

Samwer, Julia; Chen, Chinchih

Working Paper

How labor market institutions affect technological choices

ILE Working Paper Series, No. 42

Provided in Cooperation with:

University of Hamburg, Institute of Law and Economics (ILE)

Suggested Citation: Samwer, Julia; Chen, Chinchih (2020) : How labor market institutions affect technological choices, ILE Working Paper Series, No. 42, University of Hamburg, Institute of Law and Economics (ILE), Hamburg

This Version is available at:

<https://hdl.handle.net/10419/227085>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

FAKULTÄT
FÜR RECHTSWISSENSCHAFT

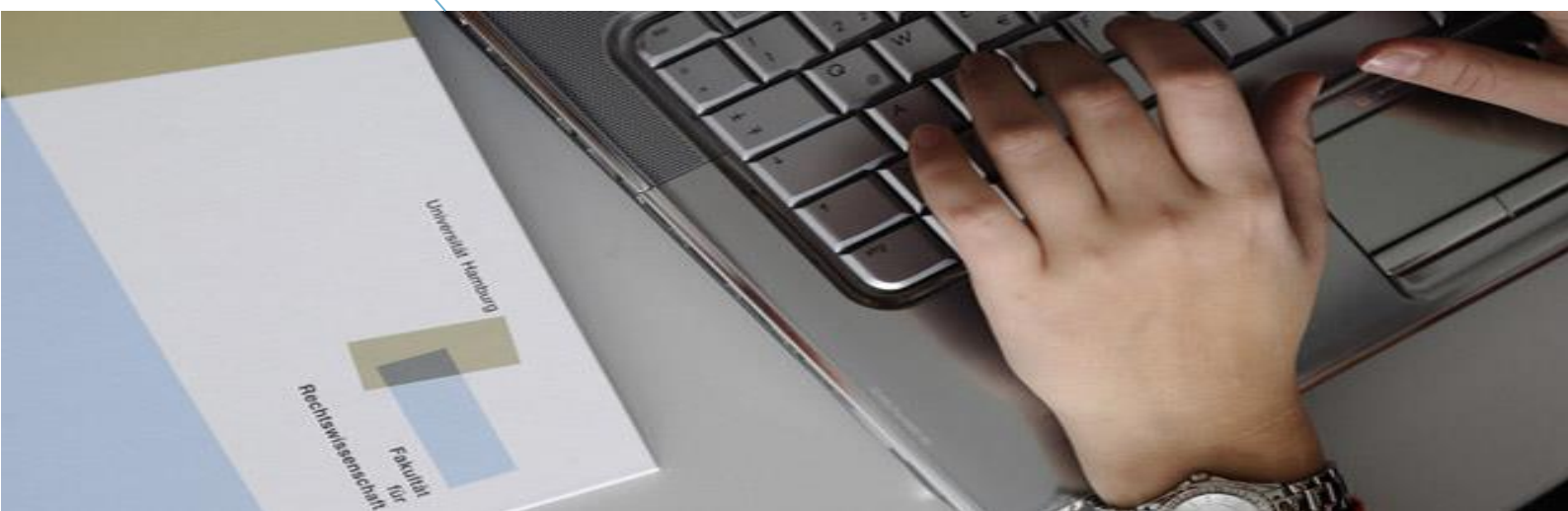
INSTITUTE OF LAW AND ECONOMICS
WORKING PAPER SERIES

How labor market institutions affect technological choices

Julia Samwer
Chinchih Chen

Working Paper 2020 No. 42

December 2020



NOTE: ILE working papers are circulated for discussion and comment purposes.
They have not been peer-reviewed.

© 2020 by the authors. All rights reserved.

Abstract

How labor market institutions affect technological choices

Julia Samwer¹ Chinchih Chen²

Abstract

Does the adoption of technological change depend on labor market institutions? The disparities in technology adoption across countries are enormous and are a major factor in explaining poverty. The returns to introducing new technology differ across countries since they depend not only on skill-levels but also on incentives provided by labor market institutions. Wage compression through unions and minimum wage laws indirectly induce investment into technology. The employer is incentivized to increase the productivity of employees and he can claim the full extra rent. The magnitude of the technological advancement also defines adoption rates. Small and cheaper technical changes are adopted in any institutional environment whereas larger technical progress is more likely to be integrated in rigid institutional settings. Using data on industrial robots and information and communication technology an empirical cross-country analysis explores the impact of institutional labor market patterns on technological choices and hence their influence on wage patterns, unemployment and inequality trends. It is shown that countries with strong individual labor protection adapt new technologies at higher rates, while at the same time the existence of strong unions and collective labor rights has a counter-effect.

