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.

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-digit 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; Guo, 2022; McGuinness et al., 2022).[2] 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;

[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 there is no rigid association between consumer's demand and employment because "Demand for commodities is not demand for labor" (Mill, 1870, vol. 1, p. 5, para. 9). The different micro–macro effects of the relationship between technological change and labor market equilibria have been described by Autor and Salomons (2018).

[2] A comprehensive overview of the main empirical evidence on the relationship between robot adoption and employment, in terms of number of employees, required tasks and inequality has been provided by Barbieri et al. (2020) and, within a meta-analytical setting, by Mondolo (2022).

Naudé, 2021). Recently, attention has been paid to the firm level determinants of robot adoption, either looking at the relationship with past performance and available skills (Koch et al., 2021), or considering the pattern of labor-saving robotic patents (Montobbio et al., 2020). Still, with a few exceptions (e.g., Cséfalvay and Gkotsis, 2020), less attention was given to the observed high country heterogeneity

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 institutions from a cross-country/cross-industry perspective. 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 influence the labor market structure and have a meaningful impact on several economic outcomes (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 one is related to the overall effect of labor laws on firms' propensity to invest, while the second one hinges on the actual degree of substitutability between robots and labor. As for the first channel, 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. As for the second, to the extent that robots can in fact substitute flexible human 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. It is not obvious, however, how much the current robot technology is able to provide worthy replacements for human workers.[3]

Other factors, however, can play a role. First, high levels of labor protection can 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 adopting robots (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., 2021b;a). 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 of workers' action (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 dis-

[3]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*).

aggregating 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 and outline the hypotheses on which the empirical investigation relies. 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. Conditions affecting robot adoption have been examined at different levels: firm, industry and country. At the firm level, Koch et al. (2021) have shown that firms that are better performing, less skill intensive and exporters are more likely to adopt robots. At the industry level, Montobbio et al. (2020) have examined the patterns of patenting in labour saving automation and robotics. They showed that patenting is driven by the position of the sector of origin in the vertical chain and that downstream segments, like the shipping and delivery industry, originate a large share of labour saving automation patents, together with medical and health activities. 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. Finally, the institutional perspective focuses on country level heterogeneity. 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, occupational flexibility represents a key comparative advantage of labor over robots. 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. The effect of labour regulation on technology adoption has been extensively examined by (Alesina et al., 2018, p.41), who showed that "labor regulation biases technology towards low skill sectors, while labor deregulation biases technology towards high skill sectors". Apart from labour market regulation, other country effects may be relevant. Countries can differ in their education systems (Arntz et al., 2016; Nedelkoska and Quintini, 2018). In a recent paper, Acemoglu and Restrepo (2022) 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.

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). Under incomplete contracting, employers' quasi-rents are vulnerable to capture by workers in the form of higher wages and better conditions of employment, thereby reducing incentives to invest. 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. On the other hand, robots can substitute human labor in a widening range of tasks, whose accomplishment would not anymore be subject to the opportunistic behaviour of humans. Tight labor laws will then 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 local 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.

Beside the aforementioned literature, 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 (2022) 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.[4] 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

[4]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, 2019).

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.

From the previous discussion, it clearly emerges how statutory employment protection can produce ambiguous effects on firms' incentives. In fact, among the several contrasting effects envisaged in the literature, it is hard to predict which ones (if any) are going to prevail. As a consequence, we approached the empirical investigation without having a strong prior regarding the overall relationship between labor regulation and robot adoption. However, despite the uncertainty regarding the overall direction of the relationship, the theory clearly predicts that, ceteris paribus, hold-up risks will always provide incentives to firms for substituting labour with flexible machines. Therefore, under the assumption that, all other things being equal, the risk of hold-up is higher in capital intensive industries, we derive the following testable hypothesis:

- H_1: The interaction between the level of protection guaranteed by labor regulation and the level sectoral capital intensity positively predicts robot adoption.

Anticipating the results, we find evidence that are consistent with this hypothesis. At the same time, however, we also find that the overall relationship between tight regulations and robot adoption tends to be negative, suggesting that the intention of overcoming labor market rigidities has not been – so far, at least – the main driver of robot adoption.

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 and the United States) and eight non-service sectors, even though the information is missing for some country–industry pairs.[5]

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). The LRI dataset provides information 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).

The LRI dataset comprehensively captures all country-level changes in labor laws over a long span of time and offers two main advantages. First, the distinction of labor laws' provisions into different subject areas allows us to assess the relationship between robot adoption and different dimensions of employment protection. Second, the index takes into account not only formal laws (including court judgments) 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.[6]

[5]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).

[6]Among other measures and benchmarks of labor regulation, the OECD Indicators of Employment Protection (IEP) is one of the most widely used. The OECD's methodology, however, has changed over time, moving from a reliance on surveys completed by governments to using firm-level surveys supplemented by secondary sources. In particular, an increased use of primary sources (including collective

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 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. Omitting pre-2006 data (or pre-2005, as in de Vries et al., 2020) is a practice common also to studies aimed at gathering evidence on the effects of automation on employment, which is justified by the increased number of applications of robots that followed the integration of automation with Artificial Intelligence that is commonly dated from the second half of the decade 2000 (Barbieri et al., 2020).

