Human Capital, Employment Protection and Growth in Europe*

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Abstract

Using data for 51 manufacturing and service sectors for the period 1970-2005 in 14 EU countries, this paper shows that employment protection legislation has a negative effect on value added growth in more human capital intensive sectors, especially in the case of countries near the technology frontier and after the 1990s. We interpret these results suggesting that technology adoption depends on the skill level of the workforce and on the capacity of firms to adjust employment as technology changes: therefore, firing costs have a stronger impact in sectors where technical change is more skill-biased and technology adoption more important.

Keywords: Employment Protection Legislation, Human Capital, Technology Adoption, Growth, Sectors.

JEL Classification: J24, J65, O47, O52.

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1 Introduction

Do labour market institutions affect economic growth? If that is the case, which are the channels through which labour regulation affects growth? How important are labour market institutions for the adoption of new technologies? Are these effects differentiated across industries? In this paper we try to answer the above questions by looking at the quantitative effect of employment protection legislation (EPL) on growth of value added and hours of work across sectors in Europe during the period 1970-2005. We do this by investigating the heterogeneous effects on industry growth of the interaction between a country's level of EPL and a sectoral measure of technology adoption intensity.[1]

In a recent paper, Ciccone and Papaioannou (2009) introduce skill biased technical change into a two sector version of the Nelson and Phelps's (1966) model of technology adoption: convincingly, they show that countries with higher levels of schooling tend to specialise in sectors with higher human capital intensity. In fact, skill biased technical change – associated with the ICT revolution that has been taking place since the beginning of the 1980s – should result in relatively faster productivity growth in skill intensive sectors (see Caselli, 1999).[2] Hence, countries with higher human capital levels should be able to adopt the new technologies – such as automated machinery and information and communication technologies – faster and therefore experience faster value added and employment growth in human capital intensive industries during the transition to the new steady state.[3]

However, the technology adoption process depends not only on the skill level of the workforce in a particular sector, but also upon the capacity of firms active in that sector to optimally adjust their employment levels as technology changes (Samaniego, 2006). If sectors experience different rates of technical change, firms operating in different sectors have heterogenous paths of adjustment of

[1] By technology adoption we mean the capacity to fully exploit the potential of recently developed technologies, and not simply imitate well established ones. Leading examples are automated machineries, information and communication technologies, flexible manufacturing systems, computer controlled machines whose productivity potential is fully exploited by highly skilled workers (Caselli, 1999).

[2] For recent empirical evidence on the relationship between human capital and productivity growth at the industry level, see Mason et al (2012).

[3] Such mechanism is also confirmed by abundant empirical evidence: see Autor et al. (2003), Machin and Van Reenen (1998), Caselli and Coleman (2001) and, more recently, Bartel et al. (2007) and Lewis (2011).

employment: in particular, the faster the rate of technical change, the higher the requirements for cutting or upgrading the workforce.[4] Hence, firing costs and labour market institutions as employment protection legislation may have a relatively stronger impact in those sectors in which technical change is faster as they reduce the expected returns on adopting new technologies.[5] In fact, for skill biased technical change at the world frontier to foster the specialisation in skill intensive sectors of countries with higher capacity of technology adoption, it is necessary that resources can be freely moved from low skill sectors to high skill ones. The existence of stringent employment protection legislation might slow down or even reduce this reallocation process, as recently noted, in the contest of a trade reform, by Kambourov (2009). Moreover, Acemoglu (2003) shows that regulations in the labour market, by compressing the wage distribution, might induce firms to invest more heavily in technologies that are complementary to low skilled workers. The increased productivity of low skilled labour could therefore reduce the relative importance of skill biased technical change for countries with heavily regulated labour markets, and this might again cause slower growth in human capital intensive sectors in countries with such labour markets (see also Koeniger and Leonardi, 2007).

During a period of strong skill biased technical change, employment protection legislation, by slowing down the adoption of the new technologies, might be more harmful in skill intensive sectors. This is because, as noted by Caselli (1999), these are the industries that "might plausibly be expected to be at the forefront of the technology revolution". Of course, an important assumption behind this result is that employment protection legislation tends to reduce the adoption of ICT technologies. Some favourable empirical evidence in this respect is offered in Figure 1 for a panel of 15 countries (the EU15 but Luxembourg plus the US) observed in the period 1990-2000. The Figure, as in Samaniego (2006), shows that personal computers adoption rates (proxied by the log of pc per capita) tend to be higher in countries that, in the preceding five years, were characterised by lower degrees of

[4] Michelacci and Lopez-Salido (2007) find that technological advances increase job destruction and job reallocation while Antelius and Lundberg (2003) offer some evidence that the rate of job turnover is higher in industries with higher shares of skilled workers; in turn, Givord and Maurin (2004) find that the job loss rate is higher in sectors with a higher share of R&D and high skilled workers.

[5] On the relationship between productivity growth, technology adoption, and EPL, see Belot et al (2007), Scarpetta and Tressel (2004), Bassanini et al (2009), Autor et al (2007), Micco and Pages (2007) and Cingano et al. (2010).

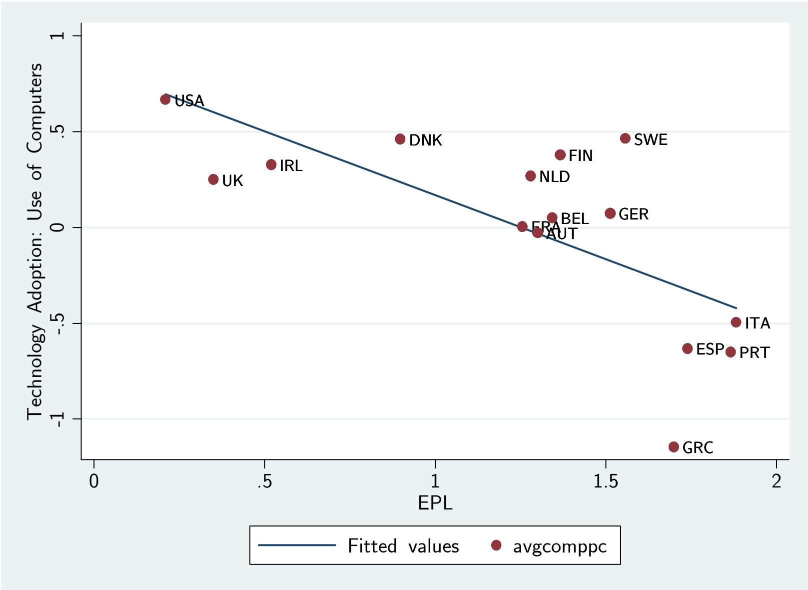

Figure 1: The Relation Between Technology Adoption and EPL

employment protection (see Gust and Marquez, 2004 and Pierre and Scarpetta, 2006).[6]

By simply allowing technology adoption to also depend on employment protection legislation in a model with skill biased technical change as the one proposed by Ciccone and Papaioannou (2009), we empirically show that EPL could negatively affect the specialisation pattern of countries by slowing down growth particularly in sectors with rapid technical change, such as human capital intensive sectors.[7] This channel is strictly related to the mechanism identified by Saint-Paul (1997) to understand the effects of EPL on the pattern of international specialisation: in his theoretical framework, countries with higher levels of EPL tend to specialise in less innovative sectors to avoid additional firing costs that are more likely to arise in sectors characterised by more drastic innovation (see also Saint-Paul, 2002b).[8]

[6] It should be noted that the negative and significant correlation between personal computer adoption rates and employment protection legislation is based on a regression where we have controlled for the log of per capita GDP, the log of the average number of schooling years in the population aged between 25 and 64, a time trend and a full set of country fixed effects. The coefficient of employment protection legislation in the regression is -0.35, with a p value of 0.07 and standard errors robust to arbitrary serial correlation within countries. The technology adoption data are taken from Comin and Hobijn (2010).

