Accounting for time-varying and nonlinear relationships in macroeconomic models

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Chapter 6

Employment Protection, Technology Choice, and Worker Allocation

Abstract

We show empirically that high-risk sectors, which contribute strongly to aggregate productivity growth, are relatively small and have relatively low productivity growth in countries with strict employment protection legislation (EPL). To understand these findings, we develop a two-sector matching model where firms endogenously choose between a safe technology and a risky technology. For firms that have chosen the risky technology, EPL raises the costs of shedding workers in case they receive a low productivity draw. In our calibrated model, high-EPL countries take less advantage of the arrival of new risky technology than low-EPL countries. Parameters estimated through reduced-form regressions of employment and productivity on exit costs, riskiness, and in particular their interaction are similar for actual cross-country data and simulated model data. Our model is consistent with the slowdown in productivity in the EU relative to the US since the mid-1990s.1

6.1 Introduction

In this chapter we provide evidence that a change in the nature of technological opportunities in the mid-1990s interacted with cross-region differences in employment protection to explain part

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1This chapter is joint work with Eric Bartelsman and Pieter Gautier.
of the observed divergence in productivity between the US and the EU. Continuing 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 is appealing to individual firms because they can fully benefit from good draws while they can limit the loss from bad draws through the option to shed workers. The increase is good at the aggregate level, as more resources flow to the firms that use the risky technology successfully. When in the mid-1990s these technological opportunities arose, the expected net benefits of adoptions were higher in countries with low EPL because the option to shut down was less costly.

This chapter draws from and combines results from a variety of different literatures. The model we use builds upon models available in the labor search literature. The relation between ICT and productivity is prominent in recent empirical growth literature. Further, our use of model calibration, and comparison of model simulations with moments and parameter estimates from data draw on a rich emerging macro literature. Finally, we expand on a sequence of empirical papers studying the effect of EPL on labor markets, productivity and macro outcomes using a new combination of cross-country industry and firm-level data sources. We discuss these points in turn.

We develop a model where the decision to produce 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 modeled as in Mortensen and Pissarides (1994) with a hazard of receiving a productivity shock. The safe sector firms are as in Pissarides (2000), and have constant, known, productivity. The sectors are connected with each other through the pool of unemployed workers from which both sectors hire. This framework is particularly useful to study labor market policies because it is simple and simultaneously solves for the labor market stocks and flows. Frictions are essential in our model to 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.

Growth accounting exercises in the US have shown most of the acceleration of output growth

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2The effects of EPL have been studied extensively in the search matching literature using a single sector model. See e.g. Brügemann (2006), Ljungqvist (2002), and Mortensen and Pissarides (1999).
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, with sunk investment and risky market outcomes. Consistent with the nature of these technologies, 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. Finally, Schaal (2012) gives evidence for an increase in idiosyncratic variance in firm growth in the US. In this chapter, we document that the variance of productivity across firms and the churn of jobs has become higher since 1995 in ICT-intensive industries. We therefore interpret the ICT revolution as giving exogenous change in the variance of productivity shocks that allows us to exploit and study the differential responses in high and low EPL countries.

The main conclusions of the empirical literature on employment protection are that the effects of EPL 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 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 and he develops a simple vintage capital model where a firm’s optimal size decreases over time when the firm’s technology falls behind the frontier (of which the speed depends on the rate of technical

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3A 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. This fits nicely with the findings of Bloom, Sadun, and Van Reenen (2012) that US multinational firms have high returns to investment in ICT in their UK subsidiaries because they only transplant the ICT implementations that were first adopted successfully in the US.
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 (in our model turnover is endogenous and depends on the choice of technology). Finally, Cuñat and Melitz (2012) show that countries with flexible labor markets concentrate their exports mainly in sectors with higher volatility. In our empirical exercises based on cross-country industry and firm-level data, we add a new set of findings to the literature on the effects of EPL on labor market performance and productivity: risky, aggregate productivity enhancing activities are harmed relatively heavily by EPL.

The economic intuition in this chapter is related to a number of other papers that study the effect of exit cost on risky technologies. In Saint-Paul (2002), countries with high EPL specialize in secure goods at the end of their product cycle with stable demand while countries with low EPL specialize in more innovative goods. Bertola (1990, 1994) shows how labor mobility costs reduce the social returns to irreversible investments and in Poschke (2009) growth is driven by entrants who imitate the firms at the frontier (EPL reduces growth by reducing entry). Berdugo and Hadad (2008) have a model where EPL make innovators choose medium-tech projects which are more flexible in their human capital requirements than high-tech projects. Those papers do not use the rich data sources that we use nor do they calibrate their model and quantify the effects of EPL on productivity and the allocation of workers.

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; 2013, labelled 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. We can simulate the model across the empirically observed variation across countries in EPL and a range of productivity shock variances consistent with

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4We want to emphasize that this chapter looks at a firm’s decision to invest in risky or safe technologies. In a paper considering the effort of workers in creating new knowledge, Acharya, Baghai and Subramanian (2010) argue that EPL may serve as a commitment device to induce workers to take more risk. They present evidence that countries with high EPL have more patenting. By contrast, and in line with our findings, Alesina and Zeira (2006) give evidence that countries with less regulations have relatively more patents in high tech sectors.

5Poschke (2009) is the only other paper that we are aware of that also calibrates his model but he uses different data sources and has a different mechanism.
evidence from firm-level data, generating simulated panel data on employment and productivity of the risky and safe sectors. Reduced form regressions of the relative size and productivity of the risky sector on EPL, riskiness, and their interaction using simulated data gives qualitatively similar results as regressions using actual cross-country panel data.

We next present robust evidence that in countries with high EPL, high-risk innovative sectors, which are often associated with intensive information and communication technology (ICT) use, are relatively small. Moreover, we confirm that productivity in the risky sectors increased relatively slowly in high EPL countries during this period. The negative relationships also holds for other exit frictions (i.e. low cost recovery of capital for exiting firms).

Overall, both the simulated data from the calibrated model and our empirical country-industry panel data exercises show that it is more advantageous to exploit new risky opportunities in low-EPL countries. Relative to the literature, our main contribution lies in the interaction between theory and evidence which allows us to quantify the effects of EPL. We find that if we would increase EPL in the US from one month of output to EU levels (seven months of output), aggregate productivity would be about 10% lower.

The chapter is organized as follows. Section 6.2 discusses our theoretical model. Section 6.3 gives an overview of the data sources used for calibration and empirical exercises. The calibration of the model and the moments we match are discussed in Section 6.4. The model predictions are presented in section 6.5. In this section, we also compare reduced from regressions from simulated and actual cross-country data. Section 6.6 shows that our main finding that risky sectors are relatively smaller and have lower productivity growth in high-EPL-countries can be identified with a difference -in-differences estimation. We conclude with some reflections on the importance of the link between EPL and productivity and with ideas for future research.

6.2 The model

This section offers a short description of the structure and assumptions of the model. The Bellman equations and derivations are delegated to Appendix 6.A.1. 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, chapter 1) while in the risky technology sector (1), firms are hit by shocks that can increase or decrease productivity as in Mortensen
All risk neutral workers are identical. A matched worker-firm pair in sector 1 produces $y + x$ where $x$ is a draw from a CDF, $F(x)$, with mean $\mu$ and variance $\sigma^2$. $F(x)$ 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 $\lambda$. When a shock occurs, firms must draw a new value of $x$ from $F(x)$. We assume that new firms start at $y$ 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 ($\lambda = 0$), sector 0 and 1 are identical and the model reduces to the Pissarides (2000, chapter 1) model.

Wages in sector $i$, follow from the generalized Nash bargaining solution with continuous renegotiation (so the wage changes after a shock occurs) and workers cannot search on the job. 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. Workers search with intensity, $s_0$, in the safe and with intensity, $s_1$, in the risky sector and we assume that the search cost are quadratic in search intensity ($\frac{1}{2}s^2_i$). This is reasonable if workers first look for the jobs that are easiest to find. The search intensities in each sector are determined by a no arbitrage condition, i.e. the net marginal benefits of search must be equal in both sectors. 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 $\delta$. 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 procedural and time costs $k$ (no severance payments). We are interested in how this firing tax distorts the sorting of firms into safe and risky sectors. In the absence of frictions, firms prefer the risky technology because

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6 The productivity shocks can be interpreted as 'business condition' shocks (Bloom, 2009) and can reflect either demand or technology shocks.

7 Another way to have both sectors coexist is to introduce love-for-variety demand for the output in both sectors or to introduce decreasing-returns-to scale. Both will make the model considerably more complex in dimensions that are not interesting for the problem we are studying here.

8 In our model, the only productive input is labor, and firing costs thus coincide with the more generic
there is no bound on positive shocks while firms have the option to close the job if a sufficiently large negative shock arrives. When there are search frictions, the two technologies coexist and the more profitable a technology is, the more people will work in the sector that uses this technology.

We define labor market tightness in each of the sectors as, \( \theta_0 = v_0/u_0 \) and \( \theta_1 = v_1/u_1 \). The total number of matches in each sector is determined by a constant-returns-to-scale matching function, \( M_0(s_0u_0, v_0) \) and \( M_1(s_1u_1, v_1) \) 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 \( m_i = M_i/u_i \). The rate at which vacancies are filled in each sector is then \( m_i/\theta_i \). The functional form of the matching function in both sectors is, \( M_i = \xi_i(s_iu_i)^\eta v_i^{1-\eta} \). We can think of EPL as a tax on the risky sector which decreases vacancy supply and lowers expected wages in that sector. In equilibrium, workers will respond by searching less intensively in the risky sector which decreases the arrival rate of workers in that sector. From the Bellman equations in Appendix 6.A.1.2 we can derive a job destruction equation for sector 1 and job creation conditions for sector 0 and sector 1. Together they jointly determine \( \theta_0, \theta_1, \) and \( x_d \).

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

\[
y + x_d = b + \frac{\beta}{2(1-\beta)} (\theta_0 c_0 + \theta_1 c_1) - \frac{\lambda}{r + \delta + \lambda} \int_{x_d}^{x_u} (1 - F(z)) dz - (r + \delta) k.
\]  

(6.1)

The risky sector job creation condition is given by

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

(6.2)

The safe sector job creation condition is given by

\[
\frac{m_0}{\theta_0} = \frac{(r + \delta + \frac{1}{2} \beta m_0) c_0}{(1-\beta)(y - b) - \frac{1}{2} \beta \theta_1 c_1}.
\]  

(6.3)

The steady-state unemployment rate and vacancy stocks follow from the following steady-state flow equations

\[
m_0 u = \delta c_0
\]  

(6.4)

The concept of exit costs. We will use the terms interchangeably. In section 6.6 we use different indicators relating to employment protection, firing costs, and capital losses at exit.
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\[ m_1u = (\delta + \lambda F(x_d))c_1. \] (6.5)

Before calibrating our model’s parameters in section 6.4, we first discuss in section 6.3 below, the data sources that we use.

6.3 Data

We use a wide variety of data sources. Some of the data sources are used for calibrating the model, some for the empirical exercises, and some for both. Table 6.1 provides an overview of the main datasets along with their country, industry, and time coverage as well as a description of the type of variables available. We organize the description of the data by the type of variables covered: industry performance data (outputs and inputs), regulatory and institutional data (EPL, exit costs), industry riskiness (moments from firm-level), and labor market data (job flows, labor force statistics).

