Institutions, Holdup and Automation[*†]

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Abstract

This paper documents a positive relationship between labor-friendly institutions and investment in industrial robots in a sample of developing and advanced economies. Institutions explain a substantial share of cross-country variation in automation. The relationship between institutions and robots is stronger in sunk cost-intensive industries, where producers are vulnerable to holdup. The result suggests that one reason for producers to invest in automation is to thwart rent appropriation by labor. As a consequence, policies aimed at supporting workers' welfare by increasing their bargaining power might actually reduce their employment opportunities.

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

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1 Introduction

Over the last decade, advances in robotics have generated concerns about labor displacement. One popular idea is that in order to tackle disruption in the labor market, governments should implement policies aimed at increasing workers' bargaining power (e.g. International Labor Organization, 2019). The main contribution of this paper is challenging such a view by documenting a positive relationship between labor-friendly institutions and investment in industrial robots. The underlying mechanism is simple. By shifting bargaining power in favor of workers, some institutions increase employers' costs and provide incentives to substitute labor with robots. As a consequence, policies aimed at increasing workers' welfare by strengthening their bargaining power might actually end up reducing their employment opportunities.

The first part of the paper uses specifications in long differences in which the change in robots per thousand workers between 1995 and 2013 is regressed on country-specific institutional variables. The results suggest that labor institutions have a substantial impact on robots' adoption. For instance, countries with strong employees' representation use twice the average number of robots per worker in the sample.

An important concern is that the positive cross-country correlation between institutions and investment in robots might be driven by omitted variables. In order to control for country-specific unobserved factors, the second part of the paper exploits country-industry-year variation in robots' adoption. The empirical analysis builds on a simple model, in which part of the capital investment made by the firm is sunk at the moment of negotiating wages. The larger the fraction of sunk investment, the larger the share of value added that firms are willing to give up to labor in order to keep capital engaged in production. In the model, the extent to which workers are able to appropriate such rents depends on their bargaining power. Therefore, the identifying assumption is that labor-friendly institutions should induce automation more in industries characterised by large sunk costs, where producers are vulnerable to holdup.[1] To measure sunk costs, they are

[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.

assumed to be inversely proportional to the share of second-hand capital expenditure in a given industry. The underlying idea is that firms should be less likely to buy second-hand capital equipment when investment is irreversible, or highly specific to a particular production process.[2] A case in point is the motor vehicle industry, in which both suppliers of components and assemblers need specific equipment that has little scope for utilisation outside the industry.[3] Specificity results in sunk costs for producers, because it makes it hard to find an alternative use of capital and fully recover the cost of investment if production does not take place. Thus, institutions increasing the bargaining power of labor should increase labor costs more in industries such as motor vehicles, which indeed is disproportionally automated in countries with labor-friendly institutions. More generally, controlling for country and industry characteristics, the relationship between labor institutions and investment in robots is found to be more than 20% stronger in sunk cost-intensive industries.

Any institution increasing labor bargaining power should induce producers to invest in robots. Therefore, this paper considers the impact of unions, strikes and specific labor market regulation, such as the presence of constitutional provisions on workers' rights and rules affecting employees' representation. The institutional variables differ in their persistence over time. On the one hand, persistent variables allow to exploit only in part the time dimension of the panel. On the other hand, variables exhibiting substantial time variation, such as union participation, might be affected by contemporaneous trends in automation, resulting in reverse causality.[4] To mitigate this concern, the third part of the paper provides additional results based on a two-stage least square estimator (2SLS). The 2SLS estimates are obtained using two alternative instrumental variables. The first is an interaction between the sample-average union rate and a dummy variable for whether a country has civil legal origins. The average union rate captures global technological and economic factors such as the development of global value chains, making the vari-

[2]Proxies of sunk costs based on second-hand capital expenditure are highly correlated to alternative measure of sunk costs, such as gross fixed investment over total output.

[3]Examples include cutting and pressing machines to stamp car bodies.

[4]The issue is discussed in more detail in Section 4.3.

able less sensitive to country-specific trends in automation. At the same time, Botero et al. (2004) show that labor tends to have more bargaining power in civil-law countries than in common-law ones. Thus, the widespread decline in union participation should be less pronounced in civil-law countries.[5] Legal systems have been established long before the development and commercialisation of automation technologies and so they are not affected by robots' adoption. To minimise the possibility of violating the exclusion restrictions, the 2SLS specifications draw from the literature on legal origins and control for variables affected by the legal system and having a potential impact on automation.[6] The second instrument considered is the average union rate in other countries.[7] Neither of these instruments solve all the potential concerns of omitted variables and reverse causality. Nevertheless, they provide a useful robustness check for the empirical methodology used in the paper. The 2SLS results are consistent with the OLS coefficients and suggest that labor-friendly institutions generate incentives to invest in industrial robots, particularly in sunk cost-intensive industries where producers are vulnerable to holdup.

The final part of the paper looks at the impact of strike activity on investment in robots. Strikes are the most powerful tool available to unions against the management. As a consequence, producers should have greater incentives to substitute humans with machines when industrial action threatens the full utilisation of capital. Exploiting different measures of industrial action in the years preceding the beginning of the sample, the results suggest that country and industries characterised by longer or more frequent strikes have adopted a larger number of robots between 1995 and 2013.

This paper contributes to the literature on determinants of investment in automation. Adoption of industrial robots differs widely across countries, even for those with similar levels of economic development and within narrowly defined industries. For instance, in 2013 the number of robots per thousand employees in manufacturing of motor vehicles

[5]Declining trends in union participations are discussed by Visser (2015), among others.

[6]The literature documents a correlation between legal origins and the degree of protection of creditors and shareholders (La Porta et al. 2000; 1999), market entry (Djankov et al., 2002), contract enforcement (Djankov et al., 2003) and securities laws (La Porta et al. 2006).

[7]For instance, the union rate in France is instrumented with the average union rate in the sample after excluding France from the calculation.

was almost 100 in France and Japan, 70 in Italy and 40 in the United States. The existing literature points to demographic trends as an explanation for such differences (Acemoglu and Restrepo, 2018a). Instead, this paper looks at labor market institutions and provides evidence that they explain a substantial share of cross-country variation in robots' adoption, between 10% and 34% depending on the specification.

Finally, this paper relates to a broader 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), but it differs from previous studies in two important dimensions. First, instead than using aggregate policy indexes, it considers a wide range of narrowly-defined labor market institutions. Second, previous work proxies technology adoption with capital accumulation and it does not distinguish between automation equipment and other categories of assets. However, the presence of holdup implies that labor-friendly institutions should encourage investment in automation, while discouraging accumulation of labor-complementing capital.[8] 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 makes it possible to disentangle the impact of institutions in shaping incentives to invest in labor-saving technology *vis-à-vis* other categories of assets.[9]

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

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

[9] 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 full dataset includes fifty-three OECD and non-OECD countries, and 18 two-digits industries from 1993 to 2013. Since industry-level variables are only available for OECD economies, part of the analysis is based on 35 countries.[10] 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). Industrial robots 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.* The IFR 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 the legal characteristics of the labor market 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.[11] 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.[12] Higher values correspond to stronger protection

[10] Data on robots are not available for Luxembourg.

[11] 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.

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

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 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.[13]

Data on industrial action is taken from the database on work stoppages of the International Labour Organization.[14] There are four measures of strike activity: i) numbers of strikes; ii) number of days lost due to strikes; iii) number of workers involved in strikes, and iv) days lost per worker. These variables are available for a number of advanced and developing countries at the one-digit industry level. The industries that can be matched to the IFR data are agriculture, mining, utilities, construction, and manufacturing. Such data re usually collected from administrative registers of the ministry of labour, the national statistical office, or workers-employers organisations. In some countries, collecting

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

[14]The data are available at the following web address: https://ilostat.ilo.org/topics/work-stoppages/

information on industrial action is mandatory and it is done by distributing standardised questionnaires.

The proxy of industry-level sunk costs are computed from data on second-hand capital expenditure by industry, from US Census Bureau.[15] The idea underlying the construction of the proxy is the following.[16] 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.[17] The indicator is based on data from STAN and the NBER-CES Manufacturing Database.[18] [19]

2.1 A First Look at The Data

There are large differences in adoption of industrial robots, even within the OECD region for countries at 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, or "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

[15] The proxy uses data for the first available year, 1994, which is then set as the base year in the estimation.

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

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

[18] As for the proxy based on second-hand capital expenditure, the alternative measure of sunk costs is based on 1994 values.

[19] 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.

used almost 80 robots per thousand employees in 2013, against 15 or 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. Figure 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.[20] Motor vehicles and Chemicals are the most sunk cost-intensive industries. 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. In the chemical industry, refining and processing takes place in large plants and requires heavy equipment. That makes investment practically irreversible.[21] Capital is thus highly specific in both industries due to the ir-

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

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

reversibility of investment, but the source of irreversibility differs. In the former, it arises for the industry-specificity of the equipment. In the latter, it is likely to arise from the large size of the equipment, which makes it hard to move it or ship it. Figure 3 suggests that the construction industry is the less sunk cost-intensive one. The reason is that most of the capital assets used in the constructions consist in relatively light equipment and vehicles. In Constructions, producers make virtually no investment in buildings, which instead constitute an important category of (at least partially) irreversible investment in other manufacturing industries. Therefore, firms in the construction business are more likely to purchase machinery in second-hand markets, which results in a lower measure of sunk costs. Figure 5 plots the industry-average of the alternative sunk cost variable, computed across all countries from which information is available, against the sunk cost measure based on second-hand capital expenditure. The chart shows that there is a positive correlation between the two proxies.

