Human Capital, Employment Protection and Growth in Europe*

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Abstract

Using data for a large sample of manufacturing and service sectors in 14 EU countries, this paper shows that the value added and TFP growth rate differential between high and low human capital intensive industries is greater in countries with low than countries with high levels of employment protection legislation. We also find that such negative effect of EPL is slightly stronger for countries near the technology frontier, in the manufacturing sector 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.

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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 long/medium run quantitative effects of employment protection legislation (EPL) on growth of value added, hours of work and total factor productivity (TFP) across sectors in a set of European countries. 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 – might result, under some conditions, 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 relatively 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

[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] In particular, these conditions refer to the sources of technical change and to the assumptions on the elasticitiy of substitution among skilled and unkilled labour in the production function.

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

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 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 EPL 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 EPL might slow down or even reduce this reallocation process, as recently noted, in the contest of a trade reform, by Kambourov (2009).[6]

During a period of strong skill biased technical change, EPL, by slowing down the adoption of the new technologies, might be more harmful for productivity growth 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 EPL 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 observed in the period 1990-2000. The Figure, as in Samaniego (2006), shows that personal computers adoption rates (proxied by the log of average computer per capita) tend to be higher in countries that, in the preceding five years,

[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] Various studies find a negative relationship between productivity growth and EPL. See, among others, Scarpetta and Tressel (2004), Bassanini et al (2009), Autor et al (2007), Micco and Pages (2007) and Cingano et al. (2010, 2013). By way of contrast, theoretical papers by Poschke (2009) and Lagos (2006) suggest the possibility of a positive impact of EPL on productivity, as empirically found for a panel of OECD countries by Belot et al (2007). Moreover, see Bartelsman et al. (2010), Cuñat and Melitz (2012) and Poschke (2010) for recent papers dealing with the effect of EPL on the specialisation pattern of countries. See also Cappellari et al (2012) for a more comprehensive review of the literature on EPL and productivity, and Bertola (1994) and Hopenhayn and Rogerson (1993) for seminal papers on the aggregate effects of labour legislation on growth. Finally, Feldmann (2009) provides empirical evidence on the impact of labour regulation on unemployment.

[6] 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).

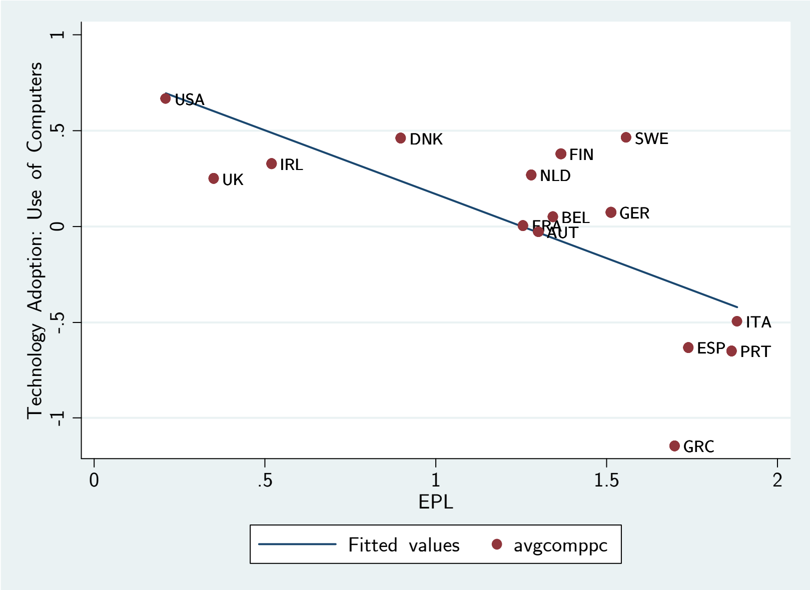

Figure 1: The Relation Between Technology Adoption and EPL

were characterised by lower degrees of EPL (see Gust and Marquez, 2004 and Pierre and Scarpetta, 2006).[7]

By simply allowing technology adoption to also depend on employment protection legislation in a framework 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.[8] 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).

[7]It should be noted that the negative and significant correlation between personal computer adoption rates and EPL reported in Figure 1 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 EPL 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).

[8]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.

In order to study the relations discussed above, in this paper we first analyse the effects 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. Moreover, because in our theoretical framework EPL affects value added growth through its effect on technical change in human capital intensive industries, we should also expect a negative relationship between EPL and the productivity growth differential between skill intensive and other industries. We therefore further extend our analysis on the growth effects of EPL by estimating various TFP growth regressions for the period 1990-2005 on a more aggregate sample of 24 sectors.

In our empirical framework 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 overcoming standard econometric problems of omitted variable bias and reverse causality through a difference-in-difference approach.

Our results clearly suggest that the growth rate differential between high and low human capital intensive industries is greater in a country with low than a country with high EPL. Our baseline estimates indicate that the value added growth rate differential, over the period 1970-2005, 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 -0.7% 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. Moreover, we also find, for the period 1990-2005, a negative relationship between EPL and the TFP growth differential between skill intensive and other industries.

We check the robustness of the main results considering various different specifications. First, we consider the possibility that EPL may have a differential impact on growth depending on the country's distance from the technological frontier. Second, we examine whether the 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, ICT, physical capital and layoff intensities (Bassanini et al., 2009) or sectoral riskiness (Bartelsman et al., 2010). Third, we include interactions between human capital intensity and country level variables potentially correlated with EPL such as union power, wage bargaining coordination, unemployment benefits, minimum wages, and the level of product market regulations. Fourth, we also consider different indicators of EPL. Fifth, we consider the potential endogeneity of EPL by instrumenting it with political economy variables. 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). We conclude that our robustness checks confirm the baseline results.

Our paper contributes to previous work in different 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. Second, 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. Third, by using a long period of time, we are able to capture long run effects of labour market regulation, whereas previous papers focused on short run dynamics mostly considering only the manufacturing sector during the 90s.

The rest of the paper is organised as follows. In Section 2 we present the identification and estimation framework. Section 3 describes the data, while results are discussed in Section 4. We conclude in Section 5.

2 Estimation and Identification

Our empirical framework is similar to that of Ciccone and Papaioannou (2009) and is based on the difference-in-difference 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:

$$\Delta \ln y_{s,c,1970-05} = \alpha(HCINT_{s,1970} * EPL_{c,1970-00}) + \gamma W_s^{'} Z_c + \delta \ln y_{s,c,1970} + v_s + u_c + \varepsilon_{s,c} \quad (1)$$

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; $HCINT_s$ is the human capital intensity of each industry at the beginning of the period in 1970; EPL_c is the country average degree of employment protection over the period 1970-2000.[9] $W_s^{'}$ are sector level variables (e.g., R&D and physical capital intensity); Z_c are country level variables; $\ln y_{s,c}$ is the log of the dependent variable at the beginning of the period; while v_s, u_c and $\varepsilon_{s,c}$ are sector and country specific fixed effects and a conventional error term, respectively. 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.