Country–industry data on employment and capital stocks have been retrieved from EU KLEMS (release 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

agreements) – that we believe is crucial for the purposes of the present analysis – started with relatively recent IEP Version 4, that is available only from 2013 onwards (for an overview of changes and limits of the OECD index, see Adams and Deakin, 2015). Moreover, the IEP scores captures only four dimensions (against the forty dimensions of the LRI) and would not allow to make a distinction, for instance, between substantive and procedural constraints to dismissal. Finally, the sample of countries in the IEP is smaller and does not contain data for Bulgaria and Romania.

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.[7]

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. A ten-year interval, in fact, seems a reasonable span of time to study the relationship between labor regulation and robot adoption, in particular after considering the level of resolution allowed by the available data, the longitudinal persistence of the level of employment protection guaranteed by national labor laws, and the length of the time intervals used in the reference literature.[8] However, as further discussed in Section 4.3, we also explore the relationship between labor regulation and robot adoption using two five-years intervals.

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

[7]Following La Porta et al. (2008), we group countries according to five different legal origins: English (United Kingdom, United States), French (Belgium, France, Greece, Italy, Netherlands, Portugal, Spain), German (Austria, Germany), Scandinavian (Denmark, Finland, Sweden), and Socialist (Bulgaria, Czech Republic, Hungary, Romania, Slovakia).

[8]For example, Acemoglu and Restrepo (2022) focus their analysis on a twenty-year period.

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, the share of workers employed in the manufacturing sector, the share of labor force with advanced education, and the age-dependency ratio,[9] 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. As discussed at the end of Section 2, we do not have a strong prior on the sign of β_1, which is the direct effect of the level of employment protection on robot adoption. On the one hand, in fact, 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 regulation raises adjustment costs, that negatively affect investment, and tight laws on dismissal can prevent firms from substituting workers, thus slowing down robotization.

However, as anticipated in the outline of hypothesis H_1, we expect 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 somehow 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

[9]We include the fertility rate as a proxy for the age structure of the labor force, which, as discussed in Acemoglu and Restrepo (2022), can influence the patterns of robot adoption. While we include a control for level of the age-dependency ratio at the beginning of the period, our results hold also if we control for the ageing of the labor force in a similar fashion of Acemoglu and Restrepo.

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 metric 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 proxy 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.[10]

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. In the same fashion, also the values referring to year 2011 (that we use in Section 4.3), are the average of years 2010-2012.

The summary statistics for the main variables used in the empirical analysis are reported in Table 1. In ten years, the average robot density, that is measured at the country–industry level, almost doubled. In particular, it increased by roughly six units, from about 6.7 robots per worker in 2006 to 12.7 robots per worker in 2016. Despite the clear positive trend, however, $\Delta RpW_{c,s}$ exhibits a substantial variability, and it decreases in about one out of six cases. Also the LRI indexes, which are measured at the country level, and the proxies of capital intensity, taken at the country–industry level, exhibit a fairly high variability that can be conveniently used for the purposes of the empirical analysis.

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 protection offered by dismissal laws, which are reported in Table 2. 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

[10]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%.

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 3.

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. hypothesis H_1 and 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 4, 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 (i.e., model (5) of Table 3) 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 3 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 2). In line with our expectations, the estimates (reported in Tables 5 and 6) 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, we perform four 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 in current LCUs 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/wages ratio relates capital and compensation of employees, and therefore is more directly associated with the balance of power between capital and labor within each country and industry. The estimates obtained using the capital/wages ratio, reported in Table 7, turn out to be 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 largely due to the difference in size of the two measures (the average value taken by the capital–sales ratio is about seven times larger).

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 estimates of the weighted regressions are reported in Table 8 and appear largely consistent with those 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 3.

As a third check, we partition the observations in two groups performing a k-medians cluster analysis and re-estimate the full model augmented by dummy variables indicating to which cluster each country belongs. Working as fixed effects, these dummies are meant to further control for the presence of time-invariant heterogeneity that is common to all the countries belonging to a same cluster and may lead the groups to follow different trajectories. The first two clusters (CL1, CL2) are identified on the basis of the 2006 LRI scores, while the third one (CL2) on the 2006 level of GDP per capita. More specifically, CL1 has been identified on the basis of all the nine dimensions associated with the discipline of dismissal (cf. Table 2), while CL2 on the basis of all the forty dimensions of labor regulation included in the LRI database. The dummies take value one to indicate that an observation belongs to the cluster of countries that guarantee, on average, the higher level of protection or, for the fourth cluster, that are characterized by a higher level of income per capita. The estimates, reported in Table 9, are in line with the main results. On the one hand, the lack of statistical significance of the dummies of model (2) and (3) suggests that the controls and the sets of fixed effects included in the specification of the full model are able to absorb a large amount of heterogeneity. On the other hand, the fact that the only significant dummy is the one associated with the level of statutory protection against dismissal highlights the particular relevance of this area of labor regulation. In particular, the negative sign indicate that, ceteris paribus, robot adoption has been slower the group of countries characterized by more stringent provisions against workers' dismissal.

