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Robots and Labor Regulation: A Cross-Country/Cross-Industry Analysis*

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Abstract

This work discusses and empirically investigates the relationship between labor regulation and robotization. In particular, the empirical analysis focuses on the relationship between the discipline of workers' dismissal and the adoption of industrial robots in nineteen Western countries over the 2006–2016 period. We find that high levels of statutory employment protection have been negatively associated with robot adoption, suggesting that labor-friendly national legislations, by increasing adjustment costs (such as firing costs), and thus making investment riskier, provide less favorable environments for firms to invest in industrial robots. We also find, however, that the correlation is positively mediated by the sectoral levels of capital intensity, a hint that firms do resort to industrial robots as potential substitutes for workers to reduce employees' bargaining power and to limit their hold-up opportunities, which tend to be larger in sectors characterized by high levels of operating leverage.

JEL Codes: K31, O31.
Keywords: Robot adoption, Labor regulation, Hold-up.

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1 Introduction

Even though the presence of industrial robots in production lines dates back at least forty years, the increase in their rate of adoption observed in recent years is unprecedented. In fact, according to the International Federation of Robotics (IFR), while the stock of industrial robots operating worldwide roughly doubled between 1993 and 2011, it took less than seven years to double again and, since 2014, it has registered an impressive two-digits annual growth. Such an increase in the pace of robotization, combined with the concurrent and equally rapid diffusion of other automation technologies, has contributed to a resurfacing of the long-standing debate on technological unemployment and, along with it, the concerns regarding the disruptive social consequences associated with labor displacement (Autor and Dorn, 2013; Brynjolfsson and McAfee, 2014; Baldwin, 2019).[1] In particular, after a seminal study by Frey and Osborne (2017) dismally concluded that a substantial share of the jobs currently available in the US are at risk of being automated within the next few decades (a projection that has been partially toned down by an ensuing analysis by Nedelkoska and Quintini, 2018), several works have studied how automation affects labor market dynamics, producing mixed findings (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). By mainly focusing on the consequences of robotization and automation, however, most of the economic research conducted so far has paid little attention to the drivers and determinants of robot adoption, which could contribute to explaining the great amount of heterogeneity concealed behind the aggregate figures (e.g., Figure 1 visually shows the apparent lack of correlation between robot adoption and economic growth). Indeed, while technological progress has been central to the rise of robots, a limited understanding of the factors that determine why countries and industries follow trajectories that are so remarkably different in terms of robot adoption remains an important gap in the literature and, more importantly, poses substantial limitations to the policy debate about the most appropriate strategies to address the challenges and seize the opportunities associated with the ongoing automation revolution (Brynjolfsson and McAfee, 2014; Baldwin, 2019).

In this paper, we attempt to shed some light on the determinants of robot adoption by studying and discussing the relationship between robotization and labor market in-

[1] Since David Ricardo's chapter "On Machinery" (Ricardo, 1891), there has been a lively discussion among economists about the potential displacement of labor by machines. On the one hand, according to Say's law, technological unemployment is not permanent because, if technological progress reduces the prices of commodities, it will also increase their demand. This, in turn, will translate into an increase in labor demand (cf. Neisser, 1942). On the other hand, others have been arguing that "Demand for commodities is not demand for labor" (Mill, 1870, vol. 1, p. 5, para. 9) and there is no rigid association between consumer's demand and employment. The different micro–macro effects of the relationship between technological change and labor market equilibria have been described by Autor and Salomons (2018).

stitutions. More precisely, focusing on nineteen high- and middle-income countries over the 2006–2016 period, we study whether and to what extent the interplay between legal labor protections and the idiosyncratic characteristics of different industries can explain the substantial cross-country and cross-industry variability observed in the patterns of robot adoption. In doing so, we pay particular attention to dismissal laws, which represent the single most important piece of legislation affecting labor flexibility and whose effects have been extensively studied and discussed in the literature (e.g., Lazear, 1990; Autor et al., 2006; Bird and Knopf, 2009; Acharya et al., 2014; Alesina et al., 2018). Moreover, we also explore the relationship between robotization and other dimensions of labor regulation, such as the discipline of fixed-term contracts and industrial action that, as suggested by a consolidated literature, could affect labor flexibility (e.g., Botero et al., 2004; Kahn, 2007; Acharya et al., 2013).

From a theoretical perspective, labor market regulations can influence robot adoption via two main channels. The first hinges on the actual degree of substitutability between robots and labor, while the second one is related to the overall effect of labor laws on firms' propensity to invest. On the one hand, to the extent that robots in fact can substitute labor, laws that guarantee a high degree of employment protection may provide an incentive for investing in robots, since this would represent a viable strategy for a firm to cope with a rigid labor market environment. This can be particularly relevant in the case of capital-intensive industries, since a high level of investment in traditional capital goods increases — ceteris paribus — workers' hold-up opportunities and bargaining power (Card et al., 2014), whereas the gains from substituting labor are lower in a flexible labor market. However, it's not obvious how much the current robot technology is able to provide worthy replacements for human workers,[2] and it should also be noted that, even in the case of perfect substitutability, tight labor laws could prevent firms from substituting workers with robots altogether by restricting the cases in which firms are authorized to shrink the labor force. On the other hand, high levels of statutory employment protection increase adjustment costs and make firms more vulnerable to negative shocks, thus eroding the incentives to invest and to adopt innovative technologies (Parente and Prescott, 1994; Banker et al., 2013; Bartelsman et al., 2016; Serfling, 2016; Calcagnini et al., 2018). Therefore, and especially where the rule of law is effective (Caballero et al., 2013), labor-friendly regulations can contribute to delay robot adoption.