<table>
<thead>
<tr>
<th>Source</th>
<th>Periods</th>
<th>Countries</th>
<th>Industries</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>EUKLEMS</td>
<td>1970-2005</td>
<td>EU+US</td>
<td>30, market sector</td>
<td>Output, factor inputs, prices, PPPs</td>
</tr>
<tr>
<td>OECD-EPL</td>
<td>1985-2005*</td>
<td>OECD</td>
<td>Aggregate</td>
<td>EPL indicators</td>
</tr>
<tr>
<td>WB-CDB</td>
<td>2004-2007</td>
<td>World</td>
<td>Aggregate</td>
<td>Entry/ firing costs, rigidities</td>
</tr>
<tr>
<td>BHS</td>
<td>1990s</td>
<td>OECD, Asia, Lat Am</td>
<td>16, manufacturing.</td>
<td>Moments from firm surveys</td>
</tr>
<tr>
<td>ONS/Eurostat</td>
<td>2001-2005</td>
<td>13 EU countries</td>
<td>30, market</td>
<td>Moments from firm surveys</td>
</tr>
<tr>
<td>JOLTS</td>
<td>2000-2003</td>
<td>USA</td>
<td>broad SIC sectors</td>
<td>Job flows data</td>
</tr>
<tr>
<td>OECD/LFS</td>
<td>1989-2009</td>
<td>OECD</td>
<td>Aggregate</td>
<td>Labor force stats</td>
</tr>
</tbody>
</table>

Table 6.1: Data sources

**Industry Data.** The main source for measuring country and industry performance is the published EUKLEMS dataset (O’Mahony and Timmer 2009), a country/industry panel with information on employment, hours worked, value added, and prices. These data are used to generate employment share and productivity series by country and sector. The employment share of a sector is computed using hours worked as the labor input variable. Labor productivity is computed as deflated, PPP-adjusted value added per hour worked for each country and sector, while TFP growth is taken directly from the published database. The EUKLEMS source is used in the model calibration (safe and risky sector employment share and productivity for the US), and in the empirical exercises (industry time series with employment share and productivity for 18 countries).

**Exit Costs and other regulatory indicators.** The regulatory 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). 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 e.g. hiring and firing costs or time to start a business are available for many countries from 2004 to the present. The OECD-EPL dataset is used in model calibration (US values) and in the empirical exercises (country panel). The WB-CDB data are used for robustness in the empirical exercises. The time average of these indicators by country is provided in the Appendix.

**Riskiness** Information on the riskiness of a sector is sourced from the literature and from our own calculations using firm-level moments (BHS and ONS/Eurostat, 2008). These two datasets have been collected using the method of ‘distributed micro data research’ (Bartelsman, Haltiwanger, and Scarpetta 2009, 2013). The data sets include moments computed from the underlying distributions in confidential firm-level data sets available at national statistical offices, aggregated to the country, industry, and year level. First, the 1990s data has been collected for a selection of OECD countries, mostly for firms in manufacturing. Next, through a project coordinated by the UK Office of National Statistics (ONS/Eurostat 2008) and funded by Eurostat, information was compiled 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. Among the variables included in the database are indicators of ICT usage, cross-sectional variance in productivity, and productivity dispersion measured as the ratio of the most productive quartile of firms relative to the mean, broken down by by country, sector and year.

For model calibration and empirical exercises, we need to define the risky and the safe sector and find a way to measure the variance of the underlying productivity shocks in the risky sector. We would ideally map data on all jobs in the economy into a safe and a risky grouping. However, since most of our data is at the industry level, we generate a mapping from each industry to the risky or the safe sector. The mapping will be based on 3-digit (ISIC Rev 3) industries. The strategy for our benchmark calibration is to start with a ranking of industry riskiness and then allocate industries to the safe or risky sector such that roughly half of the aggregate employment

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9The 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.
falls in each sector.

In the available data, we have no direct measure of the variance of the underlying shocks faced by 'risky' firms. Instead, we have ex-post measures of the distribution of productivity observed across firms in each industry in the national data sets. As our model shows, the observed variance is truncated with respect to the underlying distribution of shocks, and the point of truncation depends on firing costs. While the industry ranking based on ex-post variance is not affected because ex-post and ex-ante variance move monotonically with exit costs, we prefer a measure that is less sensitive to exit costs. For our baseline empirical results we therefore use as the industry-riskiness indicator a measure of productivity dispersion computed as the ratio of labor productivity of the top quartile of firms to the mean. The industry-riskiness indicator, averaged over time and across countries, is used to rank industries by riskiness and to aggregate the industry data into safe and risky sectors.\(^{10}\) For purposes of the country/industry regressions in section 6.6, we use the ordinal ranking, normalized to run from -0.5 to 0.5, rather than the cardinal values because it is robust to the endogenous truncation.

For robustness checks, we use other proxies for industry riskiness from the ONS and BHS data sets, namely the observed productivity variance across firms and an industry average indicator of ICT intensity, measured by the proportion of workers with access to broadband internet. As will be described later, this measure of ICT intensity is significantly correlated with other productivity variance and other measures of riskiness.\(^{11}\) The model calibration and simulation exercises give very similar results for the different proxies, as do the main country/industry panel regressions.\(^{12}\)

**Labor force data** The JOLTS data from the US Bureau of Labor Statistics provides time series on job openings, layoffs and turnover by broad sector (SIC based) of the US economy for 2000-2003. More recent data for 2003-2012 is available using the new industry classification NAICS. These data are used for model calibration. Finally, data from the OECD LFS (labor force survey) provide information on stocks of workers in various states (out-of-labor force, employed, unemployed) that are needed for model calibration.

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\(^{10}\)The safe-risky classifications are presented in Appendix 6.C.

\(^{11}\)The set of ordinal rankings, as well as the set of cardinal riskiness indicators are correlated with each other across the 22 industries, with correlation coefficients between 0.75 and 0.85.

\(^{12}\)See Appendix 6.B for detail. We have run all regressions using the cardinal values of the riskiness indicators as well, with no qualitative difference in results.
In our calibration, 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 $l = 0.7684$. 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.

We use the JOLTS data for the labor market flows. Mapping the data into measures for the safe and risky sector is not easy. First, the JOLTS data is based on two-digit industry codes, while our safe-risky indicators are 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 in JOLTS, that is $s_{\text{safe}} = s_{\text{risky}} = 0.029$. 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 $p_{\text{high}} = 16\%$ high-skilled, $p_{\text{medium}} = 68\%$ medium-skilled and $p_{\text{low}} = 16\%$ low-skilled employees, while the risky sector consists of $p_{\text{high}} = 35\%$ high-skilled, $p_{\text{medium}} = 58\%$ medium-skilled and $p_{\text{low}} = 7\%$ low-skilled workers, based on the EUKLEMS industry data. 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 $s_{\text{safe}}^{\text{medium}}$ and $s_{\text{risky}}^{\text{medium}}$, 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 6.A.3, this assumption implies that $s_{\text{safe}}^{\text{medium}} = 0.0267$ and $s_{\text{risky}}^{\text{medium}} = 0.0348$. In the safe sector of our model, there is only exogenous separation and hence we set the exogenous job destruction rate to $\delta = 0.0267$. Now the endogenous job destruction rate must be $\lambda F(x_d) = s_{\text{medium}}^{\text{risky}} - \delta = 0.0081$. 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 compute the relative sector sizes by aggregating the EUKLEMS industry data for the US, using the safe-risky classification. This gives us $u = 0.0423$, $e_0 = 0.3394$ and $e_1 = 0.3867$. 

6.4 Calibration

In the first steps of the calibration, we use the data, described above, to find parameters on labor force participation, unemployment, and separation rates. In the second step, we set several other parameters at values from other studies 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 $\lambda$, the mean $\mu$, and the standard deviation $\sigma$—together with the firing costs parameter $k$ such that we match the observed truncated cross-sectional distribution of US productivity. The shape comes from the productivity shock parameters and the 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.

6.4.1 Parameters from other studies

Following Pissarides (2009), and similar to Shimer (2005) and Hall and Milgrom (2008), we set the monthly interest rate to $r = 0.004$. First, we set unemployment benefits to $b = 0.5$. 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 $\beta$—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 median worker whose replacement rate 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 $\eta$ and $\xi$ 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 $\xi = 0.3$.\footnote{As is well known from the literature, the matching efficiency parameter $\xi$ and the vacancy costs parameters $c_0$ and $c_1$ are not separately identified.}

The parameter values that come from other studies can be found in Table 6.2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
<th>Motivation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y$</td>
<td>1</td>
<td>productivity</td>
<td>safe sector</td>
</tr>
<tr>
<td>$r$</td>
<td>0.004</td>
<td>monthly interest rate</td>
<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>$\eta$</td>
<td>Nash bargaining share worker</td>
<td></td>
</tr>
<tr>
<td>$b$</td>
<td>0.5</td>
<td>unemployment benefits</td>
<td></td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.5</td>
<td>matching elasticity</td>
<td></td>
</tr>
<tr>
<td>$\xi$</td>
<td>0.3</td>
<td>matching efficiency</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.2: Calibration according to the literature

### 6.4.2 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 6.3.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
<th>Motivation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$l$</td>
<td>0.7684</td>
<td>size labor force</td>
<td></td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.0267</td>
<td>Poisson rate ex. job destr.</td>
<td></td>
</tr>
<tr>
<td>$c_0$</td>
<td>0.2092</td>
<td>vacancy costs safe sector</td>
<td></td>
</tr>
<tr>
<td>$c_1$</td>
<td>0.4184</td>
<td>vacancy costs risky sector</td>
<td></td>
</tr>
<tr>
<td>$z_0$</td>
<td>1.1354</td>
<td>search costs safe sector</td>
<td></td>
</tr>
<tr>
<td>$z_1$</td>
<td>1.1354</td>
<td>search costs risky sector</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.3: Calibration in order to match the US labor market stocks and flows

### 6.4.3 Matching the cross-sectional distribution of US productivity

In this step, we set the ex-ante productivity shock parameters—the arrival rate $\lambda$, the mean $\mu$, and the standard deviation $\sigma$—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 6.4.

#### Cross-sectional mean and variance in the model
Let \( \hat{y} \) 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 \( y + \frac{1}{1-F(x_d)} \int_{x_d}^{x_u} zdF(z) \). 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 follows from, \[
\hat{y} = y + s \frac{1}{1-F(x_d)} \int_{x_d}^{x_u} zdF(z) = y + \frac{\lambda}{\delta + \lambda} \int_{x_d}^{x_u} zdF(z).
\]
The variance of output per worker in the risky sector is \[
\hat{\sigma}^2 = s \frac{1}{1-F(x_d)} \int_{x_d}^{x_u} (y + z - \hat{y})^2 dF(z) + (1 - s) (y - \hat{y})^2
\]
\[
= \frac{\lambda}{\delta + \lambda} \left( \int_{x_d}^{x_u} z^2 dF(z) - \frac{\lambda}{\delta + \lambda} \left( \int_{x_d}^{x_u} zdF(z) \right)^2 \right).
\]
Productivity shocks are assumed to follow a normal distribution with mean \( \mu \) and standard deviation \( \sigma \). Using the analytic expressions for the truncated normal distribution, we can simplify the expressions for \( \hat{y} \) and \( \hat{\sigma}^2 \) as follows
\[
\hat{y} = y + \frac{\lambda}{\delta + \lambda} \left( 1 - \Phi \left( \frac{x_d - \mu}{\sigma} \right) \right) \mu + \varphi \left( \frac{x_d - \mu}{\sigma} \right) \sigma
\]
\[
\hat{\sigma}^2 = \frac{\lambda}{\delta + \lambda} \left( \left( 1 - \Phi \left( \frac{x_d - \mu}{\sigma} \right) \right) \left( \mu^2 + \sigma^2 \right) + \varphi \left( \frac{x_d - \mu}{\sigma} \right) (x_d + \mu) \sigma \right) - (y - \hat{y})^2
\]
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 difference 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 \( \pi_{safe}^{medium} \) and \( \pi_{risky}^{medium} \), 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 6.A.4, this assumption implies that \( \hat{y} = \pi_{risky}^{medium} / \pi_{safe}^{medium} = 1.4844 \), if we take \( \pi_{risky}^{safe} = 1.8306 \) 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 $\hat{y} = 1.1$. Accordingly, we set our target for the cross-sectional variance to $\hat{\sigma}^2 = 0.16$, 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 (6.2) and (6.1); 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 $\lambda = 0.1038$, $\mu = 0.0519$, $\sigma = 0.5332$, $k = 1.2653$ (and $x_d = -0.7039$), see Appendix 6.A.2 for details.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>0.1038</td>
<td>Poisson rate productivity shock</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.0519</td>
<td>mean productivity shock</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.5332</td>
<td>standard deviation productivity shock</td>
</tr>
<tr>
<td>$k$</td>
<td>1.2653</td>
<td>firing costs</td>
</tr>
</tbody>
</table>

Motivation: endog. job destruction (JOLTS, EUKLEMS); cross-sectional mean (EUKLEMS); cross-sectional variance (BHS); stocks and flows (OECD LFS, JOLTS, EUKLEMS)

Table 6.4: Calibration in order to match the cross-sectional distribution of US productivity

### 6.5 Assessing 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 chapter is the whether the response of an economy to an increase in the standard deviation of productivity shocks in the risky sector, $\sigma$ depends, upon the level of firing costs, $k$ in a country. The simulations thus consist of computing steady state employment and productivity outcomes for a wide range of $k$ and $\sigma$.

