Automating Labor: Evidence from Firm-level Patent Data

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Abstract

Do higher wages lead to more automation innovation? To answer this question, we first introduce a new measure of automation by using the frequency of certain keywords in the text of patents to identify automation innovations in machinery. We validate our measure by showing that it is correlated with a reduction in routine tasks in a cross-sectoral analysis in the US. Then, we build a firm-level panel dataset on automation patents. We combine macroeconomic data from 41 countries and information on geographical patent history to build firm-specific measures of low-skill and high-skill wages. We find that an exogenous increase in low-skill wages leads to more automation innovation with an elasticity between 2 and 4. An increase in high-skill wages tends to reduce automation innovation. Placebo regressions show that the effect is specific to automation innovations. Finally, we use the Hartz labor market reforms in Germany as an event study and find that they are associated with a relative reduction in automation innovations.

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1 Introduction

Do higher wages lead to more labor-saving innovations? And if so, by how much? At a time of fast technological progress in automation technologies such as robotics and AI and of political campaigns pushing for higher minimum wages, answering these questions is of central importance. Even more so because the endogeneity of automation innovations matters for the long-term effects of policy interventions (Hémous and Olsen, 2018). Yet, the literature on the effect of wages on labor-saving technological change 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 wages on automation *innovations*.

Answering this question requires overcoming two challenges: identifying automation innovations and finding a source of exogenous variation in wages from the perspective of innovating firms. To overcome the first challenge, we build a new method of classifying 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. Our identification strategy is ideally suited for innovations in equipment and we restrict attention to those innovations. 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 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 robots. According to our laxer measure, the share of automation innovations among innovations in machinery has increased from 12.8% in 1999 to 20.5% in 2014. 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. Automation is uncorrelated with computerization and captures a different form of technological change but has similar effects.

At the country level, technology and wages are co-determined. To isolate exogenous variation in wages, we therefore exploit firm-level variations in the wages faced by the potential customers of innovating firms by exploiting variations in innovating firms' exposure to international markets. We expand on 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. For each firm which undertakes automation innovations, we compute how much it has patented pre-sample in machinery in each country. We take this information as a proxy for the 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 wages proxy for the average wage 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, but with a smaller elasticity, 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 domestic country-year fixed effects and continues to hold when we decompose firm-specific wages into a domestic and a foreign part. Moreover, we use the geographical localization of firms' inventors to compute the local knowledge stocks which firms are exposed to. We find strong evidence of local knowledge spillovers which suggest that the long-term effects of an increase in wages on automation innovations are larger than the short-term effects. Yet, more automation innovations in a firm are associated with fewer future automation innovations. We run placebo regressions with low-automation patents in machinery and find no effect of low-skill wages on automation innovation.

Finally, we look at the effect of the Hartz reform in Germany in 2002-2004, which aimed at increasing labor market flexibility making the use of labor more attractive and consequently lowering the incentive for automation innovation. We focus on patents from the countries with the highest exposure to Germany, excluding Germany itself. While foreign firms most exposed to Germany were increasingly doing automation innovations relative to other innovations in machinery until the Hartz reform, 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 literature on the effects of technological change on wages and employment,[1] yet the empirical 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 and Acemoglu and Restrepo (2018a) relate demographic trends to robot adoption. Our paper differs in at least two ways. First, our analysis is broader since it covers a range of automation technologies and 40 countries. Second, we focus on innovation instead of adoption,[2] which matters because the economic drivers of innovation may differ from those of adoption: it may be less responsive to macroeconomic variables such as wages and knowledge spillovers are likely to play a greater role. There is essentially no empirical literature on automation innovations: Alesina, Battisti and Zeira (2018) find in cross-country regressions that labor market regulations are positively correlated with innovation in low-skill intensive sectors, which is consistent with a model where innovation is low-skill labor-saving; and a recent working 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]

[1] See for instance Autor, Katz and Krueger (1998), Autor et. al. (2003), Bartel, Ichniowski and Shaw (2007) or Autor and Dorn (2013), 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 also Aghion, Bergeaud, Boppart, Klenow and Li, 2019, and Akcigit and Ates, 2019, for other factors behind the drop of the labor share).

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

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

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

The use of text analysis using keywords has developed rapidly in economics since Gentzkow and Shapiro (2010). More closely related, 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 and compares it with existing measures. Section 3 introduces a simple model to motivate the analysis. Section 4 describes our empirical strategy and the data we use. Section 5 contains the results of the main analysis on the effect of wages on automation innovations. Section 6 discusses the event study of the Hartz reform. Section 7 concludes. Appendix B provides details on our automation classification and additional robustness checks.

2 Classifying automation patents

In the following we describe the patent data as well as 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.

[4] Three other papers have used ADHMV's methodology: Noailly and Smeets (2015) use it to look at innovation in electricity generation, Coelli, Moxnes and Ulltveit-Moe (2018) use it to look at the effect of trade policy on innovation and Aghion, Bénabou, Martin and Roulet (2019) to look at 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 looking separately at the effect of the domestic and foreign variables.

2.1 Patent data

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

[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 thousand have an EPO patent with a description in English.

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

2.2 Choosing automation keywords

In the following we explain how we choose our automation keywords. Most of our keywords come from the automation technologies identified in Doms, Dunne and Troske (DDT, 1997) and Acemoglu and Restrepo (AR, 2018).[8] We complemented 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 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).

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

[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 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.

automation or not. This is the procedure in Mann and Püttmann (2018). We believe our approach has several advantages. First, we found that classifying patents as automation is a difficult task: often looking at a single patent in isolation is not enough, and one needs to look at several patents within the same technological 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 therefore 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 Defining automation technological categories and automation patents

As discussed above 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 to ensure that the prevalence of keywords measure is based on a sufficiently large number of 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

[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 will 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.

starting year does not affect our classification much. To select automation C/IPC codes, we further restrict attention to C/IPC codes which belong to technological fields which are associated with equipment. There are 34 technological fields (see Figure A.7) and we focus on "machine tools", "handling", "textile and paper machines" and "other special machines", which we refer to as "machinery" patents (we use machinery and equipment interchangeably). Our classification scheme captures a broader set of automation technologies than what is relevant for our empirical analysis including Roombas and military drones. We adjust the set of technological codes accordingly.[11] For pairs of 4 digit IPC codes, we assume that they belong to the relevant technological field when at least one of the 4 digit codes belongs to the relevant technological field. Similarly, the combinations of 4 digit IPC code and G05 or G06 belong to the relevant technological fields if the 4 digit code belongs to that group.

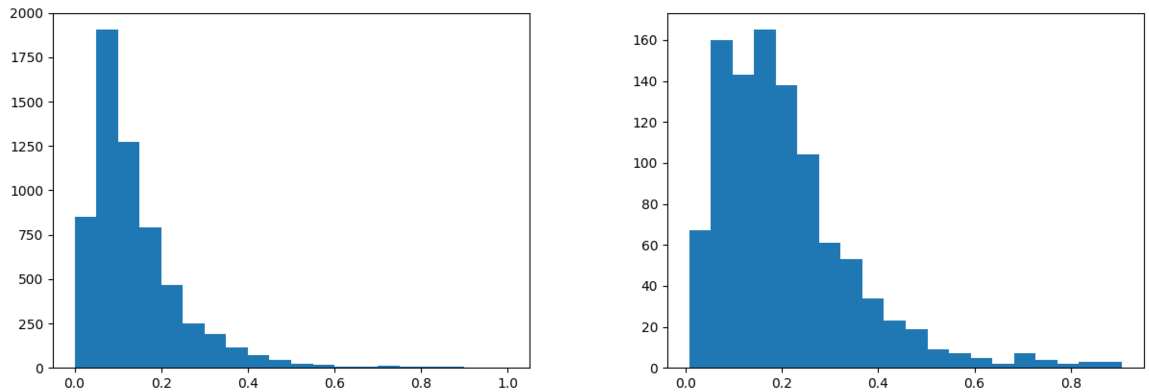
We extensively checked the C/IPC codes and sampled patents from each category to ensure that the procedure delivered reasonable results. However, the validation exercises and the main empirical exercise where carried out after the classification was set.

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 some 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,

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

Code	Description	Number of patents	All share	Rank (over 1009)	Robot share	Automat* share	CNC share
			– 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

Table 2: Examples of 6-digit C/IPC codes in relevant technological fields



(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

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 the "machinery" technological field (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 the relevant technological fields. Yet, a few codes have a high prevalence measure. Appendix B.1 gives additional statistics on the prevalence measures.

Consequently, we define 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. 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).[12] We refer to the two classifications as auto90 and auto95 depending on the threshold used. We can similarly define subcategories of automation patents such as robot90 which correspond to patents which contain at least one technological group for which the frequency of the keywords related to robots (uniquely) is above the threshold defining auto90. By definition all robot90 patents are also auto90 patents.

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

Figure 2 shows two automation patents. Both are automated storage cabinets and are counted as automation patents because they contain the IPC 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.