Finally, as a fourth check, we also run a series of regressions with country fixed effects. While country fixed effects were not included in the main specifications (because they would have absorbed $\widehat{\beta}_1$), they can nevertheless be used to further check the robustness of the estimates of the coefficients associated with capital intensity and with the interaction term to the presence of country-level time-invariant unobserved heterogeneity. The results of this exercise are reported in Table 10. Specifically, the first two columns report the results of two country fixed effects models (with and without industry fixed effects) for the relationship between robot adoption and overall protection against dismissal, while the models in columns (3)-(4) and (5)-(6) employ the level of substantive protection and procedural protection respectively. Overall, even though we observe a rise in the p-value of $\widehat{\beta}_3$ in the first two models (which, however, remains below the 10% threshold), the results are reasonably consistent with those of Tables 3, 5, and 6, therefore contributing to mitigate the concerns that the results of the analysis are driven by country-level time-invariant unobserved heterogeneity that the control variables and the sets of fixed effects included in the main specifications are not able to fully capture.

4.3 Five-year intervals and advancements in robot technology

Considering the level of resolution allowed by a cross-country cross-industry analysis and the longitudinal stability of the LRI scores, the correlation patterns between labor regulation and the pace of robot adoption can be only observed over a sufficiently long span of time. Hence, we have so far reported the estimates from ten-year differences specifications, focusing on the country-sectoral change in robots per worker between 2006 and 2016. This approach, however, does not allow to study the longitudinal stability of the coefficients. To do so, we re-estimate the baseline model for the sub-periods 2006-2011 and 2011-2016 and for the stacked-differences specifications (with a period fixed effect).

The first three columns of Table 11 report the estimates of the stacked-differences specifications which, in terms of sign and statistical significance, turn out to be consistent with the main results reported in Table 3. Unsurprisingly, the fixed effect associated with the second period turns out to be positive and significant, indicating that, consistently with the rapid progress and increased availability of automation technologies, robot adoption has accelerated after 2011.

The results of the estimates for each sub-period are reported in columns (4)-(9) of Table 11. On the one hand, the estimated coefficients maintain the sign and the significance of the main results and are therefore consistent with the proposed narrative about the dual nature of industrial robots. On the other hand, it is worth noticing that the estimates of the coefficient associated with the interaction term are systematically larger for the second period. Considering that – according to the proposed interpretation – the effect of labor regulation on robot adoption mediated by capital intensity, β_3, is correlated to the degree at which robots can effectively substitute flexible human labor, the result is suggestive of an increasing elasticity of firms' investment in robot due the sophistication of robot technology occurred during that decade. In other words, a possible explanation is that, because of the progress in automation technology, the robots built in the 2011-2016 period were more capable of replacing workers than those of the previous five-year period and therefore firms were more likely to invest in this technology in contexts characterized by strict regulations and high hold-up risks. It follows that, to the extent that this interpretation is correct and that the advancements in robot technology will continue to erode the 'flexibility advantage' of human labor, we can expect a change in the relationship between labor regulation and robot adoption in the future, with the former becoming a more straightforward predictor of the latter.

4.4 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 12, while that between robot adoption and the discipline of workers' industrial action is in Table 13. 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. At the same time, however, they tend to be less robust than those obtained using the protection against dismissal, thus suggesting a less straightforward relationship between robotization and these alternative dimensions of labor regulation.

4.5 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 for the present 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. The empirical analysis indicates 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 robot technologies. Indeed, high levels of employment protection translate into higher adjustment costs, which make investment riskier. Hence, in this respect, industrial robots exhibit a behavior that is typical of any form of physical capital: in the presence of tight regulations, firms tend to invest less.

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 the hold-up risk by industrial workers, a risk that, all other things being equal, tends to be higher in capital-intensive sectors. Indeed, if labor regulation poses substantial limits to the circumstances in which firms are allowed to dismiss workers, a relatively small number of workers can threaten to interrupt the production flow of an expensive plant while discounting a low risk of being laid off, thus enjoying high negotiation power. In this case, to the extent that robots can effectively replace workers, firms will have a strong incentive to automatize the processes on which the production flow depends upon, from relatively standard operations typically performed by ware-housemen, such as the palletizing and the handling of materials, to more industry-specific activities. By interacting country-level measures of statutory protection against dismissal and country–industry measures of capital intensity, we find empirical evidence that is consistent with this hypothesis, as the effect employment protection mediated by capital intensity turns out to be positive and significant. However, while this result is indicative that the willingness of firms to replace labor does represent a driver for the adoption of industrial robots in non-service sectors, the overall results of the empirical analysis suggest that it has not been – so far, at least – the most important one. In fact, except in the context of highly capital intensive industries, our estimates indicate that, in the 2006-2016 period, it has been outweighted by the opposing dynamics captured by the direct effect of labor regulation.

