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Institutions, Holdup and Automation

Abstract

This paper documents a positive relationship between labor-friendly institutions and investment in industrial robots in a sample of advanced economies. Institutions explain a substantial proportion of cross-country variation in automation. The relationship between institutions and robots is stronger in sunk cost-intensive industries, where producers are more vulnerable to holdup. This suggests that automation is used by producers as a tool to thwart rent appropriation by labor.

JEL-Codes: O330, O430, O570, J500.

Keywords: automation, robots, holdup, institutions, unions, sunk costs, appropriability, bargaining, frictions, rents, technology adoption.

Giorgio Presidente
World Bank
Jakarta / Indonesia
giopresidente@gmail.com

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1 Introduction

Adoption of industrial robots within narrowly defined industries differs widely across advanced countries. For instance, in 2013 the number of robots per thousand employees in manufacturing of motor vehicles was almost 100 in France and Japan, 70 in Italy and 40 in the United States. Such countries have similar levels of economic development and equal access to international markets. Therefore, differences in adoption are unlikely to be due to robots' price differences. One potential explanation is that adoption lags are due to the presence of frictions, which lower the expected returns on automation and discourage firms from undertaking an otherwise profitable investment. An alternative explanation, however, is that automation is *driven*, rather than discouraged by frictions. Consistent with such a view, the main contribution of this paper is documenting a positive relationship between institutions increasing the bargaining power of labor and investment in industrial robots for a sample of OECD economies. The theoretical underpinning of the result is simple. By shifting bargaining power in favor of workers, certain labor institutions increase employers' costs, thus providing incentives to substitute workers with robots.

The literature has focused on demographic change as the main driver of investment in industrial robots (Acemoglu and Restrepo, 2018a). This paper looks at another potential driver, namely "labor-friendly" institutions: i) constitutional provisions on workers' rights, ii) the strength of employees' representation in industrial relations, and iii) trade unions. Indeed, countries with stronger institutional protection of workers' rights, centralised bargaining systems and higher unionisation rates are shown to use more robots per worker. The findings of this paper suggests that institutional factors might be at least as important as demographics in explaining automation. Differences in institutions predict 30% of variation in the number of robots per worker in use in the OECD region, a percentage three times larger than the contribution of demographic trends.

The empirical methodology developed in this paper is based on the following idea. If labor-friendly institutions induce automation because they increase labor costs, then the relationship between institutions and robots should be stronger in industries characterised by large sunk costs, where producers are more vulnerable to holdup.[1] A case in point is the motor vehicles industry, in which both suppliers of components and assemblers need specialised equipment that has little scope for utilisation outside the industry.[2]

[1] Holdup arises when a fraction of the returns on an agent's relationship-specific investment is ex post appropriable by one of the contracting parties.

[2] Examples include pressing and cutting machines to stamp autos' bodies.

Specificity results in sunk costs for producers, because it makes hard to find an alternative use of capital and fully recover the cost of investment if production does not take place. In turn, sunk costs increase the share of value added firms are willing to give up to labor for keeping capital engaged in production. It follows that institutions increasing the bargaining power of labor should increase labor costs more in industries such as Motor Vehicles, which indeed is highly automated in countries with labor-friendly institutions.

The estimates suggest that labor institutions have a substantial impact on on robots' adoption. For instance, countries with constitutional provisions on labor use 5 robots per thousand employees more than countries without constitutional provisions. On average across all industries, that corresponds to the difference between the median (United Kingdom) and the 90th percentile (Denmark) of the sample distribution. Moreover, due to the presence of holdup, the impact of labor-friendly institutions on automation grows by as much as 20% in sunk cost-intensive industries.

In previous work, Acemoglu and Restrepo (2018a) provide some evidence of a positive correlation between union membership and investment in robots. However, this is the first paper considering a wide range of narrowly-defined institutions and undertaking a systematic evaluation of their impact on automation. This paper is also related to the literature on labor regulation and technology adoption (e.g. Alesina, Battisti, and Zeira, 2018; Cette, Lopez, and Mairesse, 2016; Autor, Kerr, and Kugler 2007; Caballero and Hammour, 1997). However, previous work proxies technology adoption with capital accumulation and it does not distinguish between automation equipment and other categories of assets. The results of this paper suggest that due to holdup, labor-friendly institutions should encourage investment in automation, while discouraging accumulation of labor-complementing capital.[3] Thus, using aggregate capital as a measure of technology adoption can be seriously misleading. This paper overcomes the issue by exploiting data on shipments of industrial robots - a narrowly defined class of automation technology, which allows to disentangle the impact of institutions in shaping incentives to invest in labor-saving technology *vis-à-vis* other categories of assets.[4]

The rest of the paper is organised as follows. Section 2 describes the data; Section 3 introduces the main ideas explored in the paper; Section 4 discusses the empirical methodology and presents the results. Section 5 concludes.

[3] Cardullo, Conti, and Sulis (2015) provide evidence that unions lower investment per worker.

[4] The same data on shipments of industrial robots have been used by Graetz and Michaels (2018), and Acemoglu and Restrepo (2018a; 2017)

2 Data

The panel used in this paper includes 35 OECD countries and 18 two-digits industries from 1993 to 2013. The dataset is constructed from multiple sources, which are described in this section. The details on variables' construction can be found in the Section A of the appendix.

Data on shipments of industrial robots are obtained from the International Federation of Robotics (IFR), which collects data from each national robotics association. Since almost all robots suppliers are members of national associations, the dataset includes virtually all robots used worldwide. An advantage of the data is that the IFR has a common protocol to count robots, so that it ensures consistency across countries and years. Information is available for each country, 2 digits industry and year. A potential issue of the IRF data is that shipments are counted in "units". Therefore, in the paper robots are assumed to have a similar impact irrespectively of their size or complexity. Data on shipments are used to construct the stock of operational robots in each country-industry-year cell.

Data on legal characteristics concerning labor are taken from Adams, Bishop, and Deakin (2016). The first group of variables includes measures describing the extent of constitutional protection of the rights to form unions, to bargain collectively and to strike.[5] The second group of variable measures the extent in which closed shops are allowed, union agreements extend to non-union firms in the same industry or economy-wide, and whether workers have power of co-decision making with the management. All such variables vary at the country-year level and take values between 0 and 1 to reflect gradations in their lexicometric score.[6] Higher values correspond to stronger protection of rights (e.g. 1 if right to unionise is explicitly granted by the Constitution), or stronger employee representation (e.g. 0.5 if pre-entry closed shops are prohibited but post-entry closed shops are permitted). The analysis will employ two synthetic indexes of "labor-friendliness". The first one measures the constitutional protection of labor rights by taking a simple average of the variables measuring: i) the constitutional protection of the right to form trade unions; ii) the constitutional protection of the right to be represented in collective bargaining, and iii) the constitutional protection of the right to strike. The second index measures the strength of employees' representation in industrial relations and it is constructed as the simple average of the variable measuring: i) the constitutional protection of the right to form trade unions; ii) the constitutional

[5] One exception is the United Kingdom. The UK does not have a codified constitution, however, public policy since the late nineteenth century unambiguously recognised union formation.

[6] See Section A of the appendix for more details.

protection of the right to be represented in collective bargaining; iii) whether closed shops are allowed; iv) whether unions agreements extend to non-union firms, and v) whether workers have power of co-decision with the management.

Data on unionisation are taken from Visser (2015) and Armingeon, et al. (2013). Two measures of unions' incidence are considered: union density - net union membership as a proportion wage and salary earners in employment, and union coverage - employees covered by collective bargaining agreements as a proportion of all wage and salary earners in employment with the right to bargain. Union density and union coverage vary at the country-year level.[7]

The proxy of industry-level sunk costs are computed from data on second-hand capital expenditure by industry, from US Census Bureau. The idea underlying the construction of the proxy is the following.[8] When investment is irreversible, firms should rely less on second-hand capital markets. Therefore, in such industries the share of second-hand capital should be lower. The main proxy of sunk cost-intensity is then the inverse share of second-hand capital in each 2 digits-industry. An alternative proxy of sunk costs used in this paper is simply the industry-level share of gross fixed investment in total output.[9] The indicator is constructed combining data from STAN and the NBER-CES Manufacturing Database.[10]

2.1 A First Look at The Data

There are large differences in adoption of industrial robots in the OECD region, even across countries with similar levels of per capita income. In the motor vehicles industry, which alone accounts for almost half of the total robots usage in the OECD region, the number of robots per thousand employees, henceforth "robot density", is 5 in Ireland, 40 in the Netherlands and roughly 100 in Belgium, Korea, France, and Japan. In 2013, the United States used 10 robots per thousand employees less than Italy and 20 less than Germany and Spain. Such heterogeneity is not limited to Motor vehicles and it is even more extreme in other industries, such as electronics' manufacturing. In Electronics, Korea and Japan used almost 80 robots per thousand employees in 2013, against 15 or

[7]In some cases, especially for union coverage, the series are discontinued and so the number of available observations is lower.

[8]The methodology is borrowed from Cardullo, Conti, and Sulis (2015)

[9]Balasubramanian and Sivadasan (2009) discuss different measures of sunk costs used in the literature.

[10]The NBER-CES Manufacturing Database provides 6 digits-level information on gross fixed investment, shipment and inventories. To construct the proxy, first output is constructed summing shipments with the change of inventories. Then, the proxy of sunk costs is obtained dividing gross fixed investment by output, converting NAICS code into ISIC Rev. 4, and taking the median value within each 2 digits-level industries.

less in other OECD economies.

At the same time, countries differ widely in labor institutions. Figure 1 presents the value of the two indexes measuring the constitutional protection of labor rights and the strength of employee representation. There is substantial cross-country variation in such indicators, with Anglo-Saxon countries displaying lower protection of labor compared to other OECD economies. Figures 2 plots union rates over years by country. Union density tends to be higher in Nordic Countries (above 50 percent), but it varies significantly across economies and tends to be declining over time. Union density is below 15 percent in the US, between 20 and 25 percent in Japan, and around 40 percent in Italy. Union coverage tends to be higher than density, due to the impact of collective agreements extending to non-union workers. Union coverage is above 50 percent in most European countries - almost 100 percent in Spain, France and Italy. The United States and Japan have a relatively low union coverage, well below 20 percent.

A crucial difference between the legal characteristics described in the previous paragraph and union rates is their time variation. Legal characteristics are deeply rooted in countries' legislation and so they tend to be very persistent. Figure 1 shows that with the exception of some East-European country, there is only very limited time variation in the indexes. On the contrary, unionisation rates vary substantially between and within countries.