Figure 4 shows the value of the strike variables. The values reported refer to the mean value between 1990 and 1995, for both advanced and developing countries.[22] The figure shows that most of the strike activity took place in the manufacturing sector. One exception is Mining, where over 350 thousand days were lost for each worker involved in industrial action.

3 Institutions, Holdup and Automation

This section formalises the main concepts used in the empirical analysis and 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. This is especially true for OECD countries, as they are similarly integrated in international markets.[23] The standard explanation for cross-country differences in technology adoption is the presence of frictions. Examples include lack

[22]Details about the empirical methodology can be found in Section 4.4

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

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 6 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 cross-country heterogeneity of institutions, 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 7 depicts the relationship between the 1995-2015 change in the number of robots per thousand workers and the 1994 union membership rate.[24] 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 7 displays the correlation between the change in robots' adoption over the same period and the 1994 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.[25] On the contrary,

[24]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.

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

in most European countries with 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.[26] 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 7 provides some evidence in support of the hypothesis. Countries with higher labor shares in 1994 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*.[27] 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. This section develops a simple model to help framing the analysis.

the employer does not have the legal obligation to recognise minority-unions as a collective bargaining agent, which limits considerably their power.

[26]One example is a dispute between a private airline company and a trade union in Ireland (Ryanair Limited vs 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.

[27]See Grout (1984), and Hart and Moore (1988).

Consider the case in which a producer builds a plant and purchases machinery *before* hiring workers.[28] If investment is irreversible, the cost of capital is sunk at the moment of 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. The extent to which labor is able to extract rents depends on its 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

$$w = \beta\big(y + k\sigma\big) \tag{1}$$

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 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 more realistic model in which investment responds to changes in bargaining power.

[28] 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 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.

Turning again to the descriptive evidence, data show that automation and sunk costs are indeed related. Figure 8 displays the proxy of sunk cost-intensity on the horizontal axis and the log number of industrial robots per thousand employees in 2013 on the vertical axis. 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 assets.

As any other piece of machinery and equipment, industrial robots are included in accounts of aggregate capital.[29] 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.[30]

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.[31] But if capital *substitutes* labor, as for the case of robots, every dollar of investment in labor-saving technology reduces the de-

[29]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.*

[30]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.

[31]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).

pendency 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.[32] Figure 9 supports such a hypothesis. The horizontal axis shows the proxy of sunk cost-intensity. The vertical axis shows the residuals of a regression of the log-number of robots per employee (top panel) and capital per employee (bottom panel) on: i) base year country covariates, interacted with year fixed effects, and ii) the 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. The residuals are then averaged for each industry across high and low union density countries.[33] The top panel of the figure shows that the positive relationship between robots and sunk cost is steeper for high union density countries. Being highly substitutable for human labor, robots are more intensely adopted in country-industries where the holdup is more severe. However, the bottom panel of Figure 9 shows that the relationship between aggregate capital and sunk costs is flatter in high union density countries. Most assets composing the aggregate capital stock complement labor and so investment is lower in country-industries characterised by severe holdup.

Section B of the appendix shows that a negative relationship between labor bargaining power and labor-complementing capital arises in a model with *ex ante* investment and *ex post* wage bargaining.

[32]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, as discussed further below, the available evidence suggest that robots account for only a small percentage of the aggregate capital stock.

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

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?[34] This section addresses 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, while $R2^{noinst}$ is the adjusted-R2 of the same model without institutions. Analogous calculation can be used to compute the contribution of population ageing.

To following model is estimated with OLS in order to obtain $R2^{inst}$,

$$\Delta R/L_c = \beta_0 + \beta_1 Inst_{c,1994} + \beta_2 Ageing_c + BX_{c,1994} + \varepsilon_c \tag{3}$$

The dependent variable $\Delta R/L_c$ is the country-wide yearly average change in the number of industrial robots per thousand workers between 1995 and 2013.[35] The variable $Inst_{c,1994}$ is the base year value of the institutional variable. $Ageing_c$ measures demographic trends and it is constructed as in Acemoglu and Restrepo (2018a). The variable 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 $X_{c,1994}$ includes the base-year values of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling, and iv) number of robots per worker.[36] The error term is

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

[35] The years included in the sample are constrained by data availability.

[36] Total employment, GDP at constant prices, and total population are taken from the Penn World

denoted by ε_c.

Table 1 presents the results of estimating (3) using the different institutional variables. Columns 1 to 4 of Table 1 show the estimates for the full set of countries, while columns 5 to 8 use the OECD sample. There is a positive correlation between labor-friendly institution and adoption of industrial robots at the country-level. For instance, the estimates in columns 1 and 2 imply that countries with labor-friendly institutions invest, respectively, in 0.03 and 0.05 additional robots per year. That corresponds to 0.5 and 0.9 additional robots over the 18 years of the sample. The quantitative impact of institutions is substantial, as the mean number of robots per thousand employees in 2013 is 0.45 for the full set of countries (the standard deviation is 0.8). In the OECD sample, the institutional variables tend to be larger and are highly significant. For instance, in column 7 the coefficient on union density implies that a 25 percentage points increase in union density, roughly the difference between the US and Italy, corresponds to a 0.016 additional robots per thousand workers per year. Over the 18 years of the sample, such number translates in 0.3 additional robots per thousand workers (the OECD-average in 2013 is 0.8).

The ageing variable is only significant in column 4 and with the OECD sample. This is not surprising, as population ageing is much more pronounced in advanced economies. The last two rows of Table 1 report the values of (2) for institutional and demographic variables.[37] Institutions explain a lower share of variation in the dependent variable than ageing. However, depending on the institutional variable, in most cases the contribution of institutions is comparable to that of demographics. The value of $R2^{inst}$, ranges from 10% to 34%. In sum, the results in Table 1 suggest that: i) there is a positive relationship between labor-friendly institutions and investment in industrial robots, especially across OECD countries, and ii) institutions explain a lower but comparable share of sample variation in automation.

The country-level results in Table 1 are robust to alternative specifications. Table

Tables 9.1. Average years of schooling are taken from the Barro-Lee dataset.

[37]The quantity $\Delta R2^{age}$ is obtained similarly by comparing $R2^{inst}$ to the R2 of the model $\Delta R_c = \beta_0 + \beta_1 Inst_{c,1994} + BX_{c,1994} + \varepsilon_c$.

C1 includes additional labor market institutions that are likely to affect labor costs. In this specification, the ageing variable becomes not significant and the R2 contribution of the institutional variables become disproportionally larger, exception made for columns 3 and 7, in which the coefficient on union density is not significant. The results in Table C1 mitigates the concern that the positive relation between the main institutional variables used in the analysis and investment in robots is due to omitted variables. However, due to limited data availability, the number of observations drops when including additional controls. Table C2 of the appendix shows estimates for a specification in which the dependent variable is the change in the number of robots per thousand workers between 1995 and 2007, which excludes the years since the Great Recessions. The results are consistent with the baseline specification in Table 1. 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 C3 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 C3 is difficult to interpret. However, the table shows that results are qualitatively similar to Table 1, suggesting that the baseline coefficients are not capturing an increasing trend in capital accumulation.

4.2 Industry-level Results: Holdup and Investment in Industrial Robots

This section exploits country and industry variation in robot density to explore the specific mechanism through which institutions 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 rents. The following empirical model is used to test such a hypothesis,

$$S/L_{cit} = \gamma_0 + \gamma_1(Inst_{ct} \times \sigma_i) + BX_{ct} + u_{ct} + u_{it} + \varepsilon_{cit} \tag{4}$$

The dependent variable in (4) is shipments of *new* industrial robots per thousand employees to every country, two digits industry and year.[38] The choice of the dependent variable in (4) is similar to Acemoglu and Restrepo (2018a), which in the country-industry-year specification, use shipment of new robots rather than their aggregate stock. Country-industry variables are only available for OECD economies. Thus, the results of this section are based on a sample of 35 OECD countries.

The industry-level measure of sunk costs is σ_i. The vector X_{ct} includes all the controls used in Table 1, but in this specification they are fixed at the base year value and then interacted with year effects. Since $Inst_{ct}$ varies at the country-year level, the inclusion of country-year effects u_{ct} precludes the estimation of the country-average impact of institutions. However, the advantage of estimating (4) over (3) is that country-year fixed effects mitigate the possibility of bias arising from the presence of country-specific time-varying unobservable factors, such as demand shocks and the impact of other institutions. The variable u_{it} denotes industry-year fixed effects and ε_{cit} is the error term. Errors are clustered at the country-level and all estimates are weighted by the base-year industry share of employment in each country.[39]

The coefficients of interest in (4) is γ_1, which quantifies the differential impact of institutions in industries characterised by different levels of sunk costs. The variable σ_i is computed from US data in the base-year (1994), which is then dropped from the sample.[40] This strategy mimics Rajan and Zingales (1998) and minimises the possibility that the impact of institutions would affect industry-level investment in robots, contaminating the proxy of sunk costs. Indeed, 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. Evidence in support of the identifying assumption is given by the fact that the median within-country

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

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

[40] 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.

variation of σ_i is greater than its cross-country variation for a given industry.

One concern is that robots' investment in the United States could have affected the share of second-hand capital in 1994, biasing σ_i. However, that seems unlikely, for three reasons. First, 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 in total manufacturing of the whole industry is just 3.4% in 2013. Second, the definition of robots suggest that they are flexible machines and so it is unlikely that producers would sold them when they face negative demand shocks or related events. Third, in 1994 industrial robots where not yet widespread in US manufacturing. Such arguments mitigate the concern that 1994 US investment in robots might have biased σ_i.

