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Institutions, Holdup and Automation

Giorgio Presidente

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INSTITUTIONS, HOLDUP AND AUTOMATION*†

Giorgio Presidente

Oxford Martin School, Oxford University

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Abstract

What drives investment in automation technologies? 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

JEL classification : O32, O33, L16, J50, O57

*Contacts: giorgio.presidente@oxfordmartin.ox.ac.uk; giopresidente@gmail.com

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1 Introduction

Over the last decade, advances in robotics have generated concerns about labor displacement. While a growing body of literature investigates the economic impact of robots, the equally important question of what drives investment in automation has received much less attention. The main contribution of this paper is making a step toward filling that gap, by documenting a positive relationship between labor-friendly institutions and investment in industrial robots. The underlying mechanism is simple. Labor-friendly institutions increase labor bargaining power and wages, providing an incentive to substitute workers with robots.

The first part of the paper estimates specifications in long differences for fifty-three advanced and developing countries. The change in the total number of robots per thousand workers between 1995 and 2013 is regressed on country-specific institutional variables in 1994. Results suggest that labor institutions have a substantial impact on automation. For instance, countries with strong employees' representation use twice the average number of robots per worker in the sample. Moreover, cross-country differences in labor institutions are found to explain up to one third of the total variation in robots' adoption in the sample.

To mitigate the concern that the cross-country correlations between institutions and robots are driven by omitted variables, the second part of the paper exploits country-industry-year variation in robots' adoption and industrial action. The empirical methodology is based on the idea that a fall in robots' price should be associated to more robots in countries and industries characterised by longer or more frequent strikes, which are detrimental to firms' profitability. The inclusion of country- and industry-year fixed effects helps purging the estimates from the impact of other institutions and differences in human capital endowment, as well as industry-specific factors such as demand and supply shocks, or the task composition of employment.[1] The results are consistent with the cross-country estimates and suggest that robots' adoption between 1995 and 2013

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

has been stronger in countries and industries with a high incidence of industrial action before 1995.

The finding of a positive correlation between labor-friendly institutions and automation has important implications. For instance, a popular idea is that in order to tackle disruption in the labor market, governments should reform institutions as to increase workers' bargaining power (e.g. International Labor Organization, 2019). However, the finding of a positive relationship between labor-friendly institutions and investment in robots, suggests that policies aimed at protecting workers from automation might actually end up reducing their employment opportunities.

Another contribution of this paper is providing a set of results suggesting that labor-friendly institutions increase investment in labor-substituting capital and discourages the use of labor-complementing capital. To guide the analysis, the third part of the paper develops a simple model of technological choice with wage bargaining. Firms can chose between using a traditional technology employing capital and labor or using robots, which perfectly substitute for labor. Institutions increase workers' ability to extract rents at the expenses of firms. When labor is essential in production i.e. capital and labor are complementary, firms cannot avoid rent extraction and respond by investing less. When automation is an alternative i.e. capital and labor are substitutes, firms produce with robots to minimise dependency from labor and thwart appropriation. In the model, firms face sunk costs at the moment of hiring. Since part of the initial investment cannot be recovered if workers walk away and production does not take place, workers exploit their bargaining power to extract rents. The higher the sunk cost, the higher the rents workers can extract, the higher the incentives to invest in robots. Industries characterised by a high incidence of sunk costs should then be disproportionately automated in countries with labor-friendly institutions. In line with the assumption and 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.

The model predicts an opposite relationship between institutions, sunk costs and investment when capital complements labor. In line with such prediction and consistent with the idea that most capital assets are characterised by some degree of complementarity with labor, the relationship between institutions, sunk costs and *aggregate* investment found in the data is negative. A case in point is the motor vehicle industry. Motor vehicles is an industry characterised by large sunk costs, because both suppliers of components and assemblers need specific equipment that has little scope for utilisation outside the industry.[2] That makes it hard to find an alternative use of capital and fully recover the cost of investment if production does not take place. In countries with high union rates, for instance, Motor vehicles tends to be highly automated but with a relatively low aggregate-capital to labor-ratio.

The last part of the paper addresses the concern that the positive (negative) relationship between labor-friendly institutions, sunk costs and robots (aggregate investment) is affected by reverse causality. For instance, unions might be weaker when automation is stronger, as firms can credibly threaten to fire workers if they join the union. Similarly, unions might be stronger *because* an industry is labor-intensive and firms are heavily dependent on workers. That being the case, the OLS coefficients might be biased towards zero. To mitigate such concerns, the paper experiments with different instrumental variables, such as countries' legal origins that have an impact on current union rates but are unlikely to be affected by contemporaneous trends in automation. While none of the instruments considered solve all the potential concerns of omitted variables and reverse causality, they provide a useful robustness check for the empirical methodology used in the paper. Results show that the 2SLS estimates are larger than the OLS coefficients and suggest that labor-friendly institutions generate incentives to invest in industrial robots, but discourage investment in other categories of assets, particularly in sunk cost-intensive industries where producers are vulnerable to holdup.

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 (Grout, 1984). Several contributions have studied investment in presence of holdup, but they have reached different conclusions. For instance, Cardullo, Conti, and Sulis (2015), Acemoglu and Shimer

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

(1999), and Connolly et al. (1986) advocate a negative relationship. Card et al. (2014) find no significant relationship, while holdup boosts long-run investment in Caballero and Hammour (1997).[3] None of these papers take explicitly into account the role of capital-labor substitution and study the implications of the holdup using data on robots.

This paper relates as well to a growing strand of literature studying the *impact* of robots on economic outcomes (e.g. Acemoglu and Restrepo, 2017; Graetz and Michaels, 2018, and Dauth, Findeisen, Suedekum, and Woessner, 2019). Instead, the main contribution of this paper is exploring the *determinants* of investment in automation. Motivated by the wide cross-country heterogeneity in the use of industrial robots, Acemoglu and Restrepo (2018a) point to demographic trends as the chief explanation for such differences. 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. The findings of this paper are consistent with Belloc et al. (2020), which document a positive correlation between the strength of establishment-level employee representation and the use of automation technologies.

The rest of the paper is organised as follows. Section 2 presents the descriptive evidence to motivate the analysis and the cross-country empirical results; Section 3 presents additional results on the impact of industrial actions on robots' adoption; Section 4 presents a model, which is used to guide the country-industry-year analysis; Section 5 presents the empirical methodology and the country-industry-year results, and Section 6 concludes.

2 Cross-country Differences in Automation and Labor Market Institutions

This section motivates the analysis by presenting the main data and some descriptive evidence based on fifty-three OECD and non-OECD countries from 1993 to 2013. Section 2.2 quantifies the impact of labor institutions on robots' adoption in the cross-country

[3] See Belloc et al. (2020) for a discussion of the issue.

sample.

Detailed information on data sources are provided in the online Data Appendix A. Summary statistics of the variables used in this section can be found in Table A1 in the online Data Appendix.

2.1 Cross-country Data and Descriptive Evidence

Data on shipments of industrial robots are obtained from the International Federation of Robotics (IFR). Data on shipments are used to construct the stock of operational robots in each country-industry-year cell. 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.*

As any other piece of machinery and equipment, industrial robots are included in accounts of aggregate capital.[4] However, the definition of industrial robots suggests that they differ in one fundamental dimension from most other categories of capital equipment: they are characterised by a high degree of substitutability with human labor, i.e. they are labor-saving technologies. Unlike industrial robots, most other categories of assets included in capital accounts are characterised by some degree of complementarity with labor. Buildings, (non-autonomous) vehicles and the vast majority of machine tools are examples of labor-complementing capital. Indeed, estimates from different countries and levels of aggregation suggest that the elasticity of substitution between aggregate capital and labor is generally less then unity (see Klump et al., 2007). Sections 4 and 5.4 will study theoretically and empirically the implications that differences in the degree of substitution with labor have on the relationship between labor institutions and investment.

The data show that there are large differences in adoption of industrial robots, even

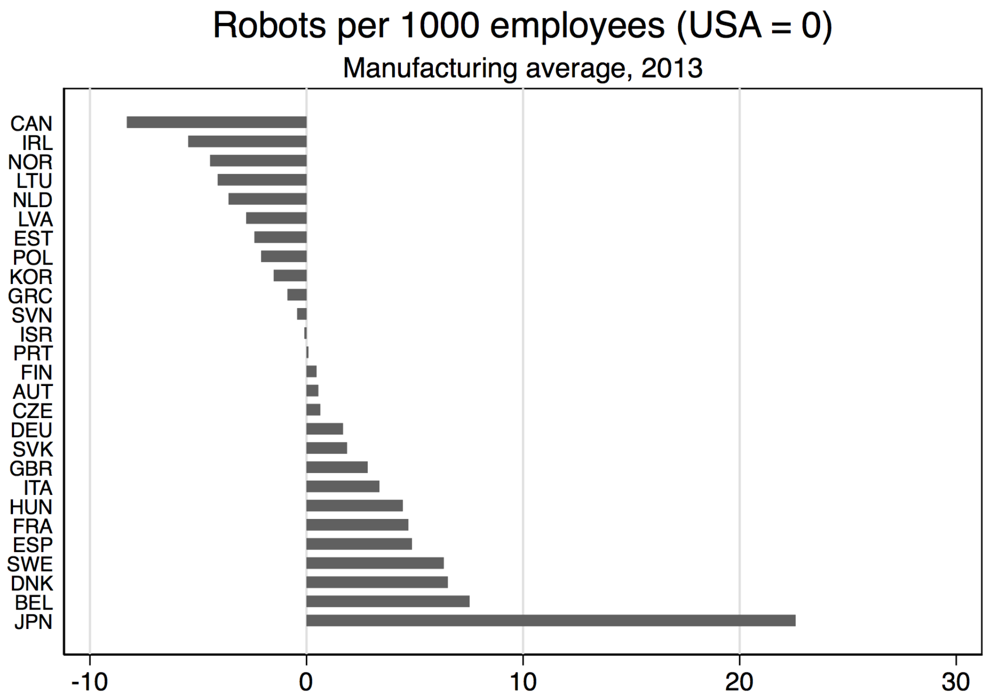
[4]The industrial classification ISIC rev. 4 includes robots in *28- Machinery and Equipment n.e.c.* There is no specific category for industrial robots. For instance, robots with applications related to handling materials are classified under *2816 - manufacture of lifting and handling equipment.*

within the OECD region between countries at similar levels of *per capita* income and narrowly defined industries. For instance in Motor vehicles, which alone accounts for almost half of the total robots usage in the OECD region, the number of robots per thousand employees, "robot density" hereafter, 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, where Korea and Japan used almost 80 robots per thousand employees in 2013, against 15 or less in other OECD economies.