Other factors, however, can play a role. First, high levels of labor protection can

[2]Tesla's recent story is a real-world instructive example. After months of unsuccessful attempts to scale up production of the Tesla Model 3 through automation, Elon Musk tweeted: "Yes, excessive automation at Tesla was a mistake. To be precise, my mistake. Humans are underrated." Installing and adapting robots to the various tasks turned out to be harder than expected, pushing the company to meet its demand backlog by hiring thousands of workers (Korosec, 2018, from *Fortune*).

spur both employees and employers to make *complementary* investments in human and physical capital, potentially resulting in technological lock-ins that can increase the costs of robot adoption (Milgrom and Roberts, 1990; Aoki, 2001; Antonelli, 2012). Second, to complicate things further, unions can push for robot adoption to increase the safety of the working environment and to ease the physical effort on the part of employees (for the case of blue-collar workers, see Gihleb et al., 2020; Belloc et al., 2020; Caselli et al., 2021). However, if robots displace unskilled and routinary occupations, the increased productivity gap between skilled and unskilled workers may undermine their coalition, reduce the level of unionization, and increase the costs of coordination (Iversen and Soskice, 2020). In such cases, unions may end up opposing robot adoption. It follows that, as thoroughly discussed in the ensuing sections of the paper, the likely presence of contrasting dynamics makes it difficult to predict the sign of the relationship between labor regulation and robot adoption.

The results of our analysis indicate that labor regulation significantly correlates with the dynamics of robot adoption. In particular, we find that dismissal laws providing a high degree of protection to employees are overall negatively correlated with robot adoption. We also find, however, that they positively and significantly interact with the sectoral level of capital intensity. In other words, all else being equal, robotization has been more pronounced in the capital-intensive sectors of countries characterized by a labor-friendly legislation on dismissal. Hence, while not conclusive, our results are consistent with the idea that, by increasing hold-up opportunities for workers, labor regulations that provide high levels of employment protection produce two effects. On the one hand, by raising adjustment costs, high levels of statutory protection make firms more vulnerable to adverse economic shocks and therefore disincentivize overall investment. On the other hand, to the extent that robots do not behave opportunistically and can substitute labor in an increasing number of tasks, tight labor regulations foster robotization in capital-intensive sectors, that is where the risk of hold-up is higher. As thoroughly discussed in the paper, these two seemingly opposite effects of labor laws highlight the dual nature of robots, which are both physical capital, and therefore negatively affected by adjustment costs (such as firing costs), and substitutes for labor, and so positively influenced by protective labor legislations. Importantly, our interpretation is reinforced by the fact that, after disaggregating legislation on workers' dismissal on the basis of its different dimensions, we find that the results hold only if we consider regulations that pose "substantive" rather than simply "procedural" constraints to dismissal.

The remainder of the paper is organized as follows. In Section 2, we further discuss the mechanisms through which labor regulation may affect robot adoption. In Section 3, we illustrate the data and the empirical strategy, while the results are presented and discussed in Section 4. Section 5 concludes.

2 Labor Regulation and Determinants of Robot Adoption

Our work mainly relates to three strands of the literature. First, it directly contributes to the still limited literature on the drivers and determinants of robot adoption and, in particular, to those studies that look at the topic from an institutional perspective. For example, Fornino and Manera (2021) showed that, under the assumptions of perfect factor substitutability and that hiring and dismissing workers is quicker and less costly than buying and selling robots, labor and robots can coexist only to the extent in which labor regulations do not excessively reduce the flexibility of labor. In fact, according to the authors, flexibility represents a key comparative advantage of labor over robots. In a recent paper, Acemoglu and Restrepo (2019b) employed cross-country and US labor markets data to show that demographic changes associated with the ageing of the workforce are likely to be a relevant determinant of robot adoption. In particular, they argued that, among other reasons, firms adopt industrial robots to make up for the relative scarcity of middle-aged workers. In another paper, Belloc et al. (2020) used cross-country firm-level data from the European Company Survey to study the relationship between the presence of employee representation and the adoption of automation technologies, finding a positive association between the two. According to their interpretation, the presence of workers' representative bodies favours the introduction of technologies that are complementary to labor and whose adoption requires a "skill-improving" redesign of the job. Finally, in a paper that challenged some popular beliefs regarding the disruptive nature of the current wave of robotization in the manufacturing sector, Fernández-Macías et al. (2021) highlighted that robot adoption seems to be driven by technological regimes and the routine intensity of different sectors.

Second, we draw on the literature on the hold-up problem (Williamson, 1985; Hart, 1995), which has provided contrasting insights on how the risks of opportunistic behaviors by either workers or firms may influence robot adoption. Indeed, depending on the perspective from which one looks at robots, the risk of hold-up could either foster or hinder investment in automation and robots. On the one hand, if robots are simply considered to be another form of capital investment, the literature seems to suggest a negative relationship between high levels of statutory employment protection, which increases firms' exposure to employees' hold-up risk and robot adoption. In fact, given the unknown unknowns that characterize new investments, the difficulties in describing innovative activities ex ante make contracts susceptible to ex post renegotiation (Aghion and Tirole, 1994). In our case, under incomplete contracting, employees' quasi-rents are vulnerable to capture by workers in the form of higher wages and better conditions of employment, thereby reducing investment incentives. For example, Grout (1984) showed that in a setting in which firms make their investment decisions before wage negotiations take place, a positive shock on workers' bargaining power increases the quasi-rents they receive without paying any capital cost; anticipating this, firms decide to invest less. Similarly, Van der Ploeg (1987) showed that workers have an incentive to announce the intention of asking for low wages in the future, because this encourages present investment in capital. However, once the "machines" are installed – namely, once the firm has committed itself to specific investments – workers have an incentive to shirk their commitments. Hence, in the absence of complete contracts that can eliminate hold-up risks, firms will reduce investment in capital. As a result, labor-friendly regulations will negatively influence the desired capital stock, and hence the rate of investment. At the same time, to the extent that robots can substitute workers and do not engage in opportunistic behaviours, tight labor laws will also provide incentives for firms to invest in robots to substitute labor, thus mitigating hold-up risks.