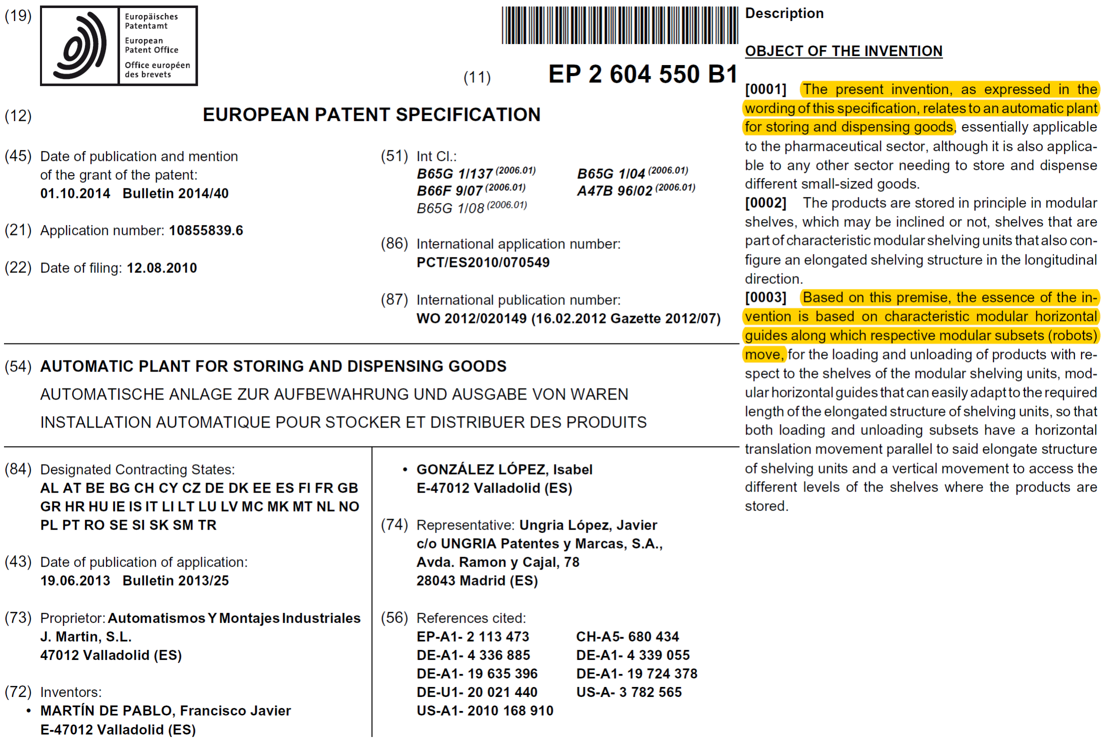
2.4 Trends in automation innovations

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.[13] Several studies have documented that biadic patents are of higher quality 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). 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.[14]

Figure 3 below shows the evolution of automation patents in the set of biadic patents. Panel (a) shows that worldwide, the share of automation patents declines in the 1990s from 17.4% to 12.8% for the laxer auto90 measure and from 8.8% to 6.4% for the stricter auto95 measure before increasing quickly to reach 20.5% for auto90 and 9.5% for auto95 in 2014—Figure A.8 in the Appendix shows that automation patents in machinery represent between 1.9 and 3.5% of all patents with the auto90 definition and it also reports the raw numbers of auto90 and auto95 patents. One interpretation is that

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

[14]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.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Description

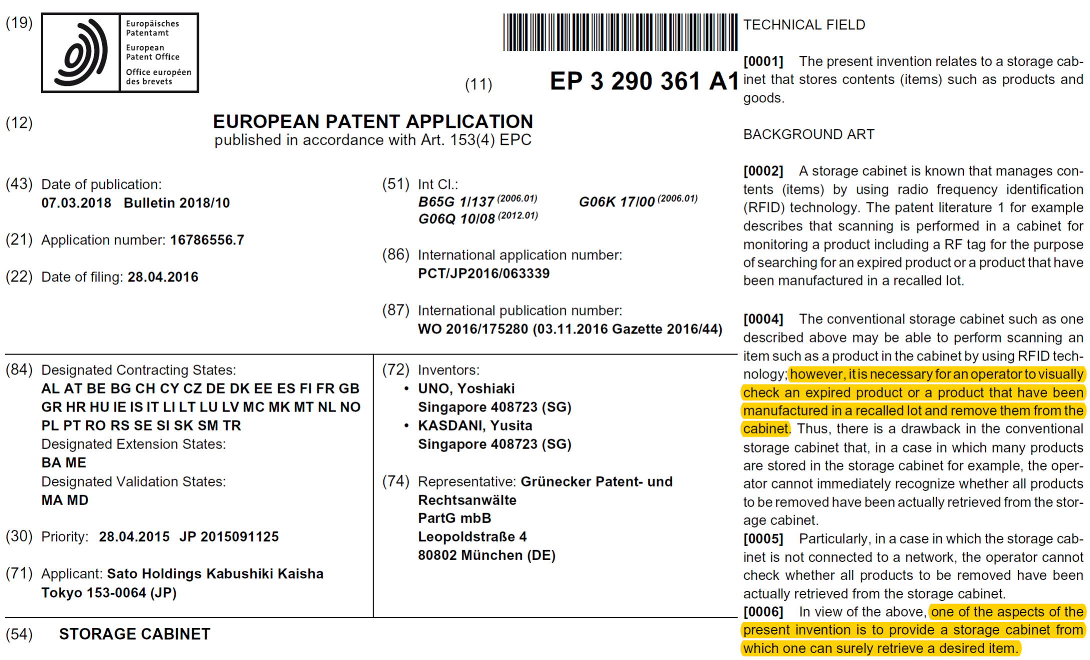
OBJECT OF THE INVENTION

[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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(54) STORAGE CABINET

TECHNICAL FIELD

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

BACKGROUND ART

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

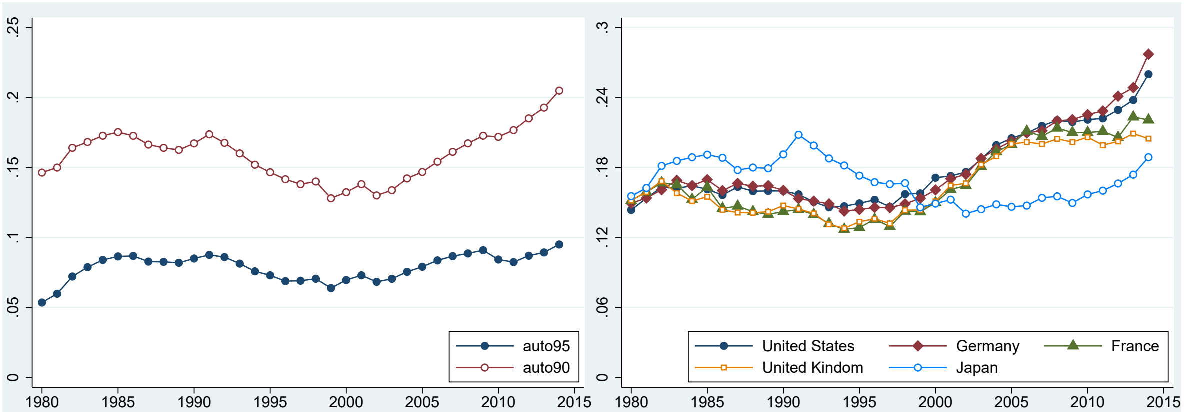
[0004] The conventional storage cabinet such as one described above may be able to perform scanning an item such as a product in the cabinet by using RFID technology; however, it is necessary for an operator to visually check an expired product or a product that have been manufactured in a recalled lot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

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

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

(b) Example without keywords

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



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

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

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

globalization made cheap low-skill labor abroad available in the 1990s and contributed to a temporary decline in automation, which has since reversed. Panel (b) computes the share of automation patents for the auto95 measure for biadic patents conditional on the patent being protected in certain countries. The graphs show that for UK, French, German and US patents, the decline of the 1990s is less pronounced and the rise of the 2000s is very stark. In Japan, the decline of the 1990s is more pronounced and the recent growth more timid there. As a result while the share of automation patents was the highest in Japan in the 1980s and early 1990s, it is now the lowest among these countries. In the Appendix, Figure A.9 reports the share of automation patents in machinery according to the nationality of applicants, the trends are roughly similar but the share of Japanese patents remains higher (suggesting that the relative decline in the share of automation patents at the JPO is due to foreign firms). These country trends are similar with the auto90 measure.

2.5 Automation patents and robots

Recent papers (Graetz and Michaels, 2018, or Acemoglu and Restrepo, 2017) have used data on industrial robots from the International Federation of Robotics (IFR) to measure automation. The IFR reports stocks of robots by country and sectors based on yearly surveys of robot suppliers.

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 stock of industrial robots in 2011 minus the stock of robot in 1997 divided by total employment in manufacturing in 1997 (employment data come from the OECD database). Table 3 reports the correlation across 27 countries between this measure of robotization and our measures of automation, namely the shares of auto95 and auto90 patents within machinery among biadic patents applied for in each country and computed over the years 1997-2011. 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 (robot90 and robot80) we find a somewhat larger coefficient (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 according to the ISIC Rev 4 classification between 1997 and 2011 for Germany and between 2004 and 2011 for the US (technically the IFR data aggregate the robot stocks at the level of US, Canada and Mexico). 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 (still using OECD data). 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 similarly measure the share of auto95, auto90, robot90 and robot80 patents in machinery for each sector over the same time periods.[15] Appendix Table A.15 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) in 1997-2011 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, 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

[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).

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).

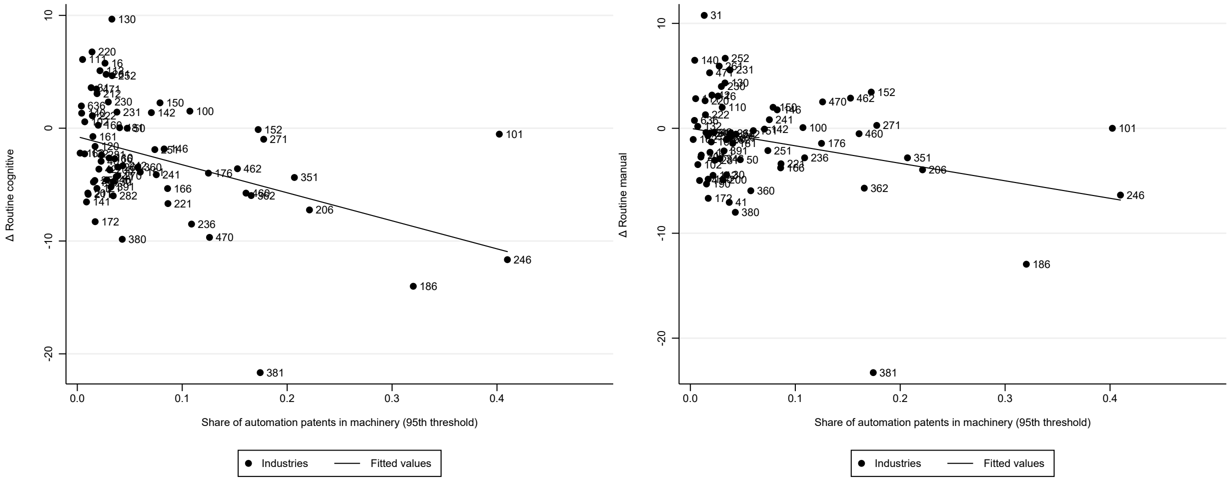
focus specifically on robotic patents, we find correlation coefficients up to 0.74 and 0.78 for the robot80 measure.

