Labor Services At Will
Regulation of Dismissal and Investment in Industrial Robots*

Giorgio Presidente

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Abstract

Using data on shipments of industrial robots, this paper finds a positive relationship between employment protection legislation (EPL) and investment in industrial robots. A structural model suggests that EPL acts a constraint on the ability of adjusting employment in response to shocks. With strict regulation firms have the incentive to substitute human labor with machines providing services more flexibly. The model predicts that incentive to automate is stronger in volatile sectors, where uncertainty about business conditions makes adjustment more urgent and regulation more binding for firms. Accordingly, data show that EPL induces automation disproportionately in sectors characterized by large time-series volatility or cross-sectional dispersion in growth rates.

Unlike the existing literature focusing on relative prices, this paper suggests that firms might invest in automation to overcome the adjustment costs generated by regulation. Robots increase productivity not because they are better or faster then humans at performing certain tasks, they rather improve allocative efficiency. The empirical contribution of the paper is using robots to measure automation. Since robots are explicitly designed to perform tasks otherwise performed by humans, they are a tighter proxy than "computer capital". Different timing of labor reforms in a panel of OECD countries is used to assess the causal effect of EPL on automation, identified from the before-after effect on sectoral investment in robots in reformed countries (the "treatment group"), vis-a-vis the before-after effect in countries where EPL did not change (the "control group").

Keywords: regulation; technology adoption; automation; adjustment costs; allocative efficiency

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*Affilitations: Paris School of Economics and OECD. Contact: giopresidente@gmail.com; +33680605947.

1 Introduction

The purpose of this paper is to shed light on the reasons leading firms to invest in automation.[1] It is often assumed that machines are *a priori* more productive than humans, because they are better or faster at performing certain tasks. For instance, in Autor, Levy and Murnane (2003), or Zeira (1998), the assumption of frictionless labor markets results in automation decisions depending exclusively on the relative price of labor vis-a-vis technology.[2] But in the presence of rigidities such as those generated by regulation, this paper shows that distortions in the allocation of labor - the substituted factor - let automation decisions depending not only on relative prices.

I develop and tests a model in which employment protection legislation (EPL) induces firms to invest in automation. By constraining hiring and firing, EPL creates adjustment costs resulting in firms being too small in booms and too large in slumps. Deviations from optimal size imply allocative inefficiency (e.g. labor hoarding), causing lower productivity.[3] On the other hand, rules on dismissal constraint the use of labor, but not that of capital. That makes capital services much more flexible to adjust than employment in response to shocks.

The empirical part of the paper uses data on shipment of industrial robots to construct a proxy for automation. Since robots are explicitly designed to perform tasks otherwise performed by humans, they constitute a tight measure of automation - an advantage over existing studies using broader proxies, such as "computer capital".[4] [5] The simplest way of testing our theory would be relating investment in robots and country-level indexes of regulation. However, so specified the strategy would pose two major challenges to identifying causality. First, EPL and investment in robots might be both driven by a large number of common omitted variables. For instance, the government might put in place comprehensive reforms affecting either the propensity to innovate and social policy. The second challenge is reverse causality. How can we be sure that are not trends in automation to pull labor market reforms? Therefore, to help guiding the empirical exercise I develop a structural model, which suggests that the incentive to automate due to EPL is stronger in volatile sectors, where uncertainty about business conditions increase the flexibility requirements of firms.

As in Rajan and Zingales (1998), I construct a simple test based on an interaction

[1]The answer might seem obvious at first. As technological progress takes place, it reduces the cost of automation and allows firms to substitute workers for machines in an increasing number of productive tasks. This fact - the logic goes -, combined with a natural tendency for wages to grow, inevitably leads firms to invest in automation.

[2]In these models, an exogenous decline of technology prices is used to model the greater productivity of machines vis-a-vis human labor.

[3]"Labor hoarding" refers to the situation in which firms keep too many workers on the payroll because adjustment costs would make it even more expensive to dismiss and then re-employing them when better business conditions arise.

[4]Computers might and might be not used for automation purposes, because they can substitute or complement a large number of tasks, making very difficult to isolate one effect or the other.

[5]The International Federation of Robotics categorizes robots according to their field of application, such as "handling materials", "assembling", "painting", "cutting", etc...

term relating EPL and a sectoral measure of uncertainty. The approach allows controlling for sector, country and year fixed effects, making the estimated coefficient less subject to omitted variable bias. Exploiting two digit-level sectoral information mitigates concerns of reverse causality, since national level labor reforms are less likely to be affected by sector-specific trends.

To identify the causal effect of regulation on automation, I exploit differences in timing of labor reforms in a panel of 14 countries, and 18 manufacturing and non-manufacturing sectors. Identification comes from the before-after effect on sectoral investment in robots in reformed countries (the "treatment group"), vis-a-vis the before-after effect in countries where EPL did not change (the "control group").

The rest of the paper is organized as follows. The next section reviews the literature; Section 2 develops a theoretical model; Section 3 presents the identification strategy; Section 4 describes the data; Section 5 presents the results; Section 6 details the construction of the uncertainty proxies; Section 7 provides some evidence on the fact that adjustments of capital services are larger than fluctuations in employment, and Section 8 concludes.

1.1 Determinants and Impact of Automation

This paper exploits information on shipment of industrial robots as a proxy of automation. Few other papers have used such data, mostly to look at the *impact* of automation rather than its *determinants*. For instance, consistently with the idea that automation improves allocative efficiency, Graetz and Michael (2015) show that robots increase value added and productivity, but they have only a limited impact on hours worked.[6] Acemoglu and Restrepo (2016) obtain different results for the United States, where robots are found to decrease both wages and employment.

The bulk of the literature has only partially investigated the causes underlying automation decisions.[7] At the macroeconomic level, to explain the evolution of factor shares and unemployment after the 1970s, Caballero and Hammour (1997; 1998) and Blanchard (1997), propose the idea that firms shift to capital-intensive technologies in response to tight labor regulation.[8] Therefore, although not explicitly discussed, the idea that technology is used to overcome inefficiencies created by regulation is not new.

[6]That is consistent with the findings of this paper too, because if automation is used to substitute *inflexible* factors, that means that it could be used even to make up for scarce labor inputs. For instance, consider a firm that does not hire workers to avoid the cost of dismissal in case of bad times. In that case, robots substitute human labor, but they do not displace workers (which were not hired in the first place).

[7]One exception is Acemoglu and Restrepo (2017), in which aging of the working age population induces investment in robots.

[8]In their papers, technology is embodied in capital, which being inelastic in the short-run it becomes vulnerable to appropriation of quasi-rents by labor. Shifts in capital-labor relations in favor of the latter would cause an increase of the labor share, but also unemployment and a bust in productivity due to resource misallocation. In the medium and long-run, firms would then gradually shift factor proportions towards capital-intensive projects in order to thwart appropriation.

This paper narrows the analysis of such a mechanism and it provides robust evidence on it.

In existing models of automation, equilibrium technology is a function of labor and technology prices, where the latter are exogenously given as in Autor et al. 2003, or Zeira, 1998. The assumption of exogenous technology prices is common in theories of innovation in which improvements in science "push" the technology in use. By contrast, the view of on adoption emphasized by this paper suggests that is technology demand, affected by the institutional system, to ultimately "pull" automation.[9] The distinction between push and pull theories of technical change is important for policy. The current debate on "the future of work" or "jobs at risk of automation" seems to implicitly adopt a pure science-push view, which assumes a path for technology driven by what science makes achievable, rather than what is needed by firms.[10] Technological determinism annihilates any scope for intervention that goes beyond targeting the supply of skills (e.g. training), because distorting technology prices would be inefficient from an economic point of view. However, if the view in this paper is correct, labor market policy can be used at least in the short and medium run as a policy tool, aimed at removing firms' automation incentives, to mitigate employment displacement.

Bartelsman et al. (2016) link regulation, uncertainty and investment in information and communication technologies (ICT), showing that EPL reduces both the size and growth of ICT-intensive sectors. While their findings might seem to contradict the claim that EPL induces automation, it should be noticed that systems of accounts do not place industrial robots in the ICT-producing sector, but rather into "Machinery and Equipment".[11] In Bartelsman et al. (2016), the authors focus on ICT capital because such assets are the important contributors to productivity growth, not because they want to study the effect of EPL on *automation*. For this reason, findings in Bartelsman et al. (2016) are fully consistent with those in this paper.

More broadly, it is common to think of ICT capital as a proxy of automation.[12] However, by no means all technologies labeled as ICT are used for automation purposes.[13] As a consequence, using "ICT capital" or computers as a proxy of automation can be seriously misleading.[14] Findings in Cette et al. (2016) are indeed suggestive, because they show that EPL increases deepening of machinery and equipment, rather than ICT capital.

[9] To say it in the words of Freeman and Soete (1997), while in "demand-pull" theories of innovation the process starts with "the recognition of a need", "science-push" theories are based on the belief that "markets cannot evaluate a revolutionary new product of which it has no knowledge" and therefore the process of innovation originates with "original research activity" and random scientific discovery.

[10] E.g. Frey and Osborne, 2017

[11] e.g. ISIC rev 4, 2816 "manufacture of lifting and handling equipment".

[12] E.g. Autor et al., 2003.

[13] ICT is a broad category including very different technologies, ranging from computer hardware to software, from digital radio and television to smart-phones and any other device used to digitally store or transfer information.

[14] The focus of this paper are industrial robots, which are highly concentrated in manufacturing. ICT are presumably very important for automating tasks in services industries, so computers would constitute a better proxy of automation in that case.

The view of automation proposed in this paper is reminiscent of the "Habakkuk Hypothesis" (1962), relating factor scarcity with incentives to adopting technology, which ultimately leads to economic development. However, here I emphasize the impact of a non-price component on the profitability of automation that was not present in Habakkuk's work. While in the latter technology was used to substitute a *scarce* factor, i.e. relatively expensive, in this paper it is used to substitute a rather *inflexible* one, which being costly to adjust deteriorates allocative efficiency and so productivity. Both scarcity and redundancy can induce automation. The Habakkuk Hypothesis somehow implied a beneficial role for scarcity, because by inducing substitution and technological upgrade, it also increased productivity. On the contrary, in this paper no claim is made on the overall impact of employment regulation. What I show here is that automation can be used to compensate the efficiency losses due to regulation, not that the post-automation level of productivity would be higher than in case of no regulation at all.

Work by Acharya et al. (2012) provide theoretical and empirical support for the idea that EPL stimulates innovative effort, as measured by patents. According to the authors, job protection helps firms committing to not punish failures of employees, encouraging risky but innovative projects. Therefore, the general result of their paper is that EPL spurs innovation, which although being based on a very different theoretical interpretation, it is broadly consistent with the findings of this paper.[15]

2 The Model

A representative consumer derives utility over a large number of goods $q(s)$, each representing total output of sector s.

In each sector, a representative firm produces the final good by combining intermediates $q(s,i)$,

$$q(s) = \exp\left\{ \int_0^1 \ln q(s,i) di \right\}$$

A firm i produces one and only one variety of intermediate good. Intermediate goods are obtained by performing a large number of activities or tasks, each indexed by a. Services of tasks are transformed into intermediate goods by a CES technology,

$$q(s,i) = \left[\int_0^1 q(s,i,a)^{\frac{\epsilon-1}{\epsilon}} da \right]^{\frac{\epsilon}{\epsilon-1}}$$

where ϵ determines the elasticity of substitution between tasks.