Figure 3 displays the proxy of sunk cost-intensity.[11] Constructions is the less sunk cost-intensive industry, while Motor vehicles and Chemicals are the most sunk cost-intensive. As noticed in the introduction, in Motor vehicles suppliers of components and assemblers use highly specialised equipment that does not have much use outside that industry. Similarly, in the chemical industry refining and processing takes place in large plants and requires heavy equipment. That makes investment practically irreversible and specific to the firm.[12] Such characteristics make capital investment largely irreversible in both industries. In the former, the irreversibility arises for the industry-specificity of the equipment. In the latter, specificity is likely to arise from the large size of the equipment, which makes it hard to move it or ship it. Instead, most of the capital assets used in the construction industry consist in relatively light equipment, and vehicles. In Constructions, virtually no investment is made in buildings, which instead constitute an important category of (at least partially) irreversible investment in other manufacturing industries.

[11] The US Census Bureau does not report information for the agricultural sector and Repair and installation.

[12] Cement kilns, which are hundreds of meters long, are one example of large-scale machinery used in chemical manufacturing.

3 Institutions, Holdup and Automation

This section introduces the main ideas discussed in the paper. It also provides descriptive evidence in support of the hypothesis that institutions shifting bargaining power in favor of labor induce investment in industrial automation.

The large differences in robots investment described in Section 2.1 are unlikely to be due to robot-price differences, as OECD countries are similarly well integrated in international markets.[13] The standard explanation for cross-country differences in technology adoption is the presence of frictions. Examples include lack of education (Nelson and Phelps, 1966), organisational capital (Brynjolfsson and Hitt, 2000; Brynjolfsson, Rock, and Syverson, 2017), credit constraints (Parente and Prescott, 1994), or labor market rigidities (Bartelsman, Gautier, and De Wind, 2016). However, a first look at the data suggests that the view according to which frictions are responsible for countries to "lag behind" in terms of adoption might be inappropriate for industrial robots. Figure 4 presents the number of industrial robots per thousand employees in manufacturing in 2013, relative to the United States. While considered the most innovative country in the world and an efficiency benchmark in comparative macroeconomic studies, the United States uses less robots than most other OECD economies.

Motivated by the wide heterogeneity of institutions across OECD countries, this paper investigates whether differences in labor market institutions can explain the differences in robots adoption found in the data. The descriptive evidence is consistent with such a hypothesis. The top panel of Figure 5 depicts the relationship between the 1995-2015 change in the number of robots per thousand workers and the 1993 union membership rate.[14] The figure shows that countries with higher union membership adopted a larger number of robot per worker over the period considered. The central panel of Figure 5 displays the correlation between the change in robots' adoption over the same period and the 1993 value of an index of constitutional protection of labor rights. Again we observe a positive relation between institutions and automation. Constitutional provisions can heavily affect labor bargaining power. For instance, in the US where the right to collective bargaining is not granted by Constitution, workers need to follow costly and time-consuming procedures in order to join a trade union and be represented in wage negotiations.[15] On the contrary, in most European countries with

[13] Robot price trends have been documented in Graetz and Michaels (2018)

[14] Each dot in the figure represents the country-average residual from a regression of long-run differences in robots per worker on the explanatory variables, after partialling out the impact of the 1993 stock of robots per worker, economic and demographic variables.

[15] To join a union, workers must either be given voluntary recognition from their employer or have a

constitutional provisions, employers cannot refuse to engage in collective bargaining. In such countries, workers benefit of stronger representation and are more likely to obtain higher wage, or to win industrial disputes.[16] Therefore, strong unions or a legal environment improving the bargaining position of workers should increase employers' labor costs, thereby creating incentives to invest in automation. According to such a view, countries in which functional income is biased toward labor should automate the most, because producers have greater incentives to redistribute rents from labor to capital. The relationship depicted in the bottom panel of Figure 5 supports the hypothesis. Countries with higher labor shares in 1993 experienced a larger increase in adoption of robots. Thus, the descriptive evidence presented so far suggests that investment in automation is at least partially driven by an attempt to redistribute rents from labor to capital.

The remaining part of this section presents two concepts that will allow to further refine the identification strategy, so to provide a stronger test for the relationship between institutions and automation.

3.1 Sunk Costs and Rent Appropriability

When producers make *ex ante* irreversible investment and wages are negotiated *ex post*, workers are in a position to extract rents from the production relationship, creating a problem of *holdup*.[17] Appropriability arises because at the time of wage negotiation, investment is sunk for producers. Thus, labor-friendly institutions should increase labor costs more in sunk cost-intensive industries, thereby providing strong incentives to invest in automation. The following simple example can be useful to clarify the idea.

Consider the case in which a producer builds a plant and purchases machinery *before* hiring workers.[18] If investment is irreversible, the cost of capital is sunk at the moment of

majority of workers in a bargaining unit (e.g. the plant or department) vote for union representation. To win representation, in a first stage at least 30% of employees need to give written support. Then, after 90 days a secret ballot election is conducted and representation is certified if a simple majority of the employees is in favor. If majority is not reached, the National Labor Relations Act allows workers to form a minority-union, which represents the rights of only those members who choose to join. However, the employer does not have the legal obligation to recognise minority-unions as a collective bargaining agent, which limits considerably their power.

[16] One example is a dispute between a private airline company and a trade union in Ireland (Ryanair Limited v Labour Court & Impact, 2007). In that occasion, the Supreme court ruled that while the employer was obliged by Constitution to recognise the pilots' trade union, it had no legal obligation to recognise its role in collective bargaining.

[17] E.g. Grout (1984), and Hart and Moore (1988).

[18] There are different ways to rationalise the timing assumption. One is considering that building a factory might take time and often it requires an upfront payments from the producer. In a typical situation, workers would not be hired before everything is ready for production. Another interpretation is that matching is frictional and investment must be sunk before workers and firms meet (Acemoglu

hiring, i.e. cannot be recovered if production does not take place. Anticipating that the initial investment would be lost if they refuse to provide their services, workers *hold up* the producer by demanding higher wages. The larger the sunk costs, the larger the rent labor can appropriate. For instance, let the initial investment for plants and equipment be k. Let $\sigma \in [0,1]$ be the fraction of capital lost if production does not take place. Then, a fraction of investment σk is sunk at the moment of hiring and so the outside option for the producer is $-\sigma k$. If instead production does take place, the producer earns $y - w$, where y is the value of production and w labor compensation. Thus, the net value of engaging in production for producers is $y - w + \sigma k$, which is increasing in the sunk cost-intensity σ.

However, the extent to which labor is able to extract rents depends on labor bargaining power. To see this, let $\beta \in [0,1]$ represent labor bargaining power. Assuming that wages are negotiated through Nash Bargaining and that the outside option of workers is zero for simplicity, the bargained wage is given by

$$w = \beta\big[y - k(1-\sigma)\big] \tag{1}$$

Equation (1) implies that the wage' cross derivative with respect to bargaining power and sunk cost intensity is $w''_{\beta\sigma} = k > 0$. Therefore, an increase in bargaining power provides stronger incentives to automate in sunk cost-intensive industries. That is the basic idea on which Section 4.2 of the identification strategy builds upon. Section B of the appendix shows that under plausible parameter values, the positive relation between wages, bargaining power and sunk costs continues to hold in a slightly richer model in which investment responds to changes in bargaining power.

Turning back to the descriptive evidence, consistent with the hypothesis on which identification is based, the data show that automation and sunk costs are indeed related. Figure 6 displays on the horizontal axis the proxy of sunk cost-intensity and on the vertical axis the log number of industrial robots per thousand employees in 2013. Each dot in the chart represents a two digits-industry. There is a clear positive correlation between industry-level sunk costs and automation.

3.2 Institutions, Holdup and Aggregate Capital

Since several previous studies have used aggregate capital as a proxy of technology adoption, it is useful to discuss how industrial robots differ from other categories of

and Shimer, 1999). The third possible interpretation of the assumption is that it captures the fact that wages are periodically re-negotiated between firms and workers.

assets.

Industrial robot are defined by ISO 8373:2012 as *an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.* As any other piece of machinery and equipment, industrial robots are included in accounts of aggregate capital.[19] However, the definition of industrial robots suggests that they differ in one fundamental dimension from most other categories of capital equipment: they are autonomous, reprogrammable and have a high degree of physical dexterity. Therefore, robots are characterised by a high degree of substitutability with human labor, i.e. they are labor-saving technologies.[20]

In line with the holdup literature, Cardullo, Conti, and Sulis (2015) show that institutions increasing the bargaining power of labor should discourage capital accumulation, because a fraction of the returns on investment are appropriated by labor through higher wages. However, the crucial assumption for their argument is that capital and labor are complementary factors of production. Indeed, most categories of assets are characterised by some degree of complementarity with labor.[21] But if capital *substitutes* labor, as for the case of robots, every dollar of investment in labor-saving technology reduces the dependency from human workers by lowering their marginal product (Acemoglu, 2010). It follows that the relationship between labor-friendly institutions and investment should have opposite signs for robots and aggregate capital.[22] Theoretical arguments for such a negative relationship are provided in Section B of the appendix.

Figure 7 presents descriptive evidence supporting the idea. The horizontal axis shows the proxy of sunk cost-intensity, while each dot represents the difference in the log-number of robots per employee (top panel) and capital per employee (bottom panel)

[19]The industrial classification ISIC rev. 4 includes robots in *28- Machinery and Equipment n.e.c.* There is no specific category for industrial robots. For instance, robots with applications related to handling materials are classified under *2816 - manufacture of lifting and handling equipment.*

[20]Autor, Levy, and Murnane (2001) introduce the idea that routine-manual tasks are the easiest to automate, because they can be codified in instructions that can be performed by machines.

[21]Buildings, (non-autonomous) vehicles and the vast majority of machine tools are examples of labor-complementing capital. Estimates from different countries and levels of aggregation suggest that indeed the elasticity of substitution between aggregate capital and labor is generally less then unity (see Klump et al., 2007).

[22]Strictly speaking, one should consider the difference between robots and non-robots capital. Unfortunately, such measures are not available. Neither are the appropriate price indexes for robots, which would allow to detract their value from the aggregate capital stock. However, robots account for a very small percentage of the aggregate capital stock. For instance, US 6 digits-level industry data include industrial robots in NAICS *33351 Metalworking Machinery Manufacturing.* The industry includes power-driven hand tools, welding and soldering equipment, and industrial robots. The share of value added of the *whole* 6 digits industry in total manufacturing is just 3.4%.

between countries with high and low union density.[23] The top panel of the figure shows that the relationship is increasing for robots.[24] Being highly substitutable for human labor, robots are more intensely adopted in country-industries where the holdup is more severe. As expected, however, the bottom panel of Figure 7 shows that the relationship is decreasing for capital. Most assets composing the aggregate capital stock complement labor and so investment is lower in country-industries characterised by severe holdup.

