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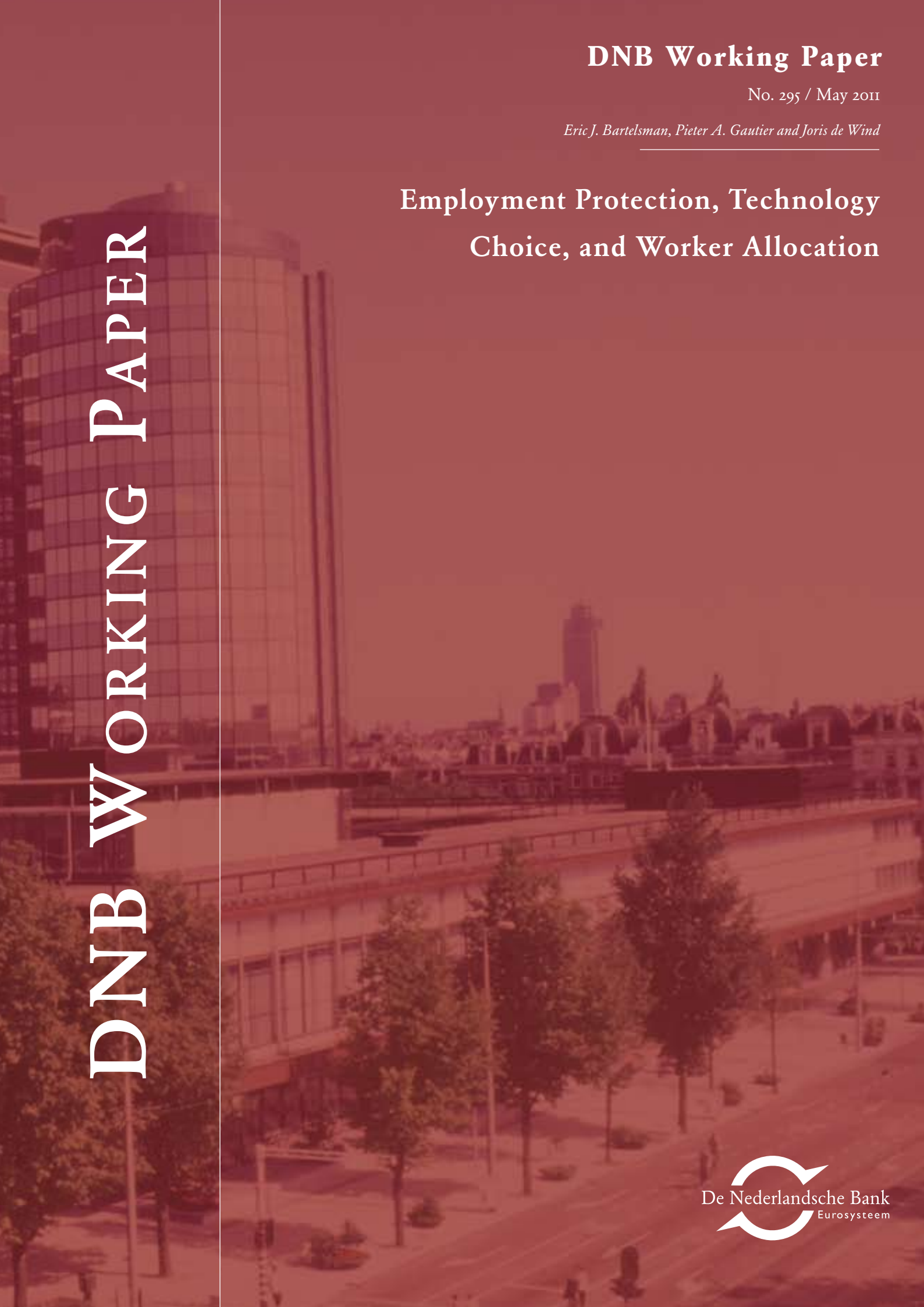

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Eric J. Bartelsman, Pieter A. Gautier, and Joris de Wind*

* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Employment Protection, Technology Choice, and Worker Allocation*

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Abstract

We show empirically that high-risk innovative sectors are relatively small in countries with strict employment protection legislation (EPL). To understand the mechanism, we develop a two-sector matching model where firms endogenously choose between safe and risky technology. Simulations with our calibrated model are consistent with the data: Strict EPL discourages choosing the emerging risky technology because it is more costly to shed workers upon receiving a bad productivity draw.

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This mechanism helps explain the slowdown in productivity in the EU relative to the US since the mid-1990s that often is associated with lagging adoption of information technology in the EU.

Keywords: employment protection legislation, exit costs, information and communication technologies, heterogeneous productivity, risky technology, innovation, sectoral allocation

JEL Codes: J65, O38

1 Introduction

In this paper we argue that a change in the nature of technological opportunities in the mid-1990s interacted with cross-region differences in employment protection to become a prominent cause of the observed divergence in productivity between the US and the EU. The emergence of accelerating improvements in computing power coupled with steepening adoption rates of communication technology resulted in a large variance in realized productivity and profits for firms choosing to use these technologies. The increase in variance is good for aggregate productivity and appealing to individual firms because good news is unbounded while bad news is bounded by the option to exit or fire workers. When in the mid-1990s these technological opportunities arose, the expected net benefits of exploring this technology were higher in countries with low EPL because the option to shut down was less costly. We give robust evidence that in countries with high EPL, high-risk innovative sectors (which are associated with intensive ICT use) are relatively small. The negative relationship also holds between other exit frictions (i.e. low cost recovery of capital for exiting firms) and the relative size of risky sectors. We explain the empirical findings using a matching model with endogenous technology choice, i.e. firms can choose between a risky and a safe technology. In a calibrated version of the model, high firing or exit costs reduce the number of jobs in the risky sector, lower productivity in the risky sector, and lower aggregate productivity.

Our paper draws from and combines results from a variety of different literatures. The main question we look at is prominent in the literature on innovation, ICT and productivity growth. The model we use is derived from models in the search literature that mostly have been used to study the effects of frictions (including EPL) in labor markets, but recently these models are used for studying allocation and productivity as

well. Further, our use of model calibration, and comparison of model simulations with moments and parameter estimates from data draw on a rich macro literature. Finally, we follow a lengthy sequence of papers studying the effect of EPL on labor markets and macro outcomes. We discuss these points in turn.

Growth accounting exercises in the US have shown most of the acceleration of output growth to be due to ICT capital deepening and to increases in TFP associated with ICT use (for an overview of the findings, see Jorgenson, Ho, and Stiroh 2008). Cross-region comparisons (van Ark, O'Mahony, and Timmer 2008) show that ICT production and use has been much lower in the EU than in the US and that this may explain much of the relative slowdown. The growth accounting literature is not, however, capable of explaining *why* the ICT producing sector in the EU is smaller, *why* ICT investment and thus ICT-capital deepening is lower, *why* the contribution from ICT-using industries is smaller, and thus *why* aggregate productivity diverges. The link we make between technology choice and employment protection and exit costs in general depends on the special nature of information and communication technology. A nice case study of such risky innovation is given by McAfee and Brynjolfsson (2008), where the benefits of adopting an innovative ICT system arise in conjunction with a reorganization of the production process. The success of the innovation can only be determined by experimenting with the new organization in the market. In case of failure, the configuration of the hardware, software, process, and organization structure needs to be changed again, while in case of success, the system is scaled up, for example by replicating it in other locations. This fits nicely with the findings of Bloom, Sadun, and Van Reenen (2007) that US multinational firms have high returns to investment in ICT in their UK subsidiaries because they only transplant the ICT implementations that were adopted successfully in the US.

Consistent with this innovation strategy, Brynjolfsson, McAfee, Zhu, and Sorell (2008), find that the cross-sectional variance of firm-level profits in ICT intensive industries is higher, and has been increasing steadily since 1995, relative to the cross-sectional variance of profits in firms in low ICT uptake industries. In many cases, the ICT and organizational investments do not lead to success and require either another round of attempts at getting the implementation right, or exit. In this paper, we find that the variance of productivity across firms and the churn of jobs has become higher since 1995 in ICT intensive industries. While the direction of causality is difficult to ascertain, this evidence shows that higher rates of adoption of new technology coincide with increased cross-sectional variation in profits, productivity, market share, and employment. Further, it is not only the cross-sectional variation that increases (which could be the result of, for example, increased heterogeneity in the capital labor ratio associated with increased ICT intensity), but also the variance of growth rates of market shares, and the churn of jobs.

Although we do not explicitly model the process of experimental innovation, our model is consistent with it. In our model, the decision to innovate not only requires a fixed entry fee but also requires some complementary factor input, say labor, with an associated flow of factor payments. Firms can choose to enter in a risky or a safe sector that differ in their productivity dynamics. Specifically, in the risky sector firms are modelled as in Mortensen and Pissarides (1994) and in the safe sector firms are as in Pissarides (2000). Both sectors are connected with each other through the pool of unemployed workers from which both sectors hire and EPL reduces the risky and increases the safe sector. This framework is particularly useful to study labor market policies because it is simple and simultaneously solves for the labor market stocks and flows.[1] Frictions are essential in our model to

[1]The effects of EPL have been studied extensively in the search matching literature using a single sector model. See e.g. Brügeman (2006), Ljungqvist (2002), and Mortensen and Pissarides (1999).

explain the coexistence of vacancies and unemployed workers, but they also are needed to allow for an equilibrium where both high and low productivity firms can simultaneously exist. As in Mortensen and Lentz (2008), a key factor for aggregate productivity is the allocation of workers to different firms.

We calibrate our model for the US using a variety of sources including the EUKLEMS dataset (O'Mahony and Timmer 2009) and a novel dataset built up from firm-level sources (Bartelsman, Haltiwanger, and Scarpetta 2009, from now on called BHS). By exploring new data sources we are able to get more information on primitives that previously had to be fixed at arbitrary values in model calibrations. For example, we use our model to derive a relation between the underlying ex-ante mean and variance of the productivity distribution in the risky sectors and the observed (truncated) mean and variances. Further we can generate experiments such as considering the effect of changing the estimated US level of EPL (one month of production) to European levels (seven months of production).[2] Simulated data generated from the model in this manner shows the same relationship between sector size and EPL interacted with riskiness that we find in the actual data.

By now there exists a huge literature on the effects of EPL on labor market performance based on cross-country evidence.[3] The main conclusions are that the effects on employment are negative but small. Labor force participation is typically smaller in countries with strong EPL and the effects on unemployment are essentially zero. EPL reduces the flows in and out of employment and increases unemployment duration. Autor, Kerr, and Kugler (2008) give some evidence that EPL reduces productivity at the

[2]There is a lot of variation in severance payments and procedural cost within Europe. Severance payments range from from 0 in e.g. the UK and Belgium to 18 months in Italy and 20 months in Portugal for a worker who has been employed for 20 years. In many European countries, severance payments are equal to one month salary for each year worked.

[3]See e.g. the seminal work of Bertola (1990) and the literature overview in Bassanini et al. (2009).

plant level but they cannot rule out that their results are (partly) due to confounding economic shocks. Samaniego (2006) gives evidence that EPL is negatively correlated with ICT diffusion. Bassanini, Nunziata, and Venn (2009) give evidence that productivity in high turnover industries is relatively low if EPL is strong which is consistent with our findings. However, in our model, turnover is endogenous and depends on the choice of technology.[4] Our paper is to our knowledge the first one that gives evidence that firing costs may harm productivity and innovation by decreasing the size of innovative sectors. The mechanism that we propose is related to Saint-Paul (2002) where countries with high EPL specialize in secure goods at the end of their product cycle while countries with low EPL specialize in more innovative goods.

The paper is organized as follows. Section 2 summarizes the stylized facts on the productivity divergence. Section 3 discusses our theoretical model which is calibrated in section 4. Section 5 shows our main empirical finding that risky sectors are relatively smaller in high-EPL-countries. We conclude with some reflections on the importance of this link between EPL and productivity and with ideas for future research.