The variable σ_i is normalised to have zero mean and standard deviation equal to 1 in the weighted sample. Therefore, γ_1 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. The evidence is consistent with the hypothesis that labor-friendly institutions induce automation more in sunk cost-intensive industries, where workers can hold up the producer and demand higher wages. The only coefficient that is not statistically significant is in column 3. Section 4.3 below addresses potential reasons.

One might be concerned 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 C4 of the appendix presents the results of estimating (4) using an alternative identification strategy, based on proxies of sunk costs that are country-specific. The alternative proxy is the 2 digits industry-level gross fixed investment share of total output. Such variable is instrumented with the base year, median level of the same quantity computed from 6 digits industries in the United States. Table C4 shows 2SLS estimates using this strategy and the results are consistent with those in Table 2, although the number of observations is lower because the NBER-CES dataset includes only manufacturing industries. Importantly, the first stage F statistics is high in all specifications (between F = 22 and F = 57), implying that the countries in the sample have similar sunk cost intensities in each industry. That suggests that at least part of the technological characteristics of the US, do carry over to industries in other OECD countries.

Since most categories of capital assets are complementary to labor, the relationship between aggregate investment and labor-friendly institutions should be negative in sunk cost-intensive industries. Indeed, Table C5 of the appendix shows that unlike for robots, there is a negative correlation between institutions, sunk costs and aggregate investment. The results in Table C5 can then be seen as a test for the arguments discussed in Section 3.2, as well as the analytical results of the model in Section B.

4.3 Union rates, Holdup and Automation: 2SLS Estimates

By increasing average wages and lowering firms' profitability (Hirsch, 2017; Taschereau-Dumouchel, 2017), unions should create strong incentives to invest in automation. However, one potential issue with regressing S/L_{cit} on union rates is that they might be contemporaneously affected by trends in technology, resulting in reverse causality. For instance, in industries exposed to automation, employers might credibly threaten to displace workers if they join a union. That being the case, the OLS coefficients might be biased towards zero. Thus, to mitigate concerns of reverse causality, this section experiments with two instrumental variables that are less likely to be correlated with country-specific trends in robots' adoption.

Findings in Botero et al. (2004) suggest that workers have higher bargaining power in civil-law systems. Therefore, the process of de-unionisation documented by Visser (2015) should evolve differently in such countries, relative to those with a common-law system. Figure A2 of the appendix shows that in civil-law countries, union rates tend to be higher and to decline less rapidly than in common-law countries, especially in the first years of the sample. Therefore, exploiting countries' legal origins, the first instrument is a "Bartik style" interaction between the OECD-average union rate and a dummy taking value 1 if the country has civil legal origins. Average union rates capture the general trend in de-unionisation, which is driven by global development of technology and global value chain and so they are presumably less sensitive to country-specific trends in robots' adoption. At the same time, differences in legal systems developed around the 12th century, long before the development and commercialisation of automation technologies.

Instrumenting union rates with countries' legal origins can help mitigating the concern of 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 as well.[41] Therefore, to mitigate the possibility of violating the exclusion restrictions, the specification using legal origins as an instrument, includes as well 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.[42] In addition, are included the labor rights and employee representation indexes used in the previous part of the analysis, plus redundancy compensation and the share of parliamentary seats of social democratic and other left parties in government.[43]

Tables C6 of the appendix presents the first stage regressions of union rates and their interaction with the industry-level proxy of sunk costs on the instruments based on legal origins. The table shows that all the significant coefficients have the expected sign and

[41]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.

[42]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.

[43]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).

are in line with the idea that union rates are higher in civil law countries.

Columns 1 to 4 of Table 3 presents the first group of 2SLS estimates. All coefficients have the expected sign, although the interaction term in column 1 is not significant at conventional levels (p-value = 0.102). One potential reason is the low F statistics associated to the specifications using union density as explanatory variables (columns 1 and 3).[44] Instead, for the specifications using union coverage in columns 2 and 4, the coefficients are all significant and the first stage F statistics above F = 10.[45] The coefficients in column 2 imply that 10% additional union coverage is associated to 0.17 additional robots per thousand workers. In sunk const-intensive industries, the relationship becomes more than 20% stronger. The specifications with country-year fixed effects in columns 3 and 4 show that the interaction coefficients are positive and significant, and of similar magnitude than those in columns 1 and 2.

Columns 5 to 8 of Table 3 present the results obtained with an alternative instrument, the average union rates in other countries.[46] While the main effect of the institutional variables are not significant, the interaction terms are positive, significant and of comparable magnitude of those obtained in columns 1 to 4. Due to the larger variation of the instrument, which by construction is country-specific, the alternative instrument has more power than that based on legal origins. As a result, the first stage F statistics above 20 in all specifications.

To summarise, the 2SLS coefficients on the interaction terms between union rates and sunk costs in Table 3 are all significant and larger than the OLS coefficients in Table 2. Thus, the results of this section support the hypothesis that reverse causality could bias the estimated impact of unions on investment in robots toward zero.

4.4 Strikes and Automation

This section studies the impact of industrial actions on adoption of robots. Strikes are the most powerful tool that unions can use against the management during industrial

[44]Stock and Yogo (2002) propose that a first stage F statistics below 10 signals a weak instrument.

[45]Indeed, Table C6 shows that the R2 of the specifications involving union density is lower than the R2 of those involving union coverage.

[46]Table C7 of the appendix presents the first stage regressions.

disputes. Therefore, in country-industries characterised by intense industrial action, producers should have greater incentives to substitute human labor with machines.[47] The empirical specification used in this part of the analysis is:

$$S_{cjt} = \rho_0 + \rho_1 (P_t^{US} \times \bar{Strike}_{cj}) + CX_{ct} + u_{ct} + u_{jt} + u_{cj} + \eta_{cjt} \tag{5}$$

Model (5) exploits information on industrial action by country c, industry j and year t. The coefficient of interest is ρ_1, which multiplies an interaction between two variables. The first is the log-price of semiconductors in the United States, P_t^{US}.[48] The second variable is a measure of strike activity in each country-industry cell, $Strike_{cj}$. To mitigate concerns of reverse causality between strikes and investment in robots, strike activity is averaged over the five years preceding the beginning of the sample.[49] The idea underlying the identification strategy is the following. As technology improves and robots become cheaper, in order to edge against future production stoppages, firms having experienced more strike-related disruption should invest more intensively in robots relative to other industries. Since robots' prices data are available only for a very few countries, the price of semiconductors in the US is used instead as a proxy for technological advances.[50] Figure A3 of the appendix shows that semiconductor prices in the United States and the robots' price index for the available countries are indeed positively correlated.[51]

As in the previous specification, X_{ct} includes country covariates in the base year, interacted with year effects. One difference between specifications (4) and (5) is the level of industry aggregation.[52] In order to maximise the size of the sample, the dependent variable in (5) is shipments of robots, rather than shipment per worker.[53] To take into

[47] There is a large literature studying the determinants of strike activity, e.g. Tracy (1986), Card (1990a), and Card (1990b). However, that topic goes beyond the focus of this paper, which is on the impact of industrial action on investment in industrial robots.

[48] Data on US producer price index for semiconductor and other electronic components are taken from the FRED database at the following web address: https://fred.stlouisfed.org/series/PCU33443344

[49] Results are robust to averaging strike activity over ten years before the beginning of the sample.

[50] The US is then dropped from the sample.

[51] Robots' price indexes are taken from the IFR reports.

[52] The ILO data on industrial action is only available at one-digit level.

[53] Information on employment by industry is scarce for non-manufacturing industries, which would

account the relative size of industries in each country, (5) includes country-industry fixed effects, u_{cj}. The variable $\bar{Strike}_{cj}$ is normalised to have zero mean and unitary standard deviation. Standard errors are clustered by country and one-digit industry.

The results of estimating (5) with OLS are presented in Table 4. Columns 1-4 show the results for the full sample of advanced and developing economies, while columns 5-8 focus on OECD countries. The coefficient on all variables, exception made for the number of days lost per worker, are negative and significant.[54] [55] For instance, in column 1 the coefficients implies that a ten percent decline in the price of semiconductor is associated to 23 new robots in country-industries with a large number of workers involved in industrial action (i.e., cells one standard deviation above the sample mean). Reflecting the larger adoption of industrial robots in the OECD region, the coefficient in column 5 is much larger: a ten percent reduction in semiconductor prices corresponds to roughly 60 additional units shipped, which corresponds to 14 percent of the average number of annual shipments in the OECD sample.

5 Conclusions

This paper documents a positive relationship between institutions increasing the bargaining power of labor and adoption of industrial robots, in both advanced and developing economies. The results, which are robust to several different specifications, lend support to the hypothesis that producers use automation to minimise the dependency from workers and thwart rent appropriation.

Institutions explain up to 34% of the sample variation in adoption of robots, a proportion comparable to the estimated contribution of demographic trends - to date the only alternative driver of investment in robots considered by the literature. Together,

considerably reduce the size of the sample.

[54]One potential reason for the lack of significance of the coefficient in columns 3 and 7 is mismeasurement. While the numerator of the strike indicator is collected from administrative data, the denominator usually comes from labour force surveys.

[55]If errors are clustered at the country-level, the coefficient on the number of strikes becomes not significant at conventional levels.