We conduct simulations that vary the exit cost parameter $k$ to be consistent with the value of
the OECD EPL indicator for each country in our data set, ranging from \( k = 1.27 \) to \( k = 6.53 \).\(^{14}\) This range is comparable to roughly one and a half month of production and seven months of production or about one year of wages.\(^{15}\) For each simulated 'country' (or value of \( k \)), we generate 11 observations by varying \( \sigma \) or the standard deviation of productivity draws from 0.3 through 0.8. This describes well the range of productivity dispersion found across the industries within the risky sector, and with suggestive evidence that there likely has been an increase over time in the standard deviation of productivity shocks in the risky sector, \( \sigma \).

We want to compare actual cross-county observations with the simulated data. Unfortunately, in constructing the actual cross-country data set, there are no time series available on the underlying variance of the shock for the risky sector. In the next paragraph we will describe several pieces of evidence that show that riskiness has increased over time, in association with increases in ICT. This evidence leads us to use ICT capital expenditure shares as a proxy for riskiness in comparing model simulations with actual data.

In the following subsection we provide a description of the steady-state outcomes of the main model variables as we vary \( k \) and \( \sigma \). We follow with an empirical exercise comparing simulated model outcomes with actual data. We run reduced form regressions of employment share (and relative productivity) of the risky sector on EPL, riskiness, and their interaction. These regression will be done using the simulated data set as well as actual cross-country time series for the risky sector relative to the safe sector. The similarity of regression coefficients can be seen as a validation of the model that was calibrated using other moments.

### 6.5.1 Does \( \sigma \) rise with ICT?

Ideally, the evolution of \( \sigma \) would be captured by a forward-looking measure of the underlying productivity variance facing each firm as they decide between opening one type of vacancy versus another. Instead, we have measures of the observed cross-sectional variance of productivity of incumbent firms in manufacturing industries for a small selection of countries for the 1990s and a slightly different measure of the variance for all industries in a larger selection of countries for the 2000s. The latter are used as indicators of the relative riskiness of industries, but may not

---

\(^{14}\)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 6.C for details.

\(^{15}\)In the model we do not have capital in the production function so that wages and production are much closer to each other.
provide a good signal of changes over time in the variance of shocks to all risky ventures.

We do have empirical evidence suggesting that during this period the increasing adoption of Information and Communications Technology (ICT) by firms is associated with an increase in riskiness. 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 firms starts diverging in the mid-1990s (Brynjolfsson, McAfee, and Zhu 2009).

Similar evidence is found by analyzing the ONS country/industry panel data set. Table 6.5 below shows results for the regression of the variance of the cross-sectional distribution of labor productivity across firms in an industry on the percentage of workers with broadband access within the industry. The data (labeled ONS/Eurostat in Table 6.1) cover the years 2001 through 2005, during which time the penetration of broadband was growing rapidly.\(^{16}\)

\[
\sigma_{c,i,t} = \alpha + \beta B_{c,i,t} + \sum \delta_j D_j + \varepsilon_{c,i,t} \tag{6.6}
\]

where \(\sigma\) is the standard deviation 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 6.5.\(^{17}\)

Further evidence on the increasing risk associated with ICT comes from US job creation and destruction data. Using our industry ICT-intensity ranking, we group the US industries into high-ICT and low-ICT groups and create indicators of gross jobs flows and 'entry-exit jobs flows'\(^{16}\) Using similar data through 2010 for a larger selection of countries, the relationship is even stronger. See Bartelsman et al. (2014).

\(^{16}\)We ran the regression with all combinations of country, industry, and/or time dummies. 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 omitted variable that boosts both the variance of productivity and the use of broadband, for example declining prices of ICT goods and services.
Levels | First-differences
---|---
$\beta$ | 0.97 (2.47) | 2.03 (3.72)
$R^2$ | 0.40 | 0.07
D.F. | 650 | 461

Fixed effects: country, industry, time

Source: Authors’ calculations using the ONS dataset (ONS 2008).

Table 6.5: Productivity variance and broadband use

(employment-weighted gross firm turnover) for the two aggregates. Next, we average the gross job flows (job creation plus job destruction divided by employment) and entry-exit flows (job flows of employees shed through firm exit plus hires at entering firms divided by employment) for the periods 1986-1994 and 1995-2004. Table 6.6 shows that gross job flows increased over time for the high-ICT industries, with little change for the low-ICT industries.

<table>
<thead>
<tr>
<th>Gross Job Flows</th>
<th>Entry-Exit Job Flows</th>
</tr>
</thead>
<tbody>
<tr>
<td>High ICT Industries</td>
<td>17.5</td>
</tr>
<tr>
<td>Low ICT Industries</td>
<td>17.5</td>
</tr>
</tbody>
</table>

Source: Authors’ calculations using the LBD (Jarmin and Miranda, 2002).

Table 6.6: Gross job flows

6.5.2 Simulation results

The results of the simulation are presented in Table 6.7 and in Figure 6.5.2. 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. This range represents a rough doubling of the variance of the underlying productivity shocks in the risky sector. The response to this shock differs substantially between economies with low and economies with high firing costs.

We see that in a country with low EPL it becomes more attractive to open jobs in the risky sector ($\theta_1$ and $e_1$ increase strongly) when a new technology with a greater variance arrives. With low EPL, a country can benefit maximally from the option value to close a job if a bad shock appears and we see that there will be more endogenous job destruction. Further, productivity in the risky sector, $\hat{y}$, increases sharply because the increased variance combines with the truncation of low draws. Aggregate productivity, $\pi \equiv \frac{e_0 + e_1 \hat{y}}{e_0 + e_1}$, increases, both through the intra-sector effect, the increase in $\hat{y}$, and the inter-sector effect, the increase in $e_1$. Finally, we use total output, including a measure of home production for non-participants, net of vacancy
and search costs as a measure for social welfare, which is labeled as $\Omega$ in the table. Social welfare unambiguously increases in a low EPL country as $\sigma$ increases.

By contrast, in a high EPL country ($k = 6.53$) it becomes more costly to adopt the new technology because it is very costly to exercise the shut-down option. Therefore, $\theta_1$ and $e_1$ increase only slightly. Consequently, total productivity and welfare also increase only slightly in a high-EPL country. The relatively small productivity increase is due to both a selection effect (less truncation in the risky sector) and because the allocation response in the risky sector is curtailed sharply relative to that in low-EPL countries.

<table>
<thead>
<tr>
<th></th>
<th>Benchmark $\sigma = 0.50$</th>
<th>High $\sigma = 0.75$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$k = 1.27$</td>
<td>$k = 4.91$</td>
</tr>
<tr>
<td>$x_d$</td>
<td>-0.6976</td>
<td>-1.1650</td>
</tr>
<tr>
<td>$\lambda F(x_d)$</td>
<td>0.0069</td>
<td>0.0008</td>
</tr>
<tr>
<td>$y$</td>
<td>1.0901</td>
<td>1.0492</td>
</tr>
<tr>
<td>$S_1(0)$</td>
<td>3.9208</td>
<td>3.7513</td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>1.4387</td>
<td>1.2056</td>
</tr>
<tr>
<td>$e_1$</td>
<td>0.3732</td>
<td>0.3490</td>
</tr>
<tr>
<td>$w_1(0)$</td>
<td>0.9594</td>
<td>0.9505</td>
</tr>
<tr>
<td>$S_0$</td>
<td>2.2476</td>
<td>2.4161</td>
</tr>
<tr>
<td>$\theta_0$</td>
<td>1.2428</td>
<td>1.6595</td>
</tr>
<tr>
<td>$e_0$</td>
<td>0.3543</td>
<td>0.3838</td>
</tr>
<tr>
<td>$w_0$</td>
<td>0.9655</td>
<td>0.9629</td>
</tr>
<tr>
<td>$u$</td>
<td>0.0499</td>
<td>0.0357</td>
</tr>
<tr>
<td>$e_1/(e_0 + e_1)$</td>
<td>0.5130</td>
<td>0.4763</td>
</tr>
<tr>
<td>$\pi$</td>
<td>1.0462</td>
<td>1.0234</td>
</tr>
<tr>
<td>$\Omega$</td>
<td>0.9238</td>
<td>0.9187</td>
</tr>
</tbody>
</table>

Table 6.7: Model simulation

The left panel of Figure 6.5.2 illustrates the effects of changing $\sigma$ on employment, for different levels of $k$. If the firing costs are low enough, employment in the risky sector increases with $\sigma$ 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, $\sigma$ 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 $\sigma$ or high firing costs. The reduced effect of firing costs on employment share with low $\sigma$ occurs because the amount of firing becomes very small as the firing threshold shifts to the left.

The right panel of Figure 6.5.2 shows that aggregate productivity and welfare decreases in $k$ and increases in $\sigma$. The relative productivity of the risky sector decreases with $k$ because high exit costs shift the threshold of firing to a lower level of productivity. Aggregate productivity...
Figure 6.1: Model Simulations, varying riskiness: $\sigma$

decreases rapidly when $k$ increases, both because the relative productivity declines and because the share of resources allocated to the risky sector declines.

To state the results differently, we can look at the economic benefits that a policy maker could expect to achieve by reducing EPL, say from the level of Portugal, $k = 6.53$, to that of the Netherlands, $k = 4.91$. We can track what happens to risky sector productivity and employment share, as well as aggregate productivity and our measure of social welfare, when EPL is reduced in a period of low technological uncertainty, and contrast it to the benefits in a period of high uncertainty. When uncertainty is relatively low, endogenous job destruction will increase, but continues to remain low. The intra-sector productivity channel is very weak, with only a slight increase in $\hat{y}$, and the effect on employment share in the risky sector also is negligible. By contrast, when riskiness is high, risky sector productivity increases by 2 percentage points, as does risky sector employment share. Our welfare measure rises by less than aggregate productivity, because of an increase in costs associated with reallocation. In our simulation, the largest effects are found by reducing EPL further, to the level of the US. When technological uncertainty is high, this will boost aggregate productivity by nearly 10 percentage points.

Overall, the allocation of workers to the risky sector is not very sensitive to firing costs when $\sigma$ is low and when firing costs are high, because essentially all jobs are ‘hoarded’. Further, the effect of firing costs on risky sector allocation and productivity becomes stronger (more negative)

---

18 The mapping from $k$ in our model to the cardinal value of the OECD indicator of EPL for regular jobs, is given in the appendix.
6.5. ASSESSING THE EFFECTS OF EPL AND RISING RISKINESS

as $\sigma$ increases and $k$ decreases. In section 6.6 we show that this non-linear pattern is confirmed in the data. Below, we provide evidence that low and high-EPL countries indeed 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.