Keywords: Technology Adoption, Labor market Institutions, Robot intensity

JEL Classification: O33, K31, P48

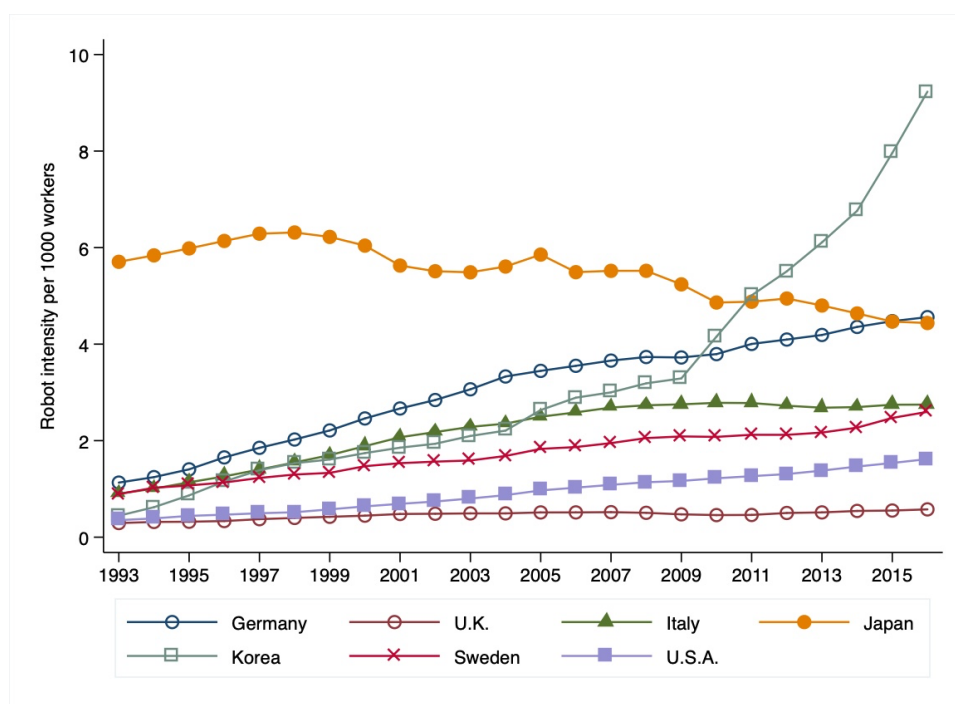
¹ Institute for Law and Economics, University of Hamburg, Johnsallee 35, 20148 Hamburg, Germany

² Oxford Martin School, University of Oxford, 34 Broad Street, Oxford OX1 3BD, Uk.

1 INTRODUCTION

Developed countries have taken very different technological paths in the past decades. The US has a lower density of robots than many European counterparts (Figure 1). The same holds for the level of automation or labor-augmenting technologies (Beaudry and Green 2003). What are the factors that cause such different pathways in countries with comparable developmental and educational levels? Traditional explanations are based on differences in industry patterns, demographics (ageing societies have a stronger interest to invest into technology) and exposure to international trade. It appears that countries with stricter labor market institutions incentivize deeper investments into technology.

Figure 1 Robot Intensity, 1993-2015



Note: Robot Intensity is the robot stock relative to the dependent employment in full-time equivalents (FTE). Source IFR, OECD, own calculation.

Technical change in the 21st century is largely regarded as skill enhancing rather than skill replacing.³ Since 1970 the US is characterized by a sharp increase in overall inequality. The returns to education increased but at the same time the country saw a large increase of the

³ This stands in contrast to the 20th century when many low-skilled jobs were replaced by machines.

supply of skilled workers. In response to that high-school premia would have been expected to slow down. The opposite happened which leads to the assumption that skill-biased technological change informed the rising inequality (Acemoglu 2002). It means technological progress impacts various dimensions of skill differently. Progress in Information and Communication Technology (ICT) and automation accelerate the demand for skills.

The rate of technology adoption can explain income per capita differences across developed countries that are not due to human or physical capital (Klenow and Rodriguez-Clare 1997). The divergence in wage inequality across countries over the past decades (strong increase in Anglo-Saxon countries such as US, UK, Canada, but lower in Germany and the Nordics) could partially result from different incentives to choose technological options, caused by prevalent labor market institutions (Acemoglu 2002). Classic models find that relative skill supply increased faster in Europe and wage-setting institutions prevented wage dispersion. A higher minimum wage and stronger unionization lead to lower wage inequality (Lumieux, di Nardo and Fortin 1995) and the notion of union power in compressing wages is widely accepted in the literature (Card et al. 2004). The effect of union power is therefore twofold, it suppresses wage inequality but at the same time opposes the replacement of workers through technology. Contrary to that, minimum wage laws and difficult dismissal procedures increase the cost of an employee and incentivize the investment into the productivity. The supply-demand-framework of skills can only explain part of the differences of wage inequality trends (Acemoglu 2003). Beaudry and Green (2003) for example describe different physical accumulation paths that led to a rise in wage inequality in the US but not in Germany. Although skills and thus human capital developed in parallel, Germany invested more into physical capital (e.g. technology) while the US underinvested and did not respond to technological change in the same manner.⁴ They observe these difference but do not identify whether this is caused by political, institutional or economic circumstances. This paper aims to contribute to this question by examining distinct features of labor market institutions.

The purpose of the paper is to show that labor market institutions are a major determinant of technology adoption. We are especially interested in individual labor protection and collective labor protection. For each type we use a different indicator provided by the OECD (EPRC and EPC).⁵ They do not overlap and allow to disentangle the effect of individual dismissal cost vs.

⁴ Beaudry and Green (2003) use an endogenous technological adoption model. The key implication is the existence of a balanced accumulation path such that if physical and human capital are accumulated according to the dictates of the path then the wage structure will not change.