Differences in adoption are unlikely to be due to differences in robot prices, especially among OECD countries similarly integrated in international markets. Evidence on robot prices for six large economies is documented in Graetz and Michaels (2018), which present very limited cross-country price variation. An alternative explanation for cross-country differences in technology adoption is the presence of frictions. Examples include lack of education (Nelson and Phelps, 1966), organisational capital (Brynjolfsson and Hitt, 2000), credit constraints (Parente and Prescott, 1994), or labor market rigidities (Bartelsman, Gautier, and De Wind, 2016). However, data suggest that frictions are unlikely to explain differences in adoption. Figure 1 shows robot density in OECD countries relative to the United States for the manufacturing industry in 2013. 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 in labor market institutions, this paper investigates whether they can explain the differences in robots' adoption. Data on institutions are taken from Adams, Bishop, and Deakin (2016), Visser (2015), and Armingeon, et al. (2013). The data show that institutions are much more "labor-friendly" in some countries than in others. For instance, the constitutional protection of labor rights and the strength of employee representation tend to be lower in Anglo-Saxon countries than in most countries in Continental Europe. Union coverage is above 50 percent in

Figure 1: 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

most European countries - almost 100 percent in Spain, France and Italy, while in the United States and Japan coverage is well below 20 percent.

In countries with labor-friendly institutions, the cost of labor should be higher for firms. Therefore, due to the high degree of substitution with labor emphasised in the definition of industrial robot, incentives to automating production should be higher in countries with labor-friendly institutions. Descriptive evidence is consistent with the hypothesis. The top panel of Figure 2 depicts the relationship between the 1995-2015 change in the number of robots per thousand workers and the 1994 union membership rate.[5] 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 2 displays the correlation between the change in robots' adoption over the same period

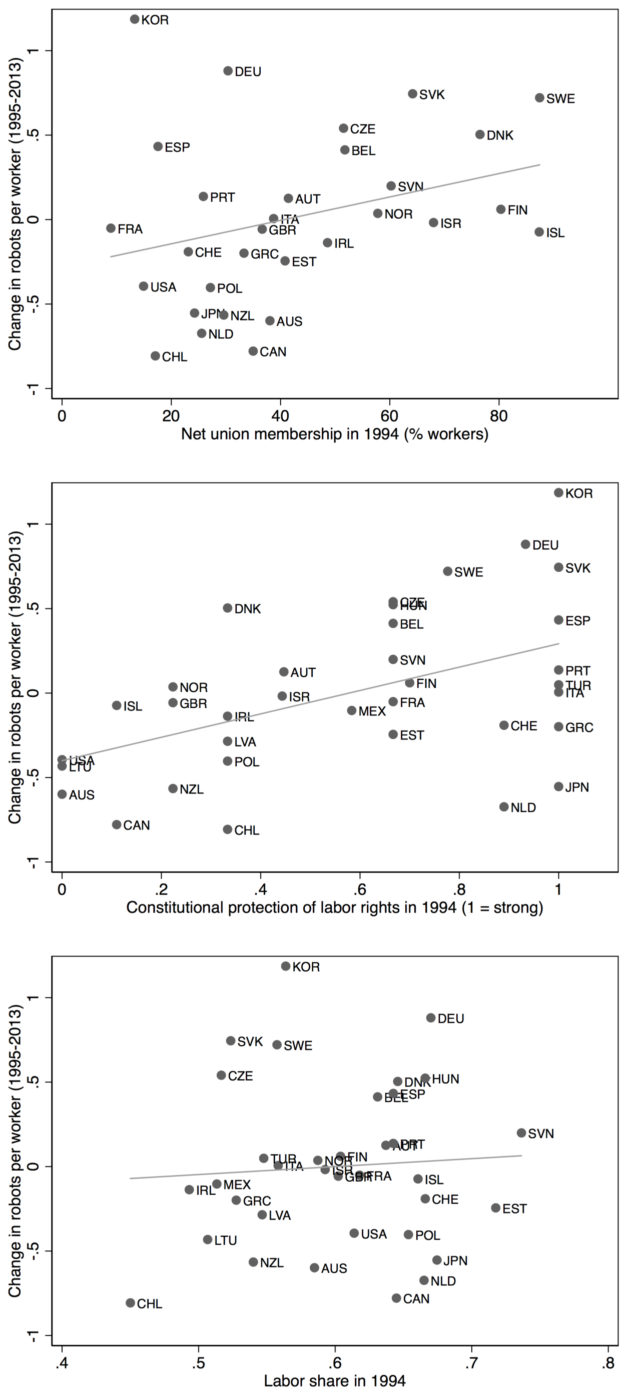
[5]Each dot in the figure represents the country-average residual from a regression of long-run differences in robots per worker on the explanatory variables, after partialling out the impact of the 1993 stock of robots per worker, economic and demographic variables.

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.[6] On the contrary, 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.[7] 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 2 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.

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

[7] 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.

Figure 2: 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)

2.2 What Proportion of Cross-country Differences in Automation Can Be Explained by Institutions?

This section quantifies the contribution of institutions in explaining cross-country differences in robots' adoption.

The analysis is based on the following linear model:

$$\Delta R/L_c = \beta_0 + \beta_1 Inst_{c,1994} + \beta_2 Ageing_c + BX_{c,1994} + \varepsilon_c \tag{1}$$

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.[8] The variable $Inst_{c,1994}$ is the base year value of the institutional variable. Four institutional variables are considered: i) constitutional protection of labor rights; ii) strength of employees' representation in industrial relations; iii) union membership, and iv) union coverage, which measures the share of employees covered by contractual agreements between firms and unions. All such variables vary between zero and one, with higher values corresponding to institutions likely to increase the bargaining power of labor (see the online Data Appendix for details).

Although the focus of this paper is on labor institutions, (1) accounts for the potential impact of demographic trends, which are considered by Acemoglu and Restrepo (2018a) the chief driver of automation technologies. $Ageing_c$ measures population ageing 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 $X_{c,1994}$ in (1) includes the base-year values of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling; iv) number of robots per worker, and v) a dummy taking value 1 if a country is an OECD member.[9] The error term is denoted by ε_c.

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

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

2.2.1 Cross-country Results: Estimated Parameters

Table 1 presents the results of estimating (1) 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 results in Table 1 are robust to several alternative specifications, such as using the EPL index compiled by the OECD.[10] Table C1 in the online Tables Appendix includes additional labor market institutions that are likely to affect labor costs.[11] The results in Table C1 mitigate the concern that the positive relation between institutions and robots in Table 1 is due to omitted variables.

[10]The EPL index is only available for 28 OECD countries in 1994 and it does not make possible a comparison with the full sample of advanced and developing economies. Moreover, the index bundles together many different aspects of labor legislation, including firing costs and unemployment benefits, which are instead included separately in Table C1. The results of estimating (1) with the EPL index as the institutional variable are available upon requests.

[11]Due to the lower availability of data, the number of observations drops when including additional controls. Moreover, data limitations for some variables impose to use sample averages, rather than 1994 values. For these reasons, the results of Table C1 are presented in the appendix.

Table C2 in the online Tables 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. Table C3 in the online Tables Appendix 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 just capturing an increasing trend in capital accumulation.

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

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, and v) a dummy taking value 1 if a country is an OECD member. 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.

2.2.2 Explaining Sample's Variation in Robots' Adoption: Institutions *vs* Demographics

Based on estimates of (1), it is possible to assess the relative contribution of institutions and demographics in explaining cross-country variation in automation. Results from three different methods suggest that differences in labor institutions account for a substantial share of cross-country variation in robot density, and that their contribution is similar to that of demographic trends.

The first method is the calculation of partial R2.[12] The results are presented in Table 2, which reports the number of observations and the partial R2 for the full and OECD sample, respectively.[13] The partial R2 for demographic trends is 0.23 for the full sample and 0.33 for the OECD sample. Again, it is not surprising that ageing has a higher contribution in explaining automation in advanced economies, where population ageing is a stronger trend. In the full sample, labor rights and employee representation have a similar partial R2, roughly 70% the size of ageing. In the OECD sample, the two variables have a partial R2 that is very similar to the one of the ageing variable. At the same time, union rates tend to have a much lower partial R2. Section 5.5 will address in detail the potential reasons for why the impact of union rates might be underestimated when using OLS.

Another intuitive metrics can be obtained by calculating the following quantity:

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

where $\bar{R}2$ is the adjusted-R2 of (1) and $R2^{noinst}$ is the adjusted-R2 of the same model without institutional variables (but including ageing). Analogous calculation are performed to compute the contribution of population ageing, $\Delta R2^{age}$. Table 3 report the values of (2) for institutional and demographic variables.[14] As suggested by tables 2 and C4, institutions explain a lower share of variation in robots' investment than ageing. However, the contribution of institutions in explaining cross-country differences in automation

[12]The partial R2 is calculated by estimating a reduced version of (1) that only includes $X_{c,1994}$ and computing the residuals. The residuals are then regressed on (1) without $Ageing_c$ to obtain the partial R2 of $Inst_{c,1994}$. A similar procedure is used to obtain the partial R2 of the ageing variable.

[13]Unlike in Table 1, Table 2 restricts the sample to have the same number of observations for each variable. This is done to ensure that the partial R2 is comparable across specifications.

[14]The underlying specifications used for the construction of Table 3 are identical to those used for Table 1.

is substantial, ranging from 10% to 34% depending on the variable considered.

As a robustness test, Table C4 in the online Tables Appendix reports standardised coefficients. The table shows that all institutional variables have an impact that is slightly lower but of comparable magnitude to the ageing variable. For instance, the coefficients in columns 1 and 5 suggest that an increase of one standard deviation in expected ageing and the institutional variable would increase the number of robots per thousand workers by roughly the same amount in both samples. Moreover, in the restricted samples used in Table C4, union rates are significant and their impact is at least 60% the size of the impact of the ageing variable.

Table 2: Partial R2 for institutional and demographic variables.

	Full sample		OECD sample	
VARIABLES	N	Partial R2	N	Partial R2
Expected aging	46	0.230	35	0.326
Labor rights in Constitution	46	0.159	35	0.290
Strong employee representation	46	0.170	35	0.261
Union density	46	0.00162	35	0.0248
Union coverage	46	0.0417	35	0.108

The table presents the number of observations and the partial R2 for each variable considered. The partial R2 is obtained by first taking the residuals of a regression of the 1995-2013 average annual change in robots per thousand workers on base year values of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling; iv) number of robots per thousand workers, and v) a dummy taking value 1 if a country is an OECD member. Then, the partial R2 is defined as the R2 of a regression of such residuals on the base year values of each institutional variable and ageing.

Table 3: Contribution of institutional and demographic variables in explaining sample variation of 1995-2013 average annual changes in robots per thousand workers.

