6571***	0.6549***	0.6552***	0.6594***
	(0.0514)	(0.0513)	(0.0503)	(0.0563)	(0.0561)	(0.0566)	(0.0572)	(0.0595)	(0.0591)
Spillovers own	0.6456***	0.6462***	0.8154***	1.4309***	1.4270***	1.4308***	1.4198***	1.4215***	1.4172***
	(0.2076)	(0.2225)	(0.1787)	(0.1139)	(0.1151)	(0.1160)	(0.1192)	(0.1309)	(0.1322)
Spillovers other	-0.3546	-0.3559	-0.5197***	-1.1991***	-1.1837***	-1.1971***	-1.2744***	-1.2764***	-1.2597***
	(0.2214)	(0.2362)	(0.1192)	(0.1684)	(0.1736)	(0.1735)	(0.1956)	(0.2102)	(0.2067)
Fixed effects	F + Y	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	50070	50070	50070	50040	50040	50040	48765	48765	48765
Firms	3338	3338	3338	3336	3336	3336	3251	3251	3251

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(3) include firm and year fixed effects, while (4)-(9) include firm and country-year fixed effects. Stock variables are calculated with respect to the dependent variable. In columns (7)-(9) foreign minimum wages are interacted with the share of foreign minimum wages in total minimum wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. Foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the country-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.13: 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)	(6)	(7)	(8)	(9)	(10)
Low-skill wage	2.7140***	2.6338***	1.9084***	2.1264**	2.5733***	2.7044***	4.1859***	3.9769***	1.4172**	1.1137
	(0.8686)	(0.8933)	(0.6949)	(0.8261)	(0.9691)	(1.0238)	(1.3286)	(1.2666)	(0.7192)	(0.8024)
High-skill wage	-1.7475**	-1.8694**	-2.4692***	-2.2154***	-2.1163**	-1.9409**	-1.3163	-2.3907**	-2.0329***	-2.3743**
	(0.7943)	(0.8603)	(0.7517)	(0.7790)	(0.9229)	(0.9578)	(0.8454)	(0.9545)	(0.7025)	(0.9521)
GDP gap	0.0285*	0.0283*	0.0153	0.0149	0.0254	0.0262	0.0431**	0.0440**	0.0158	0.0148
	(0.0158)	(0.0158)	(0.0146)	(0.0146)	(0.0161)	(0.0161)	(0.0171)	(0.0172)	(0.0152)	(0.0153)
Labor productivity		0.3056		-0.5012		-0.4125		2.6369**		0.6389
		(0.9422)		(0.7122)		(0.7779)		(1.2281)		(0.9348)
Stock own	-0.1439***	-0.1444***	-0.1501***	-0.1493***	-0.1454***	-0.1446***	-0.1446***	-0.1474***	-0.1457***	-0.1462***
	(0.0510)	(0.0511)	(0.0510)	(0.0510)	(0.0510)	(0.0511)	(0.0506)	(0.0509)	(0.0506)	(0.0508)
Stock other	0.6392***	0.6390***	0.6391***	0.6396***	0.6403***	0.6405***	0.6485***	0.6455***	0.6434***	0.6424***
	(0.0600)	(0.0601)	(0.0598)	(0.0597)	(0.0600)	(0.0599)	(0.0596)	(0.0596)	(0.0592)	(0.0592)
Spillover own	0.5795*	0.5887*	0.8540**	0.8568**	0.6503*	0.6444*	0.4874*	0.5675**	0.6379**	0.6536**
	(0.3073)	(0.3093)	(0.3471)	(0.3459)	(0.3451)	(0.3456)	(0.2862)	(0.2879)	(0.3217)	(0.3275)
Spillover other	-0.3314	-0.3499	-0.4295*	-0.4312*	-0.3447	-0.3310	-0.2943	-0.4228*	-0.2826	-0.2962
	(0.2259)	(0.2344)	(0.2332)	(0.2332)	(0.2220)	(0.2219)	(0.2399)	(0.2510)	(0.2403)	(0.2414)
Fixed Effect	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	50115	50115	50115	50115	50115	50115	50115	50115	50115	50115
Firms	3341	3341	3341	3341	3341	3341	3341	3341	3341	3341
Clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions include a dummy for no stock and no spillover. Columns (1) to (6) are on manufacturing wages and columns (7) to (10) on total wages. In columns (1) and (2), macroeconomic variables are deflated with the local manufacturing PPI and converted in USD in 2005. In columns (3), (4), (9) and (10) they are converted in USD every year and deflated with the US manufacturing PPI. In columns (5) and (6), macroeconomic variables are deflated with the local GDP deflator and converted in USD in 1995. In columns (7) and (8), macroeconomic variables are deflated with the local manufacturing PPI and converted in USD in 1995. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.14: Alternative weights

Dependent Variable	Auto95									
	1970-1989		1985-1994		GDP^0		GDP^1		$(w_L * L)^{0.35}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Low-skill wage	1.8155*	1.7192*	2.4739***	2.3626***	1.8685**	1.7962**	2.8690***	2.8825***	2.2007***	2.1429**
	(0.9480)	(0.9544)	(0.8691)	(0.8876)	(0.7776)	(0.8176)	(0.8855)	(0.8953)	(0.8125)	(0.8516)
High-skill wage	-0.8990	-1.0259	-1.7055**	-1.9002**	-1.3791*	-1.4820*	-1.6609**	-1.6405**	-1.4445*	-1.5237*
	(0.8354)	(0.9524)	(0.8288)	(0.8899)	(0.8226)	(0.8851)	(0.7114)	(0.7547)	(0.7847)	(0.8444)
GDP gap	0.0140	0.0138	0.0226	0.0224	0.0276*	0.0273*	0.0265*	0.0264*	0.0283*	0.0280*
	(0.0164)	(0.0164)	(0.0163)	(0.0162)	(0.0154)	(0.0153)	(0.0158)	(0.0159)	(0.0156)	(0.0154)
Labor productivity		0.3240		0.4484		0.2559		-0.0482		0.1983
		(1.0211)		(0.9649)		(0.8994)		(0.8293)		(0.9221)
Stock automation	-0.1194**	-0.1201**	-0.1337**	-0.1343**	-0.1436***	-0.1441***	-0.1429***	-0.1429***	-0.1428***	-0.1432***
	(0.0602)	(0.0603)	(0.0524)	(0.0524)	(0.0509)	(0.0511)	(0.0511)	(0.0511)	(0.0509)	(0.0509)
Stock other	0.6900***	0.6895***	0.6539***	0.6540***	0.6414***	0.6410***	0.6385***	0.6384***	0.6404***	0.6403***
	(0.0769)	(0.0769)	(0.0639)	(0.0639)	(0.0600)	(0.0600)	(0.0598)	(0.0598)	(0.0600)	(0.0600)
Spillovers automation	0.2618	0.2719	0.5655*	0.5815*	0.4091	0.4178	0.8056**	0.8051**	0.4679	0.4744
	(0.3206)	(0.3229)	(0.3154)	(0.3182)	(0.3093)	(0.3106)	(0.3340)	(0.3354)	(0.3103)	(0.3114)
Spillovers other	-0.3772	-0.3951	-0.3401	-0.3693	-0.1913	-0.2090	-0.4680**	-0.4664**	-0.2577	-0.2702
	(0.2435)	(0.2518)	(0.2303)	(0.2401)	(0.2311)	(0.2366)	(0.2265)	(0.2305)	(0.2284)	(0.2353)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	35955	35955	45735	45735	50115	50115	50115	50115	50115	50115
Firms	2397	2397	3049	3049	3341	3341	3341	3341	3341	3341

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). In columns (1) and (2) firms' country weights for the macroeconomic variables are computed over the period 1970-1989; and over the period 1985-1994 for columns (3) and (4). Columns (5) to (10) use the baseline pre-sample period of 1970-1994. Columns (5) and (6) do not adjust for GDP in the computation of the weights and columns (7) and (8) use GDP instead of $GDP^{0.35}$ to adjust for countries' size in the computation of the weights. Columns (9) and (10) adjust for total low-skilled payment instead of using GDP. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.15: Baseline regressions in 2000-2009 only