2 Stylized facts

This section presents some stylized facts on productivity, risky innovation, and sectoral allocation of labor. We start with a picture that begs the important question: Why has productivity in the EU stopped converging to the US level, and even started diverging since the mid-1990s? Using data from the EUKLEMS database, Figure 1 shows real value

[4] We want to emphasize that our paper looks at a firm's decision to invest in risky or safe technologies. By contrast, Acharya, Baghai and Subramanian (2010) consider a situation where workers make decisions on their effort in knowledge creation. They present evidence that countries with high EPL have more patenting. In this case, EPL may serve as a commitment device for firms that allow workers to take more risk.

added per hour worked in the market sector in the EU-15 versus the United States.[5] The finding has spawned an exploration into the details, breaking the pattern down into contributions of countries and industries, and further into the contributions for each factor of production. Overall, van Ark, O'Mahony, and Timmer (2008) argue that the European productivity slowdown is attributable to the slower emergence of the 'knowledge economy' in Europe compared to the United States. The findings are that the EU enjoys lower growth contributions from investment in information and communication technology and has a relatively small share of technology producing industries. The EU also has slower multifactor productivity growth than in the US where the acceleration in productivity likely is associated with advances in the innovative uses of information technology.

Figure 1: Labor productivity EU15 relative to US; source: EUKLEMS

The explanation of the *why* for these findings that we put forward in this paper has

[5]Output of the fifteen EU countries are converted to dollars using industry-of-origin purchasing power parity data from the EUKLEMS database. The same pattern emerges if one displays relative total factor productivity (TFP) which takes into account changes in both capital and labor quality. However, for consistency with measures used in our model and because these data are more consistent across source, we will stick to indicators of ppp-adjusted real value added and hours worked.

to do with the nature of innovation in both the production and use of information and communication technologies. In our model, we assume that the innovative sector also is 'high risk'. That is, a firm that invests in these technologies or sectors has a higher variance of payoffs than a firm that invests in more traditional sectors or in more traditional types of capital equipment. In a recent paper, Brynjolfsson, McAfee, Sorell, and Zhu (2008) argue that the payoff associated with ICT-related business investments comes from scaling up a successful venture after it has shown its success in smaller-scale experiments. The upshot is that investing in such experiments has a high chance of failure and a very small chance of a very high payoff. Data from Compustat, linked to the Harte-Hank indicators on firm-level ICT investments, show that the cross-sectional variance of profits of ICT-intensive firms versus non-ICT intensive firms starts diverging in the mid-nineties (Brynjolfsson, McAfee, and Zhu 2009).[6]

Similar evidence is found by analyzing a country/industry panel dataset of indicators built up from firm-level data. Using linked longitudinal data on sales and broadband use at the firm-level for 13 EU countries, Bartelsman (2008) finds that industries that have a higher percentage of workers with access to broadband internet exhibit higher variance of the distribution of firm-level sales growth.

Using the same data source, the table below shows results for the regression of the coefficient of variation of labor productivity across firms in an industry on the percentage of workers with broadband access within the industry. The data (labelled ONS, and described in the section on empirical evidence) cover the years 2001 through 2005, during

[6]See the technical appendix B for a Figure.

which time the penetration of broadband was growing rapidly.

$$C_{c,i,t} = \alpha + \beta B_{c,i,t} + \sum_j \delta_j D_j + \varepsilon_{c,i,t} \tag{1}$$

Where C is the coefficient of variation of industry productivity in country c, industry i, and year t, B is the percentage of workers in the industry with access to broadband internet, and D are dummy variables for each country, industry, and time periods. The regression is run both in levels and first differences. In both cases, the correlation is significantly positive, as shown in Table 1. [7] This correlation does not imply causality, and needs to be interpreted with care because the ex-post observed variance in an industry may already reflect the endogenous firm-level choice of whether to invest in safe or risky innovation.

	Levels	First-differences
β	0.97	2.03
	(2.47)	(3.72)
R^2	0.40	0.07
D.F.	650	461
Fixed effects	country, industry, time	country, industry, time

Table 1: Productivity variance and broadband use

The data on ICT use at the firm level, linkable to other longitudinal firm-level data is not available in the US. However, the BHS dataset includes time series information on firm entry and exit and on job creation and destruction for detailed industries in the

[7] We ran the regression with all combinations of country, industry, and or time dimmies. In first differences, all coefficients are significant and roughly equal in size. In levels, regressions with industry but no country dummies gave an insignificant (negative) correlation. This points to the possibility of an ommitted variable that boosts both the variance of productivity and the use of broadband, for example decling prices of ICT goods and services.

US. We use the broadband intensity of industries in Europe from the ONS dataset to rank industries by 'ICT intensity'. We use this industry ranking from Europe to split the US industries into high-ICT and low-ICT groups and create indicators of employment-weighted gross firm turnover and gross job flows for the two aggregates.[8] Next, we average the gross job turnover (job creation plus job destruction divided by employment) and employment-weighted gross firm turnover (job flows of employees shed at firm exit plus hires at entering firms divided by employment) for the periods 1986-1994 and 1995-2004. The results are shown in Table 2. The patterns are roughly the same as shown for the variance of profitability of firms by Brynjolfsson et al. (2009).

	Gross Job Flows		Entry-Exit Job Flows	
	1986–1994	1995–2004	1986–1994	1995–2004
High ICT Industries	17.5	23.1	6.8	10.4
Low ICT Industries	17.5	18.6	8.1	8.1

Table 2: Gross job flows

The next stylized facts portray the productivity and employment evolution of the EU and the US, split between high-risk industries and low-risk industries. First, we must make a ranking of riskiness. Based on the above, a good candidate measure of the riskiness of the industry is the fraction of workers with access to broadband. We calculate this ranking for the EU15 country with the lowest OECD-EPL indicator, namely the United Kingdom. Other indicators of riskiness related to the observed distribution of firm-level productivity, such as the variance of the productivity distribution across firms,

[8] The cut-off industry for high- versus low-ICT using sectors is chosen to split employment in Europe evenly.

generate the same stylized results. In section 5 we discuss this in greater detail. First, the productivity levels (ppp-adjusted real value added per hour) of the risky industries within the broad market sector are higher than the safe sector, both in the EU15 and in the US, see Figure 2. However, in the EU the risky sector productivity is forty percent higher than the safe sector, with a slight increase over time, while in the US, the risky sector starts sixty percent more productive, but rises rapidly over time and ends up twice as productive as the safe sector. Next, the share of employment going to the risky sector in the EU stays near fifty percent, while it is nearly at sixty percent in the US.[9]

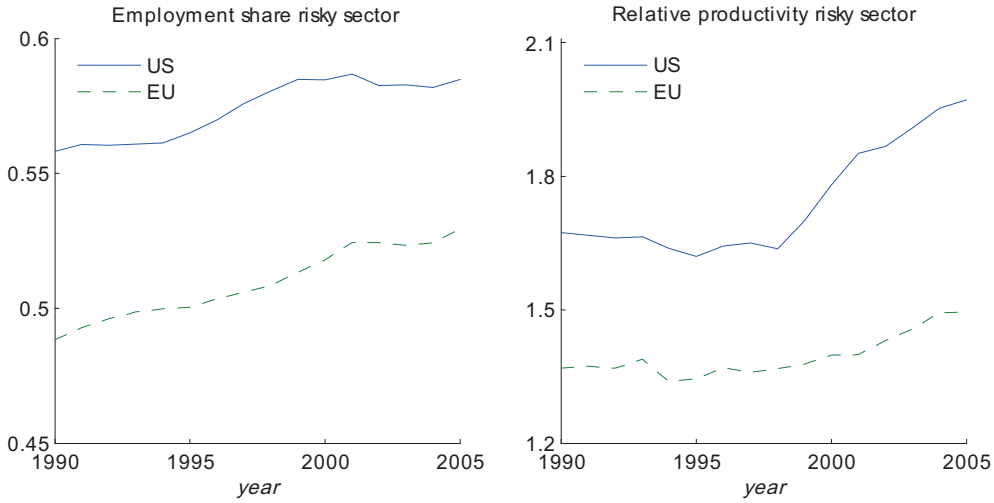

Figure 2: US and EU: risky versus safe sector

Within the EU, a nearly identical picture emerges when we split between countries with high EPL and low EPL (figure available on request). During the late-1990s high-EPL countries in the EU did not see an acceleration in productivity or employment share

[9]In our model, risky sector productivity is lower in high-EPL countries because low-productive jobs do not shut down. In the actual industry data, it is likely that firms choose between riskier and safer activities within each industry and that more safe activities lower average industry productivity in 'risky sectors' in high EPL countries.

in the risky sector. These are the main stylized facts to be explained by our model and explored further in detail in section 6. The distribution of EPL across countries does not change appreciably over time (see Nicoletti, Scarpetta, and Boylaud, 2000), thus changes in EPL alone cannot explain the productivity divergence. The core of our explanation is that employment protection makes firing more costly and makes the risky sector less attractive to open jobs. Moreover it shifts the firing threshold productivity level (below which a worker is fired) to the left and reduces the average productivity in the risky sector.

3 The model

Consider a labor market of size $l \in [0, 1]$ with search frictions and free entry of vacancies where risk neutral firms can invest in one of two technologies; a risky one or a safe one. In the safe technology sector (0), all matches are equally productive as in Pissarides (2000) while in the risky technology sector (1), firms are hit by shocks that can increase or decrease productivity as in Mortensen and Pissarides (1994). Those shocks can be interpreted as demand and or supply shocks. All risk neutral workers are identical. A matched worker-firm pair in sector 1 produces $y + x$ where x is a draw from $F(x)$ with mean μ and variance of σ^2. $F(x)$ has no mass points and at this stage we do not have to make assumptions on the support of $F(x)$. The shocks in the risky sector arrive at a (Poisson) rate λ. When such a shock occurs, firms must draw a new value of x from $F(x)$. We assume that new firms start at $y + \mu$ rather than at a finite upper support as Mortensen and Pissarides (1994) assume. In sector 0, all matched worker-firm pairs produce y. So in the absence of shocks ($\lambda = 0$) and for $\mu = 0$, sector 0 and 1 are identical and the model reduces to the Pissarides (2000) model.

Wages in sector i, w_i, follow from the generalized Nash bargaining solution with contin-

uous renegotiation (so the wage changes after a shock occurs) and workers cannot search on the job. When opening a vacancy, the firm can choose which sector to enter. Vacancy creation costs for sector 0 and 1 are given by c_0 and c_1, respectively. Both sectors are hit by exogenous job destruction shocks at a (Poisson) rate δ. After such a shock, the match ends and no exit costs have to be paid (as in Brügemann 2007). This is without loss of generality; we could alternatively assume that when exogenous job destruction occurs that firms also have to pay exit costs but this is equivalent to a decrease in y. Besides exogenous job destruction the firms in sector 1 choose a unique productivity threshold, x_d, below which a job is destroyed. So, in sector 1, both exogenous and endogenous (at rate $\lambda F(x_d)$) job destruction occurs. When a firm decides to fire a worker it must pay exit costs k. We are interested in how this firing tax distorts the sorting of firms into safe and risky sectors and the participation decision of workers.[10] In the absence of frictions, firms prefer the risky technology because there is no bound on positive shocks while firms have the option to close the job if a sufficiently large negative shock arrives.