6.5.3 Simulated and actual data regressions

As a first step to validate the model we compare regression results from simulated and actual data using the following equation:

$$
\text{dep}_{c,t} = a_0 + \alpha \sigma_t + \beta k_{c,t} + \gamma \kappa_{c,t} \sigma_t + FE + \epsilon_{c,t}
$$

(6.7)

where $\text{dep}_{c,t}$ is the dependent variable, either the employment share in the risky sector, $\frac{e_1}{e_0 + e_1}$, or the relative productivity of the risky sector, $\hat{y}$. $FE$ represents fixed effects. Based on the model simulation results, we expect a significantly negative coefficient on $\gamma$, namely that the negative impact of exit costs on risky sector employment is larger for higher $\sigma$. For the relative productivity of the risky sector as a dependent variable we also expect a negative $\gamma$ for the simulated data, given the results shown in Table 6.7 and Figure 6.5.2 above.

In the simulated data, steady states of $\frac{e_1}{e_0 + e_1}$ and $\hat{y}$ are computed for a grid of $k$ and $\sigma$ values, as described above, where $\sigma$ values are indexed by $t$, and $k$ values only by $c$. Given the inclusion of fixed effects, $\alpha$ and $\beta$ are not separately estimated for the simulated data. In the actual data, the risky and safe sectors are defined using the dispersion measure of industry riskiness.\footnote{The results do not substantively vary when aggregating safe and risky using the different proxies used to rank the industries by riskiness, as described in section 6.3.} In the actual data, $c$ denotes country (see appendix for listing) and $t$ denotes time period (from 1995 through 2005). Exit costs $k_{c,t}$ are measured using the OECD cross-country panel data for EPL on regular jobs.

As discussed above, the variable $\sigma_t$ is proxied by a measure of ICT use in the risky sector in the US. We compute the ratio of ICT capital compensation to value added for each US industry in the EUKLEMS dataset, and aggregate this measure for the risky sector. Next, we normalize the series to vary over the sample period such that it spans the same range of $\sigma_t$ as in the
CHAPTER 6. EMPLOYMENT PROTECTION, TECH CHOICE, WORKER ALLOC.

simulated data.\textsuperscript{20}

Table 6.8 provides estimates of $\gamma$ following equation 6.7. Using the simulated data, the coefficient on the interaction between riskiness and exit costs is significantly negative, both for the share of employment in the risky sector and for the relative labor productivity in the risky sector. This shows, conform the results from table 6.7, that employment in the risky sector is held back more by EPL, and productivity is retarded more by EPL as riskiness increases. The same qualitative results hold in the actual data. If indeed ICT intensity (or a time trend) is a good proxy for $\sigma$, these regressions show the similarity of features of the simulated and actual data that were not used in calibration of the model.

However, as the coefficient magnitudes for the employment share regressions show, the interaction effect, $\gamma$, for the simulated data is about 7 times larger than for the actual data. For the relative productivity regression, $\gamma$ is six times larger for the actual data than for the simulated data. By adjusting the range of $\sigma$ used in defining the time trend for the interaction term in the actual data, we could make the actual and simulated coefficient coincide for one of the two regressions, but the difference would increase for the other regression. Our interpretation of this is that the simulated data, which shows steady-state values of endogenous variables under different values of $k$ and $\sigma$ and abstracts from consumer switching frictions, overstates the scope for intra-sectoral shifts in employment that can occur in the actual economy.

<table>
<thead>
<tr>
<th></th>
<th>Simulated data</th>
<th>Actual data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Labor Share</td>
<td>Labor Productivity</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>$-17.2^{2}$</td>
<td>$-0.05^{(30.2)}$</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.97</td>
<td>0.99</td>
</tr>
<tr>
<td>D.F.</td>
<td>169</td>
<td>169</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>$k, \sigma$</td>
<td>$k, \sigma$</td>
</tr>
</tbody>
</table>

Table 6.8: Estimates of $\gamma$: Simulated and Actual data


6.6 Direct evidence

This section shows that our main result that EPL reduces employment in the risky sectors can also be identified in the data with a difference-in-difference approach. We explore the empirical

\textsuperscript{20}Very similar estimates for $\gamma$ are obtained when $\sigma_t$ is proxied with a time trend.
relationship between EPL and the allocation of resources to industries that differ in riskiness. We also consider the relationship between EPL and total factor productivity (TFP) growth. The model predicts that (i) risky industries have relatively higher levels of employment (growth) in countries with low firing costs versus countries with high firing costs; (ii) risky industries have relatively high productivity growth in low EPL countries; (iii) the effect of increases in riskiness on employment is larger (in absolute value) in countries with low firing costs and the effects of firing costs on employment are larger (in absolute value) in risky sectors. For productivity, the model shows that the effect of riskiness is larger with low firing costs, but this sensitivity is less pronounced than for employment allocation. Table 6.1 provides an overview of the data used for this exercise. 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 main variable to be explained. We also provide empirical results for employment growth and TFP growth.

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

\[
\text{dep}_{c,i,t} = \alpha + \beta k_{c,t} + \gamma R(\sigma)_i + FE + \varepsilon_{c,i,t}
\]

where \(\text{dep}_{c,i,t}\) is the dependent variable. Our main results are for regressions using labor share, or the ratio of hours worked in industry \(i\), country \(c\) and year \(t\) relative to total hours in that country and year. Further results are presented for employment growth and TFP growth as dependent variables. 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 \(\gamma\) 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. 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 parses out how changes in the policy, here \(k_{c,t}\), differentially impact different sectors, based on the expected sensitivity of

\[21\text{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 exclude utilities and nuclear fuel production.}

\[22\text{Country fixed effects are insignificant and numerically very close to zero when the dependent variable is the share of employment and the level effect of } k \text{ is included.}\]
the sector to the policy change. To our knowledge, we are the first in this literature to explicitly model how the ranking and the policy interact instead of relying on reasoned assumption about how the sensitivity varies.\textsuperscript{23}

Table 6.9 presents the baseline results for the full sample of all countries with available data for the period 1995-2005.\textsuperscript{24} 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 dispersion (the ratio of top quartile to mean) of labor productivity within an industry in each of the countries in the ONS dataset. The first column shows the results with labor share as the dependent variable when fixed effects control for industry means and industry trends; the next columns shows the results for employment growth and TFP growth, using country, industry and time fixed effects. The variable labor share is defined as the share of hours worked for that industry as a percentage of total hours for that country and year. The interpretation of the coefficient, \( \gamma \), is as follows: A movement of the EPL index by 1 point, (say from the French value of 2.5 to the Danish value of 1.5), will increase the share of employment in the riskiest industry (rank= 0.5) by slightly more than 0.5 percentage point, while reducing the share of employment in the safest sector (rank= -0.5) by the same amount. In growth rates, the interpretation is that a one point movement of EPL will boost TFP growth in the riskiest sector by slightly more than 0.5 percentage point.\textsuperscript{25}

Table 6.10 shows the result after allowing the regression coefficients \( \alpha \), \( \beta \), and \( \gamma \), 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 \( \gamma \) in the labor share regression 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 is higher

---

\textsuperscript{23} Because the employment share variable is bounded between zero and one, we have replicated the estimates 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.

\textsuperscript{24} In all our specifications we correct for heteroskedasticity in errors that can occur in our country/industry panel, using 2-way industry and country clustering, as proposed by Cameron, Gelbach and Miller. (2011).

\textsuperscript{25} The level effect of the exit costs, \( \beta \), is not shown. For the dependent variable labor share, the inclusion of industry fixed effects results in the coefficient to capture 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. For TFP growth \( \beta \) usually is insignificantly negative, as well known from the literature.
6.6. DIRECT EVIDENCE

<table>
<thead>
<tr>
<th>Labor share</th>
<th>Labor growth</th>
<th>TFP growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma$</td>
<td>$-1.08$</td>
<td>$-0.89$</td>
</tr>
<tr>
<td></td>
<td>(2.55)</td>
<td>(2.65)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.82</td>
<td>0.25</td>
</tr>
<tr>
<td>D.F.</td>
<td>4840</td>
<td>4795</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>ind mean+trends</td>
<td>ctry,ind,time</td>
</tr>
</tbody>
</table>

Table 6.9: Estimates of $\gamma$: Main regression results


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. A similar story is seen when the dependent variable is employment growth. These results are shown in table 6.11.26

<table>
<thead>
<tr>
<th>Country sub-sample</th>
<th>Industry sub-sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low risk</td>
<td>High risk</td>
</tr>
<tr>
<td>Low firing cost</td>
<td>$-2.13$</td>
</tr>
<tr>
<td></td>
<td>(4.49)</td>
</tr>
<tr>
<td>High firing cost</td>
<td>$-1.42$</td>
</tr>
<tr>
<td></td>
<td>(3.60)</td>
</tr>
</tbody>
</table>

Table 6.10: Labor share: Country/Industry sub-samples


<table>
<thead>
<tr>
<th>Country sub-sample</th>
<th>Industry sub-sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low risk</td>
<td>High risk</td>
</tr>
<tr>
<td>Low firing cost</td>
<td>$-0.78$</td>
</tr>
<tr>
<td></td>
<td>(0.61)</td>
</tr>
<tr>
<td>High firing cost</td>
<td>$-0.68$</td>
</tr>
<tr>
<td></td>
<td>(0.74)</td>
</tr>
</tbody>
</table>

Table 6.11: Labor growth: Country/Industry sub-samples


Next, we address the issue whether entry costs or financial development rather than firing

In the model, the effect of EPL interacted with riskiness on productivity does not vary systematically with the magnitude of EPL and riskiness. We find that the negative coefficient of productivity growth regressed on interacted EPL does not vary systematically in the space of EPL and riskiness, as shown in the above tables for employment.
costs are causing the small employment share of risky sectors.\textsuperscript{27} Because firms in both the safe and risky sector must pay the entry fee, we would not expect that the first-order effect of higher entry costs would discriminate between them. However, given the shorter expected life of a job in high risk sectors, fewer vacancies are needed to maintain a given level of employment in the safe than in the risky sector, so that the relative size of the sector increases with an increase in entry costs. In a simulation of the model, high entry fees (keeping the ratio of $c_0/c_1$ constant) indeed decreases the relative size of the risky sector. However, in our calibration the effect of an increase in entry fees is relatively small compared to the effect of an increase in firings costs.

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 entry-cost term. So, for example, as seen in Table 6.12, 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 6.12 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. Importantly, the exit effect on labor share remains significantly negative when entry costs are included. Further, in most specifications the entry cost coefficient is no longer significantly negative when exit costs are included. An exception is formed by the time to start a business, which remains significantly negative in all specifications.

The regression for employment and TFP growth likewise show some significant effects for the entry indicators alone, but when entry and exit indicators are both included the exit indicator generally is significantly negative, while the entry indicator becomes insignificant. The time to start a business indicator is an exception, with the exit cost no longer being significantly negative.\textsuperscript{28}

In a seminal paper, the level of financial development in a country has been found to harm the performance of sectors that rely on external finance (Rajan and Zingales, 1998). In our context, it is likely that entry in the risky sector depends on financial development as well.

\textsuperscript{27}See Koeniger and Prat (2007) for a model with both entry and firing cost.

\textsuperscript{28}Using other industries riskiness rankings, for example based on broadband penetration, exit costs remain significantly negative even when time to start a business is included.
Entry costs will be higher in countries with poorly developed financial markets, and maybe disproportionately so for the risky sector. Further, high levels of ‘financial frictions’ could affect exit decisions. Credit constraints may force suboptimal exit of firms hit by negative shocks. These also would reduce the ex-ante incentive of entry into the risky sector.

We assess the role of financial market variables, drawn from the World Bank GFDD (Martin, Asl Demirg-Kunt, Erik Feyen, and Ross Levine, 2012), in a similar way to that of entry costs, namely by running the baseline regressions with an interaction of the policy indicator and EPL, and by running the regressions with both this interaction and a second interaction term with EPL and risk. We consider Financial System Deposits, Stock Market Capitalization, Private Credit by Deposit Money Banks, Private Credit by Other Financials, and Private Bond
Market Capitalization, all in logs of the ratio to GDP.