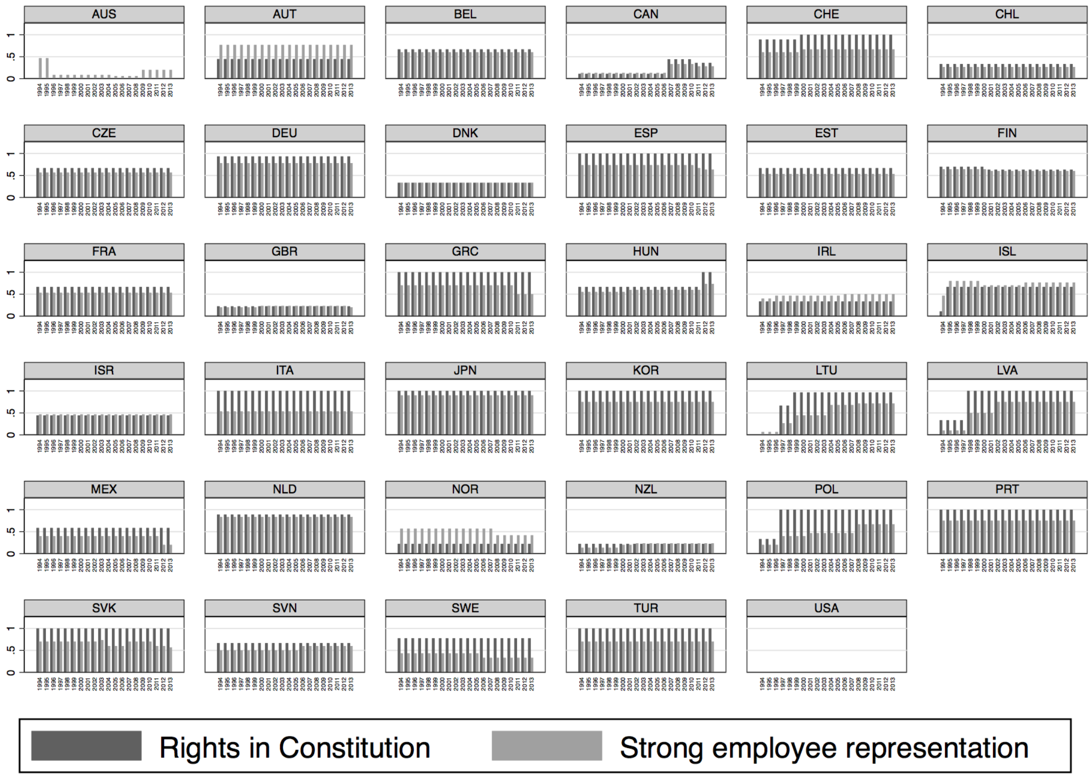
labor institutions and demographic trends account for more than half of the observed cross-country differences in automation; further research is needed to understand what explains the remain variation.

The results of the paper have two main implications. First, policies aimed at tackling disruption in the labor market by preserving workers' welfare might actually end up reducing their employment opportunities. Higher labor bargaining power is likely to result in higher labor costs for employers, which in turns create more incentives to substitute workers with robots.

The second implication concerns the effectiveness of policies aimed at promoting industrial automation. From a theoretical standpoint, a fully rational producer would invest in robots only if it helps increasing the amount of revenue generated for each unit of expenditure on inputs. Thus, policies aimed at incentivising investment in automation seem justified on the grounds that labor-saving technologies increase firms' productivity, which in turn generates additional investment and stimulates growth. Many advanced economies seem to share this view, as they spend a considerable amount of resources 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 finding of this paper that labor institutions are drivers of 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 further and undermine aggregate productivity (Acemoglu and Restrepo, 2018b).

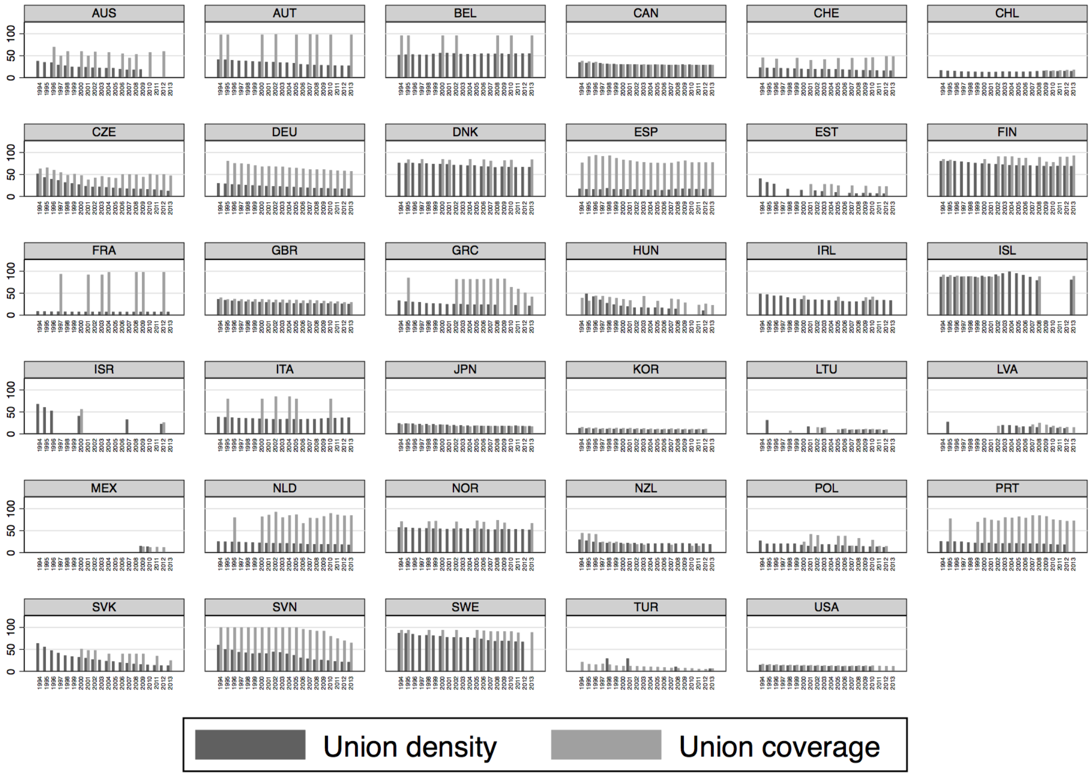
The model presented in this paper is too simple to evaluate the welfare impact of alternative policies. Nonetheless, the empirical results suggest that sunk costs and labor market frictions are ingredients that any general equilibrium model aimed at studying automation should incorporate.

Figure 1: Legal characteristics



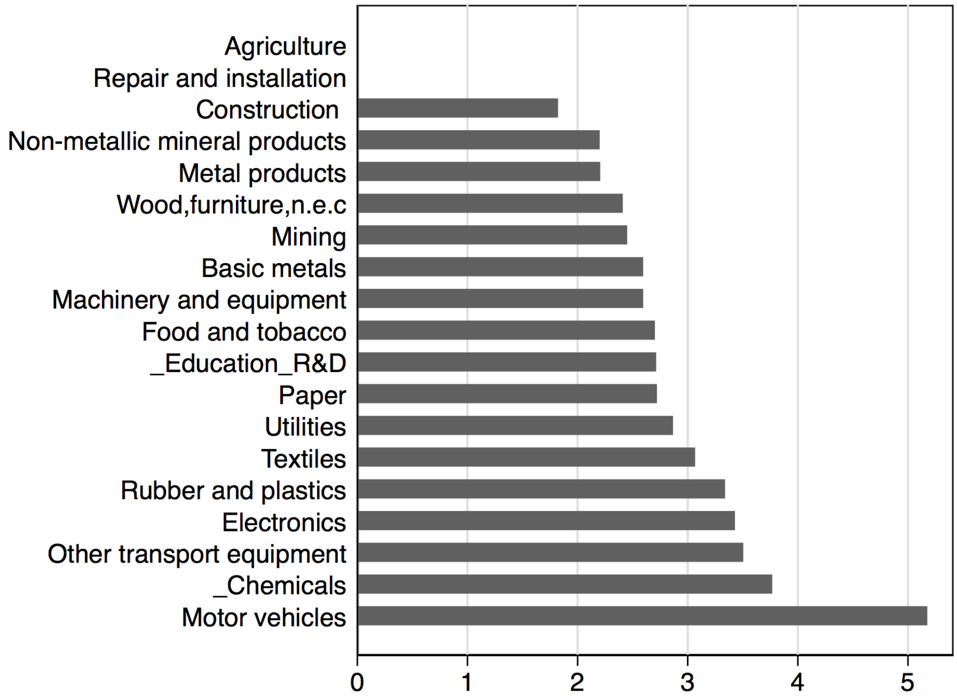
The figure shows the value of two indexes capturing legal characteristics of the labor market. Higher values corresponds to stronger constitutional protection of workers' rights or stronger employees' representation. Sources: Adams, Bishop, and Deakin (2016)

Figure 2: Union rates (%)