These two contrasting dynamics, that in our empirical setting are captured by the coefficients associated with the level of workers' protection and with its interaction with capital intensity, highlight the dual nature of industrial robots, which to some degree behave as physical capital (in its common sense) but, at the same time and up to a certain extent, are also substitutes for flexible labour. In the former case, investment in robots may be inhibited by high levels of employment protection that increase adjustment costs to negative and unpredictable shocks, creating a less favourable business environment. It the latter case, the higher is the legal employment protection and the amount of capital invested in the firm, the more credible is the threat of hold-up by workers, the higher is the incentive to invest in robots, as it would represent a viable strategy to minimize opportunistic behaviours of the employees.

While this paper provides a key to interpreting the relationship between labor regulation and robot adoption, it does not allow to draw clear and unambiguous policy prescriptions. Conversely, by highlighting the dual nature of robots, our interpretation emphasizes the complexity of the implications of labor laws. It is possible, however, to make some speculation. On the one hand, since the overall results indicate that strict employment protection regimes are associated with a lesser increase in the number of robots per worker, the goal of maintaining a labor-friendly regulation may interfere with the policy target of fostering robot adoption. On the other hand, considering that the results are sensitive to the sectoral level of capital intensity, the tenet may not apply in certain contexts (i.e., in some capital-intensive industries). Furthermore, advancements in automation technology that increase the substitutability between robots and human workers and/or a significant reduction in the costs associated to robotization may alter, in the future, the overall sign of the relationship.

These conclusions, however, are likely to miss part of the story. Indeed, in the attempt to explain the patterns of robot adoption, we discuss two possible drivers. The first one hinges on firms' willingness to invest in contexts characterized by flexible labor markets, while the second one is related to firms' incentives to reduce hold-up risks by replacing workers with robots. As a consequence, such a divergence in the rationale behind robot adoption may favour different paths of automation which, in turn, may have different consequences in terms of employment. In fact, as pointed out by Acemoglu and Restrepo (2019), the effect of automation on aggregate labor demand depends on the relative magnitude of the productivity effect and the displacement effect, and it seems plausible that the productivity gains will be lower when robots are adopted with the primary aim of defusing employees' bargaining power rather than on the basis of technical considerations on the efficiency of the production process. In this regard, beside the recent anecdotal evidence of Tesla (Korosec, 2018), the history of automotive industry provide some interesting examples: during the 1980s, some large Western car manufacturers (such as

General Motors in the United States and FIAT in Italy) invested heavily in the automation of the production processes with the aim of weakening the control of shop stewards, but ended up in an excess of automation (Camuffo and Volpato, 1996; Roberts, 2004). Hence, while these mechanisms deserve further investigation, the regulatory effort of the policy makers should be aimed at taking into proper account the hold-up problem and allowing firms to readily adjust to market dynamics. At the same time, policy efforts should be aimed at promoting labour policies that favor employment reallocation and universal insurance against the risk of unemployment. Even though these prescriptions are anything but original, they may gain new relevance in the light of the recent advancements in robot technology, which allow to automatize an increasing number of tasks but that do not always guarantee significant productivity gains. In this way, policy makers may contribute to create a more favourable environment for the adoption of labor-friendly and 'appropriate' technologies (Rodrik, 2022). For the same reasons, doubts can be raised towards now-days (post Covid-19) popular industrial policies favouring investments in new technologies and automation irrespective of motivations and impact of their introduction (Korinek and Stiglitz, 2021).