⁵ Indicators used by the OECD to describe employment protection: Employment protection regular contracts (EPRC) and employment protection collective dismissals (EPC).

collective dismissals cost (and as such union power). We show that they have opposing effects on technology adoption. It is also important to note that strict labor protection does not automatically correlate with strong union power. Individual and collective labour rights are different legal areas and may be very different by design and or execution of these rights. Unions may be very powerful in environments with generally low protection of workers (Latin American countries). However, unions can also be strong in a setting with very strong labor protection (e.g. France). Therefore, strong unions can but must not be conclusive of strong labor market institutions.

The effects of technology on overall employment are not clear. Some studies find no total effect (Dauth et al. 2019), since reallocation balances out displacement effects. Whereas others find a positive effect. Gaggl and Wright (2017) and Bessen and Righi (2019) show that information technology increases employment in many industries but decrease it in others, mainly in more mature industries. Acemoglu and Restrepo (2017), however, find a negative effect on employment. There are two types of technological change: automation and creation of new tasks (Acemoglu and Restrepo 2019). Which effect dominates and how well a society adapts to these changes, depends on its institutions and the factor endowments of production. If technology and factor endowments (human and physical capital) are complementary, the marginal value of technology is increasing in the level of the factor. That means countries with high factor endowment and complementarity tend to speedy adoption. The opposite case arises when technology and factor endowments are substitutes. Firms have a higher incentive to invest in factor saving technologies when the price of the factor is high, e.g. if wages are high.⁶ According to Comin and Hobijn (2004) technology choices are “efficient responses to differing compositions of endowment portfolios of firm and countries”.⁷

The decline in real wages of low-skilled workers paired with a rising level of technology has created enormous concerns about the future work, structural unemployment and thus the society as a whole. Little attention is paid to how and when technology is adopted in the first place. This is however crucial in defining the ways technology is accepted and if technological progress is successfully integrated into a society or not (Frey 2019). It is under the assumption that technology, once invented quickly, becomes world knowledge and can be copied and adopted everywhere. The idea that technology is exogenously given was famously defeated by

⁶ Acemoglu (2001) on formalization of this argument.

⁷ Comin and Hobijn (2004), p. 65.

Romer (1999). If we assume technology is an endogenous factor, it is more relevant to understand the political and economic circumstances under which it is adopted and reinforced. If existing legislation partly informs technology adoption, different sets of legislation will produce different outcomes.

Labor market institutions such as minimum wage laws and employment protection directly influence labor cost. We argue that labor market institutions play a major role in defining a country's technological route and are thus also predictive in wage inequality behavior. The potential mechanism at work is proposed by Acemoglu (2002). He claims that technology is more widely adopted in countries where employment protection is stronger. It makes sense to invest into technology once the employee is tied by stricter termination periods and minimum wage laws. In these cases, the employer is the full beneficiary of the additional productivity of the worker, as he has to pay and will only pay the minimum wage. The employer can claim the full rent in extra productivity. The idea is similar to the mechanism proposed in Acemoglu and Pischke (1999) which explores the circumstances under which firms invest into training their employees. Labor market institutions are also a potential factor for the differences of skill supply, which in turn affects the type of technology adoption. A strong labor protection furthermore leads to a reassignment of occupations of incumbent workers and puts the burden on young workers and labor market entrants (Dauth et al. 2019). It means there is more reallocation than displacement at work in stricter labor market institutions. We want to test that mechanism empirically across countries, as to the best of our knowledge this has not been done yet.

The question we want to answer is whether labor market institutions cause different technology levels, which in turn leads to diverging levels of inequality. Little is known on what drives the different adoption rates in countries and there are only a few studies (e.g. on lobbying) that examine the causes behind it. We add to this literature by showing how labor market institutions shape technology adoption rates. The remaining paper is organized as follows: section 2 lays the theoretical foundation. In section 3 the research design is explained and section 4 presents empirical results. Section 5 presents extended analysis and Section 6 concludes on the implications for the future workplace and inequality levels.

2 THEORETICAL FRAMEWORK

Our empirical analysis is based on the theoretical argument that labor market institutions and technology adoption rates are linked. Acemoglu (2002) made the observation that developed countries with similar factor endowments and skill-levels follow very different technological pathways. He proposes a mechanism that explains these cross-country differences based on the characteristics of their labor market institutions. We want to examine that mechanism empirically by establishing a causal link between labor market institutions (LMI) and technology through the use of an instrumental variable identification strategy that predicts labor market institutions but does not influence technology adoption directly. Prior to establishing the exact mechanisms at work, it is important to clarify the features of labor market institutions and technology. In general, there are two types of technology, ICT and robots. Since their impact on labor can be different, in terms of replacing vs. augmenting skills, we want to test for both types. In terms of labor market institutions, it is important to test for various dimensions, such as individual vs. collective labor rights. Minimum wage laws play a defining role as well as the general legal origin of a country. It has been proven that common law origin countries have in general a more liberal approach towards labor market regulation, whereas civil law countries follow a more rigid path with stricter individual rights. In our empirical analysis all these factors will be tested for.