4 Empirical Methodology and Results

4.1 Labor Institutions and Cross-country Differences in Automation

What proportion of cross-country differences in automation can be explained by differences in labor institutions? What is the relative importance of institutions and demographics in explaining automation?[25] This section aims at answering these questions.

One way to assess the contribution of labor institutions to explain cross-country differences in robot density is calculating the following quantity,

$$\Delta R2^{inst} = \left[1 - \frac{R2^{noinst}}{R2^{inst}}\right] \times 100 \tag{2}$$

where $R2^{inst}$ is the adjusted-R2 of a model which includes institutions and $R2^{noinst}$ is the adjusted-R2 of the same model without institutions. Analogous calculation can be used to compute the contribution of population ageing. Table 1 presents the models used for the comparison, the respective R2, and the contributions of institutions and ageing calculated as in (2). The dependent variable R_{ct} is the country-wide number of industrial robots per thousand workers. The variable $Inst_{ct}$ is the strength of employees' representation;[26] $Ageing_c$ is the log-difference of the ratios of population aged 55 and above to population aged 20 to 54 in 1990 and 2025, from the United Nations Population Forecasts. The vector X_{ct} includes the base-year value interacted with year dummies of: i) log-GDP per capita; ii) log-total population, and iii) average years of schooling.[27] The

[23] High union density countries have more than 34% net union membership, corresponding to the mean of the variable in the sample.

[24] Each dot in the chart represents the residuals of a regression of the dependent variable on base year country covariates interacted with year fixed effects, plus initial country-industry values of the dependent variables interacted with year dummies. Regressions are weighted by the country-industry share of employment in the base year.

[25] Acemoglu and Restrepo (2018a) argue that demographic trends are important drivers of investment in industrial robots.

[26] Similar results are obtained by using alternative institutional variables.

[27] Total employment, GDP at constant prices, and total population are taken from the Penn World Tables 9.1. Average years of schooling are taken from the Barro-Lee dataset.

Table 1: Explanatory power of institutional and demographic variables.

Reference model	$R2$	ΔR^{inst}	ΔR^{age}	ΔR^{both}
$R_{ct} = \beta_0 + \beta_1 Inst_{ct} + \beta_2 Ageing_c + BX_{ct} + \varepsilon_{ct}$	0.57	–	–	–
$R_{ct} = \beta_0 + \beta_2 Ageing_c + BX_{ct} + \varepsilon_{ct}$	0.40	30%	–	–
$R_{ct} = \beta_0 + \beta_1 Inst_{ct} + BX_{ct} + \varepsilon_{ct}$	0.52	–	9%	–
$R_{ct} = \beta_0 + BX_{ct} + \varepsilon_{ct}$	0.26	50%	35%	54%

The table presents the adjusted-R2 of each model and the contribution of institutions and demographic variables to each model's R2. The quantities in the last three columns are computed with the formula $\Delta R2^{var} = \left[1 - \frac{R^X}{R^{var}}\right] \times 100$, where R^{var} is the R2 of the reference model and R^X is the R2 of the same model without the variable var. The coefficients of each model are computed by OLS. The dependent variable is the country-wide number of industrial robots per thousand workers. The variable $Inst$ is an index measuring the strength of employees representation in industrial relations. The variable $Ageing$ represents expected ageing between 1990 and 2025. It is constructed by first computing the ratios of population aged 55 and above, to population aged 20 to 54 - in 1990 and 2025, and then taking the log-difference. All specifications include the base-year value interacted with year dummies of: i) log-GDP per capita; ii) log-total population, and iii) average years of schooling. Standard errors are robust against heteroscedasticity.

error term is represented by ε_{ct}. The β coefficients are estimated with OLS and standard errors are robust against heteroscedasticity. Table C1 of the appendix presents the estimation results and shows that there is a striking correlation between labor-friendly institution and adoption of industrial robots at the country level. The coefficients are positive and significant for all variables considered and results are robust to a number of different specifications, which are discussed in Section C.1 of the appendix.

The results in Table 1 show that institutions explain a substantial share of variation in automation across OECD economies ($\Delta R2^{inst} = 30\%$). Demographics seems a less important driver of automation than institutions ($\Delta R2^{age} = 9\%$). In a sample of advanced and developing economies, Acemoglu and Restrepo (2018a) find a much higher contribution of demographics in explaining automation, i.e. a partial R2 for the ageing variable equal to 40%. However, by ignoring labor institutions Acemoglu and Restrepo (2018a) might be overestimating the impact of ageing. Indeed, the last row of Table 1 suggests that the contributions of both variables are substantially higher when excluding the other ($\Delta R2^{inst} = 50\%$ and $\Delta R2^{age} = 35\%$).[28] Finally, Table 1 shows that together, institutions and demographic trends account for 54% of the total sample variation in the number of robots per thousand workers.

[28] Another potential explanation for such a difference is that demographic factors are more important drivers of automation in developing than advanced countries. However, that seems counterintuitive because rich countries are known to age more rapidly than less developed ones. To the extent that scarcity of middle-aged workers rises wages, the contribution of ageing in explaining automation should be larger in a sample of OECD economies.

4.2 Legal Characteristics, Holdup and Automation

This section exploits country and industry variation in robot density to explore the specific mechanism through which legal characteristics of the labor market might affect automation. Based on the arguments presented in Section 3.1, labor-friendly institutions should increase automation more in industries characterised by large sunk costs, where holdup is more severe and workers can extract higher rents from the production relationship. The empirical specification used to test such a hypothesis is

$$R_{cit} = \gamma_0 + \gamma_1 Inst_{ct} + \gamma_2 (Inst_{ct} \times \sigma_i) + BX_{ct} + u_{it} + \varepsilon_{cit} \tag{3}$$

The dependent variable in (3) is the number of industrial robots per thousand employees in every two digits industry.[29] The industry-level measure of sunk costs is σ_i. The vector X_{ct} includes the base year country covariates of Table 1, plus the ageing variable and an index of strictness of dismissal regulation.[30] The latter variable is included to account for the possibility that high firing costs might result in producers being reluctant to dismiss workers and replace them with machines. Since countries with labor-friendly institutions might also have strict dismissal regulations, failing to control for the strictness of dismissal regulation risks to underestimate the estimated coefficients. In (3), u_{it} represents industry-year fixed effects and ε_{cit} is the error term. All estimates are weighted by the base year industry share of employment in each country.[31]

The coefficients of interest in (3) are γ_1 and γ_2: the former qualifies the main effect of institutions, while the latter their differential impact in industries characterised by varying levels of sunk costs. The variable σ_i is computed from US data in 1994, which is then set as the base year and dropped from the estimation.[32] This is done to minimise the possibility of institutions themselves affecting industry-level investment, which would contaminate the proxy of sunk costs. In the United States, regulatory frictions are minimal and so the proxy is more likely to be purely determined by industry-specific technological characteristics, which should be common to all countries in the OECD region.[33] Finally, σ_i is normalised to have zero mean and standard deviation equal to

[29] The number of employees per thousand worker in every country, industry and year is taken from the OECD database STAN.

[30] The index of dismissal regulation is taken from Adams, Bishop, and Deakin (2016) and it takes values between 0 and 1, with higher values represent stricter dismissal regulation.

[31] The same weighting scheme is used in Graetz and Michaels (2018) and Acemoglu and Restrepo (2018a).

[32] Although data on robots and institutions are available from 1993, the US Census Bureau provides the series on second-hand capital expenditure from 1994 only.

[33] Robustness tests show that results are unchanged when experimenting with an alternative proxy of sunk costs and a different identification strategy.

1 in the weighted sample. Therefore, γ_2 measures the differential impact of institutions in industries one standard deviation above the average sunk cost intensity (henceforth, "sunk cost-intensive" industries).

Table 2 shows OLS estimates of γ_1 and γ_2, which are positive and significant for all the institutions considered. The magnitude of the impact is substantial. For instance, the estimates in column 7 suggest that countries with constitutional provisions on labor use more than five additional robots per thousand employees. On average across industries, that is the difference between the sample median (United Kingdom) and the 90th percentile (Denmark) of the distribution of robot density. Moreover, Table 2 shows that the impact of institutions is even stronger in sunk cost-intensive industries. For instance, the estimates in column 8 imply that the strong representation of employees entails an increase in automation 20% higher in sunk cost-intensive industries. That corresponds to almost eight additional robots per thousand employees, roughly the difference in robot density between Korea and the United States.[34] Therefore, the evidence is consistent with the hypothesis that labor-friendly institutions induce automation by allowing workers to extract rents. Rent extraction is easier in industries characterised by large sunk costs, where workers can hold up the producer. The bottom row of Table 2 reports the coefficients for the index of dismissal regulation. The negative and significant impact might reflect the high cost of dismissing workers in case of displacement, which reduces producers' incentive to invest in automation.

A battery of tests supports the reliability of the estimates in Table 2. First, by exploiting country-industry variation, the specification in (3) allows to include country-year fixed effects.[35] Fixed effects mitigate the concerns of bias arising from the presence of country-specific time-varying unobservable factors, such as demand shocks and other institutional developments. Table C5 of the appendix shows that the interaction coefficient γ_2 is still significant and it increases in size, possibly reflecting the impact of omitted variables that are negatively correlated with robot density. The second robustness test concerns the proxy of sunk cost intensity. As discussed in Section 2, the proxy of sunk costs in Table 2 is based on data from the United States. One concern is that even in a sample of OECD economies, the technological characteristics of the US might not necessarily carry over to less developed economies such as Mexico or Eastern-European countries. Therefore, Table C6 of the appendix presents the results of estimating (3) using an

[34]As expected, the magnitude of the estimated coefficients is larger when exploiting country-industry variation. Being based on economy-wide variables, the estimates in Table C1 are diluted by the presence of the service sector, which does not utilise industrial automation.

