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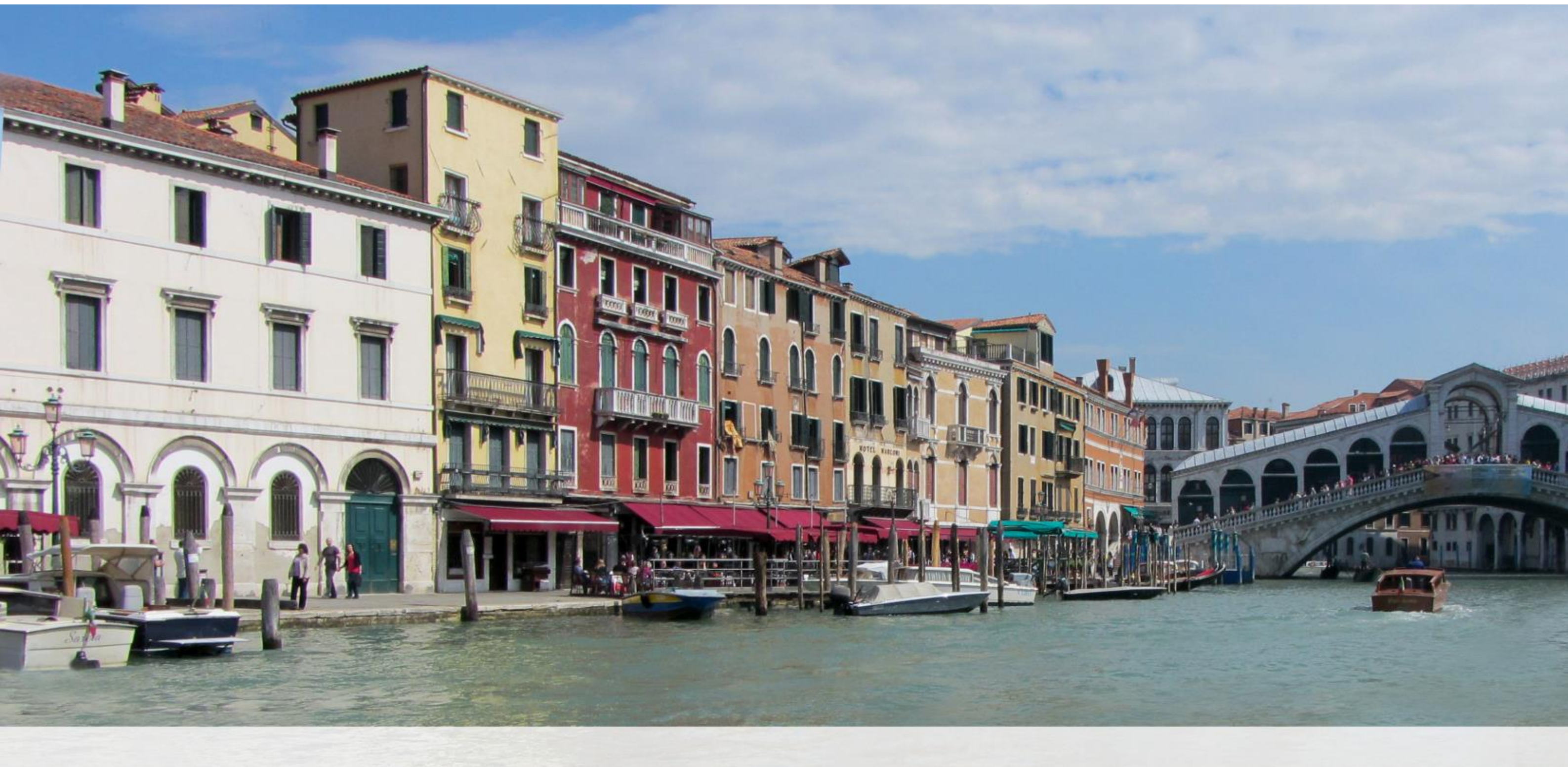

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Institutions, Hold Up and Automation

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Institutions, Hold Up and Automation[*†]

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Abstract

This paper shows that countries with labor-friendly institutions invest more in industrial robots. A model of technological choice with *ex ante* investment and *ex post* wage bargaining predicts that the link institutions-automation should be stronger in industries with large sunk costs, where producers are more vulnerable to hold up. The hypothesis is supported by country-industry variation in adoption of robots. The paper also shows theoretically and empirically that strict institutions drive up automation but down productivity, because hold up destroys incentives to accumulate labor-complementing capital. While the net effect of institutions on productivity is ambiguous, the model of this paper predicts that they should increase productivity more (reduce it less) in industries with more opportunities for automation, a prediction supported by the data.

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JEL classification : O33, O43, O57, J50

1 Introduction

Adoption of industrial robots within narrowly defined industries differs widely across advanced countries. For instance, in 2013 the number of robots per employee in manufacturing of motor vehicles was almost 100 in France and Japan, 70 in Italy and 40 in the United States. At similar levels of economic development and integration in international markets, one would expect advanced economies to have equal access to automation technology. Therefore, one view is that lags in uptake of industrial robots are due to the presence of frictions impeding adoption. Lack of complementary assets such as organisational and human capital might lower the expected returns on automation, discouraging firms from undertaking an otherwise profitable investment (Brynjolfsson, Rock, and Syverson, 2017). Such view implies that laggard economies are missing growth opportunities. Governments in many advanced economies seem to share this perspective, as they spend a considerable amount of resources in providing financial incentives to invest in robots.[1]

An alternative view is that adoption of industrial robots are driven, rather than discouraged by the presence of frictions. In particular, labor-saving technologies might be used to overcome distortions in the labor market. To the extent that strong unions or strict employment protection legislation increase labor costs, producers might use robots to become more competitive. Thus, countries with flexible labor markets such as the United States might simply not need automation as badly as France, in which nearly all employment contracts are subject to some collective agreement. Policies aimed at encouraging robot-investment in countries with strict labor institutions might still boost productivity, but it would be like curing the symptoms rather than the disease. Labor market reforms might be a more efficient solution.

This paper aims at shedding light on these issues. The first contribution of the paper is documenting that OECD economies with labor-friendly institutions use a larger number of industrial robots per worker. For instance, countries in which

[1]Horizon 2020, a multibillion Euros fund financed by the European Union, involves a large number of projects focusing on robotics; in France, the program *Pret Robotique* provides loans up to five million Euros to small and medium enterprises to encourage the adoption of automation technologies; in the United States, the 2018 tax reform provides fiscal incentives to automation by allowing companies to write off the entire cost of the capital equipment at the time of purchasing.

the right to form unions is explicitly granted by Constitution use 0.6 additional robots per thousand workers, slightly more than the difference between Italy and the United States. Legal labor institutions are deeply rooted in a country's Constitution and in most cases they are in place since long before the beginning of the sample.[2] As such, they are unlikely to be affected by trends in automation. In the empirical part of the paper, one specification exploits information on whether the constitution explicitly mentions the right to form unions as an instrument for actual unionisation rates. IV estimates are also positive and significant, of a magnitude comparable to the reduced form coefficients. The constitutional protection of the right to form unions explains between 20 and 50 percent of the sample variation in the number of robots per worker (after partialling out the contribution of GDP per capita, education and population).

The second contribution of the paper is showing theoretically and empirically that the relationship between labor-friendly institutions and automation is stronger in industries characterised by large sunk costs, where producers are more vulnerable to hold up.[3] A case in point is the manufacturing of motor vehicles, where both suppliers of components and assemblers need to invest in specialised equipment with little scope for utilisation outside the industry. The motor vehicles industry is disproportionately automated in countries with labor-friendly institutions. Investment specificity results in large sunk costs, because if production does not take place, producers cannot sell their machinery to firms in other industries.[4] Labor-friendly institutions allow workers to take greater advantage of irreversibility. For instance, unions are in a better position than individual workers to hold up producers against the low replacement value of specialised equipment and win higher wages. When the right to form unions is legally recognised, even non-union workers might threaten to form one if the employer does not meet their conditions.[5] When workers are able to extract rents at the expenses of capital, firms

[2]For instance, the Italian Constitution, which mentions the right to form trade unions in Article 19, was written in 1948.

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

[4]The mechanism should be particularly relevant for large size-equipment, which cannot be sold in international markets.

[5]See Taschereau-Dumouchel (2017) for a general equilibrium model in which the threat of unionisation drives down wages and output.

have strong incentives to invest in robots. By automating, producers lower their dependency from human labor, mitigate the severity of the hold up and thwart appropriation.

Cardullo, Conti, and Sulis (2015) show that strict labor institutions have a negative impact on investment, especially in sunk cost-intensive industries.[6] However, their finding does not contradict the result of this paper. Unlike many capital assets, robots are labor-saving technologies, which imply a high degree of substitution with labor. As such, robots reduce the dependency from human workers and so they can be used to mitigate the hold up when it originates in the labor market. To clarify this point and guide the empirical analysis, this paper presents a simple model of technological choice with labor market frictions, in which firms make *ex ante* investment and wages are bargained *ex post*. The model predicts that strict institutions discourage investment in labor-complementing capital. For a given level of labor market rigidity, the larger the sunk costs the lower the investment. This is the mechanism discussed in Cardullo, Conti, and Sulis (2015).[7] However, when capital embodies technologies that can perfectly substitute for labor, the model predicts a positive impact of institutions on investment. The larger the sunk cost (i.e. severe the hold up), the stronger the incentive to adopt robots to minimise dependency from labor and thwart appropriation. Descriptive evidence provided in this paper is consistent with such predictions. The impact of unions on the number of robots per worker increases with an industry' sunk cost-intensity, while the relationship is reversed if one considers aggregate capital-labor ratios.

In many models of technology diffusion, institutional rigidities tend to prevent, rather than induce technological development.[8] Instead, this paper relates

[6]A wide body of literature suggests that in presence of worker-specific investment, ex post rents' appropriability should discourage capital investment. For instance, a producer might be reluctant in purchasing a piece of equipment if it knows that it can only be used by a particular worker, which might then walk away before production takes place. Classic references on the topic are Grout (1984), Williamson (1985), Grossman and Hart (1986), and Hart and Moore (1990).

[7]In their paper, firms are endowed with a Cobb-Douglas production function in which capital and labor are imperfect substitutes.

[8]For instance, Parente and Prescott (1994) see regulatory constraints as barriers to technology adoption; Tressel and Scarpetta (2004) find a negative relationship between innovation and the stringency of employment protection legislation; Bartelsman, Gautier, and De Wind (2016) argue that strict employment protection legislation reduce the incentives to invest in Information Technology (IT).

to a growing body of literature in which labor market frictions are drivers of investment in labor-saving technologies.[9] Rather than focusing on the interaction between labor institutions and sunk costs, Alesina, Battisti, and Zeira (2018) study how labor institutions affect broadly defined technology in industries characterised by different skill intensities. Since labor rules bind for low skill workers, they tend to increase the cost of unskilled labor and lower the skill premium. Therefore, countries with strict institutions are more likely to invest in unskilled labor-saving and less in skilled labor-saving technology. The relationship is reversed in countries with loose regulation. Acemoglu and Restrepo (2019) look at the impact of aging on the adoption of industrial robots. They argue that scarcity of middle-age workers - those specialising in production tasks - induce firms to invest in automation to mitigate the rise in wages. In both papers, the net impact of investment in labor-saving technology on aggregate productivity is ambiguous, because it is offset by the detrimental impact of the driving factor (institutions in the former, demographics in the latter). Similarly, in the model developed in this paper, higher bargaining power has two countervailing effects. The first is to induce automation, which tends to increase productivity as firms produce the same amount of output with less labor. The second effect, due to the presence of hold up, is lowering the aggregate capital-labor ratio, which reduces productivity. The net effect of institutions on productivity depends on the parametrisation of the model. However, the latter does make an unambiguous prediction: strict labor institutions should increase productivity more (or lower it less) in industries that are more prone to automation.[10] The hypothesis is tested in the empirical section and it is supported by the data

The theoretical and empirical findings of this paper suggest that an important driver of investment in industrial robots is thwarting appropriation and redistributing rents from labor to capital. An important implication is that automation might not be seen as productivity-enhancing *per se* by producers, but rather as a solution to a problem of hold up. In other words, absent the institutionally-induced friction generating distortions in the labor market and increasing labor costs, the optimal

[9]The idea that higher prices for a factor induce adoption of a technology saving on that factor is expressed in Acemoglu (2010), Allen (2009), Zeira (1998), and Habakkuk (1962).

[10]This hypothesis is similar to the one tested in Acemoglu and Restrepo (2018) in the contest of demographic trends.

technology might be more labor intensive. Such ideas are discussed in the last part of this paper. Descriptive evidence suggests that over the sample, the least productive OECD countries invested more heavily in industrial robots. This is consistent with producers investing more heavily in robots in an attempt to overcome the productivity loss generated by strict labor market institutions. Moreover, in the early years of the sample the countries that have invested the most in robots had a much higher labor share, which then felt abruptly. The finding supports the idea that producers invest in automation to redistribute rents from labor to capital. Finally, a simulation of the model developed in the paper suggests that robots increase net output only when labor market institutions bias heavily bargaining power in favor of labor. Therefore, financial incentives to automation might be not always an effective policy measure.

The rest of the paper is organised as follows. Section 2 presents some descriptive evidence on the links between hold up and automation; Section 3 builds a model connecting labor bargaining power to investment in robots and productivity in presence of sunk costs; Section 4 presents the data; Section 5 provides the empirical results; Section 6 looks at the relationship between automation, productivity and the labor share, and performs numerical simulations of the model. Section 7 concludes.

2 Industrial Robots in OECD countries: Descriptive Evidence

2.1 Cross-country Differences in Automation

Figure 1 presents the number of industrial robots per thousand employees installed by 2 digits-industry for 35 OECD economies. There are large differences in adoption, even across countries with a similar level of per capita income. In the motor vehicles industry, which alone accounts for almost half of the total robots population in the OECD region, the number of robots for thousand employees is 5 in Ireland, 40 in the Netherlands and almost 100 in Belgium, which together to Korea, France, and Japan had the highest number of robots per employee in the sample. The United States, an early technology adopter, used 10 robots per thousand employees less than Italy and 20 less than Germany and Spain. Such heterogeneity is not limited to Motor vehicles and it is even more extreme in other industries such as electronics manufacturing, where Korea and Japan had almost 80 robots per thousand employees, against only 15 in the United States.