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 in a cross-sectional analysis on U.S. data from 1960 to 1998. Here, we provide a brief description of what we do, and we refer the reader to Appendix B.2 for details. To measure automation innovations at the sectoral level, we use USPTO 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 a concordance table provided by Lybbert and Zolas (2014). For each sector j and each period τ, we compute the share of automation patents among machinery patents applied for during this period. We denote this variable $aut_{j\tau}$. We then run regressions of the type:

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

where $\Delta T_{jk\tau}$ 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 θ). We do not first difference our measure of automation because patenting is already a measure of the flow of knowledge. We take our tasks measures directly from ALM, and therefore consider 5 types



(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

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. The initial concordance table mostly assigns our machinery patents to manufacturing sectors (see full list in Table B.4, 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. Our automation measures auto90 and auto95 are strongly correlated with each other (the coefficient is 0.86) but not correlated 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. The list of sectors plotted (which are also the sectors in the regressions) is given in Appendix Table B.4.[16] Sectors with a high share of automation patents

[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

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 as in the example given in Figure 2b).

Table 4, columns (1) to (5) report the results of regression (1) for the auto95 measure. The means of the share of automation in machinery are 0.06, 0.08 and 0.07 in the 70s, 80s and 90s. 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 1980s. To interpret a 10 pp increase, note that the standard deviation in the share of automation patents in the 1980s is 0.09, so that a 1 standard deviation increase in the automation share is associated with a decrease in routine cognitive and routine manual tasks of 2.7 and 1.9 centiles respectively. The corresponding 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 computerization variable has a larger effect 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).

Since we are interested in the effect of low- and high- skill wages on automation but do not measure the price of tasks directly, we also use the ratio of high-skill to low-skill workers (defined as college graduates over high-school dropouts and high-school graduates) as our dependent variable in cross-section regressions similar to 1.[17] Column (6) of Table 4 shows that sectors with a higher automation share also experienced a large increase in the ratio of high-skill to low-skill workers. Panel B, for instance suggests that a 10 pp increase in the share of automation patents is associated with an increase of 1.33 in the ratio of high-skill to low-skill workers in the 1980s.

In the Appendix, Table B.5 reproduces the same exercise for our laxer measure (auto90) and obtains similar results. Finally, Table B.6 reproduces the same analysis separately for each education category (as ALM) and shows that automation leads to a

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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

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).

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

3 A simple model

Before carrying out our main empirical analysis, we present a simple one-period model to clarify our argument. The model is motivated by the business structure of the largest automation innovator. In 2018, Siemens, the biggest innovator in our sample, had 31% of its work force in Germany, but only 14% of total revenue from customers based in Germany. During this year the strongest growing division of Siemens 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.[18] Siemens further directly 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

[18]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".

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 the production function:

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

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

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

We solve the model in two steps, first we derive the profits realized by machine producers, second we solve for the innovation decision. Consider an automated intermediate input (that is $\alpha(i) = 1$), then the downstream intermediate input 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 will charge a price $p_x(i) = \max\left((w/\gamma(i))^{\frac{1}{1-\nu}} w_H^{-\frac{\nu}{1-\nu}}, 1\right)$, and the intermediate input producer will use low-skill workers whenever $w_L/\gamma(i) < w_H^{\nu}$ and machines otherwise. Therefore, the machine producer can charge a higher price when low-skill wages are lower it has to charge a lower price when high-skill wages are higher since high-skill workers and machines are complement. Using that the manufacturing good is produced according to a Cobb-Douglas production function, we have that $p(i)y(i) = Y$ for all intermediates. Therefore, we can derive the profits of the machine producer for intermediate i as:

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

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

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

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

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

This expression is increasing in the low-skill wage w_L and decreasing in the high-skill wage w_H, with a smaller elasticity in absolute value. Intuitively, the incentive to replace low-skill workers with machines (and high-skill workers) increases with low-skill wages and make manufacturing firms better customers of machines and the reverse for high-skill wages. An upward shift in the low-skill workers productivity function $\gamma(i)$ 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.[19]

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

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

$PAT_{Aut,i,t}$ denotes the number of automation patents applied for by firm i in year t. $w_{L,i,t-2}$ and $w_{H,i,t-2}$ denote the average low-skill and high-skill wages faced by the customers of firm i at time $t-2$ (we explain below how we proxy for them). Section 3 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 complementary 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 are potentially sold[20] and controlling for the GDP gap allows us to capture business cycle fluctuations and changes in demand. We include this control because the literature finds that innovation in general is affected by the business cycle (see for instance Aghion, Angeletos, Banerjee, and Kalina, 2010).

$K_{Aut,i,t-2}$ and $K_{other,i,t-2}$ denote the stocks of knowledge in automation and in other technologies of firm i at time $t-2$. These knowledge stocks are computed using the perpetual inventory method.[21] $SPILL_{Aut,i,t-2}$ 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 is

[19] 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.

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

[21] To be more specific we use $\ln(1+K)$, a depreciation rate of 15% and add a dummy indicator variable for when each of knowledge stocks—automation and others—equals zero.

a firm fixed effect and δ_t is a time fixed effect. Finally, $\epsilon_{i,t}$ is an error term, which, we assume, is uncorrelated with the other right-hand side variables. The right-hand side variables are lagged by 2 years in the baseline regressions to reflect the delay between changes in R&D investments and patent applications—we investigate the role of our timing assumption in Section 5.4 below.

To control for firm-level fixed effects, we use several econometric techniques. Our baseline specification uses the Hausman, Hall and Griliches (1984) method, denoted HHG, which is the count data equivalent to the within-group estimator. Technically, this method is inconsistent with equation (3) because it requires strict exogeneity and therefore prevents the lagged dependent variable from appearing on the right-hand side (which it does through the knowledge stock $K_{Aut,i,t-2}$). Yet, the bias is small with large T, which is the case in our baseline regression (15 years). Second, we use the Blundell, Griffith and Van Reenen (1999) method, which proxies for the fixed effect by using the pre-sample average of the dependent variable.

4.2 Macroeconomic data

Our macroeconomic variables come primarily from the 2013 release of the World Input Output Tables, henceforth, WIOD (Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R. and de Vries, G. J., 2015). The database contains information on hourly labor costs across groups of educational attainment – low-skill, middle-skill and high-skill workers – for the manufacturing sector from 1995 to 2009 as well as value added and producer price indices. The dataset contains information on 40 countries, including all 27 EU countries of 2009. We obtained 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.[22] Appendix B.4 provides additional details.

[22]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.

Table 5: 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.

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 (we look at middle-skill wages in section 5.6).[23]

The countries with the highest low-skill wages in 1995 are Belgium, Sweden and Finland with \$41.9, \$42.2 and \$43.6 respectively (in 1995 dollars). The countries with the lowest high-skill wages in 2009 are India, Mexico and Bulgaria with \$0.28, \$0.61 and \$0.71, respectively. The corresponding number for the US is \$13.7. Table 5 summarizes these values 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.

[23]For our baseline sample of firms, included in Table 7 below, the correlation between low-skill and middle-skill wages is 0.94 controlling for firm and year fixed effects. It is only 0.6 for low-skill and high-skill wages. See Appendix Table A.26.

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. We do not directly observe these, and we build a proxy which is a weighted average of country-level wages where the weights reflect the market exposure of innovators. We define the average low-skill wage faced by a firm's customers $w_{L,i,t}$ as

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

where $w_{L,c,t}$ is the low-skill wage in country c at time t and $\omega_{i,c}$ is the fixed weight of country c for firm i. Firms have different exposure to different markets because of trade barriers, heterogeneous tastes of customers, or various historical accidents if exporting involves sunk cost. This measure is a shift-share instrument (Bartik, 1991). 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. We discuss the recent literature on shift-share regressions in detail in Section 5.5.[24]

To measure the weights, and in the absence of sales data for most firms involved in automation innovations, 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 the market exposure of firms. When a firm applies for a patent, it applies for protection in a specific jurisdiction, and it has to pay a fixed cost whenever it wants to expand the geographic coverage of a patent. Therefore, whether a firm protects its innovations in a country or not reflects its intent to sell or license its technology in that country (see e.g. Eaton and Kortum, 1996). Taking this into account, we compute for each firm, the fraction of its patents in the relevant technological field of machinery (not only automation) protected in each country c, $\tilde{\omega}_{i,c}$ during a pre-sample period.[25] We only count patents in the machinery because some of the biggest innovators in automation

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

[25]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.

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.[26]

Patenting indicates whether the firm intends to sell in that market. However, a larger market is likely to host more firms so that the market size per firm will generally not grow 1 for 1 with size of total market. 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.[27] As a result, the weight of country c for firm i is given by:

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

We compute weights for the 41 countries for which we have wage data. The weights are computed over the pre-sample period 1970-1994 to ensure that they are weakly exogenous as patent location could be influenced by shocks to innovation. We use the same weights to compute firm customers' average high-skill wage, productivity or GDP per capita.

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.3, we similarly show that our patent weights correlate well with trade flows. [28]

Patent data also reports where firms' innovators are located. Given that knowledge spillovers have a geographical component (Hall, Jaffe and Trajtenberg, 1993), we can use this information to build a measure of the stock of knowledge to which a firm is exposed.

[26] 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.

[27] Here we use Eaton et al. (2011) who estimate that the elasticity of French exports to the GDP of the destination country is 1 while the elasticity of the number of French exporters is 0.65, which gives an elasticity of the average export by firm of 0.35. ADHMV use a power of 1 on GDP instead of 0.35. We use different values in robustness checks in section 5.6

[28] 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.

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.[29]

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, 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.[30]

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 measure this corresponds to $3,341$ firms, which are responsible for $35,803$, or 58% of the total number of innovations (patent families). For auto90, $4,905$ firms are responsible for $61,931$, also 58% of the total. Table 6 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

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

[30]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 6: Descriptive statistics for firms in our baseline regression

Variable	Auto95		Auto90			Auto95	Auto90
Automation pantents	per year	1997-2011	per year	1997-2011		weights	
Mean	0.7	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				

A.16 gives the list of the ten biggest automation patenters in our sample.[31]

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.