Dependent variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.6434***	2.4828**	1.8409*	1.9912*	2.0772*	2.4664**	2.9215**	2.6339**	4.4721***
	(0.7284)	(0.9935)	(1.0261)	(1.0700)	(1.0718)	(1.2056)	(1.1447)	(1.1285)	(1.4064)
High-skill wage		0.2690	-0.3563	-0.5113	-0.4602	-0.2960	-1.1540	-1.4516	-0.7074
		(0.8835)	(0.8904)	(0.9219)	(0.9557)	(0.8762)	(0.9894)	(1.0716)	(0.9416)
Stock automation			-0.4117***	-0.4100***	-0.4105***	-0.4050***	-0.4375***	-0.4398***	-0.4335***
			(0.0630)	(0.0631)	(0.0628)	(0.0635)	(0.0636)	(0.0639)	(0.0639)
Stock other			0.6746***	0.6708***	0.6725***	0.6687***	0.6881***	0.6864***	0.6937***
			(0.0709)	(0.0711)	(0.0714)	(0.0708)	(0.0744)	(0.0743)	(0.0735)
GDP gap				0.0243	0.0246	0.0196	0.0419**	0.0437**	0.0360**
				(0.0164)	(0.0162)	(0.0157)	(0.0171)	(0.0174)	(0.0169)
Labor productivity					-0.1968			1.1082	
					(0.9325)			(0.9940)	
GDP per capita						-1.5031			-3.7815**
						(1.1155)			(1.4968)
Spillovers automation							0.9119**	1.0198**	1.1483***
							(0.4167)	(0.4249)	(0.4267)
Spillovers other							-0.5948*	-0.7380*	-0.8383**
							(0.3577)	(0.3820)	(0.3731)
Fixed effects	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y	F + Y
Observations	27110	27110	27110	27110	27110	27110	27110	27110	27110
Firms	2711	2711	2711	2711	2711	2711	2711	2711	2711

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG) from 2000 to 2009. All regressions include firm fixed effects and year dummies. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.16: Nickell's bias

Dependent Variable	Auto95							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	2.3903***	2.3926***	2.1515***	2.2066***	2.0925**	2.2884**	2.3955**	2.9126***
	(0.8004)	(0.8227)	(0.7991)	(0.8150)	(0.9778)	(1.0886)	(0.9713)	(1.0899)
High-skill wage	-1.5544**	-1.5510*	-0.9069	-0.5857	-2.4648**	-2.0312**	-2.5627***	-1.2324
	(0.7840)	(0.8704)	(0.6129)	(0.7453)	(0.9779)	(0.9708)	(0.9338)	(1.0583)
GDP gap	0.0276*	0.0276*	0.0266	0.0278	0.0653*	0.0651*	0.0752**	0.0761**
	(0.0159)	(0.0158)	(0.0191)	(0.0187)	(0.0343)	(0.0342)	(0.0353)	(0.0353)
Labor productivity		-0.0084		-0.7779		-0.9781		-2.6421
		(0.9696)		(1.0755)		(1.5602)		(1.6507)
Stock automation			1.1938***	1.1818***			1.1912***	1.1870***
			(0.0244)	(0.0238)			(0.0243)	(0.0235)
Stock other	0.5101***	0.5101***	0.0895***	0.0897***	0.5230***	0.5237***	0.0869***	0.0879***
	(0.0454)	(0.0453)	(0.0120)	(0.0118)	(0.0439)	(0.0440)	(0.0120)	(0.0118)
Spillovers automation	0.3519	0.3517	0.0098	-0.0315	1.3383***	1.3373***	-0.0667	-0.0518
	(0.2949)	(0.2977)	(0.0746)	(0.0689)	(0.4669)	(0.4676)	(0.0784)	(0.0767)
Spillovers other	-0.0735	-0.0730	0.0219	0.0781	-1.0318***	-1.0139***	0.1163	0.1013
	(0.2127)	(0.2227)	(0.0782)	(0.0748)	(0.3544)	(0.3558)	(0.0827)	(0.0815)
Fixed effects	F + Y	F + Y	BGVR + Y	BGVR + Y	F + CY	F + CY	BGVR + CY	BGVR + CY
Observations	50115	50115	50115	50115	50070	50070	50070	50070
Firms	3341	3341	3341	3341	3338	3338	3338	3338

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), (2), (5) and (6). In columns (3), (4), (7) and (8), 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) to (4) include year fixed effects and columns (5) to (8) country-year 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. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.17: Other innovation indicators

	Auto95							
Dependent Variable	Biadic (US, JP, EU)		Triadic		At least one citation		Citations weighted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low-skill wage	2.2776**	2.0079*	3.1886**	2.9795*	2.2198***	2.1241**	1.7405*	1.6520
	(1.0383)	(1.0785)	(1.4150)	(1.5827)	(0.8341)	(0.8720)	(1.0257)	(1.1403)
High-skill wage	-1.3409	-1.7718*	-2.3417*	-2.6759*	-1.6034**	-1.7443**	-1.8007*	-1.9515**
	(0.9663)	(1.0724)	(1.3640)	(1.3768)	(0.8099)	(0.8577)	(0.9814)	(0.9717)
GDP gap	0.0397**	0.0390**	0.0178	0.0172	0.0269*	0.0267*	0.0368*	0.0366*
	(0.0191)	(0.0191)	(0.0289)	(0.0288)	(0.0158)	(0.0157)	(0.0190)	(0.0190)
Labor productivity		0.9807		0.7272		0.3450		0.3518
		(1.1988)		(1.6987)		(0.9171)		(1.1755)
Stock automation	-0.1683***	-0.1699***	-0.3665***	-0.3677***	-0.1468***	-0.1474***	-0.2220***	-0.2223***
	(0.0597)	(0.0598)	(0.0772)	(0.0766)	(0.0557)	(0.0559)	(0.0438)	(0.0438)
Stock other	0.6342***	0.6333***	0.6500***	0.6494***	0.6457***	0.6456***	0.6805***	0.6802***
	(0.0662)	(0.0663)	(0.0875)	(0.0875)	(0.0635)	(0.0635)	(0.0688)	(0.0687)
Spillovers automation	0.3839	0.4064	0.7925	0.7981	0.5736*	0.5845*	0.1427	0.1499
	(0.4014)	(0.4028)	(0.5469)	(0.5451)	(0.3140)	(0.3151)	(0.2878)	(0.2858)
Spillovers other	-0.5402**	-0.5915**	-0.3499	-0.3742	-0.2978	-0.3187	0.1625	0.1429
	(0.2587)	(0.2715)	(0.4685)	(0.4599)	(0.2404)	(0.2468)	(0.2595)	(0.2600)
Observations	40410	40410	26310	26310	47115	47115	50115	50115
Firms	2694	2694	1754	1754	3141	3141	3341	3341

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditiona Poisson regressions fixed-effects (HHG). All regressions include firm fixed effects and year dummies. All regressions include a dummy for nc stock and no spillover. Columns (1)-(2) consider biadic patents applied for in at least two countries among US, JP, EU. Columns (3)-(4 consider triadic patents (applied for in US, JP and EU). Column (5)-(6) consider biadic patents with at least one citation within 5 years after publication. Column (7)-(8) consider biadic patents and add to each patent the number of citations within 5 years after publicatioi normalized by year and technological field. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.18: Industry-year fixed effects