There are various channels through which labor market institutions can influence technology adoption: a) Technology adoption is favored due to higher employment protection, b) technology enhancing skills are cost-effective in highly regulated labor markets, c) technology is rejected from an industry/lobby standpoint of view (not robot industry itself, but production industries reject new technologies to already existing ones (Comin and Hobijn 2009)), and d) outcomes differ per industry level (the role of technology and employment protection is different at the industry level - for example tariff vs. minimum wage). We assume that wage compression encourages the use of more advanced technologies with unskilled workers and acts to reinforce itself in Europe. In contrast, technology can harm the earnings of low-skilled workers who are not protected by this type of wage compression. However, stronger unions and a more effective worker lobby will oppose the adoption of new technologies that replace labor.

We therefore expect that investment into technology is higher in stricter institutional labor market environments. Strong collective labor rights which are usually reflected in a stronger

presence of unions will on the other hand oppose technology adoption to protect low-skill jobs. We will test whether higher union density impacts technology adoption negatively. Since union density and strong individual labor protection are usually assumed to be positively correlated, we aim to disentangle those opposing effects by using different indicators for individual and collective labor protection.

3 RESEARCH DESIGN

3.1 Data

The EU-KLEMS⁸ database and the International Federation of Robotics (IFR) provide data on robot intensity and ICT capital expenditure. To capture labor market institutions, we use data from the OECD on labor protection, that provides detailed information on individual and collective dismissal procedures. The Worldbank data is used on GDP per capita, demographics and population data. To account for legal origins, we use the data provided by LaPorta et al. (2008).

The main outcome variable is *robot intensity*, *RI*, calculated based on the total number of industrial robots installed per thousand workers.

To capture labor market institutions, the key explanatory variable is the labor protection index (*epcr*) provided by the OECD. It is a weighted index on the strictness of employment protection. It incorporates eight data items concerning regulations for individual dismissal. It gives different weightings to the procedural inconvenience, the length of notice, severance pay and general difficulties of dismissal. The more costly it is to lay off workers, the higher is the incentive to invest into their productivity. To control for the influence of unions more specifically the variable *epc* measures additional cost and procedures involved in dismissing multiple workers at a time. It is therefore an indirect measure of union power, as we assume stronger collective rights are positively correlated with strong unions. To capture the effects on technology that stem from the service sector, we will control for *ICT intensity*. It will be drawn from the ICT capital expenditures over total value added from the EU KLEMS data across

⁸ EU level analysis of capital (K), labor (L), energy (E), materials (M) and service (S) inputs. Measures economic growth, productivity, employment creation, capital formation and technological change at the industry level for all EU member states from 1970 onwards. www.euklems.net

countries over time, which exploits information about installed equipment at the industry level.⁹

We use *GDP per capita (logged)* as a main control variable to capture the overall economic condition of a country. It is usually assumed that higher rates of technology intensity correlate positively with higher levels of income. It might also enable greater political participation and give workers more negotiating power in demanding higher levels of labor rights. The government direction strongly influences local labor rights practices, where it is assumed that higher levels of democracy are accompanied with greater protection of labor rights. To control for *demographics effects*, the share of citizens above 65 is utilized. In our extended analysis we also want to control for *industry* specific patterns and especially the share of employment in industry sectors, which include manufacturing, utility and construction sectors, since robot intensity levels are closely related to the prevalent industry sectors.

Another key variable identified in the literature to predict the strictness of institutions is *legal systems* and it will also be incorporated in the analysis through the dataset provided by LaPorta et al. (2008). It splits the countries into French, German, Scandinavian, Socialist or Anglo-Saxon law systems, which we are clustering into common vs. civil law countries. We expect less labor protection in common law countries than in civil law countries.

Finally, we are aware there is a potential issue of endogeneity between our main explanatory variable labor market institutions and the overall existing level of technology. Strong institutions in general are associated with higher levels of development and stronger economic growth, which correlates with higher intensity of technology. To address this endogeneity, we use the instrumental variable *Christianity Level* that predicts strong institutions and as such is partially explanatory for strong labor market institutions but independent of the level of technology. It is a novel indicator on the exposure to the Christian church and drawn from Schulz et al. (2019). Their findings show that a longer historical exposure to the medieval western church leads to less intensive kin-based institutions and more individualistic societies. These countries are more inclined toward trust and cooperation with strangers and have better institutions as a result today. The dataset they collected contains information on the diffusion of the medieval eastern and western churches and their duration of exposure to each country in

⁹ There is some overlap between ICT (software, computing and communications equipment) and robots, since the latter typically feature computing equipment for programming and control. But most of the hardware components of robots are not considered ICT (Graetz and Michaelis 2018).

the world up until 1500 CE. On the other hand, we use *Kinship* as second instrumental variable for our collective variable *EPC*. *Kinship*, which is also collected from Schulz et al. (2019), measures the degree to which relationships play a role. Kinship norms are stronger within dense social networks and reward loyalty and conformity more than individualism, independence, fairness and cooperation. We regard it as more suitable to account for the degree of collectivism. The exclusion restriction of our instrumental variable is of particular interest here. There is very low correlation between robot intensity and especially western church exposure. The historical dimension is important, countries have been exposed to western church influence long before modern technology was introduced. The christianity level is a good predictor of institutions but has a very weak link to robot intensity.