Denote the total stock of vacancies by v and the stock of unemployment by u and define labor market tightness $\theta = v/u$. We can also define labor market tightness in each of the sectors as, $\theta_0 = v_0/u$ and $\theta_1 = v_1/u$. The total number of matches in each sector is determined by a constant-returns-to-scale matching function, $M_0(u, v_0)$ and $M_1(u, v_1)$ for respectively the safe and the risky sector. The matching functions are differentiable and strictly concave in each of their arguments. Define the total matching rate for workers in sector i as $m_i = M_i/u$. The rate at which vacancies are filled in each sector is then m_i/θ_i. In this setup, workers always impose negative congestion externalities on each other and

[10] In our model, the only productive input is labor, and firing costs thus coincide with the more generic concept of exit costs. We will use the terms interchangeably. In the empirical section we use different indicators relating to employment protection, firing costs, and capital losses at exit.

positive ones on vacancies while vacancies only cause negative congestion externalities on other vacancies in the same sector. We can think of this matching process as one where vacancies for sector 0 are posted on one page of the newspaper and vacancies for sector 1 on another page and workers pick a page at random and then a job at random from that page. Alternatively, we can think of sector 0 being located in one area and sector 1 in another area. We believe this is a reasonable assumption, i.e. posting an ICT vacancy will typically not decrease the rate at which workers meet vacancies in the financial sector. If unemployment increases, the matching rate for all workers goes down and for vacancies it goes up while if the number of vacancies in sector 1 increases, the matching rate for workers goes up and the matching rate for vacancies in sector 1 goes down. The matching rates in sector 0 are only indirectly affected. Since unemployment goes down, the matching rate for firms in sector 0 goes down but less so than in sector 1 because the congestion externality of type 0 vacancies on type 1 vacancies is absent. The functional form of the matching function is $M_i = \xi u^{\eta} v_i^{1-\eta}$.

Let V_i be the (continuous time) asset value of a vacancy and let $J_i(x)$ be the asset value of a filled job in sector i. Free entry of vacancies implies:

$$rV_0 = -c_0 + \frac{m_0}{\theta_0}\left(J_0 - V_0\right) = 0 \tag{2}$$

$$rV_1 = -c_1 + \frac{m_1}{\theta_1}\left(J_1(0) - V_1\right) = 0 \tag{3}$$

Firms pay vacancy creation costs, c_0 or c_1 and at rate $\frac{m_i}{\theta_i}$ their vacancies switch to filled jobs. Under free entry, all profit opportunities are explored in equilibrium so the value of opening a vacancy must be equal to zero in expectation. Let U be the asset value of an unemployed worker and let $E_i(x)$ be the asset value for workers employed in sector i. Let

S_0 be the value of the surplus of a match in sector 0 and $S_1(x)$ be the value of the surplus of a type x match in sector 1.

$$S_0 = J_0 + E_0 - U \tag{4}$$

$$S_1(x) = J_1(x) + E_1(x) - U \tag{5}$$

By our assumption that wages are determined by a generalized Nash bargaining solution with bargaining power β, wages in sectors 0 and 1 are implicitly determined by respectively:

$$E_0 - U = \beta S_0 \tag{6}$$

$$J_0 = (1-\beta) S_0 \tag{7}$$

$$E_1(x) - U = \max(0, \beta S_1(x)) \tag{8}$$

$$J_1(x) = \min((1-\beta)S_1(x), S_1(x)) \tag{9}$$

Note that $S_1(x)$ can be negative for certain realizations of x. The asset value for a filled vacancy in sector 0 is given by:

$$rJ_0 = y - w_0 - \delta J_0. \tag{10}$$

In the safe sector matches only end if they are hit by a job destruction shock which occurs at rate δ. In sector 1 endogenous job destruction is also possible but then firms must pay exit costs k. As mentioned before, if the job is hit by an exogenous shock δ those cost do not have to be paid. For any realization x, $J_1(x)$ solves:

$$rJ_1(x) = y + x - w_1(x) - \delta J_1(x) + \lambda \left(\int_{x_d}^{x_u} (J_1(z) - J_1(x)) \, dF(z) - F(x_d)(J_1(x) + k) \right). \tag{11}$$

A firm with realization, x, receives during the match a flow income of: $y + x - w_1(x)$. If the job is destroyed for exogenous reasons this value becomes zero, if a technology shock arrives (at rate λ), the firm can close the job and fire the worker if the shock is below an endogenous threshold, x_d, which occurs with probability $F(x_d)$ and this results in a loss of k. The firm can also decide to continue producing at the new technology if $x \geqslant x^d$ and the wealth gain or loss for a realization z is then equal to $(J_1(z) - J_1(x))$. The upper support of $F(x)$ can be arbitrary large. The threshold value for x below which the job is destroyed, x_d, follows from the following reservation value property:

$$J_1(x_d) = -k, \tag{12}$$

As long as the job is more valuable than the exit cost, it is optimal to remain operational. So the higher k, the lower the exit threshold. Similarly, the participation constraint for employed workers is that they should be at least as well of as when they are unemployed. This implies,

$$E_1(x_d) = U, \tag{13}$$

and that the match surplus at the least productive job is negative:

$$S_1(x_d) = -k, \tag{14}$$

The asset value of being unemployed is:

$$rU = b + m_0(E_0 - U) + m_1(E_1(0) - U). \tag{15}$$

Unemployed workers receive unemployment benefits b (for positive analysis this can also be interpreted as home production) and they find jobs in the safe and risky sector at rates

m_0 and m_1 respectively. Non participants enjoy home production and are not available for the labor market. Let the distribution of home production be given by H, then the labor force consists of those workers who receive a higher payoff from working than from home production:

$$l = H(rU). \tag{16}$$

The value of having a job in the safe sector is simply equal to:

$$rE_0 = w_0 - \delta(E_0 - U) \tag{17}$$

while the asset value of being employed in the risky sector is given by:

$$rE_1(x) = w_1(x) - (\delta + \lambda F(x_d))(E_1(x) - U) + \lambda \int_{x_d}^{x_u} (E_1(z) - E_1(x))\, dF(z) \tag{18}$$

Workers receive a wage $w_1(x)$, at rate $(\delta + \lambda F(x_d))$ their job is destroyed for exogenous reasons or because the lower bound threshold productivity is crossed. In that case, the worker becomes unemployed. At rate $\lambda(1 - F(x_d))$, a match is hit by a shock above the threshold and the wealth change for realization z is given by: $(E_1(z) - E_1(x))$. From the Bellman equations above we can derive a job destruction equation for sector 1 and job creation conditions for sector 0 and sector 1. Together they jointly determine θ_1, θ_1, and x_d.

Proposition 1 *The risky sector job destruction margin is implicitly defined by*

$$y + x_d = b + \frac{\beta}{1-\beta}(\theta_0 c_0 + \theta_1 c_1) - \frac{\lambda}{r + \delta + \lambda} \int_{x_d}^{x_u} (1 - F(z))\, dz - (r + \delta)\, k. \tag{19}$$

The risky sector job creation condition is given by

$$\frac{m_1}{\theta_1} = \frac{(r+\delta+\lambda)\, c_1}{(1-\beta)\left(-x_d - (r+\delta+\lambda)\, k\right)}. \tag{20}$$

The safe sector job creation condition is given by

$$\frac{m_0}{\theta_0} = \frac{(r+\delta+\beta m_0)\, c_0}{(1-\beta)\,(y-b) - \beta\theta_1 c_1}. \tag{21}$$

Derivations are delegated to Appendix A.1. The steady state unemployment rate and vacancy stocks follow from the following steady state flow equations

$$m_0 u = \delta e_0 \tag{22}$$

$$m_1 u = \left(\delta + \lambda F\left(x_d\right)\right) e_1. \tag{23}$$

4 Calibration

We calibrate the structural parameters of our model in three steps. In the first step, we fix several parameters according to standard values in the literature. In the second step, we set several other parameters at values that match the US labor market stocks and flows. In the third step, which is the key step of our calibration strategy, we set the productivity shock parameters—the arrival rate λ, the mean μ, and the standard deviation σ—together with the firing costs parameter k such that we match the observed truncated cross-sectional distribution of US productivity. The right shape comes from the productivity shock parameters and the right truncation comes from the firing costs parameter. This third step is most important for us because we are mainly interested in long-run productivity effects. Since we explore several new data sources we are able to

identify the productivity shock parameters including the arrival rate, which was set to an arbitrary value in the previous literature.

4.1 Parameters from other studies

The parameter values that we use from other studies can be found in Table 3.

Without loss of generality, we normalize the productivity of the safe sector to $y = 1$. Following Pissarides (2009), and similar to Shimer (2005) and Hall and Milgrom (2008), we set the monthly interest rate to $r = 0.004$. Following Shimer (2005), we abstain from market inefficiencies due to search externalities by assuming that the Hosios condition $\beta = \eta$ is satisfied and we set unemployment benefits to $b = 0.4$. This lies at the upper end of the range, if interpreted entirely as unemployment benefits. It is, however, relatively low, if the interpretation includes leisure. Hall and Milgrom (2008), for example, think of 0.71 as a reasonable estimate for the flow value of unemployment and think of 0.25 as a reasonable estimate for unemployment benefits. In our model, we distinguish between non-participation and unemployment and assume that only non-participants can fully enjoy leisure. Note that our calibration is different from the calibration of Hagedorn and Manovskii (2008)—high b and low β—and hence we may not be able to explain the cyclical properties of labor market tightness. They are however interested in the marginal worker while we are more interested in the average worker whose value of non-market production is lower. It is worthwhile noting that our key results on long-run productivity effects and the sectoral allocation of workers are robust to changes along this dimension.

We do not have appropriate industry-level vacancy data. Having such data is not crucial though; we can calibrate the matching function parameters η and ξ using aggregate data. We take the matching elasticity from Pissarides (2009), that is $\eta = 0.5$,

which is similar to Hall and Milgrom (2008) and consistent with the evidence provided in Petrongolo and Pissarides (2001). Without loss of generality, we normalize the matching efficiency parameter to $\xi = 0.3$.[11]

Parameter	Value	Description	Motivation
y	1	productivity safe sector	normalization
r	0.004	monthly interest rate	Pissarides (2009)
β	η	Nash bargaining share worker	Hosios condition
b	0.4	unemployment benefits	Shimer (2005)
η	0.5	matching elasticity	Pissarides (2009)
ξ	0.3	matching efficiency	normalization

Table 3: Calibration according to the literature

4.2 Matching the US labor market stocks and flows

In this step, we set several parameters in order to match the US labor market stocks and flows. We combine aggregate data from the OECD LFS (stocks) and the JOLTS (flows) with industry-level data from the EUKLEMS. The parameter values set in this step can be found in Table 4.

We set labor market participation l to match the labor market stocks data from the OECD LFS. That is, we set labor market participation to $l = 0.77$. We do not back out the underlying distribution of home production, because it is not identified using only US data. We carry out various robustness checks and find that endogenizing labor market participation would strengthen our key results. Results are available on request.

Our safe-risky classification is based on the ONS database. We rank industries in the UK—having the lowest OECD-EPL of the EU15 and hence being the closest related

[11] As is well known from the literature, the matching efficiency parameter ξ and the vacancy costs parameters c_0 and c_1 are not separately identified.

to the US—by their broadband intensity. We split the industry ranking according to EU15 employment and call the top half risky and the bottom half safe. This ranking is consistent with the stylized facts presented in section 2. We have also experimented with ranking by variance in productivity and with calling the top quartile risky and the bottom quartile safe, with similar calibration results.

We set the exogenous job destruction rate δ to match the labor market flow data from the JOLTS. Distinguishing between the safe and risky sector is not easy. First, the JOLTS data is based on two-digit industry codes, while our safe-risky classification is based on three-digit industry codes. This makes it difficult to use industry-level data from the JOLTS. Therefore, we set the total separation rate of both the safe and the risky sector equal to the total separation rate of the manufacturing sector, that is $s^{safe} = s^{risky} = 0.029$. Secondly, the safe and risky sector differ in our model only in terms of riskiness, while in the real world they also differ in other dimensions. There is, for example, a big difference in skill composition. That is, the safe sector consists of $p^{safe}_{high} = 14\%$ high-skilled, $p^{safe}_{medium} = 68\%$ medium-skilled and $p^{safe}_{low} = 18\%$ low-skilled, while the risky sector consists of $p^{risky}_{high} = 37\%$ high-skilled, $p^{risky}_{medium} = 57\%$ medium-skilled and $p^{risky}_{low} = 6\%$ low-skilled, based on the EUKLEMS. It is important to take this into account, because low-skilled workers face a much higher separation rate than high-skilled workers. The difference can easily be a factor five, see for example Moscarini (2003). Our aim is therefore to match the model with the medium-skilled separation rates s^{safe}_{medium} and s^{risky}_{medium}, which we construct from the data. For this purpose, we assume that within-sector differences are the same for the safe and risky sector. As we show in Appendix A.3, this assumption implies that $s^{safe}_{medium} = 0.026$ and $s^{risky}_{medium} = 0.035$. In the safe sector of our model, there is only exogenous separation and hence we set the exogenous job destruction rate to $\delta = 0.026$.