5.1 Baseline results

Our baseline results are contained in Table 7. The dependent variable is the number of biadic patents that qualify as automation when we use a threshold of the 95th percentile for 6 digit C/IPC codes (auto95). The regression is carried over the years 1997-2011 for the dependent variable and 1995-2009 for the independent variables, a constraint imposed by the availability of wage data for a large number of countries. Skill-dependent wages are measured in the manufacturing sector and we deflate by the producer price index in the same sector.

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-

[31]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).

Table 7: 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. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

skill wages as a control. As predicted by the model, high-skill wages enter with a negative coefficient which is smaller in magnitude than the low-skill wage (though not statistically significant). Column (3) adds control for the firm's stock of knowledge: a higher stock of automation knowledge within the firm reduces the amount of automation innovation, suggesting that firms do not become more specialized in automation technologies over time. Column (4) controls for the GDP gap, automation innovations appear to be 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 follows. 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 (with an elasticity between 0.54 and 0.86 depending on specifications). 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, and we therefore we cluster standard errors at the domestic country (i.e. the country of largest weight) level in Appendix Table A.17. If anything clustering at the country level tends to reduce the standard error on low-skill wages.[32]

Appendix Table A.18 repeats Table 7 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, which is in line with auto95 measure being a stricter measure of automation. This also helps explain the magnitude of our elasticities in Table 7: 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 Focusing on foreign wages

Country-level shocks which we have not controlled for may affect both innovation and wages. Insofar as firms are mainly affected by the shock of 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. It 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 automation innovations 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.[33] Furthermore, in section 5.3 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 8 reproduce the columns (7), (8) and (9) of Table 7 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

[32] A potential explanation for the negatively correlated error terms, is that a successful automation innovation by one firm will reduce the incentive for its competitors since the market has already been captured.

[33] A related concern arises from offshoring: 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 8: 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 with stock variables include a dummy for no stock and no spillover. In columns (4)-(6) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, 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), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. In columns (1)-(3), there is no such interactions. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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 take into allow for some firms being more affected by foreign wages than others, and to ensure that the reported coefficient corresponds to an elasticity on total low-skill wages. The foreign macroeconomic control variables are defined similarly.[34] Once again we find a positive effect of low-skill wages on automation innovations, with

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

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

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 (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 $\omega_{i,F}$.

if anything slightly larger elasticities. Our coefficient captures the average effect of an increase in foreign low-skill wages given our controls whatever the shock behind it. Relative to Table 7, 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.19). We also reproduced the regression for the auto90 measure, we obtain similar results with slightly smaller coefficients (Appendix Table A.20). Finally, we also replaced the country-year fixed effects with the interaction of country-year dummies with the domestic weight of each firm to account that firms are more or less exposed to the domestic country. Here as well, we obtain similar results although the magnitude of the coefficient on low-skill wages is a bit smaller (Appendix Table A.21).

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 9 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 7).[35] 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 8). Neither low-skill wages nor any other macroeconomic control variables have an effect on placebo machinery innovations. The sign of low-skill

[35] 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).

Table 9: 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) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. Domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. In columns (1)-(6), there is no such interactions. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

wages even flip in columns (7) to (9).[36] We therefore 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

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 10, which reproduces column (8) of Table 7 for various types of innovations. Column (1) is essentially a robustness check which

[36]Conditioning on the 60^{th} percentile is not important and we obtain similar results with machinery innovations excluding auto95 or auto90. In fact, since automation innovations are a relatively small share of all machinery innovations, a regression on all machinery innovation gives similar results. See Appendix Table A.22.

Table 10: Innovation categories

Dependent Variable	AutoX95	Auto80	Automat* 90	Automat* 80	Robot 90	Robot 80	CNC 90	CNC 80
	(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. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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 (with a lower but not statistically so coefficient). 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. Robot90 and Robot80 were already 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 (note that by definition automat*80 patents are all auto80 but 91.5% of them are 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 macroeconomic and the spillover variables in Table 11—we keep a lag of 2 between patent applications and the stocks of

Table 11: 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 * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

patents from the firm because otherwise the dependent variable would be included in the stock of automation when we consider contemporaneous regressions or leads. Column (4) reproduces 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 found that the largest coefficient for the effect of gas prices on innovations in the car industry was at a 2 year lag). Our baseline regressions assume a 2 year lag between wages and patent applications.

Of course, innovators would not be interested about wages 2 years in the past per se, but only inasmuch as they are indicative of future wages. This is our interpretation throughout 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.[37]

[37]In that context, the difference between the significant lead coefficients in Panel A and the insignif-

We push this logic further in Appendix Table A.23, where we compute predicted future wages at time $t-2$ based on an AR(1) process with country-specific trends. We find similar results.

Minimum wage. Given its policy relevance, we also look at the effect of minimum wages using data on 22 countries.[38] Importantly, we cannot use the minimum wage as an instrument for low-skill wages: our regressions show that the high-skill wage has a significant effect and therefore should be included in the regression. If low-skill wages were to be instrumented so should high-skill wages, and 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.24. We find a positive effect of the minimum wage on automation innovations which in specifications with country-year fixed effects has p-values just above or below 0.1. Clustering standard-errors at the country-level gives significant coefficients (see Appendix Table A.25). Minimum wages are 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 than the minimum wage. 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 shift-share setting 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 of the shift-share set-up 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

icant ones in Panel B and C, could reflect that domestic wages may be easier to predict than foreign wages.

[38]We use data from the OECD. Importantly, not all countries have government-mandated minimum wages, most notably Italy and, until 2015, Germany. For Germany, 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.

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 a year and firm fixed effects); or the correlation of shocks within a country decays sufficiently rapidly that a large number of country x years is sufficient (see Appendix A2 in their paper). They advise practitioners to use appropriate controls to capture omitted variables. We follow this approach partly by including a large set of controls in our regressions and partly by including country-year fixed effects. They further encourage practitioners to apply the standard error correction of Adão, Kolesár and Morales (2019).

Adão et. al. (2019) show that standard applications with the shift-share design often lead to an over-rejection of the null of no effect. In the language of our application, the problem arises if 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. Adão et. al. (2019) use Monte Carlo simulations in a standard Bartik setting and show that in a setting where the true coefficient is zero by construction the commonly used approach rejects the null of no effect up to 55% of the cases. They derive a formulae for standard errors in an OLS setting that corrects for this problem. This formulae is not directly applicable in the current setting since we employ a Poisson estimator and deriving the corresponding correction for the Poisson estimator is beyond the scope of this paper. Instead we implement a Monte Carlo simulation like the one used in Adão et. al. (2019) and show that we do not have a similar problem of over-rejection.

Specifically, we replicate the regression in Column (9) in Table 7. 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 without replacement the entire path of wages and GDP from the existing set of wages and GDP. Figure 5 shows a histogram of the t-statistic of the low-skill wages, the main coefficient of interest, where the red line at 4.1 corresponds to the t-statistic of column (9). The empirical distribution has a heavier left tail than the expected standard normal distribution but only in 0.33% of the cases did the absolute value of the t-statistic exceed the realized t-statistic from our main regressions. 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.

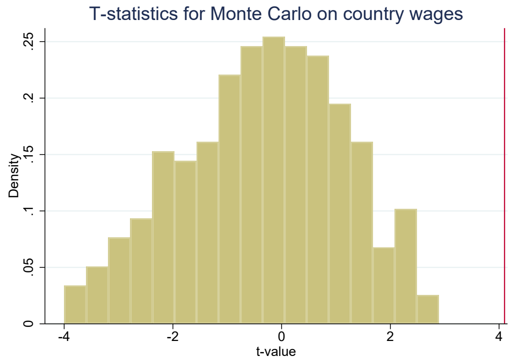


Figure 5: The t-value on the low-skill wages from a Monte Carlo simulation sampling country wages and GDP (see text for details)

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 12 reports the result. The 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 in that they are essentially treating the firms by the same macroeconomic shocks but distributed according to where the firm innovates not where it sells.

Multicollinearity and skill premium. Low-skill wages, high-skill wages and labor productivity are correlated, which could affect our regressions—although controlling for firm fixed effects and year fixed effects, the correlation coefficient is only 0.6 (see Appendix Table A.26). To deal with this issue, Appendix Table A.27 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 9 gives insignificant coefficients.

Including middle-skill wages. Previous work has often found that IT disproportionately affects middle-skill workers (e.g. Autor and Dorn, 2013). In this spirit,

Table 12: 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) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and labor productivity. Domestic (resp. foreign) GDP gap is interacted with the domestic (resp. 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 * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Appendix Table A.28 adds middle-skill wages to our regressions. Low-skill wages continue to have a large positive impact on automation, whereas middle-skill wages have a negative (though not consistently significant effect). Low-skill and middle-skill wages are highly correlated (with a coefficient of 0.94, see Appendix Table A.26), and consequently, middle-skill wages have a positive coefficient when low-skill wages are not included.

Wages and deflators. Appendix Table A.29 shows that our results are robust to 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 in USD every year. Converting in USD every year makes our macroeconomic variables more correlated and increases the importance of short-term fluctuations.