For further analysis we have also run regressions similar to that estimated in equation (1) for the period 1990-2005 using as dependent variable the average rate of growth of value added, hours of work and TFP. In this case, $HCINT_s$ – as well as all other sector level variables – is calculated for the year 1990; all other country level variables are calculated accordingly: we refer to the data section and the Appendix for further details.

In this framework, a negative sign for the interaction coefficient α would imply that the growth rate differential between high and low human capital intensive industries is greater in a country with low than a country with high EPL.[10] The identifying assumption behind equation (1) is that EPL

[9] As we explain in the Data section, our main indicator for EPL is available only for the period 1970-2000.

[10] Note that the interaction term can be also interpreted in terms of marginal effects of EPL. In particular $\alpha < 0$ means that a marginal effect of EPL on growth is more negative in industries with higher levels of human capital intensity. See Bassanini and Garnero (2013) for an extensive discussion of the identification strategy for difference-in-difference models à la Rajan and Zingales (1998).

is likely to be more binding in more skill intensive sectors. 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 sector human capital intensity in 1970 or the country capital-output ratio and the sectoral physical capital intensity in 1970. In particular, all regression specifications include the interaction between human capital intensity and both the level of schooling at the beginning of the period and its accumulation over the sample period. 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.

The inclusion of $W_s' Z_c$ is important because it has long been recognised in international trade theory that countries with an abundant factor tend to specialise in industries that use intensively that factor (for a recent discussion on the empirical evidence on this issues, see 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 $HCINT_s$ and country level variables such as other labour market institutions and proxies for product market regulation.

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. Besides, we check that our main results are not sensitive to the benchmarking bias highlighted by Ciccone and Papaioannou (2010). Finally, we also run a weighted least square regression in order to take into account the possibility that sectoral data might suffer from measurement error, which is likely to be inversely correlated with the size of the sector.

3 Data

3.1 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 difference-in-difference 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. 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 basic sample is based on 595 (618) observations in the case of value added (hours) growth regressions. In Table 1 we report main summary statistics for industries at the top and bottom quartile of the human capital intensity distribution.

Data for total factor productivity (TFP) growth are from the 2009 release of the EUKLEMS database. It is important to note that in this case the EUKLEMS data are based on an higher level of aggregation: in particular the 51 sectors we consider for the value added and hours of work regressions are aggregated into 24 (manufacturing and non manufacturing) sectors. What is more, such database does not provide information on TFP growth for Greece and Portugal. Moreover, in order to maximise the number of countries in our sample we have restricted this analysis to the period

Table 1: Descriptive Statistics, Growth of Value Added and Hours of Work, and Human Capital Intensity

Sector (ISIC REV 3.1 Classif.)	Value Added Growth 70-05	Hours of Work Growth 70-05	Human Capital Intensity 1970	Value Added Growth 90-05	Hours of Work Growth 90-05	Human Capital Intensity 1990
Research and development	0.0394	0.0339	14.4197	0.0356	0.0358	14.0458
Computer and related activities	0.0725	0.0617	14.3614	0.0851	0.0715	14.6784
Activities related to finance	0.0380	0.0383	14.1775	0.0599	0.0340	14.6519
Other business activities	0.0389	0.0405	13.6339	0.0306	0.0400	13.9614
Office, accounting, computing	0.0651	-0.0066	13.4828	0.0569	-0.0241	14.2324
Insurance and pension funding	0.0274	0.0133	13.4812	0.0137	0.0046	14.2004
Coke, refined petroleum and...	0.0135	-0.0154	13.1708	0.0054	-0.0255	13.6373
Financial intermediation	0.0436	0.0147	13.0936	0.0349	-0.0007	13.9574
Other air transport	0.0250	0.0025	13.0511	0.0208	-0.0081	14.0544
Forestry	0.0058	-0.0232	13.0160	-0.0005	-0.0220	13.8460
Chemicals and chemical prod.	0.0451	-0.0075	12.9635	0.0320	-0.0116	13.5474
Extraction of crude petroleum	-0.0257	0.0041	12.8607	0.0035	-0.0201	13.4545
Other transport equipment	0.0144	-0.0151	12.8481	0.0042	-0.0197	13.8804
...	...	...	...	...	...	...
Tobacco	-0.0000	-0.0371	11.2078	-0.0112	-0.0493	13.1967
Other Inland transport	0.0248	0.0016	11.1633	0.0145	0.0019	12.6544
Hotels and Restaurants	0.0156	0.0127	11.0701	0.0126	0.0155	12.5365
Other mining and quarrying	0.0115	-0.0159	10.8800	-0.0038	-0.0172	12.3700
Renting of machinery and equip.	0.0488	0.0374	10.7804	0.0526	0.0247	12.4203
Wood and cork	0.0220	-0.0098	10.6958	0.0178	-0.0085	12.2475
Fishing	0.0010	-0.0210	10.6882	0.0027	-0.0224	12.8330
Agriculture	0.0166	-0.0300	10.6672	0.0071	-0.0287	12.4122
Wearing, apparel, dressing	-0.0225	-0.0532	10.5816	-0.0436	-0.0777	12.0089
Leather and footwear	-0.0197	-0.0451	10.5209	-0.0453	-0.0616	12.0488
Textiles	-0.0115	-0.0390	10.5165	-0.0236	-0.0475	12.1075
Recycling	0.0510	0.0029	10.5165	0.1112	-0.0013	12.0089
Mining of coal and lignite;	-0.0028	-0.0618	10.0537	-0.0581	-0.1187	12.4269
Total (51 sectors)	0.0264	-0.0029	12.0038	0.0211	-0.0073	13.1779

Notes: We report summary statistics for industries at the top 75th and bottom 25th percentiles of the human capital intensity distribution in 1970. Value Added (Hours of Work) Growth is the average growth rate of value added (hours of work) over the period in each sector in each country. Human capital intensity 1970 at sectoral level is calculated imputing 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 to 3 years), 17 (College 4+). 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. Human capital intensity in 1990 is calculated accordingly. See Data section for further details.

Table 2: Descriptive Statistics, TFP Growth and Human Capital Intensity

Sector	Growth of Total Factor Productivity 90-05	Human Capital Intensity 1990
Chemicals and chemical	0.0185	13.5500
Coke, refined petroleum and nuclear fuel	-0.0023	13.6400
Real estate activities	-0.0036	13.9100
Renting of meq and other business activities	-0.0141	13.7700
Rubber and plastics	0.0160	12.7200
Basic metal and fabricated metal	0.0080	12.7500
Electrical and optical equipment	0.0484	13.5700
Financial intermediation	0.0130	14.0300
Food, beverages and tobacco	0.0027	12.6900
Machinery, nec	0.0114	12.9400
Manufacturing nec; recycling	0.0035	12.4400
Other non-metallic mineral	0.0133	12.7000
Post and telecommunications	0.0386	13.7200
Pulp, paper, printing and publishing	0.0052	13.3700
Sale, maintenance and repair of motor vehicles	0.0035	13.1467
Textiles, leather and footwear	0.0102	12.0400
Transport and storage	0.0063	13.0400
Transport equipment	0.0178	13.5300
Wood and of wood and cork	0.0154	12.2500
Agriculture, hunting, forestry and fishing	0.0252	12.5300
Construction	-0.0037	12.7300
Electricity, gas and water supply	0.0148	13.5600
Hotels and restaurants	-0.0088	12.5400
Mining and quarrying	0.0013	13.1900
Total (24 sectors)	0.0100	13.0982

Notes: TFP growth is the average growth rate of total factor productivity over the period in each sector in each country. See the Data section in the paper for more details for TFP calculation. Human capital intensity in 1990 is obtained using the sectoral distribution reported in Table 1 and aggregating sectors accordingly. See Table 1 and the Data section for more details.