Now the endogenous job destruction rate must be $\lambda F(x_d) = s^{risky}_{medium} - \delta = 0.008$. This condition implicitly determines the risky sector job destruction margin and serves as a target in the next step of our calibration strategy.

Finally, we take the labor market stocks from the OECD LFS and the relative sector sizes from the EUKLEMS. Together with our safe-risky classification, this gives us $u = 0.043$, $e_0 = 0.316$ and $e_1 = 0.41$. We combine these stocks with the above flows to solve for the implied labor market tightness via the safe and risky sector flow equations (22) and (23). We set the vacancy costs c_0 and c_1 in order to match labor market tightness. Since we do not have appropriate industry-level vacancy data, we cannot distinguish between safe and risky sector vacancy costs. It seems reasonable, however, that risky sector vacancy costs are larger than safe sector vacancy costs, since these costs also include capital installment costs—the risky sector has, for example, a much larger broadband penetration. We therefore assume that $c_1 = 2c_0$. Using the job creation condition of the safe sector (21) we find that $c_0 = 0.2092$ and $c_1 = 0.4184$.

Parameter	**Value**	**Description**	**Motivation**
l	0.77	size labor force	size labor force (OECD LFS)
δ	0.026	Poisson rate ex. job destr.	ex. job destr. (JOLTS, EUKLEMS)
c_0	0.2092	vacancy costs safe sector	stocks, flows (OECD LFS, JOLTS, EUKLEMS)
c_1	0.4184	vacancy costs risky sector	stocks, flows (OECD LFS, JOLTS, EUKLEMS)

Table 4: Calibration in order to match the US labor market stocks and flows

4.3 Matching the cross-sectional distribution of US productivity

In this step, we set the ex ante productivity shock parameters—the arrival rate λ, the mean μ, and the standard deviation σ—together with the firing costs parameter k in order to match the ex post observed truncated cross-sectional distribution of US productivity. More specifically, we match the cross-sectional mean and variance of risky sector productivity and we require risky sector in and outflow to be consistent with the data. The parameter values set in this step can be found in Table 5.

Cross-sectional mean and variance in the model

Let $\widehat{y}$ be the average output per worker in the risky sector. Workers who have not yet received a shock, a fraction $1-s$, produce y. Workers who have already received at least one shock greater than x_d, a fraction s, produce on average $y + \frac{1}{1-F(x_d)} \int_{x_d}^{x_u} z dF(z)$. We can solve for the fraction s using the steady state flow equation $\lambda (1 - F(x_d)) (1-s) e_1 = (\delta + \lambda F(x_d)) s e_1$ with the flow into s on the left-hand side and the flow out of s on the right-hand side, giving us $s = \frac{\lambda}{\delta+\lambda} (1 - F(x_d))$. The average output per worker in the risky sector is

$$\widehat{y} = y + s \frac{1}{1 - F(x_d)} \int_{x_d}^{x_u} z dF(z) = y + \frac{\lambda}{\delta + \lambda} \int_{x_d}^{x_u} z dF(z).$$

The variance of output per worker in the risky sector is

$$\begin{aligned} \widehat{\sigma}^2 &= s \frac{1}{1 - F(x_d)} \int_{x_d}^{x_u} (y + z - \widehat{y})^2 dF(z) + (1-s)(y - \widehat{y})^2 \\ &= \frac{\lambda}{\delta + \lambda} \left(\int_{x_d}^{x_u} z^2 dF(z) - \frac{\lambda}{\delta + \lambda} \left(\int_{x_d}^{x_u} z dF(z) \right)^2 \right). \end{aligned}$$

Productivity shocks are assumed to follow a normal distribution with mean μ and standard deviation σ. Using the analytic expressions for the truncated normal distribution, we can

simplify the expressions for $\widehat{y}$ and $\widehat{\sigma}^2$ as follows

$$\widehat{y} = y + \frac{\lambda}{\delta + \lambda}\left(\left(1 - \Phi\left(\frac{x_d - \mu}{\sigma}\right)\right)\mu + \varphi\left(\frac{x_d - \mu}{\sigma}\right)\sigma\right)$$

$$\widehat{\sigma}^2 = \frac{\lambda}{\delta + \lambda}\left(\left(1 - \Phi\left(\frac{x_d - \mu}{\sigma}\right)\right)\left(\mu^2 + \sigma^2\right) + \varphi\left(\frac{x_d - \mu}{\sigma}\right)(x_d + \mu)\,\sigma\right) - (y - \hat{y})^2$$

where $\varphi(\cdot)$ is the probability density function of the standard normal distribution and $\Phi(\cdot)$ is its cumulative density function.

Cross-sectional mean and variance in the data

Again, it is important to take the difference in skill decomposition into account, because high-skilled workers are much more productive than low-skilled workers. This can easily be a factor three, based on evidence from the EUKLEMS. Our aim is therefore to match the model with the medium-skilled productivities π^{safe}_{medium} and π^{risky}_{medium}, which we construct from the data. For this purpose, we assume that within-sector differences are the same for the safe and risky sector. As we show in Appendix A.4, this assumption implies that $\widehat{y} = \frac{\pi^{risky}_{medium}}{\pi^{safe}_{medium}} = 1.24$, if we take $\frac{\pi^{risky}}{\pi^{safe}} = 1.62$ from the EUKLEMS; however, we do not feel comfortable in matching such a high value since there may also be other mechanisms that make the risky sector more productive than the safe sector. Examples are sorting by unobservable characteristics—see for example Gautier and Teulings (2006)—and risk premia. Therefore, we match a somewhat lower value, namely $\widehat{y} = 1.1$. Accordingly, we set our target for the cross-sectional variance to $\widehat{\sigma}^2 = 0.16$, while the BHS dataset would suggest a value in the range of 0.2 to 0.3. The reason why we match a somewhat lower variance is that we want to capture the difference between risky sector variance and safe sector variance (and the latter is not zero in the data).

Combining the cross-sectional mean and variance with risky sector in and

outflow

In addition to the targets for the cross-sectional mean and variance, we obtain two additional targets via the risky sector job creation and destruction conditions (20) and (19); and we obtain one additional target via the endogenous job destruction rate, which was already determined in the previous step of our calibration strategy. This gives us five equations in four unknown structural parameters and one unknown steady state value. We solve this system of equations and get $\lambda = 0.1410$, $\mu = 0.0653$, $\sigma = 0.4989$, $k = 1.2227$ (and $x_d = -0.7245$), see Appendix A.2 for details.

Parameter	Value	Description
λ	0.1410	Poisson rate productivity shock
μ	0.0653	mean productivity shock
σ	0.4989	standard deviation productivity shock
k	1.2227	firing costs
Motivation endog. job destruction (JOLTS, EUKLEMS), cross-sectional mean (EUKLEMS), cross-sectional variance (BHS), stocks and flows (OECD LFS, JOLTS, EUKLEMS)		

Table 5: Calibration in order to match the cross-sectional distribution of US productivity

5 Simulations: the effects of EPL and rising riskiness

The calibrated model allows for simulation of steady state employment shares and relative productivity by varying any of the model parameters. Of interest for this paper is the effect of differences across economies in exit costs, k. Further, our stylized facts point towards an increase over time in the standard deviation of productivity shocks in the risky sector, σ. The simulations thus consist of computing steady state employment and

productivity outcomes for a wide range of k and σ.

We allow the exit costs to vary from the calibrated value of the US ($k = 1.2$), comparable to roughly one month of output, through low EU values ($k = 3$) to high EU values ($k = 7$), comparable to 7 months of production or about 1 year of wages.[12] The standard deviation of productivity is varied from 0.3 to 0.8. This range is consistent with the increase in riskiness that has been observed with rising ICT use.

The results are presented in Table 6 and in Figure 3. The table shows steady state outcomes for a list of variables for (i) the benchmark $\sigma = 0.5$ and (ii) a higher $\sigma = 0.75$ to capture the introduction of the new ICT. Across the columns, as firing cost increase, we see that in the risky sector there will be less firing (more labor hoarding), and because of that risky-sector productivity falls and the match surplus decreases. Consequently, less risky sector vacancies are opened and labor market tightness goes down in the risky sector. The match surplus in the safe sector goes up because the outside option of the worker goes down. Since unemployed workers are less likely to be hired in the high productivity risky sector their bargaining position with safe-sector employers goes down. The safe sector becomes larger except when risk is low and firing costs are high. In this case, employment is fairly flat, as risky sector outflow is even lower than the inflow and consequently unemployment drops. The drop in unemployment causes the safe sector to shrink despite the fact that θ_0 increases.

Next, consider what happens if $\sigma = 0.75$ (i.e. after the ICT revolution). A higher level of firing costs decreases employment in the risky sector, increases employment in the safe sector, decreases the worker's outside options, decreases wages in both sectors, and the total employment effect is positive. As firing costs rise, both the allocation shift

[12] Examples of European countries with low EPL are Denmark and the UK; examples of European countries with high EPL are Portugal and Italy. See Appendix E for details.

towards the safe sector and the increase in labor hoarding will contribute to lower overall productivity, $\pi \equiv \frac{e_0 y + e_1 \hat{y}}{e_0 + e_1}$. Finally, total output net of vacancy costs, labelled Ω in the table, unambiguously decreases as firing cost increase, irrespective of σ.

To summarize, productivity drops with increased firing costs, both from a selection effect (less truncation in the risky sector) and from a reduction in the size of the risky sector. The productivity drop due to higher firing costs increases with σ. The allocation of workers to the risky sector is not very sensitive to firing costs when σ is low and when firing costs are high, because essentially all jobs are 'hoarded'. Once σ rises, the allocation of labor to the risky sector falls with firing costs. Further, the effect of firing costs on risky sector allocation becomes stronger (more negative) as σ increases. In the next section we show that this pattern is confirmed in the data.

	Benchmark $\sigma = 0.50$			High $\sigma = 0.75$		
	$k = 1.25$	$k = 3$	$k = 7$	$k = 1.25$	$k = 3$	$k = 7$
x_d	-0.7289	-1.0098	-1.6879	-0.7806	-1.0475	-1.6930
$\lambda F(x_d)$	0.0079	0.0022	0.0000	0.0183	0.0097	0.0013
$\hat{y}$	1.0997	1.0709	1.0554	1.1817	1.1353	1.0708
$S_1(0)$	3.0123	2.9052	2.8705	3.3146	3.1254	2.9002
θ_1	1.1666	1.0851	1.0594	1.4126	1.2559	1.0814
e_1	0.4100	0.4127	0.4191	0.5860	0.4455	0.4175
$w_1(0)$	0.9790	0.9722	0.9701	0.9829	0.9616	0.9447
S_0	0.8903	1.0341	1.0760	0.1830	0.7050	1.0403
θ_0	0.4076	0.5500	0.5955	0.0172	0.2556	0.5565
e_0	0.3161	0.3190	0.3146	0.1102	0.2761	0.3150
w_0	0.9866	0.9845	0.9839	0.9973	0.9894	0.9844
u	0.0429	0.0373	0.0353	0.0728	0.0473	0.0366
$e_1/(e_0 + e_1)$	0.5657	0.5651	0.5712	0.8417	0.6174	0.5700
π	1.0563	1.0400	1.0317	1.1529	1.0836	1.0403
Ω	0.9654	0.9620	0.9582	0.9875	0.9812	0.9638

Table 6: Model simulation

The left panel of Figure 3 illustrates the effects of changing k and σ on employment.