Dependent Variable	Auto95								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	3.1486***	2.9157***	3.8864***	2.3157**	2.5169**	3.5773***	4.1573***	5.0264***	4.2013**
	(0.8208)	(0.8631)	(0.9521)	(0.9890)	(1.1159)	(1.2188)	(1.3041)	(1.5426)	(1.7227)
High-skill wage	-2.3594***	-2.7484***	-1.5763*	-2.9978***	-2.5654**	-2.1617**	-4.3227***	-3.1470**	-4.2974***
	(0.7465)	(0.8095)	(0.8099)	(0.9457)	(1.0210)	(1.0263)	(1.2915)	(1.3761)	(1.3321)
GDP gap	0.0329**	0.0324**	0.0311**	0.0709**	0.0707**	0.0731**	-0.0059	-0.0083	-0.0059
	(0.0154)	(0.0154)	(0.0153)	(0.0323)	(0.0323)	(0.0322)	(0.0470)	(0.0469)	(0.0470)
Labor productivity		0.9135			-0.9736			-1.9354	
		(0.8810)			(1.7031)			(1.4734)	
GDP per capita			-2.1529*			-3.1161*			-0.0777
			(1.2204)			(1.7989)			(1.8617)
Stock own	-0.1495***	-0.1511***	-0.1522***	-0.1586***	-0.1582***	-0.1601***	-0.1607***	-0.1603***	-0.1607***
	(0.0462)	(0.0462)	(0.0465)	(0.0466)	(0.0466)	(0.0468)	(0.0463)	(0.0461)	(0.0464)
Stock other	0.6477***	0.6479***	0.6498***	0.6549***	0.6555***	0.6548***	0.6492***	0.6470***	0.6491***
	(0.0548)	(0.0548)	(0.0546)	(0.0552)	(0.0552)	(0.0549)	(0.0550)	(0.0549)	(0.0549)
Spillovers own	0.6016**	0.6324**	0.7887**	1.3924***	1.3897***	1.3786***	1.3568***	1.3324***	1.3562***
	(0.3060)	(0.3067)	(0.3188)	(0.4759)	(0.4766)	(0.4761)	(0.4658)	(0.4651)	(0.4675)
Spillovers other	-0.2770	-0.3310	-0.4380*	-1.0750***	-1.0587***	-1.0900***	-1.0864***	-1.0802***	-1.0873***
	(0.2226)	(0.2237)	(0.2392)	(0.3623)	(0.3642)	(0.3618)	(0.3553)	(0.3527)	(0.3540)
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	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 by conditional Poisson regressions fixed-effects (HHG). Columns (1)-(3) include firm and industry-year fixed effects, while (4)-(9) include firm, industry-year and country-year fixed effects. Stock variables are calculated with respect to the dependent variable. In columns (7)-(9) foreign low-skill wages are interacted with the share of foreign low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. Foreign GDP gap is interacted with the foreign weight. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.19: Simulated regression

Dependent variable	Auto95	Mach.\auto95
Low-skill wage/ High-skill wage	2.3915***	-0.0918
	(0.9266)	(0.7354)
GDP gap	0.0690**	0.0007
	(0.0342)	(0.0161)
Stock auto95	-0.1615***	0.1248***
	(0.0531)	(0.0364)
Stock mach.\auto95	0.3777***	0.3025***
	(0.0538)	(0.0344)
Stock other	0.3316***	0.2181***
	(0.0666)	(0.0433)
Spillovers auto95	1.7759*	-1.3730**
	(1.0740)	(0.6558)
Spillovers auto95^2	-0.0399	0.0975**
	(0.0695)	(0.0480)
Spillovers mach.\auto95	4.3430	3.9003**
	(3.4179)	(1.6194)
Spillovers mach.\auto95^2	-0.2198	-0.1563*
	(0.1865)	(0.0898)
Spillovers other	-7.2627**	-0.6615
	(3.2406)	(2.0660)
Spillovers other^2	0.2543*	-0.0318
	(0.1392)	(0.0980)
Fixed effects	F + CY	F + CY
Observations	49714	155325

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). Mach.\auto95 refers to all machinery innovations except auto95 and "other" to all non-machinery innovations. All columns include firm and country-year fixed effects. All columns include three dummies for no auto95 knowledge, no mach.\auto95 knowledge and no other knowledge. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

B Appendix

B.1 Details on the classification of automation patents

B.1.1 List of keywords

For each technological category, we compute the following shares of patents:[47]

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

   (a) *Automation* or *automatization;*

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

B.1.2 Statistics on the classification

Table B.1 gives summary statistics on the shares of patents containing certain keywords across technological codes in machinery. We look at the share of automation keywords ("all" in the table) and then focus on the three main subcategories, namely automat* patents, robot patents and numerical control (CNC) patents (defined above). The 95^{th} and 90^{th} percentile for the share of automation patents in the distribution of 6 digit codes in machinery define the threshold used to categorize auto95 and auto90 patents. The distributions are quite similar for the C/IPC 6 digit codes and for pairs of IPC

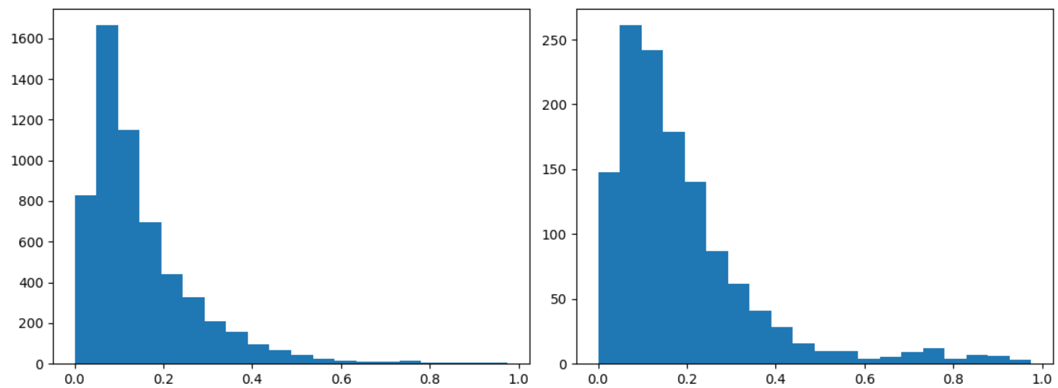
Table B.1: Summary statistics on the prevalence of keywords across technological codes in machinery

	IPC/CPC 6 digit				IPC4 + (G05 or G06)				IPC 4 pairs			
Share	all	robot	automat*	CNC	all	robot	automat*	CNC	all	robot	automat*	CNC
Mean	20.9	4.3	11.2	2.4	53.2	15.4	32.4	11.2	18.5	4.5	8.8	1.8
S. d.	14.4	8.4	9.5	5.8	19.3	17.7	11	16.5	16.3	10	9.9	4.7
p25	10.5	0.8	4.2	0	40	6.7	26.6	0.8	7.7	0.6	2.5	0
p50	18	2	8.7	0.4	54.3	10	31.9	3	13.6	1.8	5.2	0.4
p75	26.6	4.5	15.3	1.8	63.8	16	40.3	15.5	23	4.2	10.7	1.4
p90	38.7	9.1	24.3	6.1	77.9	36.4	43.3	38.2	36.8	8.9	21.7	4.4
p95	47.7	13.7	29.4	12.7	85.6	44.3	45.2	55.3	51.8	14.5	31	7.7
p99	75	35.8	43.8	33.1	90.1	82.9	59.9	56.6	84.5	60	45.3	23.1

4 digit codes (see also the histograms below).[48] As expected, the distributions are significantly shifted to the right for combinations of IPC 4 digit codes with G05 or G06. The distributions of each subcategory 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 mean share for 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 the share of automat* patents and 13.7% and 12.7% for the share of robot and CNC patents. In the right tail, the distribution of robot patents and CNC patents are quite similar.

Figure B.1 gives the histograms of the prevalence of automation keywords for all pairs of C/IPC 4 digit codes (panel a) and all pairs with at least one member in the machinery technological field (panel b). The histograms are very similar to those of C/IPC 6 digit codes in Figure 1. Figure B.2 shows the histograms for all combinations of IPC 4 digit codes with G05 or G06 (panel a), or when the IPC 4 code is in the relevant technological field (panel b). Both distributions are considerably shifted to the right, in line with expectations since G05 proxies for control and G06 for algorithmic, two set of technologies which have been used heavily in automation. There are, however, much fewer combination of these types (in part because all histograms only consider groups with at least 100 patents), and accordingly few patents can be characterized as automation innovations this way.