[7] In the working paper version of our paper, we sketch a very simple model of skill biased technical change, as the one proposed by Ciccone and Papaioannou (2009), in which we allow technology adoption to also depend on employment protection legislation.

[8] See Bartelsman et al. (2010), Cuñat and Melitz (2011) and Poschke (2009, 2010) for papers dealing with the effect of EPL on the specialisation pattern of countries.

In order to study the relations discussed above, in this paper, we analyse the effect of employment protection legislation on growth of value added and hours of work in Europe using EUKLEMS data for 51 manufacturing and service sectors for 14 countries during the period 1970-2005. In particular, we interact an indicator of EPL at the country level with a sectoral measure of human capital intensity which is invariant across countries (i.e., years of schooling in the workforce at the industry level) and is derived from US census data (as in Ciccone and Papaioannou, 2009). This methodology, first proposed by Rajan and Zingales (1998), has been proving popular among applied economists because it allows to overcome standard econometric problems of omitted variable bias and reverse causality through a difference-in-difference approach.

Our results clearly suggest that EPL has a negative effect on value added growth in more human capital intensive sectors. Our preferred estimates indicate that the growth rate differential between a sector at the 75th percentile of the human capital intensity distribution (*production of other transport equipment*) and a sector at the 25th percentile (*tobacco*) is in the range -0.5%/-0.9% in a country at the 75th percentile of the EPL distribution (Greece) with respect to a country at the 25th percentile (Austria). A similar, but slightly smaller, effect is estimated for growth of hours of work. Finally, a significant negative effect on TFP growth is also found.

We check the robustness of this result considering various different specifications. First, we examine whether our interaction between EPL and human capital intensity partly captures other interactions of EPL with industry features that might be correlated with human capital intensity, such as R&D or physical capital intensity and sectoral riskiness. Second, we consider the role of alternative determinants of industry growth by including the relevant interactions between industry and country characteristics, such as the average years of schooling at the country level and the sectoral human capital intensity, the country capital output ratio and the industry physical capital intensity, the sectoral R&D intensity and the country R&D stock. Third, we include interactions between human capital intensity and country level variables potentially correlated with EPL such as union density, strike activity, wage bargaining coordination, the level of financial development and the presence of entry barriers. Furthermore, we also consider different indicators of EPL which take into account the increasing extensive use of fixed term positions in some European economies. Fourth, we consider the potential endogeneity of EPL by instrumenting it with political economy variables. Fifth, we consider the possibility that EPL may have a differential impact on growth depending on the country's distance from the technological frontier. We finally check that our main results are not driven by benchmarking bias using a two-step instrumental variable estimator recently proposed by Ciccone and Papaioannou (2010).[9] We conclude that our robustness checks confirm the baseline results.

We add to the previous literature in various directions. First, we explore the role of labour market regulations in shaping the relation between technology adoption and growth, an aspect substantially neglected so far.[10] Moreover, by considering whether EPL disproportionately affects growth in human capital intensive industries, we offer empirical evidence on the role played by labour market institutions in driving the pattern of specialisation.[11] We argue that human capital intensity is a simple and general measure of the sectoral technology adoption propensity. The average schooling level of the workforce is in fact strictly correlated to R&D or ICT intensity, which are other natural measures of technological advances. We claim that our measure correctly captures the ability to successfully introduce recently developed technologies, as for example ICT and related technical advances, and to fully exploit their potential. Moreover, the technology adoption stage may be conceptually kept distinct from other aspects of technological change, as the production of innovation which is perhaps best captured by R&D activities: in this regard, our result that EPL slows down growth particularly in human capital intensive industries survives even after controlling for an interaction between R&D intensity and EPL. Second, by using a long period of time, we are able to capture long run effects of

[9] In fact, Ciccone and Papaioannou (2010) show that using industry data of a benchmark country as a proxy for the relevant industry characteristics (human capital intensity in our case) might lead to a significant bias in parameter estimates whose direction is not clear a priori.

[10] See Bertola (1994) and Hopenhayn and Rogerson (1993) for the aggregate effects of labour legislation on growth. Nickell et al. (2005) study the effects of EPL on labour market outcomes.

[11] In this respect, our paper is strictly related to recent work by Bartelsman et al. (2010), who provide evidence of a negative effect of high firing costs on employment especially in high-risk sectors.

labour market regulation, whereas previous papers focused on short run dynamics mostly considering only the manufacturing sector during the 90s. Finally, we show that our empirical findings are robust to other possible channels through which EPL can influence growth such as industry natural layoff propensity, as in Bassanini et al. (2009), or the degree of riskiness, as in Bartelsman et al. (2010); while, on the other hand, we experiment with other variables that may be correlated with technology adoption such as R&D or ICT intensity.

The rest of the paper is organised as follows. In Section 2 we describe the data; Section 3 contains our empirical methodology, while results are discussed in Section 4; we conclude in Section 5.

2 Data

2.1 Country-Industry Level

Data for real value added and hours of work are from the public release of the EUKLEMS database which contains detailed information on various industry-level variables for 14 OECD countries for the period 1970-2005. We extract the available data for 51 sectors according to the ISIC Rev3.1 classification for Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom. We drop other EU countries as data were not available for the complete covered period and the US, as the latter is used as the benchmark in our differences-in-differences approach. Industries considered span from agriculture to manufacturing and market services, while we do not consider public administration and defense, community personal services, education, health and social works; in Table 1 we report main summary statistics for industries at the top and bottom quartile of the human capital intensity distribution.

[Insert Table 1 about here]

For many countries we do not have information about all 51 sectors, but in no case the number of industries falls below 35, with most countries in the range 45-51. Overall, our sample is based on 595 (618) observations in the case of value added (hours) growth regressions.

2.2 Industry Level

Our measure of human capital intensity at the industry level is derived from the Integrated Public Use Microdata Series database which collects individual microdata from US census. To construct such a measure, we closely follow Ciccone and Papaioannou (2009). We impute average years of schooling for each educational attainment in 1970 as follows: 0 (no schooling), 1 (Grades 1-4), 6 (Grades 5-8), 10 (Grades 9-11), 12 (12 Grade), 14 (College 1-3), 17 (College 4+). As the IPUMS database uses a different industry classification from the one in the EUKLEMS data, we recode sectors according to our definition.[12] Then, for each sector, we calculate the share of employees in each educational attainment level and multiply this share by the average years of schooling calculated above.[13]

We also consider another industry level variable that has been recently used to study the relationship between EPL and productivity (see Bassanini et al, 2009). We have built a proxy for each industry's specific layoff propensity, proxied with the fraction of workers that had been displaced, using data from the US 1994 CPS Displaced Workers Supplement.[14] Other sector level variables that we consider in the paper are the physical capital, R&D, ICT and risk intensity. The first has been computed, as in Ciccone and Papaioannou (2009), as the ratio between real gross capital stock and value added in the US in 1970 using data taken from the EUKLEMS; in turn, R&D intensity is proxied by the R&D expenditure to value added ratio in the US in 1973 using data taken from the OECD ANBERD database;[15] ICT intensity was computed as the share of ICT expenditure in total investment outlays using EUKLEMS data; finally, as a proxy for risk intensity we use the standard deviation of the distribution of output growth across firms in the US, which has been made recently available for the manufacturing sector in the EUKLEMS database for the year 1992.

[12] The industry classification used in the IPUMS database is the Census Bureau Classification Scheme. See http://usa.ipums.org/usa/volii/97indus.shtml (accessed June 30, 2010). Details on the conversion methodology used are available upon request from the authors.