Third, our analysis intersects the vast literature that investigates how labor regulations affect economic outcomes. For example, by studying the economic consequences of wrongful-discharge laws over a two-decade span, Autor (2003) and Autor et al. (2006) concluded that these have reduced state employment by up to 1.7 percentage points and significantly contributed to the outsourcing of US jobs. On the other hand, Acharya et al. (2013; 2014) theoretically discussed and empirically investigated whether stringent labor laws create ex-ante incentives for firms and workers to undertake risky but long term rewarding activities that spur innovation. In particular, the underlying idea is that, in the presence of high levels of employment protection, firms will reduce the penalties for workers' short-term failures and employees will be more committed to pursue innovation because they perceive a lower risk of firms' hold-up. A previous study by Autor et al. (2007) highlighted that while economic theory predicts that dismissal protection will reduce overall allocative efficiency, it is inconclusive about its effects on technical efficiency. By using US firm-level data and exploiting changes in labor regulation at the state-level, they found suggestive evidence of a decline in total factor productivity. They also found, however, that the protection guaranteed by dismissal laws is positively correlated with capital deepening and, to the extent that it represents a shift toward labor-saving technologies, this result is somehow compatible with our findings. Finally, Alesina et al. (2018) discussed why countries characterized by stringent regulations (modeled as firing costs) may tend to concentrate labor-saving technologies in low-skill sectors.

Importantly, beside the hold-up problem, other arguments have been advanced to support either a positive or negative relationship between robot adoption and the institutions that regulate the labor market. As a first example, robots can contribute to making the workplace safer and reducing the physical effort of workers (Gihleb et al., 2020) and, therefore, there may be circumstances in which employees use their bargaining power — which is influenced by labor laws — to push for robot adoption (Belloc et al., 2020). In this regard, Acemoglu and Restrepo (2019b) found that higher unionization is associated with higher robot adoption. Conversely, unions may obstruct the introduction of robots if they perceive that the machines can undermine workers' coalition.[3] A second argument relates to the complementary investments in human and physical capital made by workers and firms, which tend to be incentivized by the presence of stringent labor regulations and may increase the switching costs associated with the introduction of robots in the production process. In fact, as studied for the general case of games with strategic complementarities, moving to a different equilibrium requires changes (Aoki, 2001) that "are not a matter of small adjustments made independently at each of several margins, but rather have involved substantial and closely co-ordinated changes in a whole range of firm activities. Even though these changes are implemented over time, perhaps beginning with 'islands of automation' the full benefits are achieved only by an ultimately radical restructuring" (Milgrom and Roberts, 1990, p.513). If strong labor regulation and representative bodies favored complementary investments by firms and employees in the past, this would drive to path-dependent and localized technological change that locks firms into inferior technologies, relenting the establishment of the mind-and-machine combinations that, according to McAfee and Brynjolfsson (2017), characterize the new assembly line.

3 Empirical Strategy

3.1 Data

The empirical analysis is based on a multi-level longitudinal dataset that integrates information from various sources, which are presented in this section. Overall, the dataset combines country-level information on different dimensions of labor regulation and country macroeconomic characteristics (e.g., GDP, population, etc.) with information, at the country–industry level on the stock of robots, employment, and other variables related to the sectoral business structure (e.g., the overall stock of capital, amount of sales, and wages, etc.). The final dataset includes nineteen countries (eighteen European countries

[3]By widening the gap between different groups of workers (e.g., unskilled and routinary *vs.* skilled and non-routinary), robots may increase coordination costs among workers of unionized sectors (Iversen and Soskice, 2019). More generally, unions and workers will be more likely to oppose robotization when the introduction of robots displaces labor without producing an appreciable impact on productivity (as in the case of the "so-so technologies" discussed by Acemoglu and Restrepo, 2019a).

and the United States) and eight non-service sectors, even though the information is missing for some country–industry pairs.[4]

Country-level information on labor regulation has been retrieved from the Labor Regulation Index database (LRI), which is made available by the Centre for Business Research of the University of Cambridge (Deakin et al., 2007; Adams et al., 2016) and provides quantitative data on labor laws for more than one hundred countries over the span of almost five decades. In particular, the database provides forty different time-varying scores for different dimensions of labor regulation that encompass five broad areas: *(a)* laws that define employment relationships and different forms of employment, *(b)* laws that regulate working time, *(c)* laws that regulate workers' dismissal, *(d)* laws on employee representation, and *(e)* laws regulating collective action. Each score takes a value between 0 and 1, with high values indicating that labor laws guarantee workers a high degree of protection on the particular dimension associated with the score. For example, referring to the year 2006, the score associated with the dimension "C20 - Law imposes substantive constraints on dismissal" takes a value of 1 for France, a value of 0.5 for the United Kingdom, and a value of 0 for the United States. In the period considered by the analysis, the scores present a substantial level of between-country variability but a very low level of within variability (i.e., about 3% of the total variance).

This dataset offers several advantages. First, the long time series comprehensively captures all country-level changes in labor laws, which enables us to conduct tests that alleviate econometric concerns about country-level omitted variables. Second, the categorization of labor laws into different components allows us to assess the impact on robot adoption of different categories of employment protections. Third, the index takes into account not only formal laws but also self-regulatory mechanisms, which makes it particularly comprehensive with respect to the range of rules analyzed. For example, in certain legal systems, collective bargaining agreements, which do not constitute formal law, play a role that is functionally similar to formally enacted laws.