Figure 1 presents evidence of large cross-country differences in adoption of industrial robots in all 2 digits-industries for which data are available. Due to the impact of international trade, robot-price differences are small and unlikely to explain such.[11] The standard interpretation that frictions such as insufficient human capital (Nelson and Phelps, 1966), intangible complementary assets (Brynjolfsson and Hitt, 2000, Brynjolfsson, Rock, and Syverson, 2017), credit constraints and market imperfections (Parente and Prescott,1999) might be responsible for some countries to "lag behind" in terms of adoption, seems inappropriate for industrial robots. The United States, often considered the most innovative country in the world and an economy with a minimal level of frictions, uses less robots per employee than other countries which have lagged behind in adoption of other technologies.[12]

One explanation for differences in adoption is that in countries in which the population is ageing faster experience a shortage of production workers, which producers overcome by investing in labor-saving technology (Acemoglu and Restrepo, 2019). This paper investigates another potential explanation and ask whether differences in labor market institutions can explain differences in automation across advanced economies. To motivate the analysis, Figure 2 depicts the relationship between the 1993-2015 change in the number of robots per thousand employees and the 1993 values of the labor share (top panel), union density (central panel) and an index of equal to 0 if workers' dismissal is allowed only for serious misconduct of the employee and 1 if employment is at will (bottom panel).[13] Each dot in the figure represents the country-average residual from a regression of long-run differences in robots per employee on base year values-year dummies of the follow-

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

[12]For instance, European countries such as Italy have been slower than the United States in adopting computers during the 1980s and 1990s. [CITATION]

[13]Variation between 1 and 0 represent variation in the strictness on rules on dismissal. More details can be found in the section 4.

ing variables: GDP per capita, population, average years of schooling, number of robots per employee, capital-labor ratio and the expected log-difference between 1990 and 2025 of the ratio of population aged 55 and above to that aged 20 to 54 - a measure of population aging. Figure 2 shows that countries with higher labor shares and union density in 1993 experienced a larger increase in adoption of robots. On the contrary, countries in which employment is “at will” and so firing workers is easier, experienced a lower change in the number of robots per worker used. An argument can be made that in countries where firing workers is easier should have more, not less automation. However, Dauth et al. (2018) provide evidence that employers tend to automate on the extensive margin, i.e. by opening new automated plants, rather than firing workers and replacing them with machines. Such trends are also supported by anecdotal evidence that automation in large retail companies does not induce displacement of incumbent workers, but rather a within-firm reallocation to other tasks.[14] Thus, the descriptive evidence is consistent with the idea that strict labor institutions allowing workers to extract rents from the production relationship generate incentives to invest in automation technology.

2.2 Robots and the Aggregate Capital Stock

This section emphasises the differences between industrial robots and other categories of capital assets. Industrial robot are defined by ISO 8373:2012 as *an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.* Therefore, robots differ in one fundamental dimension from other categories of capita equipment: they are automatically controlled and so characterised by a high degree of substitutability with human labor. Thus, on the one hand the presence of hold up and the consequent rent appropriation that allows labor to achieve should encourage investment in robots. On the other hand, the presence of hold up should destroy incentives to invest in capital complementing labor: the higher the dependency on workers, the larger the rents they

[14] See for instance https://www.wsj.com/articles/walmart-is-rolling-out-the-robots-11554782460

can extract from a production relationship, discouraging investment. Figure 3 presents some descriptive evidence supporting this idea. On the horizontal axis there is the industry share of capital expenditure bought on second hand markets. The assumption is that the higher the second hand capital share in total capital expenditure, the lower the sunk costs characterising an industry.[15] Therefore, high resaleability should reasonably proxy for a low incidence of industry-level sunk costs. Each dot in the charts represent the difference between countries with high and low union density in the log-number of robots per employee (top panel) and the log-capital per employee (bottom panel).[16] Figure 3 shows that the difference is increasing in the amount of industry sunk costs for the number of robots per employee, but decreasing for capital per employee. The figure supports the idea that robots are highly substitutable for human labor, and so they are more intensely adopted in country-industries where the hold up and the extent of rent extraction by labor is more severe. On the other hand, aggregate capital includes assets that are less substitutable with labor, and so investment is lower in industries with more severe hold up.

3 A Model of Technological Choice in Presence of Hold Up

To guide the empirical analysis and conduct comparative statics, this section develops a model of technological choice in presence of sunk costs leading to hold up. The model describes how institutions shifting bargaining power in favor of labor combined with sunk costs induce adoption of robots, discourage investment in capital assets characterised by a lower elasticity of substitution with labor, and affect productivity.

[15]The shares of second hand capital expenditure refer to the United States in 1994, the first year for which such information is available. Assuming that the technological characteristics of an industry carries over to other countries, information based to the US should proxy for the incidence of sunk costs in other OECD economies as well. More information on this variable can be found in Section 4.

[16]High union density countries have more than 34% net union membership, corresponding to the mean of the variable in the sample. The figure refers to residuals unexplained by country-specific factors and initial levels of robot per employee and capital per employee.

The economy is populated by a continuum of firms with a mass of measure 1 and a larger continuum of of workers each supplying inelastically one unit of homogenous labor. To enter the market, firms must first build a plant and purchase machinery by investing $k > 0$ at marginal cost p, and then decide whether to hire labor or use robots, which are perfectly substitutable for human workers. Firms pay different prices for robots due to some idiosyncratic characteristics. For instance, they could differ in their amount of routine tasks used in production, or in the technical capabilities needed to instal and operate robots. We denote by ρ the unit price of a robot and assume that it is distributed across firms according to a cumulative distribution function $G(\cdot)$. Each firm employs either one worker or one robot, so that k_l and k_r represent, respectively, the capital per worker in a labor-using firm and the capital per robot in a robot-using firm. For $i \in \{l, r\}$, output is produced with a strictly increasing and concave production function $f_i(k_i)$ and the output price is taken as the numeraire.

In labor-using firms, wages are negotiated *ex post*. Therefore, workers might benefit from higher capital intensity without sharing the cost of investment made *ex ante* by firms. This is the source of hold up in the model. The parameter $\gamma \in [0, 1]$ represents the degree of specificity investment, so that a fraction γpk is sunk once the initial capital is purchased by the firm. The parameter β represents the bargaining power of labor. The outside option of workers is assumed to be zero and equilibrium wages are determined through Nash Bargaining.

3.1 Model Solution

The model appendix in Section A shows that the solution of the model is given by the following set of equations. Equilibrium wages at labor-using firms are

$$w^*(k_l, \beta) = \beta\Big[f_l(k_l) - pk_l(1-\gamma)\Big] \tag{1}$$

The wage equation includes the impact of sunk costs. Higher γ allows workers to extract higher rents.

The profit-maximising capital investments for a labor-using firm and robot-using firm are given, respectively, by

$$f_l'(k_l^*) = p + w_k'(k_l^*, \beta) \tag{2}$$

$$f_r'(k_r^*) = p \tag{3}$$

Notice that the presence of hold up results in $w_k'(k_l^*, \beta) > 0$, which implies that in equation (2) the initial investment is lower than without sunk costs. Since robot-using firms do not depend on human labor, (3) is a standard first order condition stating that the marginal product of capital must be equal to its marginal cost.

3.2 Aggregation

The following expression is obtained by comparing profits if using robots or human labor. It defines the robot-price threshold making a firm indifferent between using the two alternative technologies,

$$\rho^* \equiv f_r(k_r^*) - f_l(k_l^*) - p(k_r^* - k_l^*) + w(k_l^*, \beta) \tag{4}$$

All firms with $\rho < \rho^*$ choose robots, while the others hire labor. Therefore, the aggregate number of robot-using and labor-using firms in the economy is give by, repsectively

$$R = G(\rho^*)$$

$$L = 1 - G(\rho^*)$$

Total output is given by

$$Y = Rf_r(k_r^*) + Lf_r(k_l^*)$$

3.3 The Relationship Between Labor Institutions, Automation and Productivity

The main dependent variable considered in the empirical section is the number of robots per employee, R/L. Higher labor bargaining power increases the robot-price threshold,

$$\frac{d\rho^*}{d\beta} = w'_\beta(k_l^*, \beta) > 0 \tag{5}$$

Therefore, when technology is labor-saving, higher β always results in a higher number of robots per employee. This is in line with the models developed in Acemoglu (2010), Alesina, Battisti, and Zeira (2018), and Acemoglu and Restrepo (2019). However, the wage equation in (1) implies that an increase in bargaining power increases investment in robots more in presence of sunk costs. This is due to the fact that workers can extract higher rents when capital investment is made ex-ante and wages are negotiated ex-post.

Section A of the appendix shows that the impact of bargaining power on output per worker can be decomposed as follows,

$$\frac{dY/L}{d\beta} = \frac{G'(\rho^*)}{\left[1 - G(\rho^*)\right]^2} f_r(k_r^*) \frac{d\rho^*}{d\beta} + f'_l(k_l^*) \frac{dk_l^*}{d\beta} \tag{6}$$

Aggregate productive depends on the extensive margin of automation, given by the first term in (6), and on the behaviour of capital per worker in labor-using firms which is represented by the last term. Since $\frac{G'(\rho^*)}{\left[1-G(\rho^*)\right]^2} f_r(k_r^*)$ is positive, strict institutions increase labor productivity because they reduce the amount of workers needed to produce a given level of output. Equation (6) implies that an increase in bargaining power should increase productivity more in economies with a lower cost of automation, i.e. economies with a stochastically dominant $G(\cdot)$. However, due to the second term in (6), the net impact of an increase in bargaining power on productivity is ambiguous. An expression for $\frac{dk_l^*}{d\beta}$ can be obtained by taking the total differential of (2) with respect to β,

$$\frac{dk_l^*}{d\beta} = \frac{w''_{\beta k}(k_l^*, \beta)}{\left[f''_l(k_l^*) - w''_{kk}(k_l^*, \beta)\right]} \tag{7}$$

Without sunk costs (and therefore, no hold up), the numerator of (7) is zero as $w'_k = 0$ and so higher bargaining power increases productivity unambiguously. However, with sunk costs, we have that

$$\frac{dk_l^*}{d\beta} = \frac{f'(k_l) - p(1-\gamma)}{f''(k_l)(1-\beta)}$$

Thus, the higher the specificity of investment γ, the stronger the negative impact of institutions on labor productivity.

To summarise, the model developed in last section delivers three testable propositions: i) economies with labor institutions resulting in high workers' bargaining power should be characterised by a high number of robots per employee; ii) the positive relationship between strict labor institutions and robots per worker should be stronger in industries characterised by large sunk costs, and iii) strict labor institutions should increase labor productivity relatively more (or reduce it less) in industries characterised by a lower cost of automation.

4 Data

This section describes data sources and the construction of the variables used in the following analysis.

4.1 Industrial Robots

Data on shipments of industrial robots are obtained from the International Federation of Robotics (IFR), which collects data from each national robotics association. Since almost all robots suppliers are members of national associations, the dataset virtually includes all robots that are actually 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 sector, country and year.

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.[17] 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

[17] 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.

perpetual inventory method, using 1993 estimates of the existing stock by the IFR as initial values.[18]

To construct the main dependent variable, the number of robots per thousand workers, IFR data are matched to two other sources. The economy-wide number of robots per worker are constructed using total employment from the Penn World Tables 9.1. For the country-industry analysis, data on robots are matched to the STAN database from the OECD. STAN include information on industry-level employees, output, value added and estimates of the capital stock. Industry-level classification have been converted as to obtain eighteen industries, roughly corresponding to 2 digits-level ISIC rev.4.[19]

4.2 Labor Market Institutions

The empirical analysis exploits two sets of variables providing information on labor market institutions. The first set of variables measures the extent in which particular labor rights are formally protected by a country's Constitution or written in the labor code. The second set of variables refers to actual unionisation rates. This section describes the two sets of variables in turn.

The first dataset on constitutional protection of labor rights is based on the comparative legal analysis conducted by Adams, Bishop, and Deakin (2016). To obtain internationally comparable information, the authors apply lexicometric techniques. This paper focuses on three aspects of labor legislation that are likely to affect the severity of hold up in the economy, namely whether: i) the right to form unions is explicitly granted by the constitution; the law imposes substantive and procedural constraints on dismissal, and iii) employers have the legal obligation to bargain with workers' representatives.

The original variables in Adams, Bishop, and Deakin (2016) take values between 0 and 1 to reflect gradations in the lexicometric scores.[20] To mitigate po-

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

[19]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.

[20]Details on the algorithm and coding used to construct the original variables, and an overview

tential mismeasurement errors and facilitate the interpretation of the results, I transform the original variables into booleans.[21] The variables are coded as follows: i) a dummy taking value 1 if, for each country and year, the right to form trade unions is expressly granted by the constitution, and 0 otherwise; ii) a dummy equal to 1 if it is enough to have a "just or fair cause" for the employer to fire a worker and no procedural constraints are required by law, and 0 if dismissal reasons are precisely defined by law and employers need to follow formal procedure to fire workers; iii) a dummy variable taking value 1 if employers have the legal duty to bargain with workers representatives, and 0 if they can lawfully refuse to bargain. Figures 4, 5 and 6 plot the variables over years by country. There is substantial institutional heterogeneity across countries, but the variables tend to be persistent over time.[22]

Figure 4 shows that only a few countries experienced constitutional reforms of the right to form unions, in al case towards greater protection of labor. In Switzerland, the Federal Constitution of 2000 specifically protected the right to form trade unions. However, prior to 2000 the right was seen as implied by constitutional guarantees of freedom of association and direct effect of ILO Conventions and Art. 11 ECHR, rather than the Swiss constitution itself. Article 73 of the Constitution (written in 1944) protected freedom of association. Act 97/1995 amended the constitution to explicitly include trade unions. The Latvian Trade Union Law of 1990 referred to a right to form trade unions 'in accordance with the Declaration on the Restoration of Independence of the Republic of Latvia. However, explicit references to unions were only included in a constitutional amendment regulating citizens' rights, freedoms and obligations in 1998. Out of 35 countries in the sample, 10 do not protect the right to form unions. Such group of countries includes the United States, Great Britain and other Anglo-Saxon countries, which tend to have more flexible labor markets compared to other economies. Figure 4 shows that the right to unionise is granted in the largest European economies: Germany,

of the main methodological issues can be found in Section B of the appendix.