[15] The authors notice that the positive effects of EPL on innovation could actually be due to firms' effort in saving on labor costs, through shifting to less labor-intensive technologies. They rule out the hypothesis because they find no increase in investment in R&D. However, it should be noticed that firms can use industrial robots just as any other capital good, without necessarily having to engage in R&D.

To perform tasks, firms can use either labor or robots, but not a combination of both.[16]

To simplify notation, I suppress the sector index and reintroduce it when needed. I assume that $q(i,a)$ is linear in labor and robots services and they have identical gross marginal productivity, but their cost differ. The cost of performing a task is stochastic.[17] The difference between using labor or robots is that when firms automate they can observe the realization of the cost-shock before allocating robots over tasks. On the contrary, firms using labor must hire workers before the shock is realized and commit to pay the equilibrium wage once production has taken place. The assumption formalizes the idea that with EPL firms deviate from optimal size and they are typically too small in booms (underestimating the realization of θ) and too large in slumps (overestimating θ).[18]

The cost of $q(i,a)$ is thus given by

$$C(i,a) = \begin{cases} w \cdot E\big[e^{-\theta(i,a)}\big] & \text{using labor} \\ \\ \rho(i) \cdot e^{-\theta(i,a)} & \text{using robots} \end{cases} \tag{1}$$

The stochastic component $\theta(i,a)$ is a cost shock. I assume that $\theta(i,a) \sim \mathcal{N}\big(0, \sigma(s)^2\big)$, so that w can be interpreted as the (geometric) average, or expected wage.[19] The rental price of robots $\rho(i)$ is firm-specific, reflecting the idea that some firms are more prone to automation than others, for instance because they have a higher content of routine tasks.[20] Both labor and robot-capital are freely mobile across tasks, firms and sectors. Productivity shocks are *iid* across firms and tasks, but their variance is sector-specific. Moreover, the distribution of the cost-shock is invariant to technology choice.[21] An important feature of the cost function (1) is that due to EPL, firms using labor rely on the expected value of the cost-shock, while automated firms can observe the $C(i,a)$ before allocating inputs.

The main assumption of the paper is that robots are more flexible inputs than human labor. In reality the initial cost of automation can be large and underutilization of capital might as well result in inefficiencies. For instance, consider the case in which a firm expects an increase in demand that never realizes. If it chooses to serve the increase in demand with robot-services, inefficiency comes from the fact that the firm has invested in capital that is not being fully utilized. But when the payback period of capital has passed, the firm consider the initial cost of automation as sunk and just

[16] The assumption increases tractability of the model, but it does not affect its main conclusions.

[17] The cost shock can be thought as random efficiency of performing the ask. The formulation is equivalent to the case of a productivity shock multiplying the production function.

[18] Modeling labor market regulation in this way allows to maintain tractability (i.e. avoiding introducing dynamics), while at the same time emphasizing the impact of hiring and firing costs.

[19] If $X \sim \text{Lognormal}(\mu, \sigma^2)$, then $X^a \sim \text{Lognormal}(a\mu,\ a^2\sigma^2)$ for $a \neq 0$.

[20] An alternative specification could involve a task-specific price for robots. However, it is more natural to assume that firms allocate robot-services of the same robot to different tasks.

[21] Thus, in the model robots are not *a priori* more productive than human workers in performing a task.

keeping the robots switched off or operating them at a lower capacity constitutes an advantage over labor, which has high idleness costs such as wages, taxes and social security contributions.

The problem of the firm is to chose technology and input demand that minimize total costs,

$$\int_0^1 q(i,a)C(i,a)\,dt \tag{2}$$

subject to institutional, technical and market constraints summarized by (1) and

$$\left[\int_0^1 q(i,a)^{\frac{\epsilon-1}{\epsilon}}da\right]^{\frac{\epsilon}{\epsilon-1}} \geq q(i) \tag{3}$$

2.1 Technological Choice

Free entry into market for of variety i drives firm profits to zero. Firm i chooses the technology that minimizes its marginal cost, given that the cost of automation is sunk - i.e. robots are already installed but using them still require a payment for their services.[22] Appendix A1 shows that the average (over all tasks performed) marginal cost of $q(i)$, denited by $\bar{mc}(i)$, is given by the Lagrange multipliers of (3) when minimizing (2),

$$\bar{mc}(i) = \begin{cases} wEe^{-\theta(i,a)} = we^{\frac{\sigma^2(s)}{2}} & \text{if using labor} \\ \\ \rho(i)\left[\int_0^1 e^{(\epsilon-1)\theta(i,a)}da\right]^{-\frac{1}{\epsilon-1}} = \rho(i)e^{-(\epsilon-1)\frac{\sigma^2(s)}{2}} & \text{if using robots} \end{cases} \tag{4}$$

Average marginal costs are increasing in rental price of robots and wage rate, and in both cases higher realizations of the productivity shocks translate in lower marginal cost. However, automated firms take advantage of decreasing returns and allocate more resources to the most productive use (cheaper tasks), which results in average marginal costs being decreasing in volatility.[23] On the other hand, using labor prevents firms from exploiting dispersion in productivity across tasks. High volatility results in large average marginal cost, because of the misallocation of resources due to the impossibility of optimally allocating labor.

Without loss of generality, within each sectors I sort firms in order of increasing price. The share of automating firms is pinned down by the function $\nu(i)$,

$$\nu(i^*) \equiv \frac{w}{\rho(i^*)}\exp\left\{\epsilon\frac{\sigma(s)^2}{2}\right\} = 1 \tag{5}$$

[22] The rental price of robots $\rho(i)$ can be thought as lease-price for robot services.

[23] The cost function is convex and decreasing in productivity and bounded above by 1.

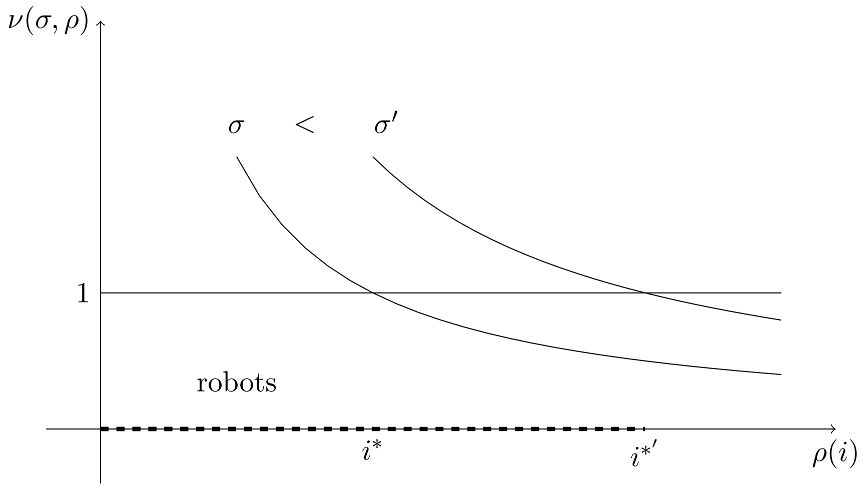

Figure 1: Technological choice. The function $\nu\big(\sigma(s),\rho(i)\big)=\frac{w}{\rho(i)}\exp\left\{\epsilon\frac{\sigma(s)^2}{2}\right\}$

From (5) we see that at price $\rho(i^*)$, firm i^* is indifferent to adopting labor or robots because they result in identical marginal cost. All firms facing a price for robots lower than $\rho(i^*)$ automate, while $1-i^*$ use labor. Intuitively, high wages increase the profitability of automation over labor, which translates in an increase of i^*. Without loss of generality I order sectors by increasing volatility. Since equation (5) shows that i^* is an increasing function of $\sigma(s)$, we write $i^*(s)$ with $i^{*\prime}(s)>0$, so that sectors characterized by higher volatility have a higher extensive margin of automation, $\frac{i^*(s)}{1-i^*(s)}$. Figure 1 illustrates graphically the idea. For given relative prices, higher volatility shifts $\nu(i)$ out, leading more firms to automate ($i^*(s')>i^*(s)$). Higher elasticity of substitution across tasks increases the probability of choosing robots over labor, because higher ϵ gives firms more flexibility in allocating inputs and so larger returns from automation. Two things are worth noticing. First, without frictions in the labor market, automation decisions depend exclusively on relative prices, as in existing frictionless models of automation. Second, the extreme cases of either full automation or no robots at all are also possible, depending on the assumptions made on $\rho(\cdot)$ and the values of w, ϵ and $\sigma(s)^2$.

2.2 Factor Demand

In equilibrium, (3) holds with equality. Upstream demand for product i is given by $q(i)=p(i)^{-1}$ and perfect competition among intermediate good firms implies $p(i)=\bar{mc}(i)$. Appendix A1 shows that aggregating demand over all firms within a sector, conditional on technology choice, we get

$$N(s)=(1-i^*(s))w^{-1}e^{-\frac{1}{2}\sigma(s)^2} \tag{6}$$

$$R(s) = \left[\int_0^{i^*(s)} \rho(i)^{-1}\, di\right] e^{\frac{\epsilon-1}{2}\sigma(s)^2}$$

For simplicity, I assume $\rho(i) = \rho(1+i)$ with $\rho > 0$, so that sectoral demand for robots is given by[24]

$$R(s) = \ln(1 + i^*(s))\rho^{-1} e^{\frac{\epsilon-1}{2}\sigma(s)^2} \tag{7}$$

As expected, (6) and (7) show that the demand for labor is decreasing in sectoral volatility, while demand for robots is increasing. Respectively, the negative and positive impact of volatility over factor demand takes place through the extensive margin, an increase of $i^*(s)$ and so the number of automating firms, and directly through the third term in (7).

2.3 Variable Degrees of Rigidity

Up to now, to keep the model as simple as possible, I maintained the assumption that all labor-using firms are unable to observe the cost function before making hiring decisions. However, the model can be extended to take into account different degrees of tightness in EPL. A straightforward way to include variable rigidity in the labor market is to add a level of aggregation to the model. Instead than directly dealing with tasks, we now think of a firm as assembling a large number of components indexed by j,

$$q(s,i) = \exp\left\{\int_0^1 \ln q(s,i,j)\, dj\right\}$$

In turn, components are produced by competitive units combining tasks,

$$q(s,i,j) = \left[\int_0^1 q(s,i,j,a)^{\frac{\epsilon-1}{\epsilon}}\, da\right]^{\frac{\epsilon}{\epsilon-1}}$$

In the extended model, I assume that a fraction f of units, common to all sectors and firms, is free to observe costs before making hiring decisions. Thus, just as the automated ones, labor-using units belonging to the interval $[0, f]$ can optimally allocate inputs over tasks. The parameter f can be interpreted as a probability of not facing court whenever applying employment at-will doctrine. Appendix A1 shows that the marginal cost of labor-using firm i is now given by

$$\bar{mc}^n(s,i) = w \exp\left\{\frac{\sigma(s)^2}{2}(1 - \epsilon f)\right\}$$

Therefore, tighter EPL (lower f) increases marginal costs, because it increases the number of units facing misallocation across tasks. Moreover,

[24] Any increasing function of i would deliver the same qualitative results.

$$\nu(\sigma, \rho, f) = \frac{w}{\rho(i)} \exp\left\{\frac{\epsilon}{2}(1-f)\sigma(s)^2\right\}$$

so that $i'(f) < 0$, i.e. tighter regulation increases the number of automated firms.