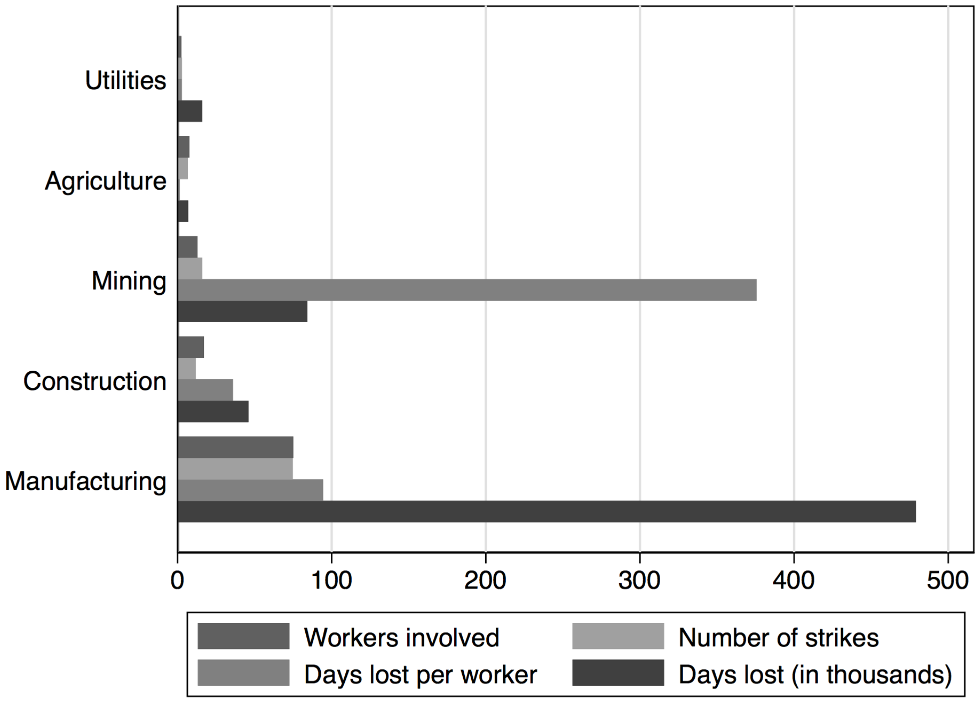
The figure shows the evolution of union rates across countries and over years. Sources: Visser (2015); Armingeon, et al. (2013)

Figure 3: Proxy of sunk costs



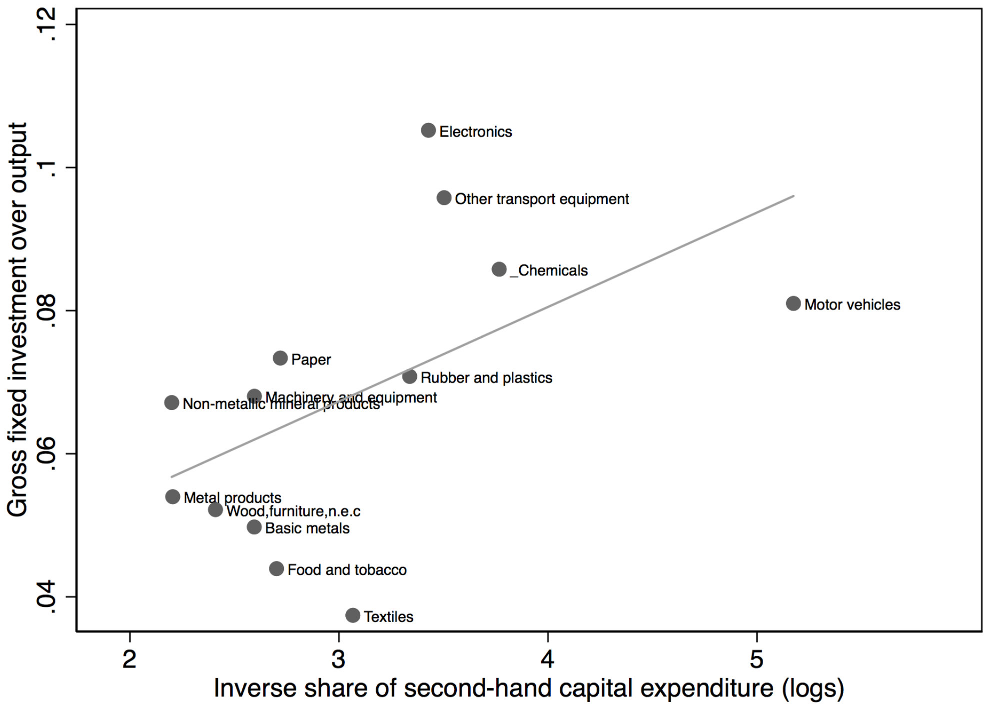
The figure shows the log of the inverse share of US second-hand capital expenditure in 1994. Industry names preceded by underscore indicate a higher level of aggregation with respect to the original 2-digit ISIC Rev.4 classification. Sources: US Census Bureau

Figure 4: Industrial action by industry (average values between 1990 and 1994)



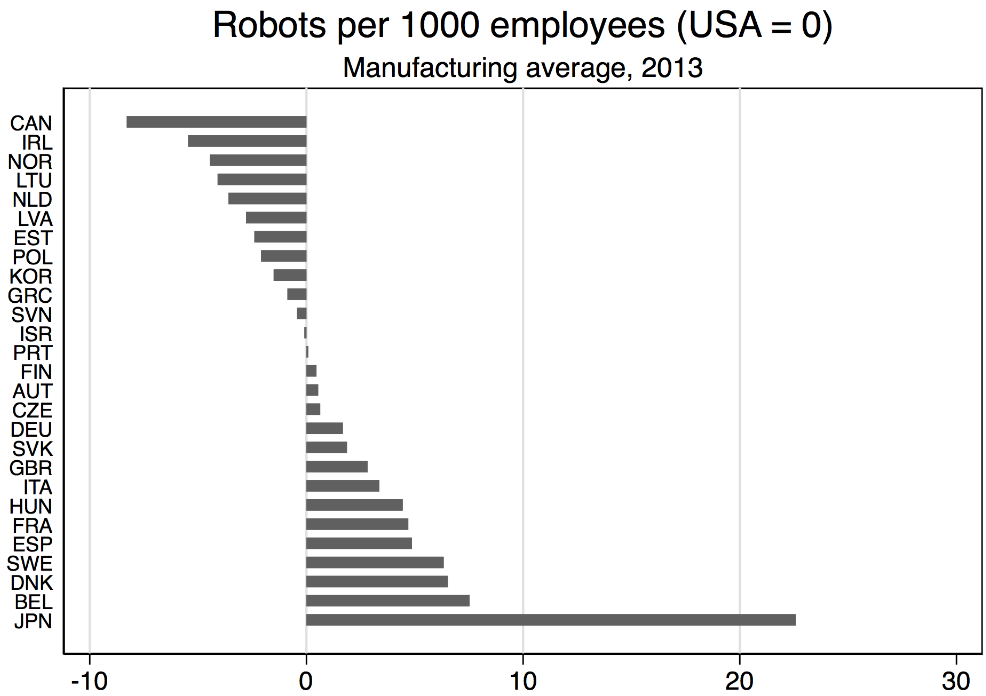
The figure shows the mean values (between 1990 and 1994) of different measures of industrial action by broad sector of economic activity.
Sources: ILO Work Stoppages Database

Figure 5: Correlation between alternative measures of sunk costs



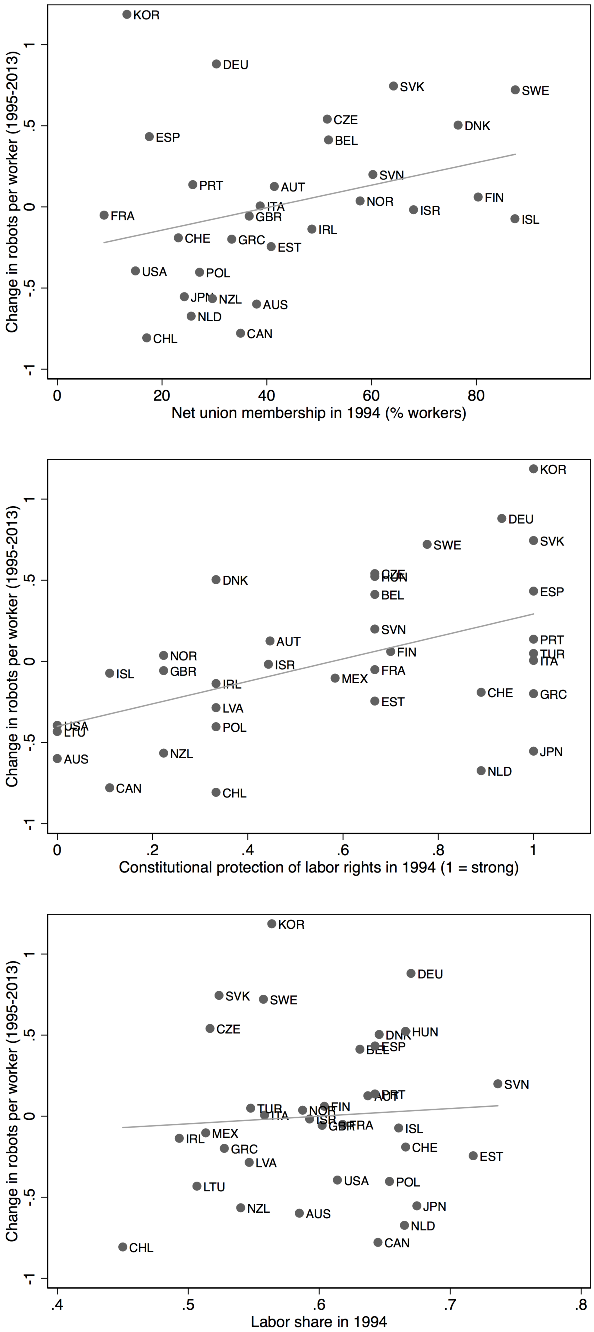
The figure shows, for each industry, the correlation between gross fixed investment over output and the log of the inverse share of second-hand capital expenditure. Industry names preceded by underscore indicate a higher level of aggregation with respect to the original 2-digit ISIC Rev.4 classification. Sources: US Census Bureau; NBER-CES dataset