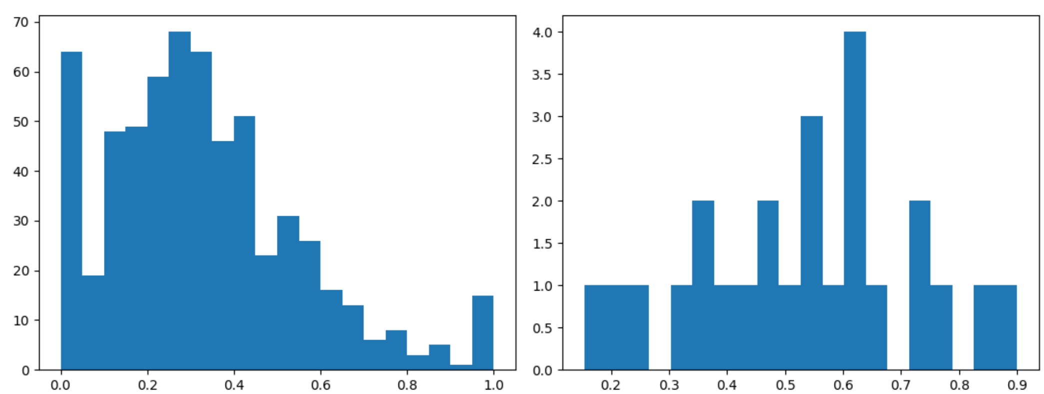
[48] The Y section of the CPC classification is organized differently from the rest of the CPC classification and is only designed to provide additional information. As a result, we ignore Y codes in our exercise.



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

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

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



(a) For all combinations of IPC4 with G05 G06

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

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

Table B.2: Identification of automation technological 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.

B.1.3 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 B.2.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 identified as automation innovations in several ways). 6 digit codes are the most relevant since they identify close to 80% of auto90 or auto95 patents alone.

Similarly, one may wonder which keywords are the most important in identifying automation patents. To do that, we define robot95 (respectively CNC95 or autm95) patents as patents which contain a technological group with a share of "robot" (respectively CNC or automat*) keywords above the threshold used to define auto95 (namely 0.4766), therefore those patents are a subset of the auto95 patents. We define robot90, CNC90, autm90, robot80, CNC80 and autm80 similarly. The other keywords are much less common. Table B.2.b reports the share of auto95, auto90 and auto80 patents which

Table B.3: 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.

belong to each subcategory. "Automat*" appears to be the most important keywords since 72% of auto95 patents are also automat*80 patents. "Robot" matters as well with 33.6% of auto95 patents which are robot80. This is true particularly at the top of the distribution: 17.7% of auto95 patents are also robot95 (more than autm95). CNC does not matter too much: only 13% of auto95 patents are CNC80.

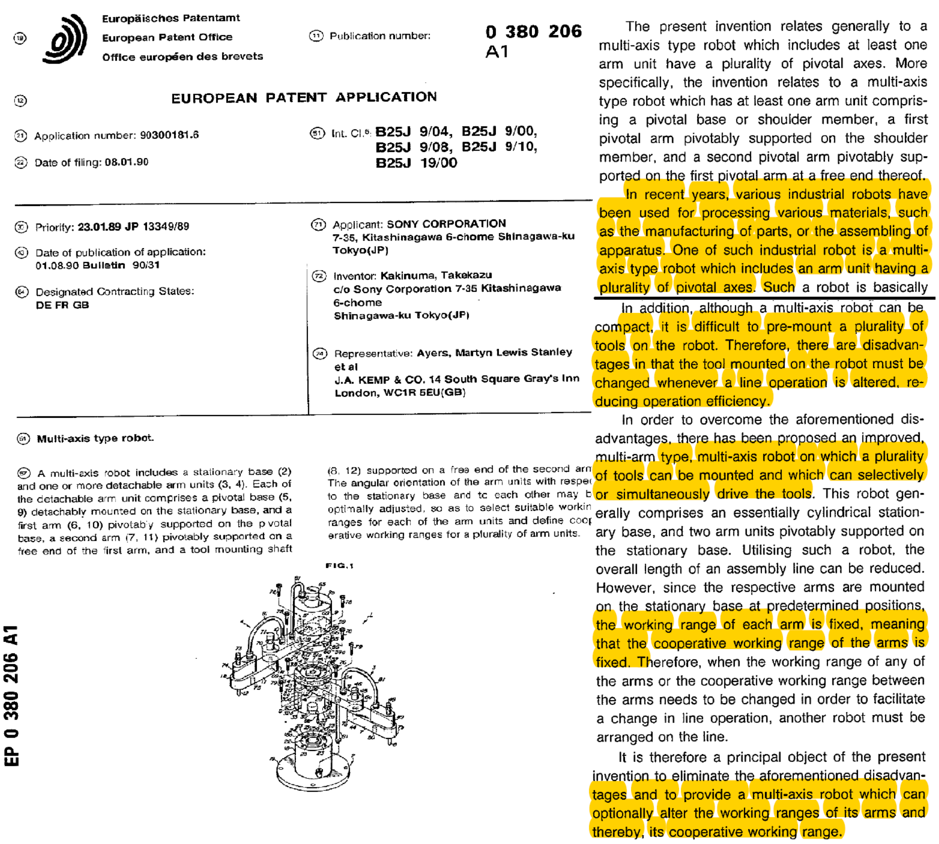
B.1.4 Stability of the classification

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 of the sample (1998-2017) and the period of our main regression analysis (1997-2011). We focus on the same set of biadic patent applications in 1997-2011. Table B.3 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.

B.1.5 Additional examples

We provide a few additional examples of automation and non-automation patents. Figure B.3 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.4 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.



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(12) **EUROPEAN PATENT APPLICATION**

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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 arn The angular orientation of the arm units with respe 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.3: Example of a high automation patent: an industrial robot

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(11) **EP 3 300 593 A1**

(12) **EUROPEAN PATENT APPLICATION**

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(51) Int Cl.:
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A01J 7/04 (2006.01) ***A01J 5/003*** (2006.01)

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(30) Priority: **31.08.2010 US 378871 P**
28.04.2011 US 201113095963

(62) Document number(s) of the earlier application(s) in accordance with Art. 76 EPC:
11746122.8 / 2 611 285

(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)

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

Remarks:
This application was filed on 24-10-2017 as a divisional application to the application mentioned under INID code 62.

(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.4: Example of a high automation patent: a milking robot

Figure B.5 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.6 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.7 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.8 describes a winch to raise and lower people, another low-automation innovation in machinery. This innovation seems rather low-skill labor com-

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(30) Priority: **10.08.89 US 391929**

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(84) Designated Contracting States:
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(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.**