Data on industrial robots have been purchased from the International Federation of Robotics (IFR), which provides information on the stock and shipment of industrial robots

[4]The countries included in the analysis are: Austria, Belgium, Bulgaria, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Netherlands, Portugal, Romania, the Slovak Republic, Spain, Sweden, the United Kingdom, the United States. The ISIC rev.4 sectors included in the analysis are: Agriculture, forestry and fishing (1–3), and Mining and quarrying (5–9); Manufacture of food products, beverages, and tobacco products (10–12); Manufacture of textiles, apparel, and leather products (13–15); Manufacture of wood products (ex. furniture), paper, and the printing and reproduction of recorded media (16–18); Manufacture of coke and refined petroleum products, chemicals, pharmaceuticals, rubber and plastic products, and other non-metallic mineral products (19–23); Manufacture of basic metals, and metal products (24–28); Manufacture of motor vehicles, trailers, and transport equipment (29–30); Water supply, sewerage, waste management, and remediation activities (36–39).

for more than 70 countries going back to 1993. Stock and shipment of robots are expressed in quantities (number of robots) rather than values, and they can be disaggregated up to the three-digit level of the ISIC rev.4 industry classification. For most of the countries, however, two-digit industry-level data have only been consistently reported since 2004/05, after the IFR undertook a revision of its classification procedures to improve the quality and the international comparability of the data.

Country–industry data on employment and capital stocks have been retrieved from EU KLEMS (released 2019). The EU KLEMS database, which is managed by the Vienna Institute for International Economic Studies, provides measures of economic growth, productivity, employment, capital formation, and technological change at up to the two-digit ISIC rev.4 industry level for the 27 countries of the European Union, as well as for Japan, the United Kingdom, and the United States.

Finally, other country-level control variables, such as GDP, share of the labor force with advanced education, share of the workers employed in the manufacturing sector, and total fertility rate, have been retrieved from World Bank's World Development Indicators (WDI).

3.2 Econometric Model

We study the relationship between robot adoption and labor regulation by estimating different variants of an empirical model in which the ten-year change in robot density at the country–industry level is a function of the interaction between the level of protection guaranteed by countries' labor laws and sectoral capital intensity. In order to reduce the concerns associated with their endogeneity, capital intensity and labor protection are both measured at the beginning of the period. Besides the baseline specification, we also estimate augmented versions of the model, which include country-level lagged controls that are likely to influence the pattern of robot adoption, and two series of fixed effects meant to control for the heterogeneity stemming from trends associated with specific industries and/or to factors related to countries' formal institutions, which we proxy using the legal origin of their judicial systems. For example, since advancements in robotics are unlikely to be homogeneous across robot applications, it is possible that the differences in the pace of robot adoption between industries that make use of different types of robots can be fully explained on the basis of exogenous technological dynamics. The inclusion of industry fixed effects is meant to mitigate this potential source of bias. On the other hand, as discussed for example by La Porta et al. (2008), legal origins correlate with a number of formal judicial institutions that, in turn, tend to be associated with different economic outcomes, including level of investment and responsiveness to growth opportunities. Hence, the inclusion of legal origin fixed effects can help identify the relationship between robot adoption and labor regulation by isolating it from other confounding factors associated with countries' overall judicial institutions.

We measure robot adoption, our dependent variable, as the ten-year change in the country–industry level of robot density, which is the number of robots per worker (RPW) calculated on the basis of the sectoral employment levels of year 2006. In formal terms, robot adoption is defined by the formula

$$\Delta RPW_{c,i} = \frac{R_{c,s,2016} - R_{c,s,2006}}{L_{c,s,2006}} \tag{1}$$

in which $R_{c,s,2006}$ and $R_{c,s,2016}$ are the IFR stock of robots operating in the industry i of country c in years 2006 and 2016, while $L_{c,s,2006}$ represents the number of workers employed in the same country–industry pair in year 2006. We use sectoral employment at the beginning of the period because it needs to be exogenous with respect to the installation of new robots.

The full specification of the empirical model, therefore, is described by the following equation

$$\Delta RPW_{c,s} = \alpha + \beta_1 LRI_{c,t_0} + \beta_2 KInt_{c,s,t_0} + \beta_3 \left(LRI_{c,t_0} \cdot KInt_{c,s,t_0} \right) + \gamma x_{c,t_0} + \delta \sigma_s + \zeta \lambda_c + \varepsilon_{c,s} \tag{2}$$

in which LRI_{c,t_0} represents an index of labor regulation in country c and $KInt_{c,s,t_0}$ is a measure of capital intensity in the (c,s) country–industry pair, both of which are measured at the beginning of the period (i.e., in 2006). With regard to the other covariates, x_{c,t_0} represents a set of country-level controls that includes the log of GDP per capita, share of workers employed in the manufacturing sector, share of labor force with advanced education, and total fertility rate,[5] all measured at the beginning of the period, while σ_s is a set of industry fixed effects, λ_c a set of legal origin fixed effects, and $\varepsilon_{c,s}$ an idiosyncratic error term.

According to the model, the relationship between labor regulation and robot adoption is defined as $\beta_1 + \beta_3 KInt_{c,s,t_0}$, meaning that it is a function of capital intensity. We do not have strong priors on the sign of β_1, which is the direct effect of the level of employment protection on robot adoption. In fact, on the one hand, if the primary reason for robot adoption is to overcome labor market rigidities and reduce the scope for workers' strategic behavior associated with a high level of employment protection by replacing them with robots, we should expect β_1 to be positive. On the other hand, labor

[5]We include the fertility rate as a proxy for the age structure of the labor force, which, as discussed in Acemoglu and Restrepo (2019b), can influence the patterns of robot adoption.

regulation raises adjustment costs, that negatively affect investment, and tight laws on dismissal can prevent firms from substituting workers, thus slowing down robotization.

We expect, however, a positive sign for β_3, which is the effect of labor regulation on robot adoption that is mediated by capital intensity. Indeed, higher levels of capital intensity are always associated with greater hold-up opportunities for workers, and therefore, since it provides an additional incentive to substitute workers, we expect the coefficient to be positive and significant.

Finally, in regard to the direct effect of capital intensity on robot adoption, we are inclined to expect a negative sign for β_2. In fact, robots represent a particular form of capital that, for a certain number of applications, can crowd out human labor and therefore, even though investment is more conspicuous in capital-intensive industries, the opportunities to use robots are more frequent in labor-intensive industries.