[35]Since $Inst_{ct}$ varies at the country-year level, the inclusion of country-year effects precludes the estimation of γ_1.

alternative identification strategy using proxies of sunk costs that are country-specific. The alternative proxy is the 2 digits industry-level gross fixed investment share of total output in the base year. Such quantities are then instrumented with their counterpart in the United States, which is then dropped by the sample prior to estimation. Table C6 shows that using the alternative sunk cost-intensity measure produces results similar to those in Table 2, but with larger coefficients.[36] Importantly, the first stage F statistics is very high in all specifications, suggesting that indeed the technological characteristics of the US carry over to industries in other OECD countries. The third test addresses one implication of the arguments presented in Section 3.2 and the model discussed in Section B. Since most categories of capital assets are complementary to labor, the relationship between aggregate investment and labor-friendly institutions should be negative. The results displayed in Table C7 of the appendix provide support in favor of the hypothesis. In particular, the coefficients show that there is a *negative* relationship between strict institutions and the log of the aggregate capital stock in sunk cost-intensive industries. For instance, columns 7 and 8 suggest that in countries protecting labor rights or with strong employee representation, capital per worker is roughly 15% lower.

4.3 Trade Unions, Holdup and Automation

This section complements the previous analysis by looking at another category of labor market institution: trade unions. By increasing average wages and lowering firms' profitability (Hirsch, 2017; Taschereau-Dumouchel, 2017), unions should create incentives to invest in automation.

The empirical specification used in this section is similar to (3), but it uses union density and union coverage as independent variables. Columns 1 and 2 of Table 3 present the OLS estimates. The coefficients in column 1 are both positive and significant. They imply that a 10% increase in union density - roughly the difference between Germany and the United States - is associated to 0.3 additional robots per thousand employees. The coefficient on the interaction term is also positive and significant, implying that the impact of union density on robot density is roughly 1/6 higher in sunk cost-intensive industries. In column 2, the main effects of union coverage is not significant, but the coefficient on the interaction is positive.

An advantage of using union rates as explanatory variables is that they exhibit substantial between *and* within country variation, which allows to exploit an additional dimension of the data. The drawback of using indicators such as union density and union

[36] The number of observations in Table C6 is lower for two reasons: the US is dropped from the sample, and the NBER-CES dataset includes only manufacturing industries.

coverage, however, is that they might be heavily affected by contemporaneous trends in technology. For instance, automation might weaken unions by reducing membership, or employers might gain bargaining power by threatening to automate. Thus, to mitigate concerns of reverse causality, one possible strategy is finding a variable that is correlated to union density but that is independent on recent technological developments. Botero et al. (2004) show that workers tend to benefit from stronger institutional protection and unions to be more powerful in civil law than in common law systems. Civil and common law systems originated in the 12th century and then they were transplanted to other countries long before the development and commercialisation of automation technologies. Therefore, columns 3 to 6 of Table 3 presents 2SLS estimates in which union rates are instrumented with a dummy taking value 1 if a country has civil law origins and zero otherwise. Instrumenting union rates with countries' legal origins can help mitigate reverse causality, but it does not constitute a panacea against all possible sources of endogeneity. In particular, legal origins might shape countries' characteristics in such a way as to induce automation above and beyond the impact of unions. That being the case, the dummy for civil law origins would violate the exclusion restrictions. The literature on legal origins suggests that common law countries have better legal protection of creditors and shareholders (La Porta et al. 2000; 1999), lower market entry barriers (Djankov et al., 2002), better contract enforcement (Djankov et al., 2003) and more efficient securities laws (La Porta et al. 2006). These factors might influence investment in automation technology.[37] Thus, columns 3 and 4 include indexes of creditor and shareholder protection, product market regulation, contract enforcement and the time needed to cash a bounced check, which is a proxy of the efficiency of securities law.[38] The specification includes additional controls such as the labor rights, employee representation and dismissal regulation indexes used in the previous section, plus the share of parliamentary seats of social democratic and other left parties in government.[39]

Table C8 of the appendix show the first stage regressions of union rates on legal origins. Both coefficients are significant at the 1 percent level and the R2 is above 0.8 in both specifications. The coefficients confirm that countries with civil law origins have higher union membership and union coverage. The 2SLS estimates of the main effects and the interaction terms in columns 3 and 4 of Table 3 are positive and highly significant.

[37]For instance, civil law countries might have lower business dynamism, which affects the kind of products produced by firms and so the set of feasible production techniques.

[38]Indexes on creditor and shareholder protection, contract enforcement and time needed to cash a check are taken from La Porta et al. (2008); the index of product market regulation is taken from the OECD.

[39]The share of parliamentary seats is weighted by the number of days in office in a given year. The variable is taken from Armingeon et al. (2013).

The first stage F statistics is above 10 in both columns, which reassures on the power of the instrument. The size of the 2SLS coefficients is substantially larger than the OLS ones, which lends support to the hypothesis that reverse causality biases downward the OLS coefficients. The estimates in column 3 imply that on average 10 percent higher union density is associated to 1.8 additional robots per thousand employees and 2.6 additional robots in sunk cost-intensive industries. The magnitude of impact is even larger for union coverage (although the power of the instrument is lower than in column 3). A 10% higher coverage is associated to 7.5 additional robots per thousand employees in the average industry. In sunk cost-intensive industries, the number of additional robots is roughly 13, almost the difference between the median and the 95th percentile of the distribution of robot density. Finally, columns 5 and 6 include country-year fixed effects and only estimate the interaction terms. The coefficients on the interactions are very similar to those in columns 3 and 4, which reassures that the observed effects are not driven by countries' industrial composition.

5 Conclusions

This paper documents that in a sample of OECD countries, there is a robust, positive relationship between adoption of industrial robots and labor-friendly institutions, i.e. laws and collective organisations that increase the bargaining power of labor. Results from various specifications lend support to the hypothesis that producers take advantage of technological progress and use automation to minimise the dependency from workers and thwart rent appropriation.

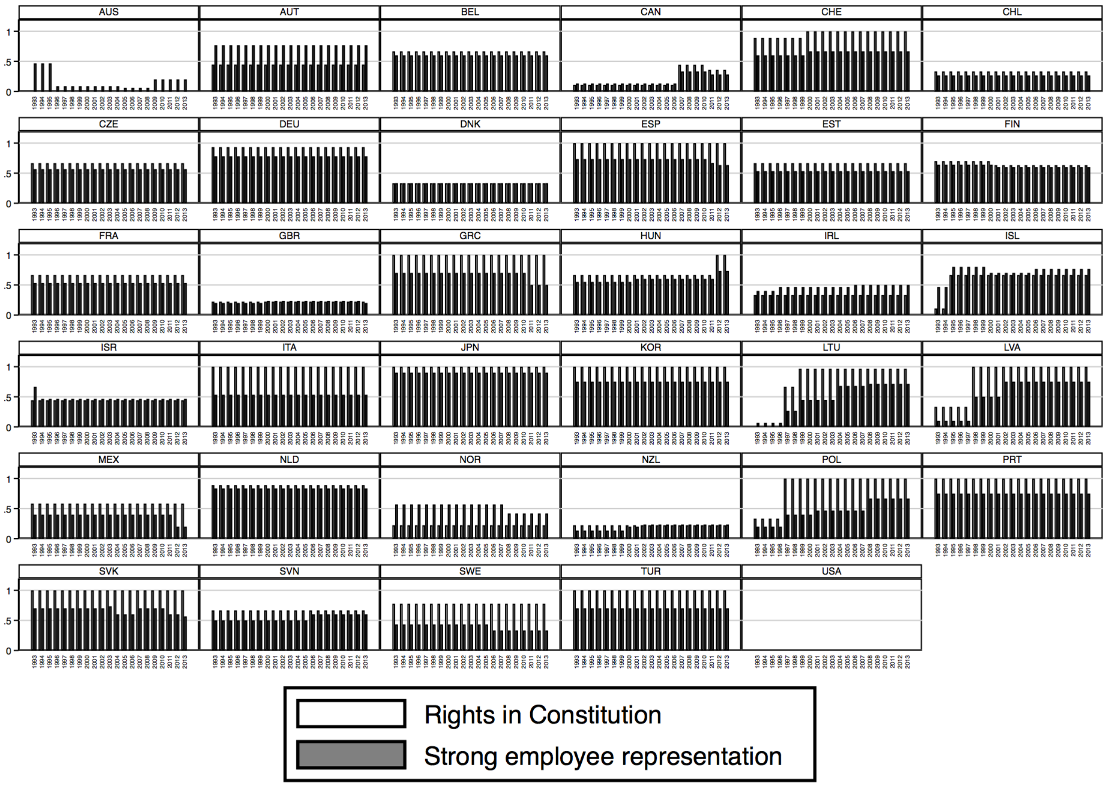
Institutions are found to explain over 30% of the sample variation in adoption of robots, a proportion three times larger than the estimated contribution of demographic trends - to date the only alternative driver of investment in robots considered by the literature. Together, labor institutions and demographic trends account for roughly half of the observed differences in automation; further research is needed to understand what explains the remain variation.

From a theoretical standpoint, rational behavior of individual producers implies that investment in robots must increase the amount of revenue generated for each unit of expenditure on inputs.[40] Thus, policies aimed at incentivising investment in automation seem justified on the grounds that labor-saving technologies increase firms' productivity, which in turn should generate additional investment and stimulate growth. Many advanced economies seem to share this view, as they spend a considerable amount of re-

[40]Such quantity is also referred to as to revenue-total factor productivity.