Figure 6: Cross-country differences in adoption of industrial robots



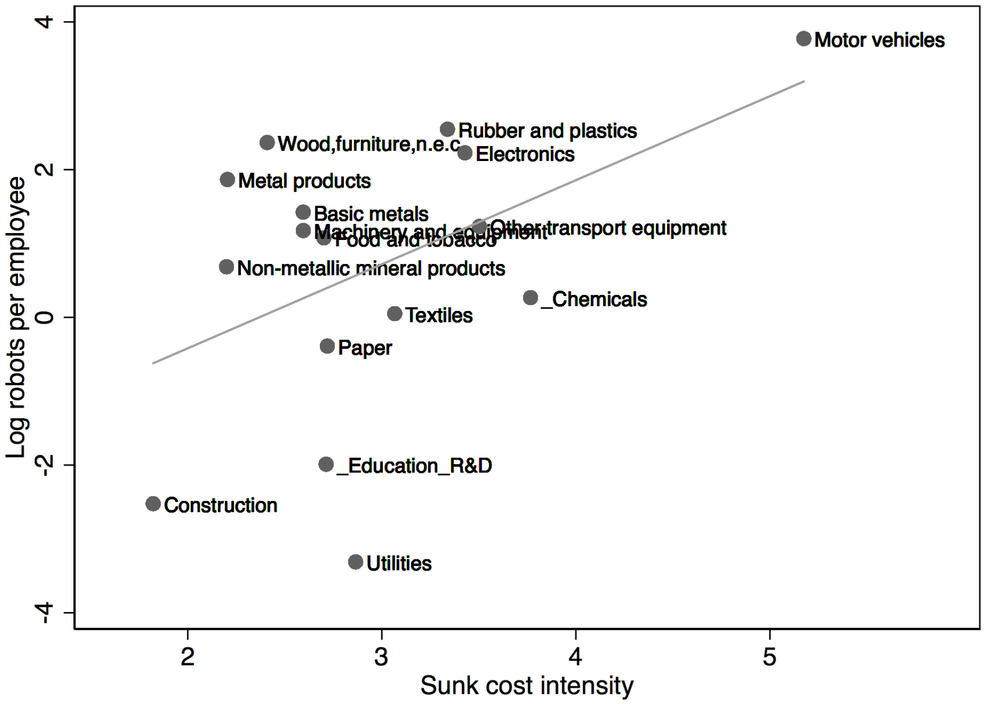
The figure shows the number of industrial robots per thousand employees used in the whole manufacturing sector, in 2013. The numbers are normalised so that the value for the United States is equal to zero. Sources: IFR; STAN

Figure 7: Industrial robots, labor institutions and the labor share



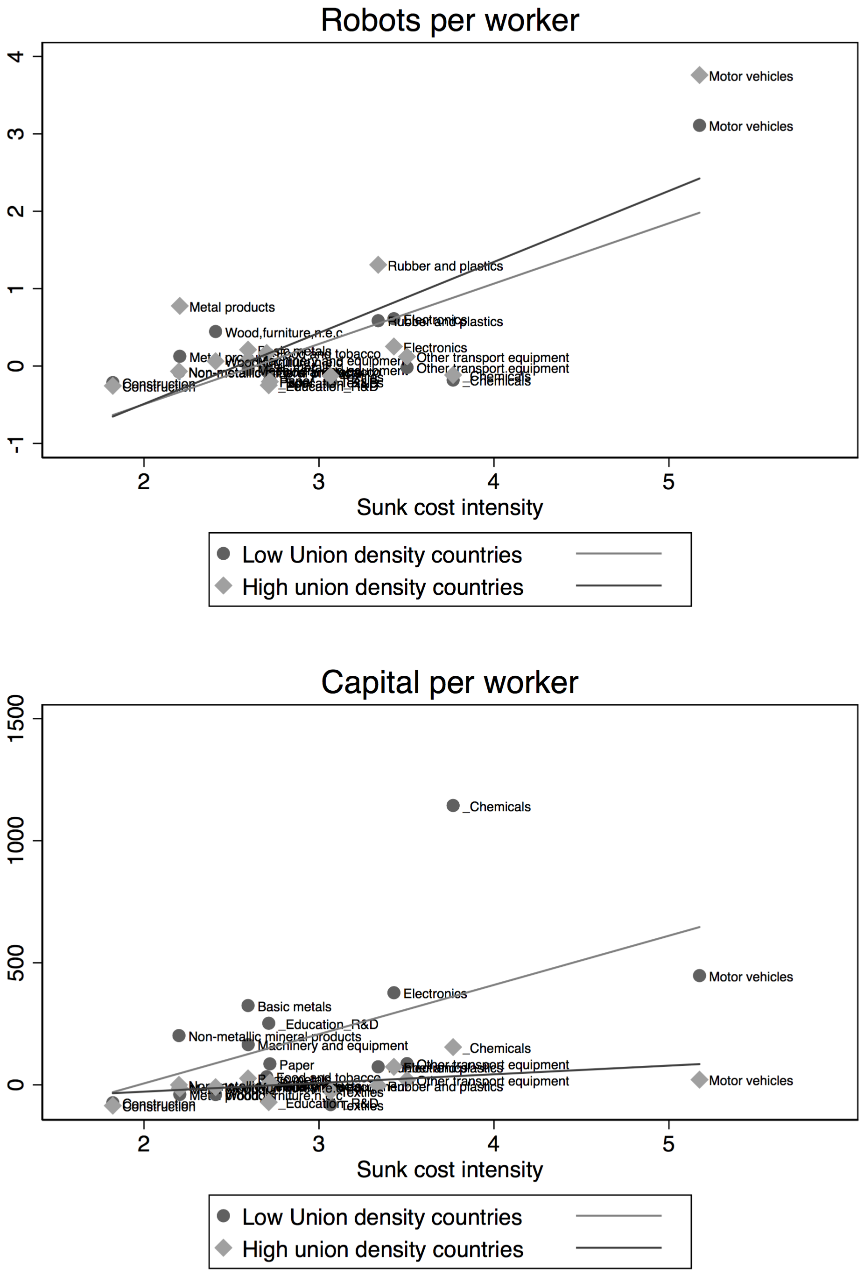
Each dot in the figure represents the country-average residual from a regression of long-run differences in robots per worker on the explanatory variables, after partialling out the impact of the stock of robots per worker in 1994, economic and demographic variables. The unexplained component is then plotted against the 1994 value of union density, the variable measuring the constitutional protection of labor rights, and the labor shares. Sources: IFR; PWT 9.1; Visser (2015); Armingeon, et al. (2013)

Figure 8: Sunk costs and automation (2013)



The figure shows the correlation between the log of the inverse share of second-hand capital expenditure and the log number of robots per thousand employees in 2013. Industry names preceded by underscore indicate a higher level of aggregation with respect to the original 2-digit ISIC Rev.4 classification. Sources: IFR; US Census Bureau

Figure 9: Robots, aggregate capital 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. Such unexplained components are then plotted against the log of the inverse share of second-hand capital expenditure. Sources: IFR; PWT 9.1; US Census Bureau

Table 1: Labor institutions, demographics and investment in industrial robots.

	DEPENDENT VARIABLE: 1995-2013 AVERAGE ANNUAL CHANGE IN ROBOTS PER THOUSAND WORKERS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample				OECD sample			
Labor rights in Constitution in 1994	0.028**				0.050***			
	(0.011)				(0.014)			
Strong employee representation in 1994		0.054**				0.068***		
		(0.023)				(0.024)		
Union density in 1994			0.021				0.066***	
			(0.022)				(0.024)	
Union coverage in 1994				0.041***				0.048***
				(0.011)				(0.016)
Expected ageing	0.048	0.056	0.064	0.084*	0.097**	0.095**	0.121**	0.110*
	(0.034)	(0.034)	(0.043)	(0.043)	(0.041)	(0.041)	(0.050)	(0.056)
Observations	53	53	49	48	35	35	35	35
R-squared	0.407	0.447	0.350	0.470	0.594	0.559	0.470	0.501
Base year country covariates	yes	yes	yes	yes	yes	yes	yes	yes
Δ^{inst} R2 (%)	22.56	29.52	10.04	32.89	34.02	29.93	16.72	21.72
Δ^{age} R2 (%)	31.15	36.98	48.71	54.93	39.47	40.44	74.58	61.04

The table presents OLS estimates of the relationship between labor institutions, ageing and investment in robots. Results refer to long-run specifications in which the dependent variable is the average annual change in industrial robots per thousand workers between 1995 and 2013. The explanatory variables are fixed at their base-year values (1994). All specifications include the base-year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling; iv) number of robots per thousand workers. Standard errors are clustered at the country-level. 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 2: OLS estimates of the impact of institutions on country-industry shipment of industrial robots per thousand employees.

DEPENDENT VARIABLE: ANNUAL SHIPMENTS OF ROBOTS PER THOUSAND WORKERS	(1)	(2)	(3)	(4)
Labor rights in Constitution x industry sunk costs	0.233*			
	(0.113)			
Strong employee representation x industry sunk costs		0.397**		
		(0.173)		
Union density x industry sunk costs			-0.075	
			(0.173)	
Union coverage x industry sunk costs				0.274*
				(0.146)
Observations	5,255	5,255	5,162	3,561
R-squared	0.597	0.603	0.581	0.599
Base year country covariates-year FE	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes
Country-year FE	yes	yes	yes	yes

The table presents OLS estimates of the relationship between labor institutions, sunk costs and annual installations of robots. The dependent variable is the country-industry shipment 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; iv) expected ageing, and v) number of robots per thousand workers. Standard errors are clustered at the country-level. 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: 2SLS estimates of the impact of union rates on country-industry adoption of industrial robots. Instruments: average union rates × dummy for civil origins (columns1-4); ii) average union rates in other countries (columns 5-8).