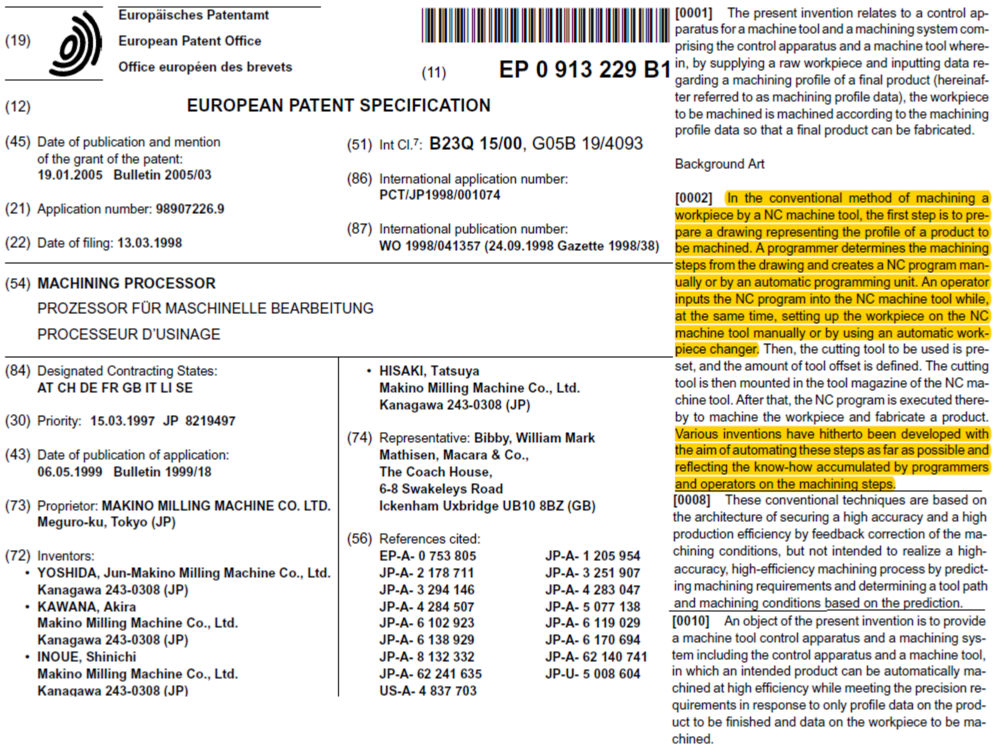
TECHNICAL FIELD

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.5: 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: **19.01.2005 Bulletin 2005/03**

(21) Application number: **98907226.9**

(22) Date of filing: **13.03.1998**

(51) Int Cl.7: **B23Q 15/00**, G05B 19/4093

(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: **06.05.1999 Bulletin 1999/18**

(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.6: Example of a high automation patent: another automated machining device

plementary as its goal is to enable workers to move in a plurality of directions. Finally Figure B.9 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.

B.2 Redoing ALM

In this Appendix, we provide details on the analysis conducted in section 2.6. We use granted patents at the USPTO between 1970 and 1998. To assign patents to sectors, we first use Lybbert and Zolas (2014) who provide a concordance table between IPC codes at the 4 digit level and NAICS 1997 6 digits industry codes (mostly in manufacturing). The concordance table is probabilistic (so that each code is associated with a sector with a certain probability). The Lybbert and Zolas concordance tables are derived by matching patents texts with industry descriptions, and as such they cannot *a priori* distinguish between sector of use and industry of manufacturing. We checked, however, that patents associated with "textile and paper machines"

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(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**

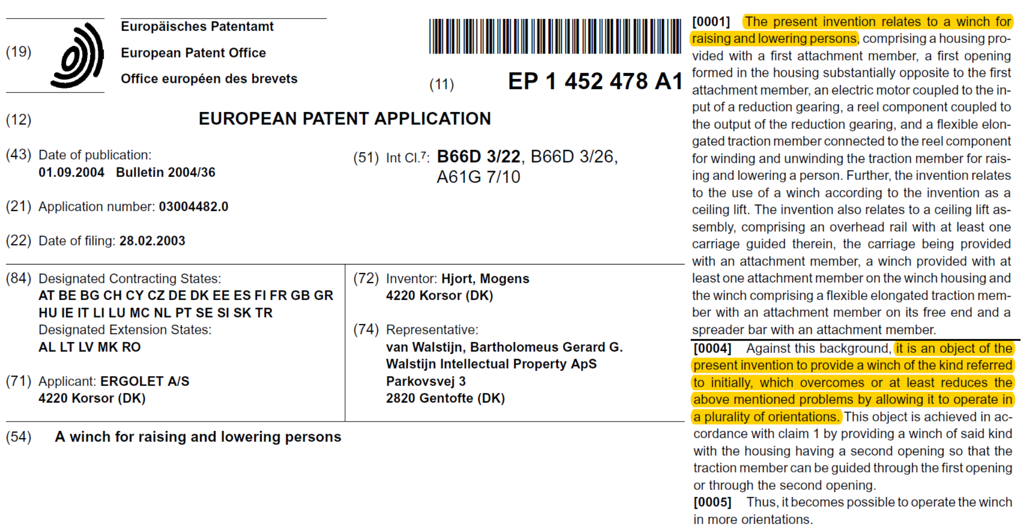
Description

[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.7: 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)

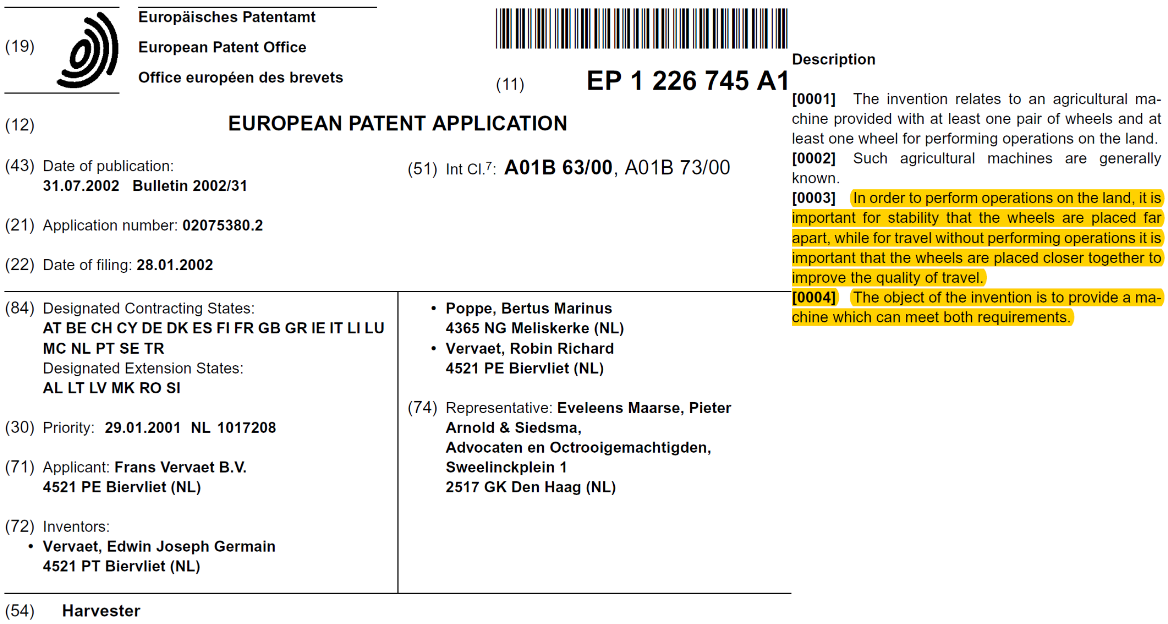
(54) **A winch for raising and lowering persons**

[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.8: Example of a low automation patent: a winch



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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.9: Example of a low automation patent: a harvester

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

The other variables are directly taken from ALM. We refer the reader to that paper for a detailed explanation. The task measures are computed using the 1977 *Dictionary of Occupational Titles* (DOT) which measure the tasks content of occupations. Occupations are then matched to industries using the Census Integrated Public Micro Samples one percent extracts for 1960, 1970 and 1980 (IPUMS) and the CPS Merged Outgoing Rotation Group files for 1980, 1990 and 1998 (MORG). The task change measure at the industry level reflects changes in occupations holding the task content of each occupation constant, which ALM refer to as the extensive margin. Since tasks measures do not have a natural scale, ALM converted them into percentile values corresponding to their rank in the 1960 distribution of tasks across sectors, so that the employment-weighted means of all tasks measure across sectors in 1960 is 50. Our analysis only uses manufacturing sectors and starts in 1970 but we kept the original ALM measure to facilitate comparison. As in ALM, the dependent variable in Table 4 corresponds to 10 times the annualized change in industry's tasks inputs to favor comparison across periods of different lengths. Computerization ΔC_j is measured as the annual change in the percentage of industry workers using a computer at their jobs between 1984 and 1997 (estimated from the October Current Population Survey supplements), multiplied by 10 to ensure that all variables are over the same time length. For all regressions, observations are weighted by the employment share in each sector. In Table 4, the ratio of high-skill to low-skill workers are measured as the ratio of college graduates (and more than college) to high-school dropouts and graduates, taken from ALM—knowing that their data in turn come from IPUMS and MORG.