3.2 Empirical strategy

We rely on two different approaches to examine the effect of labor market institutions on technology adoption rates. First, our baseline results are from panel regression with country and time fixed effects for the period between 1998 to 2013 across 43 countries.¹⁰ As shown in equation (1),

$$RI_{i,t} = \alpha + \beta_1 lmi_{ind,i,t} + \beta_2 lmi_{coll,i,t} + \beta_3 X_{i,t} + \gamma_t + \delta_i + \varepsilon_{i,t} \quad (1)$$

$RI_{i,t}$ indicates the robot intensity in country i at year t , and the main explanatory variable lmi reflects the level of labor protection. The set of control variables explained above is represented by the vector (X). Country (δ_i) and year fixed effects (γ_t) control for time-invariant country characteristics, such as geography, and time specific effects, respectively.

As mentioned above, the potential endogeneity between labour market institutions and robot adoption might cause estimation biases. To control for this, we employ two historical instrumental variables, exposure to western churches and kinship, for individual and collective protection indexes respectively.

The first stage regression of labor market institutions on christianity level is denoted as:

¹⁰ We drop countries with less than three observations to reduce the noise resulting from imbalanced panel.

$$Lmi_{ind,i,t} = \pi + \pi_2 wc_{i,t} + \zeta_{i,t} \quad (2.1)$$

$$Lmi_{coll,i,t} = \pi + \pi_3 kin_{coll,i,t} + \xi_{i,t} \quad (2.2)$$

The main equation includes two lmi indicators, one for individual and one for collective labor protection.

$$RI_{i,t} = \alpha + \beta_1 \widehat{lmi}_{i,t} + \beta_2 X_{i,t} + \gamma_t + \delta_i + \varepsilon_{i,t} \quad (3)$$

4 FINDINGS AND DISCUSSIONS

In Table 1 baseline results from the OLS and IV estimation are reported. We see a positive and significant effect of individual labor protection on robot intensity. In the OLS model (Column 2) a one unit increase in individual labor protections leads to a 0.178 increase in robot intensity, while collective labor rights reduce the effect by 0.081 points. This is in line with the IV results, where the magnitude of the effect is even stronger. See Column 8, with a 1.673 increase of robot intensity for individual LP and a negative effect of collective LP of 0.353. Adding controls on demographics (the share of the population over 65), GDP per capita and the share of industrial employment, we still see a consistent positive effect. In line with our argumentation, collective labor rights working as union power have a slightly negative effect on technology adoption. To distinguish the type of technology we use ICT expenditure intensity as a control variable, so that the part of the effect that stems from the information and communication sector is controlled for¹¹.

¹¹ Due to limitation in data availability, the number of observations drops dramatically once we introduce ICT expenditure intensity.

Table 1: Effect of Labor Protection on Robot Intensity

| | OLS | | | | | | IV | |
|--------------------------------|------------------|--------------------|--------------------|--------------------|--------------------|--------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Individual LP | 0.174 (0.106) | 0.178* (0.106) | 0.285** (0.119) | 0.285** (0.119) | 0.291** (0.119) | 0.293** (0.117) | 1.861*** (0.278) | 1.673*** (0.390) |
| Collective LP | | -0.081* (0.044) | | -0.007 (0.055) | | -0.038 (0.074) | -0.296*** (0.073) | -0.353*** (0.083) |
| Share of aged over 65 | | | 0.034 (0.023) | 0.034 (0.024) | 0.052** (0.025) | 0.052** (0.025) | | 0.017 (0.021) |
| GDP per Capita | | | -0.333* (0.176) | -0.332* (0.179) | -0.013 (0.185) | -0.014 (0.186) | | -0.263 (0.160) |
| Share of industrial employment | | | 0.013 (0.008) | 0.013 (0.009) | 0.009 (0.009) | 0.009 (0.009) | | 0.009 (0.009) |
| ICT intensity | | | | | -4.128 (4.191) | -4.219 (4.209) | | |
| Anderson LR statistic | | | | | | | 81.02 | 31.74 |
| Country fixed effects | yes | yes | yes | yes | yes | yes | yes | yes |
| Year fixed effects | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 496 | 496 | 388 | 388 | 194 | 194 | 496 | 388 |
| R-squared | 0.944 | 0.944 | 0.947 | 0.947 | 0.979 | 0.979 | 0.919 | 0.930 |

Robust standard errors in parentheses

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

The estimation results of the IV regression are reported in Column (7) and (8). The effects remain consistently positive and significant. When disentangling the effect into individual labor rights protection and collective labor rights the results also show a negative impact of collective labor rights.

5 EXTENDED ANALYSIS

To support our hypothesis we show more extensive checks below, that approach the question of the role of labor market institutions from different angles. One main concern is the role of diverging industry patterns per country that might influence technology adoption and hamper our results. Here we introduce industry fixed effects to control for this potential confounding factor. The results still remain coherent with our main analysis.

Industry fixed effects

Introducing industry fixed effects into the analysis, allows us to control for a major concern of underlying industry patterns driving the results, rather than labor market institutions.

Based on EU KLEMS industrial classification, within manufacturing, we have consistent data on the use of robots for ten disaggregated industries: food and beverages; textiles (including apparel); wood; paper and printing; plastic, chemicals and non-minerals; basic metals and metal products; industrial machinery; electronics; transportation; and miscellaneous manufacturing. Outside of manufacturing, we consolidate data from six broad industries: agriculture, forestry and fishing; mining; utilities; construction; education; and services.