Since EU KLEMS data are reported in current local currency units (LCUs), we could not measure capital intensity using the stock of capital per worker. Hence, we proxy capital intensity with the ratio between the sectoral stock of capital and sectoral sales, both provided in current LCUs. A clear advantage of this measure over a measure of capital per worker expressed in a common currency is that it helps circumvent the issues associated with the presence of cross-county differentials in price levels. As a robustness check, we also repeat the analysis using another measure of capital intensity, which is the ratio between the sectoral stock of capital and the sectoral total compensation of employees. In general, both measures turn out to be, after controlling for country and year fixed effects, highly correlated with the capital per worker measured in LCUs.[6]

Importantly, in order to reduce the influence of short-term factors (e.g., dynamics related to the business cycle, which can be particularly relevant for our proxies of capital intensity) on the results of the analysis, the value of the variables measured at the beginning and end of the period has been computed using a three-year average. Thus, values referring to 2006 are in fact the 2005-2007 average and, similarly, the values referring to 2016 are computed as the 2015-2017 average.

4 Empirical Results

4.1 Main Results

The relationship between dismissal laws and robot adoption represents the main focus of the present study. The LRI database contains nine entries related to the level of

[6] For the capital-sales ratio, the correlation is significant at the 0.1% level (t-stat = 5.0) and the R-squared of the model is 64.2%. For the capital-compensation of employees ratio, the correlation is significant at the 0.1% level (t-stat = 4.3) and the R-squared of the model is 58.0%.

protection offered by dismissal laws, which are reported in Table 1. As discussed in Section 3.1, each entry represents a different dimension of employment protection, and it is associated with a score ranging between 0 (no protection/no legal provisions on the topic) and 1 (maximum protection). In order to capture the level of statutory protection against dismissal resulting from the combined provisions of a country's labor laws, we calculate the unweighted arithmetic average over the nine dimensions, and we use it as a labor regulation index in the empirical model. The OLS estimates of the relationship between the statutory protection against dismissal and robot adoption are reported in Table 2.

All the five models find a negative and significant direct effect of the average level of protection guaranteed by dismissal laws at the beginning of the period (i.e., in year 2006) and the pattern of robot adoption in the ensuing ten years. At the same time, the models consistently find that the mediated effect of protection against dismissal is positive and significant. In other words, and in line with our expectations (cf. Section 3.2), capital intensity mediates the effect of labor regulation so that, all other things being equal, higher levels of protection against dismissal are associated with greater robotization in capital-intensive industries.

The overall sign and significance of the relationship between statutory protection against dismissal and robot adoption in correspondence to three different values of capital intensity are reported in Table 3, indicating that, at high levels of capital intensity, the mediated and direct effects of employment protection offset each other. This is graphically represented in Figure 2, which, based on the predictions of the full specification of the empirical model, reports how $\Delta\widehat{RPW}_{c,s}$ changes along with protection from dismissal at the 10th and the 90th percentiles of capital intensity. In particular, it shows that the negative relationship between robot adoption and dismissal laws is weaker in capital-intensive industries.

The results presented so far suggest two conclusions. On the one hand, between 2006 and 2016, statutory protection against dismissal was negatively associated with robot adoption. This, in turn, hints that the need to overcome labor market rigidities by substituting workers with robots is not the main story behind robot adoption. Indeed, since robotization has been more pronounced in the presence of less stringent labor regulations, it seems to be likely that business-friendly regulatory contexts (relating to labor laws, at least) that minimize adjustment costs can provide more favorable environments for firms to invest in industrial robots. On the other hand, even though it does not seem to have been the main driver of robot adoption, the results do provide empirical support for the idea that firms resort to industrial robots to reduce workers' bargaining power and to limit the scope of their hold-up opportunities, which tend to be larger in sectors characterized by high levels of operating leverage. In particular, the positive and significant coefficient of the interaction term between the level of statutory protection against dismissal and the level of capital intensity is consistent with this second conclusion. In fact, at any given level labor protection, robot adoption has been faster in capital-intensive industries; that is, where workers have greater bargaining power and opportunities for doing hold-ups.

As previously discussed, the index of statutory protection against dismissal used for the estimates reported in Table 2 is calculated as a simple arithmetic average of the individual indices associated with the nine dimensions of dismissal laws identified by Deakin et al. (2007) and Adams et al. (2016) in the LRI. Not all these dimensions, however, affect firms' ability to discharge workers in the same way. In particular, some of them impose substantive constraints to workers' dismissal, while others pose only procedural constraints. Therefore, if our interpretation of the results is correct, we expect to observe that only the labor regulation provisions that pose substantive constraints are significant in explaining robot adoption. Hence, we repeat the analysis using two separate indices of statutory protection from dismissal, each calculated as an arithmetic average of the two subgroups (cf. Table 1). In line with our expectations, the estimates (reported in Tables 4 and 5) show that only the legal provisions that pose substantive constraints on dismissal are significantly correlated with robot adoption.

4.2 Robustness

In order to check the overall robustness of the results reported in Table 2, we perform two checks. First, we repeat the analysis using another proxy of capital intensity; that is, the ratio between the total stock of capital and the aggregate compensation of employees, both measured at the country–industry level. The correlation between the two measures is high ($\rho = 0.88$), but they capture slightly different characteristics of the industry. On the one hand, the capital–sales ratio indicates how many units of capital are needed to produce one unit of sales, and therefore it can be considered as a technical relationship that reflects the operating leverage of a sector. On the other hand, the capital–compensation of employees ratio relates capital and labor expenses, and therefore is more directly associated with the balance of power between capital and labor within each country and industry. The results are reported in Table 6.