2.4 Robot-density

I define *robot-density*, $\delta(s)$, the number of robots-per-employee in a sector. Robot-density is the dependent variable in the empirical part of the paper. In terms of our model,

$$\delta(s) \equiv \frac{R(s)}{N(s)} = \frac{\ln\left[1 + i^*(s)\right]}{1 - i^*(s)} \frac{w}{\rho} \exp\left\{\frac{\epsilon}{2}(1-f)\sigma(s)^2\right\} \tag{8}$$

The model unambiguously predicts that robot-density is an increasing function of EPL, sectoral volatility and relative prices. The expression in (8) is composed of three terms. First, the extensive margin of automation - the number of firms choosing automation over human labor. Since $i^*(s)$ is increasing in $\sigma(s)^2$, so is the extensive margin of automation. The second term is given by the relative price of labor vis-a-vis technology, which has been the focus of most existing models of automation. The last term in (8) also depends positively on volatility, reflecting that demand for robots is increasing in sectoral volatility, while labor demand is decreasing. The reason is that with robots, adjusting inputs conditional on realized costs allows exploiting the convexity of the cost function. On the contrary, since labor that is subject to EPL, larger dispersion results in higher misallocation across tasks and so lower productivity.

It should be noticed that the volatility component appears in (8) because of the frictions present in the labor market. If labor was free to adjust contingently on realized productivity, differences in marginal costs in (4) would exclusively be due to relative prices, as it is emphasized in the literature on automation.

The following proposition establishes a testable, structural relationship between robot-density, EPL and sectoral volatility.

Proposition 1 *Define $EPL \equiv 1 - f$. Then, volatile sectors are disproportionately automated in strict EPL countries, i.e.*

$$\frac{\partial^2 \delta(s)}{\partial \sigma(s) \partial EPL} > 0$$

3 Identification Strategy

To test the predictions of the model, I use a unique panel dataset featuring 14 OECD countries, 18 manufacturing and non-manufacturing sectors, from 1993 to 2013. I let the dependent variable being the logarithm of robots-per-employee in country c, sector s and year t.[25] The main explanatory variable is an interaction term. The first component is a time-varying index, measuring the strictness of regulation of dismissal in a country. I assume that national labor reforms are not caused by sector-specific trends in automation. While it is possible that sectoral development might partially affect policy (e.g. by affecting the public opinion and generating political pressure), it is not plausible that it would do so systematically, across countries and in different years. The second component is a constant, sector-specific proxy of "intrinsic uncertainty", defined as the level of economic uncertainty that is independent of regulation and it is due to structural market or technological factors.

In the sample, small and large changes in regulation of dismissal have taken place in different countries and years. Thus, to assess the causal impact of EPL on automation, I exploit differences in timing of labor reforms across countries to run a difference-in-difference with multiple treatment groups and multiple time periods.[26] Identification comes from the before-after effect on sectorial investment in robots in reformed countries (the "treatment group"), vis-a-vis the before-after effect in countries where EPL did not change (the "control group").

To clarify the identification strategy, Figure 2 shows a visual difference-in-difference of a labor reform in Finland. The reform is passed in 2001 and it adds substantial red tape to hiring and firing practices.[27] The vertical axis shows the difference in innovations to robot-density in Finland with respect to the control group, composed by Denmark, Norway and Sweden, where the reform did not take place. Innovations correspond to residuals from a simple AR(1) model with country and sector specific time trends, used to isolate as much as possible the impact of the reform in 2001 and remove country and sector specific trends. Differences in innovations are expressed in percentages and they are normalized to zero in 2001, the year of the reform. The two lines represent respectively the difference over high-uncertainty sectors and all other sectors. The figure clearly

[25] The stock of operational robots is divided by the number of employees in order to "normalize" the dependent variable, making it comparable across countries and sectors. Moreover, so defined robot-density constitutes a better measure of intensity of automation and makes it less subject to bias due to increase in demand and other market conditions.

[26] See, for example, Imbens and Wooldridge (2009).

[27] The reform modified three dimension of dismissal regulation. First, while the legally mandated notice period was to be agreed by the parties, with a maximum of 6 months, a minimum of 14 days, in 2001 such period was cut to 1 month. Second, since 1970 regulation in Finland already imposed procedural constraints on dismissal except in the most serious cases of misconduct, where an employee had to be given a warning and the opportunity to change behavior prior to termination. Moreover, the employer had to consider relocating the employee. In 2001, procedural requirements became even stricter, including a right to a hearing from the court. The last intervention was probably the most drastic and it concerned the priority in re-employment. While in Finland preferential hiring were absent, since 2001 preferential hiring became required.

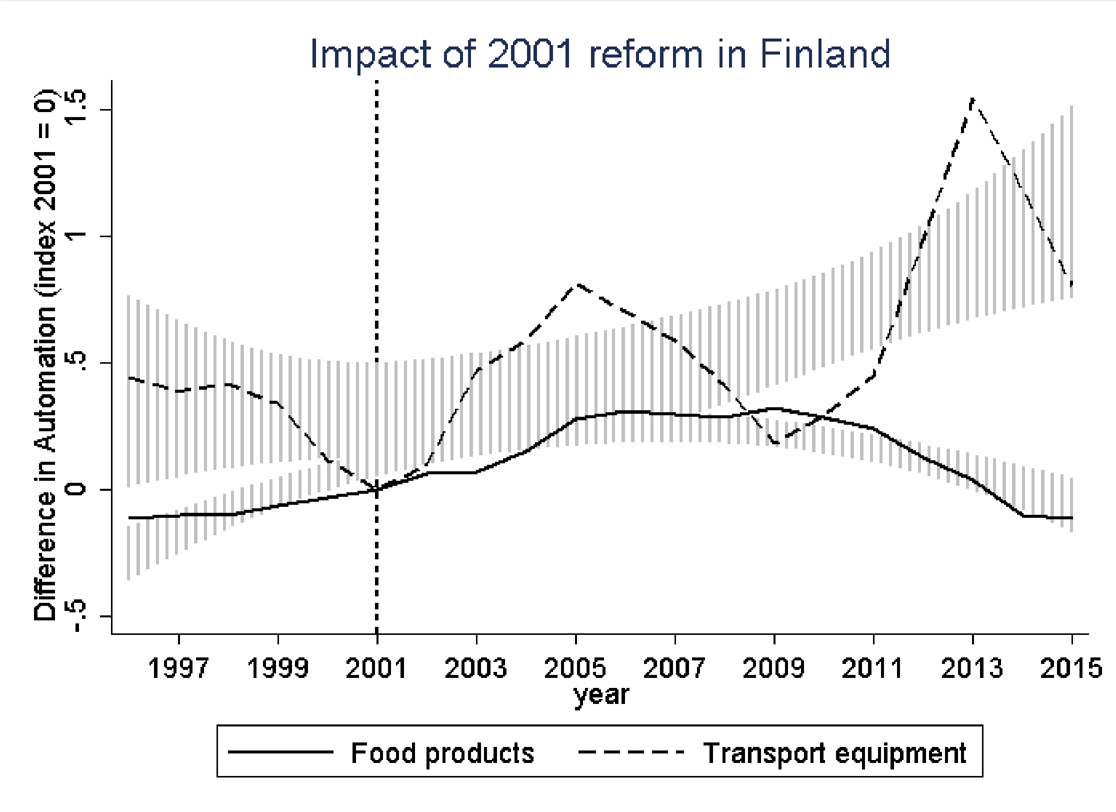

Figure 2: The figure shows the percentage difference in innovations to robot-density between Finland - which tightened regulation of dismissal in 2001 - and the control group (Denmark, Norway and Sweden), in which no reform took place. Differences in innovations to robot-density are reported for the average among high-uncertainty sectors (75th percentile) and all other sectors.

illustrates that following the reform, the most volatile sectors in Finland experienced a larger increase in robot-density with respect to the control group.

An identification strategy based on sector-specific variables allows overcoming econometric issues that are typical in cross-country studies involving institutional variables. In fact, labor market policy and country-wide investment in technology are likely to be both driven by omitted variables. For instance, a left-wing government might be more prone to keep in place strict labor market regulation and at the same time promoting education policies favoring innovation. Exploiting changes in regulation and their differential impact in intrinsically uncertain sectors, as we do in this paper, is then less subject to criticism.

To test the prediction that EPL causes an increase in robot-density disproportionately in highly volatile sectors, I specify the following model based on (8),

$$\delta_{cst} = \beta_0 + \beta_1(EPL_{ct} \times \sigma_s) + \beta_2 \tilde{w}_{cst} + \beta_2 B\boldsymbol{X}_{cst} + \beta_3 EPL_{ct} + \epsilon_{cst} \tag{9}$$

where δ_{cst} is the log of robot-density. Relative prices are given by

$$\tilde{w}_{cst} \equiv \frac{w_{ct}}{\rho_{st}}$$

In order to account for potential correlation between the error term ϵ and the explanatory variables, the vector $\boldsymbol{X}$ includes a number of control variables that will be discussed below.

In (9), the coefficient of interest is β_1. The variable $EPL_{ct} \in [0,1]$ measures the strictness of dismissal procedures. The closer to 1, the more binding is regulation. The variable σ_s is a proxy of sectorial uncertainty and it is computed with various measures of volatility on US data. The reason for using sectorial indexes based on the United States, rather than country-sector specific proxies, is that within a country EPL might be correlated with uncertainty. For instance, by distorting job flows regulation could affect output volatility, which would be captured by country-specific proxies of uncertainty. Clearly, that would make the interaction term endogenous.[28] On the other hand, the United States are the least regulated country in the sample. Therefore, proxies of sectorial uncertainty computed on the US are more likely to capture structural sectorial characteristics. These could result from turbulence of demand due to the nature of the product, fluctuations in the cost of the inputs, or the rate of scientific discovery that is peculiar to the technology used in a particular sector. Being due to fundamentals, "intrinsic uncertainty" is also likely to carry over to other countries, which justifies using the US as benchmark value for the whole sample. At the expenses of some degrees of freedom, such methodology reduces the possibility of bias.

Recent work by Ciccone and Papaioannou (2010) shows that although being frequently used, the methodology proposed by Ranjan and Zingales (1998) can deliver biased estimates of β_1. For instance, that would be the case in the presence of differences in sectoral composition between US and other countries, or if the observed correlation between sectoral volatility in the US and in other countries would be due to elements other than regulation itself. To address the issue, I use the methodology proposed by Ciccone and Papaioannou (2010) and used in Bassanini and Garnero (2013), which consists of instrumenting $EPL_{ct} \times \sigma_s$ following a two step procedure. First, I estimate the sectoral coefficient of EPL on automation κ_s, from the regression

$$\delta_{cst} = \kappa_s EPL_{ct} + FE + \epsilon_{cst}$$

Then, the interaction of EPL and predicted sector-specific slope is used as instrument for $EPL_{ct} \times \sigma_s$ and (9) is estimated with standard two-stage least squares.

4 Data

This section discusses the main sources of data used to construct the variables in model (9). The section is intended to provide the essential information needed to understand the results, which are presented in the next section.

[28]The methodology used in this paper follows the pioneering work of Ranjan and Zingales (1998).