	Full sample				OECD sample			
	Labor rights	Representation	Union density	Union coverage	Labor rights	Representation	Union density	Union coverage
Total R2	0.407	0.447	0.350	0.470	0.594	0.559	0.470	0.501
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
Observations	53	53	49	48	35	35	35	35

The variables presented in the table are obtained with the following formulas: $\Delta R2^{inst} = \left[1 - \frac{R2^{noinst}}{R2}\right] \times 100$ and $\Delta R2^{age} = \left[1 - \frac{R2^{noage}}{R2}\right] \times 100$. The underlying specifications used for the construction of Table 3 are identical to those used for Table 1.

3 Strikes and Automation

The previous section documents a positive correlation between labor-friendly institutions and investment in industrial robots. One concern is that the cross-country correlations might be biased by omitted variables. This section exploits country-industry variation in industrial action to estimate specifications that are robust to country- and industry-year unobserved characteristics.

Strikes are the most powerful tool that unions can use against the management in industrial disputes.[15] Therefore, in country-industries characterised with stronger incidence of strikes, firms should have greater incentives to substitute human labor with machines as robots become affordable.

Data on industrial action is taken from the database on work stoppages of the International Labour Organization.[16] 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. Figure A3 in the online Data Appenidix depicts the values of the strike variables. The values reported refer to the mean value between 1990 and 1995, for both advanced and developing countries. The figure shows that most of the strike activity took place in the manufacturing sector. One exception is Mining, where over 350 days were lost for each worker involved in industrial action.

The empirical specification used in this part of the analysis is:

$$S_{cjt} = \rho_0 + \rho_1(P_t^{US} \times \bar{Strike}_{cj}) + CX_{ct} + u_{ct} + u_{jt} + u_{cj} + \eta_{cjt} \tag{3}$$

Model (3) exploits information on industrial action by country c, industry j and year

[15]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.

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

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}.[17] 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.[18] 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 as a proxy for technological progress.[19] Figure A4 of the appendix shows that semiconductors' prices in the United States and the robots' price index for the available countries are indeed positively correlated.[20]

As in the previous specification, X_{ct} includes country covariates in the base year, interacted with year effects. The fixed effects u_{ct} and u_{jt} absorb country and industry-specific time-varying characteristics. In order to maximise the size of the sample, the dependent variable in (3) is shipments of robots, rather than shipment per worker.[21] To take into account the relative size of industries in each country, as well as other confounding characteristics, (3) includes country-industry fixed effects, u_{cj}. The variable $Str\bar{i}ke_{cj}$ is normalised to have zero mean and unitary standard deviation. Standard errors are clustered by country and one-digit industry.

The results of estimating (3) 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

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

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

[19] The US is then dropped from the sample prior to estimation

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

[21] Information on employment by industry is scarce for non-manufacturing industries, which would considerably reduce the size of the sample.

number of days lost per worker, are negative and significant.[22] [23] For instance, in column 1 the coefficients implies that a ten percent decline in the price of semiconductors 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 semiconductors' prices corresponds to roughly 60 additional units shipped, which corresponds to 14 percent of the average number of annual shipments in the OECD sample.

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 semiconductors' 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.

[22]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.

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

4 A Model of Technological Choice with Wage Bargaining and Sunk Costs

This section sketches a model of technological choice with wage bargaining and sunk costs. The model serves the purpose of rationalising the contrasting views expressed by the literature about the impact of institutions on investment. The key result from the model is that labor-friendly institutions encourage investment in labor-saving technology and discourage investment in labor-complementing capital. A detailed description of the model and its solution, as well as additional results can be found in the online Model Appendix B

4.1 The Model Environment

There is a single final good Y produced by a representative firm in a perfectly competitive final output market. This firm combines an infinity of intermediate goods indexed by i, with aggregate measure 1. The quantity of each intermediate good is denoted by $y(i)$. Final good firms have access to the production function $ln\, Y = a + \int_0^1 ln\, y(i)\; di$. The final good is taken to be the numerarire and so its price is set to 1.

4.2 Intermediate Good Firms

There is free entry in the production of each intermediate good variety, which pushes intermediate good producers' profits down to zero. The timing assumptions are as in Cardullo, Conti, and Sulis (2015), and Acemoglu and Shimer (1999). First, firms decide how much to invest in structures and machinery. Only then, they hire workers and bargain over wages. The timing assumptions reflect the fact that building a plant and setting up the machinery takes time. In a typical situation, workers are not hired before everything is ready for production. The assumption of *ex ante* investment and *ex post* wage bargaining implies that at least part of the investment is sunk at the moment of bargaining on wages. Anticipating that firms would lose (at least part of) their initial investment if production does not take place (e.g. a strike), workers can *hold up* firms when they bargain, by demanding higher wages.

Intermediate good varieties can be produced by one of two potential technologies. One is "traditional" and combines labor and capital. Alternatively, intermediate goods can be produced with robots only. The difference between traditional and automated firms is that the capital used by the former is characterised by some degree of complementarity with labor, while the capital used by the latter (i.e. robots) is a perfect substitute for human workers. Crucially, the assumption on the different degree of substitution with labor implies that only traditional firms are vulnerable to holdup.

4.2.1 Traditional Intermediate Good Firms

Traditional firms produce output with a constant returns to scale production function combining capital $k(i)$ and labor. Due to the timing assumptions, capital is rented before hiring at the rate $r > 1$. For simplicity, each firm is assumed to hire only one worker. Output (per worker) is given by $y(i) = f\big(k(i)\big)$.

A fraction of capital $\sigma \in [0, 1]$ is lost if production does not take place.[24] Therefore, a fraction of the initial *ex ante* investment $\sigma r k(i)$ is sunk at the moment of hiring. Assuming a Nash bargaining rule, the wage equation reads:

$$w(i) = \beta\big[p(i)f\big(k(i)\big) - rk(i)(1 - \sigma)\big] \tag{4}$$

In (4), $p(i)$ is the relative price of variety i. Equation (4) shows that wages are increasing with sunk costs. Anticipating that the initial investment would be lost if they refuse to provide their services (e.g., by striking), workers hold up the producer by demanding higher wages. The larger the sunk costs, the larger the rent labor can appropriate. However, the extent to which labor is able to extract rents depends on its bargaining power $\beta \in (0, 1)$.

Since all traditional firms are identical, they earn the same price p, invest the same amount of capital k and pay the same wage w.

[24] For simplicity, we assume that σ is the same for every variety i.

4.2.2 Automated Intermediate Good Firms

Firms produce one unit of variety i with one robot i.e. automated firms have a linear production technology. Following Alesina, Battisti, and Zeira (2018), and Zeira (1998), production of some varieties is harder to automate.[25] Without loss of generality, intermediate good varieties are ordered in such a way that higher is are more costly to automate. This is reflected in the price of robots being equal to $\frac{r}{1-i} \geq r$. The equilibrium stock of robots in automated firms is:

$$R(i) = \frac{Y}{r}(1-i) \tag{5}$$

4.2.3 Technological Choice

Let i^* be the intermediate good variety for which firms are indifferent to using traditional or automated production technologies. An expression for i^* is obtained by equating the marginal cost of the two methods of production and rearranging terms:

$$i^* = 1 - \frac{f'\big(k\big)(1-\beta)}{1-\beta(1-\sigma)} \tag{6}$$

Equation (6) describes the extensive margin of robots' adoption and defines a positive relationship between k and i^*. A large capital stock implies low returns on investment and so high marginal costs. That implies that a larger share of varieties will be produced with robots. Therefore, the model predicts that automation is higher (at least on the extensive margin) in highly industrialised countries, a prediction consistent with the data.

4.3 Equilibrium and Analysis

The online Model Appendix B shows that for given levels of output and interest rate, the unique equilibrium stock of robots R and aggregate capital k are given by the intersection

[25] For instance, as in Autor, Levy, and Murnane (2001), the production of some varieties might involve many non-routine tasks, which makes robots less suitable than human workers to produce that variety.

of two equations:

$$\phi(R,k) \equiv R - \frac{Y}{2r}\left[1 - \left(\frac{f'\big(k\big)(1-\beta)}{1-\beta(1-\sigma)}\right)^2\right] = 0$$

$$\psi(R,k) \equiv Y - f\big(k\big)\Big[\beta + (1-\beta)r\varepsilon_{f,k}\Big] - rR = 0$$

Equation $\phi(R,k)$ describes an increasing relationship between R and k, while as long as $\varepsilon_{f,k}f\big(k\big)$ is non-decreasing, $\psi(R,k)$ generates a decreasing relationship between the same variables. Figure 3 depicts the equilibrium under two different values of β, with high values representing labor-friendly institutions. For $\beta = 0.3$, the economy lies at the equilibrium represented by point A. Now suppose that β increases to $\beta = 0.7$. In such a case, wages increase and the net value of engaging in production for traditional firms drops. In turn, that generates an incentive to using robots instead, which do not bargain over wages. Both i^* and R increase, which shifts $\phi(R,k)$ up. At point A', however, there are less traditional firms and the stock of aggregate capital k is lower. That increases the marginal product of capital and lowers the cost advantage of automated firms, which mitigates the increase in i^* and shifts $\psi(R,k)$ down, up to the new equilibrium B.

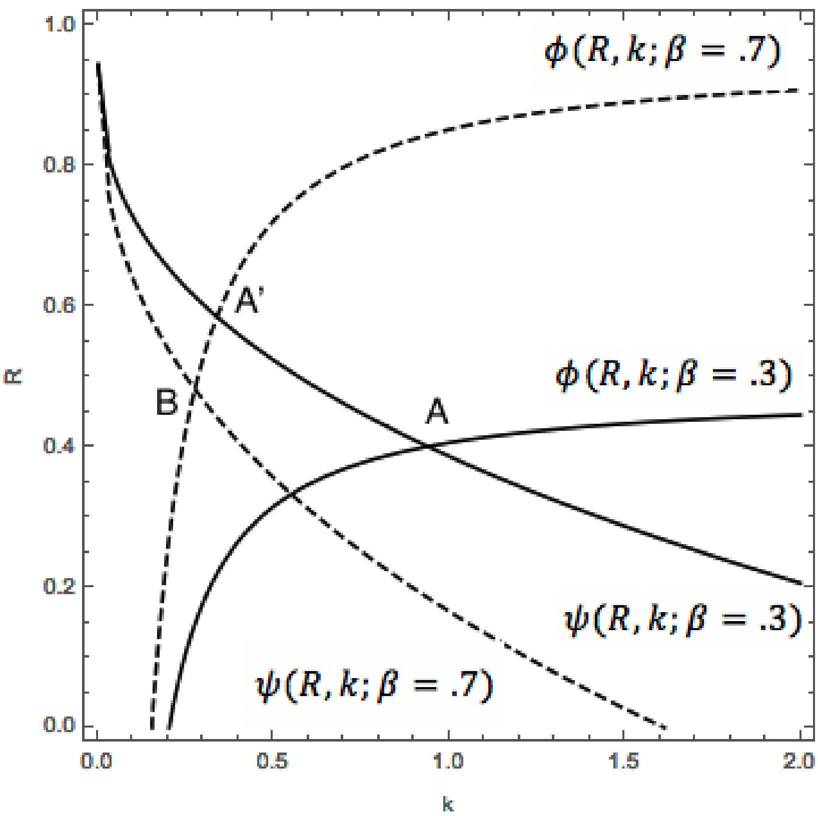
The model predicts that economies with low labor bargaining power have a high level of labor-complementing capital and a low stock of robots, while the opposite is true for high values of β. The online Model Appendix B shows that the equilibrium presents similar characteristics when output is determined endogenously, although the existence and uniqueness of the equilibrium cannot be established in general.[26]

The equilibrium conditions of the model can be used to study the how labor bargaining power and sunk costs interact in determining technological choice. Figure 4 presents the results of simulating the path of R, k, i^* and w as functions of β. Each panel plots two lines, corresponding to the cases of low and high incidence of sunk costs. Solid lines correspond to the case $\sigma = 0.1$, while dashed lines to the case $\sigma = 1$ i.e. the whole initial investment is sunk. In Panel 4a, the stock of robots is an increasing function of labor bargaining power. For any value of β, however, the R is larger when sunk costs are high.