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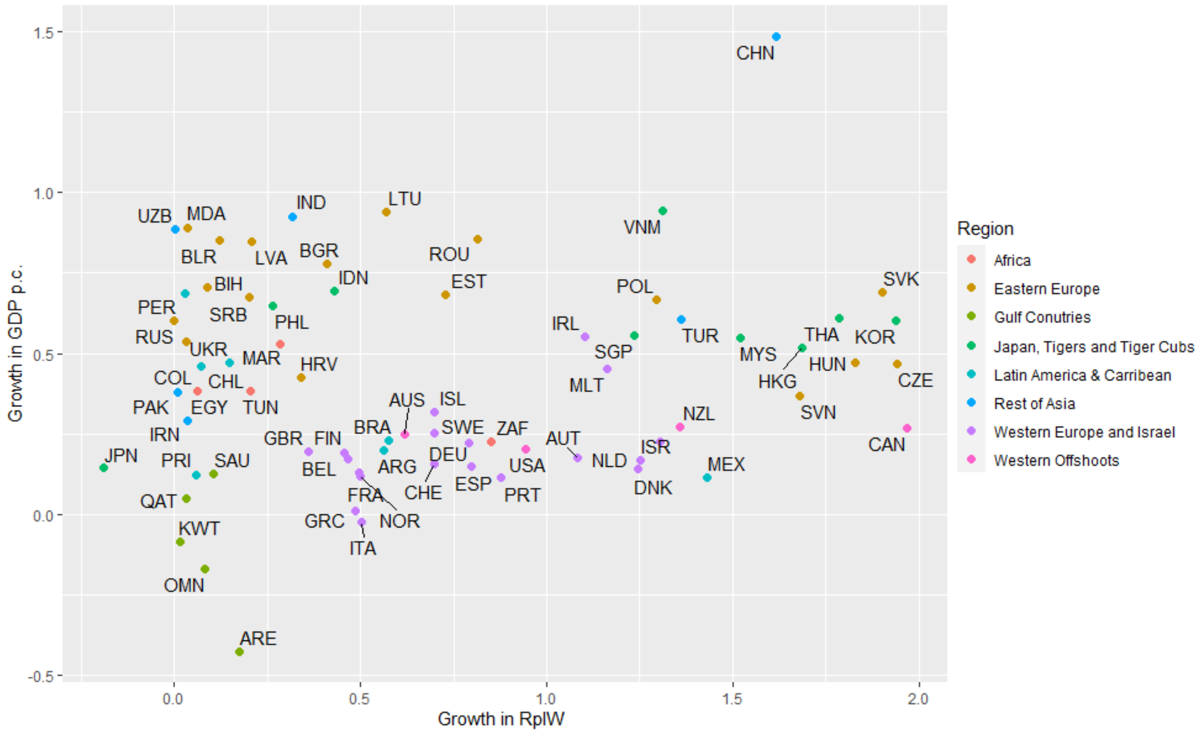
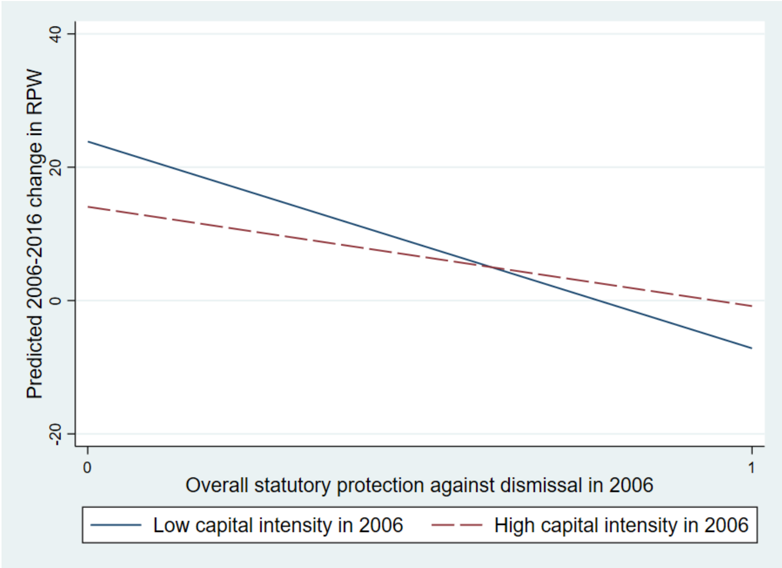
Figures and Tables

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 in year 2006 (10th and 90th percentiles). The predictions have been estimated on the basis of the full empirical model, that is model (5) of Table 3, 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: Summary statistics

Variable	Mean	Std. Dev.	p10	p50	p90
$\Delta RpW_{c,s}$	6.05	15.26	-0.29	1.54	16.26
LRI_{c,t_0} Dismissal (overall)	0.56	0.16	0.34	0.56	0.76
LRI_{c,t_0} Dismissal (substantive)	0.52	0.25	0.22	0.50	0.83
LRI_{c,t_0} Dismissal (procedural)	0.60	0.14	0.42	0.60	0.78
LRI_{c,t_0} Fixed-Term	0.67	0.22	0.42	0.67	0.93
LRI_{c,t_0} Industrial action	0.66	0.26	0.25	0.75	1.00
K/Sales$_{c,s,t_0}$	0.77	0.88	0.23	0.54	1.54
K/Wages$_{c,s,t_0}$	5.59	7.12	1.28	3.32	15.07

Notes. The table reports the summary statistics of the main variables used in the empirical analysis. The subscript c stands for *country*, s for *sector* and t_0 for 2006; the change in the number of robot per workers is registered over ten years.

Table 2: The dimensions of labor regulation: procedural and substantive constraints to 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 3: Robot adoption and statutory protection against dismissal

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
LRI Dismissal (overall)	-21.42**	-23.13**	-32.01**	-22.54**	-33.49**
	(8.96)	(10.79)	(13.18)	(9.55)	(12.12)
K/Sales	-7.09**	-8.23**	-9.26**	-6.55***	-7.53***
	(2.48)	(2.89)	(3.44)	(2.14)	(2.40)
LRI Dismissal (overall) * K/Sales	8.57**	11.05**	12.68**	10.80***	12.40***
	(3.90)	(4.59)	(5.36)	(3.50)	(3.81)
Log GDP p.c.		5.60*	17.04***	5.19*	14.49**
		(2.85)	(5.72)	(2.64)	(5.07)
Industrial Employment (%)		0.18	0.19	-0.01	0.05
		(0.56)	(0.52)	(0.49)	(0.46)
Age-dependency ratio		-1.42*	-0.68	-1.35*	-0.74
		(0.80)	(0.60)	(0.71)	(0.55)
Labor force with advanced education (%)		-0.03	0.61	-0.13	0.46
		(0.33)	(0.44)	(0.28)	(0.36)
Legal origins fixed effects			✓		✓
Industry fixed effects				✓	✓
Observations	109	109	109	109	109
R-squared	0.05	0.13	0.16	0.40	0.43