[21]Presumably, mismeasurement is less of a concern using dummy variables, as there is less ambiguity in assessing whether a right is granted or not by the constitution, rather than inferring the degree of protection.

[22]This is not a feature of the booleans. The original institutional variables coded by Adams, Bishop, and Deakin (2016) are also very persistent.

Spain, France and Italy - but also in Japan and Korea.

Figure5 shows Austria tighten regulation of dismissal in 1994, Lithuania in 2004 and Turkey in 2003. On the contrary, Hungary relaxed rules on dismissal in 2012; Figure 6 shows that Austria removed employers' duty to bargain in 1996 and Spain in 2011. On the contrary, other countries introduced it. These are Great Britain (2001), Island (1996), Israel (2000), Korea (1997), and New Zealand (2000).

Information on unionisation rates is taken from the Comparative Political Data Set 1960-2016, by Armingeon, et al. (2018).[23] The two variables measuring the actual strength of trade unions in each country and year are: i) net union membership as a proportion wage and salary earners in employment (union density), and ii) employees covered by collective bargaining agreements as a proportion of all wage and salary earners in employment with the right to bargain (union coverage). Figures 7 and 8 plot the variables over years by country. There is substantial institutional heterogeneity across countries and also over time. However, the coverage is somewhat lower than for the first set of institutional variables.

Union density tends to be higher in Nordic Countries, above 50 percent, but it varies significantly across countries and tends to be declining over time. In the United States union density is never above 15 percent, between 20 and 25 percent in Japan and around 40 percent in Italy. Union coverage is much higher than union density due to the impact of collective agreements extending to non-union workers. Union coverage is above 50 percent in most European countries - almost 100 percent in Spain, France and Italy. The United States and Japan have a relatively low union coverage, well below 20 percent. The declining trend in union coverage is visible in some countries but tends to me less marked than that of union density.

4.3 Sunk Costs

To construct proxies for industry-level sunk costs I follow Cardullo, Conti, and Sulis (2015) in using the inverse of the share of used capital in total capital expenditures by sector. The idea underlying such an index is that in industries where capital

[23]In turn, Armingeon, et al. (2018) sources data on union data from Visser (2013).

expenditure is not highly specific to the firm or the industry, there should be a larger second-hand market and the share of used capital employed should be higher. Specificity of capital can be assumed to arise from technological factors that are largely independent on country-specific conditions, at least for a sample of advanced economies such as the one used in this paper. One concern is that regulatory frictions might bias capital investment and the functioning on second-hand market, thus distorting the information conveyed by the indicator. For such a reason, the proxy of industry-level sunk costs used in this paper is based on the United States, a country where regulatory frictions are among the lowest in the sample (see Section 4.2). Data on US expenditure for used capital by industry are available from the US Census Bureau. Since trend in robots' adoption might be correlated in some way with the share of used capital employed in a given US industry, the sunk cost measures is based on shares of second-hand capital in 1994, the first year with available information.

Figure A1 of the appendix displays the sunk cost-intensity measure, which is the inverse of the share of used capital in a two digits industry in 1994. The US Census Bureau does not report information for the agricultural sector and Repair and installation. Constructions is the less sunk cost-intensive industry, while Motor vehicles is by fat the most sunk cost-intensive. As noticed in the introduction, in Motor vehicles suppliers of components and assemblers use highly specialised equipment that does not have much use outside that industry. In other words, capital investment in Motor vehicles is largely irreversible. On the contrary, in the construction industry firms do not invest much in capital structures, which tend to be a large category of assets in other manufacturing industries. Investment in vehicles and machinery and equipment are clearly much less irreversible than investment in buildings.

4.4 Routine-intensity Index

Proxies of workers' replaceability are obtained using the routine-intensity index from Marcolin et al. (2016), which are displayed in Figure A2 of the appendix. Average industry values of the index are based on individual level survey data from the Program for the International Assessment of Adult Competencies (PIAAC). In each country, the survey collects information on the specific type of tasks workers carry out on their job, as well as the economic sectors in which they work. One limitation of the indicator is that it covers only the years 2011 and 2012.[24] Yet, the advantage of using PIAAC data is that it guarantees international comparability, which makes sample averages reasonably accurate.

Figure A2 shows that, as expected, Education and R&D presents the lower incidence of routine tasks. Exception made of Machinery and Equipment, non-manufacturing industries tend to be less routine task-intensive.

5 Institutions, Hold Up and Automation: Results

This section presents the empirical results. Sub-section 5.1 uses country-year variation and establishes a positive relationship between strict labor institutions and adoption of industrial robots. The finding supports the prediction of the model in Section 3 and suggests that indeed producers might use automation as a way to overcome distortions arising in the labor market. Sub-section 5.1 also shows that the relative contribution of institutions to adoption of robots in the sample is similar to the contribution of demographic trends documented in Acemoglu and Restrepo (2019).

The sub-section 5.2 exploits country-industry-year variation. The two main results are: i) the relationship between institutions and automation is stronger in sunk cost-intensive industries, and ii) strict institutions increase productivity more (lower it less) in industries with more opportunities for automation. The findings support once again the predictions of the model in Section 3 and suggests that mitigating hold up is a driver of automation.

[24] One possibility is to use routine intensity by occupation and map the evolution of employment by country. Another possibility is using the replaceability indexes from Graetz and Michaels (2018). Both tasks are left for future research.

5.1 Country-level Results

The number of OECD countries in the sample is 35, each spanning 19 years. Given the relatively low number of clusters and time periods available, clustering at the country level risks to inflate the standard errors, especially in light of the high serial correlation of the institutional variables (Bertrand, Duflo, and Mullainathan, 2004). Therefore, the standard errors reported are not clustered by country but they take into account potential heteroskedasticity of the residuals. The empirical model relates the institutional variables to the adoption of industrial robots exploiting country-year variation,

$$Y_{ct} = \beta_0 + \beta_1 Reg_{ct} + BX_{ct} + \varepsilon_{ct} \tag{8}$$

In (8), Y_{ct} and Reg_{ct} are respectively, an outcome variable and the value of the institutional variable in country c and year t. The vector X_{ct} includes interactions of base year GDP per capita, population, average years of schooling with year dummies. Acemoglu and Restrepo (2018) show that demographic trends are important drivers of investment in industrial robots. Therefore, unless differently stated all the following specifications include the expected log-difference of the ratio of population aged 55 and above to that aged 20 to 54 between 1990 and 2025. The variable is taken from the United Nations Population Forecasts.

Table 1 presents the results of estimating (8) with OLS. Columns 1 to 4 show results for the total number of industrial robots installed per number of workers, or "robot density". All the labor market institutions considered have a positive and significant impact on robot density. The estimates in column 1 suggests that countries in which the right to form unions is granted by the constitution use 0.6 additional robots per worker. To get a sense of the magnitude, in 2013 robot density in the United States was 0.9, in Italy 1.4 and in Germany 2.6. In column 1, the R2 contribution of the institutional variable is 20% after partialling out the impact of all other controls.[25] Acemoglu and Restrepo (2019) show that a shortage of mid-aged workers specialising in production tasks drives investment in labor-saving technology. Their paper provides evidence that demographic trends account

[25]The R2 contribution is computed by diving the R2 of a reduced model (without the institutional variable) by the R2 of the model in column 1 (0.471).

for 85% of the R2 using a sample of OECD and non-OECD economies.[26] In the sample of OECD countries used in this paper, the aging variable accounts for 30% of the R2. The coefficient of the aging variable is also positive and significant, but its magnitude is around 1/3 that of the right to unionise. The impact of institutions on robot density is similar to a 30 percentage points increase in expected aging, roughly the difference between Japan and the United States.

Columns 2 and 3 of Table 1 displays the results for two additional categories of labor market institutions: rules on dismissal and employers' duty to bargain. The estimates are lower than in column 1 but always positive and significant. Column 4 shows the results of a specification including all the institutional variables. The magnitude of the coefficients drops only marginally and the coefficient are more tightly estimated, suggesting that each variable captures different aspects of labor regulation having an impact on robot density.

The main hypothesis of this paper is that producers use automation to hedge against the hold up generated by strict labor institutions. However, one might be concerned that the increase in robot density would just capture an increase in the capital stock or trends of capital deepening. Therefore, columns 5 to 8 of Table 1 use the number of robots per unit of capital instead. The table shows that results are qualitatively similar with the alternative dependent variable, suggesting that the coefficients are truly capturing trends in automation. Table A1 of the appendix reports results using log-transformed dependent variables and show that the elasticities are very similar.[27] For robustness, Table A2 of the appendix reports results using long differences. The coefficients are still positive and significant, except for the duty to bargain. However, using long differences restrict the sample size to only 35 countries.

Table 1 lend support to the hypothesis that countries protecting the right to form unions, with strict rules on dismissal and in which employers have the legal duty to bargain with employees use automation more intensively. However, one concern is that in some countries, unions could be weak despite being formally recognised by the constitution. In such cases, the estimated relationships in column

[26] They report a total R2 of 0.47, while the partial R2 of the aging variable is 0.4.

[27] The outcome variables have zero values for approximatively hundred observations. Therefore, in order to maximise sample size the main tables use dependent variables in levels.

1 of Table 1 might be spurious.

OLS regressions of robot density on actual union density are problematic because trends in automation are likely to affect union formation, resulting in reverse causality. To overcome such issues, one possibility is instrumenting union density with the dummy variable for the right to form unions. Figure 4 shows that the legal recognition of the right to form unions is a very persistent institution, in most cases being determined long before the beginning of the sample and therefore highly unlikely to be correlated with trends in robot density. Table 2 presents results of regressing robot density on union density and union coverage, instrumenting them with the institutional dummy variable.[28] The first stage's partial F statistics is above the canonical threshold of 10 proposed by Angrist and Pischke (2009). The first stage regression of union density on the institutional variable is presented in column 1of Table A3 in the appendix. The first stage confirms the positive relationship between the right to form unions and actual union density: countries in which the right to form unions is legally protected have on average 8% higher union density.

Turning to the impact of unions on robot density, the estimates in column 1 of Table 2 suggests that countries with 10 percent higher union density use 0,7 additional robots per employee, roughly corresponding to the sample's interquartile range. Acemoglu and Restrepo (2019) provide some evidence that unions increase investment in robots, but the magnitude of impact is considerably lower than in this paper. Unlike in Acemoglu and Restrepo (2019), this paper finds that unions have an impact on automation roughly three times larger than expected aging. One possible explanation for such difference is that they do not use instruments for union density. The OLS estimator might then underestimate the impact of unions on automation due to reverse causality. Table A4 provides evidence in support of the hypothesis. The table shows that failing to instrumenting for union density and union coverage results in much lower estimated coefficients. OLS estimates of the impact of unions are in line with those in Acemoglu and Restrepo (2019), roughly 1/3 of the impact of aging.

One important channel through which unions might induce automation is forcing producers to pay higher wages. Column 2 of Table 2 includes log hourly wages.

[28] Due to data availability, the observations in Table 2 are lower than in Table 1.

Since wages are likely to be endogenous to robot density, the specification in column 2 uses the variable for the duty to bargain as an instrument. The first' stage F statistics in column 1 of Table 2 is slightly below 10, but as shown in columns 2 and 3 of Table A3, the institutional variables tightly predict the endogenous regressors. Interestingly, after including (instrumented) wages, the size of the coefficient on union density drops by more than 1/3, but it remains significant and of sizeable magnitude. One potential explanation is that unions - and more broadly labor-friendly institutions, do not only affect labor costs. They also affect firms' expectation about potential costs that high workers' bargaining power might entail. For instance, the constitutional protection of the right to form unions increase the probability of non-union workers becoming unionised. Strong unions increase the credibility of the threat to strike, therefore amplifying the incentives to automation when a producers face large sunk costs. This possibility is examined in the next section, which exploits country-industry variation.

Columns 3 and 4 of Table 2 employ union coverage as an alternative endogenous explanatory variable. The results confirm those in columns 1 and 2, and despite relying on a lower number of observations, they present a tighter first stage.

5.2 Country-industry Results

The model in Section 3 makes two key predictions. The first is that strict labor institutions should increase robot density more in industries characterised by large sunk costs. In such industries, workers are in a better position to hold up producers because preventing production to take place would cause larger losses. Therefore, any legal institution shifting bargaining power in favor of workers should generate incentives to invest in robots in oder to lower the dependency from labor and mitigate the possibility of rent appropriation. The second prediction is that strict institutions should increase productivity more (reduce it less) in sectors with greater opportunities for automation. For instance, strong unions and high wages might be detrimental to firms' productivity. But in industries more prone to automation producers can reduce dependency from labor in order to become more competitive. This section exploits country-industry-year variation to test such hypotheses using the following linear model,

$$Y_{cst} = \beta_0 + \beta_1 Reg_{ct} \times \sigma_s + BX_{cst} + \eta_{cst} \tag{9}$$

The model is analogous to (8) but adapted to country-industry data. The term of interest is the interaction between country-year level institutions and an industry-specific variable σ_s, which will be either a measure of sunk costs or routine intensity. In addition to the country-year controls of the previous section, the vector X_{cst} now includes: 2 digits industry-year fixed effects; country-industry average wages and share of value added in the base year, interacted with year effects. Exploiting country-industry variation, the specification in (9) allows the inclusion of country-year fixed effects, which are useful to mitigate bias from time varying, country-specific unobserved shocks. All estimates are weighted by the countries' base year shares of employment in each industry, and errors are robust to heteroskedasticity.[29]

A key prediction of the model in Section 3 is that the increase in labor bargaining power should increase robot density more in industries characterised by larger sunk costs. To test the hypothesis, Table 3 presents the results of estimating (9), where σ_s is the measure of sunk cost-intensity discussed in Section A1. An important identifying assumption is that technological characteristics of US industries carry over to other countries.[30] Notice that using country-specific measures of sunk cost-intensity might result in biased estimates, as institutional development itself could affect the share of used capital.[31] Using industry measures based on the United States mitigates such risks, because the US is the country with the most flexible labor market in the sample and therefore sunk cost-intensity is unlikely to be affected by labor market regulation.