[13] Our measure of human capital intensity has a strong positive correlation (0.91) with the one used by Ciccone and Papaioannou (2009) for the manufacturing sectors in 1980.

[14] This is the oldest CPS survey on displaced workes we have been able to find. However, Bassanini et al. (2009) note that this measure is relatively stable over time.

[15] Unfortunately, we have been able to get information for R&D data only for a limited number of (mainly) manufacturing industries.

2.3 Country Level

The indicator of EPL at the country level is taken from Checchi and Lucifora (2002) who originally used the one by Nickell et al (2005). Data are five years average starting from the 60s; we construct an average measure of EPL from 70-75 to 95-00 that varies from 0 (less regulated) to 2 (most regulated). One pitfall of this indicator of EPL is that there is no information for Portugal and Greece: for these two countries we therefore use data taken from the most recent release of the OECD's employment protection legislation indicators, appropriately rescaled to compare it with that of Nickell et al (2001).[16] As a robustness check, we also use, as a measure of EPL, the recent OECD indicator just mentioned: in particular, we use the OECD EPL indicator EP_v1, which is an unweighted average of employment protection for regular and temporary contracts, and we construct an average measure for the period 1985-2005.[17] Furthermore, as an additional robustness check, we also consider the OECD index EP_v2, which measures EPL for the period 1998-2005 as a weighted average of EPL for regular contracts, temporary contracts and collective dismissals.

Remaining control variables are taken from different sources. From the Barro and Lee (2001) dataset we extract different measures of schooling at the country level such as years of schooling in the population with more than 25 years in 1970 and the average growth rate of this measure over the period 1970-1999.[18] From Checchi and Lucifora (2002) we also extract measures of strike activity (number of employees participating in strikes over total number of employees), union density (number of enrolled over total employees) and the tax wedge. In turn, we have used an index of coordination of wage bargaining, which takes values between 5 (i.e. economy wide bargaining) and 1 (fragmented bargaining, mostly at the company level).

Other country level controls come from conventional sources. Financial development is measured

[16] All main results are robust to dropping Greece and Portugal.

[17] The disadvantage of the OECD data is that they have information for Greece and Portugal but they do not cover the beginning of our sample period. In any case, the correlation between the two indicators is very high and equal to 0.96.

[18] For the regressions that we run over selected subperiods, we always consider the value that the different variables take at the beginning of the sample period, unless otherwise stated.

as the ratio between domestic credit to private sector and GDP and is taken from the World Bank Global Development Finance database; a measure for the rule of law has been proxied with the structure and security of property rights index reported in the Economic Freedom of the World database; trade openness is computed as the ratio between the sum of export and imports over total GDP; GDP per capita is from the most recent release (6.3) of the Penn World Tables; our measure of product market regulation is calculated as an average of entry barriers over the period of analysis taken from the OECD product market regulation database; finally, our measure of TFP is computed assuming that GDP is produced with a Cobb-Douglas technology with a labour share of one third using data from Klenow and Rodriguez-Clare (2005).

A few more words are necessary for the computation of the physical capital-output ratio. We follow Klenow and Rodriguez-Clare (1997) by computing the capital to output ratio in 1950 as $\frac{K}{Y} = \frac{I_k/Y}{g+\delta+n}$, where I_k/Y is the average investment rate in physical capital between 1950 and 1970, g and n are the average rate of growth of labour productivity and of population over the same period, respectively, and δ is the depreciation rate which is set equal to 8%. We then apply a standard perpetual inventory method to derive the capital stock (and therefore the capital output ratio) for 1970 and 1990.

The R&D stock data is obtained using data from different sources. For all countries but Greece, Belgium, Austria and Portugal we use the EUKLEMS data on the R&D stock for the market economy, which were constructed applying the perpetual inventory method to R&D expenditure data. As the EUKLEMS series start in 1980, we compute the R&D stock for previous years by applying the perpetual inventory method backwards to 1973 using OECD data on R&D expenditure from the OECD ANBERD database. For Greece, Belgium, Austria and Portugal we use the OECD expenditure data and apply the perpetual inventory method forward to derive estimates of the R&D stock for 1973 and 1990.[19]

[19] For these countries we need a value for the R&D stock in the first year. We compute this benchmark value as $R\&DSTOCK_{1973} = R\&D_{1973}/(g+\delta)$, where δ is the depreciation rate, set at 12%, g is the average rate of growth of R&D expenditure over the period 1973-1985 and R&D is R&D expenditure.

3 Estimation and Identification

Our empirical framework is similar to that of Ciccone and Papaioannou (2009) and is based on the differences-in-differences approach pioneered by Rajan and Zingales (1998) and subsequently employed in many other empirical applications. In order to evaluate whether employment protection legislation tends to reduce growth particularly in human capital intensive industries, we estimate different versions of the baseline equation:

$$\Delta \ln y_{s,c,1970-05} = \alpha(HCINT_{s,1970} * EPL_{c,1970-05}) + \gamma W_s^{'} Z_c + \delta \ln y_{s,c,1970} + v_s + u_c + \varepsilon_{s,c} \qquad (1)$$

where the dependent variable is the average rate of growth of value added or total hours worked in country c and sector s over the period 1970-2005; v_s, u_c and $\varepsilon_{s,c}$ are sector and country specific fixed effects and a conventional error term, respectively; $HCINT_s$ is the human capital intensity of each industry; EPL is the country average degree of employment protection over the period 1970-2000. Furthermore, our regression specification takes into account other possible determinants of industry growth by including the relevant country and sector interactions $W_s^{'} Z_c$, such as the country years of schooling in 1970 (and the improvements in schooling years over the sample period) and the sector human capital intensity in 1970; the country capital-output ratio and the sectoral physical capital intensity in 1970, and the industry R&D intensity and the country R&D stock in 1973. Finally, we take into account possible convergence effects by including in all regression specifications the log of the dependent variable at the beginning of the period.

In equation (1) country dummies should pick up the effects of any omitted variable at the country level, such as the quality of institutions, macroeconomic conditions over the period, social norms, etc.; in turn, industry fixed effects may capture differences in technologies or sector specific patterns of growth. A negative sign for the coefficient α would indicate that countries with higher degrees of employment protection legislation tend to grow less in schooling intensive industries: in other words, employment protection legislation tends to slow down growth disproportionately in human capital intensive industries, and as a result high-EPL countries tend to specialise in less schooling intensive industries.

The inclusion of $W_s^{'}Z_c$ is important because there is evidence that countries with an abundant factor tend to specialise in industries that use intensively that factor (Ciccone and Papaioannou, 2009). Controlling for the relevant country-industry interactions should allow us to take into account the possibility that W_s (e.g. an industry physical capital intensity) and $HCINT_s$ or Z_c (e.g. a country capital stock, the accumulation of human capital, etc.) and EPL_c are correlated: in this case, the omission of the relevant country-industry interactions would tend to bias the OLS estimates of α. In addition to this, given that there might be other country-level variables, potentially correlated with EPL, that might interact with industry schooling intensity, as a robustness check we also include additional interactions between $HCINT$ and country level variables such as GDP per capita, financial development, the respect of property rights, the stock of R&D capital, union density and other labour market institutions.

Moreover, in order to consider the possibility that EPL might interact with some other industry characteristics, in some specifications we augment our regressions with interactions between EPL and sector level variables, such as R&D, physical capital, riskiness and layoff intensities. Furthermore, given that there might be reasons to believe that causality might go in the other direction, namely from growth to employment protection legislation (see below), we also estimate a version of equation (1) in which we instrument EPL with different variables rooted in the history of each country and political economy variables. Finally, we check that our main results are not sensitive to the benchmarking bias highlighted by Ciccone and Papaioannou (2010).