	DEPENDENT VARIABLE: ANNUAL SHIPMENTS OF ROBOTS PER THOUSAND WORKERS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Civil legal origins				Unions in other countries			
Union density	1.227*				0.125			
	(0.733)				(0.163)			
Union density x industry sunk costs	0.818		0.961*		0.404*		0.742*	
	(0.500)		(0.576)		(0.206)		(0.385)	
Union coverage		1.702***				0.153		
		(0.631)				(0.101)		
Union coverage x industry sunk costs		0.464**		0.498***		0.301**		0.473***
		(0.183)		(0.191)		(0.127)		(0.179)
Observations	4,656	3,125	4,656	3,125	5,162	3,561	5,162	3,561
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes	yes	yes	yes	yes
Legal origin covariates	yes	yes	yes	yes	no	no	no	no
Industry-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Country-year FE	no	no	yes	yes	no	no	yes	yes
First stage F	5.211	10.94	8.613	115.6	40.24	44.16	20.48	48.44

The table presents 2SLS estimates of the relationship between unions, sunk costs and adoption of robots. The dependent variable are the country-industry annual installations of robots per thousand employees. 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; iv) expected ageing, v) number of robots per thousand workers. Standard errors are clustered at the country-level. 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 4: OLS estimates of the impact of strike activity on country-industry adoption of industrial robots.

	DEPENDENT VARIABLE: ANNUAL SHIPMENTS OF ROBOTS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample				OECD sample			
log-semiconductor price x workers involved (89-94 average)	-231.1**				-589.5**			
	(100.51)				(251.31)			
log-semiconductor price x number of strikes (89-94 average)		-164.3**				-214.7*		
		(66.95)				(127.69)		
log-semiconductor price x days lost per worker (89-94 average)			5.5				8.9	
			(44.82)				(59.93)	
log-semiconductor price x 100 days lost (89-94 average)				-115.6**				-499.2**
				(51.12)				(233.39)
Observations	3,511	3,473	2,214	3,585	2,305	2,267	1,664	2,381
R-squared	0.250	0.241	0.368	0.248	0.260	0.248	0.373	0.257
Number of country-industry cells	211	209	132	213	134	132	96	138
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes	yes	yes	yes	yes
Country-industry FE	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 semiconductor prices, strike activity and and adoption of robots. The dependent variable are the country-industry annual installations of robots (for every year between 1995 and 2013). 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; iv) expected ageing, and v) number of robots per thousand workers. Standard errors are clustered at the country-industry level. 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.[56] 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.[57]

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.

[56] 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.

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

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;

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.

Let output per worker 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

$$f'(k) = 1 + w'_k \tag{6}$$

Notice that the last term in (6) 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

$$w'_k = \beta\big[f'(k) + \sigma\big] \tag{7}$$

Substituting (7) into (6) yields

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

Differentiating with respect to β yields,

$$k'_\beta = \frac{1 + \sigma}{f''(k)(1 - \beta)^2} < 0 \tag{8}$$

since $f''(k) < 0$ by assumption. Therefore, $k''_{\sigma,\beta} < 0$ and higher labor bargaining power lowers aggregate investment more in sunk cost-intensive industries. The negative relationship between bargaining power, sunk costs and aggregate capital is tested in Table C5. 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

$$w'_\beta = \frac{w}{\beta} + \beta\big[f'(k) + \sigma)\big]k'_\beta \tag{9}$$

Since $k'_\beta < 0$ from (8), 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

$$w''_{\sigma,\beta} = k + \beta k'_\beta \tag{10}$$

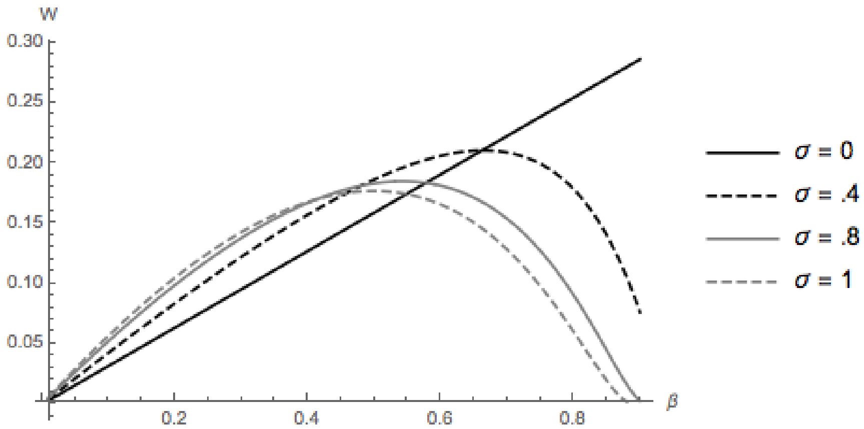
The first term in (10) is positive, but the second is negative and so it is not possible to determine the sign of $w''_{\sigma,\beta}$ analytically. Therefore, to examine the behavior of wages we rely on a numerical simulation of the system (1)-(6). The production function is assumed to be CES,

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

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: Labor institutions, demographics and investment in industrial robots (additional controls)

	DEPENDENT VARIABLE: 1995-2013 AVERAGE ANNUAL CHANGE IN ROBOTS PER THOUSAND WORKERS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample				OECD sample			
Labor rights in Constitution in 1994	0.033**				0.033**			
	(0.015)				(0.015)			
Strong employee representation in 1994		0.047*				0.048*		
		(0.028)				(0.027)		
Union density in 1994			0.031				0.033	
			(0.019)				(0.022)	
Union coverage in 1994				0.041**				0.055**
				(0.018)				(0.021)
Expected ageing	0.023	0.020	0.045	0.021	0.024	0.022	0.047	0.011
	(0.029)	(0.030)	(0.030)	(0.028)	(0.032)	(0.032)	(0.032)	(0.031)
Redundancy compensation in 1994	0.015	0.022	0.024	0.013	0.014	0.021	0.022	0.002
	(0.020)	(0.018)	(0.017)	(0.016)	(0.022)	(0.020)	(0.018)	(0.019)
Minimum wage in 1994	-0.002	-0.003*	-0.001	-0.000	-0.003	-0.004*	-0.002	-0.000
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Labor taxes and contributions (% commercial profits)	0.011	0.005	0.041	-0.007	0.017	0.014	0.050	-0.011
	(0.034)	(0.038)	(0.032)	(0.037)	(0.036)	(0.039)	(0.035)	(0.042)
Unemployment benefits expenditure (% GDP)	0.009*	0.009*	0.008*	0.006	0.009*	0.009*	0.008*	0.004
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Observations	33	33	33	33	30	30	30	30
R-squared	0.524	0.493	0.399	0.437	0.500	0.482	0.383	0.446
Base year country covariates	yes	yes	yes	yes	yes	yes	yes	yes
Δ^{inst} R2 (%)	29.93	25.56	7.884	15.97	30.76	28.13	9.498	22.32
Δ^{age} R2 (%)	2.435	1.893	10.79	2.384	2.580	2.220	12.45	0.619

The table presents OLS estimates of the relationship between labor institutions, ageing and investment in robots. Results refer to long-run specifications in which the dependent variable is the average annual change in industrial robots per thousand workers between 1995 and 2013. The explanatory variables are fixed at their base-year values (1994), exception made for labor taxes and unemployment benefits expenditure, which are country-average values due to data availability. All specifications include the base-year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling; iv) number of robots per thousand workers. Standard errors are clustered at the country-level. 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 C2: Labor institutions, demographics and investment in industrial robots (1995-2007)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DEPENDENT VARIABLE: 1995-2007 AVERAGE ANNUAL CHANGE IN ROBOTS PER THOUSAND WORKERS							
	Full sample				OECD sample			
Labor rights in Constitution in 1994	0.018**				0.023**			
	(0.007)				(0.011)			
Strong employee representation in 1994		0.033**				0.029		
		(0.015)				(0.018)		
Union density in 1994			0.025				0.046***	
			(0.016)				(0.014)	
Union coverage in 1994				0.037***				0.038***
				(0.010)				(0.011)
Expected ageing	0.014	0.019	0.022	0.034	0.055**	0.055**	0.070***	0.062**
	(0.020)	(0.020)	(0.027)	(0.026)	(0.021)	(0.021)	(0.022)	(0.026)
Observations	53	53	49	48	35	35	35	35
R-squared	0.353	0.378	0.307	0.434	0.447	0.418	0.437	0.495
Base year country covariates	yes	yes	yes	yes	yes	yes	yes	yes
Δ^{inst} R2 (%)	18.40	23.70	6.059	33.57	21.84	16.42	20.06	29.51
Δ^{age} R2 (%)	5.932	9.518	12.59	18.44	38.47	40.55	59.85	44.13

The table presents OLS estimates of the relationship between labor institutions, ageing and investment in robots. Results refer to long-run specifications in which the dependent variable is the average annual change in industrial robots per thousand workers between 1995 and 2007. The explanatory variables are fixed at their base-year values (1994). All specifications include the base-year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling; iv) number of robots per thousand workers. Standard errors are clustered at the country-level. 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: Labor institutions, demographics and investment in industrial robots (robots per unit of capital)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DEPENDENT VARIABLE: 1995-2013 AVERAGE ANNUAL CHANGE IN ROBOTS PER UNIT OF CAPITAL							
	Full sample				OECD sample			
Labor rights in Constitution in 1994	0.094**				0.190***			
	(0.038)				(0.054)			
Strong employee representation in 1994		0.183**				0.249***		
		(0.076)				(0.087)		
Union density in 1994			0.085				0.255**	
			(0.072)				(0.095)	
Union coverage in 1994				0.137***				0.178***
				(0.044)				(0.063)
Expected ageing	0.160	0.187*	0.212	0.264*	0.269*	0.265*	0.360**	0.317
	(0.107)	(0.105)	(0.135)	(0.141)	(0.142)	(0.144)	(0.169)	(0.193)
Observations	53	53	49	48	35	35	35	35
R-squared	0.599	0.623	0.571	0.623	0.736	0.707	0.655	0.669
Base year country covariates	yes	yes	yes	yes	yes	yes	yes	yes