[26]Output is endogenised by embedding the supply side into an overlapping generation model.

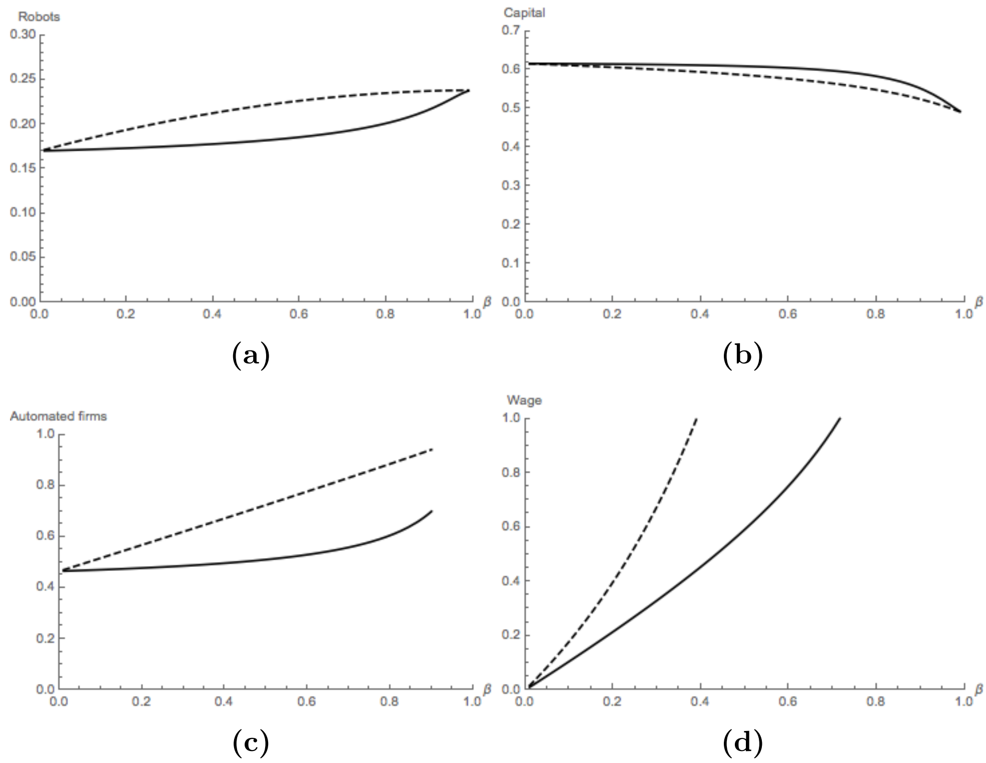
An opposite relationship is presented in Panel 4b for aggregate capital. Labor bargaining power lowers incentives to invest in labor-complementing capital, disproportionately more in presence of large sunk costs. Panel 4c shows that with high sunk costs, the share of automated firms increases much more steeply. Finally, Panel 4d confirms that higher bargaining power increases wages, disproportionately when sunk costs are large.

Figure 3: The relationship between wages, labor bargaining power and sunk cost-intensity



The figure depicts a graphic characterisation of the equilibrium. The two isoquant curves are $\phi(R, k)$ and $\psi(R, k)$. Solid lines corresponds to the case $\beta = .3$, while dashed lines to the case $\beta = .7$. The figure depicts the equilibrium for the following parametrisation: $f(k) = k^{\alpha}$, $\alpha = .4$, $r = 1.05$, $\sigma = .1$, $Y = 1$.

Figure 4: The relationship between key variables of the model, labor bargaining power and sunk costs



The figures depict the pattern of key variables as a function of β In each panel, the sold line corresponds to the case $\sigma = .1$, while the dashed line to the case $\sigma = 1$. The parametrisation used in the simulation is the following: $f(k) = k^{\alpha}$, $\alpha = .4$, $r = 1.05.$, $Y = 1$.

5 Country-industry-year Empirical Analysis

This section tests empirically the predictions of the model presented in Section 4. The empirical analysis is based on a sample of 35 OECD economies and 18 two-digits industries, from 1993 to 2015.[27] Summary statistics of all variables used in this section can be found in Table A2 of the online Data Appendix.

5.1 Quantifying Industry-level incidence of Sunk Costs

The empirical methodology in this section crucially relies on measuring industry-level sunk costs. The proxy of industry-level sunk costs are computed from data on second-hand capital expenditure by industry, from US Census Bureau.[28] The idea underlying the construction of the proxy is the following.[29] 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.[30] The indicator is based on data from STAN and the NBER-CES Manufacturing Database.[31] [32]

Figure A5 displays the proxy of sunk cost-intensity.[33] Motor vehicles and Chemicals

[27]Employment by industry is only available for OECD countries. Robots data are not available for Luxembourg.

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

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

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

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

[32]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.

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

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.[34] Capital is thus highly specific in both industries due to the irreversibility 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 A5 suggests that the construction industry is the less sunk cost-intensive. The reason is that most capital assets used in Constructions are general purpose machinery used to handle materials, machine tools and vehicles. Moreover, 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 A6 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 variables.

5.2 Empirical Methodology

The analysis is based on the following linear model:

$$S/L_{cit} = \gamma_0 + \gamma_1(Inst_{ct} \times \sigma_i) + BX_{ct} + u_{ct} + u_{it} + \varepsilon_{cit} \tag{7}$$

The dependent variable in (7) is shipments of *new* industrial robots per thousand employees to every country, two digits industry and year.[35] With respect to (3), model

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

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

(7) exploits a finer level of industry breakdown, roughly corresponding to 2 digits-level ISIC rev.4[36]

The choice of the dependent variable in (7) is similar to Acemoglu and Restrepo (2018a), which in the country-industry-year specification use shipment of new robots, rather than the stock.[37] 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 (7) over (1) 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. Including country-year effects is particularly important because it allows to purges the estimated coefficients from the potential correlation between our main independent variables and other institutions. For instance, union rates might be correlated with the generosity unemployment benefits or firing costs, which in turn might have an impact on robots' investment. The variable u_{it} denotes industry-year fixed effects. The inclusion of u_{it} aims at controlling for the impact industry-specific unobserved characteristics, such as improvements in industry-specific technology, or workforce's differences in human capital endowment and skills.[38] Including industry-year fixed effects helps as well mitigating the concern that some industry-specific characteristics correlated with sunk costs, such as routine tasks-intensity, might be driving the results.[39] The error term is denoted by ε_{cit}. Errors are clustered at the country-level and all estimates are weighted by the base-year

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

[37]Table C5 of the appendix shows that results are qualitatively identical when using the stock of robots per worker as the dependent variable in (7)

[38]For instance, improvements in machine vision could boost robots' adoption in the textile industry, where the micro-imperfections of fabrics made it difficult to automate; robots' adoption might be higher in high-tech industries with a higher number of engineers.

[39]The inclusion of industry-year fixed effects would account for such confounding effects as long as all countries in the sample have a similar skill content and routine task-intensity. This seems a relatively innocuous assumption in a sample of OECD countries.

industry share of employment in each country.[40]

In (7), the coefficients of interest is γ_1, which quantifies the differential impact of institutions in industries characterised by different levels of sunk costs. The computation of σ_i is based on 1994 data for the United States, which is then dropped from the sample prior to estimation.[41] 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 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 in 1994, robots' investment in the United States might have biased σ_i, the baseline proxy of sunk costs used in the paper. The variable σ_i is normalised to have zero mean and standard deviation equal to 1 in the weighted sample. Therefore,

[40]The same weighting scheme is used in Graetz and Michaels (2018) and Acemoglu and Restrepo (2018a). Unweighted coefficients, available upon request, are qualitatively identical but larger than the weighted ones.

[41]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.

γ_1 measures the differential impact of institutions in industries one standard deviation above the average sunk cost intensity (henceforth, "sunk cost-intensive" industries).

5.3 Institutions, Sunk Costs and Robots: Results

Table 5 shows OLS estimates of γ_1.[42] The coefficients in Table 5 suggest that institutions are associated to higher automation in sunk cost-intensive industries, roughly between 0.2 and 0.4 additional robots per thousand workers. The only coefficient that is not statistically significant is the one associated to union density in column 3.[43] 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 extract rents. Table C5 of the appendix shows that running (7) with the stock of robots per thousand workers as the dependent variable yields qualitatively identical results. Additional estimates, available upon requests, show that the results in Table 5 are also robust to assigning equal weight to each industry.

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 C6 of the appendix presents the results of estimating (7) using an alternative identification strategy, based on proxies of sunk costs that are industry and 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 C6 shows 2SLS estimates using this strategy and the results are consistent with those in Table 5, 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,

[42] The inclusion of country-year fixed effect does not allow to estimate the country-wide impact of institutions on robots' adoption.

[43] Section 5.5 addresses the potential reasons for the lack of significance.

do carry over to industries in other OECD countries.

Table 5: 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.

5.4 Institutions, Sunk Costs and Aggregate Investment: Results

The model of Section 4 suggests that the sign of the relationship between labor bargaining power, sunk costs and investment depends on the capital's degree of substitution with labor. The underlying reason is that if capital needs labor in order to become productive (i.e. capital and labor are complementary factors), workers can hold up the producer and extract part of the returns on investment. Since most categories of capital assets are complementary to labor, industry-level aggregate investment is likely to be less than perfectly substitute to labor. Therefore, the larger the sunk costs, the more severe the holdup, the lower are producers' incentives to invest in aggregate investment.[44] This

[44]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 in Section 5.2, the available evidence suggest that robots account for only a small percentage of the aggregate capital stock.

section tests such prediction empirically.