Weights. Table 13 reproduces the regressions of columns (7) and (8) of Table 7 but with alternative firm-specific weights $\omega_{i,c}$. In columns (1) and (2), we compute the patent weights over a more recent period (1985-1994 instead of 1970-1994) and obtain the same

Table 13: Alternative weights

Dependent Variable	Auto95									
	1985 − 1994		1970 − 1989		GDP^0		GDP^1		$(w_L * L)^{0.35}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Low-skill wage	2.4739***	2.3626***	1.8155*	1.7192*	1.8685**	1.7962**	2.8690***	2.8825***	2.2007***	2.1429**
	(0.8691)	(0.8876)	(0.9480)	(0.9544)	(0.7776)	(0.8176)	(0.8855)	(0.8953)	(0.8125)	(0.8516)
High-skill wage	-1.7055**	-1.9002**	-0.8990	-1.0259	-1.3791*	-1.4820*	-1.6609**	-1.6405**	-1.4445*	-1.5237*
	(0.8288)	(0.8899)	(0.8354)	(0.9524)	(0.8226)	(0.8851)	(0.7114)	(0.7547)	(0.7847)	(0.8444)
GDP gap	0.0226	0.0224	0.0140	0.0138	0.0276*	0.0273*	0.0265*	0.0264*	0.0283*	0.0280*
	(0.0163)	(0.0162)	(0.0164)	(0.0164)	(0.0154)	(0.0153)	(0.0158)	(0.0159)	(0.0156)	(0.0154)
Labor productivity		0.4484		0.3240		0.2559		-0.0482		0.1983
		(0.9649)		(1.0211)		(0.8994)		(0.8293)		(0.9221)
Stock automation	-0.1337**	-0.1343**	-0.1194**	-0.1201**	-0.1436***	-0.1441***	-0.1429***	-0.1429***	-0.1428***	-0.1432***
	(0.0524)	(0.0524)	(0.0602)	(0.0603)	(0.0509)	(0.0511)	(0.0511)	(0.0511)	(0.0509)	(0.0509)
Stock other	0.6539***	0.6540***	0.6900***	0.6895***	0.6414***	0.6410***	0.6385***	0.6384***	0.6404***	0.6403***
	(0.0639)	(0.0639)	(0.0769)	(0.0769)	(0.0600)	(0.0600)	(0.0598)	(0.0598)	(0.0600)	(0.0600)
Spillovers automation	0.5655*	0.5815*	0.2618	0.2719	0.4091	0.4178	0.8056**	0.8051**	0.4679	0.4744
	(0.3154)	(0.3182)	(0.3206)	(0.3229)	(0.3093)	(0.3106)	(0.3340)	(0.3354)	(0.3103)	(0.3114)
Spillovers other	-0.3401	-0.3693	-0.3772	-0.3951	-0.1913	-0.2090	-0.4680**	-0.4664**	-0.2577	-0.2702
	(0.2303)	(0.2401)	(0.2435)	(0.2518)	(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	45735	45735	35955	35955	50115	50115	50115	50115	50115	50115
Firms	3049	3049	2397	2397	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 1985-1994; and over the period 1970-1989 for columns (3) and (4). Columns (5) to (19) 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. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

results. Columns (3) and (4) on the other hand drop the 5 most recent years in computing the weights. We lose a large number of firms, but still obtain a positive effect of low-skill wages on automation innovations, though with slightly smaller coefficients. 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.[39] 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 ($(w_L L)^{0.35}$: one could argue that this represents a better measure than $GDP^{0.35}$ of the potential market for technology designed to automate low-skill work). We obtain similar results.

Quality. Appendix Table A.30 investigates whether our results are robust when focusing on patents of higher quality. We look at patents which have been applied for at 2 of the 3 main patent offices (EU, Japan and US), or at triadic patents which have

[39] The same concern can be addressed by keeping our baseline weight but dropping the first few years. See Appendix Table A.30 which reproduces Table 7 but only from 2000. Though the standard errors are bigger, the results are essentially the same.

been applied for at the 3 offices. Triadic patents are generally considered to be patents of very high quality. All of these give similar results. We also restrict attention to biadic patents with at least one citation within 5 years and weigh patents by citations.[40] 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 therefore may suffer from Nickell's bias. To address this issue, in Appendix Table A.31, we remove the stock of automation innovations with very little effect on the variable of interest. In addition, we use Blundell, Griffith and van Rennen (1999)'s method, which proxies for the fixed effect by using the firm's pre-sample average of the dependent variable. We obtain very similar results.

Industry-year fixed effects. Appendix Table A.33 introduces industry-year fixed effects where the industry of a firm correspond to its 2 digit industry in Orbis. The results are very similar.

6 Event study: the Hartz reforms in Germany

In this section, we 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

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

by allowing for more flexible contracts and reducing the expected cost of vacancies.

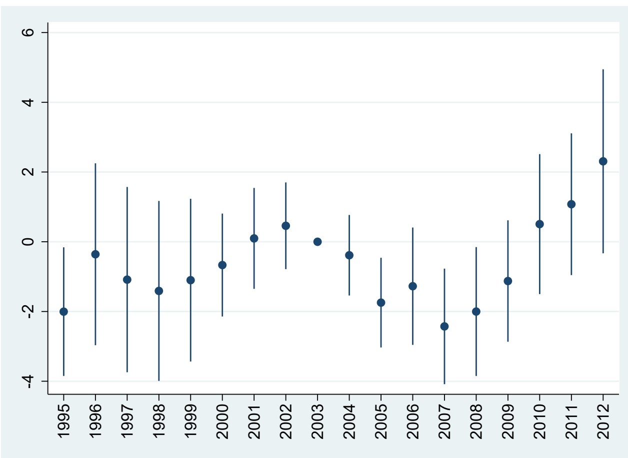
We start from the same database linking firms and patents as in our main empirical analysis of Section 5, using the same weights to measure firms' exposure to different countries and focusing on biadic patent applications as a measure of innovation. We still define the country of a firm as the country 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 United Kingdom and the United States).

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

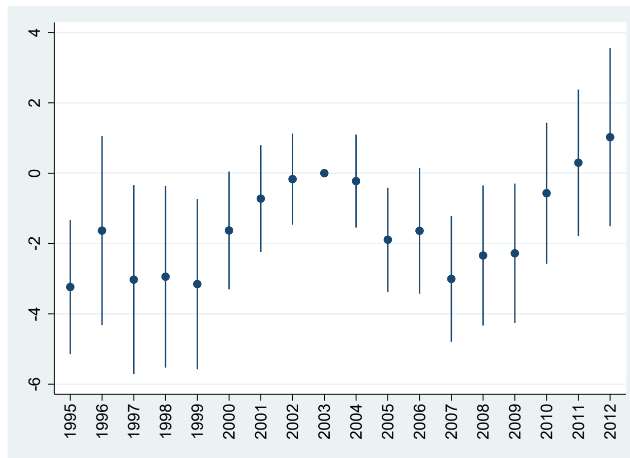
$$PAT_{Aut,i,t+2} = \exp\left(\beta_{DE} \cdot \delta_t \omega_{i,DE} + \beta_{Ka} \ln K_{Aut,i,t} + \beta_{Ko} \ln K_{other,i,t} + \delta_i + \delta_{c,t}\right) + \epsilon_{i,t}.$$

$PAT_{Aut,i,t+2}$ is still a count of automation patents, $K_{Aut,i,t}$ and $K_{other,i,t}$ continue represent firm knowledge stocks, δ_i is a firm fixed effect, $\delta_{c,t}$ is a country-year fixed effect, $\omega_{i,DE}$ is 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. The vector of coefficients β_{DE} determines by how much a firm more 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 coefficients can be interpreted as follows: a 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 then run the following Poisson regression:



(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. 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.

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

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 and $\delta_{k,c,t}$ 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 (as 2003 is still the excluded year). Figure 6.b reports the results: the pattern is similar to Figure 6.a but more striking.

To formally test that the Hartz reform created a trend break in the relative propensity of firms highly exposed to Germany to introduce automation innovations relative to other types of 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 (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 (i.e. 2000-2010 for the innovation variable) to have a panel centered on 2003 and avoid the Great Recession. Table 14 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, this time trend sharply reversed in the following 5 years. Column (1) carries out the same regression but omits the controls for the stock variables. Column (3) adds a control for the triple interaction of the German weight, a dummy for automation innovations and a dummy for post-2003. This tests whether the break in time trends is associated with a shift in levels. 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 since 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. There are no significant trends distinguishing low-automation innovations from other non-auto95 machinery innovations. Overall, this exercise suggests that the Hartz reforms reduced

Table 14: Innovation and exposure to Germany

Dependent variables	Auto 95 and other + low auto				Auto95 and low auto	Auto95 and other and low auto
	(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

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 innovation types fixed effects, country year innovation types fixed effects and controls for the year dummy times the measure of German exposure. 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. Innovation types are auto95 and (other + low auto) in columns (1) to (4), auto 95 and low auto in column (5) and auto 95, other and low auto in column (6). All regressions with stock variables include a dummy for no stock. Standard errors are clustered at the firm-level.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

the propensity of foreign firms highly exposed to Germany to introduce automation innovations.

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 types of 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.

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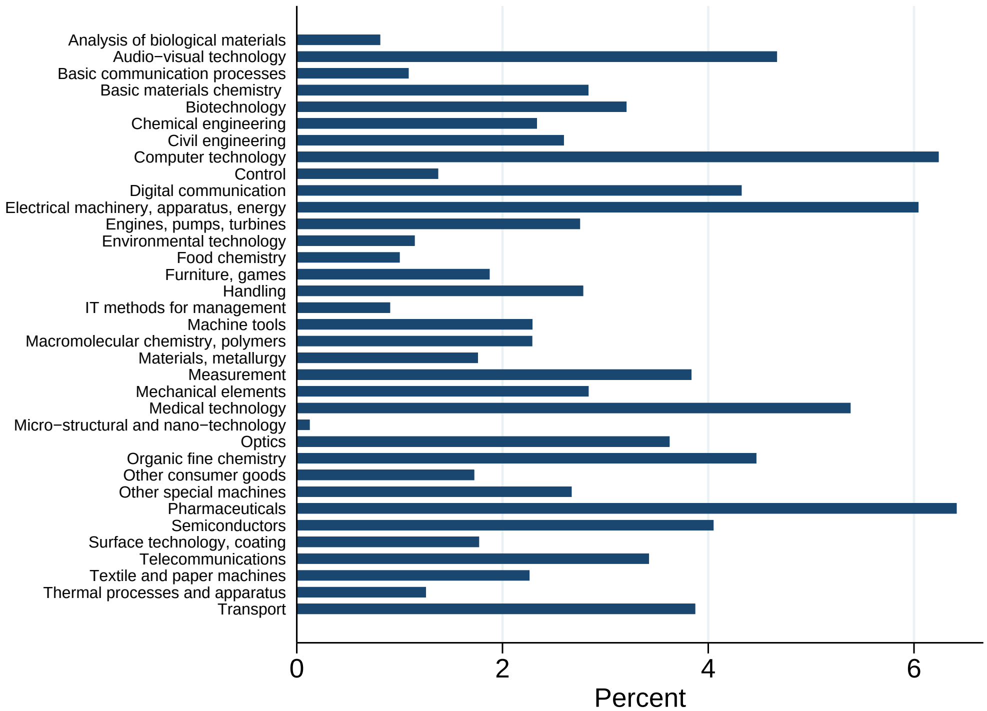
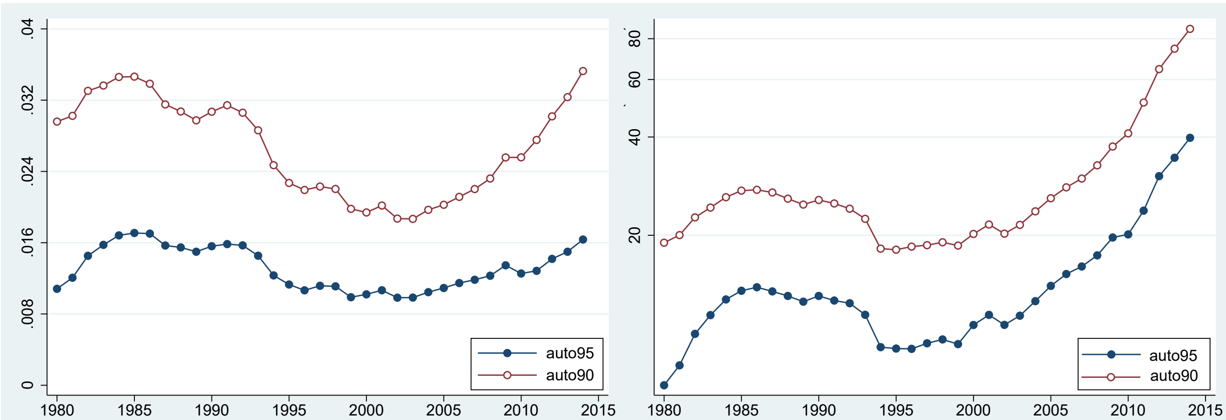