The table presents OLS estimates of the relationship between labor institutions, ageing and investment in robots. Results refer to long-run specifications in which the dependent variable is the average annual change in industrial robots per unit of capital stock between 1995 and 2013. The explanatory variables are fixed at their base-year values (1994). All specifications include the base-year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling; iv) number of robots per thousand workers. Standard errors are clustered at the country-level. 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 institutions on country-industry adoption of industrial robots per thousand employees (alternative proxy of sunk costs)

DEPENDENT VARIABLE: ANNUAL SHIPMENTS OF ROBOTS PER THOUSAND WORKERS	(1)	(2)	(3)	(4)
Labor rights in Constitution x fixed investment	0.678***			
	(0.186)			
Strong employee representation x fixed investment		0.820***		
		(0.169)		
Union density x fixed investment			1.455**	
			(0.667)	
Union coverage x fixed investment				0.395*
				(0.218)
Observations	2,904	2,904	2,891	2,051
Base year country covariates	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes
Country-year FE	yes	yes	yes	yes
First stage F	22.07	26.72	57.30	56.07

The table presents 2SLS estimates of the relationship between labor institutions, sunk costs and the adoption of robots. The dependent variable is the country-industry annual installations 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 in the base year. The proxies are instrumented with the same quantity 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 clustered at the country-level. 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 institutions on country-industry gross fixed investment per worker.

DEPENDENT VARIABLE: LOG ANNUAL GROASS FIXED AGGREGATE INVESTMENT PER THOUSAND WORKERS	(1)	(2)	(3)	(4)
Labor rights in Constitution x industry sunk costs	-0.259***			
	(0.060)			
Strong employee representation x industry sunk costs		-0.254**		
		(0.108)		
Union density x industry sunk costs			-0.065	
			(0.138)	
Union coverage x industry sunk costs				-0.091
				(0.076)
Observations	4,672	4,672	4,613	3,137
R-squared	0.963	0.961	0.958	0.968
Base year country covariates-year FE	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes
Redundancy compensation	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes
Country-year FE	yes	yes	yes	yes

The table presents OLS estimates of the relationship between institutions 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 clustered at the country-level. 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: First stage regression of Table 3. Instrument: average union rate × civil law dummy

VARIABLES	(1) Density	(2) Coverage	(3) Density x sunk costs	(4) Coverage x sunk costs	(5) Density x sunk costs	(6) Coverage x sunk costs
Average density rate x civil law	1.953***		-0.094			
	(0.352)		(0.414)			
Average density rate x civil law x industry sunk costs	-0.012		0.760***		0.723**	
	(0.029)		(0.223)		(0.257)	
Average coverage rate x civil law		1.129***		-0.448		
		(0.277)		(0.313)		
Average coverage rate x civil law x industry sunk costs		0.002		1.120***		1.107***
		(0.011)		(0.128)		(0.138)
Observations	5,050	3,411	5,050	3,411	5,050	3,411
R-squared	0.869	0.852	0.723	0.882	0.742	0.916
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes	yes	yes
Legal origin covariates	yes	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes	yes
Country-year FE	no	no	no	no	yes	yes

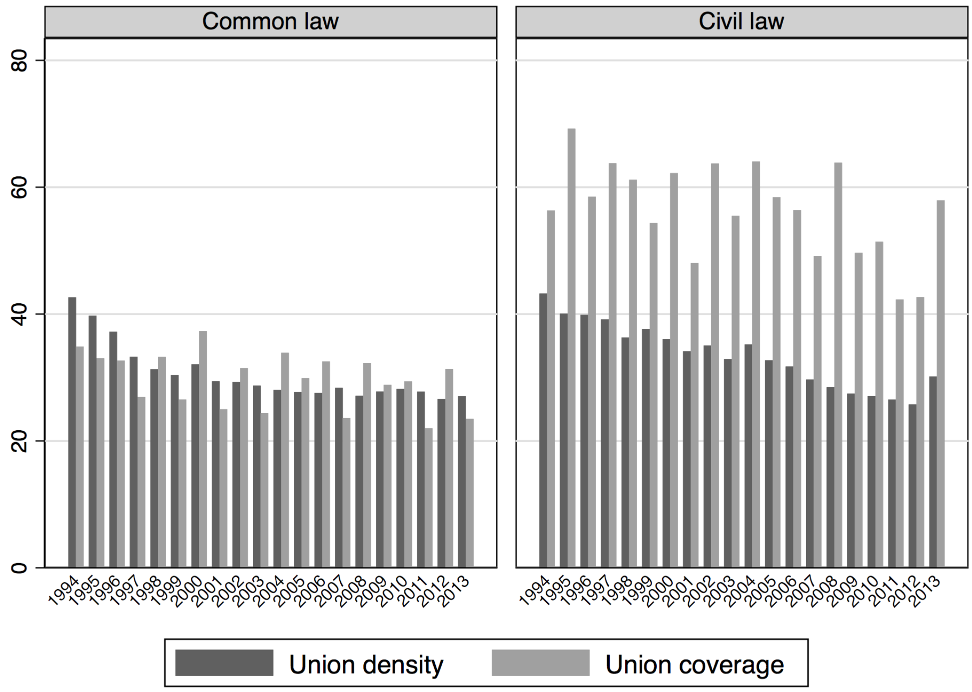
The table presents the OLS estimates of the first stage regressions of columns 1 to 4 in Table 3. All specifications include include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table C7: First stage regression of Table 3. Instrument: union rates in other countries

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Density	Coverage	Density x sunk costs	Coverage x sunk costs	Density x sunk costs	Coverage x sunk costs
Average density rate in other countries	-554.992***		-291.976***			
	(2.109)		(96.662)			
Average density rate in other countries x industry sunk costs	0.001		0.874***		1.068***	
	(0.001)		(0.108)		(0.242)	
Average coverage rate in other countries		-403.605***		-268.495***		
		(8.328)		(85.237)		
Average coverage rate in other countries x industry sunk costs		0.000		0.953***		1.178***
		(0.003)		(0.112)		(0.150)
Observations	5,715	3,981	5,715	3,981	5,715	3,981
R-squared	0.998	0.984	0.749	0.835	0.812	0.895
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes	yes	yes
Legal origin covariates	no	no	no	no	no	no
Industry-year FE	yes	yes	yes	yes	yes	yes
Country-year FE	no	no	no	no	yes	yes

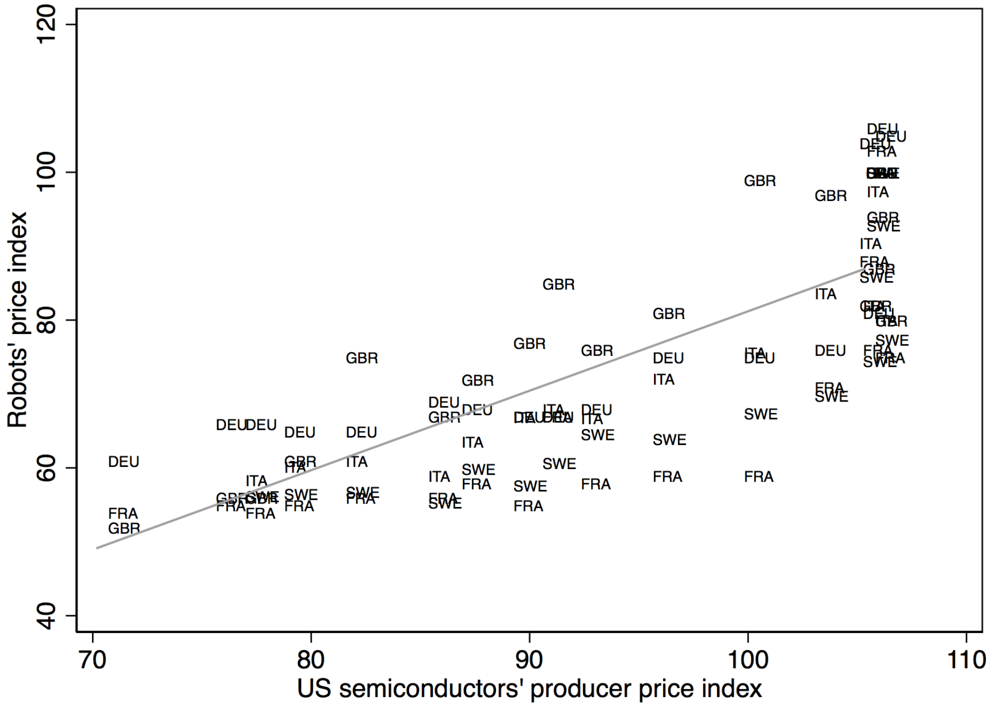
The table presents the OLS estimates of the first stage regressions of columns 5 to 8 in Table 3. All specifications include include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Figure A2: Union rates in common-law and civil-law countries



The figure shows union rates over year for countries characterised by common and civil law systems. Sources: Visser (2015); Armingeon, et al. (2013); La Porta et al. (2008)

Figure A3: Correlation between US semiconductors' producer price index and robots' price index for selected OECD countries



The figure shows the correlation between indexes of robots' price and the price index of semiconductor prices in the United states between 1990 and 2007. Sources: FRED database and IFR publications.