The results could be presented in tables similar to tables 6.12 through 6.14, but the results are straightforward. We find that the EPL interaction term does not differ substantially from the baseline, and never loses its significance when financial development indicators are added. Further, when both interaction terms are included, the only significant effect for financial frictions is found for the variable 'Private Credit by Deposit Money Banks. When this variable increases, employment growth and TFP growth are boosted in risky sectors.

In Appendix 6.B, 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. We also check to see if the interaction term differs between tradeable and non-tradeable sectors. Overall, our results are extremely robust: higher firing costs are associated with lower employment shares and employment growth in high 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. The effect is slightly higher for non-tradeables. Most of the exit cost indicators used give significantly negative $\gamma$ estimates, regardless of which of the industry riskiness-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 employment share regression to estimate the parameter $\gamma$ for each ranking. The regressions are based on 'all countries', for the period 1995-2005, use EPL Regular as exit cost indicator, and include industry fixed effects and

<table>
<thead>
<tr>
<th>Entry Cost Indicator</th>
<th>only $\gamma_{\text{entry}}$</th>
<th>$\gamma_{\text{entry}}$</th>
<th>$\gamma_{\text{exit}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting a Business - # of procedures</td>
<td>-0.32</td>
<td>-0.14</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>(1.92)</td>
<td>(0.76)</td>
<td>(2.07)</td>
</tr>
<tr>
<td>Starting a Business - time (days)</td>
<td>-0.29</td>
<td>-0.25</td>
<td>-0.43</td>
</tr>
<tr>
<td></td>
<td>(4.88)</td>
<td>(3.49)</td>
<td>(0.83)</td>
</tr>
<tr>
<td>Starting a Business - cost (pct of capital)</td>
<td>-0.01</td>
<td>0.01</td>
<td>-1.41</td>
</tr>
<tr>
<td></td>
<td>(0.75)</td>
<td>(0.83)</td>
<td>(2.57)</td>
</tr>
<tr>
<td>Difficulty of hiring (index)</td>
<td>-0.00</td>
<td>0.02</td>
<td>-1.45</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(1.46)</td>
<td>(2.72)</td>
</tr>
<tr>
<td>Barriers to entrepreneurship</td>
<td>\textbf{-4.27}</td>
<td>\textbf{-3.29}</td>
<td>\textbf{-0.87}</td>
</tr>
<tr>
<td></td>
<td>(2.74)</td>
<td>(1.93)</td>
<td>(1.83)</td>
</tr>
<tr>
<td>Barriers to entrp. license and permits</td>
<td>0.61</td>
<td>0.51</td>
<td>-1.07</td>
</tr>
<tr>
<td></td>
<td>(2.32)</td>
<td>(1.85)</td>
<td>(2.36)</td>
</tr>
<tr>
<td>none. (only exit cost: EPLRegular)</td>
<td></td>
<td></td>
<td>\textbf{-1.21}</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(2.79)</td>
</tr>
</tbody>
</table>

Table 6.14: TFP growth regressed on exit and exit+entry costs

\begin{itemize}
\item t-statistic in parenthesis. Period: 1995-2005; Industry rank: productivity dispersion; Exit Cost: EPLRegular; Fixed Eff: industry means & trends. Robust errors clustered 2-way by industry and country.
\end{itemize}
industry time trends. All the estimates of $\gamma$ reported in this chapter, as well as the estimates of $\gamma$ 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 dispersion as industry ranking and EPL Regular as firing cost indicator lies among the 1 percent largest (absolute) effects of firing costs.

6.7 Final remarks

In this chapter 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 destruction 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 the aggregate productivity response to increased riskiness by about 9 percent, partly through a direct reduction of average productivity in the risky sector, and partly through a sizeable 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. Also, we did not look at the interaction between unemployment insurance (UI) and EPL. 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.
Appendix 6.A  Model and calibration details

6.A.1  Model details

In this appendix, we lay out the model details. We first describe the setup for the matching process and explain the Bellman equations. Then, we prove the analytical characterization of the equilibrium that was given in proposition 1.

6.A.1.1  Matching process

The setup for the matching process is the same for both sectors. In sector $i$, the total number of matches follows from a Cobb-Douglas function

$$M_i = \xi u_i^\eta v_i^{1-\eta}$$  \hspace{1cm} (6.9)

where $u_i$ represents the number of efficiency units of unemployed job seekers and $v_i$ represents the number of vacancies. The number of efficiency units of unemployed job seekers is equal to the product between the number of unemployed job seekers $u$ and the average search intensity $s_i$, that is $u_i = s_i u$.

The average job finding probability can be written as

$$m_i = \frac{M_i}{u} = s_i \xi \left( \frac{\theta_i}{s_i} \right)^{1-\eta}$$  \hspace{1cm} (6.10)

where labor market tightness is defined as $\theta_i \equiv \frac{v_i}{u}$. Note that this concerns the average job finding probability rather than the individual job finding probability. Although they equal to each other in a symmetric equilibrium, it is important to make the distinction in order to determine the optimal search intensity of an individual job seeker. The job finding probability of an individual job seeker who is searching with intensity $s_i^*$ can be written as

$$m_i^* = s_i \frac{M_i}{s_i} = s_i^* \xi \left( \frac{\theta_i}{s_i} \right)^{1-\eta}.$$  \hspace{1cm} (6.11)

Unemployed job seekers, who receive unemployment benefits $b$, search in both sectors at the same time. In order to do so, they face a cost of searching that is convex in search intensity.
For simplicity, we assume that search costs are quadratic

\[
\frac{1}{2} z_i (s_i^*)^2.
\] (6.12)

The asset value for the individual job seeker can then be written as

\[
rU = \max_{s_0^*, s_1^*} \left\{ b - \frac{1}{2} z_0 (s_0^*)^2 - \frac{1}{2} z_1 (s_1^*)^2 + m_0^* [E_0 - U] + m_1^* [E_1 (0) - U] \right\}
\] (6.13)

where the asset values for workers employed in the safe and risky sector are described in the next subsection. The individual job seeker takes aggregate labor market tightness as given when choosing his search intensities \(s_0^*\) and \(s_1^*\). The first-order conditions are given by

\[
\begin{align*}
z_0 s_0^* &= m_0 \frac{s_0}{s_0} [E_0 - U] \quad (6.14a) \\
z_1 s_1^* &= m_1 \frac{s_1}{s_1} [E_1 (0) - U]. \quad (6.14b)
\end{align*}
\]

In a symmetric equilibrium, we have \(s_i^* = s_i\) and \(m_i^* = m_i\), which allows us to express the optimality conditions in terms of aggregate variables rather than individual variables

\[
\begin{align*}
z_0 s_0^2 &= m_0 [E_0 - U] \quad (6.15a) \\
z_1 s_1^2 &= m_1 [E_1 (0) - U]. \quad (6.15b)
\end{align*}
\]

The optimality conditions can be used to simplify the asset value of being unemployed

\[
rU = b + \frac{1}{2} m_0 [E_0 - U] + \frac{1}{2} m_1 [E_1 (0) - U]
\] (6.16)

which, in the symmetric equilibrium, is the same for the individual job seeker as for the representative job seeker.

The optimality conditions can also be used to substitute out the search intensities from the average job finding probabilities. For both sectors, rewrite the optimality condition via the Nash bargaining equation and the free entry condition (given in the next subsection) to express the search intensity in terms of labor market tightness

\[
s_i = \sqrt{\frac{\beta c_i \theta_i}{1 - \beta z_i}}
\] (6.17)
which, in turn, can be used to substitute out the search intensity from the expression for the job finding probability
\[ m_i = \left( \frac{\beta c_i}{1 - \beta z_i} \right)^{\frac{1}{2} \eta} \xi \theta_i^{1 - \frac{1}{2} \eta}. \] (6.18)

6.A.1.2 Bellman equations

The asset value of being unemployed was just derived in the previous subsection. In this subsection, we continue with the other asset values.

Let \( V_i \) be the asset value of a vacancy in sector \( i \) and let \( J_i(x) \) be the asset value of a filled job. Free entry of vacancies implies
\[
rv_0 = -c_0 + \frac{m_0}{\theta_0} [J_0 - V_0] = 0 \quad (6.19a)
\]
\[
rv_1 = -c_1 + \frac{m_1}{\theta_1} [J_1(0) - V_1] = 0. \quad (6.19b)
\]

Note that matches in the risky sector start at \( x = 0 \). Firms pay vacancy creation costs \( c_i \) and their vacancies switch to filled jobs at rate \( \frac{m_i}{\theta_i} \). Under free entry, all profit opportunities are exploited in equilibrium so the value of opening a vacancy must be equal to zero in expectation.

Let \( S_0 \) be the value of the surplus of a match in sector 0 and let \( S_1(x) \) be the value of the surplus of a type-\( x \) match in sector 1. Then, we have the following surplus equations
\[
S_0 = J_0 + E_0 - U \quad (6.20a)
\]
\[
S_1(x) = J_1(x) + E_1(x) - U \quad (6.20b)
\]

where \( E_0 \) and \( E_1(x) \) are the asset values for workers employed in the safe and risky sector, respectively, which are described below.

By our assumption that wages are determined by a generalized Nash bargaining solution with worker bargaining power \( \beta \), wages implicitly follow from
\[
E_0 - U = \beta S_0 \quad (6.21a)
\]
\[
J_0 = (1 - \beta) S_0 \quad (6.21b)
\]
for the safe sector, and

$$E_1 (x) - U = \max \{ 0, \beta S_1 (x) \} \quad (6.22a)$$
$$J_1 (x) = \min \{(1 - \beta)S_1 (x), S_1 (x)\} \quad (6.22b)$$

for the risky sector. The threshold value for $x$ below which a job in the risky sector is destroyed, $x_d$, is implicitly determined by the reservation value property that

$$J_1 (x_d) = -k. \quad (6.23)$$

As long as a job is more valuable (less invaluable) than paying the exit costs $k$, it is optimal for the firm 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 off as when they are unemployed, implying that

$$E_1 (x_d) = U. \quad (6.24)$$

The match surplus is negative for sufficiently low realizations of $x$ and at the least productive match the surplus is equal to the negative of the exit costs

$$S_1 (x_d) = -k. \quad (6.25)$$

The asset value of a filled vacancy in the safe sector is given by

$$rJ_0 = y - w_0 - \delta J_0. \quad (6.26)$$

The production of a match in the safe sector is always equal to $y$ out of which the worker receives a wage $w_0$. In the safe sector, matches only end when they are hit by an exogenous job destruction shock, which occurs at rate $\delta$. In the risky sector, in contrast, job destruction also occurs for endogenous reasons and in such cases firms must pay exit costs $k$. When a job (whether in the safe or risky sector) is hit by an exogenous job destruction shock those costs do not have to be paid. For any realization $x$, the asset value of a filled vacancy in the risky sector is given by

$$rJ_1 (x) = y + x - w_1 (x) - \delta J_1 (x) + \lambda \left( \int_{x_d}^x \left[ J_1 (z) - J_1 (x) \right] dF (z) - F (x_d) (J_1 (x) + k) \right). \quad (6.27)$$
The production of a type-$x$ match in the risky sector is equal to $y + x$ out of which the worker receives a wage $w_1(x)$. A job can be destroyed for exogenous reasons (no exit costs have to be paid) and also for endogenous reasons (exit costs have to be paid). The arrival rate of the exogenous job destruction shock is again $\delta$. Endogenous job destruction occurs when a new productivity shock arrives (at rate $\lambda$) and the new productivity draw falls below the endogenous exit threshold $x_d$ (with probability $F(x_d)$). If the new productivity draw falls above the endogenous exit threshold, the firm will remain operational and the gain or loss will be equal to $[J_1(z) - J_1(x)]$, where $z$ is the new productivity draw. The upper support of $F(x)$ can be arbitrary large.