4.1 Dependent Variable: Robot-density

The dependent variable, "robot-density", is the natural logarithm of the number of robots per employee in a sector. The International Federation of Robotics (IFR) collects data on shipments of industrial robots from national robot associations. Information is available for each sector, country and year. Since almost all robots suppliers are members of national associations, our data virtually include all robots that are actually used worldwide. An advantage of our data, is that the IFR has a common protocol to count robots, so that it ensures consistency across countries and years. Data on shipments are used to construct the stock of operational units using the perpetual inventory method. Following Graetz and Michaels (2015), I assume a 10% yearly depreciation rate.[29] IFR estimates are used for the initial 1993 value of the stock. More details can be found in the Appendix 7.

Figure 3 presents some descriptive statistics on robot-density. The top panel depicts the estimated number of robots every 1000 employees by country, while the bottom one provides the same information by sector. In both panels, the bars correspond to median value of the index. Manufacturing sectors tend to be the most automated, with metal products and transport equipment leading the ranking. Interestingly, the ICT-producing sector (Electronics) seems to be relatively densely automated, suggesting that manufacturing can be highly standardized even in high-tech industries.

4.2 Explanatory Variable: $EPL \times \sigma$

The main explanatory variable is an interaction term. The first component is a time-varying index, measuring the strictness of regulation of dismissal in a country. The second component is a constant, sector-specific proxy of uncertainty. I discuss them next.

4.2.1 EPL: Regulation of Employment Dismissal

Chapter 4 of ILO (2015) describes the EPL variables used in this study. The indicators are based on the methodology presented in Deakin et al. (2007), but they feature an extended country coverage. The variables consist of detailed indicators measuring the strictness of EPL and its variation over time. More information can be found in the Appendix 8, including details on the coding of the various reforms country by country. In this paper, I focus on regulation of employment dismissal because "firing and hiring costs" play a central role for the theory we seek to test. While other dimensions of EPL, or even other labor market institutions such as minimum wages would certainly create incentives to automation, they would so by simply increasing the relative cost of labor vis-a-vis robots. However, this paper is about the existence of non-wage costs that are related to factor adjustments and affect allocative efficiency. Regulation of employment dismissals is a natural candidate to be responsible for such costs.

[29]The authors experiment with alternative discount rates and claim that results are stable.

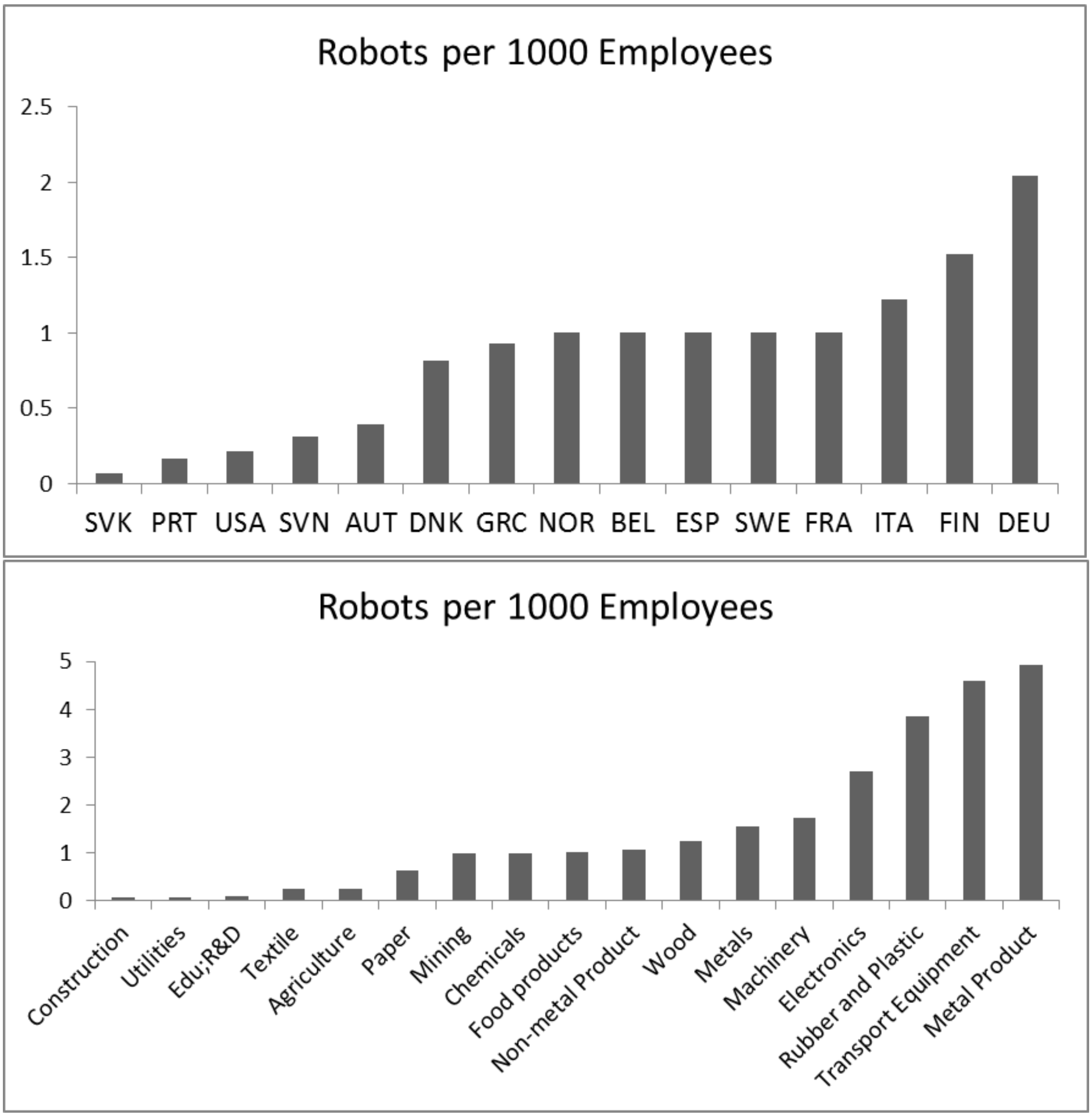

Figure 3: The figure presents the estimated stock of robots in use every 1000 employees,by country (top) and by sector (bottom). Robot-density is first averaged over all years. Then I compute the median over sectors/coutries The figures are based on IFR data.

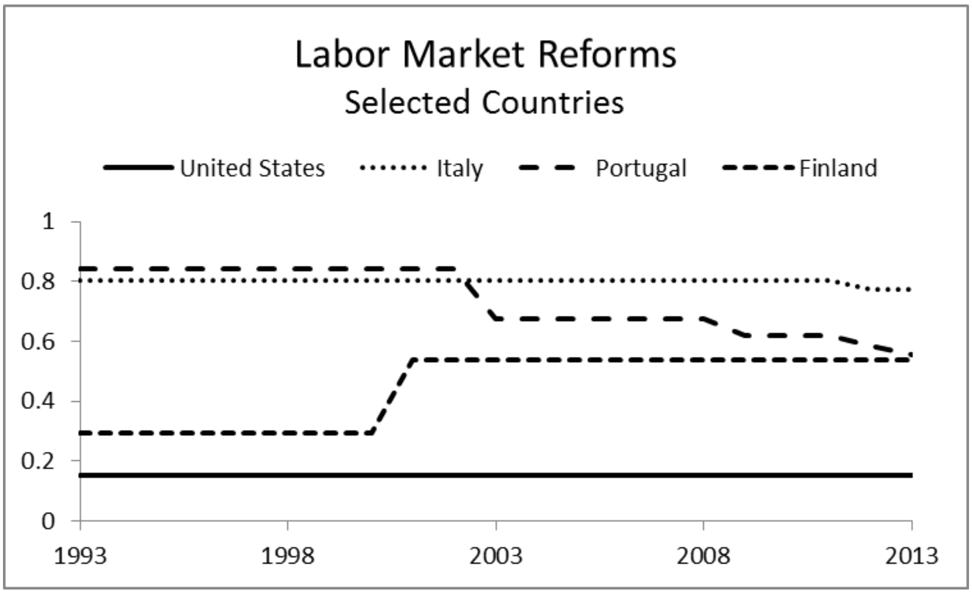

Figure 4: The original index from ILO (2015) is based on the work of Deakin et al. (2007). The index measures the strictness of regulation of employment dismissal and it goes from zero (no regulation, "employment at will") to one.

Figure 4 shows the variation of the index on regulation of dismissal for selected countries in the sample. The countries have been chosen to reflect the least and most regulated ones, and those experiencing the largest reforms, i.e. the largest increase or decrease of the index.

4.2.2 σ: Uncertainty

The identification strategy of the paper crucially relies on the proxy of sectorial uncertainty. While Section 6 provides details on the construction, here I provide the essential information to convince the reader of the validity of the uncertainty measures.

The main problem is that using country-specific indexes of uncertainty would result in biased estimates, because within a country, volatility and dispersion in growth rates are likely to be correlated to changes in legislation. Thus, I proceed by assuming that there exists a structural level of uncertainty that is specific to each sector and carries over to all countries in the sample. I then compute sector-specific "intrinsic uncertainty" for the United States, the country with the lower EPL index in the sample. Doing so minimizes the likelihood of capturing turbulence due to regulation, rather than technological or other structural factors. Intrinsic uncertainty is related to technological factors. As shown in Section 4.1, different countries have a similar cross-sector distribution of robot-density, suggesting important technological commonalities. Intrinsic uncertainty could also be related to the nature of the goods produced in a sector or the level of fluctuations in the cost of inputs, which would affect the predictability of future demand and

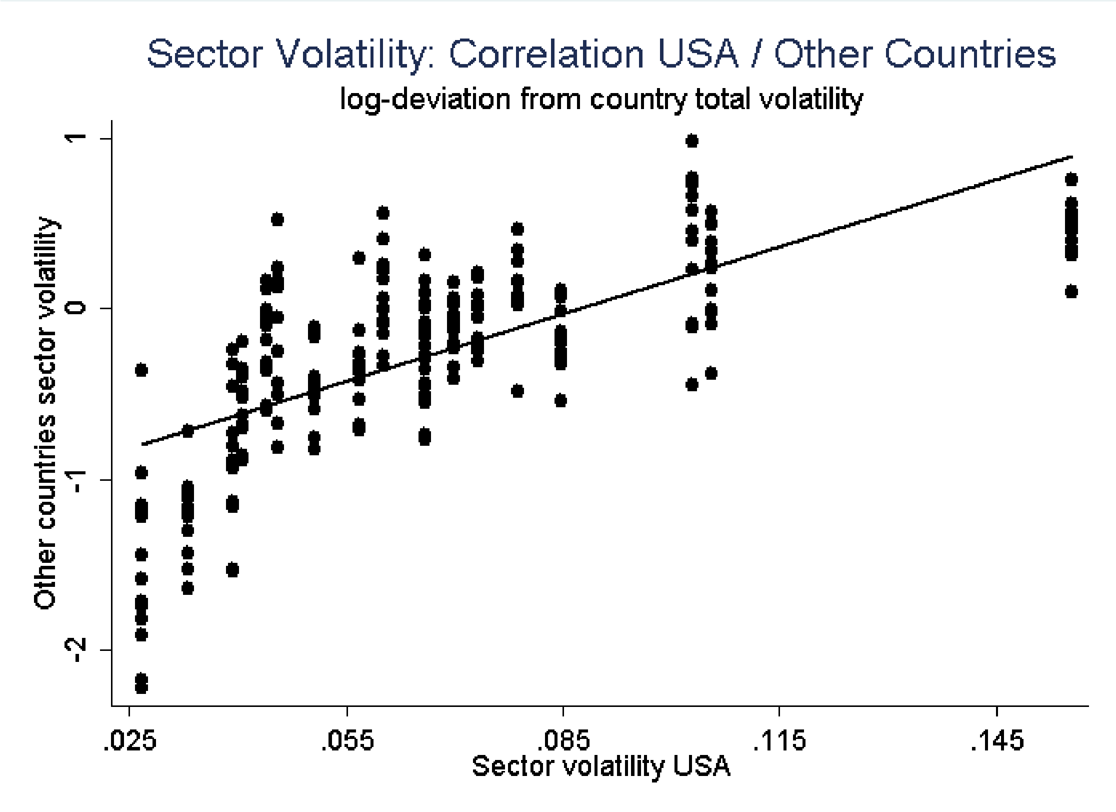

Figure 5: The figure shows the correlation between sectoral uncertainty in the United States and in other countries. Uncertainty is measured as the standard deviation of the unforecastable component of output growth and it is expressed as log deviation from a country aggregate volatility.

profits. The existence of structural characteristics creating similar level of sector-specific uncertainty, implies that the "uncertainty ranking" of economic sectors should be similar across countries. Figure 5 shows that indeed that is the case. The horizontal axis presents sectoral US uncertainty, as measured by the unforecastable component of output growth. On the vertical axis can be found uncertainty measures computed for each country. The positive correlation between US and each country' sectoral uncertainty supports the chosen identification strategy.