As a second robustness check, in order to be sure that the results are not driven by small industries in small countries, we re-estimate all the main models resorting to regressions weighted on the basis of the number of the persons employed at the level of country–sector. The results of the weighted regressions are reported in Table 7.

Overall, the results of the robustness checks are largely consistent with the findings of the main analysis. In particular, both the magnitude and statistical significance of the coefficients estimated with the weighted regressions are close to those reported in Table 2. Similarly, the estimates obtained using the capital/wages ratio are qualitatively consistent with those of the main regression, even though the size of the coefficients associated with capital intensity and the interaction term are significantly smaller, a result that is mostly due to the difference in size of the two measures (the average value taken by the capital–sales ratio is about seven times larger).

4.3 Other results

To further explore the relationship between robotization and labor regulation, we also test whether the discipline of fixed-term contracts and of workers' industrial action correlates with the adoption of industrial robots. In fact, as in the case of dismissal, these two areas of labor law can substantially affect, through different channels, the rigidity of a country's labor market and, therefore, directly and indirectly influence firms' incentives and ability to adopt industrial robots.

The relationship between robot adoption and the discipline of fixed-term contracts is reported in Table 8, while that between robot adoption and the discipline of workers' industrial action is in Table 9. Overall, the insights provided by these additional results confirm that the picture of the main analysis is consistent with the interpretation discussed in the previous sections.

4.4 Limitations

While the results of the analysis have proven robust through a number of robustness and sensitivity checks, the empirical analysis has two important limitations. A first limitation is associated with the availability of data. On the one hand, there are few available cross-country, cross-industry datasets that consistently provide, for each country–industry pair, enough data to estimate the sectoral level of capital intensity. For example, even the EU KLEMS dataset fails to provide two-digit disaggregated data on sales, employment, and stock of capital for all the countries included in the sample. On the other hand, despite being an invaluable asset for the growing literature on the effects and determinants of robotization, industry-level IFR data have some limitations. These limitations are particularly relevant for the years before 2004/2005, in which, with the exception of a few countries, a relatively large share of the robots is not allocated to any specific industry but are relegated in residual, unspecified categories. While it is possible to estimate the missing values by retrospectively projecting the industry-level robot shares observed in the following years, the appropriateness of this procedure appears questionable in this kind of analysis. As a result, in order to perform a consistent match between IFR and

EU KLEMS data and obtain a homogeneous dataset to work with, we could not use two-digit data.

The second limitation is related to the setting of the analysis. Being an observational study, we are very cautious about making causal claims. While the full model includes industry and legal origin fixed effects, and the all regressors pre-date robot adoption, we cannot rule out that the provisions of labor laws at the beginning of the period had been influenced by anticipations regarding the future trajectories of the technological progress.

5 Concluding remarks

In this paper, we investigate the relation between labor regulation and robotization. We find that – at least in the period under analysis and for the nineteen countries of the sample – high levels of statutory employment protection have been negatively correlated with the adoption of industrial robots. A possible explanation for the result is that the presence of labor market rigidities has somehow discouraged investment and the adoption of innovative technologies. Indeed, high levels of employment protection translate into higher adjustment costs, which make investment riskier. Hence, in this respect, industrial robots behave as any other form of physical capital (in its common sense). Robots, however, differ from classical physical capital in a crucial respect: they can, at least partially, substitute flexible human labor. The presence of tight labor regulations can therefore represent an incentive for firms to pursue robotization in order to reduce hold-up risk by industrial workers that, all other things being equal, tends to be higher in capital-intensive sectors. Indeed, by interacting country-level measures of employment protection with country–industry measures of capital intensity, we find evidence consistent with this hypothesis, with the mediated effect of the level of labor-friendly labor regulation turning out to be positive and significant. This result is suggestive that the willingness of firms to replace labor does represent a driver for the adoption of industrial robots in non-service sectors, even though it does not seem to be the most important one and, in most of the cases, it turns out to be offset by other dynamics. An interesting reading of the results is that they seem to highlight the dual nature of robots, which can complement labor – thus working as physical capital – while also being a direct substitute for workers.

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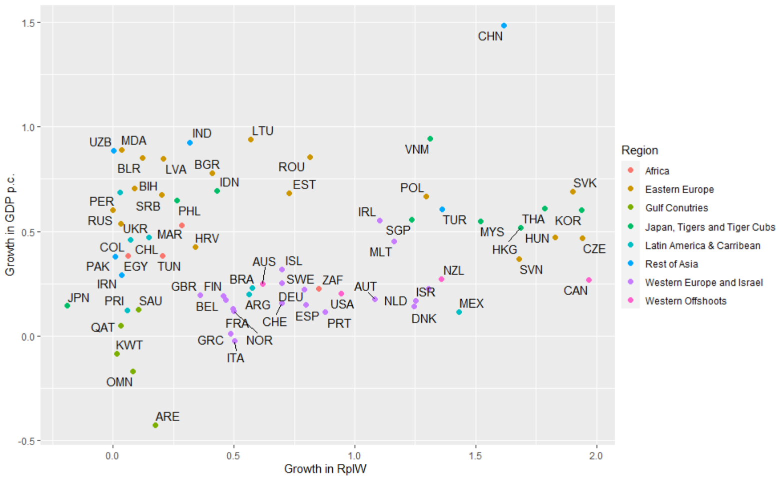
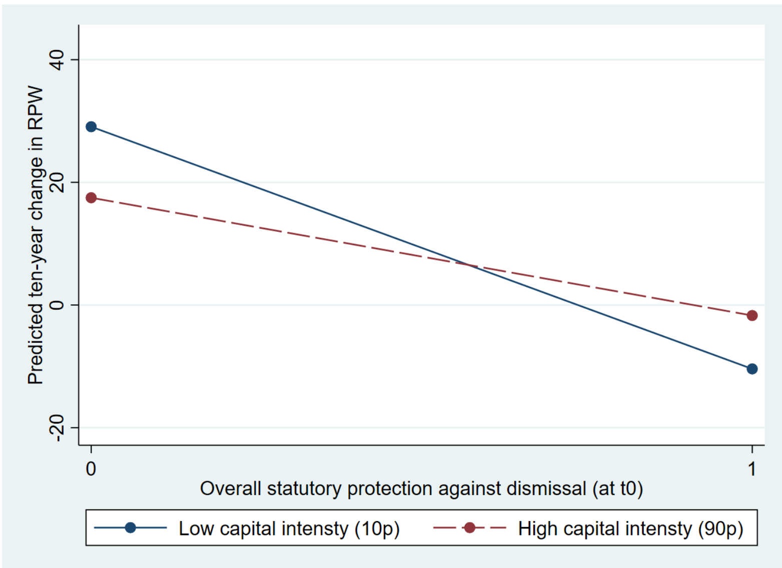
Figures and Tables