Column 1 of Table 3 shows the estimated coefficient on the interaction between the right to form unions and sunk cost-intensity. The coefficient is positive and significant, and it implies that countries protecting the right to form unions have

[29] The same weighting scheme is used in Graetz and Michaels (2018) and Acemoglu and Restrepo (2019).

[30] A similar assumption is made by Ranjan and Zingales (1998) and a large body of empirical work since then.

[31] Several papers have found a significant relationship between labor market institutions and capital accumulation. See Autor, Kerr, and Kugler, 2007; Bassanini, Nunziata, and Venn, 2009; Cette, Lopez, and Mairesse, 2016.

0.05 additional robots per employees in industries one standard deviation above the average.[32] The inclusion of country-year effects precludes the estimation of the main effect of Reg_{ct}. However, in Section 5.1 the country-wide impact was approximatively 0.6 additional robots per employee. That implies that robot density is approximatively 8 percent higher in sunk cost-intensive industries. Columns 2 and 3 of Table 3 report the impact union density and union coverage in sunk cost-intensive industries, again instrumenting unionisation rates with the dummy indicating whether a country protects constitutionally the right to form unions. The estimates in column 2 are positive and significant. They imply that countries with 10 percent higher union density use roughly 0.04 additional robots per employee in industries 1 standard deviation above the average sunk cost-intensity. Thus, the estimates are in line with those of column 1. The estimates in column 3 are not significant, possibly due to the much lower number of observations.

One concern is that even in a sample of OECD economies, the technological characteristics of the United States might not carry over to less developed countries such as Mexico or in Eastern-Europe. Therefore, Table A5 of the appendix presents the results of estimating (9) using an alternative measure of sunk costs, real gross fixed investment in each country-industry cell. Real investment is a widely used proxy of sunk costs, as discussed in Balasubramanian and Sivadasan (2009). To mitigate concerns of endogeneity that would afflict country-specific measures, the alternative variable is instrumented with the value in the United States computed from the NBER-CES Manufacturing Database.[33] Table A5 shows that the results are consistent with the alternative sunk cost-intensity measure. The estimates in columns 1 and 2 are again positive and significant. The coefficient in column 3 is again not significant (but positive), possibly due to the low number of observations and the weak first stage.

Another prediction of the model in Section 3 is that strict institutions should increase productivity more (reduce it less) in industries with larger opportunities for automation. Results in Autor, Levy, and Murnane (2001) suggest that rou-

[32] The index has been opportunely normalised to have zero mean and unit standard deviation in the employment share-weighted sample.

[33] To avoid biases due to adoption of robots, the instruments are computed for the years preceding the beginning of the sample, in which automation was lower in the United States. The United States is then dropped by the sample.

tine task-intensive industries should be those with a lower cost of automation. Therefore, one way to test the prediction is using industry-level indexes of routine task intensity discussed in Section 4.4. Table 4 reports the results of estimating (9) using such industry-specific measure. The coefficient in column 1 implies that industries with one standard deviation above the average routine task-intensity have 3 percent higher labor productivity in countries protecting the right to form unions.[34] That is consistent with the prediction the model in Section 3. Table A6 of the appendix sheds additional light on the relationship between institutions, robot density and labor productivity productivity. The positive and significant coefficient in column 1 can be interpreted as the first stage of the specification in column 1 of Table 4. It shows that indeed the institutional variable increase robot density more in routine task-intensive industries. Moreover, the estimates in column 2 of Table A6 show that robot density, instrumented by the interaction of the institutional variable and the industry-level routine intensity measure have a positive impact on labor productivity.

In column 2 of Table 4, country-year fixed effects are removed to assess the overall impact of the institutional variable on labor productivity, which is found to be negative. The estimates imply that labor productivity is roughly 20 percent lower in countries protecting the right to form unions. However, the coefficient on the interaction term suggests that institutions lower productivity 17 percent less (0.04/0.24) in industries with more opportunities for automation. In columns 3 and 4 the coefficients are not significant, probably due to the very weak first stage. The coefficients in columns 5 and 6 are similar to those of column 1 and 2. The estimates imply that a 10 percent higher union coverage lowers overall productivity by 20 percent, but only by 16 percent in industries with one standard deviation above the average routine-task intensity.

[34] Labor productivity is computed as real value added per worker, as in Graetz and Michaels (2018) and Acemoglu and Restrepo (2019).

6 Industrial Robots, Productivity and The Labor Share

The theoretical and empirical findings of this paper suggest that an important driver of investment in industrial robots is thwarting appropriation and redistributing rents from labor to capital. That being the case, countries with low productivity levels due to strict institutions should adopt robots more heavily. In other words, one should expect a negative between-country relationship between automation and productivity. Moreover, if the role of robots is thwarting rent appropriation, their adoption should result in strong shifts of functional income distribution from labor to capital.

A systematic evaluation of the impact of automation on productivity is beyond the scope of this paper. However, descriptive evidence can be used as an indirect test of the main hypothesis of this paper: automation is not necessarily seen as productivity-enhancing *per se* by producers, but rather as a solution to a problem of hold up.

This section estimates the following specification, in the spirit of Acemoglu et al. (2014),

$$\ln Y_{cst} = \beta_{94} R_{cs} + \sum_{t=95}^{13} \beta_t R_{cs} + BX_{cs} + \varepsilon_{cst} \tag{10}$$

In (10), Y_{cst} is the outcome variable in each country c, industry s and year t. The variables $\beta_t R_{cs}$ are interactions with year dummies of a time-invariant measure of automation-intensity, the average number of industrial robots per worker in each country-industry pair over the sample. To facilitate the interpretation of the results, R_{cs} has been opportunely normalised to have zero mean and unitary standard deviation in the employment-weighted sample.

The vector X_{cs} includes the same country and industry-level controls of Table **??**. The estimated coefficients are again weighted according to the 1993 share of industry employment within each country and errors are robust to heteroskedasticity. Estimates of $\left\{\hat{\beta}_{94},\ \hat{\beta}_{94} + \hat{\beta}_{95}\ ...\ \hat{\beta}_{94} + \hat{\beta}_{13}\right\}$ approximate the growth rates of robots-intensive countries over the period 1994 to 2013, relative to other OECD economies.

Figure 9 presents the results of estimating (10) with OLS. Dotted lines represent 90% confidence intervals. Although controlling for country-level economic and demographic characteristics, country fixed effects are not included and so the estimated coefficients measure the between-countries relationship between robots-intensity and the four dependent variables considered. The left panel shows that the OECD countries undertaking the largest investment in robots were 2.5% less productive than the others at the beginning of the sample. The productivity measure considered is the log of real value added per employee. The productivity gap, however, becomes narrower over the years up to 2003. Since 2003, the countries investing more in industrial robots begin to become more productive than their counterparts. This is consistent with producers investing more heavily in robots in an attempt to overcome the productivity loss generated by strict labor market institutions. The right panel of Figure 9 shows that the labor share in heavy adopters was about 15% higher at the beginning of the sample, but then it felt by more than 6% up to 2013. That is consistent with the idea that producers invest in automation to redistribute rents from labor to capital. Figure A3 of the appendix shows the results of repeating the exercise including country-fixed effects and so quantifying the within-country relationship between automation and the dependent variables. In this case, the relationship between automation and output per employee becomes positive and significant. The most automated country-industries enjoyed productivity gains of around 10%, a somewhat lower but similar number to that obtained by Graetz and Michaels (2018). The right panel of Figure A3 presents the estimated within-country impact of robots on the share of labor compensation, which is found to be negative and decreasing over the sample. Therefore, the within-country estimates are consistent with the idea that robots increase productivity but also redistribute rents from labor to capital.

The results obtained in this section hold under a variety of alternative specifications. The first concern is that sample averages of R_{cs} might capture endogenous trends, or that it fail to capture the latest vintages of industrial robots. Therefore, I repeat the exercise using averages for the years 1994-1998 and 2009-2013. The test does not lend support to the hypothesis that our primary measure of automation is inappropriate.[35] Another potential concern is that the results might depend on the choice of variables to measure automation intensity. Therefore, I repeat the exercise by using the number of industrial robots per unit of capital instead. The results are similar, but the estimates are less precise because of the several missing data on the capital stock by industry. Given that Japan and Korea are above the 90th percentile of the distribution of R_{cs}, I repeat the exercise excluding the two countries from the sample, but results are again very similar.

6.1 Impact of Automation on Net Output

Up to this point, the evidence suggests that labor-friendly market institutions lower aggregate productivity and increase the labor share, but they also provide incentives to invest in industrial robots to mitigate hold up and thwart appropriation. Consistently, the most automated countries in the OECD region were those suffering lower productivity at the beginning of the sample. Over time, the productivity gap of heavy robots' users narrowed down and it became positive in the last part of the sample. Therefore, automation might be one way to solve the hold up problem and restore productivity by overcoming rigidities originating in the labor market. Another question is whether automation can be seen as an *efficient* solution to the hold up.[36]

This section intends to shed some light on the issue by calibrating and numerically simulate the model in Section 3. A formal welfare comparison would require a much richer model and goes beyond the scope of this paper. Nevertheless, some insight can be obtain by looking at net output, defined as total production net of non-labor expenditure,

$$Y^{net} \equiv Y - pK - \frac{1}{G(\rho*)} \int_{\underline{\rho}}^{\rho*} \rho \, dG(\rho)$$

where $K = Rk_r^* + Lk_l^*$ is the aggregate capital stock and the last term is aggregate expenditure on robots, conditional on firms facing a price lower than

[35]All robustness checks are available upon request.

[36]Caballero and Hammour (1998) investigate a similar issue.They argue that strict labor market institutions in France induced a shift to capital intensive production methods to mitigate rent appropriation by labor. Substituting labor with capital contributed generated high unemployment and therefore a welfare loss.

the threshold $\rho*$. It follows that net output is equal to labor income plus profits.[37] Robot- and labor-using firms are assumed to operate the same constant returns to scale technology with capital as additional production input. Expressing all quantities in terms of capital per robot and capital per worker, the production functions are given by

$$f_r(k_r) = k_r^\alpha$$

$$f_l(k_l) = k_l^\alpha$$

The benchmark calibration is as follows: interests on capital are 5% ($p = 1.05$); the share of capital income is $\alpha = 0.4$ The sunk cost-intensity is set to 50% of the initial capital investment, $\gamma = .5$. The price of robots is assumed to follow a Pareto distribution with shape parameter set to 1 and minimum value $\underline{\rho} = 1.1$, which implies that the lowest-paying firms face a 10% interest rate to purchase robots. The fact that $\underline{\rho} > p$ is meant to reflect the large installation costs of robots and the uncertainty involved in adopting a new technology.

Figure 10 displays net output as a functions of the bargaining power parameter, β. The solid line in Figure 10 represents the evolution of Y^{net} when robots' price are so high that no firm finds it profitable to automate. In the simulation, this is obtained setting $\underline{\rho} = 10$. For large values of β, net output tends to fall steeply with labor bargaining power. When automation is prohibitively expensive, firms cannot use robots to thwart appropriation. Therefore, high bargaining power magnifies the severity of the hold up, which results in lower investment and output. The dashed line represents the evolution of Y^{net} under the benchmark calibration. Again, an increase in labor bargaining power increases wages and amplifies the impact of sunk costs in determining the hold up. As a consequence, labor-using firms invest less and produce less output. At the same time, an increase in labor bargaining power increases the number of robot-using firms. Such firms are immune to hold up and so their optimal investment and output are not affected by β. As a consequence, aggregate output tends to fall less quickly than in the non-automation case.

[37]In the model, the total number of firms is fixed and therefore some firms might earn positive profits.

However, automation is costly and so the higher labor bargaining power, the larger the aggregate expenditure on robots. Thus, for relatively low levels of β, net output is actually higher when robots are not available and so using robots to overcome distortions in the labor market is an inefficient solution to the hold up. One implication of this fact is that governments should consider to provide incentives to invest in automation only when a combination of labor market frictions and sunk costs are such to severely undermine firms' competitiveness. Even when robots might contribute to increase net output, it is not clear whether incentives to automation might be more effective than a reform of the labor market. For instance, consider the situation depicted by Figure 11. Suppose that the economy is characterised by a value of $\beta = 0.9$, so that its net output without automation is $Y_A^{net} = 1.2$. A government might choose to incentivise the use of automation in order to move the economy from point A to point B, so that $Y_B^{net} = 2$. In our stylised example, that can be achieved by lowering the minimum price for robots from $\underline{\rho}_A = 10$ to $\underline{\rho}_B = 1.1$. In practice, providing incentives to automation might require a substantial amount of resources, such as using tax revenues which might be directed alternative uses. Figure 11 suggests that one alternative that the government might consider is a structural reform aimed at reducing rigidities in the labor market. In our example, that would imply lowering the bargaining power of labor, from $\beta = 0.9$ to $\beta \sim 0.67$. Doing that would move the economy to point A', which delivers the same level of net output $Y_B^{net} = 2$.

7 Conclusions

Advanced economies differ widely in their labor market institutions. For instance, in some country the right to form trade unions is protected by the Constitution; firing workers requires legitimate reasons and strict procedural rules; unions have a large number of members, or workers' compensation is subject to sectoral agreements. Labor-friendly institutions shift bargaining power in favor of workers and allow them to extract rents at the expenses of capital through higher wages. That might give producers an incentive to invest in industrial robots more in such countries than in others, where employers can use labor with much greater flexibility.

This paper documented that indeed, countries with labor-friendly institutions invest more in industrial robots. Institutional differences explain a substantial fraction of sample variation in adoption. For instance, the constitutional protection of the right to form trade unions explains alone 20 percent of variation in the number of installed robots per worker. The impact of labor market institutions as drivers of automation are quantitatively comparable to demographic trends, which in a sample of OECD countries explain 30 percent of variation in robotics.