Table 6 shows the results of estimating (7) with annual aggregate fixed investment as the dependent variable.[45] Although only the coefficients in columns 1 and 2 are statistically significant, the negative sings of the estimated OLS parameters supports the idea that unlike for robots, there is a negative correlation between institutions, sunk costs and aggregate investment. The magnitudes of the impact in columns 1 and 2 are substantial. For instance, the coefficient in column 1 suggests that in countries with constitutional provisions on labor rights, aggregate investment is 26% lower in sunk cost-intensive industries. The results in Table 6 are in line with the findings in Cardullo, Conti, and Sulis (2015), which show that institutions increasing the bargaining power of labor lower aggregate investment per worker.

Table 6: OLS estimates of the impact of institutions on country-industry gross fixed investment per worker.

DEPENDENT VARIABLE: LOG ANNUAL 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
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 aggregate investment. The dependent variable is the log annual gross fixed aggregate investment 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.

5.5 Endogeneity of Union Rates: 2SLS Estimates

By increasing average wages and lowering firms' profitability (Hirsch, 2017; Taschereau-Dumouchel, 2017), unions should create strong incentives to invest in automation. How-

[45]As for Table 5, the inclusion of country-year fixed effect does not allow to estimate the country-wide impact of institutions on aggregate investment.

ever, 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 A8 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. On the one hand, average union rates capture the general trend in de-unionisation, which is driven by global development of technology and global value chains, and so they are presumably less sensitive to country-specific trends in robots' adoption. On the other hand, differences in legal systems developed around the 12th century, long before the development and commercialisation of automation technologies. Therefore, countries' legal system cannot be affected by trends in automation. However, while instrumenting union rates with countries' legal origins can help mitigating the concern of reverse causality, 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.[46] Therefore, to mitigate the possibility of violating the exclusion restrictions, the specification using legal origins as an instrument includes 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.[47] In addition, this specification includes 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.[48]

Tables C7 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 are in line with the idea that union rates are higher in civil law countries.

Columns 1 to 4 of Table 7 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).[49] 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.[50] 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

[46] 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.

[47] 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.

[48] 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).

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

[50] Indeed, Table C7 shows that the R2 of the specifications involving union density is lower than the R2 of those involving union coverage.

magnitude than those in columns 1 and 2.

Columns 5 to 8 of Table 7 present the results obtained with an alternative instrument, the average union rates in other countries.[51] 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.

The 2SLS coefficients on the interaction terms between union rates and sunk costs in Table 7 are all significant and larger than the OLS coefficients in Table 5. 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.

Finally, Table C9 in the online Tables Appendix looks at 2SLS estimates of the impact of union rates on aggregate investment. Also in this case, the evidence is consistent with the OLS estimates of Table 6. The specifications in columns 3, 4, 7 and 8 that include country-year fixed effects deliver negative and statistically significant coefficients, suggesting that strong unions lower incentives to invest in labor-complementary assets. As for robots, with aggregate investment the 2SLS coefficients are larger in absolute value than the OLS estimates. This is consistent with OLS coefficients being biased towards zero due to reverse causality. One potential explanation is that unions are stronger in labor-intensive industries i.e. with low investment per worker, because firms are heavily dependent on labor due to technological factors.

[51] Table C8 of the appendix presents the first stage regressions.

Table 7: 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. 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, 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.

6 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 relationship between institutions and robots is stronger in sunk cost-intensive industries, where producers are vulnerable to holdup. Therefore 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, labor institutions and demographic trends account for more than half of the observed cross-country differences in automation. Understanding what factors account for the remaining variation deserves further research.

The main implication of the results in this paper is that 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.

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INSTITUTIONS, HOLDUP AND AUTOMATION

G. Presidente

Online Appendix (not for publication)

A Data appendix

A.1 Industrial Robots

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.

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.[52] 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.[53]

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

[52]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.

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

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

A.2 Institutional Variables

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.

We consider two groups of variables. The first group includes measures describing the extent of constitutional protection of the rights to form unions, to bargain collectively and to strike.[54] 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.[55] Higher values correspond to stronger protection of rights (e.g. 1 if right to unionise is explicitly granted by the Constitution), or stronger employee representation (e.g. 0.5 if pre-entry closed shops are prohibited but

[54] 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.

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

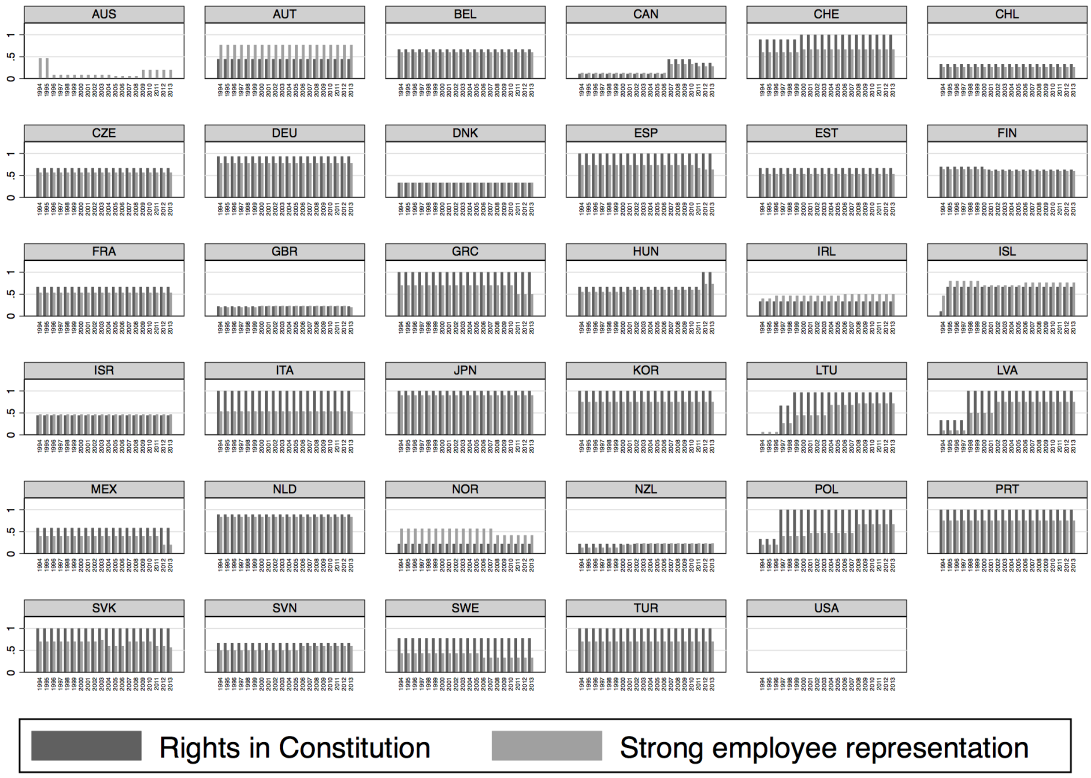
post-entry closed shops are permitted). The analysis employs two synthetic indexes of "labor-friendliness". The first one measures the constitutional protection of labor rights by taking a simple average of the variables measuring: i) the constitutional protection of the right to form trade unions; ii) 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.

Figure A1 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 A2 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.

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 and are presented in Figure A2.[56]

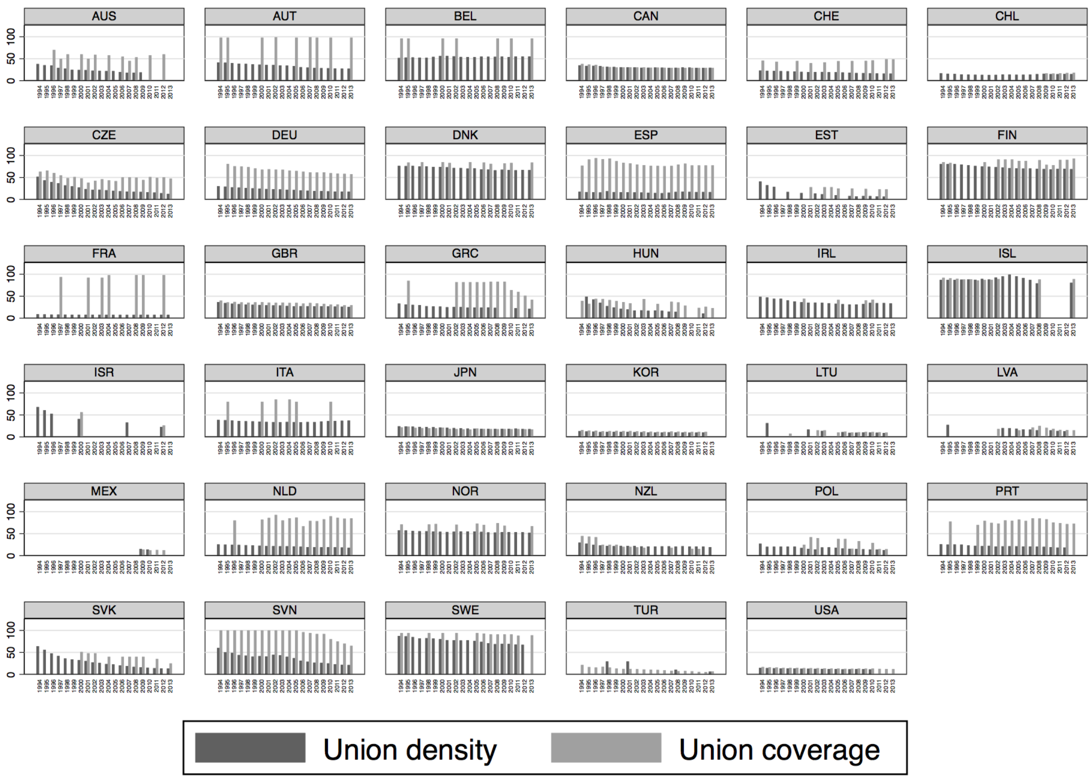
[56] In some cases, especially for union coverage, the series are discontinued and so the number of available observations is lower.