4 Results

4.1 Basic Results

We first investigate whether human capital intensive industries grew faster in countries with less strict employment protection legislation over the period 1970-2005. In columns 1 to 3 of Table 2 we measure industry growth using value added (VAg), while in columns 4 to 6 we proxy the changes in production structure with the growth rate in total hours worked (Hg). In columns 1 and 4 we start with a parsimonious specification of equation (1), as we control only for country and sector fixed effects and for initial differences in the size of sectors (by including the log of value added or hours worked in 1970). The coefficient of the interaction between the average level of employment protection over the period 1970-2005 and human capital intensity is negative and statistically significant at the 1% level in both columns 1 and 4. In the case of value added growth, the coefficient of -0.00805 implies a yearly growth differential of 0.89% between the sector at the 75^{th}percentile (*production of other transport equipment*) and at the 25^{th} percentile (*tobacco*) of human capital intensity in a country at the 25^{th} percentile of EPL (such as Austria, with an average of 1.119 over the period) compared with a country at the 75^{th} percentile of EPL (such as Greece, with an average of 1.797).[20] If we measure industry growth using data on total hours worked, we find a slightly smaller effect, namely -0.00668, which implies a growth differential of about 0.74% between the sector at the 75^{th} and the 25^{th} percentile of schooling intensity in a country at the 25^{th} percentile of EPL compared to a country at the 75^{th} percentile of EPL.

[Insert Table 2 about here]

As shown in Ciccone and Papaioannou (2009), human capital intensive industries tend to grow faster in countries with higher initial levels of schooling, the intuition being that, if technological progress has been skilled labour augmenting over the sample period, higher levels of schooling should

[20] If we consider the two countries with the highest and the lowest levels of EPL over the 1970-2005 period, namely Portugal (2.000) and the UK (0.337), the annual growth differential could be as high as 2.1%.

foster the adoption of new technologies. However, if employment protection legislation were lower in countries with more years of schooling, then the interaction term between EPL and human capital intensity might be downward biased if we do not control for years of schooling. In order to check for this possibility, in columns 2 and 5 we have included interaction terms between human capital intensity and both the years of schooling at the country level in 1970 and the country level increase in average years of schooling over the sample period. Regression results show a positive and significant coefficient for the human capital level interaction, and a positive but slightly insignificant coefficient for the accumulation term, broadly confirming the results of Ciccone and Papaioannou (2009) for a different set of countries-industries and for a longer period of time.[21] Reassuringly, the interaction term between EPL and human capital intensity is still negative and statistically significant.

Finally, in columns 3 and 6 we drop the interaction between EPL and human capital intensity in order to compare our results with those reported by Ciccone and Papaioannou (2009) in their Table 3, column 1: in the case of the value added regression we find both a level and a growth effect of human capital, with an order of magnitude that is very similar to that implied by the estimates reported in Ciccone and Papaioannou (2009): interestingly, we find that in columns 3 and 6 the magnitude of the interaction terms between human capital intensity and both the years of schooling at the beginning of the period and its accumulation over the period go up, probably suggesting an upwards bias associated to the omission of the EPL-schooling intensity interaction.[22]

Our model specification, as well as our empirical findings, suggest that EPL tends to depress value added growth particularly in high human capital intensive industries. However, because in our model EPL affects value added growth through its effect on technical change in human capital intensive industries, one should also expect that TFP growth is negatively affected by EPL in such

[21] In the case of the value added growth regression, the coefficient of the interaction between human capital intensity and the initial level of human capital implies an annual growth differential of about 0.55% between the sector at the 75^{th} percentile and at the 25^{th} percentile of human capital intensity in a country at the 75^{th} percentile of years of schooling distribution compared with a country at the 25^{th} percentile.

[22] For robustness checks to possible outliers and influential observations we also run the specifications in Table 2 dropping, one at a time, each sector and then each country. The interaction term between human capital intensity and EPL remains negative, statistically significant and with very similar magnitudes to that reported in Table 2.

industries. In turn, as discussed by Autor et al. (2007), the effect on labour productivity growth is not clear, given the *a priori* uncertain effect of EPL on employment, as firing restrictions reduce both job creation and destruction. For these reasons we run the above regressions with TFP growth and labour productivity as dependent variables.[23] Our results, which are available upon request, confirm that the interaction term between human capital intensity and EPL has a negative effect on TFP growth: in fact the coefficient (t statistic) varies between -0.0135 (-1.96) and -0.0125 (-1.76) depending on the specification adopted. On the other hand we obtain a negative (but not statistically significant) effect of EPL on labour productivity growth. This result is in line with the one found by Autor et al. (2007) in the manufacturing sector in the US. As they suggest, one possible mechanism behind this result is that the increase in adjustment costs of labour pushes firms to increase capital investment and/or change the composition of the labour force with ambiguous effects on labour productivity.

In Table 3 we try to address possible endogeneity concerns of EPL. There can be different reasons that can make EPL endogenous: for example, EPL may be simply picking up the effects of some country level omitted variables that tend to affect growth especially in human capital intensive industries (see below); alternatively, EPL and growth might be jointly determined if a country that specialises in low human capital intensity and slow growth industries is also more likely to adopt a high degree of employment protection legislation (see, for example, Saint Paul (2002a), for a theoretical model).

We use different instruments for EPL.[24] The first, quite standard in the literature, is the percentage of years of left-wing governments over the sample period: the economic rationale of using this instrument is that the country level intensity of labour regulations has been found to depend

[23] For lack of data in the EUKLEMS database, the TFP growth regressions have been run on a sample of 26 industries (without Portugal and Greece) over the period 1990-05. See the robustness section below for additional regressions run on the same estimation period.

[24] We also instrument the level of schooling with its lagged values as suggested by a large literature on the endogeneity of human capital on growth. Moreover, in the context of our study, in countries with high levels of EPL, workers can invest more in human capital to increase their probability of getting a job (or reduce the probability of being fired). Results are available upon request and confirm findings presented below.

on the political power of the left (Botero et al., 2004). For the second instrument we instead follow Bassanini et al. (2009) and we build a dummy equal to one for those countries that experienced a dictatorship spell before 1970 (excluding World War II) and zero otherwise, the intuition being that historical evidence suggests that fascist dictatorships tended to protect workers against unfair dismissals due to their paternalistic views of labour relations.

Finally, we built dummies that proxy the attitude taken by governments towards the development of labour unions in the early 20^{th} century. Using a taxonomy recently used as an instrument for the quality of today's labour relations by Mueller and Philippon (2011), it is possible to group countries into three categories, namely political inhibitors (Italy, France, Spain, Portugal and Greece), political facilitators (Germany, Austria and The Netherlands) and political neutrals (Belgium, Denmark, Finland, Ireland, Sweden and the UK). The first group is composed by countries whose government highly oppositional stance against the development of labour unions led to highly conflicting and radical labour movements; in turn, the second category considers countries whose governments co-opted labour unions into the system, which in turn led to cooperative labour unions; finally, the third category groups countries that can be considered as an intermediate case (neutral). The economic justification for using these dummies as instruments for EPL is that, in political inhibitor countries, the radical and conflicting labour unions might have pushed in the past century for legislations aimed to protect workers against unfair dismissals, unlike what might have happened in most facilitator or neutral countries, where agreements between labour unions and employers are more likely and therefore the necessity for unions to push for employment protection legislation might be less strong.