This paper has shown that labor-friendly institutions have an impact on automation not only through higher labor costs. Between 30 and 40 percent of the impact of unionisation rates on robots persists after controlling for wages. This paper has argued that in presence of sunk costs, strict labor market institutions increase the threat of being held up by labor, thus providing additional incentives to automate. For instance, in most situations producers must build the plant and purchase equipment before hiring workers or negotiating their compensation. Powerful unions might be able to renegotiate higher wages *ex post*, reducing the returns on the initial investment. Anticipating that threat, firms might preemptively prefer to minimise dependency from human labor and invest in robots. Exploiting country-industry variation, the empirical part of the paper has provided evidence in support of the hypothesis. Strict labor institutions increase investment in robots disproportionately in industries characterised by large sunk costs such as Motor vehicles, in which a substantial fraction of investment is irreversible due to specialised equipment.

By developing a model of technological choice in presence of sunk costs, this paper has shedded light on the relationship between robots and productivity when automation is driven by institutional rigidity. By exacerbating the severity of hold up and increasing labor costs, rigid institutions kill the incentive to accumulate labor-complementing capital, and a lower capital-labor ratio lowers productivity. At the same time, institutions create incentives to invest in robots. By thwarting rent appropriation, automation solves the hold up problem and create incentives to accumulate labor-substituting capital, which has a positive impact on productivity. Therefore, the net impact of strict labor institutions on aggregate productivity is ambiguous and depends on whether the latter effect is stronger then the former. In the sample of OECD countries used in this paper, the cumulative impact of institutions on productivity is negative. However, the model predicts that strict institutions should lower productivity less in industries more suitable for automation. Such prediction is supported by the data.

Automation technology is often considered a panacea against stagnant productivity. To boost competitiveness, governments in many advanced economies devote substantial resources to promote the development and uptake of industrial robots. But if the aim of automation is overcoming market frictions and redistribute rents from capital to labor, encouraging investment in robotics would be like curing the symptoms rather than the disease. Structural reforms might be a more efficient solution to low productivity. A numerical simulation of the model developed in the paper suggests that providing incentives to adopt robots would increase net output only when bargaining power is heavily biased in favor of labor. And even in such cases, a mild labor market reform would result in the same output gains obtained by providing subsidies to robots' adoption.

Finally, there are two promising directions in which the analysis of this paper might be extended. First, from the empirical side, a finer level of data aggregation would surely help disentangling the mechanisms at work. However, much of the heterogeneity in labor institutions is at the cross-country level, which would require comparable cross-country firm-level information on robots' adoption. Second, and from a more theoretical perspective, it would be interesting to develop a full fledged general equilibrium model to investigate the welfare implications of investment in automation technology. Strict labor institutions might be detrimental to firms' productivity, but they might have a positive impact on workers' welfare. At the same time, using robots to overcome distortions in the labor market might be an inefficient solution to the hold up problem, as it would lower labor demand and put individuals out of work. A formal evaluation of such possibilities is left for future research.

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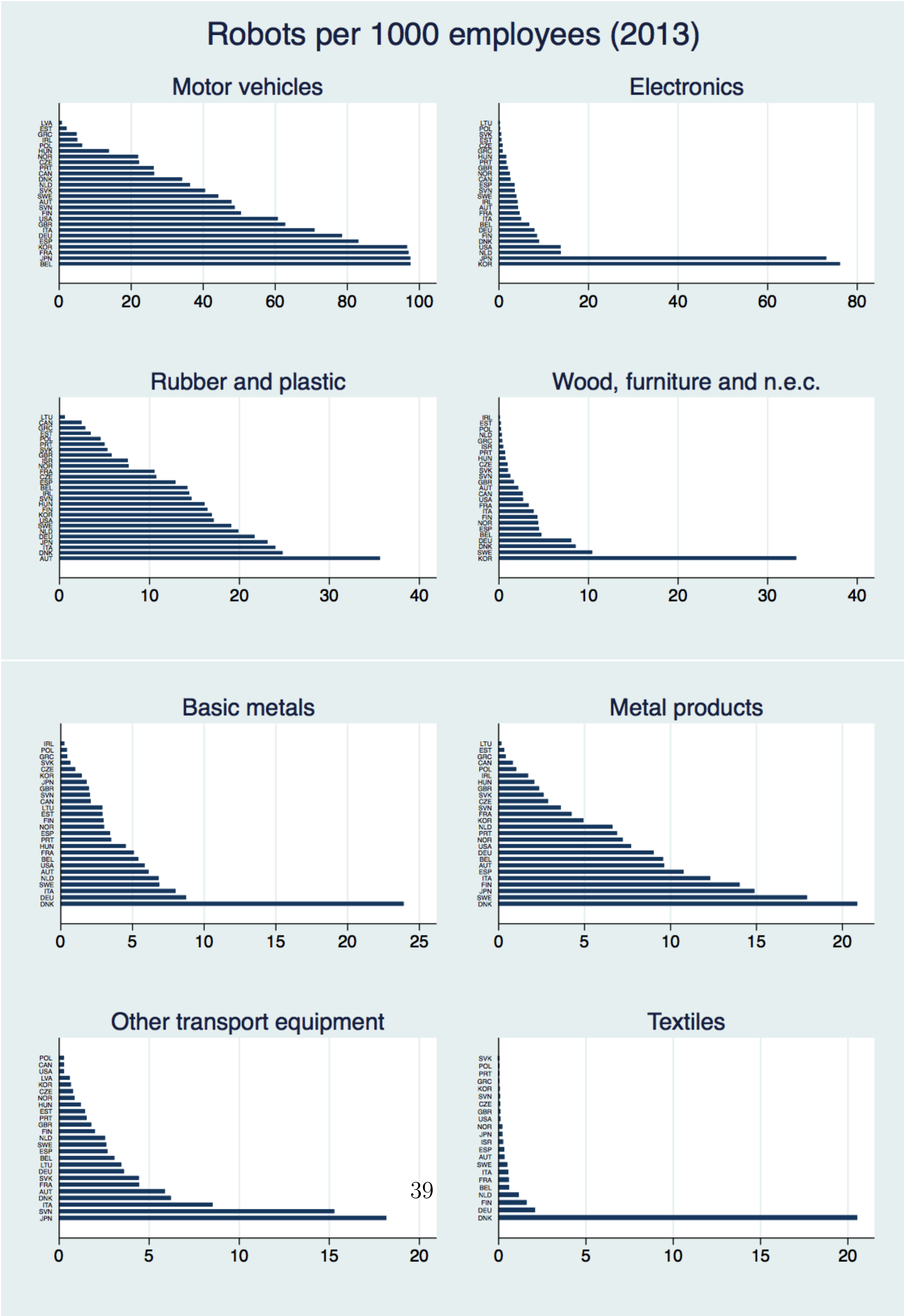
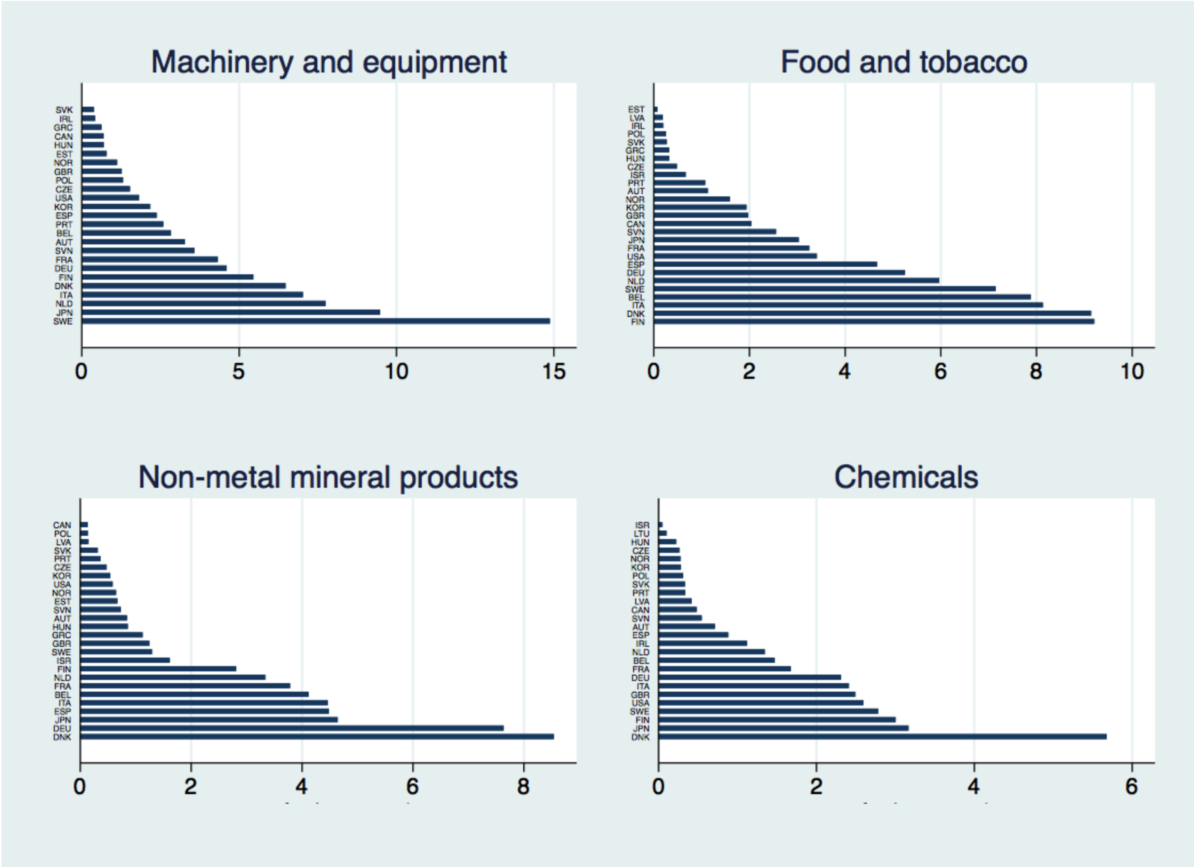
Figure 1: Cross-country differences in adoption of industrial robots

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Chemicals
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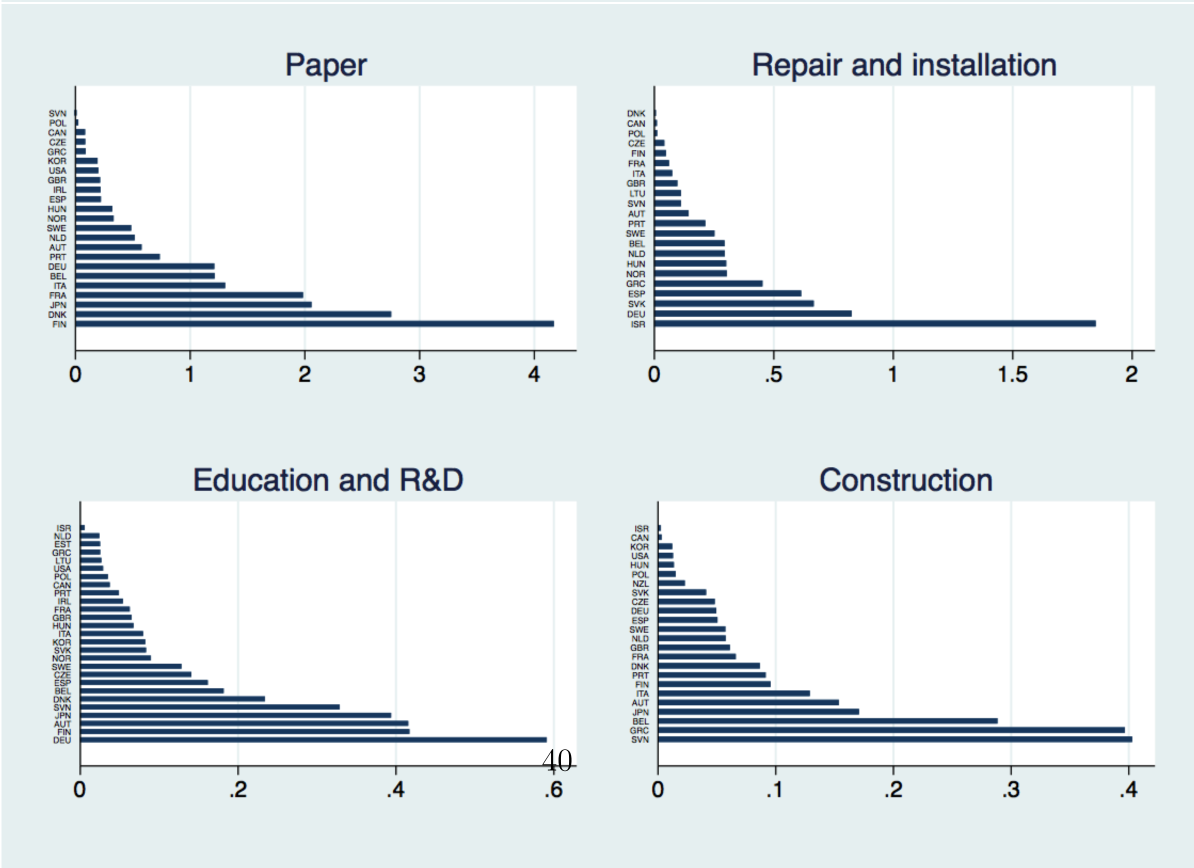
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Figure 2: Industrial robots, labor share and labor market institutions