1990-2005. In turn, information on industry levels of TFP are obtained from the GGDC productivity database (Inklaar and Timmer, 2008) which provides information for the benchmark year 1997. In order to derive the TFP level in 1990 we use the relevant TFP growth rate over the period 1990-97.[11] We end up with 24 sectors and 12 countries for a total of 288 observations; we report main summary statistics in Table 2.

[11] In other words we use the following formula $TFP_{90} = TFP_{97}/(1 + gTFP_{90-97})$.

3.2 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 to 3 years), 17 (College 4+). 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. As the IPUMS database uses a different industry classification from the one in the EUKLEMS data, we recode sectors according to our definition. Using the same source of data for the year 1990, we also calculate our measure of skill intensity used in the 1990-2005 analysis. We refer to the Data Appendix for further details regarding additional industry level control variables.[12]

3.3 Country Level

The indicator of EPL at the country level is taken from Checchi and Lucifora (2002) who used the one by Nickell et al (2005). Data are five years averages 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 Checchi and Lucifora (2002).[13]

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

[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. 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. Moreover the correlation between our measure of human capital intensity in 1970 and 1990 is equal to 0.94.

[13] Main results are robust to dropping Greece and Portugal.

employment protection for regular and temporary contracts, and we construct an average measure for the period 1985-2005.[14] 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. Finally, we consider an indicator of EPL for regular workers obtained as the weighted average of the indexes for individuals and collective dismissals in the spirit of Bassanini and Garnero (2013), available from 1998 onwards. 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.[15] We refer to the Appendix for further details regarding other country level control variables.

4 Results

4.1 Baseline Regressions

In Table 3, we start with a parsimonious specification of equation (1), as we only control for country and sector fixed effects, for initial differences in the size of sectors and for the interactions between human capital intensity and both the years of schooling at the country level at the beginning of the period and the country level increase in average years of schooling over the sample period. The inclusion of education interaction terms is important because, 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 foster the adoption of new technologies. However, if employment protection legislation were lower in countries with more years of schooling,

[14] 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.

[15] For the regressions that we run over the period 1990-2005, we always define the value accordingly, unless otherwise stated.

then the interaction term between EPL and human capital intensity might be downward biased if we do not control for country level education.

In columns 1 and 2 we analyse the differential impact of EPL between high and low human capital intensive industries on the average growth rate of value added (VAg) and total hours worked (Hg) over the period 1970-2005. The coefficient of the interaction between the average level of EPL over the period 1970-2000 and human capital intensity is negative and statistically significant at the 1% level in both columns. In the case of value added growth, the coefficient of -0.00618 implies a yearly growth differential of -0.69% between the sector at the 75^{th}percentile (*production of other transport equipment* with human capital intensity equal to 12.85) and at the 25^{th} percentile (*tobacco* with human capital intensity equal to 11.21) of human capital intensity distribution in a country at the 75^{th} percentile of EPL (such as Greece, with an average of 1.797) compared with a country at the 25^{th} percentile of EPL (such as Austria, with an average of 1.119 over the period).[16] This is not a trivial effect given that the sample average growth differential between these two sectors is equal to 2.4%.[17] If we measure industry growth using data on total hours worked, we find a slightly smaller effect, namely -0.00507, which implies a growth differential of about -0.57% between the sector at the 75^{th} and the 25^{th} percentile of schooling intensity in a country at the 75^{th} percentile of EPL compared to a country at the 25^{th} percentile of EPL.

For robustness checks to possible outliers and influential observations we also run the specifications in columns 1 and 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 those reported in Table 3.

[16] In order to ease the interpretation of the results, we can define the differential in growth rate with the following formula: $GD = \alpha * (HCINT_{75} - HCINT_{25}) * (EPL_{75} - EPL_{25})$, where GD indicates the differential in growth rate and subscripts 75 and 25 denote percentiles of human capital intensity and EPL distributions.

[17] If we drop the education interaction terms we obtain a coefficient (t statistic) of -0.00805 (-5.03) which implies a slightly higher growth differential. Conversely, if we drop the interaction between EPL and human capital intensity we find, for the value added growth regression, that both the level and the accumulation interactions are positively and statistically significant, with an order of magnitude that is very similar to that implied by the estimates reported in Ciccone and Papaioannou (2009) and notably higher than those reported in column 1. This finding suggests the existence of an upward bias in the education interaction coefficients associated to the omission of the EPL-schooling intensity interaction.

Table 3: Baseline Model

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	VAg	Hg	VAg	Hg	LPg	TFPg
Time Period	70-05	70-05	90-05	90-05	90-05	90-05
Human Capital Intensity ×	-0.00618***	-0.00507***	-0.0179***	-0.0155***	-0.00103	-0.0158**
Employment Protection	(0.00182)	(0.00133)	(0.00529)	(0.00469)	(0.00532)	(0.00672)
Human Capital Intensity ×	0.00138**	0.000996**	-0.000110	-0.00149	0.00162	-0.00223
Education Level	(0.000699)	(0.000473)	(0.00172)	(0.00140)	(0.00171)	(0.00260)
Human Capital Intensity ×	0.0402	0.00843	0.0140	0.00607	-0.0188	0.112
Education Accumulation	(0.0271)	(0.0202)	(0.0528)	(0.0344)	(0.0507)	(0.0813)
Initial Conditions	-0.0141***	-0.00974***	-0.0117***	-0.00747***	-1.07e-05	-0.0147**
	(0.00151)	(0.00117)	(0.00282)	(0.00196)	(6.94e-06)	(0.00632)
Observations	595	618	632	622	612	288
R^2	0.627	0.808	0.442	0.678	0.300	0.380
Differential in Growth Rate	-0.69	-0.57	-1.02	-0.88	-0.06	-0.69