[Insert Table 3 about here]

In columns 1 and 5 of Table 3 we instrument the interaction of human capital intensity with EPL with the interaction of human capital intensity with the left wing government indicator and the dictatorship spell dummy. First stage results, reported in the bottom part of the Table, suggest that both variables are significant and with the expected sign: countries that experienced a dictatorship spell and that had many years of left wing governments also tend to have stronger EPL. Moreover, the Hansen J statistics rejects at the 10% level the null hypothesis that the instruments are correlated with the error term and the Kleibergen-Paap LM and F statistics do not suggest problems of under-identification or weak instruments problems.[25] Second stage results suggest that the human capital intensity-EPL interaction is always negative and statistically significant with a magnitude which is only slightly lower than that reported in Table 2 for the OLS case. In columns 2 and 6 we check the robustness of these results by instrumenting the interaction between human capital intensity and EPL with the interaction of human capital intensity with the left wing government indicator and the dummies for cooperative and neutral labour origins. First stage results suggest that countries with neutral and cooperative labour origins tend to have a lower degree of EPL, while second stage results confirm that EPL tends to significantly reduce growth particularly in human capital intensive industries.[26] In columns 3 and 7 we use the dictatorship spell dummy and the labour origin dummies as instruments for EPL and main results are broadly confirmed. Finally, in columns 4 and 8 we jointly consider all three sets of instruments: again, the human capital intensity-EPL interaction is negative and statistically significant and first stage results do not display evidence of weak identification and weak instrument problems.[27]

We then test the robustness of our main results to some of the other determinants of industry growth suggested in the literature by including the relevant country and sector interactions $W_s' Z_c$. Moreover, because human capital intensity is quite different from other sector-level intensity measures that have been previously used in the literature to analyse the effect of EPL on productivity growth, we also assess whether interacting EPL with other sector level intensity measures affects our main result that EPL tends to reduce growth disproportionately in human capital intensive industries.

[25] Underidentification and weak instruments tests are availble from the authors upon request.
[26] Again, we do not have evidence of weak instrument problems.
[27] We have also explored the use of legal origin dummies as excluded instruments (as in Bassanini et al., 2009) and our main results are virtually unaltered.

First, as in Ciccone and Papaioannou (2009), in column 1 of Table 4 we include an interaction term between a country capital-output ratio and a sector physical capital intensity to take into account the possibility that, if physical and human capital intensity are correlated, then the interaction between schooling intensity and EPL might be picking up the effect of a country physical capital stock: parameter estimates show that our results are basically unchanged and the coefficient of the physical capital interaction term is not statistically significant.[28] In column 2, we interact R&D intensity with our measure of EPL. As expected, more R&D intensive sectors grow less in countries with higher level of EPL: in particular, the coefficient on the interaction term is negative and statistically significant at 10% level. However, the latter effect becomes insignificant when we jointly consider the role of human capital and R&D intensity in column 3; interestingly, the negative effect of the interaction of EPL with human capital intensity stands out.[29] This result may suggest that EPL slows down growth by affecting the adoption of technology rather than the production of innovation. Following Samaniego (2006), we further check this result calculating a measure of ICT intensity at sectoral level (proxied by the share of ICT in total investment spending in the US as of 1970, using data from EUKLEMS) and interacting this measure with EPL: results in columns 4 and 5 are very similar to those found in the case of R&D.

[Insert Table 4 about here]

Bartelsman et al. (2010) note that the proportion of high skilled workers in a sector is positively related to the riskiness of that sector, proxied by the observed variance of labour productivity within an industry averaged across countries. Therefore it might be important to take into account the possibility that our interaction is picking up such correlation. Hence, in column 6, we add an interaction term between our measure of sector riskiness and EPL. In particular, we use the standard

[28] We also consider the interaction between an industry R&D intensity and the R&D stock at the country level obtaining very similar results to those reported in column 1 of Table 4.

[29] Note that data availability allows us to consider R&D intensity only in the manufacturing sectors. As we show in Table 6, the effect in that macro-sector is stronger, this explains the higher magnitude of the interaction between human capital intensity and EPL.

deviation of the distribution of output growth across firms in the US.[30] Results indicate that although EPL tends to depress growth in risky sectors, the interaction term is not statistically significant at conventional levels; in turn, the interaction term between human capital intensity and EPL is negative and statistically significant. Similar results are obtained in column 7 when we interact EPL with a sectoral measure of layoff intensity (as in Bassanini et al, 2009), i.e., considering the negative effects of EPL on reallocation of workers. Finally, in column 8 we consider the role of physical capital intensity interacted with EPL: again, including this control doesn't affect our result.[31]

We conduct additional robustness analysis in Table 5. In column 1 and 2 we use two different measures of EPL directly available from the OECD as discussed in previous subsections. The first is an unweighted average of sub-indicators for regular contracts and temporary contracts, while the second, available only from 1998 onwards, is a weighted sum of sub-indicators for regular contracts (weight 5/12), temporary contracts (weight 5/12) and collective dismissals (weight 2/12). In fact, the second indicator should account for the structural characteristics of some EU countries, in which strong employment regulations induce firms to make intensive use of fixed-term positions, that might have different degrees of employment protection with respect to the regular ones. Because the OECD indices have a slightly higher range of variation, the coefficient in column 1 is not directly comparable with those reported in previous tables: nevertheless, the main result of a negative effect of EPL on growth in human capital intensive sectors holds.[32] The effect is reinforced in column 2 which better takes into account the increasing role of temporary contracts in some (more regulated) labour markets.[33] Then, in columns 3 to 5 we consider whether EPL is simply picking up the effect of other labour market institutions on growth. In particular, we alternatively add interaction terms between human capital intensity and union density, number of strikes, and the tax wedge. Finally,

[30] Given that our proxy for sector riskness is available only for the manufacturing sectors in 1992, the regression presented in column 6 refers to the manufacturing sectors for the period 1990-2005.

[31] Similar results are obtained when we consider hours of work; results are available upon request.

[32] We have also used the employment law index of Botero et al. (2004) and our main results are virtually unaltered.

[33] The EPL index in column 2 jointly considers the regulations for collective and individual firing restrictions; however, because the two types of regulations might have different economic effects, we also run a regression for the 1990-05 period using the OECD index of collective dismissals which confirms our main results.

in column 6, we also consider the role of wage coordination and centralisation as the effect of EPL can be neutralised by wage bargaining. The empirical estimates show that the interaction between schooling intensity and EPL is still negative and statistically significant at either 1% or 5%, and that the interactions of schooling intensity with all other labour market institutions are insignificant.[34]

[Insert Table 5 about here]

A potential criticism to using US industry data as a proxy for an industry human capital intensity might generate non-negligible bias for the human capital intensity-EPL interaction term, whose direction is not even clear a priori. In order to check the robustness of our result we therefore employ the two-step IV estimator recently suggested by Ciccone and Papaioannou (2010), to whom we refer for an in-depth discussion of the derivations.

In the first stage we estimate, for all countries but the US, the following equation with OLS :

$$\Delta \ln y_{s,c,1970-05} = v_s + u_c + \gamma_s EPL_{c,1970-05} + \varsigma_{s,c} \tag{2}$$

where γ_s are industry specific slopes and the other symbols are as in equation (1). Ciccone and Papaioannou (2010) show that the "true" human capital intensity could then be built (netting out country effects) as the predicted human capital intensity for the country with the most flexible labour market (the US), as: $\widehat{HCINT}_{s,1970} = \widehat{v}_s + \widehat{\gamma}_s EPL_{US,1970-05}$, where $^*EPL_{US,1970-05}$ is the value of our EPL indicator for the US. We then use $\widehat{HCINT}_{s,1970}$ as an instrument for $HCINT_{s,1970}$. Regression results indicate that the human capital intensity-EPL interaction is negative and statistically significant with a coefficient (t-statistic) of -0.0194 (-5.9), with a magnitude larger than in the OLS case, suggesting the existence of attenuation bias in the OLS estimates.[35]

[34] In regressions not reported, but available from the authors, we also consider the interaction between human capital intensity and duration of unemployment benefits with very similar results. We also measure a country schooling level with the percentage of the population who completed secondary or tertiary education. The results confirm that higher EPL tends to affect disproportionately growth in human capital intensive industries. Finally, very similar results hold when we measure growth with hours of work.