Figure A.7: Share of biadic patent applications in the different technical fields in 1997-2011

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.8: Trends in automation (for biadic applications)

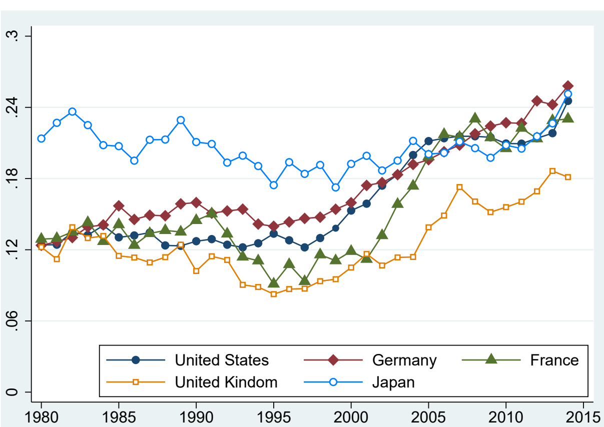


Figure A.9: Share of automation patents (auto95) in machinery by applicant's nationality.

Table A.15: Share of automation patents in machinery across sectors

SIC 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
31	All other manufacturing branches	15.7	23.2	18.7	27.9	18.9	27.7
E	Water supply; sewerage, waste management and remediation activities	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.16: Top 10 auto95 innovators in our sample

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

Table A.17: 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.18: Baseline regressions: effect of wage on automation innovations (auto90)

Dependent variable	Auto90								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	1.7307***	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.19: 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) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, 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), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. In columns (1)-(3), there is no such interactions. Standard errors are clustered at the country-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.20: 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) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, 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), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. In columns (1)-(3), there is no such interactions. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.21: 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) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, 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), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. In columns (1)-(3), there is no such interactions. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.22: All machinery innovations

Dependent variable	Machinery								
	Domestic + Foreign						Foreign		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	0.4615	0.5068	1.7568***	0.1366	0.1813	1.1875	-0.0553	0.4116	0.9712
	(0.5070)	(0.5585)	(0.5336)	(0.6721)	(0.7338)	(0.8614)	(1.0951)	(1.2570)	(1.2306)
High-skill wage	-0.0290	0.0429	1.2020**	-0.0638	0.0273	0.5109	-0.2290	0.3470	0.2678
	(0.5224)	(0.4950)	(0.5625)	(0.7663)	(0.8065)	(0.7838)	(1.2089)	(1.1884)	(1.2571)
GDP gap	-0.0211**	-0.0209**	-0.0219**	0.0080	0.0080	0.0100	0.0228	0.0221	0.0239
	(0.0086)	(0.0084)	(0.0086)	(0.0153)	(0.0153)	(0.0153)	(0.0235)	(0.0235)	(0.0234)
Labor productivity		-0.1676			-0.1986			-0.9600	
		(0.6030)			(0.9082)			(0.9293)	
GDP per capita			-3.5955***			-2.3745**			-1.6536
			(0.6309)			(1.1561)			(1.0728)
Stock machinery	0.3337***	0.3339***	0.3337***	0.3400***	0.3401***	0.3386***	0.3379***	0.3372***	0.3370***
	(0.0352)	(0.0352)	(0.0341)	(0.0341)	(0.0342)	(0.0340)	(0.0345)	(0.0346)	(0.0345)
Stock other	0.2443***	0.2444***	0.2416***	0.2456***	0.2458***	0.2454***	0.2449***	0.2442***	0.2435***
	(0.0441)	(0.0442)	(0.0426)	(0.0424)	(0.0423)	(0.0420)	(0.0413)	(0.0414)	(0.0413)
Spillovers machinery	2.7148***	2.7216***	1.9670***	1.1095**	1.1138**	1.0117**	1.0863**	1.1211**	1.0510**
	(0.4332)	(0.4335)	(0.4422)	(0.4652)	(0.4692)	(0.4640)	(0.4638)	(0.4666)	(0.4644)
Spillovers other	-2.4318***	-2.4309***	-1.8095***	-1.2125**	-1.2136**	-1.1326**	-1.1784**	-1.2191**	-1.1742**
	(0.5096)	(0.5110)	(0.5022)	(0.4859)	(0.4867)	(0.4857)	(0.4802)	(0.4839)	(0.4801)
Fixed effects	F + Y	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	160290	160290	160290	160290	160290	160290	160290	160290	160290
Firms	10686	10686	10686	10686	10686	10686	10686	10686	10686

Note: Marginal effects; Standard errors in parentheses. The independent variables are lagged by two periods. Estimation is by conditional Poisson regressions fixed-effects (HHG). In columns (1)-(3), the regressions include firm and year fixed effects. In columns (4)-(9), the regressions include firm and country-year fixed effects. All regressions with stock variables include a dummy for no stock and no spillover. In columns (7)-(9) domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. In columns (7)-(9), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. In columns (1)-(6), there is no such interactions. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.23: 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.24: Minimum wage

Dependent variable	Auto95							
	Domestic + Foreign				Foreign			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimum wage	1.5230**	1.5171**	1.4636	1.5601	1.8773	1.8401	1.8331*	1.7770
	(0.6865)	(0.6628)	(0.9127)	(0.9566)	(1.2125)	(1.2411)	(1.1117)	(1.1271)
High-skill wage	-1.2239*	-1.2358	-3.0712***	-2.6564**	-2.8017**	-2.9368	-2.7456**	-3.0195*
	(0.7166)	(0.8701)	(1.0907)	(1.1667)	(1.4072)	(1.8000)	(1.3157)	(1.7324)
GDP gap	0.0235	0.0235	0.0562	0.0563	-0.0232	-0.0232	-0.0238	-0.0236
	(0.0151)	(0.0150)	(0.0347)	(0.0347)	(0.0513)	(0.0514)	(0.0512)	(0.0513)
Labor productivity		0.0246		-0.7554		0.1730		0.3355
		(0.9249)		(1.4016)		(1.4426)		(1.3849)
Stock automation	-0.1445***	-0.1446***	-0.1548***	-0.1544***	-0.1563***	-0.1564***	-0.1562***	-0.1565***
	(0.0513)	(0.0513)	(0.0522)	(0.0523)	(0.0530)	(0.0531)	(0.0530)	(0.0531)
Stock other	0.6374***	0.6374***	0.6569***	0.6572***	0.6549***	0.6552***	0.6540***	0.6547***
	(0.0596)	(0.0596)	(0.0597)	(0.0597)	(0.0607)	(0.0607)	(0.0607)	(0.0606)
Spillovers automation	0.6456*	0.6462*	1.4309***	1.4270***	1.4198***	1.4215***	1.4157***	1.4192***
	(0.3363)	(0.3397)	(0.4958)	(0.4967)	(0.4939)	(0.4966)	(0.4929)	(0.4955)
Spillovers other	-0.3546	-0.3559	-1.1991***	-1.1837***	-1.2744***	-1.2764***	-1.2806***	-1.2846***
	(0.2408)	(0.2535)	(0.3854)	(0.3864)	(0.3795)	(0.3821)	(0.3787)	(0.3810)
Fixed effects	F	F	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	50070	50070	50040	50040	48765	48765	48795	48795
Firms	3338	3338	3336	3336	3251	3251	3254	3254

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)-(2) include firm fixed effects. Columns (3)-(8) include firm and country-year fixed effects. All regressions with stock variables include a dummy for no stock and no spillover. In columns (5)-(6) domestic (resp. foreign) minimum wages are interacted with the share of domestic (resp. foreign) minimum wages in total minimum wages computed at the beginning of the sample, and similarly for high-skill wages and VA per employee. In columns (7)-(8), they are interacted with the average shares over the sample period instead. In columns (5)-(8), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.25: Minimum wage with country level clustering