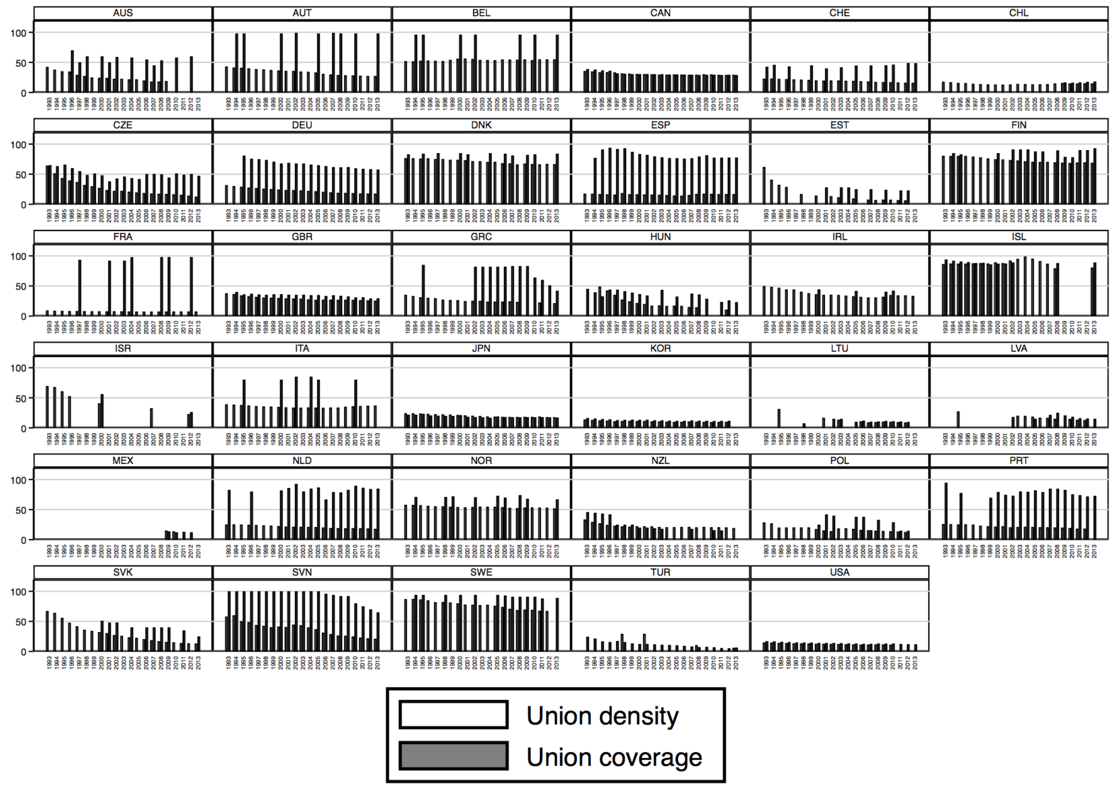
sources to incentivise industrial automation. For instance, *Horizon 2020* is a multibillion fund from the European Union that finances a large number of projects focusing on the development and adoption of industrial automation; in France, *Prêt Robotique* is a loan for medium and small enterprises to finance investment in robots. And yet, the result that labor institutions drive automation casts doubts on the potential impact of policies promoting industrial automation. For instance, countries with flexible labor markets and few robots might simply not *need* automation. In countries with rigid institutions, policies encouraging robot-investment might be beneficial for individual producers, but they could also distort allocations even further and undermine aggregate productivity (Acemoglu and Restrepo, 2018b). Thus, one direction for future research is evaluating alternative policies in a general equilibrium model with endogenous technology adoption and labor market frictions.

Figure 1: Legal characteristics.



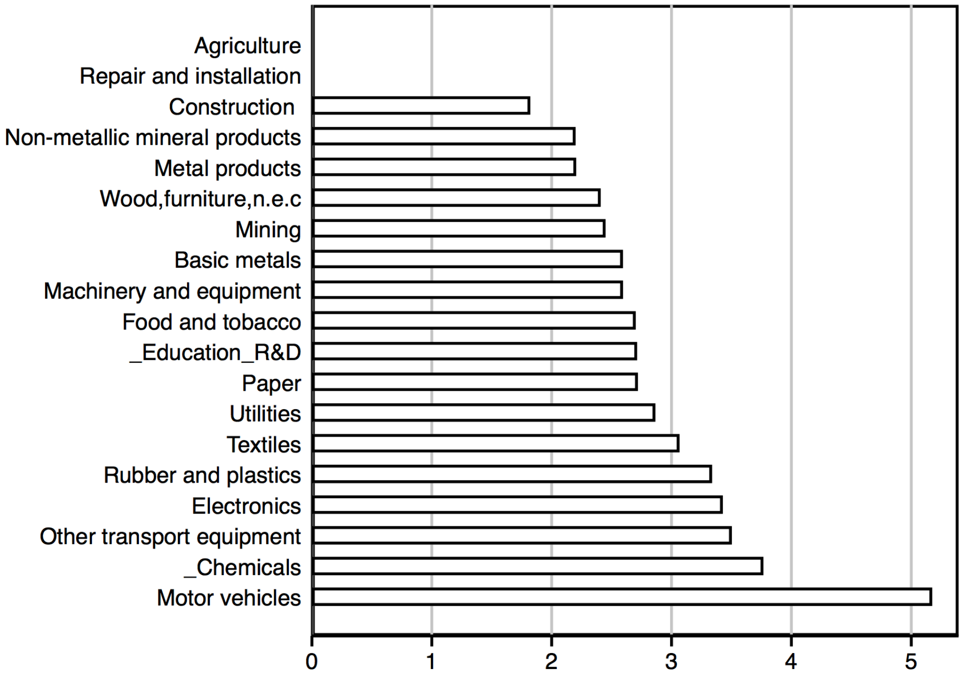
Sources: Adams, Bishop, and Deakin (2016)

Figure 2: Union rates (%).



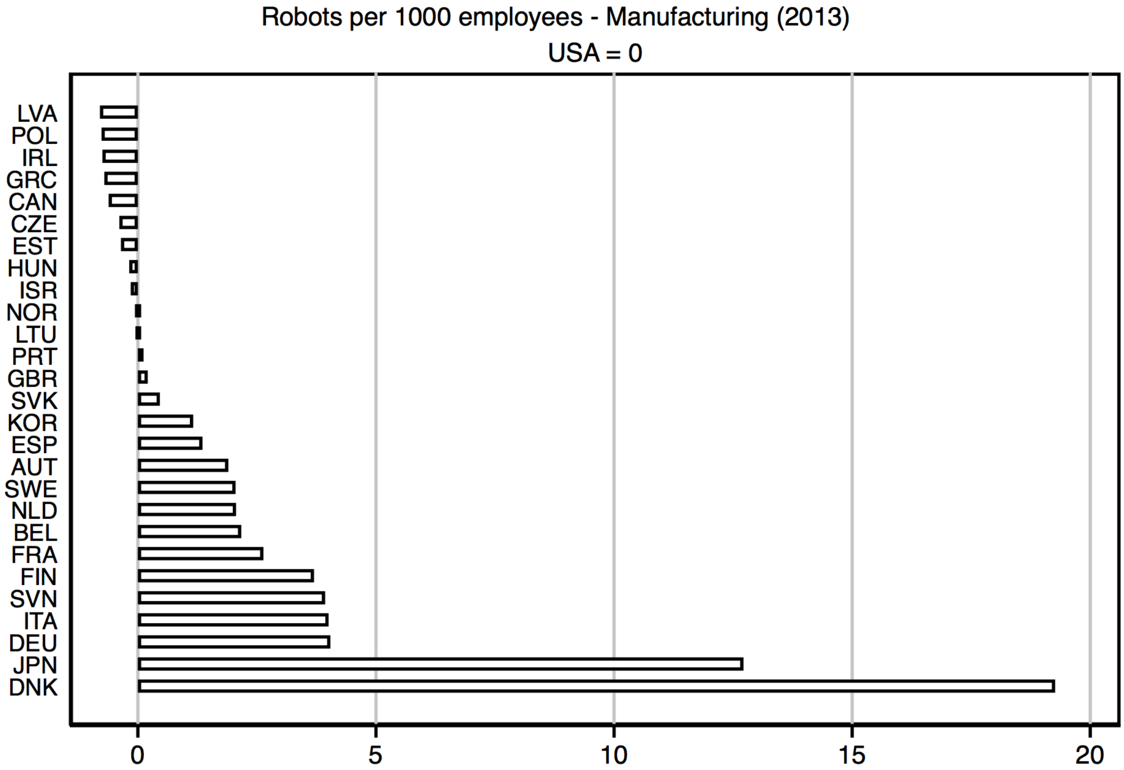
Sources: Visser (2015); Armingeon, et al. (2013)

Figure 3: Proxy of sunk costs. Inverse share of US second-hand capital expenditure in 1994 (logs).



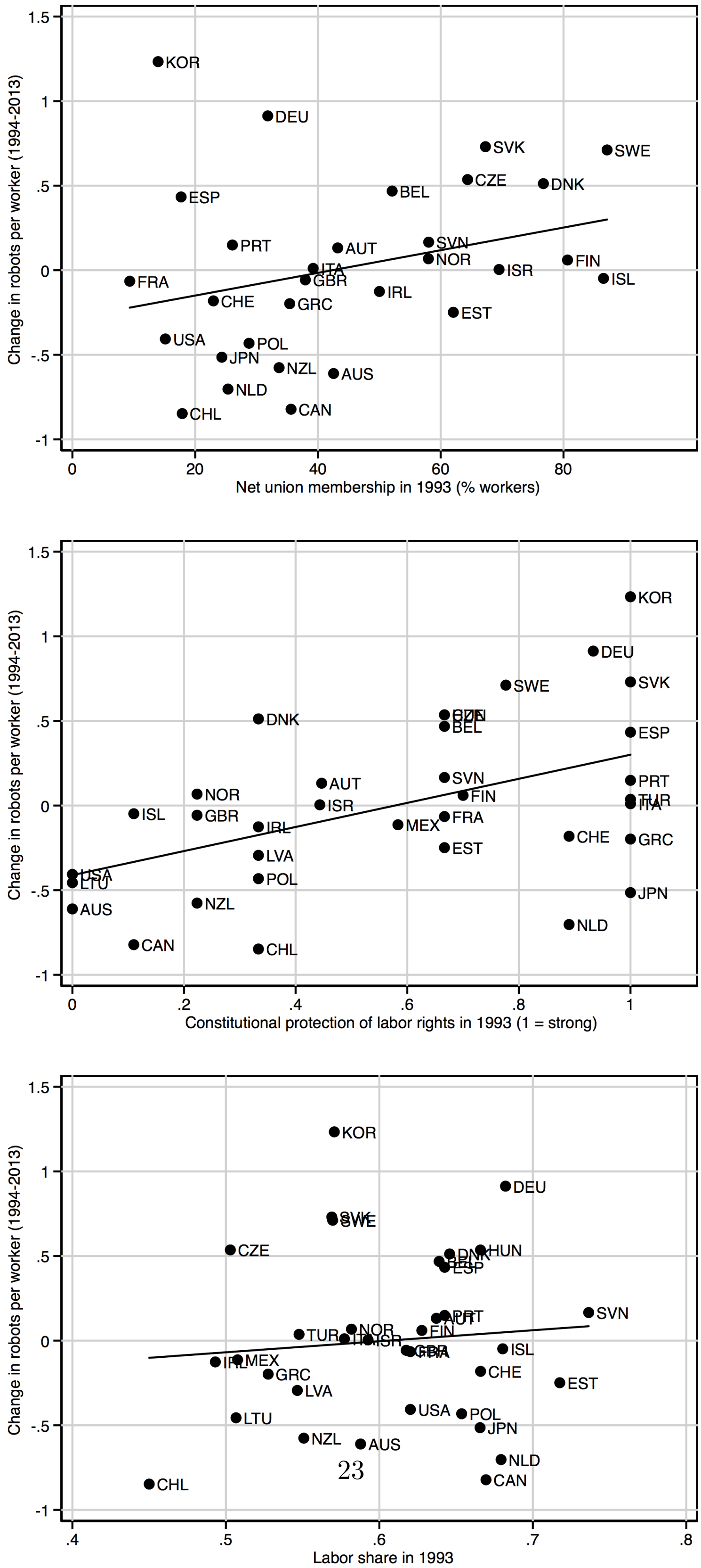
Sources: US Census Bureau

Figure 4: Cross-country differences in adoption of industrial robots.