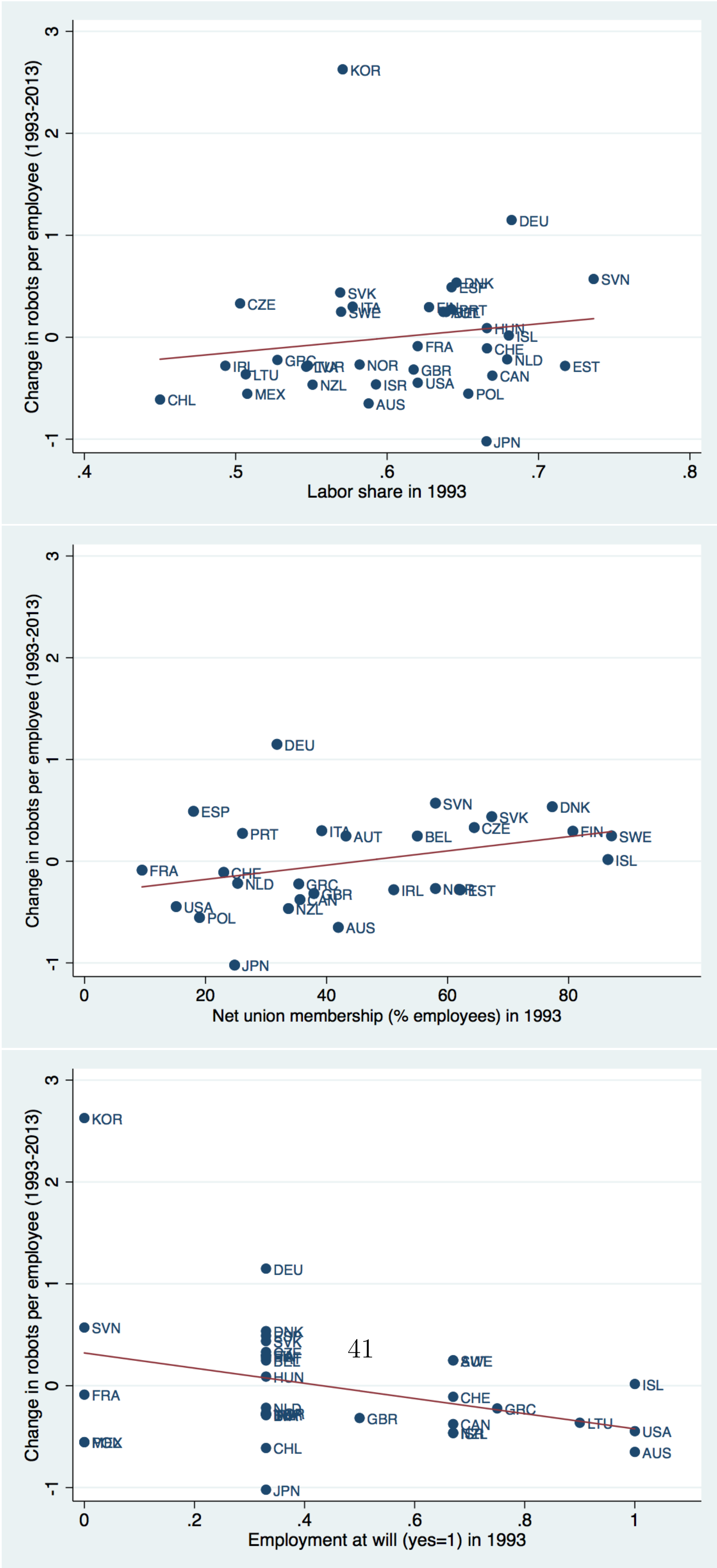


Figure 3: Sunk costs and investment in robots vs aggregate capital

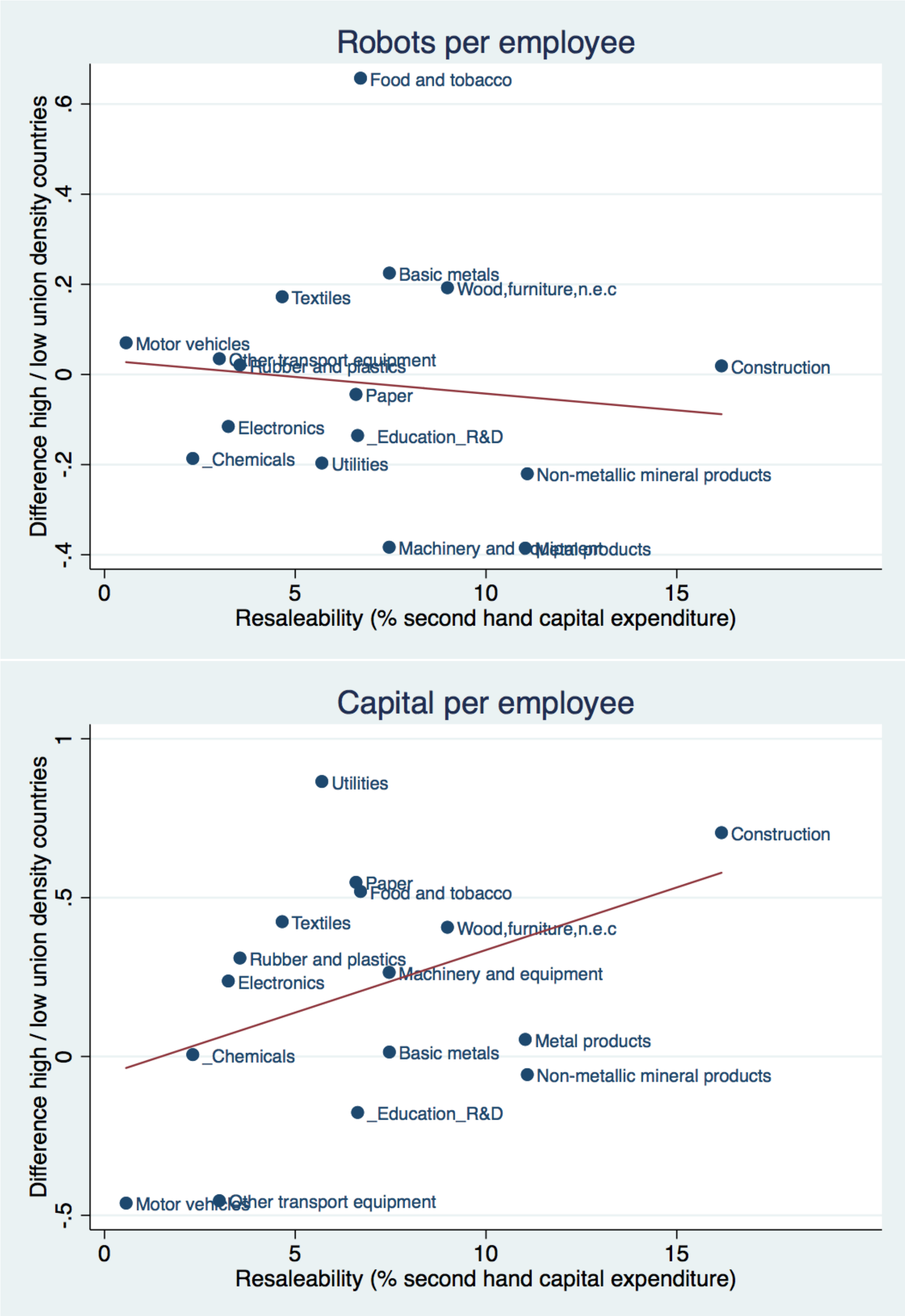


Figure 4: Dummies taking value 1 if the right to form trade unions is expressly granted by the constitution, and 0 otherwise.

Figure 5: Dummies taking value 1 if it is enough to have a “just or fair cause” to fire workers and no procedural constrains are involved; 0 if otherwise.

Figure 6: Dummies taking value 1 if employers have duty to bargain with workers' representatives, and 0 if they can lawfully refuse.

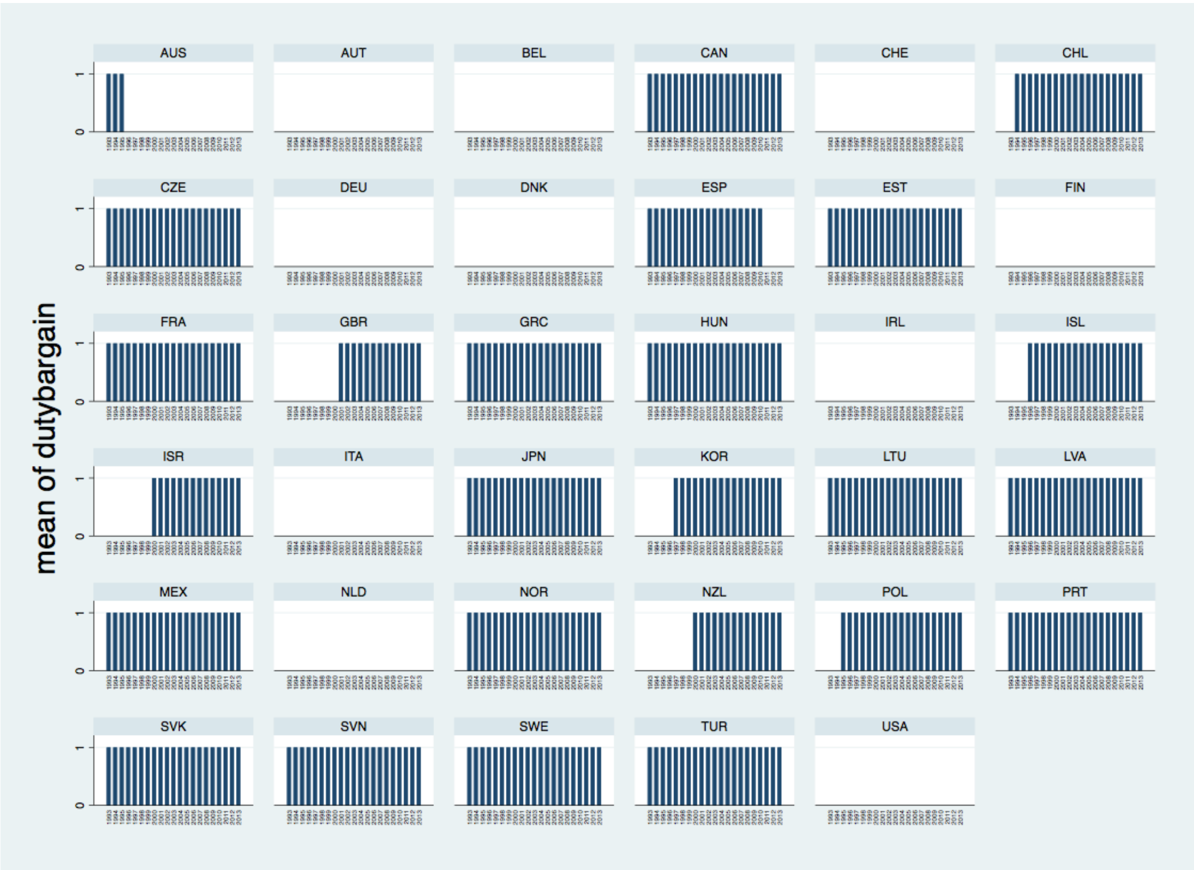


Figure 7: Union density (%)

Figure 8: Union coverage (%)

Figure 9: Dotted lines represent 90% confidence intervals. Errors are robust to heteroskedasticity. All countries have been assigned equal weight but each industry is weighted by its 1993 employment share in a given country. Countries in the sample=35; N=3600.

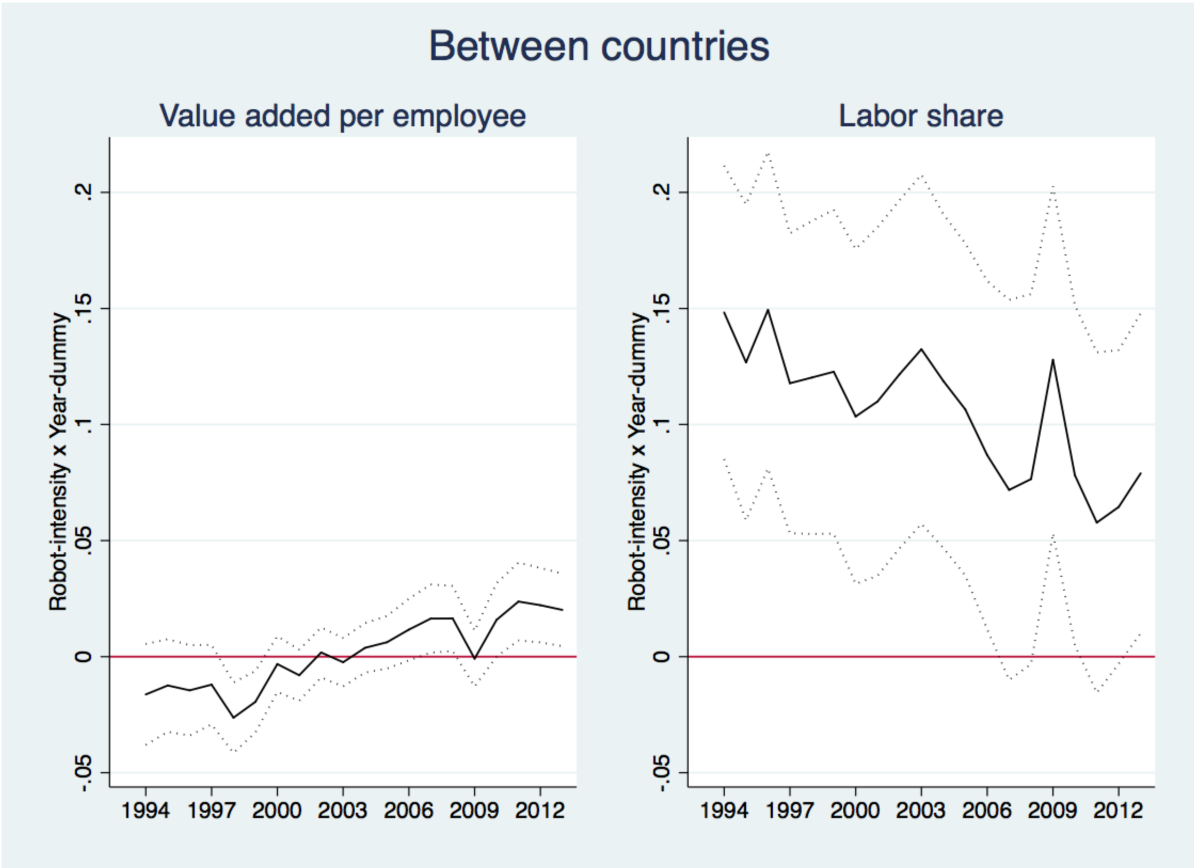


Figure 10: Numerical simulation: net output as a function of labor bargaining power