Dependent variable	Auto95							
	Domestic + Foreign				Foreign			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minimum wage	1.5230**	1.5171***	1.4636**	1.5601***	1.8773***	1.8401***	1.8331***	1.7770***
	(0.5926)	(0.4580)	(0.6148)	(0.4905)	(0.4685)	(0.6459)	(0.4272)	(0.5790)
High-skill wage	-1.2239**	-1.2358	-3.0712***	-2.6564**	-2.8017***	-2.9368***	-2.7456***	-3.0195***
	(0.5538)	(1.0144)	(0.5048)	(1.2687)	(1.0073)	(0.8003)	(0.9635)	(0.8786)
GDP gap	0.0235***	0.0235***	0.0562***	0.0563***	-0.0232	-0.0232	-0.0238	-0.0236
	(0.0046)	(0.0047)	(0.0209)	(0.0210)	(0.0246)	(0.0245)	(0.0238)	(0.0235)
Labor productivity		0.0246		-0.7554		0.1730		0.3355
		(0.9997)		(1.4283)		(1.3091)		(1.3969)
Stock automation	-0.1445***	-0.1446***	-0.1548***	-0.1544***	-0.1563***	-0.1564***	-0.1562***	-0.1565***
	(0.0385)	(0.0390)	(0.0403)	(0.0400)	(0.0392)	(0.0402)	(0.0391)	(0.0404)
Stock other	0.6374***	0.6374***	0.6569***	0.6572***	0.6549***	0.6552***	0.6540***	0.6547***
	(0.0514)	(0.0513)	(0.0563)	(0.0561)	(0.0572)	(0.0595)	(0.0569)	(0.0598)
Spillovers automation	0.6456***	0.6462***	1.4309***	1.4270***	1.4198***	1.4215***	1.4157***	1.4192***
	(0.2076)	(0.2225)	(0.1139)	(0.1151)	(0.1192)	(0.1309)	(0.1182)	(0.1314)
Spillovers other	-0.3546	-0.3559	-1.1991***	-1.1837***	-1.2744***	-1.2764***	-1.2806***	-1.2846***
	(0.2214)	(0.2362)	(0.1684)	(0.1736)	(0.1956)	(0.2102)	(0.1920)	(0.2072)
Fixed effects	F	F	F + CY	F + CY	F + CY	F + CY	F + CY	F + CY
Observations	50070	50070	50040	50040	48765	48765	48795	48795
Firms	3338	3338	3336	3336	3251	3251	3254	3254

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)-(2) include firm fixed effects. Columns (3)-(8) include firm and country-year fixed effects. All regressions with stock variables include a dummy for no stock and no spillover. In columns (5)-(6) domestic (resp. foreign) minimum wages are interacted with the share of domestic (resp. foreign) minimum wages in total minimum wages computed at the beginning of the sample, and similarly for high-skill wages and VA per employee. In columns (7)-(8), they are interacted with the average shares over the sample period instead. In columns (5)-(8), domestic (resp. foreign) GDP gap is interacted with the domestic (resp. foreign) weight. Standard errors are clustered at the country-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.26: 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.27: Skill premium

Dependent variable	Auto95					
	Domestic + Foreign				Foreign	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-skill / High-skill wage	1.9423**	2.0420***	2.1995**	2.0520**	3.5089***	3.4205***
	(0.7552)	(0.7607)	(0.9170)	(0.9049)	(1.2083)	(1.1960)
GDP gap	0.0263*	0.0268*	0.0627*	0.0620*	0.0049	-0.0017
	(0.0157)	(0.0157)	(0.0343)	(0.0343)	(0.0526)	(0.0496)
Labor productivity		0.7026		-1.0613		-0.2814
		(0.7035)		(1.1591)		(0.7369)
Stock automation	-0.1448***	-0.1456***	-0.1505***	-0.1507***	-0.1522***	-0.1524***
	(0.0509)	(0.0510)	(0.0530)	(0.0528)	(0.0526)	(0.0525)
Stock other	0.6407***	0.6402***	0.6546***	0.6556***	0.6495***	0.6480***
	(0.0599)	(0.0601)	(0.0603)	(0.0602)	(0.0602)	(0.0602)
Spillovers automation	0.5783*	0.5783*	1.4755***	1.4769***	1.4397***	1.4346***
	(0.3153)	(0.3114)	(0.4968)	(0.5004)	(0.4868)	(0.4892)
Spillovers other	-0.2349	-0.3132	-1.2535***	-1.2021***	-1.2387***	-1.2253***
	(0.2129)	(0.2328)	(0.3717)	(0.3824)	(0.3669)	(0.3755)
Fixed effects	F + Y	F + Y	F + CY	F + CY	F + CY	F + CY
Observations	50115	50115	50070	50070	50070	50070
Firms	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). Columns (1)-(2) include firm fixed effects and year dummies. Columns (3)-(6) 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 (5)-(6) 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 and VA per employee are also their interacted foreign components. Standard errors are clustered at the firm-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.28: Including middle-skill wages

Dependent Variable	Auto95								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	4.7035***		3.8985***	5.1140***		4.2760***	5.0971***		4.2398***
	(1.4991)		(1.3667)	(1.5892)		(1.4222)	(1.5759)		(1.4510)
Middle-skill wage	-3.9194**	2.3617**	-2.2614	-4.2997**	2.4746**	-2.5516	-4.0739**	2.3236**	-2.5526
	(1.6096)	(1.0085)	(1.6773)	(1.6815)	(1.0411)	(1.6819)	(1.6090)	(1.0573)	(1.6825)
High-skill wage		-1.7189*	-0.9608		-1.8154*	-1.0225		-1.9749**	-1.0756
		(0.9218)	(0.8867)		(0.9485)	(0.8960)		(0.9982)	(0.9602)
GDP gap				0.0288*	0.0216	0.0304*	0.0292*	0.0216	0.0303*
				(0.0153)	(0.0151)	(0.0157)	(0.0154)	(0.0151)	(0.0157)
Labor productivity							-0.3258	0.4545	0.1316
							(0.8572)	(0.8858)	(0.9310)
Stock automation	-0.1454***	-0.1404***	-0.1457***	-0.1460***	-0.1405***	-0.1464***	-0.1455***	-0.1415***	-0.1466***
	(0.0508)	(0.0508)	(0.0509)	(0.0509)	(0.0509)	(0.0510)	(0.0509)	(0.0510)	(0.0511)
Stock other	0.6458***	0.6394***	0.6436***	0.6456***	0.6389***	0.6433***	0.6455***	0.6387***	0.6432***
	(0.0598)	(0.0598)	(0.0600)	(0.0599)	(0.0600)	(0.0601)	(0.0599)	(0.0600)	(0.0601)
Spillovers automation	0.4733	0.4518	0.5330*	0.5007*	0.4692	0.5657*	0.4998*	0.4846	0.5694*
	(0.2891)	(0.3140)	(0.3097)	(0.2885)	(0.3143)	(0.3105)	(0.2891)	(0.3155)	(0.3120)
Spillovers other	-0.3173	-0.1874	-0.3100	-0.3478	-0.2013	-0.3416	-0.3281	-0.2315	-0.3492
	(0.2254)	(0.2208)	(0.2265)	(0.2247)	(0.2197)	(0.2257)	(0.2315)	(0.2279)	(0.2325)
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 include a dummy for no stock and no spillover. Standard errors are clustered at the firm-level * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.29: 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.30: Baseline regressions in 2000-20009 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.31: 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.32: 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 publicatior 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.33: Industry-year fixed effects

Dependent variable	Auto95								
	Domestic + Foreign			Foreign					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-skill wage	2.3157**	2.5169**	3.5773***	4.1573***	5.0264***	4.2013**	4.3562***	5.0852***	4.3077**
	(0.9890)	(1.1159)	(1.2188)	(1.3041)	(1.5426)	(1.7227)	(1.3302)	(1.5430)	(1.7067)
High-skill wage	-2.9978***	-2.5654**	-2.1617**	-4.3227***	-3.1470**	-4.2974***	-4.5869***	-3.5601**	-4.6144***
	(0.9457)	(1.0210)	(1.0263)	(1.2915)	(1.3761)	(1.3321)	(1.3283)	(1.3944)	(1.3495)
GDP gap	0.0709**	0.0707**	0.0731**	-0.0059	-0.0083	-0.0059	-0.0066	-0.0093	-0.0065
	(0.0323)	(0.0323)	(0.0322)	(0.0470)	(0.0469)	(0.0470)	(0.0471)	(0.0470)	(0.0471)
Labor productivity		-0.9736			-1.9354			-1.6865	
		(1.7031)			(1.4734)			(1.4339)	
GDP per capita			-3.1161*			-0.0777			0.0860
			(1.7989)			(1.8617)			(1.7683)
Stock automation	-0.1586***	-0.1582***	-0.1601***	-0.1607***	-0.1603***	-0.1607***	-0.1617***	-0.1615***	-0.1617***
	(0.0466)	(0.0466)	(0.0468)	(0.0463)	(0.0461)	(0.0464)	(0.0462)	(0.0460)	(0.0463)
Stock other	0.6549***	0.6555***	0.6548***	0.6492***	0.6470***	0.6491***	0.6497***	0.6478***	0.6497***
	(0.0552)	(0.0552)	(0.0549)	(0.0550)	(0.0549)	(0.0549)	(0.0549)	(0.0548)	(0.0548)
Spillovers automation	1.3924***	1.3897***	1.3786***	1.3568***	1.3324***	1.3562***	1.3558***	1.3371***	1.3563***
	(0.4759)	(0.4766)	(0.4761)	(0.4658)	(0.4651)	(0.4675)	(0.4653)	(0.4651)	(0.4665)
Spillovers other	-1.0750***	-1.0587***	-1.0900***	-1.0864***	-1.0802***	-1.0873***	-1.0740***	-1.0670***	-1.0730***
	(0.3623)	(0.3642)	(0.3618)	(0.3553)	(0.3527)	(0.3540)	(0.3538)	(0.3520)	(0.3527)
Fixed effects	F + CY +IY	F + CY +IY	F + CY +IY	F + CY +IY	F + CY +IY	F + CY +IY	F + CY +IY	F + CY +IY	F + CY +IY
Observations	49890	49890	49890	49890	49890	49890	49890	49890	49890
Firms	3326	3326	3326	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). All regressions include firm, industry-year and country-year fixed effects. All regressions with stock variables (resp. spillover variables) include a dummy for no stock (resp. no spillover). Domestic (resp. foreign) low-skill wages are interacted with the share of domestic (resp. foreign) low-skill wages in total low-skill wages computed at the beginning of the sample, and similarly for high-skill wages, GDP per capita and VA per employee. 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 share of patents:[41]

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.