[35] The first stage is an OLS regression of $HCINT_s * EPL_{c,1970-05}$ on a set of country and sector dummies, initial conditions and $\widehat{HCINT}_s * EPL_{c,1970-05}$. Both the Kleibergen-Paap LM and F statistics do not suggest problems of underidentifcation or weak instrument problems. Results obtained for hours of work are very similar.

Finally, we explore in some detail the possibility that EPL is simply proxing the effects of some other country variables that tend to affect the growth of value added and hours of work particularly in human capital intensive industries, such as the capital output ratio, the level of financial development, the respect of property rights, the per capita income level, the country stock of R&D capital, degree of trade openness and the degree of product market regulation (proxied by the OECD indicator of entry barriers in network sectors). Our empirical findings (not reported for space reasons) confirm that a higher level of EPL tends to significantly reduce value added growth particularly in human capital intensive industries.

4.2 Robustness

In this subsection we check whether there are important differences between the two subperiods 1970-1990 and 1990-2005 and between manufacturing and non manufacturing industries; finally, we check whether the impact of EPL changes with a country's distance from the technological frontier.

In Table 6 we start running a baseline regression for the two sub-periods 1970-1990 and 1990-2005 (columns 1-2 and 5-6 for value added and hours of work respectively). Our a priori expectation is that the effect of EPL should be stronger in the second period. This is because there is empirical evidence (e.g., Caselli and Coleman, 2002) suggesting that the new technologies that started to be available at the end of the 1970s have been relatively more skill biased than those prevailing before: if we take into account the adjustment costs and the time that is often required for managers to fully appreciate the potential of new technologies and to incorporate them into the companies' routines, as well as the General Purpose Technology nature of ICT, then one may think that skilled labour augmenting technical change might have been relatively weaker in the 1970s and 1980s compared to the 1990s and early 2000s. But if this is the case, then one can also think that a more stringent employment protection legislation should have been more binding in human capital intensive industries precisely over the period 1990-2005, rather than in the previous two decades. As we can see from columns 1-2 and 5-6, both the value added and hours regressions suggest that the interaction between EPL and schooling intensity had a negative effect in both sub-periods, but also that it is statistically significant only in the most recent period, thus confirming our a priori expectations.[36]

[Insert Table 6 about here]

In columns 3-4 and 7-8 we split the sample between manufacturing and non manufacturing industries in order to examine whether there is any sector level heterogeneity in the interaction between EPL and schooling intensity. Before discussing the results we should however bear in mind that this split entails a severe degrees of freedom loss, especially in the case of the non manufacturing regression. As we can see, EPL tends to significantly reduce growth in human capital intensive industries both in the case of manufacturing and non-manufacturing sectors, although the effect is much stronger in the former case.[37]

Finally, in Table 7 we allow the interaction between schooling intensity and EPL to vary with the country's distance from the technological frontier. The intuition is that EPL is likely to be more binding for a country near the technological frontier because in that case productivity growth is more likely to arise from radical innovations rather then from innovations at the margin or simply from imitation and adoption of existing technologies (Saint Paul, 2002b). In the first column we run a baseline version of equation (1) with only the log of beginning of the period value added as control variable plus a triple interaction between schooling intensity, EPL and the country's distance from the technological frontier. The latter variable has been computed as the ratio between US TFP and country c TFP at the beginning of the period and therefore a higher value indicates a country far from the technology frontier. To fully saturate the model we have also included an interaction term between schooling intensity and a country's distance from the technology frontier. Empirical

[36] If we run similar regressions for the subperiods 1970-80 and 1980-90 we find that the interaction between human capital intensity and EPL increases in absolute value in the second period, although we can still not reject the null hypothesis that is equal to zero.

[37] We also divide our sectors into ICT (including both ICT producing and using industries) and Non-ICT, using a definition proposed by Van Ark et al. (2003) and we run separate regressions for the two groups. The idea is to verify whether human capital intensity is simply capturing the more or less extensive use of ICT. Our regression results (estimates avaiable from the authors upon request) show that in both the value added and hours regressions the interaction between human capital intensity and EPL is negative and statistically significant with a very similar magnitude across the two groups.

results show that EPL tends to disproportionately reduce growth in high schooling industries but particularly in countries that are closer to the technological frontier. In order to facilitate comparisons with results displayed, in, say, Table 2, let us consider the 25^{th} percentile of TFP Distance – which corresponds to a country with a TFP in 1970 about 11% lower than the US level – and the 75^{th} percentile of TFP Distance – which corresponds to a country with a TFP about 26% lower than the US level. For the "efficient country", the coefficient of Human Capital Intensity × EPL would be equal to about -0.013, statistically significant at 1%, which in turn would imply a yearly growth differential of about 0.55% between sectors at the 75^{th} and 25^{th} percentile of human capital intensity in a country at the 25^{th} percentile of EPL compared with a country at the 75^{th} percentile of EPL. In turn, for the "less efficient country", the coefficient of Human Capital Intensity × EPL would be almost halved as it would be equal to about only -0.007 (statistically significant at 1%).

[Insert Table 7 about here]

In column 2 we repeat the same exercise, but including also the interaction of human capital intensity with years of schooling in 1970 and its improvement over the 1970-2000 period. Punctual estimates are virtually unaltered, although standard errors are higher, probably reflecting a problem of multicollinearity.[38] Finally, in column 3 we repeat the same exercise but only for the period 1990-2005: again, EPL tends to have a stronger effect in countries that are closer to the technological frontier. In this case, EPL would have a disproportionately significant negative effect in human capital intensive industries only for countries with a TFP no lower than 12 % of the US level in 1990, while it would be not significantly different from zero for remaining countries.

[38] An F test for the joint significance of human capital intensity-EPL interaction with the triple interaction including TFP distance leads us to reject the null hypothesis that they are jointly equal to zero at the 1% level.

5 Concluding Remarks

In this paper, we consider the effect of employment protection legislation on industry growth. We find that EPL tends to have disproportionately negative effects on the growth rate of value added and hours of work in more human capital intensive industries. We argue that human capital intensity reflects differences in technology adoption rates across industries and that firms in sectors in which technical change is faster have higher requirements of adjusting employment. Hence, by letting technology adoption to depend on EPL in a model of growth with skill biased technological change, we study how firing costs may have a relatively stronger impact in human capital intensive sectors in which technology adoption is faster.

Our empirical results indicate strong and statistically significant negative effects of higher levels of EPL on the growth rate of value added and hours of work in human capital intensive industries. This result is robust to a series of sensitivity checks. First, we have controlled for other determinants of industry growth by means of interactions between a country factor abundance and an industry factor intensity. Secondly, we have checked that EPL negatively affects growth in human capital intensive industries even when it is also interacted with physical capital intensity, R&D intensity, sectoral riskiness or layoff rates at the industry level. Moreover, we have also controlled for the possibility that EPL might be picking up the effects of other country characteristics by interacting human capital intensity with other country level variables, such as the level of financial development and the respect of property rights among the others. Finally, we have taken into account possible endogeneity concerns of EPL.