Given the central role covered by the proxies, I present estimation results obtained with two different measures of uncertainty that are frequently used in the literature. These are: i) the standard deviation the unforecastable component of sectoral output growth, and ii) the cross-industry dispersion in output growth of 6-digits level industries. Since robot-density is available for 2-digits sectors, proxies of uncertainty are needed at the same level of aggregation. The first proxy exploits the time series volatility of 2-digits level sectoral output. The third measure instead exploits the cross-sectional dispersion in output growth of 6-digits level industries, within each 2-digits sector. To compute cross-sectional dispersion, I use the NBER-CES Manufacturing Industry Database[30], which provides the value of shipment and the corresponding deflator. The theoretical model developed in Section 2 features cross-sectional dispersion, so that the latter measure of uncertainty is the most suitable one.[31] However, the main shortcoming of that measure is that the NBER-CES database covers only manufacturing sectors and therefore it causes a substantial loss of observations.

In the next section I present the results before detailing the construction of the proxies of uncertainty. However, given that results crucially rely on the measures of uncertainty, Section 6 is entirely devoted to their construction.

5 Results

Table 1 presents OLS estimates of (9). Because the United States is used to identify sectoral uncertainty, the country is dropped in all regressions. Country and sector fixed effects, together with country and sector-specific time trends are included to control for differences in factor endowments such as human capital, "routine-intensity" - which according to ALM facilitates the adoption of automating technologies -, differential rates of R&D investment and technical progress, and institutional shifts not captured by our EPL index. Year dummies are included to control for global shocks, such as 9/11 or the Great Recession.

The coefficient on the interaction term is positive and significant at the 1% level in both specifications. Volatile sectors are disproportionately automated in strict EPL countries, irrespectively on whether uncertainty is measured by time series volatility or cross-sectional dispersion of output growth across 6-digits industries. Detailed industry data are only available for manufacturing sectors, so in the second specification are lost almost 30% of observations. The coefficient on the interaction term remains however large and significant. To save space, the tables do not report the coefficient on the EPL main effect because it is not significant in these specifications. Relative prices are shown in the tables because they are present in (10). However, it should be noticed that because detailed information on robot prices is not available, their impact has been proxied by a set of sector-specific time trends.[32] In particular, I assume that while the price of robots is homogeneous across countries (i.e. robots are perfectly mobile across countries, just as it is usually assumed for other types of capital), there exist technological bottlenecks that are specific to different sectors, delivering sector-specific prices. Moreover, in constructing $\tilde{w}$, I use sectorial wages from STAN database, rather than countrywide wages. I do so because the assumption of perfect mobility of labor

[30] http://www.nber.org/nberces/

[31] It should not be too difficult to adapt the theoretical model to feature time series volatility. I keep that tasks for future research.

[32] In estimating the model, I feed log-wages and sector-time dummies separately into the software and then constrain the coefficient of the former to be the negative of the latter.

relies on labor being perfectly homogeneous across sectors, an admittedly simplistic assumption.[33]

Robot-density	Proxy of uncertainty std. dev. forecast error	 std. dev. cross-section
EPL × Uncertainty	34.8***	32.3***
	(4.06)	(4.94)
Relative price labor	1.4***	0.9***
	(0.11)	(0.13)
Country, sector, year FE + interactions	yes	yes
Observations	4,581	3,291
R^2	0.63	0.71

Table 1: OLS estimates of the model $\delta_{cst} = \beta_0 + \beta_1(EPL_{ct} \times \sigma_s) + \beta_2\tilde{w}_{cst} + B\boldsymbol{X} + \epsilon_{cst}$. All specifications include the main effect of EPL (although never significant). Since σ_s is constant over time, its impact is soaked up by the sector fixed effect and therefore it is reported in the table.

5.1 Endogeneity of Wages

Using real wages by sector in (9) is likely to cause severe endogeneity problems, thus resulting in biased estimates. To circumvent the problem, I use an interaction term as instrumental variable for sectorial wages.[34] The construction of instrument is based on the routine bias theory developed by ALM. The interaction term is composed by an index measuring country-level changes in workers' bargaining power, $BARGAIN$ - taken from ILO (2015), and sectorial indexs of routine-intensity. How can the composite indicator serve as a valid instrument for wages? The logic is that nation-wide reforms modifying the strength of employees' representation are expected to affect wages differently in routine-intensive sectors, where workers in occupations that are at risk of automation have weaker contractual positions.

I experiment with an index of routine intensity taken from Marcolin et al. (2016), based on individual level survey data from the Program for the International Assessment of Adult Competencies (PIAAC). The index based in survey data is presented in Figure 9 in the Appendix. In each country, the survey collects information on the specific type

[33]Using countrywide wages results in relative prices being not significant, but it leaves the main results unchanged. The reason is that country-time dummies soak up all the explanatory power of countrywide wages.

[34]The use of interaction terms as instrument is discussed in Esarey (2015).

of tasks workers carry out on their job, as well as the economic sectors in which they work. The advantage of using PIAAC data is that it guarantees international comparability, which makes sample averages reasonably accurate. However, one limitation of the indicator is that it covers only the years 2011 and 2012. Therefore, the data do not allow to detect potential shocks perturbating the structural ranking of routine-intensity.Time invariant indexes would not constitute a problem if one is willing to assume that being due to technological factors, the sectoral ranking of routine-intensity is structural. In this way, the assumption legitimates the use of routine-intensity indicators that are common to all countries in the sample.[35] Robustness checks, available upon request, show that very similar estimates can be obtained by using simple sector dummies as proxies of routine intensity. Indeed, Figure 10 in the Appendix shows that the estimated sector fixed effects and the index of routine intensity are positively related.

Thus, table 2 presents 2SLS results based on the instrument

$$w^{iv}_{cst} = BARGAIN_{ct} \times Routine_s$$

The coefficient of interest remains positive and highly significant. Relative prices remain significant as well, with the estimated coefficient being lower but still significant in the second specification. In the Appendix 2 are presented the first stages that suggest a strong negative correlation between wages and our instrument. Intuitively, tightening degree of bargaining centralization results in lower wages in the most routine intensive sectors, because it is in those sectors that firm can most easily substitute workers with machines.

	2SLS; w = routine index × BARGAIN	
Robot-density	std. dev. forecast error	std. dev. cross-section
EPL × Uncertainty	35.2***	90.3***
	(4.95)	(10.48)
Relative price labor	1.3***	0.5**
	(0.32)	(0.27)
Country, sector, year FE + interactions	yes	yes
Observations	3,333	2,301

Table 2: 2SLS estimates of the model $\delta_{cst} = \beta_0 + \beta_1(EPL_{ct} \times \sigma_s) + \beta_2\tilde{w}_{cst} + B\boldsymbol{X} + \epsilon_{cst}$, where sectorial wages are instrumented as $w^{iv}_{cst} = BARGAIN_{ct} \times Routine_s$. All specifications include the main effect of EPL (although never significant). Since σ_s is constant over time, its impact is soaked up by the sector fixed effect and therefore it is reported in the table.

[35] All countries in the sample are OECD.

5.2 Robustness

Given the relatively small number of countries in the sample, I do not cluster errors in the above results.[36] However, Appendix 3 shows that estimates are robust to clustering.Additional robustness tests that are not reported but available upon request, demonstrate that results are not driven by the most automated sector, Automotive, or the two countries with the largest change in EPL index.[37] Results are robust to the alternative methodology proposed by Ciccone and Papaioannou (2010), which consists in instrumenting the interaction term by estimating the impact of EPL on each sector and then using the interaction of EPL and sector-specific slopes as instrument for $EPL_{ct} \times \sigma_s$. In Appendix 4 can be seen that the instrumented interaction term remains highly significant. As a last robustness check, instead than using the regulation indicators from ILO, indicators from the OECD are used instead. These indicators are the well known indexes of employment protection produced and regularly updated by the OECD.[38] It can be seen from Appendix 5 that using alternative regulation indicators corroborates the results.

5.3 Impact of Regulation on Robot-density

To grasp the relative importance of relative prices and EPL in (9), I compute standardized coefficients. Results suggests that increasing of one standard deviation the relative price of labor would increase robot-density of 0.8. Increasing by one standard deviation the interaction term (the main EPL effect is not significant in the baseline specification) would increase robot-density by 0.3, suggesting a larger role for relative prices.

To further investigate the role of the regressors in (9) based on the information provided by the sample, I perform the following exercise. I compare the R^2 of the full model with that of restricted models in which I remove the regulation variables, namely the main EPL effect and the interaction term. The R^2 of the restricted model drops between 1 and 12%, depending on the specification. Repeating the exercise but now dropping the relative price delivers a decrease of the R^2 between 1 and 10%, suggesting the relative prices and regulation account for a similar fraction of variation of robot-density in the sample. However, quantifying the relative impact of the variables is tricky, since part of the impact that regulation or prices have on automation can still be captured by the trend variables included in the model. Indeed, sector and country trends are found to account for a large portion of variation in the sample, respectively 30% and 20%. Thus, while regulation and prices seems to have a non-negligible role in explaining automation, it seems that there are important sector-specific factors at play that need to be further investigated.

As an additional exercise, we can use the estimated version of (9) to compute the predicted impact of EPL on robot-density, conditional on sectoral volatility,

[36] The EPL index variates at the country level only, so residuals might be correlated.

[37] These countries are Finland, with a change of 0.24 and Portugal, with a change of -0.29. Average change is 0.09.

[38] http://www.oecd.org/els/emp/oecdindicatorsofemploymentprotection.htm

$$E\big[\delta_a - \delta_b|\sigma_s\big] = \hat{\beta_1} \times \sigma_s(EPL_a - EPL_b)$$

where a and b represent arbitrary, different values for the EPL index in a counter factual exercise. Figure 6 depicts the predicted log-difference: i) between Italy and the United States, respectively the most and least regulated countries;[39] ii) post and pre-reform in Finland, the country where the largest change in regulation of dismissal took place. The differences are reported by sectoral volatility (lowest is at the top of the chart). The differences are substantial, especially for the most volatile sectors such as Automotive, where the predicted difference between the most and least regulated countries corresponds to a factor of 3.5. In the same sector, the estimates suggest that after a reform such as that passed in Finland, the number of robots per employee should almost triplicate, as indicated by the difference of 1.5. Even in the least volatile sector, Education and R&D, both bars in Figure 7 suggest an important role for regulation in determining the intensity of automation.