The asset value for workers employed in the safe sector is simply equal to

$$rE_0 = w_0 - \delta [E_0 - U]. \quad (6.28)$$

Workers receive a wage $w_0$ and their job is destroyed for exogenous reasons at rate $\delta$. The asset value for workers employed in the risky sector is equal to

$$rE_1(x) = w_1(x) - (\delta + \lambda F(x_d)) [E_1(x) - U] + \lambda \int_{x_d}^{x_u} [E_1(z) - E_1(x)] dF(z). \quad (6.29)$$

Workers receive a wage $w_1(x)$ and their job is destroyed for exogenous or endogenous reasons at rate $\delta + \lambda F(x_d)$. At rate $\lambda (1 - F(x_d))$ a new productivity draw arrives that falls above the endogenous exit threshold $x_d$. In such cases, the gain or loss will be equal to $[E_1(z) - E_1(x)]$, where $z$ is the new productivity draw.

### 6.A.1.3 Equilibrium conditions and proof

From the Bellman equations described in the previous subsection we can derive the job destruction condition for the risky sector and the job creation conditions for the safe and risky sector that we summarized in proposition 1. Together they jointly determine $\theta_0$, $\theta_1$, and $x_d$. In this subsection, we give the derivations.

Start with the safe sector surplus equation (6.20a). The appropriate discount rate for the safe sector is $r + \delta$. The safe sector surplus equation in flow form is therefore

$$(r + \delta) S_0 = (r + \delta) J_0 + (r + \delta) [E_0 - U]. \quad (6.30)$$
The firm surplus can be substituted out via (6.26) and the worker surplus can be substituted out via the difference between (6.28) and (6.16)

\[(r + \delta) S_0 = y - b - \frac{1}{2} m_0 [E_0 - U] - \frac{1}{2} m_1 [E_1 (0) - U]. \tag{6.31}\]

Use the Nash bargaining equations (6.21a) up to and including (6.22b) to rewrite this expression in terms of firm surplus

\[(r + \delta) \frac{1}{1 - \beta} J_0 = y - b - \frac{1}{2} m_0 \beta J_0 - \frac{1}{2} m_1 \beta J_1 (0). \tag{6.32}\]

Use the free entry conditions (6.19a) and (6.19b) to rewrite this expression in terms of labor market tightness

\[(r + \delta) \frac{1}{1 - \beta} \theta_0 c_0 = y - b - \frac{1}{2} m_0 \theta_0 c_0 - \frac{1}{2} m_1 \theta_1 c_1. \tag{6.33}\]

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

\[\frac{m_0}{\theta_0} = \frac{(r + \delta + \frac{1}{2} \beta m_0) c_0}{(1 - \beta) (y - b) - \frac{1}{2} \beta \theta_1 c_1}. \tag{6.34}\]

Continue with the risky sector surplus equation (6.20b). The appropriate discount rate for the risky sector is \(r + \delta + \lambda\). The risky sector surplus equation in flow form is therefore

\[(r + \delta + \lambda) S_1 (x) = (r + \delta + \lambda) J_1 (x) + (r + \delta + \lambda) [E_1 (x) - U]. \tag{6.35}\]

The firm surplus can be substituted out via (6.27) and the worker surplus can be substituted out via the difference between (6.29) and (6.16)

\[(r + \delta + \lambda) S_1 (x) = y + x + \lambda \int_{x_d}^{x_u} S_1 (z) dF (z) - \lambda F (x_d) k - b - \frac{1}{2} m_0 [E_0 - U] - \frac{1}{2} m_1 [E_1 (0) - U]. \tag{6.36}\]

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

\[S_1 (0) = \frac{-x_d}{r + \delta + \lambda} - k. \tag{6.37}\]
Use the Nash bargaining equation (6.22b) and the free entry condition (6.19b) to rewrite the left-hand side in terms of labor market tightness

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

(6.38)

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

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

(6.39)

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

\[ (r + \delta + \lambda) S_1(x) = y + x + \lambda \int_{x_d}^{x_u} S_1(z) dF(z) - \lambda F(x_d) k - b - \frac{1}{2} m_0 [E_0 - U] - \frac{1}{2} m_1 [E_1(0) - U]. \]  

(6.40)

Integrate this expression by parts and rewrite using the reservation value property

\[ S_1(z) = \frac{1}{1 - \beta} \left[ \frac{y + x + \lambda}{r + \delta + \lambda} \int_{x_d}^{x_u} (1 - F(z)) dz - \lambda k - b - \frac{1}{2} m_0 [E_0 - U] - \frac{1}{2} m_1 [E_1(0) - U] \right]. \]  

(6.41)

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

\[ (r + \delta + \lambda) S_1(x) = y + x + \frac{\lambda}{r + \delta + \lambda} \int_{x_d}^{x_u} (1 - F(z)) dz - \lambda k - b - \frac{1}{2} m_0 [E_0 - U] - \frac{1}{2} m_1 [E_1(0) - U]. \]  

(6.42)

Use the Nash bargaining equations (6.21a) up to and including (6.22b) to express the worker surplus in terms of firm surplus

\[ (r + \delta + \lambda) S_1(x) = y + x + \frac{\lambda}{r + \delta + \lambda} \int_{x_d}^{x_u} (1 - F(z)) dz - \lambda k - b - \frac{1}{2} m_0 [E_0 - U] - \frac{1}{2} m_1 [E_1(0) - U]. \]  

(6.43)

Use the free entry conditions (6.19a) and (6.19b) to express the firm surplus in terms of labor

---

29The rule is \( \int_{x_d}^{x_u} q(z) r'(z) dz = q(z) r(z) \big|_{x_d}^{x_u} - \int_{x_d}^{x_u} q'(z) r(z) dz \). 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.
6.A. MODEL AND CALIBRATION DETAILS

market tightness

\[(r + \delta + \lambda) S_1 (x) = y + x + \frac{\lambda}{r + \delta + \lambda} \int_{x_d}^{x_u} (1 - F (z)) dz - \lambda k - b - \frac{1}{2} m_0 \frac{\beta}{1 - \beta} \theta_0 c_0 - \frac{1}{2} m_1 \frac{\beta}{1 - \beta} \theta_1 c_1 \]. \tag{6.44}

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

\[ y + x_d = b + \frac{1}{2} \frac{\beta}{1 - \beta} (\theta_0 c_0 + \theta_1 c_1) - \frac{\lambda}{r + \delta + \lambda} \int_{x_d}^{x_u} (1 - F (z)) dz - (r + \delta) k \] \tag{6.45}

which completes the proof of proposition 1.

For completeness, we also give here the steady-state flow equations as well as the accounting identity for the labor force

\[ m_0 u = \delta e_0 \] \tag{6.46a}

\[ m_1 u = (\delta + \lambda F (x_d)) e_1 \] \tag{6.46b}

\[ l = e_0 + e_1 + u \] \tag{6.46c}

from which we can calculate the steady-state unemployment rate and the sizes of the safe and risky sector. \( l \) is the size of the labor force, which is calibrated.

6.A.2 Calibration details

**Step 1.** Fix \( y = 1, r = 0.004, \beta = 0.5, b = 0.5, \eta = 0.5, \) and \( \xi = 0.3 \).

**Step 2.1.** Set \( l = 0.7684 \) and \( \delta = 0.0267 \).

**Step 2.2.** The targets for the labor market stocks are \( u = 0.0423, e_0 = 0.3394, \) and \( e_1 = 0.3867 \). The targets for the labor market separation rates are \( \delta = 0.0267 \) and \( \delta + \lambda F (x_d) = 0.0348 \). Via the safe and risky sector steady-state flow equations,

\[ m_0 u = \delta e_0 \] \tag{6.47a}

\[ m_1 u = (\delta + \lambda F (x_d)) e_1 \] \tag{6.47b}

we can solve for the implied job finding probabilities. This gives \( m_0 = 0.2141 \) and \( m_1 = 0.3181 \). For both sectors, there is a one-to-one mapping between the job finding probability \( m_i \) and the
labor market tightness $\theta_i$. The mapping depends on the vacancy cost parameter $c_i$ and the search cost parameter $z_i$, which we (at this stage) still need to calibrate.

We do not have appropriate industry-level vacancy data and therefore we cannot distinguish between safe and risky sector vacancy creation costs. It seems reasonable, however, that risky sector vacancy creation costs are higher than safe sector vacancy creation costs, since these costs also include capital installment costs—the risky sector has, for example, a much higher broadband penetration. We therefore assume that $\frac{c_1}{c_0} \equiv \alpha_c = 2$. Furthermore, we see no reason to distinguish between search costs for the safe and risky sector and therefore we assume that $\frac{z_1}{z_0} \equiv \alpha_z = 1$.

These relative costs are sufficient to pin down the relative labor market tightness $\frac{\theta_1}{\theta_0}$ from the relative job finding probability $\frac{m_1}{m_0}$. After dividing the expression for the job finding probability in the risky sector by the expression for the job finding probability in the safe sector and rewriting, we get the following condition for the relative labor market tightness

$$\frac{\theta_1}{\theta_0} = \left( \frac{m_1}{m_0} \right)^{\frac{1}{1-\frac{\eta}{2}}} \left( \frac{\alpha_z}{\alpha_c} \right)^{\frac{\eta}{1-\frac{\eta}{2}}} \quad (6.48)$$

from which we can derive a condition for the relative total vacancy creation costs in the risky sector versus the safe sector

$$\frac{\theta_1 c_1}{\theta_0 c_0} = \alpha_c \left( \frac{m_1}{m_0} \right)^{\frac{1}{1-\frac{\eta}{2}}} \left( \frac{\alpha_z}{\alpha_c} \right)^{\frac{\eta}{1-\frac{\eta}{2}}} \equiv \Psi \quad (6.49)$$

Together with the safe sector job creation condition we have now two conditions for two unknown objects (namely $\theta_0 c_0$ and $\theta_1 c_1$). We can therefore back out the values for $\theta_0 c_0$ and $\theta_1 c_1$. It is sufficient to know the value of $\theta_i c_i$ and we do not need to know the value of $\theta_i$ since in the remaining equations $\theta_i$ only shows up in combination with $c_i$. In any case, combining the expression for the ratio $\Psi$ with the safe sector job creation condition, gives the following system for the total vacancy creation costs per unemployed

$$\theta_0 c_0 = \frac{m_0 (1 - \beta) (y - b)}{r + \delta + \frac{1}{2} \beta m_0 (1 + \Psi)} \quad (6.50a)$$

$$\theta_1 c_1 = \Psi \theta_0 c_0 \quad (6.50b)$$

from which we can solve $\theta_0 c_0 = 0.2345$ and $\theta_1 c_1 = 0.6309$. 
We can calibrate the remaining model parameters and determine the model properties without knowing the specific values for the search and vacancy cost parameters. Without loss of generality, we can normalize one of the cost parameters and the remaining cost parameters will follow from the conditions laid out above (in particular, for both sectors the expression for the job finding probability in (6.18) as well as one of the \( \alpha_i \)'s; the other \( \alpha_i \) will be satisfied by construction). We set the vacancy cost parameter for the safe sector at the value that we used in an earlier version of this chapter (in which the model did not include search costs), i.e. \( c_0 = 0.2092 \). The vacancy cost parameter for the risky sector is then \( c_1 = 0.4184 \) and the search cost parameters become \( z_0 = z_1 = 1.354 \).