Notes: All regressions include country and sector fixed effects. All variables are calculated for the corresponding period. VAg, Hg, LPg and TFPg are average growth rates of value added, hours of work, labour and total factor productivity over the period. Human capital intensity at sectoral level is calculated as described in Table 1. Employment protection is the average level of EPL over the period from Checchi and Lucifora (2002). Education level is the average years of schooling (population more than 25 years) at the country level at the beginning of the period from Barro and Lee (2001). Education accumulation is the average growth rate of average years of schooling over the period. Initial conditions is the ln of value added, hours of work, labour and total factor productivity at the beginning of the period. Differential in growth rate measures (in percentage terms) the differential between a sector at the 75th percentile of the human capital intensity distribution with respect to a sector at the 25th percentile level when it is located in a country at the 75th percentile of EPL distribution with respect to a country at the 25th percentile. Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In columns 3 and 4, we run our baseline regression for the 1990-2005 period. We do this for two separate reasons. The first reflects concerns for possible problems of measurement errors in the EUKLEMS data for some countries, in particular during the period 1970-1990. The second is related to the existence of empirical evidence 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 (Caselli and Coleman, 2002). 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 EPL should have been more binding in human capital intensive industries precisely over the period 1990-2005, with respect to the previous two decades.[18] As we can see from columns 3 and 4 of Table 3, both the value added and hours regressions suggest that the interaction between EPL and schooling intensity has a larger negative effect in the more recent period, with an implied growth rate differential between high and low human capital intensive industries of 1.02% and 0.88% for the value added and hours regressions, respectively. Moreover, when running our baseline regressions (not reported in Table 3, but available upon request) for the period 1980-2005, we still find a negative and statistically significant interaction effect with an implied growth rate differential of 0.71% and 0.58% for the value added and hours equations. Such pattern is consistent with the previous hypothesis of an increasing importance of EPL in more recent decades. In fact, if we run similar regressions for the subperiods 1970-80 and 1980-90 we find that the interaction between human capital intensity and EPL is negative in both periods and larger in magnitude in the second one, although we can not reject the null hypothesis that they are both equal to zero.

Our theoretical framework, as well as our empirical findings, suggest that EPL tends to depress

[18] However, it is important to acknowledge that, as new technologies are fully implemented, firms may substitute highly educated workers with lower educated ones (Chun, 2003; O'Mahony et al., 2008). If this effect prevails, we should expect to find a smaller effect of EPL in the most recent period.

value added growth particularly in high human capital intensive industries. However, because EPL affects value added growth through its effect on technical change in human capital intensive industries, one should also expect that during the transition to the new steady state, the TFP growth differential between high and low human capital industries is greater in a country with low than a country with high EPL.[19] In turn, as discussed by Autor et al. (2007) in their study on the effects of the adoption of wrongful-discharge protection by state courts in the US, the effect on labour productivity growth is not *a priori* clear. In fact, as long as EPL increases adjustment costs of employment, firms might react by substituting physical capital for labour, thus increasing the capital/labour ratio. If this increase is sufficiently large to offset the countervailing opposite effect associated with retaining unproductive workers, labour productivity might even increase following a tightening in EPL. In turn, one should expect that the increase in the capital/labour ratio, by distorting the optimal production techniques, causes a fall in TFP, *ceteris paribus*.[20]

In the last two columns of Table 3 we shed some light on these issues by examining the impact of EPL on productivity for the period 1990-2005. As far as labour productivity growth is concerned, results in column 5 suggest that the interaction term between EPL and human capital intensity is negative albeit statistically insignificant; by way of contrast, evidence in column 6 indicates that higher EPL tends to reduce TFP growth relatively more in high skill industries.[21] This result is in line with the one found by Autor et al. (2007) in the manufacturing sector in the US: in particular, they find that while firing costs had a negative impact on TFP, they also led to an increase in the capital/labour ratio and consequently in labour productivity.[22]

[19] For a discussion of the transition to the steady state in a model of human capital, technology adoption and skill biased technological change see Ciccone and Papaioannou (2009). See also the working paper version of our study for an extension of their model with EPL as another determinant of technology adoption.

[20] Janiak and Wasmer (2014) review the literature on employment protection and capital labour ratios and present a search and matching model that yields, in the presence of complementarity between physical capital and firm specific human capital, an inverted U-shape pattern for the effects of EPL on the capital-labour ratio. Moreover, Cingano et al (2013) find, for the Italian case, that a reform that increased EPL for small firms only led to capital deepening and to a fall in total factor productivity in small firms after the reform.

[21] We recall that, due to data constraints in the EUKLEMS database, the TFP growth regressions have been run on a sample of 24 (more aggregated) industries and without Portugal and Greece.

[22] Some merely anecdotal empirical evidence consistent with this mechanism can be found by analysing the rate of growth of capital per worker over the period 1990-2005 from the most recent release of the EUKLEMS database for countries characterised by different levels of EPL, such as Italy (which is the country with the strictest levels of EPL for

A comparison of differentials in growth rates reported at the bottom of Table 3 suggests that EPL has a relatively stronger impact in the case of value added and hours of work with respect to TFP. However, the effect of EPL on technology adoption should be mostly captured by a relatively lower TFP growth in human capital intensive industries, while the impact on value added and hours could be an indirect one. In fact, following the literature on structural transformation, one could argue that the relative impact on TFP and employment also depends on the interaction at work across sectors. In particular, Ngai and Pissarides (2007) show that, in a closed economy setting, faster TFP growth in a sector leads that sector to shrink in terms of employment. The fact that, in our case, the negative effect of EPL is stronger in the case of value added and hours of work might suggest the relevance of an open economy setting and the possibility that EPL affects the specialization pattern of countries (Saint Paul 1997, 2002b; Cuñat and Melitz, 2012).

4.2 Distance to Frontier

In this subsection we check whether the impact of EPL changes with a country's distance from the technological frontier, and whether there are important differences between manufacturing and non manufacturing industries. In particular, in Table 4 we allow the interaction between schooling intensity and EPL to vary with the country's distance from the technological frontier.[23] 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 than from innovations at the margin or simply from imitation and adoption of existing technologies (Saint Paul, 2002b).[24]

In the first column we run a baseline version of equation (1) for the period 1990-05 with our

which capital stock data are available) and the UK (the country with the most flexible labour market). In particular, we have derived the rate of growth of total fixed capital per worker in the three industries with the lowest (textiles, manufacturing nec and wood) and the highest skill levels (post and telecom, pulp and financial intermediation). We found that the average yearly rate of growth differential of the capital-labour ratio between the UK (low EPL) and Italy (high EPL) was about 2 percentage points in the low skilled sectors and 1.4 percentage points in the high skill ones.

[23] Vandenbussche et al. (2006) found that the effect of skilled labour has a larger positive effect on growth closer to the technological frontier.

[24] Van Schaick and van de Klundert (2013) report empirical evidence for a panel of 23 OECD countries observed over the period 1960-2005 and show that EPL had a positive effect on labour productivity growth in the sixties and seventies but a negative one in subsequent decades.