Figure 1: Robot adoption and economic growth (2000-2018)



Notes. The figure illustrates the relationship between robot adoption (log diff in number of robots per industrial worker, X-axis) and the level of economic growth (log diff in GDP per capita, Y-axis) in the 2000–2018 period.

Figure 2: Predicted robot adoption at different levels of capital intensity



Notes. The figure reports the relationship between predicted robot adoption (i.e., predicted change in robots per worker) and the level of overall statutory protection against dismissal at two different levels of capital intensity (10th and 90th percentiles). The predictions have been estimated on the basis of the full empirical model, that is model (5) of Table 2, with all the other covariates centered at their means. The average value of overall statutory protection against dismissal observed in the data is equal to 0.56.

Table 1: Robot adoption and statutory protection against dismissal

	Procedural	Substantive
Legally mandated notice period	✓	
Legally mandated redundancy compensation	✓	
Minimum qualifying period of service for normal case of unjust dismissal	✓	
Law imposes procedural constraints on dismissal	✓	
Law imposes substantive constraints on dismissal		✓
Reinstatement normal remedy for unfair dismissal		✓
Notification of dismissal	✓	
Redundancy selection		✓
Priority in re-employment		✓

Notes. The table summarizes the nine dimensions of dismissal laws reported in Adams et al. (2016). The distinction between dimension posing procedural and substantive constraints has been drawn by the authors of the present study.

Table 2: Robot adoption and statutory protection against dismissal

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
Lag Dismissal (overall)	-23.78**	-31.34**	-42.72***	-29.96**	-42.39***
	(8.98)	(11.80)	(12.89)	(10.67)	(12.30)
Lag K/Sales	-7.60**	-8.80***	-11.07**	-6.36**	-8.27***
	(2.76)	(2.94)	(3.95)	(2.64)	(2.81)
Lag Dismissal (overall) * Lag K/Sales	9.25**	11.46**	15.38**	11.66**	14.49***
	(4.31)	(4.98)	(6.24)	(4.29)	(4.55)
Additional controls		✓	✓	✓	✓
Legal origins FE			✓		✓
Industry FE				✓	✓
Observations	109	109	109	109	109
R-squared	0.05	0.09	0.16	0.39	0.44

Notes. The table reports the OLS estimates of the relationship between robot adoption and overall statutory protection from dismissal. Additional controls, which are measured at the country level at the beginning of the period, include GDP per capita, share of workers employed in the manufacturing sector, share of labor force with advanced education, and total fertility rate. Clustered standard errors (at the country level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Marginal effect of statutory protection against dismissal on robot adoption at different levels of capital intensity

Kint	(1)	(2)	(3)	(4)	(5)
10th percentile	-21.9**	-29.0**	-39.6***	-27.6**	-39.5***
	(8.4)	(11.1)	(12.2)	(10.2)	(11.7)
Median	-19.2**	-25.6**	-35.0***	-24.1**	-35.1***
	(7.6)	(10.2)	(11.4)	(9.6)	(11.0)
90th percentile	-9.0	-13.0	-18.1	-11.3	-19.2*
	(6.4)	(8.6)	(11.1)	(8.7)	(9.4)

Notes. The table reports the estimated marginal effect of statutory protection from dismissal (overall) on robot adoption at different levels of capital intensity, namely at the 10th, 50th and 90th percentiles. Each column corresponds to the effect estimated using the empirical models of Table 2. Clustered standard errors (at the country level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Robot adoption and statutory protection against dismissal (only substantive constraints)

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
Lag Dismissal (substantive)	-20.66***	-21.72***	-22.33***	-19.92***	-21.35***
	(5.19)	(6.14)	(6.19)	(5.69)	(5.68)
Lag K/Sales	-6.16***	-6.75***	-7.85***	-3.40*	-4.26*
	(1.62)	(1.42)	(1.91)	(1.88)	(2.03)
Lag Dismissal (substantive) * Lag K/Sales	7.22***	8.09***	9.54***	6.98***	7.79***
	(2.46)	(2.28)	(2.86)	(1.69)	(2.15)
Additional controls		✓	✓	✓	✓
Legal origins FE			✓		✓
Industry FE				✓	✓
Observations	109	109	109	109	109
R-squared	0.08	0.10	0.16	0.40	0.43

Notes. The table reports the OLS estimates of the relationship between robot adoption and statutory protection from dismissal calculated only on dimensions that pose substantive constraints (see Table 1). Additional controls, which are measured at the country level at the beginning of the period, include GDP per capita, share of workers employed in the manufacturing sector, share of labor force with advanced education, and total fertility rate. Clustered standard errors (at the country level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Robot adoption and statutory protection against dismissal (only procedural constraints)