**Step 3.** The targets for the ex-post observed truncated cross-sectional mean and variance of US productivity are \( \hat{y} = 1.1 \) and \( \hat{\sigma}^2 = 0.16 \), respectively. The target for the endogenous job destruction rate is \( \hat{\lambda} = 0.0081 \). Recall from the calibration section in the main text that

\[
\begin{align*}
  y + \frac{\lambda}{\delta + \lambda} \left( 1 - \Phi \left( \frac{x_d - \mu}{\sigma} \right) \right) \mu + \varphi \left( \frac{x_d - \mu}{\sigma} \right) \sigma &= \hat{y} \quad (6.51a) \\
  \frac{\lambda}{\delta + \lambda} \left( 1 - \Phi \left( \frac{x_d - \mu}{\sigma} \right) \right) \left( \mu^2 + \sigma^2 \right) + \varphi \left( \frac{x_d - \mu}{\sigma} \right) (x_d + \mu) \sigma - (y - \hat{y})^2 &= \hat{\sigma}^2 \quad (6.51b) \\
  \lambda F(x_d) &= \hat{\lambda}. \quad (6.51c)
\end{align*}
\]

In addition to this, the risky sector job creation and destruction conditions must be satisfied, which are, for convenience, repeated here

\[
\begin{align*}
  \frac{m_1}{\theta_1} &= \frac{(r + \delta + \lambda) c_1}{(1 - \beta) (-x_d - (r + \delta + \lambda) k)} \quad (6.52a) \\
  y + x_d &= b + \frac{1}{2} \frac{\beta}{1 - \beta} (\theta_0 c_0 + \theta_1 c_1) - \frac{\lambda}{r + \delta + \lambda} \int_{x_d}^{x_u} (1 - F(z)) \, dz - (r + \delta) k. \quad (6.52b)
\end{align*}
\]

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. However, 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

$$
\frac{\lambda}{\delta + \lambda} ((1 - \Phi(\tilde{x}_{d} - \tilde{\mu})) \tilde{\mu} \sigma + \varphi (\tilde{x}_{d} - \tilde{\mu}) \sigma) = \hat{y} - y \tag{6.53a}
$$

$$
\frac{\lambda}{\delta + \lambda} ((1 - \Phi(\tilde{x}_{d} - \tilde{\mu})) (\tilde{\mu}^2 + 1) \sigma^2 + \varphi (\tilde{x}_{d} - \tilde{\mu}) (\tilde{x}_{d} + \tilde{\mu}) \sigma^2) = (y - \hat{y})^2 + \tilde{\sigma}^2 \tag{6.53b}
$$

and divide the latter by the former to express $\sigma$ explicitly in terms of $\tilde{x}_{d}$ and $\tilde{\mu}$

$$
\sigma = \frac{((y - \hat{y})^2 + \tilde{\sigma}^2) ((1 - \Phi(\tilde{x}_{d} - \tilde{\mu})) \tilde{\mu} + \varphi (\tilde{x}_{d} - \tilde{\mu}))}{(\hat{y} - y) ((1 - \Phi(\tilde{x}_{d} - \tilde{\mu})) (\tilde{\mu}^2 + 1) + \varphi (\tilde{x}_{d} - \tilde{\mu}) (\tilde{x}_{d} + \tilde{\mu}))}. \tag{6.54}
$$

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

$$
((\hat{y} - y)^2 = \frac{\lambda ((1 - \Phi(\tilde{x}_{d} - \tilde{\mu})) \tilde{\mu} + \varphi (\tilde{x}_{d} - \tilde{\mu}))^2 ((y - \hat{y})^2 + \tilde{\sigma}^2)}{(\delta \Phi(\tilde{x}_{d} - \tilde{\mu}) + \lambda) ((1 - \Phi(\tilde{x}_{d} - \tilde{\mu})) (\tilde{\mu}^2 + 1) + \varphi (\tilde{x}_{d} - \tilde{\mu}) (\tilde{x}_{d} + \tilde{\mu}))}. \tag{6.55}
$$

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 $\sigma$ from the explicit expression for $\sigma$.

3. Calculate $\mu$ and $x_{d}$ by multiplying their tilde counterpart by $\sigma$.

4. Calculate $\lambda$ 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 $\lambda = 0.1038$, $\mu = 0.0519$, $\sigma = 0.5332$, and $k = 1.2653$ (and $x_{d} = -0.7039$).
6.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

\[
\frac{s_{\text{safe}}^{\text{high}}}{s_{\text{safe}}^{\text{low}}} = \frac{s_{\text{risky}}^{\text{high}}}{s_{\text{risky}}^{\text{low}}} = \omega_h^s < 1 \quad (6.56a)
\]

\[
\frac{s_{\text{safe}}^{\text{medium}}}{s_{\text{safe}}^{\text{low}}} = \frac{s_{\text{risky}}^{\text{medium}}}{s_{\text{risky}}^{\text{low}}} = \omega_l^s > 1. \quad (6.56b)
\]

We set \(\omega_h^s = 0.4\) and \(\omega_l^s = 2\), 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

\[
s_{\text{safe}} = p_{\text{safe}}^{\text{high}} s_{\text{safe}}^{\text{high}} + p_{\text{safe}}^{\text{medium}} s_{\text{safe}}^{\text{medium}} + p_{\text{safe}}^{\text{low}} s_{\text{safe}}^{\text{low}} \quad (6.57a)
\]

\[
s_{\text{risky}} = p_{\text{risky}}^{\text{high}} s_{\text{risky}}^{\text{high}} + p_{\text{risky}}^{\text{medium}} s_{\text{risky}}^{\text{medium}} + p_{\text{risky}}^{\text{low}} s_{\text{risky}}^{\text{low}} \quad (6.57b)
\]

we can now solve for the medium-skilled separation rates

\[
s_{\text{safe}}^{\text{medium}} = \frac{s_{\text{safe}}}{p_{\text{high}}^s \omega_h^s + p_{\text{medium}}^s \omega_l^s} = 0.0267 \quad (6.58a)
\]

\[
s_{\text{risky}}^{\text{medium}} = \frac{s_{\text{risky}}}{p_{\text{high}}^r \omega_h^r + p_{\text{medium}}^r \omega_l^r} = 0.0348. \quad (6.58b)
\]

In the safe sector of our model, there is only exogenous separation and hence we set the exogenous job destruction rate to \(\delta = 0.0267\). Now the endogenous job destruction rate must be \(\lambda F(x_d) = s_{\text{risky}}^{\text{medium}} - \delta = 0.0081\). This condition implicitly determines the risky sector job destruction margin and serves as a target in the third step of our calibration procedure.

6.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

\[
\frac{\pi_{\text{safe}}^{\text{high}}}{\pi_{\text{safe}}^{\text{low}}} = \frac{\pi_{\text{risky}}^{\text{high}}}{\pi_{\text{risky}}^{\text{low}}} = \omega_h^\pi > 1 \quad (6.59a)
\]

\[
\frac{\pi_{\text{safe}}^{\text{medium}}}{\pi_{\text{safe}}^{\text{low}}} = \frac{\pi_{\text{risky}}^{\text{medium}}}{\pi_{\text{risky}}^{\text{low}}} = \omega_l^\pi < 1. \quad (6.59b)
\]
We set $\omega_h^\pi = 2.4$ and $\omega_l^\pi = 0.8$, implying a factor three difference between high-skilled and low-skilled and medium-skilled much closer related to low-skilled than to high-skilled. From the skill decomposed productivities

$$\pi^{\text{safe}} = p_{\text{high}}^\pi \omega_h^\pi + p_{\text{medium}}^\pi \omega_m^\pi + p_{\text{low}}^\pi \omega_l^\pi$$

(6.60a)

$$\pi^{\text{risky}} = p_{\text{high}}^\pi \omega_h^\pi + p_{\text{medium}}^\pi \omega_m^\pi + p_{\text{low}}^\pi \omega_l^\pi$$

(6.60b)

we can now solve for the medium-skilled productivities

$$\pi_{\text{medium}}^{\text{safe}} = \frac{\pi^{\text{safe}}}{p_{\text{high}}^\pi \omega_h^\pi + p_{\text{medium}}^\pi \omega_m^\pi + p_{\text{low}}^\pi \omega_l^\pi}$$

(6.61a)

$$\pi_{\text{medium}}^{\text{risky}} = \frac{\pi^{\text{risky}}}{p_{\text{high}}^\pi \omega_h^\pi + p_{\text{medium}}^\pi \omega_m^\pi + p_{\text{low}}^\pi \omega_l^\pi}$$

(6.61b)

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

$$\hat{y} = \frac{\pi^{\text{risky}}}{\pi^{\text{safe}}} \frac{p_{\text{high}}^\pi \omega_h^\pi + p_{\text{medium}}^\pi \omega_m^\pi + p_{\text{low}}^\pi \omega_l^\pi}{p_{\text{high}}^\pi \omega_h^\pi + p_{\text{medium}}^\pi \omega_m^\pi + p_{\text{low}}^\pi \omega_l^\pi}$$

(6.62)

### Appendix 6.B Robustness checks: alternative estimates of $\gamma$

In Table 6.15, 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 $\gamma$ and the t-statistic are presented. The general pattern for the share of employment is consistent: higher firing costs are associated with lower employment shares in high risk industries and higher shares in low risk industries. Both in shares and in growth rates, the effect for employment is higher in the latter part of the sample period, consistent with the outcome of the model simulation with rising risk. For TFP growth, the effect appears to be limited to the earlier period, from 2000 onwards the effect is insignificant.

Finally, Tables 6.16, 6.17, and 6.18 show the results for labor share, employment growth, and TFP growth respectively, and vary 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 data set and is measured as the percentage of workers with access to broadband internet (Broadband). The next measure is
### 6.B. ROBUSTNESS CHECKS: ALTERNATIVE ESTIMATES OF $\gamma$

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<td>EUN</td>
<td>-1.07 (2.41)</td>
<td>-0.83 (2.28)</td>
<td>-1.28 (2.59)</td>
<td>-3.90 (4.11)</td>
<td>-0.30 (0.64)</td>
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<td>EUR</td>
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<td>-1.16 (2.38)</td>
<td>-0.66 (1.36)</td>
<td>-3.43 (2.75)</td>
<td>-0.55 (0.61)</td>
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<td>-1.15 (2.43)</td>
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<td>-0.52 (0.98)</td>
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<tr>
<td>ALL</td>
<td>-1.04 (2.45)</td>
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<td>-1.06 (2.12)</td>
<td>-2.41 (3.61)</td>
<td>0.13 (0.31)</td>
</tr>
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</table>

Table 6.15: Employment Share: 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 6.C for country listing.

our base measure, (Dispersion), computed as the ratio of productivity of the top quartile of firms to the mean in an industry. Because firing costs truncate from below, this indicator may be less affected by firing costs than the overall variance of productivity.\(^{30}\) The last column (Variance) shows the variance of labor productivity across industries. All industry riskiness rankings are averaged across countries in the ONS data set. The exit cost indicators are described and the 2004 values for each country are given in Appendix 6.C. The results for employment share regressions are quite robust across specifications. 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 6.C shows the values of these indicators for each country in our sample in 2004.

---

\(^{30}\)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.
### Table 6.16: Employment Share: Alternative exit cost and riskiness indicators

The tables 6.19 through 6.21 show results for the basic regressions, but with country indicators of financial development rather than exit costs, and with both financial and exit costs, interacted with riskiness. These results already are described in the main text.

Below, we show the results of the randomly selected 1200 industry rankings that we mentioned at the end of section 6. Figure 6.2 shows the point estimates for $\gamma$ with confidence bounds. All the estimates of $\gamma$ fall within the 5 percent largest negative estimates.