Table 4: Distance to Frontier and Sectoral Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	VAg	TFPg	VAg Manuf.	VAg Non Manuf.	VAg Manuf.	VAg Non Manuf.	TFPg Manuf.	TFPg Non Manuf.
Time Period	90-05	90-05	70-05	70-05	90-05	90-05	90-05	90-05
Human Capital Intensity ×	-0.0218***	-0.0188***	-0.0106***	-0.00448**	-0.0266***	-0.0110	-0.0219*	-0.00987
Employment Protection	(0.00535)	(0.00697)	(0.00361)	(0.00188)	(0.00989)	(0.00719)	(0.0124)	(0.00786)
Human Capital Intensity ×	0.000438*	0.000335**						
Employment Protection ×	(0.000272)	(0.000168)						
TFP Distance								
Human Capital Intensity ×	-0.000487	-2.39e-05						
TFP Distance	(0.000325)	(0.000200)						
Human Capital Intensity ×	0.000966	-0.00123	0.00322**	0.000317	0.00310	-0.00246	0.000209	-0.00257
Education Level	(0.00233)	(0.00246)	(0.00144)	(0.000674)	(0.00375)	(0.00204)	(0.00546)	(0.00213)
Human Capital Intensity ×	0.0294	0.0784	0.135**	-0.0133	0.125	0.00562	0.319**	-0.0281
Education Accumulation	(0.0557)	(0.0818)	(0.0615)	(0.0268)	(0.141)	(0.0513)	(0.145)	(0.0511)
Initial Conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	546	288	310	285	331	301	180	108
R^2	0.476	0.494	0.638	0.699	0.452	0.466	0.389	0.658

Notes: All regressions include country and sector fixed effects. All variables are calculated for the correspoding period. VAg, TFPg, human capital intensity, employment protection, education level, education accumulation, initial conditions are calculated as in Table 3. Manuf and Non Manuf are manufacturing and non manufacturing sectors, respectively. Human capital intensity × TFP distance in columns (1) and (2) is the interaction of human capital intensity with distance calculated as TFP_{Fsc}/TFP_{sc}, where TFP_{Fsc} is the TFP of the leader country c in sector s in our sample. The triple interaction also includes EPL. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

usual controls plus a triple interaction between schooling intensity, EPL and the distance from the technological frontier of each country-industry observation: a positive coefficient for such interaction term would indicate that the negative effect of EPL gets smaller in the case of observations that are far from the technological frontier.[25] 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 results confirm that EPL tends to disproportionately reduce growth in high schooling industries and that this effect is slightly stronger in the case of country-industry pairs that are closer to the technological frontier. In order to facilitate comparisons with results displayed in Table 3, let us consider the 10th and the 90th percentile of TFP Distance: in the case of the "efficient country-industry", the coefficients of the double and triple interactions imply an yearly growth differential of about 1.2% between the sectors at the 75th percentile and at the 25th percentile of human capital intensity in a country at the 75th percentile of EPL compared with a country at the 25th percentile of EPL; in turn, this growth differential falls to less than 1.1% in the case of country-industry pairs that are farther from the technological frontier. In column 2 we report a similar regression for TFP growth during the period 1990-2005. Empirical estimates confirm the results for value added growth: in particular, the negative growth differential is about 0.8% in the case of country-industries near the technological frontier, but it falls to about 0.6% for country-industries that are far from the technological frontier. These results therefore suggest that the growth differential between high and low human capital intensive industries is greater in a country with high than a country with low EPL and that this effect is slightly more relevant in the case of country-industry observations that are closer to the technological frontier.[26]

[25] The distance from the frontier is built as TFP_{Fsc}/TFP_{sc} , where TFP_{Fsc} is the TFP of the leader country c in sector s in our sample: therefore, an increase in the frontier term means that a country lags further behind the technological frontier. It is important to note that, in the case of the value added regression, we have information on TFP levels at a higher level of aggregation and therefore, for most sectors, the distance from the frontier term reflects this lack of information. For instance, while we have separate information on value added growth for the sectors "food and beverage" and "tobacco", the distance from the frontier is available only for the aggregate sector "food, beverages and tobacco".

[26] Because industry TFP levels might be badly measured, we have also estimated regressions where the distance from the frontier is defined at the country and not at the industry level; in particular, we have assumed as TFP leader the US. The drawback of this approach is that it implicitly assumes each industry within a country to be characterised by

In the other columns of Table 4 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 regressions. Results consistently show that the effect of EPL is stronger in the case of manufacturing industries, both in the case of value added and TFP growth regressions, confirming the existence of some heterogeneity across groups of industries.[27]

4.3 Other Estimation Methods

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).

In order to address this issue, we use different instruments for EPL. 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 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

the same distance from the frontier; moreover, a large body of empirical studies has shown that the US are not the industry leader in all industries. Our empirical estimates (available upon request) confirm that the negative impact of EPL in skill intensive industries gets larger as the country approaches the frontier, with a magnitude that is even stronger than that reported in the text.

[27] In the 1990-05 period the interaction between sectoral human capital intensity and the country level of EPL is poorly estimated in the case of the non-manufacturing regressions, particularly in the case of TFP growth, where the number of observations is however really low. Note also that, in the case of TFP regressions, the larger coefficient for manufacturing does not necessarily imply a larger relative effect, as the TFP growth rates were larger in manufacturing.

against unfair dismissals due to their paternalistic views of labour relations.

In columns 1 to 4 of Table 5 we report IV regressions for value added and hours of work both for the 1970-2005 and the more recent 1990-2005 period. First stage results, reported in the bottom part of the Table, suggest that excluded instruments are significant and with the expected sign. 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 rk Wald F statistics do not suggest weak instruments problems.[28] Second stage results suggest that the human capital intensity-EPL interaction is always negative and statistically significant with a magnitude which is slightly larger than that reported in Table 3 for the OLS case. However, although the importance of left-wing governments as an instrument for EPL has been previously used in the literature (Bassanini et al, 2009; Fiori et al, 2012), it may be argued that not only may left-wing governments adopt more stringent EPL, but that they may also implement other policies that relatively favor the growth of low skill industries. For this reason, we have also run IV regressions without the percentage of years of left-wing governments over the sample period. Empirical results, reported in Table A1, confirm those reported in Table 5, with somewhat larger effects and no indication of a weak instrument problem, as suggested by Kleibergen-Paap rk Wald F statistics, similar to those reported in Table 5.[29] This whole set of results is also confirmed in the case of TFP growth regressions.

In the EUKLEMS data, some industries account for a very low share of total value added, with possibly badly measured variables; moreover the level of aggregation of industry data is somewhat arbitrary as large industries are aggregates of smaller ones. However, in OLS regressions small industries receive equal weight as larger ones, resulting in possible bias in regression coefficients. For

[28] We have also rejected the null of underidentification using the Kleibergen-Paap rk LM statistics. Results are available from the authors upon request.

[29] Moreover, using a taxonomy recently proposed as an instrument for the quality of today's labour relations by Mueller and Philippon (2011), we have also run regressions including in our set of instruments dummies that proxy the attitude taken by governments towards the development of labour unions in the early 20^{th} century. The justification for using these dummies as instruments for EPL is that countries with more conflicting labour unions might have pushed in the past for legislations aimed to protect workers against unfair dismissals (see Data Appendix for further details). Finally 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.