Notes. The table reports the OLS estimates of the relationship between robot adoption and overall statutory protection from dismissal. All the explanatory variables refer to the beginning of the period (i.e., year 2006). Clustered standard errors (at the country level) are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Marginal effect of statutory protection against dismissal on robot adoption at different levels of capital intensity

K/Sales	(1)	(2)	(3)	(4)	(5)
10th percentile	-19.7**	-20.9*	-29.5**	-20.4**	-31.0**
	(8.4)	(10.2)	(12.6)	(9.0)	(11.6)
Median	-17.1**	-17.6*	-25.7**	-17.1*	-27.3**
	(7.6)	(9.3)	(11.9)	(8.2)	(10.9)
90th percentile	-8.6	-6.6	-13.0	-6.3	-14.9
	(6.1)	(7.7)	(10.9)	(6.1)	(9.0)

Notes. The table reports the estimated marginal effect of statutory protection from dismissal (overall) on robot adoption at different levels of sectoral capital intensity, namely at the 10th, 50th and 90th percentiles (measured in 2006). Each column corresponds to the effect estimated using the empirical models of Table 3. 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 substantive constraints)

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
LRI Dismissal (substantive)	-19.60***	-16.53**	-18.02**	-15.26**	-17.64**
	(5.06)	(6.91)	(7.03)	(6.23)	(6.31)
K/Sales	-5.86***	-6.93***	-7.34***	-4.20**	-4.54**
	(1.45)	(1.30)	(1.56)	(1.57)	(1.75)
LRI Dismissal (substantive) * K/Sales	6.91***	8.69***	9.04***	7.05***	7.43***
	(2.22)	(1.76)	(2.25)	(1.42)	(1.80)
Log GDP p.c.		5.82*	16.37**	5.12*	13.52**
		(2.95)	(5.77)	(2.55)	(4.88)
Industrial Employment (%)		0.11	0.01	-0.08	-0.14
		(0.51)	(0.47)	(0.44)	(0.39)
Age-dependency ratio		-1.32	-0.67	-1.23	-0.70
		(0.87)	(0.68)	(0.77)	(0.62)
Labor force with advanced education (%)		-0.02	0.50	-0.13	0.32
		(0.30)	(0.42)	(0.26)	(0.33)
Legal origins fixed effects			✓		✓
Industry fixed effects				✓	✓
Observations	109	109	109	109	109
R-squared	0.08	0.13	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 LRI dimensions that are associated with substantive constraints to workers' dismissal (see Table 2). All the explanatory variables refer to the beginning of the period (i.e., year 2006). 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 (only procedural constraints)

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
LRI Dismissal (procedural)	-2.39	-15.15	-34.69	-17.21	-37.02*
	(13.39)	(18.33)	(21.61)	(16.64)	(20.92)
K/Sales	-3.03	-2.81	-2.90	-3.51	-4.37
	(3.56)	(3.69)	(5.36)	(3.97)	(4.59)
LRI Dismissal (procedural) * K/Sales	1.46	0.68	0.44	6.83	6.50
	(5.94)	(6.95)	(10.13)	(7.30)	(7.65)
Log GDP p.c.		3.09	19.88***	2.34	17.23**
		(3.58)	(6.90)	(3.71)	(6.63)
Industrial Employment (%)		1.07	0.99	0.70	0.72
		(0.86)	(0.92)	(0.78)	(0.82)
Age-dependency ratio		4.65	8.81	2.56	6.17
		(8.34)	(14.38)	(7.49)	(13.47)
Labor force with advanced education (%)		0.10	0.99	-0.00	0.79
		(0.44)	(0.69)	(0.39)	(0.65)
Legal origins fixed effects			✓		✓
Industry fixed effects				✓	✓
Observations	109	109	109	109	109
R-squared	0.02	0.05	0.13	0.33	0.39

Notes. The table reports the OLS estimates of the relationship between robot adoption and statutory protection from dismissal calculated only on LRI dimensions that are associated with procedural constraints to workers' dismissal (see Table 2). All the explanatory variables refer to the beginning of the period (i.e., year 2006). 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 (alternative measure of capital intensity)

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
LRI Dismissal (overall)	-20.94**	-20.84*	-30.87**	-21.95**	-32.67**
	(7.88)	(11.29)	(14.21)	(9.98)	(12.96)
K/W	-0.69**	-0.72**	-0.82**	-0.58*	-0.69**
	(0.28)	(0.27)	(0.30)	(0.30)	(0.30)
LRI Dismissal (overall) * K/W	1.10	1.09	1.19*	1.49*	1.53**
	(0.69)	(0.65)	(0.65)	(0.85)	(0.76)
Log GDP p.c.		4.84	16.53***	3.74	13.00**
		(2.81)	(5.73)	(2.77)	(4.92)
Industrial Employment (%)		0.11	0.16	-0.06	0.03
		(0.54)	(0.51)	(0.44)	(0.43)
Age-dependency ratio		-1.48*	-0.74	-1.21*	-0.66
		(0.79)	(0.60)	(0.68)	(0.53)
Labor force with advanced education (%)		-0.08	0.55	-0.16	0.40
		(0.35)	(0.45)	(0.26)	(0.34)
Legal origins fixed effects			✓		✓
Industry fixed effects				✓	✓
Observations	109	109	109	109	109
R-squared	0.03	0.12	0.16	0.40	0.43