Table B.5 reproduces Table 4 but with the laxer auto90 measure. The results are very similar—the only difference is that the coefficient on routine manual tasks is not significant at the usual levels in the 90s.[49]

Table B.6 reproduces the Table 5 of ALM by carrying the analysis of Table 4 for each education groups over the time period 1980-1998 with the auto95 measure (the results are very similar with auto90). The table shows that automation reduces the amount of routine tasks undertaken by high-school dropouts and high-school graduates. Following ALM, Panel F computes the average effect of automation in tasks changes (from Panel A) and how much of this average effect can be explained by changes within educational groups (from Panels B to E). We find that changes within educational categories explain a significant share of the overall reduction in routine tasks but changes in educational composition also play a role, in line with Column 6 of Table 4. In contrast, ALM found that nearly all of the decline in routine tasks due to computerization came from within educational group changes.

To allocate patents according to their industry of manufacturing (which we use for Table 5), we proceed as follows. First, we use the Eurostat concordance table (van Looy, Vereyen and Schmoch, 2014) which maps 4-digit IPC codes to 2 or 3 digit NACE rev 2 sectors to allocate all US machinery patents to sectors fractionally according their C/IPC

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

Table B.4: List of sectors in the ALM regressions

ind6090	Title	Auto95
16	Ag production crops and livestock; Ag services; Horticultural services	0.026
30	Forestry	0.035
31	Fishing, hunting and trapping	0.013
40	Metal mining	0.023
41	Coal mining	0.037
42	Crude petroleum and natural gas extraction	0.021
50	Nonmetallic mining and quarrying, except fuel	0.048
66	Construction	0.036
100	Meat products	0.107
101	Dairy products	0.402
102	Canned and preserved fuits and vegetables	0.007
110	Gain mill products	0.030
111	Bakery products	0.005
112	Sugar and confectionary products	0.022
120	Beverage industries	0.017
121	Misc. food preparations, kindred products	0.019
130	Tobacco manufactures	0.033
132	Knitting mills	0.007
140	Dyeing and finishing textiles, except wool and knit goods	0.004
141	Floor coverings, except hard surfaces	0.009
142	Yarn, thread, and fabric mills	0.071
146	Primary aluminum & other primary metal industries	0.083
150	Misc. textile mill products	0.079
151	Apparel and accessories, except knit	0.060
152	Misc. fabricated textile products	0.172
160	Pulp, paper, and paperboard mills	0.020
161	Misc. paper and pulp products	0.015
162	Paperboard containers and boxes	0.003
166	Screw machine products; Metal forgings & stampings; Misc. fabricated metal products	0.086
172	Printing, publishing, and allied industries except newspapers	0.017
176	Engine and turbines; Construction and material handling machines; Metalworking machinery; Machinery, except electrical, n.e.c.; Not specified machinery	0.125
181	Drugs	0.040
186	Electronic computing equipment; Office and accounting machines	0.320
190	Paints, varnishes, and related products	0.015
200	Petroleum refining	0.031
201	Misc. petroleum and coal products	0.010
206	Household appliances; Radio, TV & communications equipment; Electric machinery, equipment & supplies, n.e.c., not specified electrical machinery, equipment & supplies	0.221
211	Other rubber products and plastics footwear and belting + tires and inner tubes	0.010
212	Misc. plastic products	0.019
220	Leather tanning and finishing	0.014
221	Footwear, except rubber and plastic	0.086
222	Leather products, except footwear	0.014
230	Logging	0.030
231	Sawmills, planning mills, and millwork	0.038
236	Railroad locomotives and equipment; Cycles and misc transporation equipment; Wood buildings and mobile homes	0.109
241	Misc. wood products	0.075
242	Furniture and fixtures	0.043
246	Scientific and controlling instruments; Optical and health service supplies	0.410
250	Glass products	0.017
251	Cement, concrete, gypsum and plaster products	0.074
252	Structural clay products	0.033
261	Pottery and related products	0.027
262	Misc. nonmetallic mineral and stone products	0.038
270	Blast furnaces, steelworks, rolling and finishing mills	0.039
271	Iron and stell foundaries	0.178
281	Cutlery, handtools, and other hardware	0.023
282	Fabricated structural metal products	0.034
346	Plastics, synthetics and resins; Soaps and cosmetics; Agricultural chemicals; Industrial and miscellaneous chemicals	0.028
351	Transportation equipment	0.207
360	Ship and boat building and repairing	0.058
362	Guided missiles, space vehicles, ordnance, aircraft and parts	0.166
380	Photographic equipment and supplies	0.043
381	Watches, clocks and clockwork operated devices	0.174
391	Misc. manufacturing industries and toys, amusement and sporting goods	0.032
460	Electric light and power	0.161
462	Eletric and gas, and other combinations	0.153
470	Water supply and irrigation	0.126
471	Sanitary services	0.018
636	Grocery stores; Retail bakeries; Food stores, n.e.c.	0.004

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

Table B.5: Changes in task intensity and skill ratio across sectors and automation (auto90)

	(1) Δ Nonroutine analytic	(2) Δ Nonroutine interactive	(3) Δ Routine cognitive	(4) Δ Routine manual	(5) Δ Nonroutine manual	(6) Δ H/L
Panel A: 1970 - 80, n=67						
Share of automation patents in machinery	0.82	3.57	-17.95***	-10.60***	-0.89	0.11**
	(3.51)	(4.32)	(4.22)	(3.74)	(5.13)	(0.05)
Δ Computer use 1984 - 1997	-7.16	-2.99	-18.91***	-3.26	14.86*	0.08
	(5.71)	(7.03)	(6.86)	(6.09)	(8.36)	(0.09)
Intercept	0.92	2.14*	4.34***	3.39***	-1.70	0.04***
	(1.00)	(1.23)	(1.20)	(1.07)	(1.47)	(0.02)
R^2	0.02	0.01	0.31	0.12	0.05	0.08
Weighted mean Δ	-0.05	2.17	-0.90	1.49	0.42	0.07
Panel B: 1980 - 90, n=67						
Share of automation patents in machinery	9.01*	13.29**	-25.37***	-13.79***	9.70**	0.73***
	(5.41)	(6.23)	(4.96)	(4.28)	(4.72)	(0.19)
Δ Computer use 1984 - 1997	24.75**	22.95*	-13.41	-1.55	-5.37	0.39
	(10.34)	(11.90)	(9.49)	(8.18)	(9.02)	(0.37)
Intercept	-3.15*	-1.21	3.55**	1.69	-2.39	-0.06
	(1.77)	(2.03)	(1.62)	(1.40)	(1.54)	(0.06)
R^2	0.13	0.13	0.32	0.14	0.06	0.21
Weighted mean Δ	1.86	4.17	-2.22	-0.59	-1.74	0.11
Panel C: 1990 - 98, n=67						
Share of automation patents in machinery	9.23**	10.63*	-13.47***	-6.24	3.95	0.42***
	(4.57)	(6.22)	(5.12)	(4.19)	(4.76)	(0.12)
Δ Computer use 1984 - 1997	27.31***	28.19**	-25.09***	-26.11***	8.05	0.73***
	(8.27)	(11.25)	(9.26)	(7.58)	(8.61)	(0.22)
Intercept	-2.93**	-1.93	2.23	2.41*	-2.55*	-0.08**
	(1.44)	(1.96)	(1.61)	(1.32)	(1.50)	(0.04)
R^2	0.20	0.14	0.20	0.19	0.03	0.29
Weighted mean Δ	2.45	3.79	-3.44	-2.36	-0.79	0.09

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

Table B.6: Changes in task intensity and skill ratio across sectors and automation (auto95) by skill groups