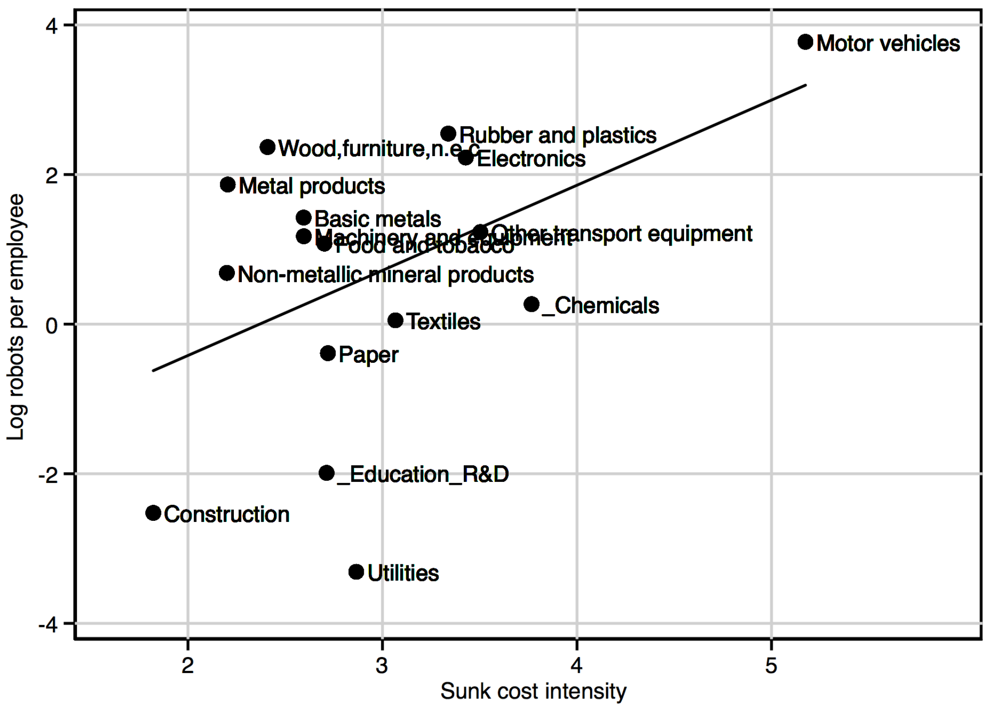
Sources: IFR; STAN

Figure 5: Industrial robots, labor institutions and the labor share.



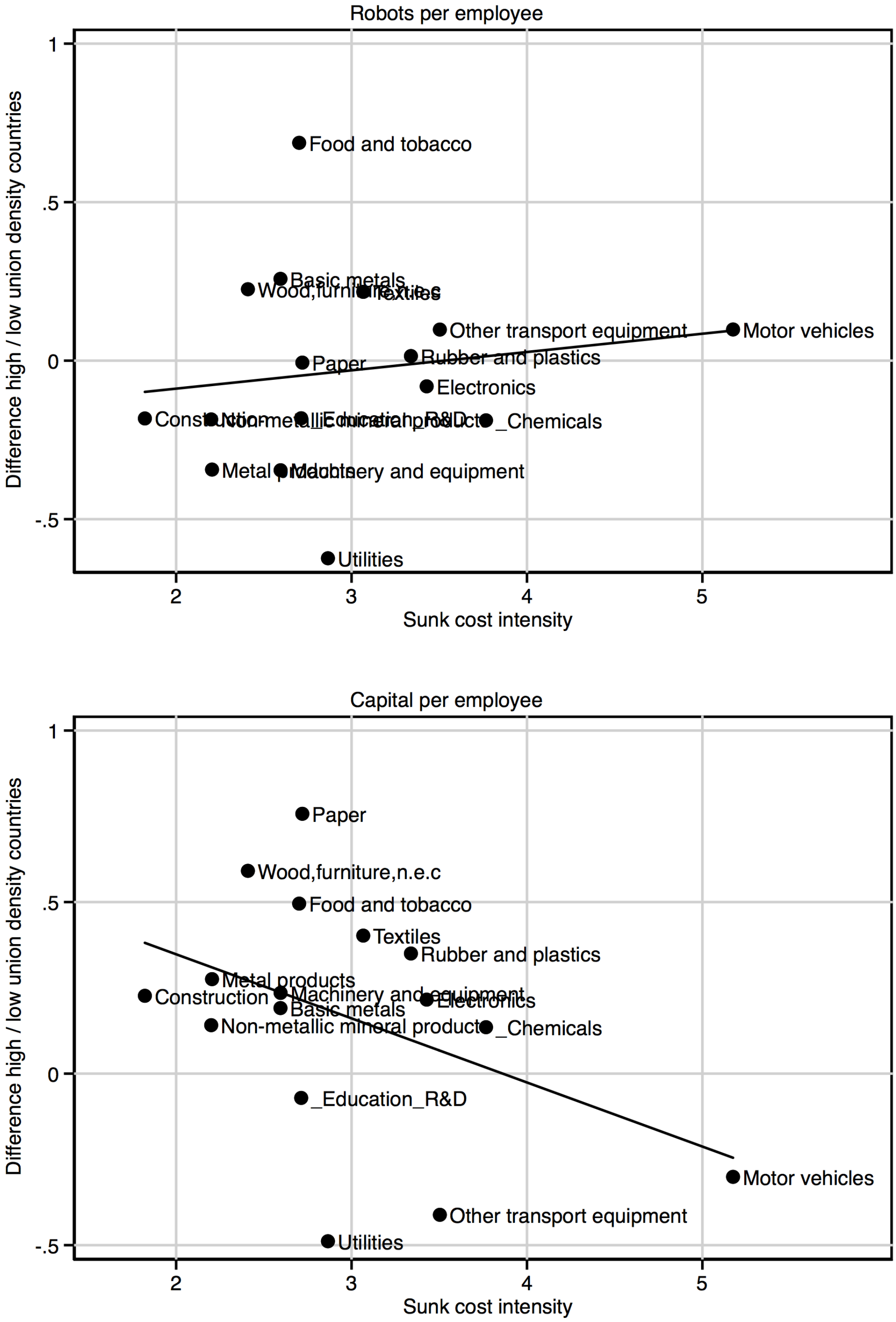
Each dot in the figure represents the country-average residual from a regression of long-run differences in robots per worker on the explanatory variables, after partialling out the impact of the 1993 stock of robots per worker, economic and demographic variables. Sources: IFR; PWT 9.1; Visser (2015); Armingeon, et al. (2013)

Figure 6: Sunk costs and automation (2013).



Sources: IFR; US Census Bureau

Figure 7: Aggregate capital, robots and sunk costs.



Each dot in the chart represents the residuals of a regression of the dependent variable on base year country covariates interacted with year fixed effects, plus initial country-industry values of the dependent variables interacted with year dummies. Regressions are weighted by the country-industry share of employment in the base year. Sources: IFR; PWT 9.1; US Census Bureau

Table 2: OLS estimates of the impact of legal characteristics on country-industry adoption of industrial robots per thousand employees.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	R/L	R/L	R/L	R/L	R/L	R/L	R/L	R/L
i) Right to unionise	4.847***							
	(0.586)							
Right to unionise x sunk cost intensity	0.780***							
	(0.109)							
ii) Right to collective bargaining		1.547***						
		(0.257)						
Right to collective bargaining x sunk cost intensity		0.586***						
		(0.104)						
iii) Right to strike			2.921***					
			(0.322)					
Right to strike x sunk cost intensity			0.520***					
			(0.102)					
iv) Closed shop allowed				4.134***				
				(0.680)				
Closed shops allowed x sunk cost intensity				0.838*				
				(0.429)				
v) Extension of collective agreement					0.829***			
					(0.196)			
Extension collective agreements x sunk cost intensity					1.229***			
					(0.160)			
vi) Co-decision making						0.787**		
						(0.393)		
Co-decision x sunk cost intensity						0.859***		
						(0.138)		
Labor rights in Constitution (i-iii)							5.253***	
							(0.622)	
Labor rights in Constitution x sunk cost intensity							0.483***	
							(0.106)	
Strong employee representation (i-ii,iv-vi)								6.444***
								(0.885)
Strong employee representation x sunk cost intensity								1.176***
								(0.176)
Strict dismissal regulation	-4.501***	-1.890***	-4.815***	-3.488***	-1.084***	-1.940***	-5.026***	-3.728***
	(0.678)	(0.434)	(0.699)	(0.622)	(0.401)	(0.328)	(0.764)	(0.642)
Observations	5,559	5,559	5,559	5,559	5,559	5,559	5,559	5,559
R-squared	0.510	0.501	0.508	0.508	0.507	0.496	0.513	0.515
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-year FE	no	no	no	no	no	no	no	no

The table presents OLS estimates of the relationship between legal characteristics, sunk costs and the adoption of robots. The dependent variable is the country-industry stock of industrial robots per thousand employees. The proxy of sunk cost-intensity is the inverse share of second-hand capital expenditure in a given 2 digits-industry. All specifications include include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with ⋆⋆⋆ are significant at the 1% level, with ⋆⋆ are significant at the 5% level, and with ⋆ are significant at the 10% level.