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. All the explanatory variables refer to the beginning of the period (i.e., year 2006). 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 protection against dismissal (weighted regressions)

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
LRI Dismissal (overall)	-23.28***	-23.87**	-33.16**	-22.84**	-35.13***
	(6.64)	(8.77)	(12.17)	(8.09)	(11.13)
K/Sales	-6.90***	-7.53***	-8.59***	-6.55***	-7.71***
	(1.89)	(2.27)	(2.90)	(1.63)	(1.94)
LRI Dismissal (overall) * K/Sales	8.63***	10.03***	11.78**	10.50***	12.37***
	(2.86)	(3.46)	(4.35)	(2.62)	(3.22)
Log GDP p.c.		4.85*	15.58***	4.97**	13.94***
		(2.48)	(4.83)	(2.32)	(4.40)
Industrial Employment (%)		0.14	0.15	-0.02	0.05
		(0.48)	(0.45)	(0.45)	(0.42)
Age-dependency ratio		-1.24*	-0.60	-1.23*	-0.67
		(0.69)	(0.49)	(0.64)	(0.46)
Labor force with advanced education (%)		-0.11	0.44	-0.17	0.37
		(0.28)	(0.38)	(0.25)	(0.31)
Legal origins fixed effects			✓		✓
Industry fixed effects				✓	✓
Observations	109	109	109	109	109
R-squared	0.06	0.13	0.17	0.37	0.40

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 9: Robot adoption and statutory protection against dismissal - Cluster dummies

Dep. var: ΔRpW	(1)	(2)	(3)
LRI Dismissal (overall)	-86.30***	-38.08**	-31.90**
	(16.13)	(13.57)	(14.28)
K/W	-6.64**	-8.24***	-7.37***
	(2.53)	(2.18)	(2.39)
LRI Dismissal (overall) * K/W	11.06***	13.84***	12.06***
	(3.79)	(3.70)	(3.88)
CL1: LRI dismissal (overall)	-18.29***		
	(5.02)		
CL2: LRI all dimensions		3.65	
		(5.81)	
CL3: GDP p.c.			-1.36
			(7.19)
Legal origins fixed effects	✓	✓	✓
Industry fixed effects	✓	✓	✓
Additional controls	✓	✓	✓
Observations	109	109	109
R-squared	0.45	0.43	0.43

The table reports the OLS estimates of the relationship between robot adoption and overall statutory protection from dismissal. The full model is augmented by the inclusion of dummies obtained by clustering countries according to the labor regulatory regimes and average income. CL1 has been identified according has been identified on the basis of all the nine dimensions associated to the discipline of dismissal, CL2 on all the forty dimensions of labor regulation of the LRI database, CL3 on the 2006 level of GDP per capita. The dummies indicate the belonging to the cluster of countries that guarantee, on average, the higher level of protection or, in the case of CL3, that are characterized by a higher level of income per capita. Clustered standard errors (at the country level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Robot adoption and statutory protection against dismissal (country fixed effects)

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)	(6)
K/Sales	-7.75**	-6.82**	-6.89***	-5.07***	0.32	-3.93
	(3.26)	(2.61)	(1.67)	(1.69)	(6.32)	(4.29)
LRI Dismissal (overall) * K/Sales	9.66*	8.84*				
	(5.03)	(4.71)				
LRI Dismissal (substantive) * K/Sales			7.77***	5.55**		
			(2.31)	(2.57)		
LRI Dismissal (procedural) * K/Sales					-4.52	3.74
					(12.42)	(9.24)
Country fixed effects	✓	✓	✓	✓	✓	✓
Industry fixed effects		✓		✓		✓
Observations	109	109	109	109	109	109
R-squared	0.25	0.50	0.26	0.50	0.25	0.50

The table reports the OLS estimates of the relationship between robot adoption and overall statutory protection from dismissal. Clustered standard errors (at the country level) are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 11: Robot adoption and statutory protection against dismissal (five-year periods)