Figure A1: Legal characteristics



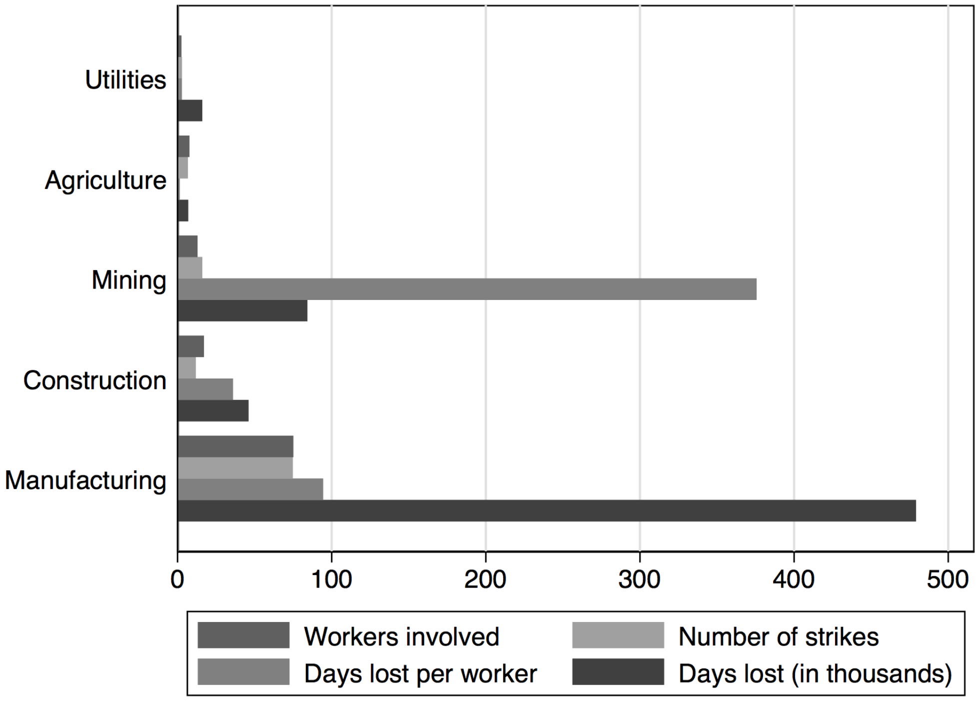
The figure shows the value of two indexes capturing legal characteristics of the labor market. Higher values corresponds to stronger constitutional protection of workers' rights or stronger employees' representation. Sources: Adams, Bishop, and Deakin (2016)

Figure A2: Union rates (%)



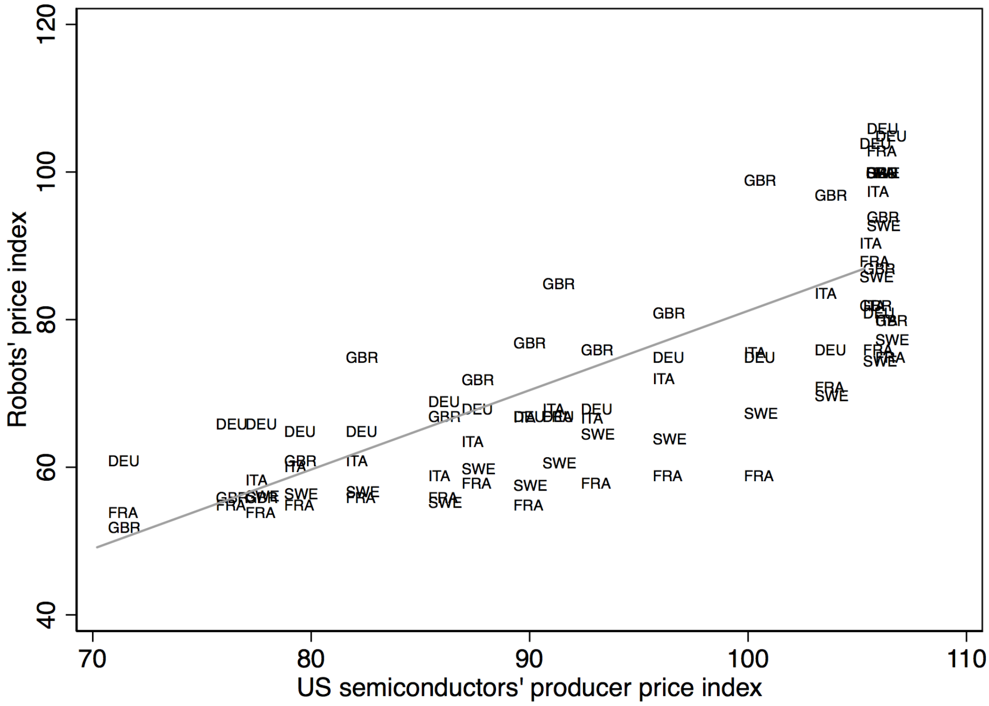
The figure shows the evolution of union rates across countries and over years. Sources: Visser (2015); Armingeon, et al. (2013)

Figure A3: Industrial action by industry (average values between 1990 and 1994)



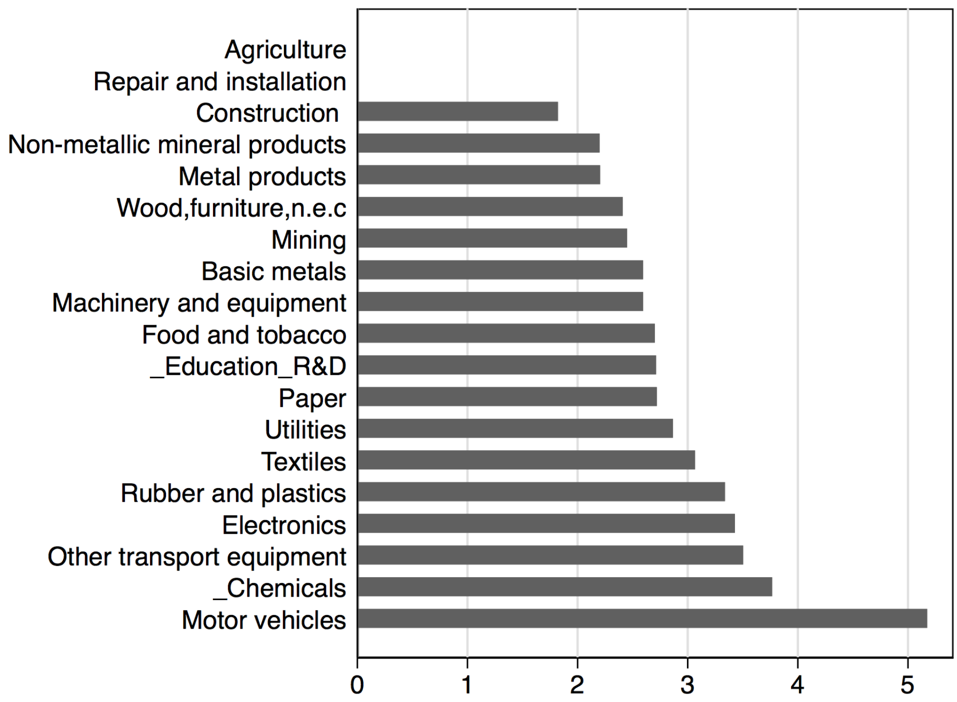
The figure shows the mean values (between 1990 and 1994) of different measures of industrial action by broad sector of economic activity.
Sources: ILO Work Stoppages Database

Figure A4: Correlation between US semiconductors' producer price index and robots' price index for selected OECD countries



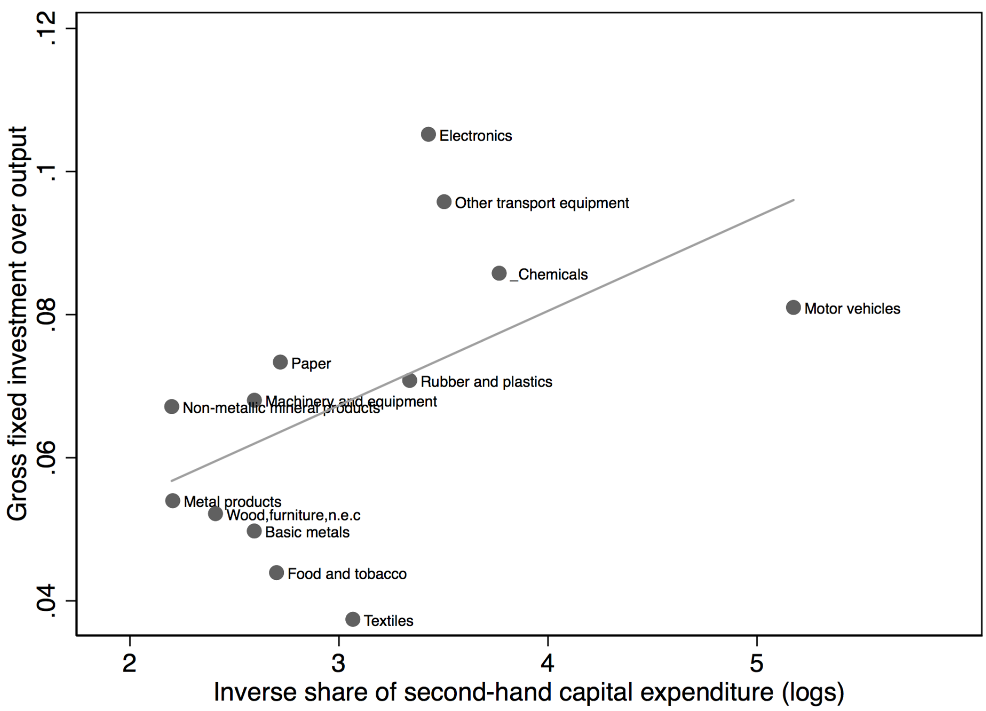
The figure shows the correlation between indexes of robots' price and the price index of semiconductors' prices in the United states between 1990 and 2007. Sources: FRED database and IFR publications.