Table 2: Industry fixed effects

| | OLS | | | IV | |
|--|----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Individual LP | 0.206*** (0.031) | 0.191*** (0.031) | 0.185*** (0.031) | 3.719*** (0.496) | 2.991*** (0.413) |
| Collective LP | -0.165*** (0.017) | -0.149*** (0.018) | -0.142*** (0.020) | -5.845*** (0.411) | -5.227*** (0.347) |
| Anderson LR statistic | | | | 18.83 | 26.57 |
| Demographic controls | Yes | Yes | Yes | No | Yes |
| Industry control | No | Yes | Yes | No | No |
| ICT intensity | No | No | Yes | No | No |
| Country, year and industry fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,465 | 3,330 | 2,430 | 4,275 | 4,155 |
| R-squared | 0.971 | 0.972 | 0.980 | 0.417 | 0.573 |

Note: Demographic controls include share of aged over 65, and log of GDP per capita in OLS, and share of aged over 65 in IV. Industry control indicates the share of industrial employment. Robust standard errors in parentheses.

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

To reduce the poor sample from the IFR data we begin the analysis in 1998 where the EPC data starts. The trend is very similar even as we introduce more controls. Individual labor protection remains positive and collective labor rights negative. The magnitude of the effect is very similar to our results in Table 1 and does not drop much when introducing industry fixed effects.

Legal Origin

Since we assume that common law countries have a more liberal approach towards regulation and specifically labor market regulation than civil law countries we examine this relationship in more detail. Clustering our country set into legal origin and including all fixed effects and controls we find a positive and significant impact of civil law countries on robot intensity. This stands in comparison to common law countries where the effect is very small and non-significant. We opted for a comparative strategy rather than a simple dummy approach to show the difference across countries in more detail. The results further strengthen our hypothesis that institutional factors matter in technology adoption.

Table 3: Effect of Labor Protection on Robot Intensity Civil vs Common Law

| | Civil Law | | | Common Law | | |
|----------------|--------------------|---------------------|---------------------|-------------------|-------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Individual LP | 0.321** (0.131) | 0.487*** (0.156) | 0.400*** (0.140) | -0.006 (0.097) | 0.029 (0.153) | -2.414 (3.574) |
| Collective LP | -0.045 (0.056) | -0.004 (0.065) | -0.002 (0.091) | -0.004 (0.055) | 0.012 (0.085) | -0.447 (0.642) |
| Demographics | | 0.014 (0.020) | 0.070** (0.029) | | 0.029 (0.018) | 0.118 (0.169) |
| GDP per capita | | -0.379 (0.250) | -0.165 (0.201) | | -0.040 (0.081) | 2.583 (4.322) |
| Industry | | | 0.027** (0.011) | | | -0.003 (0.042) |
| ICT intensity | | | -0.594 (4.752) | | | -45.974 (68.146) |
| Constant | 0.045 (0.428) | 3.327 (2.207) | -0.232 (1.913) | 0.107 (0.240) | 0.120 (0.791) | -24.298 (42.365) |
| Country FE | yes | yes | yes | yes | yes | yes |
| Year FE | yes | yes | yes | yes | yes | yes |
| Observations | 391 | 317 | 166 | 105 | 83 | 28 |
| R-squared | 0.942 | 0.948 | 0.980 | 0.943 | 0.946 | 0.956 |

Robust standard errors in parentheses

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

Minimum Wage

Minimum wage laws directly influence labor cost. They increase the cost of an employee and incentivize the investment into their productivity. The employer is able to claim the full extra rent gained through the investment into technology and rising productivity levels. We therefore expect the effect of minimum wages on robot intensity to be similar to labor protection.

Table 4: The effect of Minimum Wage on Robot Intensity OLS

| | Year fixed effects | | Industry and Year fixed effects | |
|----------------|---------------------|---------------------|---------------------------------|---------------------|
| | (2) | (3) | (2) | (3) |
| Min wage | 0.377*** (0.106) | 0.378*** (0.106) | 0.058*** (0.013) | 0.056*** (0.013) |
| GDP per capita | 0.052 (0.183) | 0.042 (0.186) | 0.034 (0.047) | -0.003 (0.049) |
| Demographics | -0.000 (0.021) | 0.005 (0.029) | -0.004 (0.005) | 0.012* (0.007) |
| Industry | | 0.005 (0.011) | | 0.014*** (0.003) |
| Constant | -2.070 (1.832) | -2.162 (1.855) | -0.103 (0.437) | -0.390 (0.426) |
| Observations | 538 | 538 | 3,675 | 3,675 |
| R-squared | 0.878 | 0.878 | 0.956 | 0.957 |

Robust standard errors in parentheses

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

Table 4 reports cross country and cross industry results on the effect of a minimum wage on robot intensity. In both cases the minimum wage has a positive and significant effect on the adoption of technology. This further supports our hypothesis but from a different perspective, as minimum wage is another reflection of labor protection. Not only the cost of dismissal is relevant, but hiring costs play a role in technology adoption. The more expensive a worker is the more it makes sense invest into his productivity.