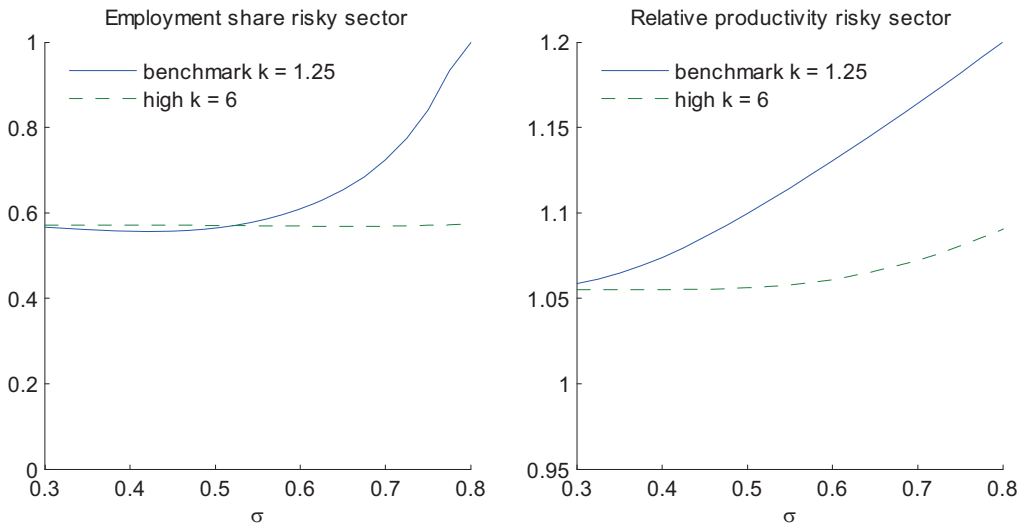

Figure 3: Simulation σ and k

If the firing costs are low enough, employment in the risky sector increases with σ because more vacancies are opened in the risky sector which implies that fewer unemployed workers are available for the safe sector. For higher firing costs, σ needs to be higher before risky sector employment 'escapes' from full labor hoarding and can benefit from the increased risk by truncating the bad draws. For a given level of riskiness, employment in the risky sector decreases with firing costs, k, although the effect is small with low levels of σ or high firing costs. The reduced effect of firing costs on employment share with low σ occurs because the amount of firing becomes very small as the firing threshold shifts to the left.

The right panel of Figure 3 shows that the relative productivity decreases in k and increases in σ. The relative productivity of the safe sector decreases with k because high exit costs shift the threshold of firing to a lower level of productivity. Aggregate productivity decreases rapidly when k increases, both because the relative productivity declines and because the share of resources allocated to the risky sector declines. As the variance of the productivity shock increases, the risky sector becomes more attractive so

it grows while the safe sector shrinks. Further, because of the firing threshold, average productivity of jobs in the risky sector increases in σ. The model can also explain that in countries with high firing cost the risky sector does not increase in response to an increase in σ and consequently productivity also remains almost constant. To the contrary in countries with low firing cost, the employment share of the risky sector and aggregate productivity strongly increases in response to a new technology with a higher σ as occurred at the end of the nineties. So, consistent with our empirical findings discussed in the next section, low and high-EPL countries respond differently to the arrival of new risky technology associated with the adoption of information and communication technologies. This helps explain the slowdown in productivity in the EU relative to the US since the mid-1990s.

6 Data and empirical results

In this section we explore the empirical relationship between EPL and the allocation of resources to risky sectors. The model predicts that (i) risky industries have relatively higher levels of employment in countries with low firing costs versus countries with high firing costs, (ii) the effect of the ICT revolution (increases in σ) is larger in countries with low firing cost. Further, the model predicts that the sensitivity of employment to firing costs is higher when riskiness is higher, and that the sensitivity is lower when firing costs are high.

Table 7 provides an overview of the data used for this exercise. The EUKLEMS database (O'Mahony and Timmer 2009) provides measures of output, hours worked, other factor inputs, prices, and industry purchasing power parities for EU countries and for US, for disaggregated industries covering the whole economy from 1970 through 2004. We use

the share of hours worked in an industry relative to total hours worked in all industries in each country and time period as the variable to be explained.[13]

The firing cost indicators are available from two sources. First, a country-time panel dataset collected at the OECD (Nicolleti et al. 2000), provides indicators of the stringency of employment protection (EPL).[14] The time dimension of this dataset may contain interpolations between actual component level information collected from OECD member countries in specific years, and thus has less reliability than the cross-country dimension. A complementary dataset of indicators of 'Costs of doing business' (CDB), including entry and exit costs has been compiled by the World Bank (see Djankov, La Porta, Lopez de Silanes, and Schleifer 2002). Current indicators on, for example, hiring and firing costs, or time to start a business, are available for many countries from 2004 to the present.

Finally, as a source of information on the riskiness of a sector, we make use of two datasets collected using the method of 'distributed micro data research' (Bartelsman, Haltiwanger, and Scarpetta 2009). These datasets include moments computed from the underlying distributions in confidential firm-level datasets available at national statistical offices, aggregated to the country, industry, and year level. First, for the 1990s data has been collected for a selection of OECD countries, mostly for firms in manufacturing. Next, a project, coordinated by the UK Office of National Statistics (ONS 2008), and funded by Eurostat, compiled information from linked longitudinal business registers, production surveys, and e-commerce surveys for 13 EU countries for firms in all sectors of the economy for the years 2001 to 2005.

[13]We limit our study to industries in the Market Sector, defined similarly to that in the EUKLEMS dataset. The market sector includes industries in manufacturing, trade, finance and business services, but excludes agriculture, government and services. We also exlcude utilities and nuclear fuel production.

[14]The OECD index is based on 18 factors of employment protection of regular workers against individual dismissal, specific requirements for collective dismissals and regulation of temporary employment.

Source	Periods	Countries	Industries	Variables
EUKLEMS	1970-2005	EU+US	30, market sector	Output, factor inputs, prices, PPPs
OECD-EPL	1985-2005*	OECD	No info	EPL indicators
WB-CDB	2004-2007	World	No info	Entry/ firing costs, rigidities
BHS	1990s	OECD, Asia, Lat Am	16, manufacturing.	Moments from firm surveys
ONS/Eurostat	2001-2005	13 EU countries	30, market	Moments from firm surveys

Table 7: Data sources

In the available data, we have no direct measure of the variance of shocks faced by firms choosing the 'risky' sector. Instead, we have the variance of the cross-sectional distribution of productivity observed across firms in each industry in the national datasets. As our model shows, for firms choosing risky strategies the observed variance is truncated with respect to the underlying distribution of shocks, and the point of truncation depends on firing costs. However, in the model the observed productivity variance moves monotonically with the variance of the underlying shocks for any level of firing costs. For our baseline empirical results we therefore use as the sectoral-riskiness indicator the observed variance of labor productivity within an industry averaged across countries. For robustness, we also use other proxies for industry riskiness from the ONS and BHS datasets.

To rank industries according to riskiness, the above indicators from the BHS or the ONS dataset are averaged over time (and across countries where noted) and are turned into an ordinal index of industry-specific 'riskiness.' This ordinal ranking is then normalized into a uniform index ranging from -0.5 for the lowest risk to 0.5 for the highest risk sector.

The first results are presented for a regression equation of the following general form:

$$e_{c,i,t} = \alpha + \beta k_{c,t} + \gamma k_{c,t} R(\sigma)_i + FE + \varepsilon_{c,i,t} \tag{24}$$

where $e_{c,i,t}$ is the ratio of hours worked in industry i, country c and year t relative to total hours in that country and year. The exogenous variable $k_{c,t}$ is the firing cost or exit cost indicator, and $R(\sigma)_i$ is the rank of the industry risk, with a higher rank being more risky. The parameter γ measures the effect of the regulatory environment interacted with the indicator of industry risk on the share of employment in the industry. Depending on specification, industry and country fixed effects FE (mean levels, including the level effect of R_i or country and industry mean levels and industry trends) are swept out with appropriate dummy variables.[15] This type of specification has become widespread in evaluation of the impact of policy or environment on performance, e.g. Rajan and Zingales (1998). Essentially, the equation uses difference-in-differences to identify how changes in the policy, here $k_{c,t}$, differentially impact different sectors, based on the expected sensitivity of the sector to the policy change. To our knowledge, we are the first in this literature to explicitly model the interaction between the ranking and the policy instead of relying on reasoned assumption about the sensitivity.[16]

Table 8 presents the baseline results for the full sample of all countries with available data for the period 1995-2005. The firing cost variable used is the OECD indicator for stringency of employment protection for regular workers, and the riskiness indicator is based on the observed variance of labor productivity within an industry in each of the countries in the ONS dataset. Column (1) shows the results when fixed effects control for industry means and fixed time effects, and column (2) shows the results when both the

[15] Country fixed effects are insignificant and numerically very close to zero because the dependent variable is a share and the level effect of k is included.

[16] Because the employment share variable is bounded between zero and one, we have replicated all our results with a logistic transformation of the dependent variable. The qualitative results, equation fit, and p-level of all estimates are roughly equivalent, but the parameter value is less easily interpreted. In all our specifications we correct for heteroskedasticity in errors that likely occur, using 2-way industry and country clustering, as proposed by Cameron et al. (2010).

industry means and industry specific time trends are removed. The dependent variable is the share of hours worked for that industry as a percentage of total hours for that country and year. The interpretation of the coefficient, γ, is as follows: A movement of the EPL index by 1 point, (say from the German value of 2.7 to the Belgium value of 1.7), will increase the share of employment in the riskiest industry (rank=.5) by 0.5 percentage point, while reducing the share of employment in the safest sector by the same amount.[17]

	(1)	(2)
γ	-1.01	-1.01
	(2.75)	(2.98)
R^2	0.84	0.85
D.F.	5508	5494
Fixed effects	industry mean	industry mean and trend

Table 8: Regression results

t-statistic in parenthesis. Period: 1995-2005; Industry rank: productivity variance; ExitCost: EPLRegular. See Appendix E for country and industry listing. Robust estimation of error variances using 2-way industry and country clusters

Table 9 shows the result after allowing the regression coefficients α, β, and γ, to vary for four groups of observations, split by countries with high versus low firing costs, and by industries with high risk and low risk. For all four groups, the estimate of γ is negative. With the 2-way clustered robust standard errors the effective sample size becomes rather small, and the coefficient is not significant at the 10% level for the groups of low-risk industries. Looking across the rows, the (absolute value of the) impact of firing costs

[17]The level effect of the exit costs, β, is not shown. Because of the specification of the dependent variable as a share, and the inclusion of industry fixed effects, the coefficient captures small interactions between means of EPL and means of shares over time and countries. The coefficient is always very insignificant and close to zero in magnitude.

is higher in the high-risk industry sub-sample, consistent with the outcome of the model simulation. In the model, firing costs become particularly onerous when riskiness is high. Looking down the columns, the impact of firing costs is lower with high firing costs, also consistent with the model. When firing costs already are high, there is less scope for a further reduction in employment share by raising these costs because the amount of firing already is minimal.

	Industry sub-sample	
Country sub-sample	Low risk	High risk
Low firing cost	−1.95	−3.96
	(1.73)	(2.40)
High firing cost	−1.22	−2.66
	(1.83)	(2.42)

Table 9: Country/Industry sub-samples

t-statistic in parenthesis. Period: 1995-2005; Industry Rank: productivity variance; ExitCost: EPLRegular; Fixed Eff: industry means & trends. Robust errors clustered 2-way by industry and country. See Appendix E for country and industry listing.

Next, we address the issue whether entry costs rather than firing costs are causing the small employment share of risky sectors. Our first thoughts are that firms in both the safe and risky sector must pay the entry fee, so that the first-order effect of higher entry costs would not discriminate between them. However, given the shorter expected life of a job in high risk sectors, more entry fees must be made to maintain employment there compared to the safe sector, reducing its size in equilibrium. In terms of the search model, fewer vacancies are needed to maintain the necessary flows into the safe sector, so that its relative size may increase with increase in entry costs. In a simulation of the model, high entry fees (keeping the ratio of c_0/c_1 constant) decrease the relative size of

the risky sector. However, if firing costs are increased from the calibrated value, the effect of higher entry fees on relative size is much smaller.