Figure A5: Proxy of sunk costs



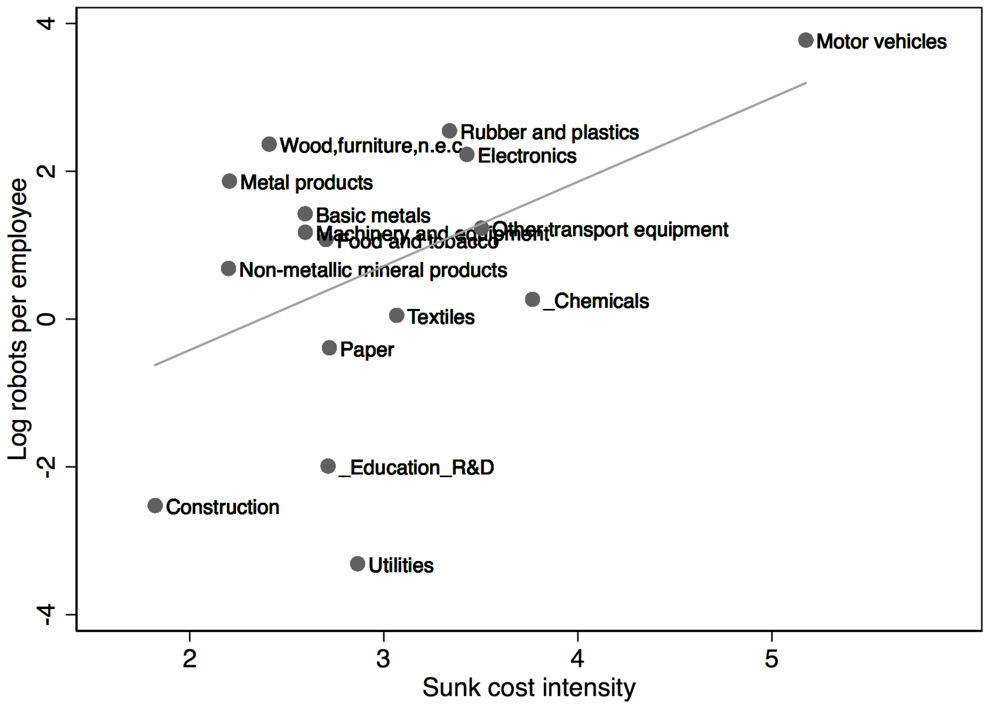
The figure shows the log of the inverse share of US second-hand capital expenditure in 1994. Logs are taken to improve the readability of the figure. Industry names preceded by underscore indicate a higher level of aggregation with respect to the original 2-digit ISIC Rev.4 classification. Sources: US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

Figure A6: Correlation between alternative measures of sunk costs



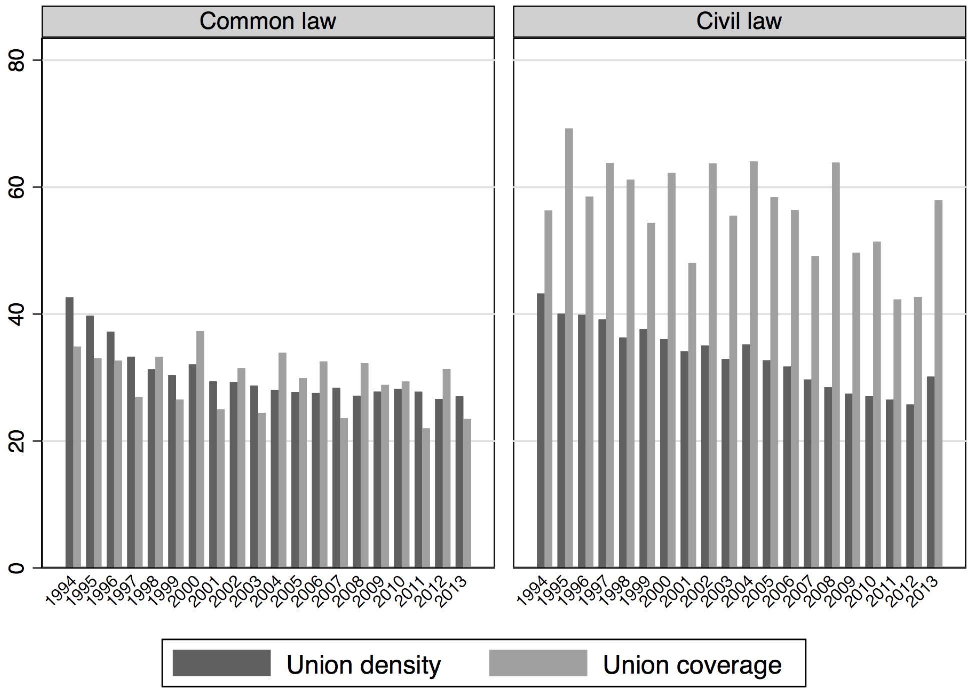
The figure shows, for each industry, the correlation between gross fixed investment over output and the log of the inverse share of second-hand capital expenditure. Industry names preceded by underscore indicate a higher level of aggregation with respect to the original 2-digit ISIC Rev.4 classification.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

Figure A7: 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. Logs are taken to improve readability of the figure, while the analysis employs levels. 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 A8: 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)

Table A1: Summary statistics: country-level variables.

	Full sample					OECD sample				
VARIABLES	N	mean	sd	min	max	N	mean	sd	min	max
Change in robots per thousand workers between 1995 and 2013	75	0.0122	0.0257	-0.0183	0.167	35	0.0235	0.0327	-0.0183	0.167
Change in robots per units of capital between 1995 and 2013	75	0.0271	0.110	-0.614	0.479	35	0.0486	0.149	-0.614	0.479
Change in capital-labor ratio between 1995 and 2013	75	0.399	0.378	-0.769	1.746	35	0.363	0.192	0.138	0.766
Labor rights in Constitution in 1994	53	0.581	0.352	0	1	35	0.578	0.343	0	1
Strong employee representation in 1994	53	0.482	0.225	0	0.900	35	0.494	0.238	0	0.900
Union density in 1994	50	0.307	0.186	0.0795	0.890	35	0.310	0.204	0.0795	0.890
Union coverage in 1994	49	0.483	0.295	0.0150	0.982	35	0.523	0.305	0.112	0.982
Expected aging	67	0.526	0.246	0.0159	1.277	35	0.531	0.179	0.259	1.237
Robots' stock per thousand workers in 1994	75	0.203	0.597	0	4.760	35	0.379	0.816	0	4.760
Average years of schooling in 1994	69	8.430	2.190	3.362	12.59	35	9.761	1.509	5.444	12.59
Log population in 1994 (millions)	75	2.654	1.730	-1.328	7.103	35	2.535	1.451	-1.328	5.573
Log real GDP per capita in 1994	75	9.596	0.919	7.463	11.63	35	9.981	0.523	8.945	11.05

Table A2: Summary statistics. Country- and industry-level variables

VARIABLES	N	mean	sd	min	max
Robots' yearly shipments per thousand workers	8,040	0.469	1.602	0	30.40
Robots' total stock per thousand workers	8,040	3.284	10.97	0	198.2
Log real aggregate fixed investment per thousand workers	6,188	3.334	1.956	-1.766	12.33
Labor rights in Constitution	12,274	0.675	0.305	0	1
Strong employee representation	12,274	0.549	0.205	0.0600	0.900
Union density	10,583	0.320	0.209	0.0631	0.991
Union coverage	7,752	0.528	0.303	0	1
Inverse share of second-hand capital expenditure (US)	10,982	27.65	38.52	6.183	176.7
Aggregate gross fixed investment over output (US)	8,398	0.0283	0.00806	0.0160	0.0483
Aggregate gross fixed investment over output	3,458	0.0670	0.0338	0.00364	0.204

B Model Appendix

The profits function of final good's producers is given by

$$\Pi \equiv \exp\left\{a + \int_0^1 ln\, y(i)\ di\right\} - \int_0^1 p(i)y(i)\ di \tag{B1}$$

The first order conditions deliver the demand for each intermediate good variety i:

$$y(i) = \frac{Y}{p(i)} \tag{B2}$$

B.1 Traditional Intermediate Good Firms

Traditional firms produce output with a constant returns to scale production function combining capital $K_t(i)$ and labor. For simplicity, we assume that a firm employs only one worker. Output per worker is thus given by

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

A fraction of investment $\sigma rk(i)$ is then sunk at the moment of hiring, which implies that the firm's outside option is $-\sigma rk(i)$. If production does take place, the firms earns $p(i)f\big(k(i)\big) - w(i)$. Thus, traditional producer i's net value of engaging in production is $p(i)f\big(k(i)\big) - w(i) - rk(i)(1-\sigma)$, which is increasing in the fraction of sunk investment.

For a worker, the value of being employed is $w(i)$. For simplicity, we assume that an unemployed worker earns nothing, so that their outside option is zero. We assume that wages are negotiated between workers and firms using a Nash bargaining rule. Letting $\beta \in [0,1]$ representing labor bargaining power, we have

$$\max_{w(i)} \ \Big[p(i)f\big(k(i)\big) - w(i) - rk(i)(1-\sigma)\Big]^{1-\beta}\Big[w(i)\Big]^{\beta}$$

Taking logs and differentiating with respect to $w(i)$ delivers the wage equation (4).

We now characterise the optimal initial investment. The profit function of traditional firm i is given by

$$\pi(i) \equiv p(i)f\big(k(i)\big) - w(i) - rk(i) = p(i)f\big(k(i)\big) - \beta\big[p(i)f\big(k(i)\big) - rk(i)(1-\sigma)\big] - rk(i)$$

The first order conditions with respect to capital are:

$$p(i)f'\big(k(i)\big) = w_{k'(i)} + r = \beta\big[p(i)f'(k(i)) - r(1-\sigma)\big] + r$$

Where $w_{k'(i)}$ is the first derivative of the wage equation with respect to capital. Rearranging the previous conditions, we get:

$$p(i)f'\big(k(i)\big) = \frac{r[1-\beta(1-\sigma)]}{1-\beta} \tag{B3}$$

Notice that $w_{k'(i)}$ enters the first order conditions because wages are negotiated after the initial investment is made, as firms anticipate that workers can reap some of the benefits of higher investment without sharing the initial cost of the investment. To see this, suppose that σ is high. Larger σ implies that the RHS of (B3) is higher. Due to decreasing returns to capital, that implies a lower optimal investment due to holdup. On the contrary, when $\sigma = 0$ and there are no sunk costs, the RHS of (B3) becomes equal to r, which determines the frictionless optimal capital investment.

The optimality condition (B3) can be used to derive an expression for the equilibrium price of each variety i,

$$p(i) = \frac{r[1-\beta(1-\sigma)]}{f'\big(k(i)\big)(1-\beta)}$$

Since all traditional firms are equal, they chose the same initial investment and face the same equilibrium price, which is given by

$$p = \frac{r[1-\beta(1-\sigma)]}{f'\big(k\big)(1-\beta)} \tag{B4}$$

Notice that since there is free entry in the intermediate goods' market, (B4) must equal traditional firms' marginal cost.

B.2 Automated Intermediate Good Firms

Due to free entry in the production of all varieties, firm i's equilibrium price must equal the marginal cost of production:

$$p(i) = \frac{r}{1-i} \tag{B5}$$

Unlike in (B4), the equilibrium price of automated firms depends on i, which is reflected in an higher marginal cost of producing varieties close to $i = 1$ using robots. Substituting the equilibrium price of the automated producer (B5) into the final good firms' demand (B2), we get the equilibrium stock of robots in automated firms (5).