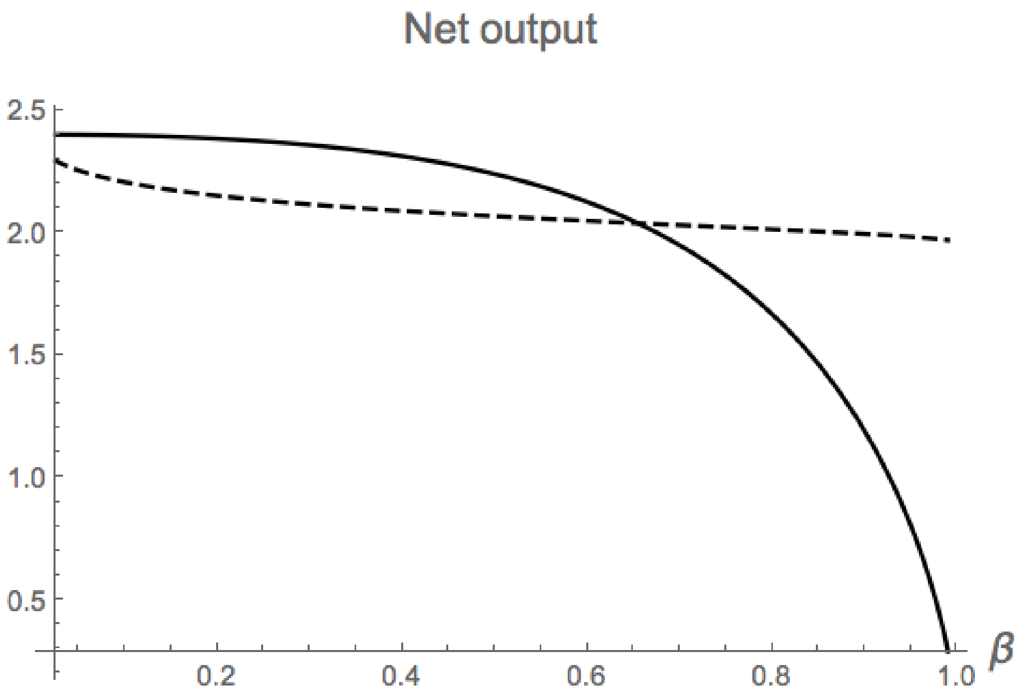


Figure 11: Incentives to automation vs structural reforms

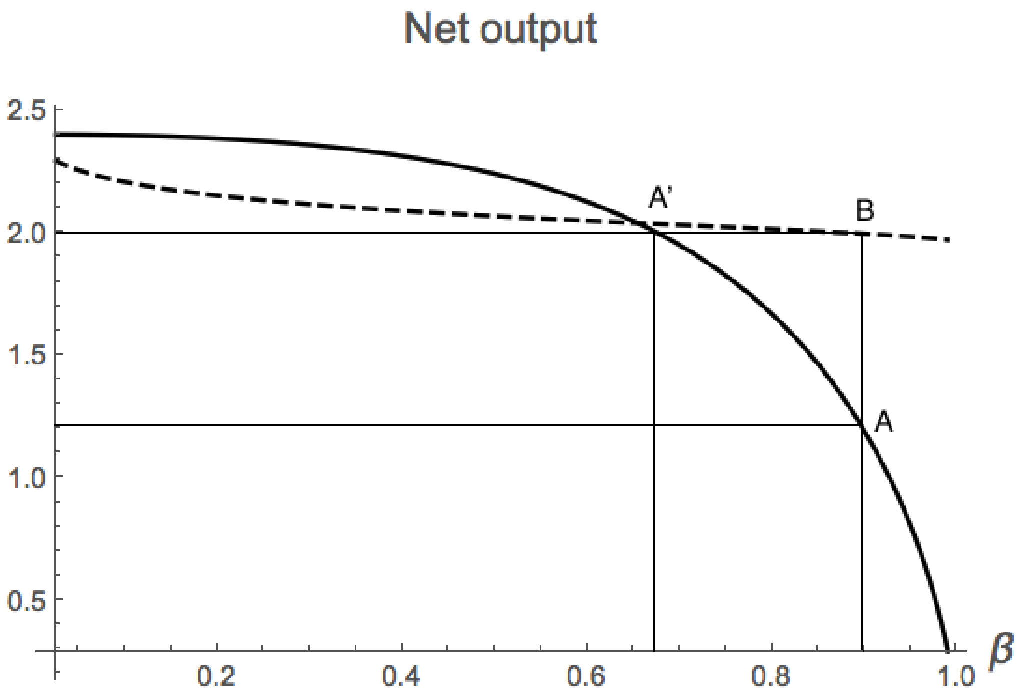


Table 1:

VARIABLES	(1) R/L	(2) R/L	(3) R/L	(4) R/L	(5) R/K	(6) R/K	(7) R/K	(8) R/K
Right to unionise	0.567***			0.534***	2.241***			2.095***
	(0.067)			(0.064)	(0.280)			(0.262)
Rules on dismissal		0.408***		0.372***		1.528***		1.434***
		(0.079)		(0.068)		(0.319)		(0.275)
Duty to bargain			0.222**	0.228***			1.635***	1.655***
			(0.096)	(0.088)			(0.420)	(0.390)
Aging between 1990 and 2025	1.761***	1.943***	2.057***	1.775***	8.385***	9.118***	9.740***	8.635***
	(0.196)	(0.213)	(0.232)	(0.201)	(0.779)	(0.856)	(0.940)	(0.801)
Observations	665	665	665	665	665	665	665	665
R-squared	0.471	0.431	0.413	0.501	0.444	0.406	0.413	0.490
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2:

VARIABLES	(1) R/L	(2) R/L	(3) R/L	(4) R/L
Union density	7.046***	2.352**		
	(1.618)	(1.200)		
Union coverage			5.344***	2.059***
			(1.010)	(0.714)
Log hourly wage		0.269***		0.332***
		(0.049)		(0.066)
Aging between 1990 and 2025	3.749***	3.074***	3.384***	3.377***
	(0.530)	(0.273)	(0.972)	(0.452)
Observations	462	462	254	254
Base year country covariates-year FE	yes	yes	yes	yes
First stage F	16.20	8.018	31.90	13.35

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3:

VARIABLES	(1) R/L	(2) R/L	(3) R/L
Right to unionise x sunk cost intensity	0.047**		
	(0.022)		
Union density x sunk cost intensity		0.436**	
		(0.203)	
Union coverage x sunk cost intensity			0.008
			(0.067)
Observations	3,691	3,172	1,675
R-squared	0.597		
Aging between 1990 and 2025	yes	yes	yes
Baseline country covariates-year FE	yes	yes	yes
Industry-year FE	yes	yes	yes
Country-year FE	yes	yes	yes
First stage F		21.29	69.25

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4:

VARIABLES	(1) Y/L	(2) Y/L	(3) Y/L	(4) Y/L	(5) Y/L	(6) Y/L
Right to unionise x routine intensity	0.030***	0.042***				
	(0.009)	(0.009)				
Right to unionise		-0.242***				
		(0.075)				
Union density x routine intensity			1.942	3.118		
			(1.953)	(2.499)		
Union density				-23.633		
				(19.539)		
Union coverage x routine intensity					0.219**	0.390***
					(0.104)	(0.130)
Union coverage						-1.983*
						(1.035)
Observations	3,862	3,862	3,321	3,321	1,745	1,745
R-squared	0.992	0.985				
Aging between 1990 and 2025	yes	yes	yes	yes	yes	yes
Baseline country covariates-year FE	yes	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes	yes
Country-year FE	yes	no	yes	no	yes	no
First stage F			1.016	0.721	18.32	9.363

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A Model Appendix

In this economy, wages are obtained through Nash bargaining and so they maximise the joint surplus from a successful production relationship,

$$S \equiv \Big[f_l(k_l) - w(k_l, \beta) - pk_l(1-\gamma)\Big]^{1-\beta} w(k_l, \beta)^{\beta}$$

The first term in the expression for S is the net surplus for the firm. Notice that with a positive amount of specificity $\gamma > 0$, in case production does not take place, the firm is only able to recover a fraction of the initial investment. I interpret the specificity of investment as solely determined by technological factors.[38] By reducing the outside option of the firm, specificity increases indirectly the bargaining power of labor. This can be seen from the equilibrium wage equation,

$$w^*(k_l, \beta) = \beta\Big[f_l(k_l) - pk_l(1-\gamma)\Big] \tag{11}$$

Higher γ corresponds to higher bargained wages. The profit-maximising capital investment for a labor-using firm is given by

$$f_l'(k_l^*) = p + w_k'(k_l^*, \beta) \tag{12}$$

In (12), since $w_k'(k_l^*, \beta) > 0$, the hold up generated by the *ex post* wage negotiation reduces investment per worker.

Firms decide wether to enter the market and what technology to adopt in case of entry: labor- or robot-using. To do so, they compare their profits conditional on the two technologies. Profits for robot-using firms are $\pi_r = f_r(k_r) - \rho - pk_r$. If a firm decides to use labor, it earns $\pi_l = f_l(k_l) - w(k_l, \beta) - pk_l$. Clearly, firms enter the market if either $\pi_r \geq 0$ or $\pi_l \geq 0$.

The following expression defines the price threshold making a firm indifferent between using labor or robots,

[38] It might also be determined by economic or institutional factors. For instance, a piece of equipment that is not useful for other firms or industries is highly specific. Similarly, the absence of well-functioning second hand markets would prevent the firm to resell it in case production does not take place. Even labor institutions might be responsible for increasing γ. For instance, firing costs would imply that in case the producer wants to layoff workers and employ differently its capital, a fraction of the initial investment might be lost due to severance payments.

$$\rho^* \equiv f_r(k_r) - f_l(k_l) - p(k_r - k_l) + w(k_l, \beta) \tag{13}$$

Thus, a firm uses robots if and only if $\rho \leq \rho^*$.

The following equation pins down the profit-maximising capital investment in robot-using firms, which are not subject to hold up because with robots products are independent on human labor,

$$f_r'(k_r^*) = p \tag{14}$$

In the model, the parameter describing the bargaining power of workers summarises the effect of labor institutions on the economy. We first study how changes in β affect automation decisions. Taking the total derivative of (13) and rearranging we get,

$$\frac{dk_r}{d\beta}\left[f_r'(k_r) - p\right] - \frac{dk_l}{d\beta}\left[f_l'(k_l) - p - w_k'(k_l, \beta)\right] + w_\beta'(k_l, \beta)$$

Evaluating the previous expression at the optimum given by (14) and (12), we have that the terms in square brackets are zero and so

$$\frac{d\rho^*}{d\beta} = w_\beta'(k_l^*, \beta) > 0 \tag{15}$$

Therefore, higher bargaining power increases the maximum price that firms are willing to pay to invest in robots. Since each firm employs either only on robot or only one worker, the number of robots per worker in the economy is given by

$$\frac{R}{L} = \frac{G(\rho^*)}{1 - G(\rho^*)}$$

These results imply that higher bargaining power increases the number of robots per worker, even in absence of hold up.

We now turn to the relationship between automation and aggregate productivity, which is defined as total output per worker.[39] In the model, total output

[39]The same productivity measure is used in Acemoglu and Restrepo (2018; 2017), Alesina, Battisti, and Zeira (2018), and Graetz and Michaels (2018).

per worker is given by

$$\frac{Y}{L} = \frac{G(\rho^*)}{\left[1 - G(\rho^*)\right]} f_r(k_r^*) + f_l(k_l^*)$$

Taking the total derivative of the previous equation with respect to β, we obtain

$$\frac{G'(\rho^*)}{\left[1 - G(\rho^*)\right]^2} f_r(k_r^*) \frac{d\rho^*}{d\beta} + \frac{G(\rho^*)}{\left[1 - G(\rho^*)\right]} f_r'(k_r^*) \frac{dk_r^*}{d\beta} + f_l'(k_l^*) \frac{dk_l^*}{d\beta}$$

From (14), the capital of robot-using firms is independent of β, so that the second term in the previous equation is zero. Thus, the expression relating aggregate productivity to labor bargaining power is

$$\frac{dY/L}{d\beta} = \frac{G'(\rho^*)}{\left[1 - G(\rho^*)\right]^2} f_r(k_r^*) \frac{d\rho^*}{d\beta} + f_l'(k_l^*) \frac{dk_l^*}{d\beta} \tag{16}$$

Aggregate productive depends positively on the extensive margin of automation, given by the first term in (16). Such a positive impact is due to the reduction in aggregate employment, which boosts productivity. Since $\frac{d\rho^*}{d\beta} > 0$ by (15), equation (16) implies that an increase in bargaining power should increase productivity more in economies with a lower cost of automation, i.e. economies with a stochastically dominant $G(\cdot)$.

Due to the second term in (16), the net impact of an increase in bargaining power on productivity is ambiguous. An expression for $\frac{dk_l^*}{d\beta}$ can be obtained by taking the total differential of (12) with respect to β,

$$\frac{dk_l^*}{d\beta} = \frac{w''_{\beta k}(k_l^*, \beta)}{\left[f_l''(k_l^*) - w''_{kk}(k_l^*, \beta)\right]} \tag{17}$$

Without sunk costs (and therefore, no hold up), the numerator of (17) is zero as $w_k' = 0$ and so higher bargaining power increases productivity unambiguously. However, with sunk costs, we have that

$$\frac{dk_l^*}{d\beta} = \frac{f'(k_l) - p(1-\gamma)}{f''(k_l)(1-\beta)}$$

Thus, the higher the specificity of investment γ, the stronger the negative impact of institutions on labor productivity.

B Construction of the institutional variables n Adams, Bishop, and Deakin (2016)

The original institutional measures used to construct the dummy variables used in this paper are taken from the comparative legal analysis in Adams, Bishop, and Deakin (2016) "CBR Labour Regulation Index - Cambridge Centre for Business Research". In particular, Adams, Bishop, and Deakin (2016) measure the protection of the right to form trade unions in the country's constitution or equivalent with the following coding: 1 if a right to form trade unions is expressly granted by the constitution; 0.67 if trade unions are described in the constitution as a matter of public policy or public interest; 0.33 if trade unions are otherwise mentioned in the constitution or there is a reference to freedom of association which encompasses trade unions, and 0 otherwise. Using the same methodology, the right to strike in the country's constitution or equivalent is quantified by the following coding: 1 if a right to industrial action is expressly granted by the constitution; 0.67 if strikes are described as a matter of public policy or public interest; 0.33 if strikes are otherwise mentioned in the constitution, and 0 otherwise. For both variables, variation in the strength of the law are reflected in further gradations between 0 and 1.