Our empirical findings, using a collection of indicators on costs of doing business, from Djankov et al. (2002), likewise are mixed. When we run our basic specification of employment share in an industry regressed on the entry cost indicator, and the indicator interacted with the industry riskiness ranking, we sometimes find significantly negative effects on the interacted term. So, for example, as seen in Table 10, in countries where the time to start a business is high, high risk industries will have lower employment. When we included both entry and exit costs, Table 10 shows that the coefficient on the interacted employment protection variable remains significant when the entry costs variables are included, but that the size of the coefficient is reduced slightly. None of the entry cost indicators have a significantly negative interaction effect when exit costs are included as well.

Entry Cost Indicator	only γ_{entry}	γ_{entry}	γ_{exit}
Starting a Business - # of procedures	$-.20$ (1.75)	$-.08$ (1.00)	$-.88$ (2.86)
Starting a Business - time (days)	$-.14$ (2.51)	$-.08$ (1.31)	$-.71$ (1.90)
Starting a Business - cost (pct of capital)	$-.06$ (1.01)	$-.02$ (0.54)	$-.98$ (3.40)
Difficulty of hiring (index)	$-.02$ (1.42)	$-.04$ (.35)	$-.97$ (2.43)
Barriers to entrepreneurship	$-.61$ (1.63)	$-.32$ (1.04)	$-.89$ (3.24)
Barriers to entrp. license and permits	.22 (1.98)	.13 (.73)	$-.96$ (2.73)
none. (only exit cost: EPLRegular)			-1.01 (2.98)

Table 10: Labor share regressed on exit and entry costs
t-statistic in parenthesis. Period: 1995-2005; Industry rank: productivity variance; Exit Cost: EPLRegular; Fixed Eff: industry means & trends. Robust errors clustered 2-way by industry and country.

In the Appendix D, various other robustness checks are conducted, with variations in the country sample used, the time periods, the indicators for industry riskiness, and the variables related to layoff and exit costs. Overall, our results are extremely robust: higher firing costs are associated with lower employment shares in high risk industries and higher shares in low risk industries. The effect is never lower in the latter part of the sample period, consistent with the outcome of the model simulation with rising risk. The effect varies a bit across the different country samples, and it seems that inclusion of the transition economies weakens the effect. All the exit cost indicators used give significantly negative γ estimates, regardless of which of the riskiness industry-rank indicators we select.

As an additional robustness check, we randomly select 1200 industry rankings from all possible ordinal rankings of our 26 industries and run our baselines regression to estimate the parameter γ for each ranking. The regressions are based on 'all countries', for the period 1995-2000, use EPL Regular as exit cost indicator, and include industry fixed effects and industry time trends. All the estimates of γ reported in this paper, as well as the estimates of γ for all the permutations of firing costs, rankings, and samples we have explored, fall well within the 5 percent largest negative estimates in our regressions with random rankings. Our preferred estimate with the productivity variance as industry ranking and EPL Regular as firing cost indicator lies among the 1 percent largest (absolute) effects of firing costs.

7 Final remarks

In this paper we argue that the extent to which a country can benefit from the advantages of risky technologies depends on the institutional arrangements on firing and bankruptcy. The more employment protection there is, the more costly it is to exercise the job de-

struction or firm exit option. This mechanism can explain why the US was better able to explore the benefits of the new information technology starting in the mid-1990s. We construct a matching model with endogenous technology choice (risky or safe) and find that if we calibrate the model to the US that firing cost are in the order of about one month of production. If we increase this level to European levels (7 months of production), this reduces aggregate productivity by about 10 percent, partly through a direct reduction of average productivity in the risky sector, and partly through a significant reduction of activity (employment) in the risky sector.

One of our simplifying assumptions was that workers are risk neutral. A natural question to ask is whether EPL is more desirable if workers are risk averse? This is not obvious since EPL makes the unemployment state less attractive because it increases unemployment duration and risk averse workers prefer the differences between the good and bad state to be small. In other words, it puts the burden of unemployment on a smaller group. In richer models where optimal UI benefits and EPL are determined jointly, optimal EPL may well be positive.

In future work we want to further explore the role of risky technologies on long term productivity and growth. Simple simulations show that if the price of financing risky projects increases and it becomes more costly to open risky vacancies, this can have substantial effects on productivity.

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Appendices

A Proofs and derivations

A.1 Equilibrium conditions: proof of proposition 1

In this appendix, we give an analytical characterization of the equilibrium and we also provide derivations.

Proposition 2 *The risky sector job destruction margin is implicitly defined by*

$$y + x_d = b + \frac{\beta}{1-\beta}\left(\theta_0 c_0 + \theta_1 c_1\right) - \frac{\lambda}{r+\delta+\lambda}\int_{x_d}^{x_u}\left(1 - F\left(z\right)\right)dz - \left(r+\delta\right)k.$$

The risky sector job creation condition is given by

$$\frac{m_1}{\theta_1} = \frac{\left(r+\delta+\lambda\right)c_1}{\left(1-\beta\right)\left(-x_d - \left(r+\delta+\lambda\right)k\right)}.$$

The safe sector job creation condition is given by

$$\frac{m_0}{\theta_0} = \frac{\left(r+\delta+\beta m_0\right)c_0}{\left(1-\beta\right)\left(y-b\right) - \beta\theta_1 c_1}.$$

Proof Start with the safe sector surplus equation (4). The appropriate discount rate for the safe sector is $r+\delta$. The safe sector surplus equation in flow form is therefore

$$\left(r+\delta\right)S_0 = \left(r+\delta\right)J_0 + \left(r+\delta\right)\left(E_0 - U\right).$$

The firm surplus can be substituted out via (10) and the worker surplus can be substituted out via the difference between (17) and (15)

$$\left(r+\delta\right)S_0 = y - b - m_0\left(E_0 - U\right) - m_1\left(E_1\left(0\right) - U\right).$$

Use the Nash bargaining equations (6) up to and including (9) to rewrite this expression in terms of firm surplus

$$(r+\delta)\frac{1}{1-\beta}J_0 = y - b - m_0\frac{\beta}{1-\beta}J_0 - m_1\frac{\beta}{1-\beta}J_1(0).$$

Use the free entry conditions (2) and (3) to rewrite this expression in terms of labor market tightness

$$(r+\delta)\frac{1}{1-\beta}\frac{\theta_0 c_0}{m_0} = y - b - m_0\frac{\beta}{1-\beta}\frac{\theta_0 c_0}{m_0} - m_1\frac{\beta}{1-\beta}\frac{\theta_1 c_1}{m_1}.$$

Rearrange some terms to arrive at the safe sector job creation condition

$$\frac{m_0}{\theta_0} = \frac{(r+\delta+\beta m_0)c_0}{(1-\beta)(y-b)-\beta\theta_1 c_1}.$$

Continue with the risky sector surplus equation (5). The appropriate discount rate for the risky sector is $r+\delta+\lambda$. The risky sector surplus equation in flow form is therefore

$$(r+\delta+\lambda)S_1(x) = (r+\delta+\lambda)J_1(x) + (r+\delta+\lambda)(E_1(x)-U).$$

The firm surplus can be substituted out via (11) and the worker surplus can be substituted out via the difference between (18) and (15)

$$(r+\delta+\lambda)S_1(x) = y+x+\lambda\int_{x_d}^{x_u} S_1(z)\,dF(z) - \lambda F(x_d)\,k - b - m_0(E_0-U) - m_1(E_1(0)-U).$$

Calculate the difference $S_1(0) - S_1(x_d)$. Most terms including the integral drop out. Rewrite using the reservation property $S_1(x_d) = -k$

$$S_1(0) = \frac{-x_d}{r+\delta+\lambda} - k.$$

Use the Nash bargaining equation (9) and the free entry condition (3) to rewrite the left-hand side in terms of labor market tightness

$$\frac{1}{1-\beta}\frac{\theta_1 c_1}{m_1} = \frac{-x_d}{r+\delta+\lambda} - k.$$

Rearrange some terms to arrive at the risky sector job creation condition,

$$\frac{m_1}{\theta_1} = \frac{(r+\delta+\lambda)\, c_1}{(1-\beta)\left(-x_d - (r+\delta+\lambda)\, k\right)}.$$

To derive the implicit expression for the risky sector job destruction margin go back to

$$(r+\delta+\lambda)\, S_1(x) = y+x+\lambda \int_{x_d}^{x_u} S_1(z)\, dF(z) - \lambda F(x_d)\, k - b - m_0 (E_0 - U) - m_1 (E_1(0) - U).$$

Integrate this expression by parts[18] and rewrite using the reservation property $S_1(x_d) = -k$

$$(r+\delta+\lambda)\, S_1(x) = y+x+\lambda \int_{x_d}^{x_u} S_1'(z)\,(1-F(z))\, dz - \lambda k - b - m_0 (E_0 - U) - m_1 (E_1(0) - U).$$

The derivative of the risky sector surplus is simply the reciprocal of the discount factor implying that

$$(r+\delta+\lambda)\, S_1(x) = y+x+\frac{\lambda}{r+\delta+\lambda} \int_{x_d}^{x_u} (1-F(z))\, dz - \lambda k - b - m_0 (E_0 - U) - m_1 (E_1(0) - U).$$

Use the Nash bargaining equations (6) up to and including (9) to express the worker surplus in terms of firm surplus

$$(r+\delta+\lambda)\, S_1(x) = y+x+\frac{\lambda}{r+\delta+\lambda} \int_{x_d}^{x_u} (1-F(z))\, dz - \lambda k - b - m_0 \frac{\beta}{1-\beta} J_0 - m_1 \frac{\beta}{1-\beta} J_1(0).$$

[18] The rule is $\int_{x_d}^{x_u} q(z)\, r'(z)\, dz = q(z)\, r(z)\,|_{x_d}^{x_u} - \int_{x_d}^{x_u} q'(z)\, r(z)\, dz$. For $q(z)$, we use $q(z) = S_1(z)$ and $q'(z) = S_1'(z)$. For $r(z)$, we use $r'(z) = f(z)$ and $r(z) = F(z) - 1$. Note the -1 which simplifies the derivations.

Use the free entry conditions (2) and (3) to express the firm surplus in terms of labor market tightness

$$(r+\delta+\lambda)\,S_1(x) = y+x+\frac{\lambda}{r+\delta+\lambda}\int_{x_d}^{x_u}(1-F(z))\,dz-\lambda k-b-m_0\frac{\beta}{1-\beta}\frac{\theta_0 c_0}{m_0}-m_1\frac{\beta}{1-\beta}\frac{\theta_1 c_1}{m_1}.$$

Finally, evaluate this expression in $x = x_d$ and rewrite using the reservation property $S_1(x_d) = -k$. This brings us to the implicit expression for the risky sector job destruction margin

$$y + x_d = b + \frac{\beta}{1-\beta}(\theta_0 c_0 + \theta_1 c_1) - \frac{\lambda}{r+\delta+\lambda}\int_{x_d}^{x_u}(1-F(z))\,dz - (r+\delta)\,k.$$

■

A.2 Calibration details

Step 1. Fix $y = 1$, $r = 0.004$, $\beta = 0.5$, $b = 0.4$, $\eta = 0.5$ and $\xi = 0.3$.

Step 2.1. Set $l = 0.77$ and $\delta = 0.026$.

Step 2.2. The targets for the labor market stocks are $u = 0.043$, $e_0 = 0.316$ and $e_1 = 0.41$. The targets for the labor market separation rates are $\delta = 0.026$ and $\delta + \lambda F(x_d) = 0.035$. Via the safe and risky sector steady state flow equations

$$\begin{aligned} m_0 u &= \delta e_0 \\ m_1 u &= (\delta + \lambda F(x_d))\, e_1 \end{aligned}$$

we can solve for the implied labor market tightness, giving us $\theta_0 = 0.4056$ and $\theta_1 = 1.1677$. We set the vacancy costs c_0 and c_1 in order to match labor market tightness. Using our assumption that $c_1 = 2c_0$ and the job creation condition of the safe sector

$$\frac{m_0}{\theta_0} = \frac{(r+\delta+\beta m_0)\,c_0}{(1-\beta)(y-b)-\beta c_1\theta_1}$$

we find $c_0 = 0.2092$ and $c_1 = 0.4184$.