We also find that the effect of EPL on value added growth is stronger in the more recent years than during the 70s and 80s, and in the manufacturing than in the service sector; finally, we show that EPL tends to disproportionately reduce growth in high schooling industries but particularly in countries that are closer to the technological frontier. We also report some evidence that EPL negatively influences TFP growth during the transition to the steady state. This confirms our baseline result that EPL reduces growth in the more advanced countries and dynamic sectors of the economy.

Our analysis has also some implications for the relative dynamics of productivity and GDP growth of EU countries and the US over the last 40 years. As the growth literature suggests, GDP growth during the 1960s and 1970s was mainly driven by physical capital accumulation and TFP growth, resulting in an effective catching up process between most EU countries and the US. In particular, in the decades after World War II, TFP growth in Europe was mainly achieved through a more efficient use of inputs, exploitation of scale economies and the introduction of already well established technologies. In that environment, strong employment protection did not affect the scope for catching up and the existence of a highly skilled workforce was probably not a necessary condition for achieving strong TFP growth. However, with the 1980s and especially the 1990s, sustainable high rates of GDP growth had to be achieved through strong productivity growth. As Aghion and Howitt (2006) suggest, after the catching up with the technological frontier had been completed, growth rates had to be more related to direct innovations and to the adoption of recently developed new technologies (like ICT, automated machinery, etc. whose implementation requires a more skilled workforce) that are more dependent than before on experimentation, short term relationships, better selections of workers and a more flexible labour market: as a result, more stringent EPL might have had a more detrimental impact on growth in the last two decades.

In order to provide some empirical evidence to back this conjecture, in Figure 2 we plot the difference in average TFP growth for the two decades after and before 1980 against average EPL during the observation period. The strong and significant negative correlation (which may be observed also for labour productivity and GDP) suggests that countries with higher levels of EPL are those that experienced a slowdown in their growth rates during the most recent decades. Although purely suggestive, such evidence provides additional empirical support for our thesis that labour market institutions such as employment protection legislation, by altering the incentives to adopt and exploit the full potential of new technologies, might be an important channel to understand differences in relative long run growth dynamics.

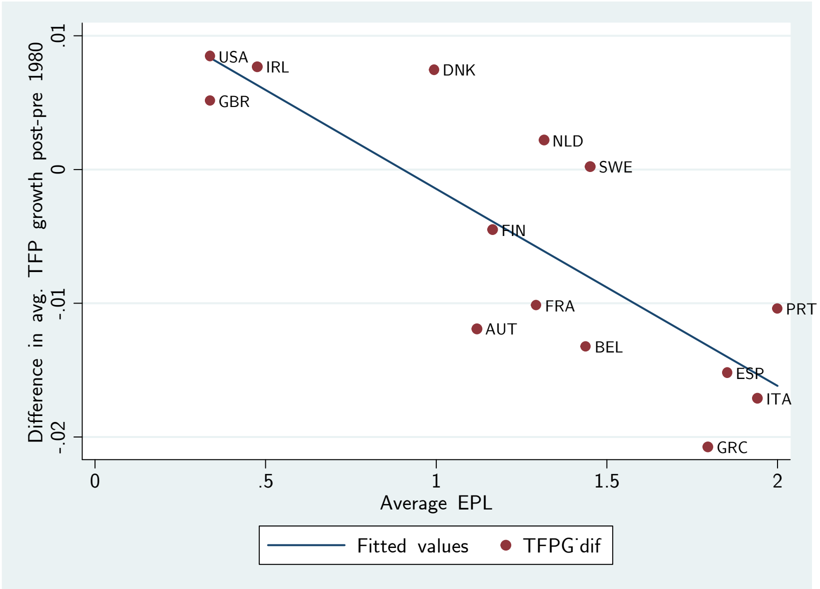

Figure 2: Changes in TFP growth post-pre 1980 versus EPL

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Table 1: Descriptive Statistics, Main Sector Level Variables

Sector	Value Added Growth	Hours of Work Growth	Human Capital Intensity	Physical Capital Intensity	Layoff Intensity
Research and development	0.0394	0.0339	14.4197	0.2654	0.0840
Computer and related activities	0.0725	0.0617	14.3614	0.2654	0.1466
Activities related to finance	0.0380	0.0383	14.1775	0.1029	0.0725
Other business activities	0.0389	0.0405	13.6339	0.2654	0.1308
Office, accounting and computing	0.0651	-0.0066	13.4828	3.3791	0.1359
Insurance and pension funding	0.0274	0.0133	13.4812	0.1029	0.0827
Coke, refined petroleum and nuclear	0.0135	-0.0154	13.1708	16.4665	0.1010
Financial intermediation	0.0436	0.0147	13.0936	0.1029	0.0963
Other air transport	0.0250	0.0025	13.0511	4.0836	0.1059
Forestry	0.0058	-0.0232	13.0160	5.5045	0.0556
Chemicals and chemical products	0.0451	-0.0075	12.9635	0.9268	0.0722
Extraction of crude petroleum	-0.0257	0.0041	12.8607	4.8681	0.1454
Other transport equipment	0.0144	-0.0151	12.8481	0.8246	0.1162
...	...	...	...	...	...
Tobacco	-0.0000	-0.0371	11.2078	1.1122	0.0323
Other Inland transport	0.0248	0.0016	11.1633	4.0836	0.1037
Hotels and Restaurants	0.0156	0.0127	11.0701	1.1696	0.1057
Other mining and quarrying	0.0115	-0.0159	10.8800	4.8681	0.1091
Renting of machinery and equipment	0.0488	0.0374	10.7804	0.2654	0.1101
Wood and cork	0.0220	-0.0098	10.6958	0.8073	0.1170
Fishing	0.0010	-0.0210	10.6882	5.5045	0.1186
Agriculture	0.0166	-0.0300	10.6672	5.5045	0.0628
Wearing, apparel, dressing	-0.0225	-0.0532	10.5816	1.4301	0.1233
Leather and footwear	-0.0197	-0.0451	10.5209	1.4301	0.1236
Textiles	-0.0115	-0.0390	10.5165	1.4301	0.0956
Recycling	0.0510	0.0029	10.5165	1.0505	0.1186
Mining of coal and lignite;	-0.0028	-0.0618	10.0537	4.8681	0.1972
Total (51 sectors)	0.0264	-0.0029	12.0038	2.6889	0.1017

Note: We report main summary statistics for industries at the top and bottom quartile of the human capital intensity distribution.

Table 2: Baseline Model

	(1) VAg	(2) VAg	(3) VAg	(4) Hg	(5) Hg	(6) Hg
Human Capital Intensity ×	-0.00805***	-0.00618***		-0.00668***	-0.00507***	
Employment Protection	(0.0016)	(0.0018)		(0.0012)	(0.0013)	
Human Capital Intensity ×		0.00138**	0.00248***		0.000996**	0.00192***
Education Level		(0.00070)	(0.00062)		(0.00047)	(0.00042)
Human Capital Intensity ×		0.0402	0.0500*		0.00843	0.0153
Education Accumulation		(0.027)	(0.027)		(0.020)	(0.020)
Initial Conditions	-0.0139***	-0.0141***	-0.0140***	-0.00938***	-0.00974***	-0.00974***
	(0.0015)	(0.0015)	(0.0015)	(0.0011)	(0.0012)	(0.0012)
Observations	595	595	595	618	618	618
R^2	0.62	0.63	0.62	0.81	0.81	0.80

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions include country and sector fixed effects.