B.3 Technological Choice

It is possible to determine the minimum level of industrialisation such that at least some producer finds it profitable to use robots, $\underline{\mathrm{k}}$:

$$f'(\underline{\mathrm{k}}) = \frac{[1-\beta(1-\sigma)]}{1-\beta} \tag{B6}$$

The RHS of (B6) is increasing in both σ and β (but it is independent on r), implying that the more labor-friendly institutions are, and the larger the sunk costs, the lower the minimum level of industrialisation required to make automation profitable. In the absence of sunk costs ($\sigma = 0$), $f'(\underline{\mathrm{k}}) = 1$. This implies that robots' adoption is independent on labor market institutions, and that there will be automation whenever the capital is large enough so that the marginal returns on capital are less than the marginal returns on robots, which is 1 due to the assumption of linear technology for automated producers.

B.4 Equilibrium

Rearranging (6), plugging it into (5) and aggregating over all automated varieties deliver an equilibrium condition linking R and k:

$$R = \frac{Y}{2r}\left[1 - \left(\frac{f'\big(k\big)(1-\beta)}{1-\beta(1-\sigma)}\right)^2\right] \tag{B7}$$

Total output must be equal to functional income:

$$Y = (1-i^*)(w+rk) + rR \tag{B8}$$

Using (6) and substituting (4) into (B8), delivers a second equilibrium condition:

$$Y = f\big(k\big)\Big[\beta + (1-\beta)r\varepsilon_{f,k}\Big] + rR \tag{B9}$$

Where $\varepsilon_{f,k} \equiv \frac{f'(k)k}{f(k)}$ is the elasticity of the traditional firms' output to capital.

For given levels of output and interest rate, the equilibrium stock of robots R and traditional capital k is given by the intersection of the two curves defined by equating (B7) and (B9) to zero:

$$\phi(R,k) \equiv R - \frac{Y}{2r}\left[1 - \left(\frac{f'\big(k\big)(1-\beta)}{1-\beta(1-\sigma)}\right)^2\right] = 0$$

$$\psi(R,k) \equiv Y - f\big(k\big)\Big[\beta + (1-\beta)r\varepsilon_{f,k}\Big] - rR = 0$$

Equation $\phi(R,k)$ describes an increasing relationship between R and k, while as long as $\varepsilon_{f,k} f\big(k\big)$ is non-decreasing, $\psi(R,k)$ generates a decreasing relationship between the same variables. Therefore, the equilibrium exists and it is unique.

B.5 Endogenous Output

A simple way to endogenise Y is assuming that the economy is populated by overlapping generations. Each generation lives two periods, and is composed of a continuum of agents with aggregate measure 1. There is zero population growth. The objective of a member of the generation born at time t is to maximise:

$$ln(C_t^y) + \delta\, ln(C_{t+1}^o)$$

where C_t^y (C_{t+1}^y) is her consumption when young (old), and $\delta < 1$ is the discount parameter. The only endowment of an agent is one unit of labor, which is supplied inelastically when young. Individual budget constraints are given by

$$C_t^y = W_t - B_{t+1}$$

$$C_{t+1}^o = r_{t+1} B_{t+1}$$

Where W_t is total labor income, B_t savings and $r_{t+1} > 1$ is the real interest rate between period t and $t+1$. The solution to the consumers problem gives delivers the optimal savings function:

$$B_{t+1} = \frac{\delta}{1+\delta} W_t \tag{B10}$$

Savings are transformed into productive capital:

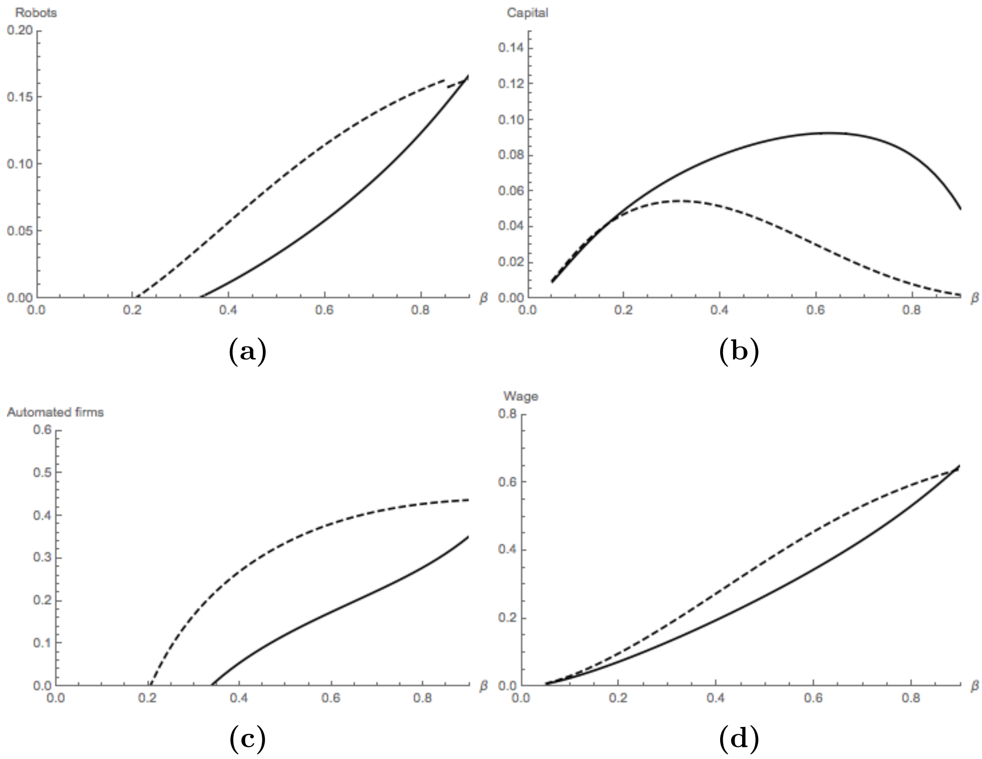
$$B_{t+1} = (i - i_t^*) k_t + R_t$$

Both types of capital fully depreciate after one period. Substituting the previous conditions into (B10), noticing that $W_t = (i - i_t^*) w_t$, and using (4) and (6), we get

$$\frac{1-\beta(1-\sigma)}{f'\big(k_t\big)(1-\beta)} \left[1 + \frac{\delta}{1+\delta} \beta r (1-\sigma)\right] k_t + R_t = \frac{\delta}{1+\delta} \beta r f\big(k_t\big) \tag{B11}$$

Equations (B11), (B9) and (B7) can be used to determine the equilibrium with endogenous output. Figure B1 shows that the relationship between β, σ and robots is very similar to the case of fixed output (panels B1a and B1c). However, when output is endogenous, the behaviour of aggregate capital is slightly different. Panel B1b shows that for very low levels of β, an increase in bargaining power initially increases aggregate capital. This is due to the fact that consumers save labor income and therefore when wages are excessively low, the stock of capital is low too. However, as β exceed a certain value, aggregate capital starts to decrease with bargaining power because wages increase as well (panel B1b). This is especially the case with large sunk costs, the case represented by the dashed curves in Figure B1.

Figure B1: The relationship between key variables of the model, labor bargaining power and sunk costs with endogenous aggregate output.



The figures depict the pattern of key variables as a function of β In each panel, the sold line corresponds to the case $\sigma = .1$, while the dashed line to the case $\sigma = 1$. The parametrisation used in the simulation is the following: $f(k) = [\alpha k^{\rho} + (1 - \alpha)]^{\frac{1}{\rho}}$, $\alpha = .4$, $r = 1.05$, $\rho = .5$, $\delta = .0$.

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

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)

	DEPENDENT VARIABLE: 1995-2007 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	0.018**				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)

	DEPENDENT VARIABLE: 1995-2013 AVERAGE ANNUAL CHANGE IN ROBOTS PER UNIT OF CAPITAL							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	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: Standardised OLS coefficients of the relationship between labor institutions, ageing and the average annual change in industrial robots per thousand workers between 1995 and 2013.

	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	0.408**				0.528**			
	(2.90)				(3.53)			
Strong employee representation		0.491**				0.495**		
		(2.96)				(2.83)		
Union density			0.322*				0.410**	
			(2.28)				(2.77)	
Union coverage				0.400***				0.452**
				(3.62)				(3.06)
Expected ageing	0.411*	0.427*	0.473	0.467	0.529*	0.521*	0.659*	0.599
	(2.11)	(2.32)	(1.89)	(1.97)	(2.33)	(2.32)	(2.42)	(1.97)
Observations	46	46	46	46	35	35	35	35
Base year country covariates	yes	yes	yes	yes	yes	yes	yes	yes

The table presents standardised OLS coefficients quantifying 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, and v) a dummy taking value 1 if a country is an OECD member. 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 stock of industrial robots per thousand employees.

DEPENDENT VARIABLE: TOTAL STOCK OF ROBOTS PER THOUSAND WORKERS	(1)	(2)	(3)	(4)
Labor rights in Constitution x industry sunk costs	2.049*			
	(1.079)			
Strong employee representation x industry sunk costs		3.518*		
		(1.782)		
Union density x industry sunk costs			0.070	
			(1.374)	
Union coverage x industry sunk costs				2.055*
				(1.029)
Observations	5,255	5,255	5,162	3,561
R-squared	0.547	0.554	0.532	0.521
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 total number of robots per worker. The dependent variable is the country-industry stock of industrial robots per thousand employees. The proxy of sunk cost-intensity is the inverse share of second-hand capital expenditure in a given 2 digits-industry. All specifications include include year effects times the base-year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling; 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 C6: 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 C7: First stage regression of Table 7. 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 7. All specifications include include year effects times the base year of: i) log-GDP per capita; ii) log-total population; iii) average years of schooling. Standard errors are robust against heteroscedasticity. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table C8: First stage regression of Table 7. 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 7. 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 C9: 2SLS estimates of the impact of union rates on country-industry gross fixed investment per worker. Instruments: average union rates $\times$ dummy for civil origins (columns1-4); ii) average union rates in other countries (columns 5-8).

DEPENDENT VARIABLE: LOG ANNUAL AGGREGATE INVESTMENT PER THOUSAND WORKERS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Union density	2.052*				1.866			
	(1.241)				(1.390)			
Union density x industry sunk costs	-0.453*		-0.356*		1.054		-0.525*	
	(0.244)		(0.194)		(0.952)		(0.288)	
Union coverage		2.885**				-0.268		
		(1.403)				(1.118)		
Union coverage x industry sunk costs		-0.146		-0.156**		0.332		-0.264**
		(0.099)		(0.068)		(0.368)		(0.123)
Observations	4,177	2,743	4,177	2,743	4,613	3,137	4,613	3,137
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Expected ageing	yes	yes	yes	yes	yes	yes	yes	yes
Characteristics affected by legal origins	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	6.933	6.174	9.932	145	31.83	45.80	17.89	44.99

The table presents 2SLS estimates of the relationship between unions, sunk costs and aggregate investment. The dependent variable is the log annual gross fixed aggregate investment 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, 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.