Step 3. The targets for the ex post observed truncated cross-sectional mean and variance of US productivity are $\widehat{y} = 1.1$ and $\widehat{\sigma}^2 = 0.16$. The target for the endogenous job destruction rate is $\hat{\lambda} = 0.008$.

$$y + \frac{\lambda}{\delta + \lambda}\left(\left(1 - \Phi\left(\frac{x_d - \mu}{\sigma}\right)\right)\mu + \varphi\left(\frac{x_d - \mu}{\sigma}\right)\sigma\right) = \hat{y}$$

$$\frac{\lambda}{\delta + \lambda}\left(\left(1 - \Phi\left(\frac{x_d - \mu}{\sigma}\right)\right)\left(\mu^2 + \sigma^2\right) + \varphi\left(\frac{x_d - \mu}{\sigma}\right)(x_d + \mu)\,\sigma\right) - (y - \hat{y})^2 = \hat{\sigma}^2$$

$$\lambda F(x_d) = \hat{\lambda}.$$

In addition to this, the risky sector job creation and destruction conditions must be satisfied.

$$\frac{m_1}{\theta_1} = \frac{(r + \delta + \lambda)\,c_1}{(1 - \beta)\left(-x_d - (r + \delta + \lambda)\,k\right)}$$

$$y + x_d = b + \frac{\beta}{1 - \beta}\left(\theta_0 c_0 + \theta_1 c_1\right) - \frac{\lambda}{(r + \delta + \lambda)}\int_{x_d}^{x_u}\left(1 - F(z)\right)dz - (r + \delta)\,k.$$

This gives us five equations in four unknown structural parameters and one unknown steady state value. Solving this highly non-linear system of equations is not easy. Standard Matlab equation solvers are not able to find the solution without good starting values. We can solve the system of equations by exploiting its underlying quasi triangular structure. But first, preparatory algebra is needed to uncover its quasi triangular structure.

Define $\tilde{\mu} \equiv \frac{\mu}{\sigma}$ and $\tilde{x}_d \equiv \frac{x_d}{\sigma}$. Rewrite the targets for the cross-sectional mean and variance

$$\frac{\lambda}{\delta + \lambda}\left(\left(1 - \Phi\left(\tilde{x}_d - \tilde{\mu}\right)\right)\tilde{\mu}\sigma + \varphi\left(\tilde{x}_d - \tilde{\mu}\right)\sigma\right) = \hat{y} - y$$

$$\frac{\lambda}{\delta + \lambda}\left(\left(1 - \Phi\left(\tilde{x}_d - \tilde{\mu}\right)\right)\left(\tilde{\mu}^2 + 1\right)\sigma^2 + \varphi\left(\tilde{x}_d - \tilde{\mu}\right)\left(\tilde{x}_d + \tilde{\mu}\right)\sigma^2\right) = (y - \hat{y})^2 + \hat{\sigma}^2$$

and divide the latter by the former to express σ explicitly in terms of $\tilde{x}_d$ and $\tilde{\mu}$

$$\sigma = \frac{\left((y-\hat{y})^2+\hat{\sigma}^2\right)\left(\left(1-\Phi\left(\tilde{x}_d-\tilde{\mu}\right)\right)\tilde{\mu}+\varphi\left(\tilde{x}_d-\tilde{\mu}\right)\right)}{\left(\hat{y}-y\right)\left(\left(1-\Phi\left(\tilde{x}_d-\tilde{\mu}\right)\right)\left(\tilde{\mu}^2+1\right)+\varphi\left(\tilde{x}_d-\tilde{\mu}\right)\left(\tilde{x}_d+\tilde{\mu}\right)\right)}.$$

Use this expression and the target for the endogenous job destruction rate to substitute out σ and λ from the target for the cross-sectional mean to express $\tilde{\mu}$ implicitly in terms of $\tilde{x}_d$

$$(\hat{y}-y)^2 = \frac{\hat{\lambda}\left(\left(1-\Phi\left(\tilde{x}_d-\tilde{\mu}\right)\right)\tilde{\mu}+\varphi\left(\tilde{x}_d-\tilde{\mu}\right)\right)^2\left((y-\hat{y})^2+\hat{\sigma}^2\right)}{\left(\delta\Phi\left(\tilde{x}_d-\tilde{\mu}\right)+\hat{\lambda}\right)\left(\left(1-\Phi\left(\tilde{x}_d-\tilde{\mu}\right)\right)\left(\tilde{\mu}^2+1\right)+\varphi\left(\tilde{x}_d-\tilde{\mu}\right)\left(\tilde{x}_d+\tilde{\mu}\right)\right)}.$$

We have now uncovered the underlying quasi triangular structure. For a given $\tilde{x}_d$ we can successively work through the following iterative scheme.

1. Solve for $\tilde{\mu}$ from the implicit expression for $\tilde{\mu}$. This is a non-linear equation that can be solved using a standard Matlab equation solver.

2. Calculate σ from the explicit expression for σ.

3. Calculate μ and x_d by multiplying their tilde counterpart by σ.

4. Calculate λ from the target for the endogenous job destruction rate.

5. Calculate k from the risky sector job creation condition.

6. Calculate the difference between the left-hand side and the right-hand side of the risky sector job destruction condition. The integral on the right-hand side can be computed using a standard Matlab numerical integration routine.

Simply choose $\tilde{x}_d$ such that the risky sector job destruction condition clears. This gives us $\lambda = 0.1410$, $\mu = 0.0653$, $\sigma = 0.4989$, $k = 1.2227$ (and $x_d = -0.7245$).

A.3 Separation rates for medium-skilled workers

Under the assumption that within-sector differences are the same for the safe and risky sector, we get

$$\begin{aligned}\frac{s^{safe}_{high}}{s^{safe}_{medium}} &= \frac{s^{risky}_{high}}{s^{risky}_{medium}} = \omega^s_h < 1\\ \frac{s^{safe}_{low}}{s^{safe}_{medium}} &= \frac{s^{risky}_{low}}{s^{risky}_{medium}} = \omega^s_l > 1.\end{aligned}$$

We set $\omega^s_h = 0.4$ and $\omega^s_l = 2$, implying a factor five difference between high-skilled and low-skilled and medium-skilled a bid closer related to low-skilled than to high-skilled. From the skill decomposed separation rates

$$\begin{aligned}s^{safe} &= p^{safe}_{high} s^{safe}_{high} + p^{safe}_{medium} s^{safe}_{medium} + p^{safe}_{low} s^{safe}_{low}\\ s^{risky} &= p^{risky}_{high} s^{risky}_{high} + p^{risky}_{medium} s^{risky}_{medium} + p^{risky}_{low} s^{risky}_{low}\end{aligned}$$

we can now solve for the medium-skilled separation rates

$$\begin{aligned}s^{safe}_{medium} &= \frac{s^{safe}}{p^{safe}_{high}\omega^s_h + p^{safe}_{medium} + p^{safe}_{low}\omega^s_l} = 0.026\\ s^{risky}_{medium} &= \frac{s^{risky}}{p^{risky}_{high}\omega^s_h + p^{risky}_{medium} + p^{risky}_{low}\omega^s_l} = 0.035.\end{aligned}$$

This gives us $s^{safe}_{medium} = 0.026$ and $s^{risky}_{medium} = 0.035$. In the safe sector of our model, there is only exogenous separation and hence we set the exogenous job destruction rate to $\delta = 0.026$. Now the endogenous job destruction rate must be $\lambda F(x_d) = s^{risky}_{medium} - \delta = 0.008$. This condition implicitly determines the risky sector job destruction margin and serves as a target in the next step of our calibration strategy.

A.4 Cross-sectional targets to match

Under the assumption that within-sector differences are the same for the safe and risky sector, we get

$$\begin{aligned}\frac{\pi^{safe}_{high}}{\pi^{safe}_{medium}} &= \frac{\pi^{risky}_{high}}{\pi^{risky}_{medium}} = \omega^{\pi}_{h} > 1\\ \frac{\pi^{safe}_{low}}{\pi^{safe}_{medium}} &= \frac{\pi^{risky}_{low}}{\pi^{risky}_{medium}} = \omega^{\pi}_{l} < 1\end{aligned}$$

We set $\omega^{\pi}_{h} = 2.4$ and $\omega^{\pi}_{l} = 0.8$, implying a factor three difference between high-skilled and low-skilled and medium-skilled being much closer related to low-skilled than to high-skilled. From the skill decomposed productivities

$$\begin{aligned}\pi^{safe} &= p^{safe}_{high}\pi^{safe}_{high} + p^{safe}_{medium}\pi^{safe}_{medium} + p^{safe}_{low}\pi^{safe}_{low}\\ \pi^{risky} &= p^{risky}_{high}\pi^{risky}_{high} + p^{risky}_{medium}\pi^{risky}_{medium} + p^{risky}_{low}\pi^{risky}_{low}\end{aligned}$$

we can now solve for the medium-skilled productivities

$$\begin{aligned}\pi^{safe}_{medium} &= \frac{\pi^{safe}}{p^{safe}_{high}\omega^{\pi}_{h} + p^{safe}_{medium} + p^{safe}_{low}\omega^{\pi}_{l}}\\ \pi^{risky}_{medium} &= \frac{\pi^{risky}}{p^{risky}_{high}\omega^{\pi}_{h} + p^{risky}_{medium} + p^{risky}_{low}\omega^{\pi}_{l}}.\end{aligned}$$

In our model, only the ratio $\frac{\pi^{risky}_{medium}}{\pi^{safe}_{medium}}$ is identified (because we have normalized safe sector productivity to $y = 1$) and must be equal to $\widehat{y}$, that is

$$\widehat{y} = \frac{\pi^{risky}}{\pi^{safe}}\frac{p^{safe}_{high}\omega^{\pi}_{h} + p^{safe}_{medium} + p^{safe}_{low}\omega^{\pi}_{l}}{p^{risky}_{high}\omega^{\pi}_{h} + p^{risky}_{medium} + p^{risky}_{low}\omega^{\pi}_{l}}.$$

B Further evidence on ICT and profit dispersion

In a recent paper, Brynjolfsson, McAfee, Sorell, and Zhu (2008) argue that the payoff associated with ICT-related business investments comes from scaling up a successful venture after it has shown its success in smaller-scale experiments. The upshot is that investing in such experiments has a high chance of failure and a very small chance of a very high payoff. Data from Compustat, linked to the Harte-Hank indicators on firm-level ICT investments, show that the cross-sectional variance of profits of ICT-intensive firms versus non-ICT intensive firms starts diverging in the mid-nineties (Brynjolfsson, McAfee, and Zhu 2009), see Figure 4.