The estimates obtained in this paper suggest that tightening EPL increase the number of robots per employee in a sector, not that EPL increases productivity. Automation is rather used to compensate the efficiency loss due to regulation and so whether robots increase productivity above what it would have been in the absence of EPL is an open issue. While a general equilibrium model is essential to obtain estimates of the overall impact of EPL on welfare, a very rough calculation of the potential impact of EPL on productivity can be made as follows. According to Graetz and Michaels (2015), for instance, robot-density contributes for about 10% of annual GDP and labor productivity growth. Thus, a rough calculation would imply that in an average volatility sector, tightening EPL - an increase of the index from zero to one - would lead to a 0.8% increase in annual GDP growth.[40] At the same time, whether EPL is ultimately detrimental for workers depends on the potentially displacing effect of robots on employment. For instance, using again the estimates from Graetz and Michaels (2015),we would conclude that tightening EPL implies a -0.59% reduction in employment.[41] In a sense, these simple calculations suggest an important point, that reforming the labor market can be used as a tool to mitigate the disruptive effect of automation on employment, especially in highly volatile sectors.

6 Proxies of Uncertainty

Objective measures of sectorial uncertainty are not easily available. Broadly speaking, measures of uncertainty can be based on either the time variation of a variable, or on

[39]The average value of the EPL index in Italy is 0.8, while 0.15 in the United States

[40]Given our estimates, increasing the EPL index from zero to one in an average volatility sector would lead to an increase in robot-density equal to $1 \times 35.2 \times .06 = 2.1$. Multiplying the change for the marginal contribution of robot-density to GDP growth as presented by Graetz and Michaels, 0.37, delivers 0.78%. It should be noticed that our definition of robot-density is not identical to their definition, since they use hours worked rather than number of employees.

[41]The estimated coefficient for the impact of robot-density on hours is -0.28.

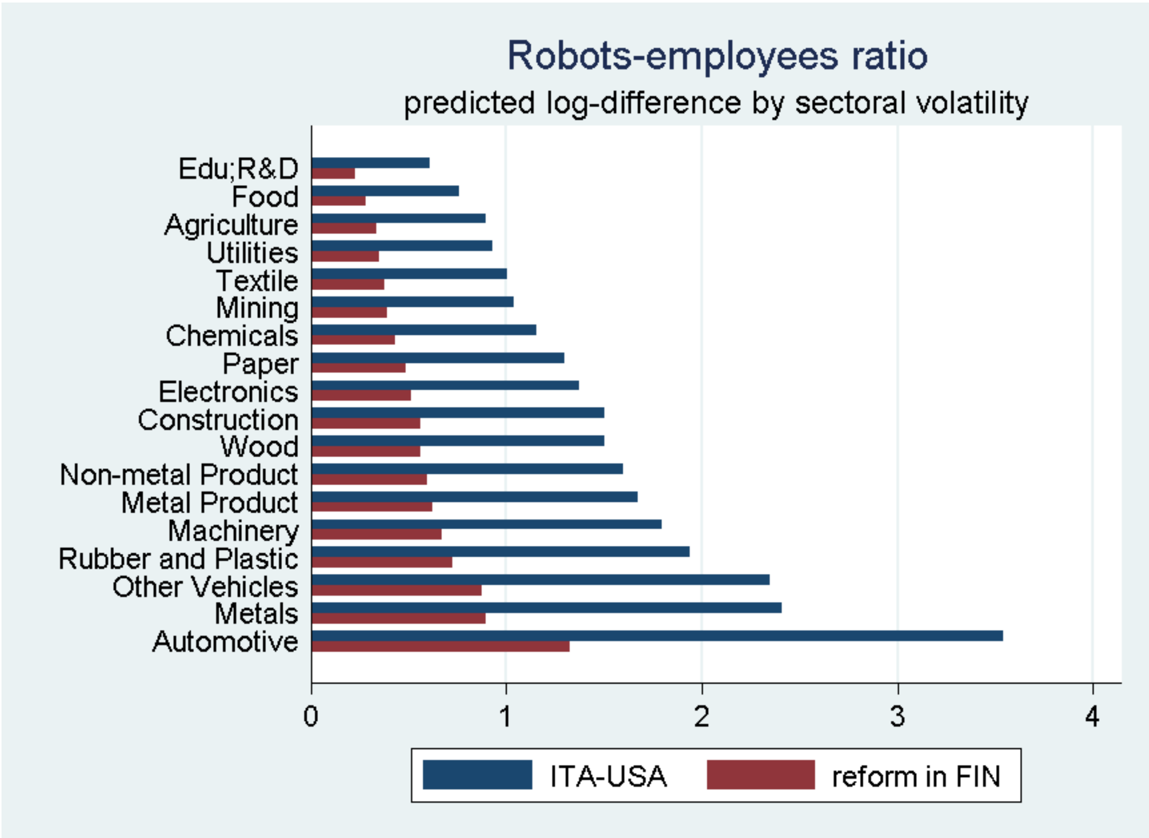

Figure 6: Italy and the United States are , respectively, the most and least regulated countries. Finland is the country where the largest reform took place. The differences are reported by sectoral volatility (lowest is at the top of the chart)

its cross-sectional dispersion. Examples of the first kind of indicators can be found in Ramey and Ramey (1995), which use the standard deviation of output growth and of its forecast errors.[42] Time series measures of uncertainty are found to be strongly correlated to cross-sectional ones. For instance, Bloom (2009) shows that the time volatility of stock prices is correlated to the dispersion of productivity and output growth at both firm and industry level. Therefore, following the literature, in this paper I present results based on different proxies of uncertainty. These are: i) the standard deviation the unforecastable component of output growth, and ii) the cross-industry dispersion in output growth of 6-digits level industries.[43] The first indicator is simply the annual volatility of real output growth, computed from the STAN database.[44] The second indicator is the volatility of the unforecastable component of output growth, obtained by computing the residuals of the simple forecasting equation

$$g_{cst} = \mu + \rho g_{cst-1} + \boldsymbol{\delta z}_{cst} + \eta_{cst} \tag{10}$$

The dependent variable in (10) is the growth rate of real sectoral output and $\boldsymbol{z}_{cst}$ is a vector of controls.[45] As discussed in Section 4.2.2, I use US-based sectoral indicators as proxies for intrinsic uncertainty. I do so in order to minimize the likelihood to capture structural factors, rather than fluctuations due to regulation. Figure 5 shows that the uncertainty ranking in the United States is positively correlated with that in other countries. However, more formal evidence can be obtained by running a simple OLS regression of the following type:

$$\sigma_{cs} = \alpha_0 + \alpha_1 \sigma_s^{us} + u_c + \epsilon_{cs} \tag{11}$$

where u_c represent country fixed effects. In (11), the inclusion of the fixed effects is needed to control for the large cross-country differences in volatility. As emphasized above, what is need for the validity of the estimation strategy is that the relative ranking is preserved across countries. Estimating (11) gives the results in Table 3, which show that indeed the correlation is large and highly significant.[46] Thus, the estimates suggest that structural factor determining intrinsic uncertainty in the United States carry over to other countries, implying that using uncertainty proxies computed with US data can be used to do inference over the whole sample.

Instead than exploiting time series volatility, the third indicator exploits the cross-sectional spread of industry-level productivity growth. To compute the proxy, I use the NBER-CES Manufacturing Industry Database, which provides shipment and deflator

[42]Using growth rates, rather than levels excludes deterministic trends from the computation of the standard deviation. This is important, since deterministic trends are fully forecastable and therefore their contribution to volatility cannot be interpreted as an additional source of uncertainty.

[43]Stock price volatility is an alternative proxy of uncertainty. However, this paper focuses on frictions inherent to the production process and therefore output volatility seems a more suitable option.

[44]http://www.oecd.org/sti/ind/stanstructuralanalysisdatabase.htm

[45]Regression results are shown in the Appendix 6.

[46]The regression is carried out using a previous version of the STAN database (OECD). The reason is that the latest version, used in all other parts of the paper, does not include the United States.

VARIABLES	(1) Sectorial volatility
σ_s^{us}	0.8***
	(0.118)
Country FE	yes
Observations	211
R-squared	0.332

Table 3: OLS estimates of α_1 for the model $\sigma_{cs} = \alpha_0 + \alpha_1 \sigma_s^{us} + u_c + \epsilon_{cs}$.

for 6-digits manufacturing industries in the United States, from 1958 to 1992. An important shortcoming of the uncertainty proxies computed with the NBER-CES database is that they cover manufacturing sectors only. Moreover, since I do not have information available on detailed industries for other countries, I cannot compare the correlation between the US-based indicators and the country-specific ones. However, some supporting evidence is presented in Figure 8, which shows that time series and cross-sectional measures of uncertainty are positively correlated, at least for the United States.

7 Employment and Capital Adjustment Cost

The model developed in Section 2 suggests that conditional on sector volatility, firms should respond to shocks with larger adjustment of capital than labor. More specifically, the idea is that capital *services* are less costly to adjust than labor services. Capital and labor services can be defined, respectively, as

$$KS = K \times u$$

and

$$LS = E \times h$$

where K is the stock of capital, u capital utilization, E is employment and h is hours worked per-worker. Both factors can be adjusted by firms along two margins, extensive and intensive. However, since h is clearly bounded, adjusting labor necessarily require intervening on the extensive margin, employment, which is costly due to EPL.[47] On the contrary, adjusting the workweek of capital is at complete discretion of the firm, because capital can run 24/7 and it is not subject to any constrain on its utilization. Indeed, Figure 8 shows that changes in utilization rate of capital tend to be much more volatile than changes in employment. Estimates of utilization rates by sector for the United States are taken from Gorodnichenko and Shapiro (2011).[48] To compute the

[47]It could be argued that firms could use shift labor in order to let labor services run 24/7. However, shift labor is an increasingly rare practice, mostly due to its negative effects on workers' health.

[48]http://www-personal.umich.edu/ shapiro/data/SPC/index.htm, while employment from the NBER-CES Manufacturing Industry Database.