Table 5: Endogeneity of Employment Protection, IV and WLS Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	VAg	Hg	VAg	Hg	TFPg	VAg	VAg
Time Period	70-05	70-05	90-05	90-05	90-05	70-05	70-05
Human Capital Intensity ×	-0.00643**	-0.00572***	-0.0324**	-0.0150	-0.0369**	-0.00459**	-0.0194***
Employment Protection	(0.00266)	(0.00201)	(0.0161)	(0.00977)	(0.0179)	(0.00199)	(0.00328)
Human Capital Intensity ×	0.00133*	0.000884*	-0.00267	-0.00147	-0.00554	0.000911	–
Education Level	(0.000755)	(0.000518)	(0.00322)	(0.00199)	(0.00396)	(0.000705)	
Human Capital Intensity ×	0.0387	0.0111	0.0526	0.00557	0.186*	-0.0441	–
Education Accumulation	(0.0257)	(0.0189)	(0.0727)	(0.0420)	(0.0985)	(0.0300)	
Initial Conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	595	618	632	622	288	595	595
R^2	0.302	0.807	0.437	0.678	0.363	0.862	0.591
First Stage Results (Only excluded instruments are reported)							
Human Capital Intensity ×	0.0114***	0.0107***	0.00245***	0.00354***	0.00320**	–	–
Years Left Government	(0.00106)	(0.000997)	(0.000889)	(0.000888)	(0.00147)		
Human Capital Intensity ×	0.561***	0.544***	0.398***	0.371***	0.378***	–	–
Dictatorship Spell	(0.0374)	(0.0388)	(0.0345)	(0.0381)	(0.0481)		
Predicted H C Intensity ×							19.6062***
Employment Protection							(1.5793)
Hansen J Statistic (p value)	0.2702	0.1716	0.2665	0.723	0.495	–	–
Kleibergen-Paap rk Wald F	193.7	223.8	92.5	81.7	31.0	–	154.1

Notes: All regressions include country and sector fixed effects. First stage also includes interactions of human capital intensity with education level, human capital intensity with education accumulation, initial conditions and country and sector fixed effects. VAg, Hg, TFPg, human capital intensity, EPL, education level, education accumulation, initial conditions are calculated as in Table 3. Years of left government is the percentage of years of left-wing governments over the sample period. Dictatorship spell is a dummy equal to one for those countries that experienced a dictatorship spell before 1970 and zero otherwise. See Data Appendix for more details. Regression in column (6) uses a weighted least squares method that uses sectoral value added at the beginning of the period as weights. Regression in column (7) is an IV regression that controls for benchmarking bias: see section 4.3 in the paper for further details. Regressions in cols (1) to (5) have been estimated with the two-step efficient GMM estimator automated in the Ivreg2 routine in Stata. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

this reason, in column 6 we report a WLS regression weighting observations according to sectoral value added in 1970. Results show a slight reduction in the size of the interaction coefficient, which is however still significant at 5% level.

A potential criticism to using US industry data as a proxy for industry human capital intensity is that the latter might generate non-negligible bias for the human capital intensity-EPL interaction term, whose direction is not even *a priori* clear. In order to check the robustness of our result we therefore employ the IV estimator recently suggested by Ciccone and Papaioannou (2010). They propose to instrument $HCINT_s \times EPL_c$ in equation (1) above with a two-step procedure: first, we obtain predicted industries slopes $\widehat{\gamma}_s$ of EPL by estimating with OLS for all countries but the US the following equation:

$$\Delta \ln y_{s,c,1970-05} = v_s + u_c + \gamma_s EPL_{c,1970-00} + \varsigma_{s,c}. \quad (2)$$

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: $\widehat{HCINT}_{s,1970} = \widehat{v}_s + \widehat{\gamma}_s EPL_{US,1970-00}$, where $EPL_{US,1970-00}$ is the value of our EPL indicator for the US. We then use $\widehat{HCINT}_{s,1970} \times EPL_c$ as an instrument for $HCINT_s \times EPL_c$ in a standard two-stage least squares procedure. Regression results, reported in column 7 for the value added regression indicate that the human capital intensity-EPL interaction is negative and statistically significant, with a magnitude larger than in the OLS case, suggesting the existence of attenuation bias in the OLS estimates.[30]

4.4 Robustness

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 $W_s^{'} Z_c$

[30] Both the Kleibergen-Paap LM and F statistics do not suggest problems of underidentifcation or weak instrument problems.

in equation (1). Moreover, because human capital intensity is quite different from other sector-level intensity measures that have been previously used in the literature in order 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.

First, as in Ciccone and Papaioannou (2009), in column 1 of Table 6 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.[31] In column 2, we add an interaction of R&D intensity with our measure of EPL, because R&D could be considered as an alternative proxy for the sectoral propensity to technology adoption and/or innovation. As expected, more R&D intensive sectors grow less in countries with higher level of EPL, although the coefficient is not statistically significant; more importantly, the negative effect of the interaction of EPL with human capital intensity stands out.[32] This result may suggest that EPL slows down growth by affecting the adoption of technology rather than the production of innovation, as proxied by R&D intensity. 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 3 are very similar to those found in the case of R&D.

Moreover, in column 4 we consider the role of physical capital intensity interacted with EPL: again, including this control doesn't affect our result. In the remaining columns 5 to 8, we run similar selected regressions for the period 1990-2005, and we consistently find a negative interaction between skill intensity and EPL. In particular, in column 7 we interact EPL with a sectoral measure of

[31] 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 6.

[32] Note that data availability allows us to consider R&D intensity only in the manufacturing sectors.

Table 6: Different Sectoral Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	VAg	VAg	VAg	VAg	VAg	VAg	VAg	VAg
Time Period	70-05	70-05	70-05	70-05	90-05	90-05	90-05	90-05
Human Capital Intensity ×	-0.00616***	-0.0133***	-0.00599***	-0.00607***	-0.0325***	-0.0179***	-0.0182***	-0.0350***
Employment Protection	(0.00181)	(0.00414)	(0.00184)	(0.00178)	(0.0112)	(0.00529)	(0.00535)	(0.01158)
Physical Capital Intensity ×	-0.000687							
Capital Output Ratio	(0.00128)							
R&D Intensity ×		-0.00919			-0.0141			
Employment Protection		(0.0164)			(0.0160)			
ICT Intensity ×			-0.000155					
Employment Protection			(0.000153)					
Physical Capital Intensity ×				-0.000707		-0.000285		
Employment Protection				(0.000805)		(0.00156)		
Layoff Intensity ×							-0.0502	
Employment Protection							(0.108)	
Riskiness Intensity ×								-0.1036
Employment Protection								(0.1847)
Human Capital Intensity ×	0.00139**	0.00331**	0.00138**	0.00139**	0.00202	-0.000118	-0.000146	0.0016
Education Level	(0.000702)	(0.00166)	(0.000698)	(0.000694)	(0.00421)	(0.00172)	(0.00172)	(0.0042)
Human Capital Intensity ×	0.0404	0.157**	0.0402	0.0402	0.171	0.0140	0.0140	0.1753
Education Accumulation	(0.0272)	(0.0753)	(0.0271)	(0.0271)	(0.160)	(0.0529)	(0.0529)	(0.1578)
Initial Conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	595	266	595	595	289	632	632	303
R^2	0.628	0.648	0.628	0.628	0.421	0.442	0.442	0.469