	(1) Δ Nonroutine analytic	(2) Δ Nonroutine interactive	(3) Δ Routine cognitive	(4) Δ Routine manual	(5) Δ Nonroutine manual
Panel A: Aggregated within-industry change					
Share of automation patents in machinery	9.53**	17.97***	-26.66***	-17.09***	12.57***
	(4.53)	(5.39)	(4.83)	(3.90)	(4.30)
Δ Computer use 1984 - 1997	24.91***	23.81***	-17.75***	-11.53**	0.47
	(6.36)	(7.56)	(6.79)	(5.48)	(6.03)
Intercept	-2.36**	-1.01	2.05*	1.73*	-2.37**
	(1.03)	(1.22)	(1.10)	(0.89)	(0.98)
R^2	0.26	0.27	0.39	0.29	0.12
Weighted mean Δ	2.05	3.88	-2.62	-1.29	-1.34
Panel B: Within industry: High school dropouts					
Share of automation patents in machinery	2.41	13.61	-26.19***	-5.80	4.56
	(7.89)	(10.85)	(6.94)	(6.22)	(6.35)
Δ Computer use 1984 - 1997	11.70	18.08	15.84	8.68	-9.95
	(11.08)	(15.24)	(9.74)	(8.73)	(8.91)
Intercept	-4.47**	-8.45***	0.87	0.55	1.16
	(1.79)	(2.47)	(1.58)	(1.41)	(1.44)
R^2	0.02	0.05	0.19	0.02	0.02
Weighted mean Δ	-2.56	-4.73	1.20	1.39	0.04
Panel C: Within industry: High school graduates					
Share of automation patents in machinery	-7.08	6.50	-26.09***	-13.43***	9.62*
	(5.47)	(7.05)	(5.64)	(4.25)	(5.37)
Δ Computer use 1984 - 1997	9.30	-0.76	-14.39*	-2.86	6.71
	(7.69)	(9.90)	(7.92)	(5.96)	(7.54)
Intercept	-2.86**	2.19	2.25*	0.00	-1.43
	(1.24)	(1.60)	(1.28)	(0.97)	(1.22)
R^2	0.04	0.01	0.30	0.14	0.06
Weighted mean Δ	-2.03	2.57	-1.88	-1.45	0.30
Panel D: Within industry: Some College					
Share of automation patents in machinery	-11.94	-7.49	-4.92	-5.92	12.48*
	(8.04)	(7.31)	(6.01)	(5.72)	(6.56)
Δ Computer use 1984 - 1997	7.05	13.85	-14.68*	-14.11*	9.14
	(11.29)	(10.26)	(8.44)	(8.03)	(9.20)
Intercept	-1.10	0.31	0.38	2.21*	-2.74*
	(1.83)	(1.66)	(1.37)	(1.30)	(1.49)
R^2	0.04	0.04	0.06	0.07	0.07
Weighted mean Δ	-0.97	1.78	-2.17	-0.33	-0.43
Panel E: Within industry: College graduates					
Share of automation patents in machinery	-6.54	-7.28**	-11.58*	-7.70	17.00***
	(4.25)	(3.59)	(6.48)	(7.74)	(6.03)
Δ Computer use 1984 - 1997	14.44**	9.29*	-5.55	-7.69	11.14
	(6.00)	(5.06)	(9.14)	(10.91)	(8.50)
Intercept	-0.94	0.17	-1.22	-0.14	-5.35***
	(0.97)	(0.82)	(1.48)	(1.77)	(1.38)
R^2	0.01	0.09	0.06	0.03	0.14
Weighted mean Δ	0.69	0.99	-2.93	-1.86	-2.40
Panel F: Decomposition of automation effects into within and between education group					
Explained task Δ	0.73	1.38	-2.04	-1.31	0.96
Within educ groups (%)	-63.96	15.80	72.32	54.61	81.96
Between educ groups (%)	163.96	84.20	27.68	45.39	18.04

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

codes (we allocate to 3 digit sectors whenever the decomposition within 2 digit industries is complete). We then allocate patents to NAICS 2007 sectors (at the 3 to 6 digits level) using a weighted concordance table that we created by combining an unweighted concordance table (available on Eurostat's website) and US employment data from the County Business Patterns for 2008. Next, we allocate patents to NACIS 1997 using concordance tables from the US Census Bureau website. From NAICS 1997, we follow the same steps as before to allocate patents to the consistent Census industries used by ALM. Once we restrict attention to industries with at least 50 machinery patents in per decade, we can compute the share of automation patents in machinery for 58 sectors.

To allocate patents according their sector of use (also used in Table 5), we first build an input-output table as follows. We take the input-output table from 2007 from the Bureau of Economic Analysis (we choose the "Use Table, Before Redefinitions, Producer Value, 405 Industries"). We use concordance tables between NACE Rev 2 and NAICS 2012 from Eurostat and the BEA concordance table between NAICS 2012 and the input-output table industries to generate for each 2-3 digit NACE Rev 2 industry the using frequency in NAICS 2012 (at the 3 to 6 digits level). Using the previous concordance table between 4 digit IPC codes and 2-3 digit NACE Rev 2 industries of manufacturing, we can then compute for each 4 digit IPC code the probability that it is used in each NAICS 2012 industry and allocate patents fractionally accordingly. We then follows similar steps as above to allocate them to the ALM consistent Census industries. We can compute the share of automation patents in machinery for 125 sectors.

B.3 Macroeconomic variables

Our main source of macroeconomic variables is the *World Input Output Database (WIOD)* from Timmer, Dietzenbacher, Los, Stehrer and de Cries (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 producer price indices both for manufacturing and for the whole economy. Their data on skill is based on the 1997 International Standard Classification of Education (ISCED) system, 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 manually 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 separately 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. Table B.7 provides summary statistics for low-skill and high-skill wages for all our countries for our baseline measure (i.e. manufacturing labor costs deflated by the manufacturing PPI and converted in USD in 1995).

The primary data source for the hourly minimum wage data is *OECD Statistics.* 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 (+1 payments in December and July). 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 the case of 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.

For the US, we use data from FRED for state minimum wages and calculate the nation-level minimum wage as the weighted 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. Correspondingly, we follow Dickens, Machin and Manning (1999) and use the wage levels agreed upon by local wage councils. These were in effect from 1909 until 1993. For, 1995-1998, the four years in our sample where no official minimum wage existed, we use the nominal level from 1993. We use the employment-weighted industry average across manufacturing industries. Finally, Germany did not have a minimum wage during the time period we study. Instead, we follow Dolado, Kramarz, Machin, Manning, Margolis and Teulings (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.*

Table B.7: Country-level summary statistics on low-skill and high-skill labor costs