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
Lag Dismissal (procedures)	-4.86	-18.96	-38.21	-19.94	-38.48
	(13.44)	(19.37)	(23.70)	(17.48)	(22.62)
Lag K/Sales	-3.40	-3.05	-3.44	-3.54	-4.37
	(3.85)	(3.83)	(5.37)	(4.40)	(4.71)
Lag Dismissal (procedures) * Lag K/Sales	1.76	0.77	0.91	7.21	6.76
	(6.45)	(7.12)	(9.97)	(8.34)	(7.95)
Additional controls		✓	✓	✓	✓
Legal origins FE			✓		✓
Industry FE				✓	✓
Observations	109	109	109	109	109
R-squared	0.02	0.06	0.13	0.36	0.41

Notes. The table reports the OLS estimates of the relationship between robot adoption and statutory protection from dismissal calculated only on dimensions that pose procedural constraints (see Table 1). Additional controls, which are measured at the country level at the beginning of the period, include GDP per capita, share of workers employed in the manufacturing sector, share of labor force with advanced education, and total fertility rate. Clustered standard errors (at the country level) are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Robot adoption and statutory protection against dismissal (alternative measure of capital intensity)

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
Lag Dismissal (overall)	-22.44**	-29.54**	-41.35***	-29.15***	-40.88***
	(7.92)	(10.92)	(13.78)	(8.96)	(12.26)
Lag K/W	-0.67**	-0.75***	-0.95***	-0.56	-0.75**
	(0.25)	(0.25)	(0.29)	(0.36)	(0.32)
Lag Dismissal (overall) * Lag K/W	1.05	1.19*	1.45**	1.89**	1.92**
	(0.63)	(0.59)	(0.66)	(0.85)	(0.76)
Additional controls		✓	✓	✓	✓
Legal origins FE			✓		✓
Industry FE				✓	✓
Observations	109	109	109	109	109
R-squared	0.04	0.08	0.15	0.40	0.44

Notes. The table reports the OLS estimates of the relationship between robot adoption and overall statutory protection from dismissal. The measure of capital intensity, K/W, is the ratio between the stock of capital and aggregate compensations to employee, both measured at the country–industry level. Additional controls, which are measured at the country level at the beginning of the period, include GDP per capita, share of workers employed in the manufacturing sector, share of labor force with advanced education, and total fertility rate. Clustered standard errors (at the country level) are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Robot adoption and statutory protection against dismissal (weighted regression)

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
Lag Dismissal (overall)	-25.10***	-31.40***	-44.08***	-30.10***	-45.44***
	(6.68)	(9.22)	(11.65)	(8.77)	(11.05)
Lag K/Sales	-7.29***	-7.79***	-9.92***	-6.27***	-8.29***
	(2.09)	(2.23)	(3.33)	(2.08)	(2.31)
Lag Dismissal (overall) * Lag K/Sales	9.04**	10.04**	13.73**	10.87***	13.97***
	(3.18)	(3.65)	(5.11)	(3.55)	(3.94)
Additional controls		Yes	Yes	Yes	Yes
Legal origins FE			Yes		Yes
Industry FE				Yes	Yes
Observations	109	109	109	109	109
R-squared	0.06	0.11	0.17	0.37	0.42

Notes. The table reports the weighted OLS estimates of the relationship between robot adoption and overall statutory protection from dismissal. Regressions are weighted according to the logarithm of country–sectoral employment at the beginning of the period. Additional controls, which are measured at the country level at the beginning of the period, include GDP per capita, share of workers employed in the manufacturing sector, share of labor force with advanced education, and total fertility rate. Clustered standard errors (at the country level) are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Robot adoption and statutory limitations to fixed-term contracts

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
Lag Fixed-term	-26.61***	-26.60***	-39.89***	-21.93***	-34.57***
	(6.19)	(5.62)	(9.73)	(5.39)	(9.40)
Lag K/Sales	-9.66***	-9.74***	-13.46***	-4.16	-8.70***
	(2.06)	(2.20)	(3.41)	(2.63)	(2.59)
Lag Fixed-term * Lag K/Sales	9.83***	10.24***	14.75***	6.03**	10.31***
	(2.18)	(2.41)	(4.03)	(2.85)	(3.36)
Additional controls		Yes	Yes	Yes	Yes
Legal origins FE			Yes		Yes
Industry FE				Yes	Yes
Observations	109	109	109	109	109
R-squared	0.11	0.12	0.19	0.40	0.45

Notes. The table reports the weighted OLS estimates of the relationship between robot adoption and statutory limitations to the use of fixed-term contracts, which is calculated as the average of the scores associated with "Fixed-term contracts are allowed only for work of limited duration", "Fixed-term workers have the right to equal treatment with permanent workers" and "Maximum duration of fixed-term contracts". Additional controls, which are measured at the country level at the beginning of the period, include GDP per capita, share of workers employed in the manufacturing sector, share of labor force with advanced education, and total fertility rate. Clustered standard errors (at the country level) are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9: Robot adoption and statutory protection for workers' industrial action

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
Lag Industrial action	-10.97	-17.23*	-16.10	-13.26	-13.06
	(6.96)	(9.15)	(11.40)	(9.02)	(11.04)
Lag K/Sales	-8.03***	-8.63***	-8.70***	-3.75	-4.22
	(2.04)	(2.57)	(2.75)	(3.30)	(3.52)
Lag Industrial action * Lag K/Sales	8.26***	9.50**	9.22**	6.83*	6.54
	(2.85)	(3.56)	(4.15)	(3.91)	(4.26)
Additional controls		Yes	Yes	Yes	Yes
Legal origins FE			Yes		Yes
Industry FE				Yes	Yes
Observations	109	109	109	109	109
R-squared	0.03	0.06	0.12	0.36	0.40

Notes. The table reports the weighted OLS estimates of the relationship between robot adoption and statutory protection for workers' industrial action, which is calculated as the average of the scores associated with "Right to unionization", "Right to collective bargaining", "Duty to bargain" and "Right to industrial action". Additional controls, which are measured at the country level at the beginning of the period, include GDP per capita, share of workers employed in the manufacturing sector, share of labor force with advanced education, and total fertility rate. Clustered standard errors (at the country level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.