Table 3: OLS and 2SLS estimates of the impact of union rates on country-industry adoption of industrial robots.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		2SLS			
VARIABLES	R/L	R/L	R/L	R/L	R/L	R/L
Union density	3.254***		18.087***			
	(0.295)		(1.948)			
Union density x sunk cost intensity	0.492*		7.949***		8.129***	
	(0.253)		(1.009)		(1.014)	
Union coverage		-0.653		75.502***		
		(0.571)		(16.254)		
Union coverage x sunk cost intensity		1.468***		5.237***		4.044***
		(0.241)		(0.699)		(0.446)
Creditors' right index			0.123	3.116***		
			(0.109)	(0.970)		
Shareholders' protection index			2.111**	66.908***		
			(0.948)	(16.539)		
Product market regulation			0.839	-2.238		
			(0.654)	(4.023)		
Contract enforcment index			-2.005***	-9.144***		
			(0.341)	(1.679)		
Time to cash a bounced check			-1.146***	5.702***		
			(0.216)	(1.165)		
Labor rights in Constitution			-13.450***	-8.246***		
			(1.767)	(3.036)		
Strong employee representation			21.004***	41.244***		
			(3.018)	(7.133)		
Power of leftist parties			-0.017***	0.089***		
			(0.006)	(0.023)		
Strict dismissal regulation	-1.519***	-0.626	1.225*	-34.965***		
	(0.406)	(0.575)	(0.744)	(4.950)		
Observations	5,418	3,865	4,912	3,429	4,912	3,429
R-squared	0.489	0.480				
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes
Expeccted ageing	yes	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes	yes
Country-year FE	no	no	no	no	yes	yes
First stage F			288.4	14.47	478.5	3440

The table presents OLS and 2SLS estimates of the relationship between unions, sunk costs and adoption of robots. The dependent variable is the country-industry stock of robots per thousand employees. Columns 1 and 2 show to OLS estimates. Columns 3-4 show the 2SLS estimates, in which the dummy for civil law systems is used as an instrument for union rates. All specifications include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

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A Data appendix

A.1 Industrial Robots

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.[41] The resulting shares are used to construct the deliveries by sector. As in Graetz and Michaels (2018), the construction of the stock of operational robots is obtained by assuming a yearly depreciation rate of 10% and applying the perpetual inventory method, using 1993 estimates of the existing stock by the IFR as initial values.[42]

To construct the main dependent variable, the number of robots per thousand workers, IFR data are matched to two other sources. The economy-wide number of robots per worker are constructed using total employment from the Penn World Tables 9.1. For the country-industry analysis, data on robots are matched to the STAN database from the OECD. STAN include information on industry-level employees, output, value added and estimates of the capital stock. Industry-level classification have been converted as to obtain eighteen industries, roughly corresponding to 2 digits-level ISIC rev.4. These are: Agriculture, Food and tobacco, Textiles, Paper, Wood and furniture, Chemicals, Rubber and plastics, Non-metallic mineral products, Basic metals, Metal products, Electronics, Machinery and equipment, Motor vehicles, Other transport equipment, Repair and installation of machinery, Construction, and Education and R&D, and Utilities.

A.2 Construction of the institutional variables in Adams, Bishop, and Deakin (2016)

The original institutional measures used to construct the dummy variables used in this paper are taken from the comparative legal analysis in Adams, Bishop, and Deakin (2016) "CBR Labour Regulation Index - Cambridge Centre for Business Research". Adams, Bishop, and Deakin (2016) apply the leximetric methodology developed by Lele and Siems (2007), and Adams and Deakin (2014).

In a nutshell, the procedure consists in the following steps:

1. identification of a general phenomenon of interest;

[41] I experiment with two alternatives, namely taking simple averages over all the available years and using the observation for the most recent available year. Results are virtually unchanged.

[42] The IFR does provide estimates of the stock, but it adopts a different assumption that robots fully depreciate after twelve years.

2. development of a conceptual construct (regulation or protection);
3. identification of indicators or variables which, singly or together, express the construct in numerical terms;
4. development of a coding algorithm which sets out a series of steps to be taken in assigning numerical values to the primary source material;
5. identification of a measurement scale which is embedded in the algorithm;
6. allocation of weights, where necessary or relevant, to the individual variables or indicators;
7. aggregation of the individual indicators in an index which provides a measure of the phenomenon of interest, to be used in statistical analysis.

Primary sources were retrieved from texts available in law libraries or online, wherever possible in their original language. Alternatively, translated texts where authorised by the government of the country concerned or by an international organisation. Legal rules based on either statutory and case law are examined. The latter are coded in the year in which they comes into force, while the former in the year in which judgments are reported. Administrative regulation and collective agreements are coded in the variables when they are functional equivalents to statutes or court decisions, such as sector-level collective agreements having *erga omnes* effect due to extension legislation. In addition to mandatory rules, the variables include default rules with a reduction in the score to indicate their non-binding nature. For federal states, whenever a law does not operate in a uniform way in a given country, the law for applying to the sub-unit of that state where the most significant firms are based is used instead. The dataset in principle codes for the law as it applies to an indeterminate employment relationship, unless the indicators explicitly refer to a particular type of employment contract. If laws differ in their effects according to the size and location of the enterprise or different groups of workers, the dataset codes for the minimal or less protective standards.

B Model Appendix

This section explore more in depth the simple model sketched in Section 3.1 and provides some theoretical basis for the identification strategy in Section 4 and the tests conducted in Section **??**.

Let output to be produced with a constant returns to scale production function using capital and labor, where the latter is taken to be the numeraire. Then,

$$y = F(k, 1) \equiv f(k)$$

The optimal initial capital is given by

$$f'(k) = 1 + w'_k \tag{4}$$

Notice that the last term in (4) enters the first order conditions because wages are negotiated after the initial investment has been made. Therefore, firms anticipate that workers can reap some of the benefits of higher investment without sharing the cost. That is the source of holdup in the model. The expression for w'_k is

$$w'_k = \beta\big[f'(k) - (1-\sigma)\big] \tag{5}$$

Substituting (5) into (4) yields

$$f'(k) = \frac{1 + \beta(1-\sigma)}{1-\beta} > 1$$

Since $f''(k) < 0$ by assumption, when $\sigma > 0$ firms invest sub-optimally due to holdup.

Moreover, substituting (5) into (4) and totally differentiating with respect to β yields,

$$k'_\beta = \frac{f'(k) - (1-\sigma)}{f''(k)(1-\beta)} < 0 \tag{6}$$

Therefore, $k''_{\sigma,\beta} < 0$ for $\sigma > 0$ and higher labor bargaining power lowers aggregate investment more in sunk cost-intensive industries. This is idea tested in Table **??**. Notice that if $\sigma = 0$, the first order conditions for capital are simply $f'(k) = 1$ and so $k'_\beta = 0$.

Totally differentiating (1) with respect to β, this time taking into account the response of capital to changes in bargaining power, yields

$$w'_\beta = \frac{w}{\beta} + \beta\big[f'(k) - (1-\sigma)\big]k'_\beta \tag{7}$$

Since $k'_\beta < 0$ from (6), we have that unlike for the case in which capital is held constant, wages might decrease with labor bargaining power for high values of β. Differentiating w'_β with respect to σ we get

$$w''_{\sigma,\beta} = k + \beta k'_\beta \tag{8}$$

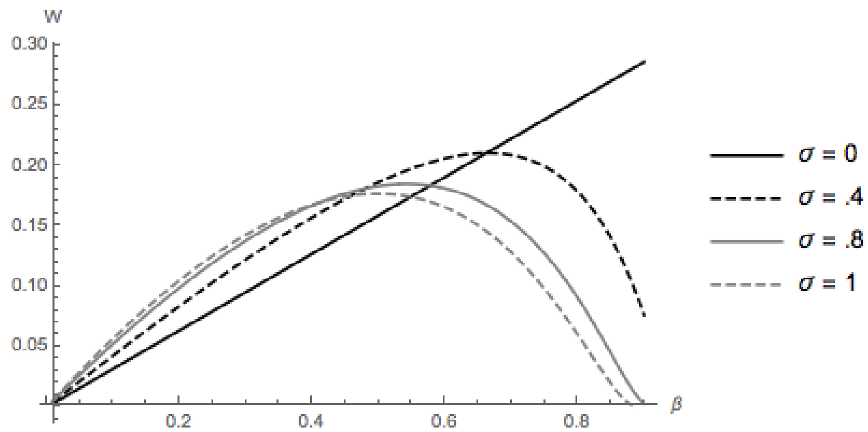
The first term in (8) is positive, but the second is negative and so it is not possible to determine the sign of $w''_{\sigma,\beta}$ analytically. Therefore, to examine the behavior of wages we rely on a numerical simulation of the system (1)-(4). The production function is assumed to be CES,

$$y = \left[ak^\alpha + (1-a)k^\alpha\right]^{1/\alpha}$$

with $a = 0.33$ and $\alpha = -.5$. Results are qualitatively similar for different parametrisation. The results of the simulation are presented in Figure A1, which plots w as a function of β for different values of σ.

The figure shows that there is a non-monotonic relationship between wages and labor bargaining power. For relatively low values of β, $w'_\beta > 0$ and $w''_{\sigma,\beta} > 0$, as in Section 3.1. However, for high values of β wages start to fall due to the decrease in the capital stock and disproportionately so for sunk cost-intensive industries. The literature has provided a wide range of estimates for β, depending on samples, models and calibration methods. However, in a review of the existing literature Cardullo, Conti, and Sulis (2015) identifies a plausible range for β to be 0.4-0.6, while some authors have argued for a value much closer to zero (e.g. Hagedorn and Manovskii, 2008). Therefore, while determining the sign of $w''_{\sigma,\beta}$ remains an open empirical question, values of β large enough to offset the mechanisms described in this paper seem unlikely in practice.

Figure A1: The relationship between wages, labor bargaining power and sunk cost-intensity



The figure shows the simulate behavior of the wage w as defined in equation (1) when labor bargaining power β increases, for different values of sunk cost-intensity σ. In the numerical simulation, $y = \left[ak^{\alpha} + (1-a)k^{\alpha}\right]^{1/\alpha}$, $a = 0.33$ and $\alpha = -.5$.

C Tables Appendix

Table C1: OLS estimates of the impact of legal characteristics on country-wide adoption of industrial robots per thousand workers.