	2006-2016			2006-2011			2011-2016		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LRI Dismissal (overall)	-16.11***	-9.97**	-16.68***	-13.74***	-8.61***	-13.97***	-23.52**	-11.40	-23.59**
	(4.30)	(3.68)	(3.88)	(4.65)	(2.80)	(4.10)	(8.54)	(7.43)	(8.41)
K/Sales	-3.89***	-3.42***	-3.41***	-3.10*	-2.21***	-2.43**	-5.13**	-4.85***	-4.94***
	(1.22)	(0.81)	(0.85)	(1.50)	(0.64)	(0.86)	(2.02)	(1.59)	(1.52)
LRI Dismissal (overall) * K/Sales	4.95**	4.63***	4.82***	4.10*	3.50**	3.99**	6.43*	5.91**	6.23**
	(1.94)	(1.34)	(1.38)	(2.30)	(1.26)	(1.60)	(3.22)	(2.48)	(2.44)
Log GDP p.c.	8.92***	3.98***	7.85***	5.76***	2.12**	4.98***	12.61***	5.79***	11.05***
	(2.09)	(0.89)	(1.84)	(1.91)	(0.77)	(1.60)	(3.45)	(1.45)	(3.38)
Industrial Employment (%)	0.17	0.04	0.10	0.12	0.02	0.07	0.48	0.12	0.35
	(0.19)	(0.18)	(0.17)	(0.16)	(0.14)	(0.13)	(0.39)	(0.34)	(0.37)
Age-dependency ratio	-0.52*	-0.80***	-0.53**	-0.15	-0.37*	-0.17	-0.78	-1.15**	-0.77
	(0.26)	(0.27)	(0.25)	(0.16)	(0.21)	(0.14)	(0.47)	(0.41)	(0.46)
Labor force with advanced education (%)	0.23	-0.08	0.16	0.17	-0.09	0.12	0.59*	0.02	0.44
	(0.14)	(0.11)	(0.11)	(0.16)	(0.11)	(0.13)	(0.32)	(0.30)	(0.31)
Time fixed effect (2011-16 dummy)	3.01***	2.53**	2.69***						
	(1.07)	(0.99)	(0.96)						
Legal origins fixed effects	✓		✓	✓		✓	✓		✓
Industry fixed effects		✓	✓		✓	✓		✓	✓
Observations	218	218	218	109	109	109	109	109	109
R-squared	0.17	0.37	0.39	0.17	0.39	0.42	0.19	0.43	0.44

The table reports the OLS estimates of the relationship between robot adoption and overall statutory protection from dismissal. The reference time period is five years. All the explanatory variables refer to the beginning of the five-year period (i.e., year 2006 and 2011). Clustered standard errors (at the country-year level for models (1)-(3) and at the country level for models (4)-(9)) are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12: Robot adoption and statutory limitations to fixed-term contracts

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
LRI Fixed-Term	-26.14***	-27.56***	-37.17***	-23.51***	-32.86***
	(6.90)	(5.73)	(8.90)	(5.68)	(8.62)
K/Sales	-9.24***	-9.79***	-13.61***	-4.91*	-9.30***
	(2.25)	(2.08)	(3.23)	(2.44)	(2.51)
LRI Fixed-Term * K/Sales	9.47***	10.50***	15.20***	6.68**	11.09***
	(2.48)	(2.24)	(3.88)	(2.53)	(3.27)
Log GDP p.c.		0.33	5.42	-0.09	4.05
		(2.88)	(4.93)	(2.95)	(4.92)
Industrial Employment (%)		0.47	0.47	0.18	0.22
		(0.59)	(0.49)	(0.48)	(0.41)
Age-dependency ratio		-0.74	15.19*	-2.28	11.53
		(6.31)	(8.35)	(5.52)	(7.78)
Labor force with advanced education (%)		0.26	1.52***	0.12	1.22**
		(0.34)	(0.46)	(0.29)	(0.44)
Legal origins fixed effects			✓		✓
Industry fixed effects				✓	✓
Observations	109	109	109	109	109
R-squared	0.11	0.13	0.20	0.39	0.44

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 LRI 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". All the explanatory variables refer to the beginning of the period (i.e., year 2006). Clustered standard errors (at the country level) are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Robot adoption and statutory protection for workers' industrial action

Dep. var: ΔRpW	(1)	(2)	(3)	(4)	(5)
LRI Industrial action	-9.96	-15.82*	-15.80	-12.65	-13.45
	(6.50)	(8.83)	(10.51)	(8.84)	(10.43)
K/Sales	-7.27***	-8.16***	-8.43***	-3.90	-4.61
	(1.86)	(2.47)	(2.60)	(3.22)	(3.41)
LRI Industrial action * K/Sales	7.36**	8.96**	9.12**	6.58*	6.75
	(2.57)	(3.49)	(3.88)	(3.74)	(4.05)
Log GDP p.c.		0.70	15.21*	0.53	13.06*
		(3.49)	(7.41)	(3.60)	(6.87)
Industrial Employment (%)		0.66	0.15	0.37	-0.06
		(0.75)	(0.66)	(0.66)	(0.57)
Age-dependency ratio		-1.14	-1.04	-2.03	-3.06
		(8.71)	(14.30)	(8.31)	(13.60)
Labor force with advanced education (%)		0.21	0.79	0.06	0.54
		(0.46)	(0.67)	(0.41)	(0.63)
Legal origins fixed effects			✓		✓
Industry fixed effects				✓	✓
Observations	109	109	109	109	109
R-squared	0.03	0.06	0.13	0.34	0.38

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 LRI scores associated with "Right to unionization", "Right to collective bargaining", "Duty to bargain" and "Right to industrial action". All the explanatory variables refer to the beginning of the period (i.e., year 2006).. Clustered standard errors (at the country level) are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.