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

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*);

   (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 fort numerical control instead of North Carolina.

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

B.1.2 Statistics on the classification

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

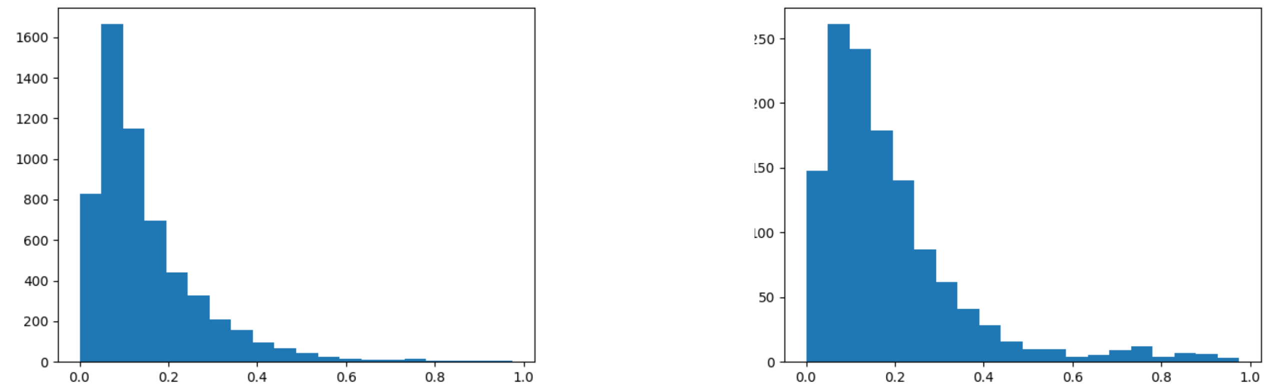
Note: This table computes summary statistics on the share of patents with any automation keywords, robot keywords, automat* keywords or CNC keywords for each type of technological categories (6 digit codes, pairs of 4 digit codes and combinations of ipc4 codes with G05 or G06) within machinery with at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

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 4 digit codes (see also the histograms below). 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, however 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.

B.1.3 How are auto90 and auto95 patents identified?

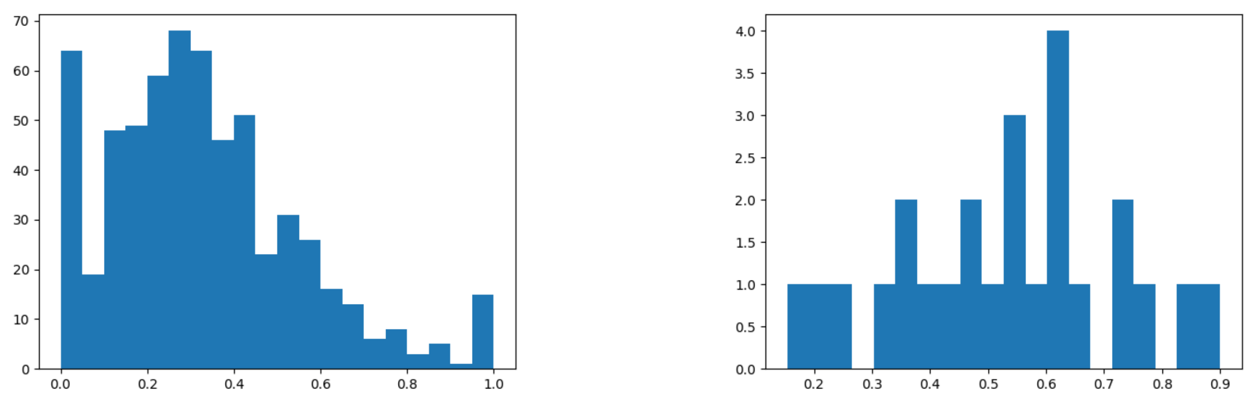
Given that our classification procedure is relatively complex, we assess here which features dominate. To do so, we focus on the set of $15,212,134$ biadic patent applications in 1997-2011 (corresponding to the $3,187,536$ patent families which have patent applications in at least two countries), since this corresponds to the set on which we run our main regressions. There are $310,458$ auto95 patent applications corresponding to



(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.

61, 788 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 appear to be the most relevant since they are enough to 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 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 since 17.7% of auto95 patents are also robot95 (more than autm95). CNC does not matter too much: only 13% of auto95 patents are CNC80.

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.

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.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). In this exercise we are interested in matching patents with a sector of use and not the inventing sector (which is what is provided by the Eurostat concordance table for instance). The Lybbert and Zolas concordance tables are derived by matching patents texts with industry descriptions, and as such they cannot *a priori* distinguish between sector of use and industry of manufacturing. We checked, however, that patents associated with "textile and paper machines" for instance are associated with the textile and paper sectors and not with the equipment sector (as is the case with the Eurostat concordance table). We attribute patents to sectors fractionally in function of their IPC codes. To assign patents to the consistent Census industry codes used by ALM, we first use a Census concordance table (https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html) to go from NAICS 1997 to Census industry codes 1990, then we use the concordance table of ALM to get to the consistent Census industry codes of ALM. Finally, for each sector and each time period, we compute the sums of automation patents and machinery patents and take the ratio to be our measure of automation intensity. We exclude sectors with less than 50 machinery patents (which is why the number of sectors varies across time periods). We are left with 66 to 68 sectors, with only 7 of them not in manufacturing.

The other variables are directly taken from ALM. We refer the reader to that paper for a detailed explanation. The task measures are computed using the 1977 *Dictionary of Occupational Titles* (DOT) which measure the tasks content of occupations. Occupations are then matched to industries using the Census Integrated Public Micro Samples one percent extracts for 1960, 1970 and 1980 (IPUMS) and the CPS Merged Outgoing Rotation Group files for 1980, 1990 and 1998 (MORG). The task change measure at the industry level reflects changes in occupations holding the task content of each occupation constant, which ALM refer to as the extensive margin. Since tasks measures do not have a natural scale, ALM converted them into percentile values corresponding to their rank in the 1960 distribution of tasks across sectors, so that the employment-weighted means of all tasks measure across sectors in 1960 is 50. Our analysis only uses manufacturing sectors and starts in 1970 but we kept the original ALM measure to facilitate comparison. As in ALM, the dependent variable in Table 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.[42]

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

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

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

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 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.

B.3 Validating our weights approach

In this Appendix, 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).

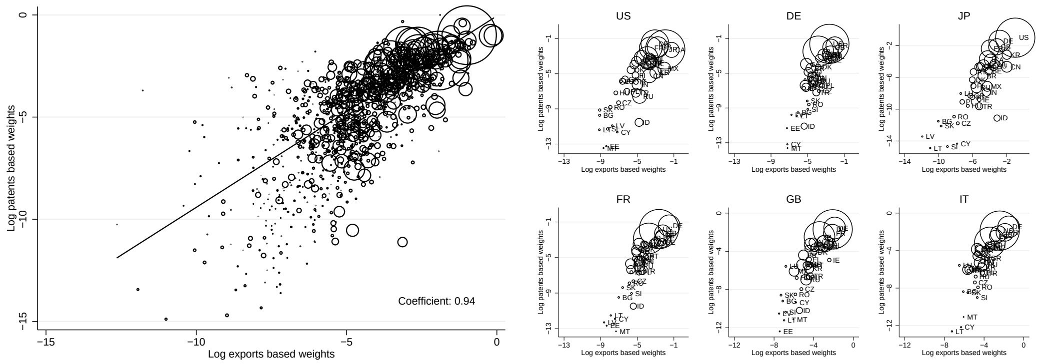
The second step is to build similar weights based on exports. To do that, we collect sectoral bilateral trade flow from UN Comtrade data between between 1995 and 2009 for 40 countries (Taiwan is not included in the data). To obtain trade flows in machinery, we use a concordance table between 4 digit IPC codes and 2 or 3 digits NACE Rev 2 codes provided by Eurostat, 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 and each country, we compute the share of patents over the period 1995-2009 which are in machinery according to our definition.[43] This gives us a

[43]To do that we use a fractional approach: each patent is allocated NACE sectoral weights (and

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



(a) All countries

(b) Trade from the 6 largest countries

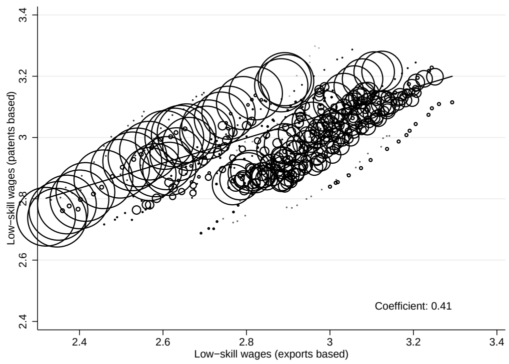
Figure B.3: Bilateral patent flows and trade flows in machinery. Panel (a) plots log patent based weights, which are a weighted average of the destination country's weights in the (foreign) patent portfolio of firms from the origin country, against export shares in machinery over the years 1995-2009. 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.

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 could compute trade based weights for each year but here we report results based on 1996 only (there are a few missing observations for 1995).

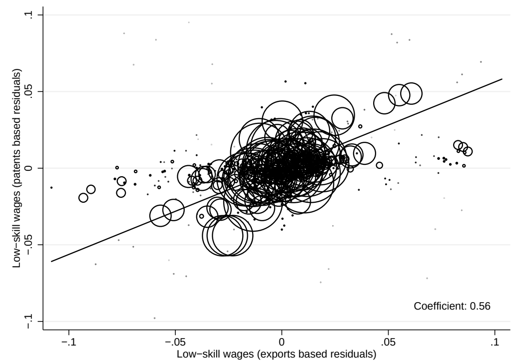
Figure B.3 plots the patent-based weights against the trade-based weights. Panel (b) focuses on a few origin countries while Panel (a) plots all countries together. We find a strong correlation between the two measures with a regression coefficient of 0.94 (when observations are weighted by the trade flow in 1996).

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.4. 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.

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.4: 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.

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.4 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 both 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 use this data to calculate the GDP gap as the deviations of log GDP from HP-filtered log GDP using a smoothing parameter of 6.25.

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 the Sabine Lenz at the *Statistical Agency of Germany.*