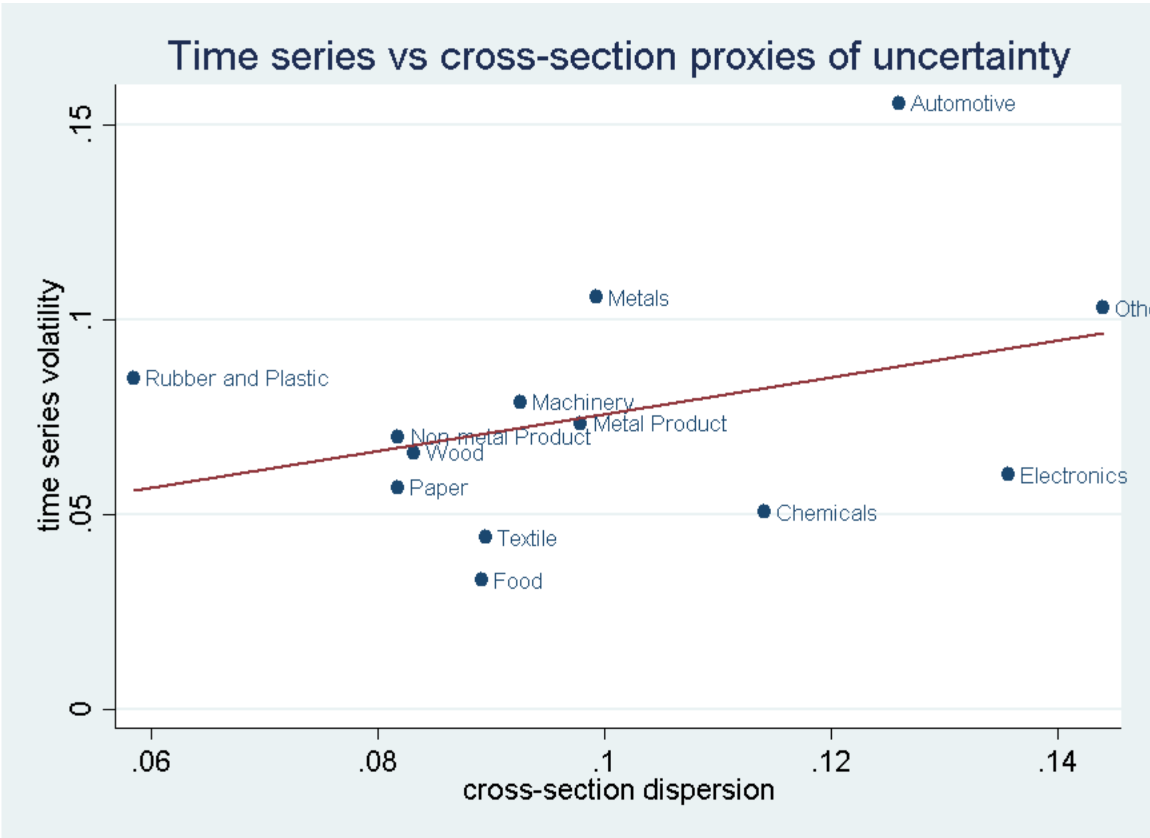

Figure 7: The figure presents correlations between cross-sectional and time-series uncertainty measures. The cross-sectional measure is the standard deviation of output growth in 6-digits manufacturing industries. Time series uncertainty is the annual standard deviation of the unforecastable component of output growth. Data refer to the United States.

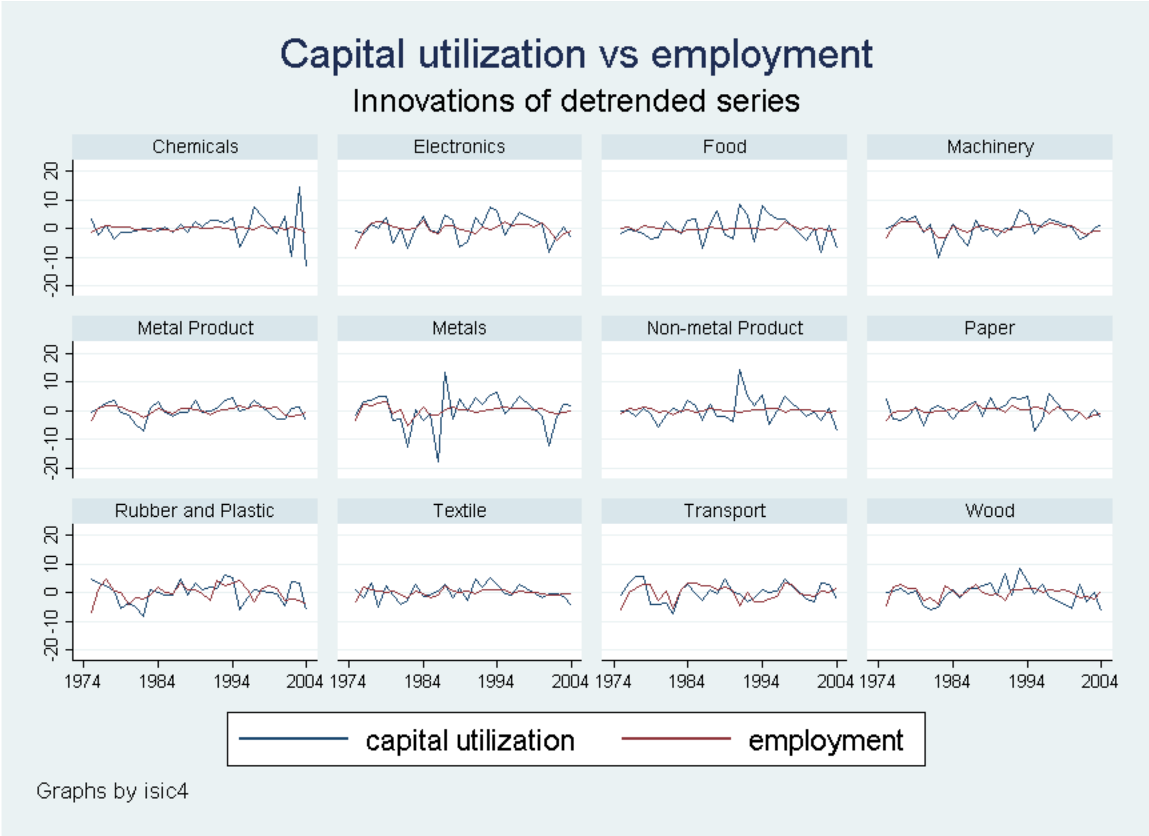

Figure 8: The series are obtained by computing the residuals of a regression of both variables on year dummies and an AR(1) component.

innovations, each series has been regressed on year dummies and an AR(1) component, removed to obtain net changes in capital services and employment.

The literature on adjustment costs has provided evidence on the higher flexibility of capital services with respect to labor. For instance, Shapiro (1986) provides estimates of capital utilization based on the assumption that shift labor can be used to increase the workweek of capital. Estimates confirm the intuition that adjusting the utilization of capital is much less costly -almost costless indeed - than adjusting labor inputs.[49] [50]

[49]The reason is that the workweek of capital is essentially costless to adjust, due to the very low premium needed to be paid to workers for late night shifts.

[50]In Shapiro (1986), human labor is needed to increase the utilization of capital, because of capital-labor complementarity. Therefore, one would expect the cost of capital utilization to further decrease when dealing with robots, representing a rather substituting technology.

8 Conclusions

This paper proposes a theory of automation in which machines do not increase productivity because they are faster or better than humans at doing things, but rather because they increase allocative efficiency. The theory is based on the empirical observation, robust to different specifications and alternative datasets, that volatile sectors are disproportionately automated in countries with strict rules on employment dismissal. The paper exploits a dataset on shipment of industrial robots, which constitute a better proxy of automation as compared to studies using "computer capital".

I develop a model in which EPL does not apply to machines and so robots can be used to substitute workers and circumvent the adjustment costs produced by regulation. In equilibrium, the intensity of automation is higher in volatile sectors, where uncertainty about business conditions increases the flexibility requirements of firms. Importantly the model shows that regulation gives firms an incentive to automate even when machines are just as productive as human workers.

In such a framework, an empirical exercise suggests that the impact of EPL on automation is substantial, but also that relative prices seems to be quantitatively more important, since they explain a large portion of variation in robot-density in the sample.

This paper is about *determinants* of automation. No claim is made on the desirability of EPL in terms of productivity, since regulation is found to increase robot-density, not productivity itself. If anything, the model suggests that EPL has a negative impact, because it deteriorates allocative efficiency. How the post-automation level of productivity compares to the level of productivity prevailing without regulation (and so without automation), is an important open issue. Neither claims are made in terms of the welfare effect of EPL, since such an assessment would necessarily require a general equilibrium model. I intend to address both issues in my future research.

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Appendix

A1. Model Appendix

Average marginal cost of firm i

The Lagrangian of the optimization problem of the firm is

$$L \equiv \int_0^1 q(i,a)C(i,a)\,da - \lambda\left\{\left[\int_0^1 q(i,a)^{\frac{\epsilon-1}{\epsilon}}da\right]^{\frac{\epsilon}{\epsilon-1}} - q(i)\right\}$$

where $C(i,a)$ is given by (1). First order conditions with respect to $q(i,a)$ deliver

$$C(i,a) = \lambda q(i,a)^{-\frac{1}{\epsilon}}q(i)^{\frac{1}{\epsilon}}$$

Rising both sides to the power $1-\epsilon$ and integrating over all tasks,

$$\bar{mc}(i) \equiv \lambda = \begin{cases} wEe^{-\theta(i,a)} = we^{\frac{\sigma^2(s)}{2}} & \text{if using labor} \\ \\ \rho(i)\left[Ee^{(\epsilon-1)\theta(i,a)}\right]^{-\frac{1}{\epsilon-1}} = \rho(i)e^{-(\epsilon-1)\frac{\sigma^2(s)}{2}} & \text{if using robots} \end{cases}$$

Notice that to get the second line we use the fact that

$$\int_0^1 e^{(\epsilon-1)\theta(i,a)}\,da = \int_{-\infty}^{\infty} e^{(\epsilon-1)\theta(i,a)}\,dG(\theta(i,a))$$

Total factor demand at sector s

Conditional upon the choice of technology, optimizing firms have factor demand given by either

$$R(i) = \rho(i)^{-1}e^{\frac{\epsilon-1}{2}\sigma(s)^2}$$

or

$$N(i) = w^{-1}e^{-\frac{1}{2}\sigma(s)^2}$$

Recall that firms cannot use both technologies, so that the quantity $\frac{R(i)}{N(i)}$ has no meaning. Integrating firms' demand over all firms, distinguishing between automated ($i \geq i^*(s)$) and non-automated ($i < i^*(s)$), and assuming $\rho(i) = \rho(1+i)$, we get

$$N(s) = (1 - i^*(s))w^{-1}e^{-\frac{1}{2}\sigma(s)^2}$$

$$R(s) = \ln(1 + i^*(s))\rho^{-1}e^{\frac{\epsilon-1}{2}\sigma(s)^2}$$

Average marginal cost of firm i in the extended model

In the extended model, there is a continuum of units as additional layer between firm and tasks. The marginal cost of unit can be

$$\bar{mc}(s,i,j) = \begin{cases} wEe^{-\theta(s,i,j,a)} = we^{\frac{\sigma^2(s)}{2}} & \text{if using labor \& } \in [f,1] \\ \\ w\big[Ee^{(\epsilon-1)\theta(s,i,j,a)}\big]^{-\frac{1}{\epsilon-1}} = we^{-(\epsilon-1)\frac{\sigma^2(s)}{2}} & \text{if using labor \& } \in [0,f] \\ \\ \rho(s,i)\big[Ee^{(\epsilon-1)\theta(s,i,j,a)}\big]^{-\frac{1}{\epsilon-1}} = \rho(s,i)e^{-(\epsilon-1)\frac{\sigma^2(s)}{2}} & \text{if using robots} \end{cases}$$

The problem of the firm is minimizing

$$\int_0^1 p(s,i,j)q(s,i,j)\,dj$$

subject to

$$\exp\left\{\int_0^1 \ln q(s,i,j)\,dj\right\} \geq q(s,i)$$

The Lagrange multiplier is

$$\lambda = \exp\left\{\int_0^1 \ln p(s,i,j)\,dj\right\}$$

Since $p(s,i,j) = \bar{mc}(s,i,j)$ and for the case of labor-using firms, only a fraction f can optimize contingently on the realization of the cost shock, we have that

$$\lambda^n \equiv \bar{mc}^n(s,i) = \exp\left\{f \ln we^{-(\epsilon-1)\frac{\sigma^2(s)}{2}} + (1-f)\ln we^{\frac{\sigma^2(s)}{2}}\right\} = w\exp\left\{\frac{\sigma(s)^2}{2}(1-f\epsilon)\right\}$$

A2. First Stages Estimation

VARIABLES	std. dev. time series sector wage	std. dev. cross-section sector wage
REPRESENT × Routine	-0.685***	-0.760***
	(0.136)	(0.124)
EPL × Uncertainty	1.450***	10.21***
	(0.560)	(1.149)
Constant	-0.872***	-0.757***
	(0.214)	(0.205)
Observations	3,333	2,301
R-squared	0.984	0.991

Table 4: First stage estimation of (9), relative to the results in Table 2.