<table>
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<tr>
<th>Exit Cost</th>
<th>Riskiness indicator</th>
<th>Variance</th>
<th>Broadband</th>
<th>Dispersion</th>
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<tr>
<td>Exit Loss</td>
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<td>$-5.28$</td>
<td>$-3.44$</td>
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<td></td>
<td>(1.89)</td>
<td>(3.22)</td>
<td>(1.84)</td>
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<tr>
<td>Exit Cost (pct)</td>
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<td>$-23.79$</td>
<td>$-15.81$</td>
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<td></td>
<td>(1.89)</td>
<td>(3.38)</td>
<td>(1.96)</td>
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</tr>
<tr>
<td>Firing Rules</td>
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<td>$-0.41$</td>
<td>$-0.34$</td>
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<td></td>
<td>(1.96)</td>
<td>(2.47)</td>
<td>(2.20)</td>
<td></td>
</tr>
<tr>
<td>Firing Cost</td>
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<td>$-4.38$</td>
<td>$-3.78$</td>
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</tr>
<tr>
<td></td>
<td>(2.43)</td>
<td>(3.30)</td>
<td>(2.63)</td>
<td></td>
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<tr>
<td>EPL Overall</td>
<td>$-0.67$</td>
<td>$-1.12$</td>
<td>$-0.81$</td>
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<tr>
<td></td>
<td>(2.58)</td>
<td>(3.90)</td>
<td>(2.70)</td>
<td></td>
</tr>
<tr>
<td>EPL Regular</td>
<td>$-1.03$</td>
<td>$-1.32$</td>
<td>$-1.08$</td>
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<tr>
<td></td>
<td>(2.80)</td>
<td>(3.45)</td>
<td>(2.55)</td>
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<thead>
<tr>
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<th>Riskiness indicator</th>
<th>Variance</th>
<th>Broadband</th>
<th>Dispersion</th>
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<td>$-0.31$</td>
<td>$-2.15$</td>
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<tr>
<td></td>
<td>(1.13)</td>
<td>(0.22)</td>
<td>(1.12)</td>
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<tr>
<td>Exit Cost (pct)</td>
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<td>$-2.02$</td>
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<tr>
<td></td>
<td>(1.91)</td>
<td>(0.45)</td>
<td>(1.92)</td>
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<td>$-0.26$</td>
<td>$-0.21$</td>
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<td></td>
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<td>(0.87)</td>
<td>(0.71)</td>
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<td>$-2.76$</td>
<td>$-2.99$</td>
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<td></td>
<td>(3.91)</td>
<td>(2.62)</td>
<td>(3.93)</td>
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<tr>
<td>EPL Overall</td>
<td>$-0.53$</td>
<td>$-0.62$</td>
<td>$-0.52$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.56)</td>
<td>(1.44)</td>
<td>(1.46)</td>
<td></td>
</tr>
<tr>
<td>EPL Regular</td>
<td>$-0.85$</td>
<td>$-0.63$</td>
<td>$-0.89$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.77)</td>
<td>(1.77)</td>
<td>(2.65)</td>
<td></td>
</tr>
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</table>

**t-statistic in parenthesis. Period: 1995-2005; Fixed Eff: industry means & trends. See Appendix 6.C for indicator definitions and country and industry listing. Robust errors clustered 2-way by industry and country.**
### Table 6.18: TFP Growth: Alternative exit cost and riskiness indicators

<table>
<thead>
<tr>
<th>Riskiness indicator</th>
<th>Exit Cost</th>
<th>Variance</th>
<th>Broadband</th>
<th>Dispersion</th>
</tr>
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<tbody>
<tr>
<td>Exit Loss</td>
<td>1.70</td>
<td>-0.20</td>
<td>-2.22</td>
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<tr>
<td></td>
<td>(0.73)</td>
<td>(0.09)</td>
<td>(0.85)</td>
<td></td>
</tr>
<tr>
<td>Exit Cost (pct)</td>
<td>-18.06</td>
<td>-5.69</td>
<td>-18.79</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.69)</td>
<td>(0.60)</td>
<td>(2.43)</td>
<td></td>
</tr>
<tr>
<td>Firing Rules</td>
<td>0.20</td>
<td>0.02</td>
<td>0.29</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.05)</td>
<td>(0.65)</td>
<td></td>
</tr>
<tr>
<td>Firing Cost</td>
<td>-4.27</td>
<td>-2.56</td>
<td>-4.79</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.08)</td>
<td>(1.68)</td>
<td>(3.97)</td>
<td></td>
</tr>
<tr>
<td>EPL Overall</td>
<td>-0.95</td>
<td>-1.03</td>
<td>-1.12</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.09)</td>
<td>(2.46)</td>
<td>(2.77)</td>
<td></td>
</tr>
<tr>
<td>EPL Regular</td>
<td>-1.09</td>
<td>-0.65</td>
<td>-1.21</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.34)</td>
<td>(1.52)</td>
<td>(2.79)</td>
<td></td>
</tr>
</tbody>
</table>


**Figure 6.2: Estimates of $\gamma$ with random $R(\sigma)$**
### Financial Indicator | only $\gamma_{\text{findev}}$ | $\gamma_{\text{findev}}$ | $\gamma_{\text{exit}}$
--- | --- | --- | ---
Bank Deposits | 0.47 (0.52) | 0.77 (0.79) | -1.12 (2.46)
Stock Market Capitalization | 1.22 (1.55) | 0.92 (1.22) | -0.80 (2.51)
Bank Credit | 0.77 (0.85) | 1.03 (1.06) | -1.17 (2.45)
Other Credit | 1.15 (1.15) | 1.05 (1.08) | -1.04 (2.59)
Private Bonds | 0.70 (1.60) | 0.60 (1.42) | -0.94 (2.51)
none. (only exit cost: EPLRegular) | | | -1.08 (2.55)

### Table 6.19: Labor share regressed on financial development


### Financial Indicator | only $\gamma_{\text{findev}}$ | $\gamma_{\text{findev}}$ | $\gamma_{\text{exit}}$
--- | --- | --- | ---
Bank Deposits | 1.59 (1.74) | 1.87 (2.00) | -1.01 (2.87)
Stock Market Capitalization | 0.88 (1.56) | 0.60 (1.09) | -0.73 (2.47)
Bank Credit | 1.33 (1.68) | 1.57 (1.89) | -1.04 (2.82)
Other Credit | 1.42 (1.81) | 1.34 (1.71) | -0.84 (2.54)
Private Bonds | 0.47 (2.13) | 0.38 (1.59) | -0.81 (2.22)
none. (only exit cost: EPLRegular) | | | -0.89 (2.65)

### Table 6.20: Labor growth regressed on financial development


### Financial Indicator | only $\gamma_{\text{findev}}$ | $\gamma_{\text{findev}}$ | $\gamma_{\text{exit}}$
--- | --- | --- | ---
Bank Deposits | 0.47 (0.69) | 0.94 (1.45) | -1.26 (2.98)
Stock Market Capitalization | 1.57 (2.53) | 1.08 (1.58) | -0.88 (1.81)
Bank Credit | 1.06 (1.67) | 1.55 (2.30) | -1.35 (3.00)
Other Credit | 0.43 (0.54) | 0.26 (0.33) | -1.20 (2.76)
Private Bonds | 0.90 (1.57) | 0.70 (1.19) | -1.06 (2.37)
none. (only exit cost: EPLRegular) | | | -1.21 (2.79)

### Table 6.21: TFP growth regressed on financial development

### Appendix 6.C  Data documentation tables

<table>
<thead>
<tr>
<th>Country</th>
<th>overall EPL</th>
<th>reg. EPL</th>
<th>Firing Rules</th>
<th>Firing Cost</th>
<th>Exit Cost</th>
<th>Exit Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUS</td>
<td>1.19</td>
<td>1.50</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>AUT</td>
<td>1.93</td>
<td>2.37</td>
<td>2.0</td>
<td>0.02</td>
<td>0.18</td>
<td>0.27</td>
</tr>
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<td>BEL</td>
<td>2.18</td>
<td>1.73</td>
<td>0.5</td>
<td>0.16</td>
<td>0.04</td>
<td>0.14</td>
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<tr>
<td>CZE</td>
<td>1.90</td>
<td>3.31</td>
<td>1.5</td>
<td>0.22</td>
<td>0.18</td>
<td>0.85</td>
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<td>0.5</td>
<td>0.00</td>
<td>0.04</td>
<td>0.37</td>
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<td>0.56</td>
<td>0.15</td>
<td>0.23</td>
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<td>FIN</td>
<td>2.02</td>
<td>2.17</td>
<td>2.0</td>
<td>0.26</td>
<td>0.04</td>
<td>0.12</td>
</tr>
<tr>
<td>FRA</td>
<td>3.05</td>
<td>2.47</td>
<td>2.0</td>
<td>0.32</td>
<td>0.09</td>
<td>0.54</td>
</tr>
<tr>
<td>GER</td>
<td>2.35</td>
<td>2.68</td>
<td>2.0</td>
<td>0.69</td>
<td>0.01</td>
<td>0.44</td>
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<td>GRC</td>
<td>2.83</td>
<td>2.41</td>
<td>2.0</td>
<td>0.24</td>
<td>0.09</td>
<td>0.57</td>
</tr>
<tr>
<td>HUN</td>
<td>1.52</td>
<td>1.92</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IRL</td>
<td>1.11</td>
<td>1.60</td>
<td>1.0</td>
<td>0.13</td>
<td>0.09</td>
<td>0.12</td>
</tr>
<tr>
<td>ITA</td>
<td>1.95</td>
<td>1.77</td>
<td>2.0</td>
<td>0.02</td>
<td>0.18</td>
<td>0.57</td>
</tr>
<tr>
<td>JPN</td>
<td>1.84</td>
<td>2.44</td>
<td></td>
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</tr>
<tr>
<td>NLD</td>
<td>2.12</td>
<td>3.05</td>
<td>3.5</td>
<td>0.17</td>
<td>0.04</td>
<td>0.13</td>
</tr>
<tr>
<td>POL</td>
<td>1.74</td>
<td>2.23</td>
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<tr>
<td>PRT</td>
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<td>2.5</td>
<td>0.95</td>
<td>0.09</td>
<td>0.27</td>
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<tr>
<td>SWE</td>
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<td>2.86</td>
<td>2.0</td>
<td>0.26</td>
<td>0.09</td>
<td>0.19</td>
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<td>0.5</td>
<td>0.22</td>
<td>0.06</td>
<td>0.14</td>
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<td>USA</td>
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<td>0.17</td>
<td>0.0</td>
<td>0.00</td>
<td>0.07</td>
<td>0.20</td>
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Table 6.22: Exit cost indicators, by country (time averages)
<table>
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<th>Description</th>
<th>Dispersion</th>
<th>Variance</th>
<th>Broadband</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food, Beverages and Tobacco</td>
<td>16</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>Clothing</td>
<td>7</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>Wood, Wood Products, Cork</td>
<td>4</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>Pulp, paper, publishing</td>
<td>10</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>Chemicals</td>
<td>18</td>
<td>16</td>
<td>16</td>
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<tr>
<td>Rubber and plastics</td>
<td>1</td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td>Other Non-metallic minerals</td>
<td>15</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Metals and Machinery</td>
<td>3</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Machinery n.e.c.</td>
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<td>3</td>
<td>11</td>
</tr>
<tr>
<td>Equipment</td>
<td>12</td>
<td>8</td>
<td>15</td>
</tr>
<tr>
<td>Motor Vehicles and Transport Equipment</td>
<td>6</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>Misc Manufacturing</td>
<td>5</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>Electricity, Gas and Water Supply</td>
<td>17</td>
<td>19</td>
<td>13</td>
</tr>
<tr>
<td>Sale, maintenance and repair of motor vehicles</td>
<td>11</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>Wholesale trade and commission trade, ex motor vehicles</td>
<td>19</td>
<td>17</td>
<td>18</td>
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<tr>
<td>Retail trade, except of motor vehicles and motorcycles</td>
<td>8</td>
<td>15</td>
<td>8</td>
</tr>
<tr>
<td>Hotels and Restaurants</td>
<td>9</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td>Transport</td>
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<td>12</td>
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<td>Post and Telecommunications</td>
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<td>Business Services</td>
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<td>18</td>
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</tr>
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</table>

Table 6.23: Country samples used in empirical exercise

Table 6.24: Industries with riskiness ranking

Risky industries in **Bold.**