VARIABLES	(1) R/L	(2) R/L	(3) R/L	(4) R/L	(5) R/L	(6) R/L	(7) R/L	(8) R/L
i) Right to unionise	0.913***							
	(0.111)							
ii) Right to collective bargaining		0.563***						
		(0.073)						
iii) Right to strike			0.678***					
			(0.065)					
iv) Closed shop allowed				0.747***				
				(0.164)				
v) Extension of collective agreement					0.533***			
					(0.089)			
vi) Co-decision making						0.472***		
						(0.073)		
Labor rights in Constitution (i-iii)							1.195***	
							(0.114)	
Strong employee representation (i-ii,iv-vi)								1.936***
								(0.205)
Expected ageing	1.782***	1.571***	1.801***	1.639***	2.090***	1.724***	1.482***	1.257***
	(0.197)	(0.193)	(0.200)	(0.194)	(0.219)	(0.234)	(0.181)	(0.167)
Observations	665	665	665	665	665	665	665	665
R-squared	0.481	0.461	0.491	0.465	0.463	0.425	0.530	0.569
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes

The table presents OLS estimates of the relationship between legal characteristics and the adoption of robots. The dependent variable is the stock of industrial robots per thousand workers. All specifications include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

C.1 Robustnes

Table C2 shows estimates obtained with log-transformed dependent variables. The results are consistent with the baseline specification in Table C1.[43]. Table C3 presents estimates for a long differences specification (1995-2013), in which the dependent variable is the average annual change in robots per worker. The base year value of the dependent variable is added to the set of controls. The coefficients are broadly in line with those in Table C1. For instance, columns 7 and 8 suggest that the number of robots per worker increased, respectively, by 0.04 annually in countries protecting the labor rights and by 0.06 in those with strong employee representation. That corresponds, respectively, to 0.7 and 1.1 additional robots over the whole period, which is somewhat lower but comparable with the results in Table C1. Coefficients are not always significant for individual

[43] The reason for using the dependent variable in levels as main outcome is that about hundred observations have zero stock of robots.

institutions, which might be due to the very low number of observations resulting from using cross-country variation alone. As in Acemoglu and Restrepo (2018a), the ageing variable is always significant with the long-difference specification. The last robustness test addresses the concern that the increase in robot per worker is simply capturing trends in capital deepening. That would contradict the views expressed in this paper, as Section 3.2 argues that the relationship between labor-friendly institutions and aggregate capital should be negative. Thus, Table C4 uses the number of robots per unit of capital as dependent variable. Given the statistical difficulties in defining "units of capital", the magnitude of the coefficients in Table C4 is difficult to interpret. However, the table shows that results are qualitatively similar to Table C1, suggesting that the baseline coefficients are not capturing an increasing trend in capital accumulation.

Table C2: OLS estimates of the impact of legal characteristics on country-wide adoption of industrial robots per thousand workers (in logs).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	ln(R/L)	ln(R/L)	ln(R/L)	ln(R/L)	ln(R/L)	ln(R/L)	ln(R/L)	ln(R/L)
i) Right to unionise	2.089***							
	(0.200)							
ii) Right to collective bargaining		0.734***						
		(0.136)						
iii) Right to strike			1.644***					
			(0.142)					
iv) Closed shop allowed				0.684***				
				(0.205)				
v) Extension of collective agreement					0.409***			
					(0.133)			
vi) Co-decision making						2.556***		
						(0.183)		
Labor rights in Constitution (i-iii)							2.313***	
							(0.183)	
Strong employee representation (i-ii,iv-vi)								3.021***
								(0.239)
Observations	558	558	558	558	558	558	558	558
R-squared	0.571	0.500	0.599	0.486	0.483	0.624	0.596	0.582
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes

The table presents OLS estimates of the relationship between legal characteristics and the adoption of robots. The dependent variable is the log of the stock of industrial robots per thousand workers. All specifications include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table C3: Specification in long-differences (1995-2015) for the regressions in Table C1.

VARIABLES	(1) Δ R/L	(2) Δ R/L	(3) Δ R/L	(4) Δ R/L	(5) Δ R/L	(6) Δ R/L	(7) Δ R/L	(8) Δ R/L
Right to unionise in 1994	0.003***							
	(0.001)							
Right to collective bargaining in 1994		0.001						
		(0.001)						
Right to strike in 1994			0.002**					
			(0.001)					
Closed shop allowed in 1994				0.000				
				(0.001)				
Extension of collective agreement in 1994					0.001			
					(0.001)			
Co-decision making in 1994						0.003***		
						(0.001)		
Labor rights in Constitution in 1994							0.003***	
							(0.001)	
Strong employee representation in 1994								0.005***
								(0.001)
Expected ageing	0.005***	0.005***	0.006***	0.006***	0.006***	0.004***	0.005***	0.004***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	35	35	35	35	35	35	35	35
R-squared	0.537	0.414	0.503	0.392	0.406	0.571	0.594	0.626
Base year country covariates	yes	yes	yes	yes	yes	yes	yes	yes

The table presents OLS estimates of the relationship between legal characteristics and the adoption of robots. The dependent variable is the annual change in industrial robots per thousand workers between 1995 and 2013. All specifications include the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling; iv) the dependent variable. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table C4: OLS estimates of the impact of legal characteristics on country-wide adoption of industrial robots per unit of aggregate capital.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	R/K	R/K	R/K	R/K	R/K	R/K	R/K	R/K
i) Right to unionise	0.005***							
	(0.001)							
ii) Right to collective bargaining		0.003***						
		(0.000)						
iii) Right to strike			0.003***					
			(0.000)					
iv) Closed shop allowed				0.005***				
				(0.001)				
v) Extension of collective agreement					0.002***			
					(0.000)			
vi) Co-decision making						0.003***		
						(0.000)		
Labor rights in Constitution (i-iii)							0.006***	
							(0.001)	
Strong employee representation (i-ii,iv-vi)								0.010***
								(0.001)
Observations	665	665	665	665	665	665	665	665
R-squared	0.318	0.335	0.305	0.381	0.254	0.264	0.395	0.484
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes

The table presents OLS estimates of the relationship between legal characteristics and the adoption of robots. The dependent variable is the stock of industrial robots per unit of aggregate capital. All specifications include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table C5: OLS estimates of the impact of legal characteristics on country-industry adoption of industrial robots per thousand employees; country-year fixed effects

VARIABLES	(1) R/L	(2) R/L	(3) R/L	(4) R/L	(5) R/L	(6) R/L	(7) R/L	(8) R/L
Right to unionise x sunk cost intensity	1.769***							
	(0.218)							
Right to collective bargaining x sunk cost intensity		1.654***						
		(0.210)						
Right to strike x sunk cost intensity			1.534***					
			(0.187)					
Closed shops allowed x sunk cost intensity				3.865***				
				(0.762)				
Extension collective agreements x sunk cost intensity					1.871***			
					(0.223)			
Co-decision x sunk cost intensity						2.346***		
						(0.234)		
Labor rights in Constitution x sunk cost intensity							1.844***	
							(0.220)	
Strong employee representation x sunk cost intensity								3.128***
								(0.361)
Observations	5,559	5,559	5,559	5,559	5,559	5,559	5,559	5,559
R-squared	0.563	0.563	0.563	0.566	0.566	0.563	0.564	0.570
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-year FE	yes	yes	yes	yes	yes	yes	yes	yes

The table presents OLS estimates of the relationship between legal characteristics, sunk costs and the adoption of robots. The dependent variable is the country-industry stock of industrial robots per thousand employees. The proxy of sunk cost-intensity is the inverse share of second-hand capital expenditure in a given 2 digits-industry. All specifications include include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table C6: OLS estimates of the impact of legal characteristics on country-industry adoption of industrial robots per thousand employees (alternative proxy of sunk costs).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	R/L	R/L	R/L	R/L	R/L	R/L	R/L	R/L
Right to unionise x fixed investment	4.436***							
	(0.578)							
RIght to collective bargaining x fixed investment		6.429***						
		(0.746)						
Right to strike x fixed investment			5.295***					
			(0.613)					
Closed shops x fixed investment				9.665***				
				(0.410)				
Extension collective agreements x fixed investment					5.226***			
					(0.572)			
Co-decision x fixed investment						1.874***		
						(0.562)		
Labor rights in Constitution x fixed investment							6.069***	
							(0.680)	
Strong employee representation x fixed investment								7.033***
								(0.715)
Observations	2,904	2,904	2,904	2,904	2,904	2,904	2,904	2,904
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes	yes	yes	yes
First stage F	903.4	266	632.1	1106	1194	910.7	492.4	1349

The table presents 2SLS estimates of the relationship between legal characteristics, sunk costs and the adoption of robots. The dependent variable is the country-industry stock of industrial robots per thousand employees. The proxy of sunk cost-intensity is the share of gross fixed investment over output in each 2 digits-industries. The proxies are instrumented with the same variable in the United States, which is then dropped by the sample. All specifications include include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table C7: OLS estimates of the impact of legal characteristics on country-industry capital-labor ratio.

VARIABLES	(1) log(K/L)	(2) log(K/L)	(3) log(K/L)	(4) log(K/L)	(5) log(K/L)	(6) log(K/L)	(7) log(K/L)	(8) log(K/L)
Right to unionise x sunk cost intensity	-0.104***							
	(0.020)							
Right to collective bargaining x sunk cost intensity		-0.174***						
		(0.018)						
Right to strike x sunk cost intensity			-0.139***					
			(0.015)					
Closed shops allowed x sunk cost intensity				-0.114***				
				(0.034)				
Extension collective agreements x sunk cost intensity					0.031			
					(0.020)			
Co-decision x sunk cost intensity						-0.083***		
						(0.026)		
Labor rights in Constitution x sunk cost intensity							-0.159***	
							(0.019)	
Strong employee representation x sunk cost intensity								-0.137***
								(0.028)
Observations	4,081	4,081	4,081	4,081	4,081	4,081	4,081	4,081
R-squared	0.961	0.962	0.961	0.960	0.960	0.960	0.961	0.961
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-year FE	yes	yes	yes	yes	yes	yes	yes	yes

The table presents OLS estimates of the relationship between legal characteristics, sunk costs and the capital-labor ratio. The dependent variable is the log of country-industry stock of aggregate capital per thousand employees. The proxy of sunk cost-intensity is the inverse share of second-hand capital expenditure in a given 2 digits-industry. All specifications include include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table C8: First stage regression of Table 3.

VARIABLES	(1) Union density	(2) Union coverage
Civil law	0.665***	0.223***
	(0.009)	(0.032)
Creditors' right index	-0.034***	0.014**
	(0.002)	(0.005)
Shareholders' protection index	0.583***	-0.694***
	(0.019)	(0.086)
Product market regulation	-0.549***	-0.232***
	(0.012)	(0.055)
Contract enforcment index	0.013***	-0.011
	(0.004)	(0.013)
Time to cash a bounced check	0.141***	0.026***
	(0.003)	(0.009)
Labor rights in Constitution	0.140***	-0.226***
	(0.013)	(0.029)
Strong employee representation	-0.151***	-0.150***
	(0.017)	(0.054)
Power of leftist parties	0.000	-0.001**
	(0.000)	(0.000)
Strict dismissal regulation	-0.150***	0.432***
	(0.014)	(0.060)
Observations	5,495	3,832
R-squared	0.890	0.840
Base year country covariates-year FE	yes	yes
Expeccted ageing	yes	yes
Industry-year FE	yes	yes
Country-year FE	no	no

The table presents the OLS estimates of the first stage regression of Table 3. All specifications include include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.