Table 3: Endogeneity of Employment Protection, IV Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	VAg	VAg	VAg	VAg	Hg	Hg	Hg	Hg
Human Capital Intensity ×	-0.00644**	-0.00498*	-0.00719***	-0.00626**	-0.00576***	-0.00398*	-0.00588***	-0.00535***
Employment Protection	(0.0027)	(0.0029)	(0.0026)	(0.0025)	(0.0020)	(0.0023)	(0.0020)	(0.0019)
Initial Conditions	-0.0141***	-0.0140***	-0.0141***	-0.0141***	-0.00974***	-0.00974***	-0.00974***	-0.00974***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Observations	595	595	595	595	618	618	618	618
R^2	0.30	0.30	0.30	0.30	0.23	0.23	0.23	0.24
First Stage Regressions								
Human Capital Intensity ×	0.0114***	0.0114***		0.00952***	0.0107***	0.0111***		0.00855***
Years Left Government	(0.0015)	(0.0017)		(0.0015)	(0.0015)	(0.0015)		(0.0014)
Human Capital Intensity ×	0.561***		0.498***	0.432***	0.544***		0.523***	0.445***
Dictatorship Spell	(0.041)		(0.033)	(0.039)	(0.034)		(0.029)	(0.029)
Human Capital Intensity ×		-0.639***	-0.535***	-0.358***		-0.578***	-0.507***	-0.376***
Neutral Labour Origins		(0.10)	(0.079)	(0.067)		(0.088)	(0.070)	(0.061)
Human Capital Intensity ×		-0.297***	-0.331***	-0.196***		-0.332***	-0.292***	-0.217***
Cooperative Labour Origins		(0.11)	(0.061)	(0.054)		(0.087)	(0.053)	(0.049)
Hansen J Statistic (p value)	0.2702	0.6437	0.4353	0.4738	0.1716	0.7876	0.5804	0.5367

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions include country and sector fixed effects and interactions between human capital intensity and schooling levels and accumulation.

Table 4: Different Sectoral Characteristics

	(1) VAg	(2) VAg	(3) VAg	(4) VAg	(5) VAg	(6) VAg	(7) VAg	(8) VAg
Human Capital Intensity ×	-0.00803***		-0.0170***		-0.00786***	-0.03011***	-0.00814***	-0.00795***
Employment Protection	(0.0016)		(0.0039)		(0.0016)	(0.0103)	(0.0016)	(0.0016)
Physical Capital Intensity ×	-0.000674							
Capital Output Ratio	(0.0013)							
R&D Intensity ×		-0.0448*	-0.0100					
Employment Protection		(0.023)	(0.017)					
ICT Intensity ×				-0.000402**	-0.000155			
Employment Protection				(0.00018)	(0.00015)			
Riskiness Intensity ×						-0.05008		
Employment Protection						(0.0577)		
Layoff Intensity ×							-0.0423	
Employment Protection							(0.062)	
Physical Capital Intensity ×								-0.000699
Employment Protection								(0.00081)
Initial Conditions	-0.0139***	-0.0148***	-0.0155***	-0.0136***	-0.0140***	-0.0133**	-0.0139***	-0.0139***
	(0.0015)	(0.0025)	(0.0024)	(0.0015)	(0.0015)	(0.0055)	(0.0015)	(0.0015)
Observations	595	266	266	595	595	246	595	595
R^2	0.62	0.61	0.64	0.61	0.62	0.44	0.62	0.63

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions include country and sector fixed effects.

Table 5: Different Measures of EPL and Other Labour Market Institutions

	(1) VAg	(2) VAg90_05	(3) VAg	(4) VAg	(5) VAg	(6) VAg
Human Capital Intensity × Employment Protection	-0.00408***	-0.00941***	-0.00613***	-0.00476**	-0.00633***	-0.00657**
	(0.00092)	(0.0031)	(0.0018)	(0.0019)	(0.0020)	(0.0026)
Human Capital Intensity × Education Level			0.00263**	0.000563	0.00182	0.00124
			(0.0012)	(0.0014)	(0.0012)	(0.00090)
Human Capital Intensity × Education Accumulation			0.0783**	0.0450	0.0485	0.0387
			(0.039)	(0.031)	(0.040)	(0.028)
Human Capital Intensity × Union Density			-0.00598			
			(0.0075)			
Human Capital Intensity × Strike Activity				-0.0230		
				(0.015)		
Human Capital Intensity × Tax Wedge					0.00429	
					(0.013)	
Human Capital Intensity × Wage Coordination						0.000392
						(0.0015)
Initial Conditions	-0.0139***	-0.0115***	-0.0151***	-0.0154***	-0.0153***	-0.0141***
	(0.0015)	(0.0028)	(0.0017)	(0.0016)	(0.0016)	(0.0015)
Observations	595	632	461	511	511	595
R^2	0.62	0.44	0.68	0.67	0.67	0.63

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions include country and sector fixed effects.

Table 6: Different Periods and Sectors

	(1) VAg70_90	(2) VAg90_05	(3) VAg Manufact.	(4) VAg Non Manuf.	(5) Hg70_90	(6) Hg90_05	(7) Hg Manufact.	(8) Hg Non Manuf.
Human Capital Intensity ×	-0.000177	-0.0209***	-0.0106***	-0.00448**	-0.000219	-0.0171***	-0.00491**	-0.00379***
Employment Protection	(0.0021)	(0.0052)	(0.0036)	(0.0019)	(0.0015)	(0.0049)	(0.0023)	(0.0014)
Human Capital Intensity ×	0.00338***	0.000661	0.00322**	0.000317	0.00241***	-0.00165	0.00210**	0.000468
Education Level	(0.00093)	(0.0023)	(0.0014)	(0.00067)	(0.00063)	(0.0016)	(0.00086)	(0.00050)
Human Capital Intensity ×	0.0660**	0.0289	0.135**	-0.0133	0.0445**	0.00516	0.0537	-0.0248
Education Accumulation	(0.027)	(0.056)	(0.062)	(0.027)	(0.020)	(0.033)	(0.034)	(0.026)
Initial Conditions	-0.0164***	-0.0137***	-0.0138***	-0.0153***	-0.0127***	-0.00882***	-0.00682***	-0.0144***
	(0.0017)	(0.0031)	(0.0020)	(0.0021)	(0.0014)	(0.0023)	(0.0013)	(0.0021)
Observations	513	546	310	285	535	535	323	295
R^2	0.63	0.46	0.64	0.70	0.79	0.72	0.68	0.83

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions include country and sector fixed effects.

Table 7: Distance to Frontier

	(1) VAg	(2) VAg	(3) VAg90_05	(4) Hg	(5) Hg	(6) Hg90_05
Human Capital Intensity ×	-0.0572*	-0.0447	-0.189**	-0.0172	0.00709	-0.0944*
Employment Protection	(0.034)	(0.042)	(0.077)	(0.021)	(0.026)	(0.049)
Human Capital Intensity ×	-0.0571	-0.0463	-0.244**	-0.0228	0.00234	-0.100
TFP Distance	(0.043)	(0.052)	(0.099)	(0.027)	(0.031)	(0.061)
Human Capital Intensity ×	0.0396	0.0299	0.160**	0.00763	-0.0106	0.0738*
Employment Protection ×	(0.027)	(0.033)	(0.072)	(0.017)	(0.021)	(0.045)
TFP Distance						
Human Capital Intensity ×		0.000712	0.00219		0.00113*	-0.00178
Education Level		(0.00092)	(0.0043)		(0.00061)	(0.0029)
Human Capital Intensity ×		0.0399	0.000669		0.0171	-0.0133
Education Accumulation		(0.028)	(0.061)		(0.020)	(0.035)
Initial Conditions	-0.0136***	-0.0137***	-0.0137***	-0.00987***	-0.0101***	-0.00883***
	(0.0016)	(0.0016)	(0.0032)	(0.0013)	(0.0013)	(0.0023)
Observations	548	548	546	583	583	535
R^2	0.61	0.61	0.47	0.80	0.81	0.72

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All regressions include country and sector fixed effects.