Country	**Low Skill Wages**				**High Skill Wages**			
	Mean	Min	Max	Std.Dev.	Mean	Min	Max	Std.Dev.
Australia	14.0	12.9	15.3	0.71	24.0	20.7	28.8	2.94
Austria	19.6	17.5	23.1	1.81	42.5	39.4	46.5	2.26
Belgium	34.7	29.5	41.9	3.27	53.0	46.0	61.2	4.15
Bulgaria	0.9	0.7	1.3	0.13	2.5	1.6	4.3	0.57
Brasil	2.1	1.8	2.5	0.22	11.8	9.3	13.7	1.22
Canada	13.5	11.7	16.5	1.56	23.9	18.0	32.5	3.94
Switzerland	27.6	24.5	29.2	1.50	57.7	51.3	61.6	3.27
China	0.7	0.4	0.8	0.11	1.2	0.7	1.6	0.32
Cyprus	8.0	7.1	9.8	0.92	12.1	11.2	13.0	0.56
Czech Republic	2.4	1.4	3.6	0.64	6.2	3.9	8.7	1.33
Germany	20.8	19.2	22.0	0.76	50.5	42.4	59.2	4.58
Denmark	25.3	22.1	30.0	2.81	36.2	32.0	43.3	3.67
Spain	14.4	13.9	15.7	0.55	22.5	21.4	23.9	0.71
Estonia	2.5	1.1	4.7	1.22	3.9	2.2	5.4	1.11
Finland	31.4	23.4	43.6	6.70	43.0	28.1	63.7	11.79
France	27.7	19.1	34.7	5.59	50.4	37.2	60.2	7.56
United Kingdom	22.2	16.3	29.6	4.92	44.5	32.6	60.5	9.95
Greece	6.9	6.3	7.7	0.43	10.6	8.2	11.8	1.12
Hungary	2.5	2.2	3.1	0.27	8.2	7.4	9.7	0.66
Indonesia	1.1	0.8	1.7	0.30	4.5	2.3	6.6	1.63
India	0.2	0.2	0.3	0.03	0.9	0.8	1.4	0.19
Ireland	16.3	12.4	24.6	4.24	23.3	17.4	35.5	6.67
Italy	17.8	16.9	18.6	0.53	36.6	30.8	44.1	4.99
Japan	26.2	22.3	31.1	2.82	40.8	36.2	48.0	4.02
Korea	9.5	5.5	14.6	3.17	16.1	9.3	24.3	5.33
Lithuania	2.8	1.5	6.0	1.32	4.2	2.9	5.4	0.87
Luxembourg	26.2	23.2	28.8	1.57	46.4	32.9	55.3	8.19
Latvia	2.4	1.3	3.3	0.59	4.6	2.5	6.4	1.10
Mexico	0.9	0.6	1.0	0.13	3.4	2.6	4.0	0.42
Malta	9.7	7.7	18.9	3.24	27.7	22.6	47.6	6.29
Netherlands	23.9	21.5	28.0	1.88	42.3	36.1	46.8	3.66
Poland	3.6	2.2	4.8	0.66	9.2	5.9	10.9	1.32
Portugal	6.6	5.4	7.3	0.50	19.2	15.9	20.6	1.37
Romania	1.3	0.9	1.8	0.24	3.6	2.9	4.6	0.41
Russian Federation	1.0	0.7	1.2	0.17	3.2	2.4	3.8	0.50
Slovakia	2.9	1.8	4.8	0.98	7.1	4.0	11.6	2.60
Slovenia	4.8	3.7	6.4	1.03	13.0	10.5	15.6	1.88
Sweden	31.1	19.9	42.4	7.50	48.1	34.4	56.6	7.37
Turkey	3.5	1.7	5.0	1.08	10.0	5.0	13.8	2.91
Taiwan	6.8	6.2	7.5	0.41	10.4	9.0	11.5	0.78
United States	13.3	11.6	15.0	1.17	36.6	27.6	46.4	6.75

Notes: Summary statistics for low-skill and high-skill labor costs in manufacturing per hour for each country. Wages are deflated across years using the local PPI in manufacturing and converted in USD in 1995.

B.4 Firm-level patent weights

B.4.1 Additional information on the construction of the patent weights

We give additional details on how we compute firm level patent weights. First, note that we exclude firms which have more than half of their patents in countries for which we do not have wage information.

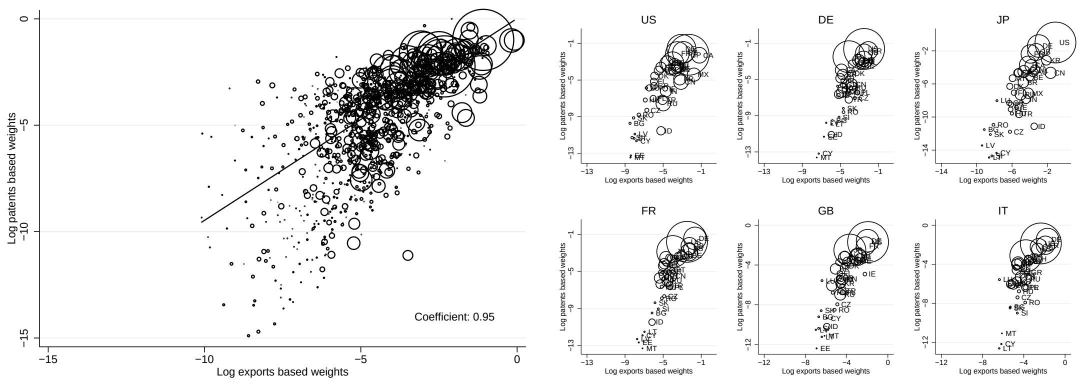
Second, we take the following steps in order to deal with EP patents. We assign EP patents to countries when they enter into the national phase. A firm's untransferred EP patents are assigned using information on where that firm previously transferred its EP patents. If a firm does not have any already 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.

B.4.2 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 domestic country d of a firm based on the location of its headquarters (according to the country code of its 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 domestic 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 1970 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



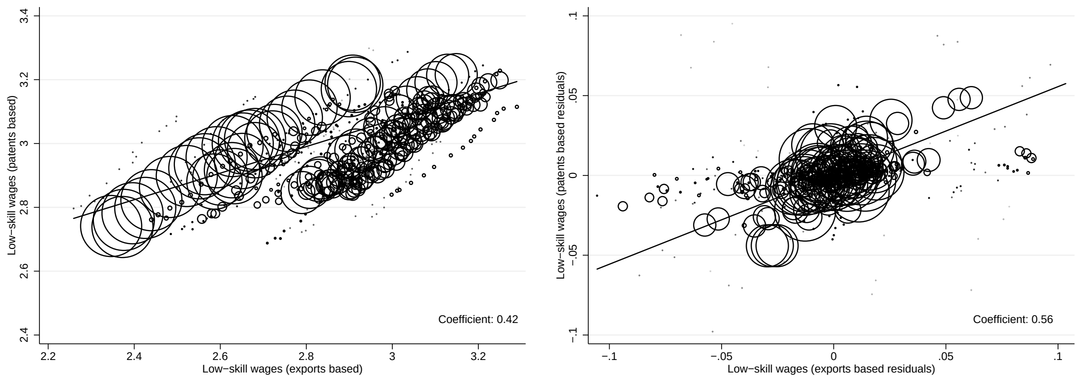
(a) All countries **(b)** Trade from the 6 largest countries

Figure B.10: 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.

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.[50] This gives us a machinery weight for each industry code and each country. 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.10 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).

[50] 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.11: 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.

Another way to summarize how close the two distributions are is to compute what low-skill wages would be according to either sets of weights. We do this in Figure B.11. There 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, we find that they are strongly correlated. Panel (b) reports the same foreign log low-skill wages but taking away country and year fixed effects. We find a regression coefficient of 0.56, when observations are weighted by the number of machinery patent in the country over the 1997-2011 time period.

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.

B.5 Details on the simulations

Simulation of the direct effect and the direct effect plus the stock effect are straightforward for the fixed-effects Poisson model. However, recomputing the spillovers involves two issues.

First, our model only applies to the number of innovations; we do not know where these firms innovate. Therefore, in order to recompute the spillovers, we need to make an assumption on the location of the simulated innovations. Our assumption is natural in the context of our regressions: We assume that a simulated innovation of a firm is located according to the firm's inventor weights, which are the weights that are used to construct the spillover variables. We assign the simulated innovations proportionally to the firm's inventor weights. One could alternatively assume that innovations are invented at only one of the countries and draw that country according to the weight distribution. However, this would only further increase the noise in our simulations, and it is not necessarily better since many innovations are indeed invented in multiple countries.

A second complication when doing the overall simulation is related to the fact that the biadic innovations of the firms in our sample are only 58% of the total biadic innovations in 1997--2011. This is because we do not have weights for all the firms that do relevant automation or machinery innovation in our sample period. Therefore, the number of inventions in a country in a given year consists of an in-sample count plus an out-of-sample count. We make the assumption that the firms not in our sample respond in the same way as the firms in our sample. Hence, when computing the country-level innovation counts by assigning simulated innovations to countries using the firms' inventor weights, we assume that the ratio of the in-sample count to the out-of-sample count stays constant. That way if the in-sample simulated count increases by, say, 5% the entire count would increase by the same amount.