Notes: All regressions include country and sector fixed effects. All variables are calculated for the correspoding period. VAg, human capital intensity, employment protection, education level, education accumulation, initial conditions are calculated as in Table 3. Physical capital intensity is the ratio between sectoral real gross capital stock and value added in the US at the beginning of the period. See Data Appendix for calculation of the capital output ratio. RD intensity is RD sectoral expenditure over value added in US at the beginning period. ICT intensity is the share of ICT expenditure in total investment outlays. Layoff intensity is the sectoral fraction of workers that had been displaced. Riskiness intensity is the standard deviation of the distribution of output growth across firms in the US. See Data Appendix for further details. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

layoff intensity (as in Bassanini et al, 2009) considering the negative effects of EPL on the reallocation of workers, and our results for the interaction between EPL and skill intensity are confirmed. Finally, we follow Bartelsman et al. (2010), who 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 output within each US industry. Hence, in column 8, we add an interaction term between our measure of sector riskiness and EPL: in particular, we use the standard deviation of the distribution of output growth across firms in the US (only available for the manufacturing sector). 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.[33]

We conduct additional robustness analysis in Table 7. 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, available from 1985 onwards, while the second, available only from 1998 onwards, is a weighted sum of sub-indicators for regular contracts, temporary contracts and collective dismissals.[34] 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 both columns are 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. Then, in column 3 we follow Bassanini and Garnero (2013) considering an indicator of EPL for regular workers obtained as a weighted average of the indexes for individual and collective dismissals. In fact, it may be argued that in skill intensive industries

[33] In regressions not reported, but available from the authors upon request, we use a different measure of sectorial risk, based on the volatility of TFP in manufacturing industries, as recently proposed by Castro et al (2013). The interaction between EPL and human capital intensity for the 1990-2005 period is still negative and statistically significant, while the interaction between riskiness and EPL is negative and marginally significant (p-value equals 0.102).

[34] Because this indicator is available from 1998, we run the regression only for the period 1990-2005.

what really matters is EPL for regular workers.[35] Empirical estimates suggest that EPL for regular workers tend to reduce value added growth particularly in skill intensive sectors.

In columns 4 to 7 we consider whether EPL is simply picking up the effect of other labour market institutions or country level variables on growth. In fact, it is well known in the literature that there is some degree of complementarity/substitutability among labour institutions. For this reason, all regressions include interaction terms between human capital intensity and union density, the Kaitz minimum wage index, the tax wedge, the level of wage coordination and the benefit replacement rate. Moreover regressions in columns 5 and 7 also include the interaction of human capital intensity with a proxy for product market regulation, proxied by the OECD indicator of entry barriers in network sectors, given recent evidence on the complementarity between labour flexibility and product market liberalisation (Fiori et al, 2012). The empirical estimates show that the interaction between schooling intensity and EPL is still negative and statistically significant.[36]

Finally, in Table 8 we present additional robustness for TFP growth regressions. In columns 1 to 5 we essentially replicate regressions in previous Table 6 for value added growth, and our main result of interest is confirmed. Moreover, in the remaining columns we check that the results for the interaction between EPL and human capital intensity is robust to alternative EPL indexes (column 6 to 9) and to the inclusion of different labour market institutions. Reassuringly, our main results are unaltered.[37]

[35] However, because human capital intensive industries tend to be more volatile, it may be argued that also in these sectors the level of EPL for temporary workers matters.

[36] In regressions not reported, but available from the authors, we also consider the interaction between human capital intensity and coverage of union bargaining agreements as an alternative proxy for union power with very similar results. We also experimented by including the labour market institutions variables one at a time, and results are virtually unchanged.

[37] Regression equations in Tables 7 and 8 that include controls for labour market institutions and product market regulation interactions are robust to alternative inclusion of interactions between human capital intensity and country level variables such as financial development, the capital output ratio, the R&D stock, etc.

Table 7: Different Measures of EPL and Other Labour Market Institutions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable	VAg	VAg	VAg	VAg	VAg	VAg	VAg
Time Period	70-05	90-05	90-05	70-05	70-05	90-05	90-05
Human Capital Intensity ×				-0.0100**	-0.0116**	-0.0638***	-0.0621***
Employment Protection				(0.00448)	(0.00526)	(0.0164)	(0.0166)
Human Capital Intensity ×	-0.00292***						
Unweighted EPL OECD	(0.00101)						
Human Capital Intensity ×		-0.00769**					
Weighted EPL OECD		(0.00378)					
Human Capital Intensity ×			-0.0144***				
EPL Regular Workers			(0.00524)				
Human Capital Intensity ×				-0.00848	-0.00277	-0.0703***	-0.0641**
Union Density				(0.00981)	(0.0109)	(0.0260)	(0.0251)
Human Capital Intensity ×				-0.00848	-0.00277	-0.00900	-0.0251
Kaitz Minimum Wage Index				(0.00981)	(0.0109)	(0.0392)	(0.0413)
Human Capital Intensity ×				0.00138	-0.00487	0.0141	0.00770
Benefit Replacement Rate				(0.00897)	(0.00998)	(0.0192)	(0.0186)
Human Capital Intensity ×				0.00203	0.00306	0.00977***	0.00868**
Wage Coordination				(0.00281)	(0.00296)	(0.00373)	(0.00427)
Human Capital Intensity ×				0.0184	0.0344	0.131**	0.124**
Tax Wedge				(0.0217)	(0.0322)	(0.0634)	(0.0626)
Human Capital Intensity ×					0.00422		0.00435
Entry Barriers					(0.00561)		(0.00437)
Human Capital Intensity ×	0.00157**	0.00107	0.000969	0.00138	0.00168	-0.00146	0.00199
Education Level	(0.000690)	(0.00175)	(0.00182)	(0.00258)	(0.00258)	(0.00336)	(0.00514)
Human Capital Intensity ×	0.0450*	-0.0158	-0.0316	0.0344	0.000733	0.0635	0.0857
Education Accumulation	(0.0271)	(0.0513)	(0.0497)	(0.0848)	(0.0960)	(0.0857)	(0.0870)
Initial Conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	595	632	632	511	511	546	546
R^2	0.625	0.438	0.442	0.671	0.672	0.474	0.475

Notes: All regressions include country and sector fixed effects. All variables are calculated for the correspoding period. VAg, human capital intensity, EPL, education level, education accumulation, initial conditions are calculated as in Table 3. Unweighted EPL OECD is an unweighted average of EPL for regular and temporary contracts. Weighted EPL OECD is a weighted average of EPL for regular contracts, temporary contracts and collective dismissals. EPL Regular Workers is a weighted average of EPL for individual and collective dismissals. Union density is the number of enrolled over total employees. Wage coordination index is the level of bargaining. Kaitz minimum wage index, Benefit replacement, Tax wedge and Entry barriers are defined in the Data Appendix. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Additional TFP Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	TFPg	TFPg	TFPg	TFPg	TFPg	TFPg	TFPg	TFPg	TFPg
Time Period	90-05	90-05	90-05	90-05	90-05	90-05	90-05	90-05	90-05
Human Capital Intensity ×	-0.0151**	-0.0212*	-0.0162**	-0.0142**	-0.0171***	-0.0402**			
Employment Protection	(0.00673)	(0.0111)	(0.00695)	(0.00693)	(0.00654)	(0.0181)			
Human Capital Intensity ×							-0.00740**		
Unweighted EPL OECD							(0.00364)		
Human Capital Intensity ×								-0.00975**	
Weighted EPL OECD								(0.00442)	
Human Capital Intensity ×									-0.0114*
EPL Regular Workers									(0.00619)
Physical Capital Intensity ×	-0.00144								
Capital Output Ratio	(0.00186)								
R&D Intensity ×		0.00526							
Employment Protection		(0.0213)							
Riskiness Intensity ×			1.07e-09						
Employment Protection			(4.58e-09)						
Layoff Intensity ×				0.132					
Employment Protection				(0.108)					
Physical Capital Intensity ×					0.000709				
Employment Protection					(0.00142)				
Human Capital Intensity ×						Yes			
Other Labour Institutions									
Human Capital Intensity ×	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education Controls									
Initial Conditions	Yes	Yes	Yes	Yes	Yes	Ye	Yes	Yes	Yes
Observations	288	156	288	288	288	288	288	288	288
R^2	0.381	0.406	0.380	0.381	0.380	0.389	0.378	0.379	0.379