6 CONCLUSION

In this paper we claim that technology adoption is generally higher in countries with stronger labor market institutions presented by the degree of labor protection. The effect is twofold.

Individual labor protection in the form of dismissal procedures or minimum wage laws have a positive effect. We claim that this is due to stronger incentives to invest into productivity and hence technology of protected workers that are more costly. Collective labor protection in the form of stronger unions, however, presents stronger opposition to technology adoption and has a negative effect on robot intensity. It reflects unions' general sceptism towards new technology that potentially replaces jobs in the short run. We tested the mechanism empirically using OLS and IV estimation techniques. All our results show a consistently positive effect of stricter market institutions on technology adoption. Stronger union density and collective labor rights have a small negative effect on technology adoption rates. To ensure the effects are not driven by different national industry patterns, we also introduced industry fixed effects. The results remained consistently positive. We were also interested in the effect of employment protection on the ICT sector, controlling for different types of technology adoption. The results hint towards a positive effect, but remain insignificant due to poor data availability. Overall, we conclude that the productivity of less-skilled workers increases in stricter labor market environments and implies less skill-biased technical change. Secondary effects such as displacement and reallocation effects are mediated differently by the existing labor market institutions but are not part of the analysis in this paper. This will be an area for future research.

REFERENCES

Acemoglu, D., and Autor, D. (2011). Skills, tasks and technologies: implications for employment and earnings. *Handbook of Labor Economics* 4b:1043-1171.

Acemoglu, D., and Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review* 108(6):1488-1542.

Acemoglu, D., and Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives* 33(2): 3-30.

Acemoglu, D. (2002). Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature* 40(1): 7-72.

Acemoglu, D. (2003). Cross-Country Inequality Trends. *The Economic Journal* 113: 121-149.

Acemoglu, D., and Pischke, J.-S. (1999). Beyond Becker: Training in Imperfect Labour Markets. *The Economic Journal* 109: 112-142.

Acemoglu, D., Aghion, P., and Violante, G. (2001). Deunionization, technical change and inequality. *Carnegie-Rochester Conference Series on Public Policy* 55(1): 229-264.

Autor, D., Krueger A., and Katz, L. (1998). Computing Inequality: Have computers changed the labor market? *The Quarterly Journal of Economics* 113:1169-1214.

Autor, D., Levy F., and Murnane, R.J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics* 118(4):1279-1333.

Beaudry, P. and Green, D. (2003). Wages and Employment in the United States and Germany: What explains the differences? *American Economic Review* 96(3): 573-602.

Berman, E., Bound J., and Machin, St. (1998). Implications of Skill-Biased Technological Change: International Evidence. *The Quarterly Journal of Economics* 113(4):1245-1279.

Bessen, J., and Righi, C. (2019). Shocking Technology: What Happens When Firms Make Large IT Investments? Boston University School of Law, Law and Economics Research Paper No. 19-6.

Card, D., Lemieux, T., and Riddell, W.C. (2004). Unions and wage inequality. *Journal of Labor Research* 25(4): 519-559.

Caselli, F. (1999). Technological Revolutions. *American Economic Review* 89(1): 78-102.

Caselli, F., and Coleman, W.J. (2002). The U.S. Technology Frontier. *American Economic Review* 92(2):148-152.

Comin, D., and Hobijn, B. (2004). Cross-country technology adoption: Making the theories face the facts. *Journal of Monetary Economics* 51(1): 39-83.

Comin, D. and Hobijn, B. (2009). Lobbies and technology diffusion. *Review of Economics and Statistics* 91(2): 229-244.

Dauth, W., Findeisen, S., Suedekum J., and Woessner, N. (2019). The Adjustment of Labor Markets to Robots. Working Paper.

<https://sfndsn.github.io/downloads/AdjustmentLaborRobots.pdf>

DiNardo, J., Fortin, N.M., and Lemieux, T. (1995). Labor Market Institutions and the Distribution of Wages 1973-1992: A Semiparametric Approach. *Econometrica* 64(5):1001-1044.

Frey, C. (2019). *The technology trap: Capital, labor, and power in the age of automation*. Princeton University Press.

Gaggl, P., and Wright, G. (2017). A Short-Run View of What Computers Do: Evidence from a UK Tax Incentive. *American Economic Journal: Applied Economics* 9(3): 262-94.

Grossman, G.M., and Helpman, E. (1991). *Innovation and Growth in the Global Economy*. MIT Press, Cambridge.

Graetz, G., and Michaels, G. (2018). Robots at Work. *The Review of Economics and Statistics*. Vol 100(5): 753-768.

Klenow, P.J., and Rodriguez-Clare, A. (1997). The neoclassical revival in growth economics: Has it gone too far? *NBER Macroeconomics Annual* 12:73-103.

Krueger, A. (1993). How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984–1989. *The Quarterly Journal of Economics* 108(1): 33-60.

Krueger, A. (1999). Measuring Labor's Share. *American Economic Review* 89:45-51.

LaPorta, R., Lopez-de-Silanes, F., and Shleifer, A. (2008). The economic consequences of Legal Origins. *Journal of Economic Literature* 46(2): 285-332.

Machin, S., and Van Reenen, J. (1998). Technology and Changes in Skill Structure: Evidence from Seven OECD Countries. *Quarterly Journal of Economics* 113(4):1215-1244.