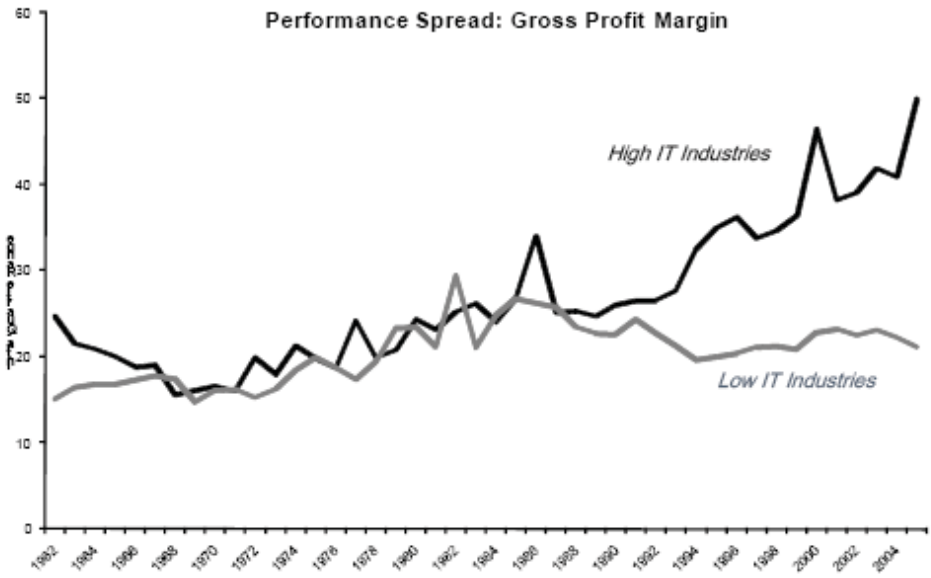

Figure 4: Variance of gross profit margin, source: Brynjolfsson et al. (2009)

C High versus low-EPL EU countries

A nearly identical picture emerges when we split the EU15 into countries with high EPL and low EPL (see Figure 5). During the late-1990s high-EPL countries in the EU did not see an acceleration in productivity or employment share in the risky sector. These are the main stylized facts to be explained by our model and explored further in detail in section 6. The distribution of EPL across countries does not change appreciably over time (see Nicoletti, Scarpetta, and Boylaud, 2000), thus changes in EPL alone cannot explain the productivity divergence. The core of our explanation is that employment protection makes firing more costly and makes the risky sector less attractive to open jobs. Moreover it shifts the firing threshold productivity level (below which a worker is fired) to the left and reduces the average productivity in the risky sector. The EPL distribution has not changed much in the nineties so this by itself cannot explain the US-Europe divergence but our story is that the US was able to better explore the benefits from the new risky ICT technologies that became available during the nineties.

D Robustness checks: alternative estimates of γ

In Table 11, the time periods are varied, as are the country samples. The country samples vary by including or excluding non-EU OECD members, or including/excluding transition economies. For ease of comparison, only the parameter γ and the t-statistic are presented. Overall, the general pattern is consistent: higher firing costs are associated with lower employment shares in high risk industries and higher shares in low risk industries. The effect is never lower in the latter part of the sample period, consistent with the outcome of the model simulation with rising risk. The effect varies a bit across the different country-

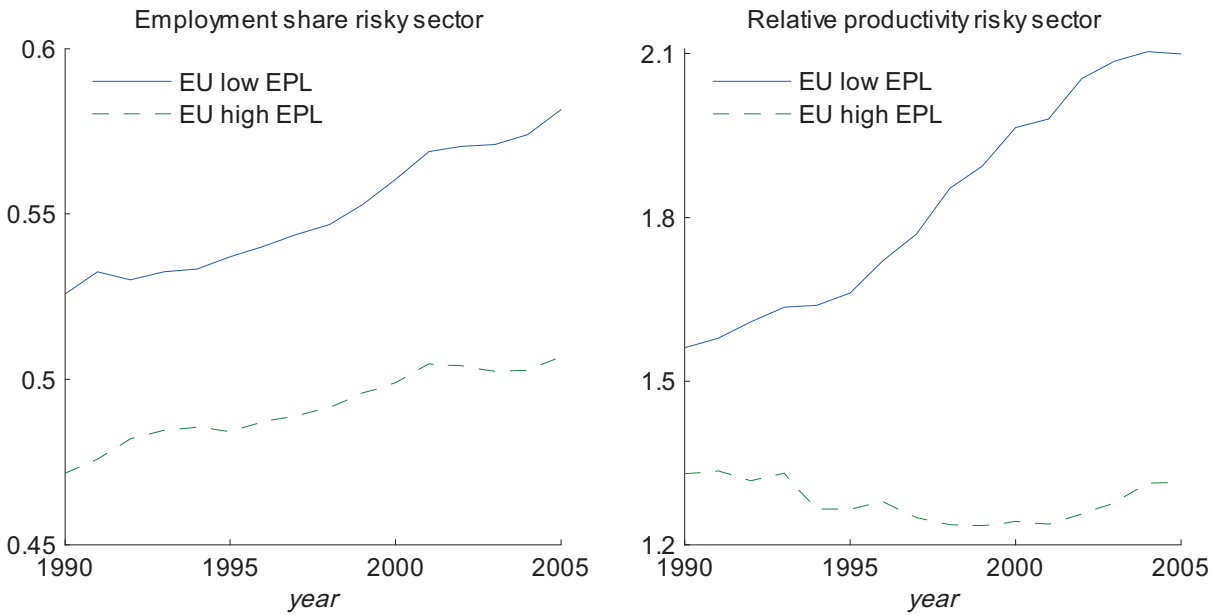

Figure 5: High and low-EPL EU countries: risky versus safe sector

samples, and it seems that inclusion of the transition economies weakens the effect.

Finally, Table 12 varies the indicators used for exit costs and for ranking of riskiness of industry. The first alternate indicator of riskiness captures the adoption and intensity of the use of broadband internet by firms in each industry, from the ONS dataset and is measured as the percentage of workers with access to broadband internet (DSL pct). The next measure is the ratio of productivity of the top quartile of firms to the mean in an industry, (P4/P). Because firing costs truncate from below, this indicator may be less affected by firing costs than the overall variance of productivity.[19] The last column

[19]We also use riskiness indicators drawn from firm-level distributions in the UK which has the lowest level of exit costs in the EU. The US has even lower firing costs than the UK, but the US productivity variance is only available for manufacturing industries. We test all our results for all industries with the UK-based riskiness indicator or for manufacturing sectors only, with US or EU-based riskiness indicators, with very similar results as presented in our main tables.

	sub-period	
Sample	1995-2000	2000-2005
EUN	−1.02	−1.02
	(2.92)	(3.07)
EURO	−.92	−.95
	(3.03)	(3.09)
OECD	−0.83	−.84
	(3.05)	(3.09)
EU	−0.87	−0.88
	(3.01)	(3.05)
ALL	−1.01	−1.01
	(2.91)	(3.05)

Table 11: Country/Period sub-samples

t-statistic in parenthesis. Industry rank: productivity variance; ExitCost: EPLRegular; Fixed Eff: industry means & trends. Robust errors clustered 2-way by industry and country. See Appendix E for country listing.

shows our base measure, the variance of productivity. All industry riskiness rankings are averaged across countries in the ONS dataset. The exit cost indicators are described and the 2004 values for each country are given in Appendix E. For each exit cost indicator, the effect is largest when the riskiness ranking is based upon broadband penetration, slightly lower for the width of the top of the productivity distribution and smallest for the overall variance measure of industry riskiness.

The first four exit cost indicators are sourced from the World Bank Cost of Doing Business Database and the last two from the OECD. The first two exit cost indicators are not directly associated with costs of shedding workers, but relate to the percentage of annual revenue that is spent on exit (Exitcost%), and the percentage of capital investment that may be reclaimed upon exit (Exitloss%). The other indicators are related to costs of employment protection (an indicator of difficulty of firing, Firerule, and an indicator of cost, Firecost%). Appendix E shows the values of these indicators for each country in our sample in 2004.

	Riskiness indicator		
Exit Cost	DSLpct	P4/P	Variance
Exitloss%	−4.85	−3.47	−2.75
	(2.49)	(1.75)	(2.89)
Exitcost%	−21.51	−15.38	−12.36
	(2.84)	(1.82)	(1.66)
Firerule	−0.42	−0.36	−0.32
	(.66)	(.72)	(0.73)
Firecost	−4.04	−3.64	−3.02
	(2.33)	(2.79)	(1.66)
EPLoverall	−1.04	−0.80	−0.64
	(2.39)	(2.39)	(2.30)
EPLregular	−1.21	−1.04	−1.01
	(2.63)	(2.46)	(2.98)

Table 12: Alternate exit cost and riskiness indicators

t-statistic in parenthesis. Period: 1995-2005; Fixed Eff: industry means & trends. See Appendix E for indicator definitions and country and industry listing. Robust errors clustered 2-way by industry and country.

As an additional robustness check, we randomly select 1200 industry rankings from all possible ordinal rankings of our 26 industries and run our baselines regression to estimate the parameter γ for each ranking. The regressions are based on 'all countries', for the period 1995-2000, use EPL Regular as exit cost indicator, and include industry fixed effects and industry time trends. Figure 6 shows the point estimates for γ with confidence bounds. All the estimates of γ reported in this paper, as well as the estimates of γ for all the permutations of firing costs, rankings, and samples we have explored, fall well within the 5 percent largest negative estimates. Our preferred estimate with the productivity variance as industry and EPL Regular as firing cost lies among the 1 percent largest (absolute) effects of firing costs.

E Data documentation tables

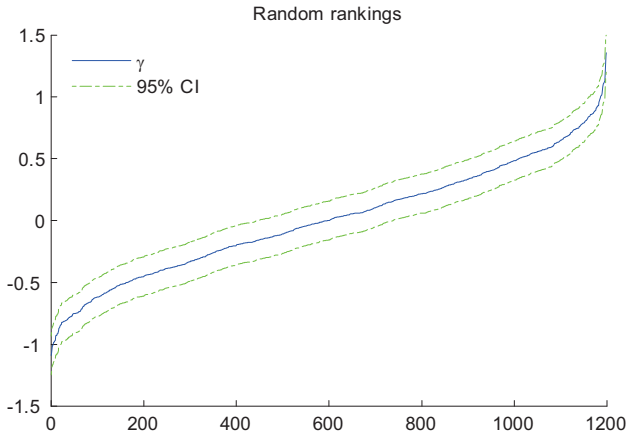

Figure 6: Estimates of γ with random $R(\sigma)$

Country	overall EPL	reg. EPL	Firing Rules	Firing Cost	Exit Cost	Exit Loss
AUS	1.19	1.50				
AUT	1.93	2.37	2.0	0.02	0.18	0.27
BEL	2.18	1.73	0.5	0.16	0.04	0.14
CZE	1.90	3.31	1.5	0.22	0.18	0.85
DNK	1.42	1.47	0.5	0.00	0.04	0.37
ESP	3.05	2.61	1.5	0.56	0.15	0.23
FIN	2.02	2.17	2.0	0.26	0.04	0.12
FRA	3.05	2.47	2.0	0.32	0.09	0.54
GER	2.35	2.68	2.0	0.69	0.01	0.44
GRC	2.83	2.41	2.0	0.24	0.09	0.57
IRL	1.11	1.60	1.0	0.13	0.09	0.12
JPN	1.84	2.44				
HUN	1.52	1.92				
ITA	1.95	1.77	2.0	0.02	0.18	0.57
NLD	2.12	3.05	3.5	0.17	0.04	0.13
POL	1.74	2.23				
PRT	3.67	4.33	2.5	0.95	0.09	0.27
SVK	1.92	3.47				
SWE	2.24	2.86	2.0	0.26	0.09	0.19
UK	0.75	1.12	0.5	0.22	0.06	0.14
USA	0.21	0.17	0.0	0.00	0.07	0.20

Table 13: Exit Cost Indicators, 2004

(X excludes countries from sample)				
ALL	EUN	EU	EURO	OECD
AUS	X	X	X	
AUT				
BEL				
CZE		X		X
DNK			X	
ESP				
FIN				
FRA				
GER				
GRC				
HUN		X		X
IRL				
ITA				
JPN	X	X	X	
NLD				
POL		X		X
PRT				
SVK		X		X
SWE				
UK			X	
USA	X	X	X	

Table 14: Country samples used in empirical exercise

Description
Food, Beverages and Tobacco
Clothing
Wood, Wood Products, Cork
Pulp, paper, publishing
Coke, refined petroleum and nuclear fuel
Chemicals
Rubber and plastics
Other Non-metallic minerals
Metals and Machinery
Machinery n.e.c.
Equipment
Motor Vehicles and Transport Equipment
Misc Manufacturing
Electricity, Gas and Water Supply
Construction
Sale, maintenance and repair of motor vehicles
Wholesale trade and commission trade, ex of motor vehicles
Retail trade, except of motor vehicles and motorcycles
Hotels and Restaurants
Transport
Post and Telecommunications
Banking
Business Services
Personal Services

Table 15: Industries included in empirical exercise

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