Notes: All regressions include country and sector fixed effects. All variables are calculated for the correspoding period. TFPg, human capital intensity, employment protection, education level, education accumulation, initial conditions are calculated as in Table 3 for the period 1990-2005. Controls in columns (1) to (5) are defined in Table 6. Other Labour Institutions in column (6) are: Union density, Wage coordination, Tax wedge, Benefit replacement rate, and Kaitz index for minimum wages. We also include Entry barriers. More details are in Table 6 and Data Appendix. Different indicators for EPL in columns (7) to (9) are defined in Table 7, see also the Data section for more details. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

5 Concluding Remarks

In this paper, we consider the effect of employment protection legislation on industry growth. We find that the growth differential between high and low human capital intensive industries is greater in a country with low than a country with high EPL. 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 framework 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 a strong and statistically significant negative relationship between EPL and the growth rate differential between high and low human capital intensive industries for value added, hours of work and TFP. 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 labour market institutions by interacting human capital intensity with measures of union power, minimum wages, benefit replacement rates, etc. Finally, we have taken into account possible endogeneity concerns of EPL either due to reverse causality or measurement error.

We also find that the effect of EPL on the value added growth differential between high and low skill sectors is stronger in the most recent years and in the manufacturing sector. Finally, we show that EPL disproportionately reduces value added and TFP growth in high schooling industries particularly in countries that are closer to the technological frontier.

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 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.

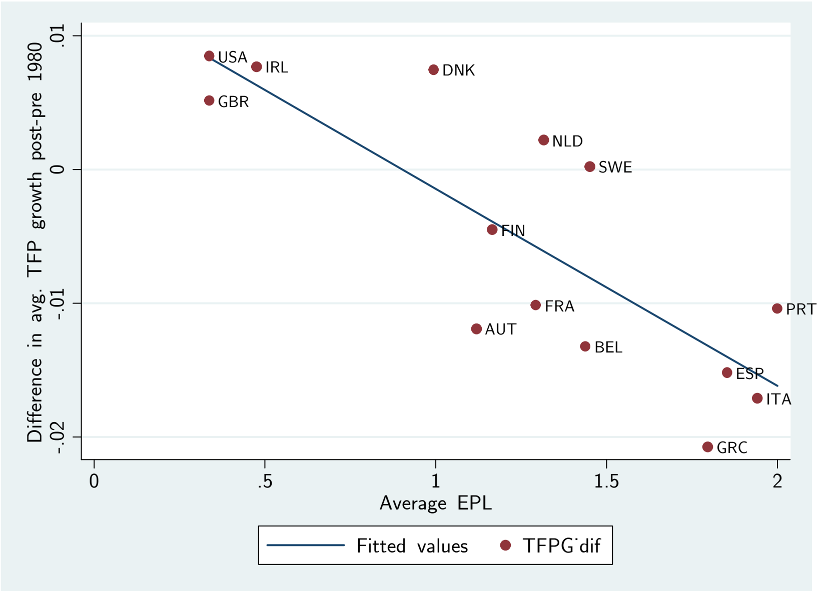

Figure 2: Changes in TFP growth post-pre 1980 versus EPL

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Data Appendix

Other Industry Level Data

In our analysis, we also consider other industry level variables that might interact with EPL or have been recently used to study the relationship between EPL and productivity. First, following 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.[38] 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 (1990) 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 (1990) using data taken from the OECD ANBERD database;[39] ICT intensity was computed as the share of ICT expenditure in total investment outlays using EUKLEMS data; finally, as a proxy for risk intensity (see Bartelsman et al., 2010) 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.

Other Country Level Data

From Checchi and Lucifora (2002) we also extract measures of union density (number of enrolled over total employees), minimum wage (as captured by the Kaitz index, namely the ratio between statutory minimum wage and average wage), tax wedge and unemployment benefits replacement rate. 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). For robustness, we use an alternative measure of union power, as proposed by Visser (2011). The latter is calculated as the number of employees covered by wage bargaining agreements as a proportion of all wage and salary earners in employment with the right to bargaining, expressed as percentage. 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 country level 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).

[38] 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.

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

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 for 1970 and 1990.

The R&D stock 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. In turn, financial development is measured as the ratio between domestic credit to private sector and GDP and is taken from the World Bank Global Development Finance database.

Finally, to take into account possible endogeneity concerns of EPL, we augment our set of instruments described in the main text with additional 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.

Table A1: Endogeneity of Employment Protection, IV Regressions, Only One Instrument

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	VAg	Hg	VAg	Hg	TFPg
Time Period	70-05	70-05	90-05	90-05	90-05
Human Capital Intensity ×	-0.0079***	-0.0071***	-0.0365**	-0.0146	-0.0321*
Employment Protection	(0.0030)	(0.0022)	(0.0166)	(0.0097)	(0.0191)
Human Capital Intensity × Education Level	Yes	Yes	Yes	Yes	Yes
Human Capital Intensity × Education Accumulation	Yes	Yes	Yes	Yes	Yes
Initial Conditions	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	595	618	632	622	288
R^2	0.30	0.23	0.05	0.06	0.37
First Stage Results (Only excluded instruments are reported)					
Human Capital Intensity ×	0.717***	0.697***	0.424***	0.417***	0.366***
Dictatorship Spell	(0.0464)	(0.0427)	(0.0332)	(0.0361)	(0.052)
Kleibergen-Paap rk Wald F	238.7	265.7	161.6	133.0	48.8

Notes: All regressions include country and sector fixed effects. First stage also includes interactions of human capital intensity with education level, human capital intensity with education accumulation, initial conditions and country and sector fixed effects. VAg, Hg, TFPg, human capital intensity, EPL, education level, education accumulation, initial conditions are calculated as in Table 3. Dictatorship spell is a dummy equal to one for those countries that experienced a dictatorship spell before 1970 and zero otherwise. See Data Appendix for more details. Regressions in cols (1) to (5) have been estimated with the two-step efficient GMM estimator automated in the Ivreg2 routine in Stata. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.