Romer, P. (1990). Endogenous Technological Change. *Journal of Political Economy* 98(5):71-102.

Potrafke, N. (2013). Globalization and labor market institutions: international empirical evidence. *Journal of Comparative Economics* 41(3): 829-842.

Presidente, G. (2019). Institutions, Hold-Up and Automation. CESifo Working Paper No. 7834.

Schulz, J.F., Bahrami-Rad, D., Beauchamp, J.P., and Henrich, J. (2019). The Church, intensive kinship, and global psychological variation. *Science* 366 (6466).

Visser, J. (2015). Data Base on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts, 1960-2014 (ICTWSS). http://archive.uva-aiaa.net/uploaded_files/regular/ICTWSScodebook50-2.

APPENDIX

A1: Summary Statistics

| Summary Statistics | Obs | Mean | Std. Dev. | Min | Max |
|---------------------------|------------|-------------|------------------|------------|------------|
| Labor Protection | 477 | 2.41 | 0.59 | 0.98 | 4.1 |
| Robot intensity | 582 | 0.89 | 1.19 | 0.00 | 6.3 |
| Church West | 581 | 5.22 | 2.97 | 0 | 9.75 |
| Church East | 581 | 0.27 | 1.22 | 0 | 7.61 |
| Collective Labor Rights | 477 | 2.86 | 1.09 | 0 | 5.13 |
| Manufacturing Share | 582 | 26.61 | 5.64 | 15.56 | 43.54 |
| Share age over 65 | 582 | 0.15 | 0.037 | 0.04 | 0.25 |
| GDP | 580 | 10.31 | 0.45 | 8.27 | 11.08 |
| Common Law | 582 | 0.19 | 0.39 | 0 | 1 |
| Civil Law | 582 | 0.32 | 0.46 | 0 | 1 |

A2: Summary Statistics by Country

| <i>A. 1993 Levels Averaged by Country</i> | | | | |
|--|-----------|----------|--------|-------|
| | #robots/H | ln(VA/H) | ln(VA) | ln(H) |
| Australia | 0.07 | 3.30 | 9.56 | 6.26 |
| Austria | 0.63 | 3.09 | 8.64 | 5.55 |
| Belgium | 1.20 | 3.72 | 8.94 | 5.22 |
| Denmark | 0.42 | 3.52 | 8.41 | 4.89 |
| Finland | 0.68 | 3.15 | 8.29 | 5.14 |
| France | 0.79 | 3.37 | 10.63 | 7.26 |
| Germany | 1.71 | 3.38 | 11.00 | 7.63 |
| Greece | 0.00 | 2.53 | 8.76 | 6.23 |
| Hungary | 0.05 | 1.68 | 7.50 | 5.82 |
| Ireland | 0.00 | 3.26 | 8.05 | 4.79 |
| Italy | 1.13 | 3.17 | 10.54 | 7.37 |
| Netherlands | 0.25 | 3.60 | 9.35 | 5.75 |
| South Korea | 0.28 | 1.90 | 9.76 | 7.86 |
| Spain | 0.36 | 3.21 | 10.12 | 6.91 |
| Sweden | 1.39 | 3.21 | 8.69 | 5.47 |
| United Kingdom | 0.50 | 3.38 | 10.62 | 7.24 |
| United States | 0.41 | 3.39 | 12.27 | 8.88 |
| Mean | 0.58 | 3.11 | 9.48 | 6.37 |
| <i>B. Changes from 1993-2007 Averaged by Country</i> | | | | |
| | #robots/H | ln(VA/H) | ln(VA) | ln(H) |
| Australia | 0.12 | 0.22 | 0.34 | 0.12 |
| Austria | 0.61 | 0.51 | 0.32 | -0.19 |
| Belgium | 1.23 | 0.29 | 0.20 | -0.09 |
| Denmark | 1.57 | 0.19 | 0.17 | -0.02 |
| Finland | 1.05 | 0.43 | 0.39 | -0.04 |
| France | 1.20 | 0.29 | 0.14 | -0.15 |
| Germany | 2.73 | 0.28 | 0.02 | -0.26 |
| Greece | 0.03 | 0.16 | 0.04 | -0.12 |
| Hungary | 0.08 | 0.56 | 0.37 | -0.20 |
| Ireland | 0.10 | 0.44 | 0.65 | 0.20 |
| Italy | 1.39 | 0.17 | 0.10 | -0.06 |
| Netherlands | 0.54 | 0.24 | 0.19 | -0.05 |
| South Korea | 1.31 | 0.71 | 0.45 | -0.26 |
| Spain | 1.21 | 0.13 | 0.31 | 0.18 |
| Sweden | 0.80 | 0.43 | 0.46 | 0.04 |
| United Kingdom | 0.34 | 0.26 | 0.14 | -0.12 |
| United States | 0.97 | 0.27 | 0.28 | 0.01 |
| Mean | 0.90 | 0.33 | 0.27 | -0.06 |

Notes: H stands for million hours worked. Value added (VA) is measured in millions of 2005 US\$, converted from local currencies using 2005 nominal exchange rates where applicable. Country-level and overall means are weighted by each industry's 1993 share of hours within a country.