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 ('labour law');
2. development of a conceptual construct ('regulation', from the viewpoint of the employer, or 'protection', from that of the worker);
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 (or 'permanent') 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.

C Figures

Figure A1: Proxy of sunk costs based on the share of used capital (1994).

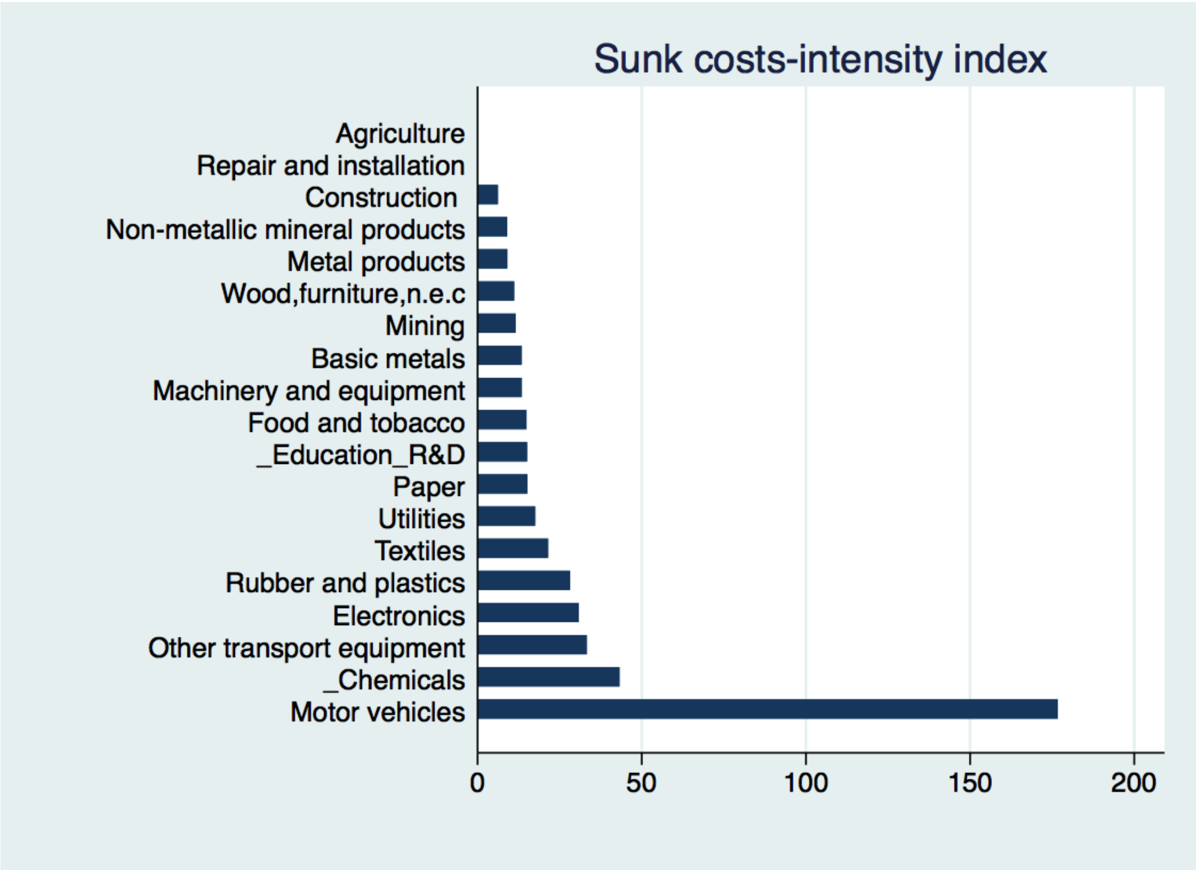


Figure A2: Routine intensity Index from Marcolin et al. (2016).

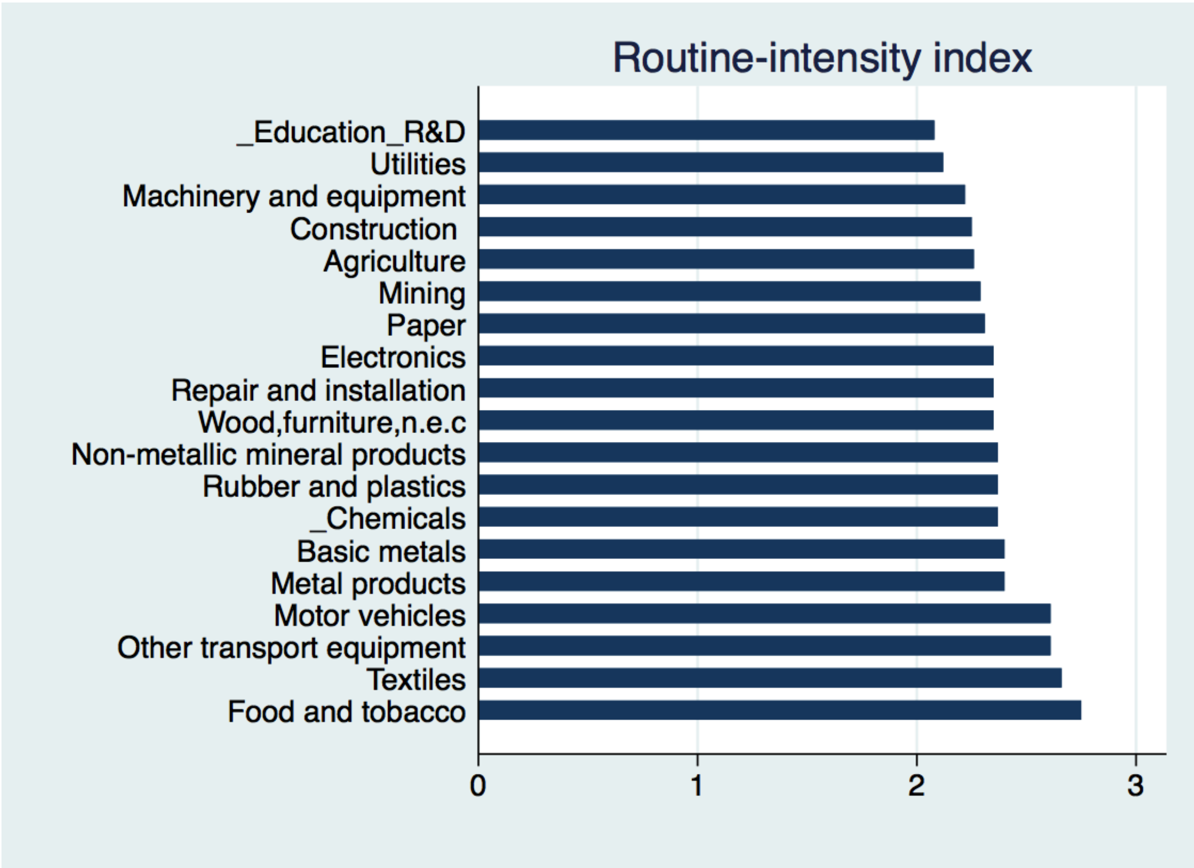
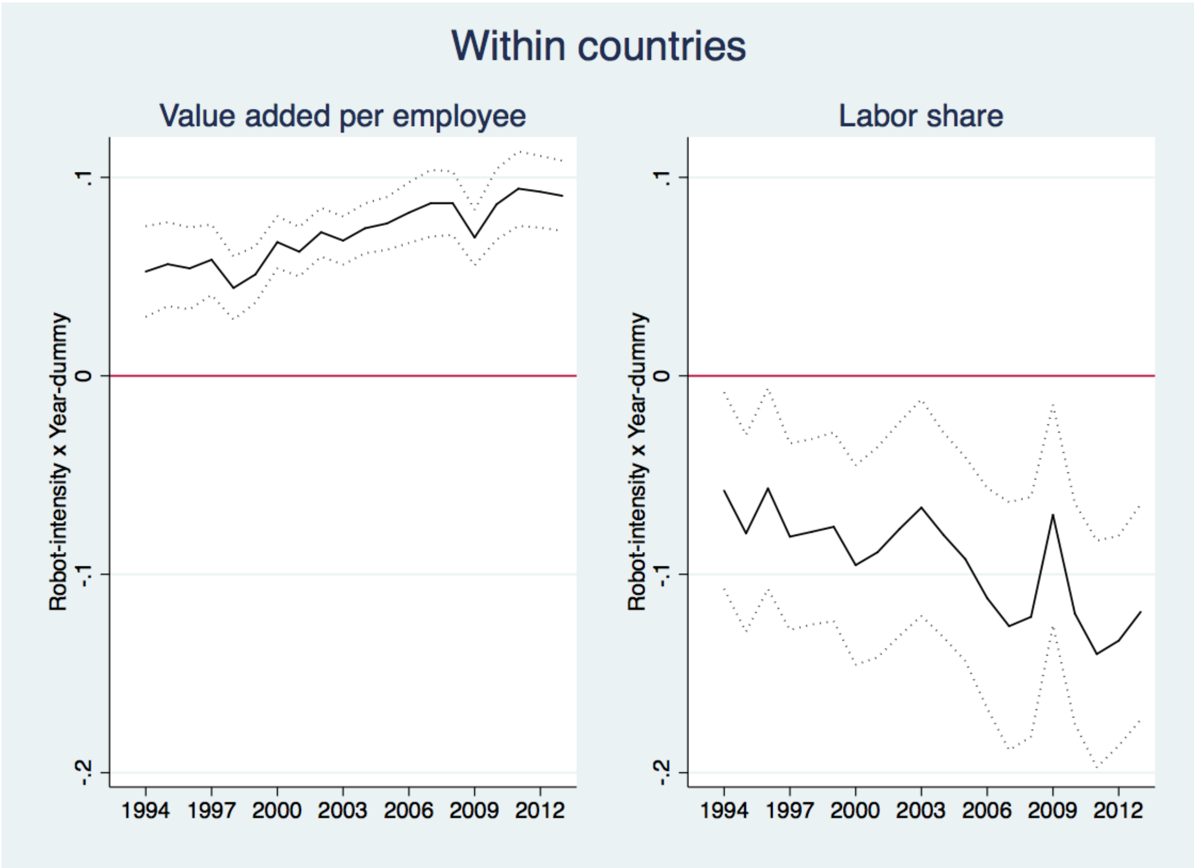


Figure A3: Dotted lines represent 90% confidence intervals. Errors are robust to heteroskedasticity. All countries have been assigned equal weight but each industry is weighted by its 1993 employment share in a given country. Countries in the sample=35; N=3600.



D Tables

Table A1:

VARIABLES	(1) log R/L	(2) log R/L	(3) log R/L	(4) log R/L	(5) log R/K	(6) log R/K	(7) log R/K	(8) log R/K
Right to unionise	1.096***			1.087***	0.931***			0.910***
	(0.163)			(0.163)	(0.147)			(0.150)
Rules on dismissal		0.629***		0.591***		0.586***		0.541***
		(0.164)		(0.165)		(0.164)		(0.168)
Duty to bargain			-0.044	-0.184			0.094	-0.027
			(0.126)	(0.129)			(0.119)	(0.124)
Aging between 1990 and 2025	1.926***	2.409***	2.567***	1.698***	2.043***	2.439***	2.637***	1.895***
	(0.260)	(0.249)	(0.253)	(0.276)	(0.246)	(0.229)	(0.233)	(0.254)
Observations	558	558	558	558	558	558	558	558
R-squared	0.597	0.556	0.541	0.612	0.546	0.513	0.497	0.560
Base year country covariates-year FE	yes	yes	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2:

VARIABLES	(1) Change R/L	(2) Change R/L	(3) Change R/L	(4) Change R/K	(5) Change R/K	(6) Change R/K
Right to unionise in 1994	0.032**			0.220**		
	(0.014)			(0.096)		
Rules on dismissal in 1994		0.035**			0.252**	
		(0.014)			(0.114)	
Duty to bargain in 1994			-0.028			-0.175
			(0.017)			(0.123)
Aging between 1990 and 2025	0.117	0.114	0.102	0.994	0.970	0.908
	(0.071)	(0.071)	(0.066)	(0.611)	(0.609)	(0.566)
Observations	35	35	35	35	35	35
R-squared	0.404	0.376	0.403	0.475	0.455	0.463
Baseline country covariates	yes	yes	yes	yes	yes	yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3:

VARIABLES	(1) Union denisty	(2) Union denisty	(3) Log hourly wage	(4) Union coverage	(5) Union coverage
Right to unionise	0.083***	0.085***	0.143	0.214***	0.216***
	(0.021)	(0.021)	(0.210)	(0.038)	(0.037)
Duty to bargain		-0.025	1.671***		-0.047
		(0.017)	(0.143)		(0.035)
Observations	462	462	665	254	254
R-squared	0.509	0.511	0.563	0.577	0.580
Base year country covariates-year FE	yes	yes	yes	yes	yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4:

VARIABLES	(1) R/L	(2) R/L	(3) R/K	(4) R/K
Union density	1.504***		5.372***	
	(0.162)		(0.690)	
Union coverage		-0.166		-2.215*
		(0.275)		(1.233)
Aging between 1990 and 2025	2.758***	3.376***	12.410***	16.009***
	(0.451)	(0.631)	(2.155)	(2.899)
Observations	462	254	462	254
R-squared	0.436	0.416	0.368	0.389
Base year country covariates-year FE	yes	yes	yes	yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5:

VARIABLES	(1) R/L	(2) R/L	(3) R/L
Right to unionise x fixed investment	0.484***		
	(0.085)		
Union density x fixed investment		2.581***	
		(0.450)	
Union coverage x fixed investment			11.626
			(17.212)
Observations	2,684	2,338	1,150
Aging between 1990 and 2025	yes	yes	yes
Baseline country covariates-year FE	yes	yes	yes
Industry-year FE	yes	yes	yes
Country-year FE	yes	yes	yes
First stage F	18.16	15.04	0.187

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A6:

VARIABLES	(1) Robot density	(2) Y/L
Right to unionise x routine intensity	0.794***	
	(0.184)	
Robot density		0.038***
		(0.013)
Observations	3,862	3,862
R-squared	0.597	
Aging between 1990 and 2025	yes	yes
Baseline country covariates-year FE	yes	yes
Industry-year FE	yes	yes
Country-year FE	yes	yes
First stage F		18.51

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1