A3. Clustered Errors

Given the relatively low number of countries in the sample, the results presented in Section 4 are obtained without clustering errors at the country level. While to date there is no commonly accepted theory establishing what a suitable number of cluster is, common sense would suggest that since variation in the EPL indicators takes place at the country level, errors in (9) are likely to be correlated within a country. For this reason, tables 5and 6 show results for each of the specifications in Section 5 obtained clustering errors at the country level. It can be seen that the interaction term remains large and highly significant in all specifications and in the first column of each tables the main effect become positive and significant. The latter is due to the fact that errors of the regression of EPL on robot-density are negatively correlated across sector within a country. The reason might be that EPL has a different impact on sectors with a high share of routine occupations, effect taken into account by the sector dummies.

	Proxy of uncertainty	
Robot-density	std. dev. forecast error	std. dev. cross-section
EPL × Uncertainty	34.83***	32.34**
	(12.50)	(14.76)
Relative price labor	1.337**	0.867**
	(0.535)	(0.432)
EPL	9.938***	-2.322
	(1.488)	(1.661)
Country, sector, year FE + interactions	yes	yes
Clustered errors (country level)	yes	yes
Observations	4,581	3,291

Table 5: OLS estimates of the model $\delta_{cst} = \beta_0 + \beta_1(EPL_{ct} \times \sigma_s) + \beta_2 \tilde{w}_{cst} + B\boldsymbol{X} + \epsilon_{cst}$. Since σ_s is constant over time, its impact is soaked up by the sector fixed effect and therefore it is reported in the table.

Robot-density	2SLS; w = routine index × BARGAIN std. dev. forecast error	std. dev. cross-section
EPL × Uncertainty	35.27**	90.31**
	(16.08)	(38.82)
Relative price labor	1.354***	0.554
	(0.483)	(0.380)
EPL	13.29***	-5.771
	(1.135)	(3.815)
Country, sector, year FE + interactions	yes	yes
Clustered errors (country level)	yes	yes
Observations	3,333	2,301

Table 6: 2SLS estimates of the model $\delta_{cst} = \beta_0 + \beta_1(EPL_{ct} \times \sigma_s) + \beta_2\tilde{w}_{cst} + B\boldsymbol{X} + \epsilon_{cst}$, where sectorial wages are instrumented as $w^{iv}_{cst} = BARGAIN_{ct} \times Routine_s$. Since σ_s is constant over time, its impact is soaked up by the sector fixed effect and therefore it is reported in the table.

A4. Instrumenting the Interaction Term

VARIABLES	**Robot-density** std. dev. forecast error
EPL × Uncertainty	108.2***
	(7.204)
Relative price labor	1.291***
	(0.113)
Country, sector, year FE + interactions	yes
Observations	4,581

Table 7: Estimation of equation (9) using the the methodology proposed in Ciccone and Papaioannou (2010).

A5. Alternative Regulation Indicators

Robot-density	Proxy of uncertainty	
	std. dev. forecast error	std. dev. cross-section
EPL $\times$ Uncertainty	8.243***	6.884***
	(1.207)	(1.457)
Relative price labor	1.342***	-
	(0.11)	-
Country, sector, year FE + interactions	yes	yes
Observations	4,437	3,187

Table 8: OLS estimates of the model $\delta_{cst} = \beta_0 + \beta_1(EPL_{ct} \times \sigma_s) + \beta_2 \tilde{w}_{cst} + B\boldsymbol{X} + \epsilon_{cst}$. The indicators of employment protection are taken from the OECD. All specifications include the main effect of EPL (although never significant). Since σ_s is constant over time, its impact is soaked up by the sector fixed effect and therefore it is reported in the table.

A6. OLS Estimates of Equation (10)

VARIABLES	(1) sector grate
grY_1	0.04
	(0.035)
Constant	0.02**
	(0.011)
Sector FE	yes
Observations	792
R-squared	0.032

Table 9: AR(1) regression coefficient for unforecastable component of output growth.

A7. Details on IFR robot data

One problem with the IRF data is that for several countries, particularly in the early years of the sample, a breakdown of shipments by sector is not available and they are grouped under the label "unspecified". For these countries, shares by sectors are estimated using information for the years in which the breakdown is available, taking simple averages and using the resulting coefficient to construct the deliveries by sector.

In this paper, the construction of the stock of operational robots is obtained by assuming a yearly depreciation rate of 10%. The IFR adopts a different assumption about robots, in that they fully depreciate after twelve years. However, as in Michael and Graetz (2016), here I prefer to construct the stock by following a more conventional perpetual inventory method.

A8. Details on ILO labor law data

The data compiled by ILO (2015) have several advantages with respect to most commonly used indicators of labor protection. The first one is that they encompass several dimensions of employment protection legislation. Although the focus of this paper is on dismissal procedures, the wealth of information present in such data offers promising research opportunities. Moreover, the index for dismissal procedures itself is an average of nine very detailed indicators, which makes it possible to assess the impact of various dimension of dismissal law. Another advantage is that by capturing the time dimension of change in regulation, the data allow a panel specification that is useful to alleviate identification problems typical of cross-country studies. The third advantage of these data is that they take into account not only formal laws, but also self-regulatory mechanisms such as bargaining coordination.

Detailed information on the reforms that took place in each country can be found here: http://www.cbr.cam.ac.uk/datasets/

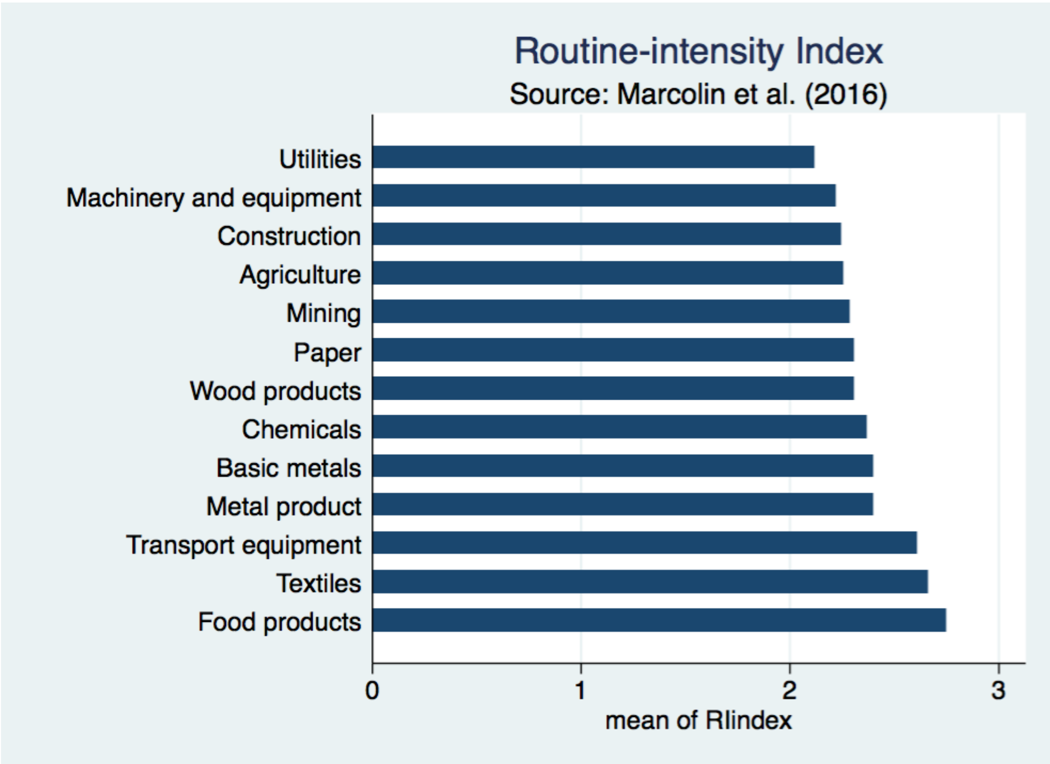

Figure 9: The sector-specific routine-intensity index used in the paper.

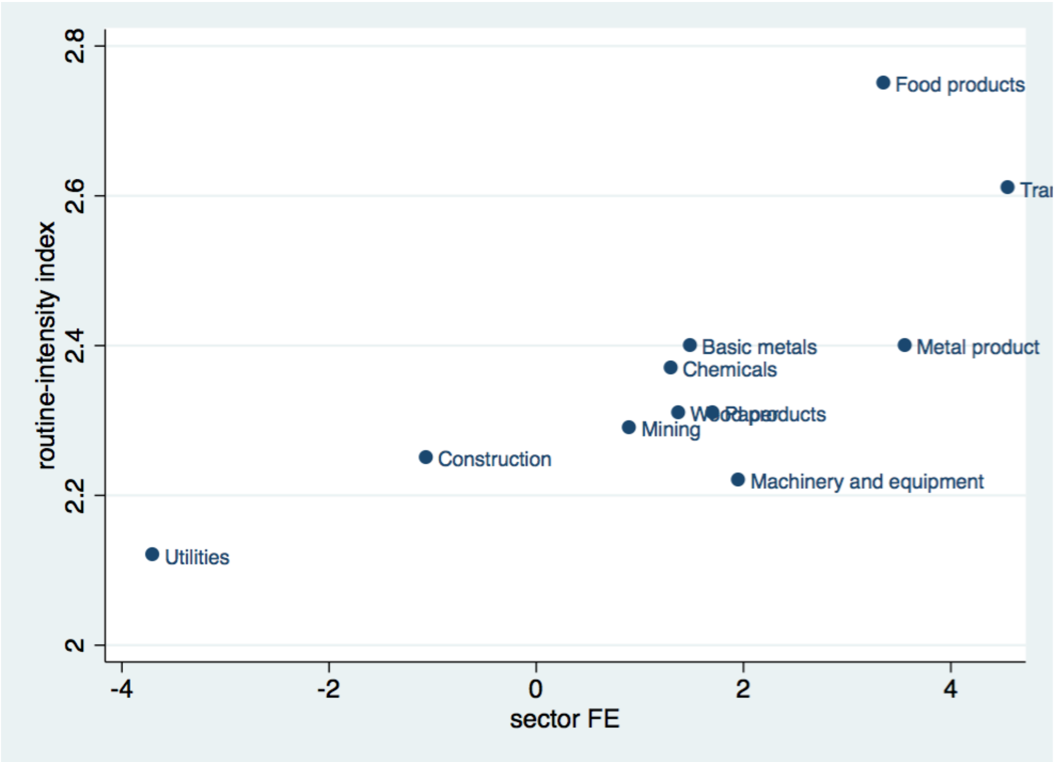

Figure 10: Correlation between survey-based proxies of routine intensity, from Marcolin et al. (2016), and estimated sector-dummies.