Employment Protection, Innovation and the Labor Market

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Andreas Bastgen

Referent:	Christian Holzner
Koreferent:	Timo Wollmershäuser
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Namen der Berichterstatter:

Christian Holzner

Timo Wollmershäuser

Andreas Haufler

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Contents

Preface

This dissertation analyzes how employment protection legislation (EPL) and technological change affect the labor market. EPL is a main institutional feature of the labor market. Typically, it is meant to provide job security to workers by restricting firms possibility to layoff workers. Technological change is widely recognized as key contributor to economic growth including the growth of real wages. However, as far as technological change is skill-biased unfavorable distributional side-effects may arise.

The main goal of EPL is to provide higher job security to workers. Risk averse workers value stable employment relationships as they provide constant income streams. In addition, EPL strengthens the bargaining power of incumbent workers. On the other side, EPL reduces firm profits as firms may not optimally respond to negative shocks. Either they have to pay firing costs or to operate with a suboptimal amount of workers. The EPL effect on employment is theoretically ambiguous. The value of employing a worker is clearly decreasing in firing costs. Thus, in a frictionless labor market EPL will always cause a decline in employment. However, in a frictional labor market EPL may positively affect aggregate employment via lower turnover. The canonical Mortensen-Pissarides (MP) search and matching model is able to reflect this theoretical ambiguity (see for example Cahuc and Zylberberg (2004)).

Autor, Donohue, and Schwab (2006) use data on the adoption of wrongful-dismissal laws by U.S. state courts to empirically assess employment effects of EPL. They find robust evidence that one wrongful-dismissal doctrine, the implied-contract exception, significantly reduces state employment rates by 0.8% to 1.7%. Chapter 2 of this dissertation develops an theoretical model to show that the employment effect of EPL depends on the composition (rationing versus frictional) of unemployment. Model predictions are empirically tested using the same legal dataset as Autor, Donohue, and Schwab (2006).

Evidence for the effect of EPL on productivity is also mixed. Clearly EPL restrains worker reallocation. As many papers (see Foster, Haltiwanger, and Krizan (2001), Disney, Haskel, and Heden (2003), Baldwin and W.Gu (2006) and Bartelsman, Haltiwanger, and Scarpetta (2009) among others) identify worker reallocation as a key source of productivity growth, a negative association between EPL and productivity seems to be likely. In addition, implementation and enforcement costs associated with EPL may further depress productivity. However, the literature also identified several channels working in the opposite direction. Pierre and Scarpetta (2004a), for example, show that EPL incentivize firms to invest more in training. Zoega and Booth (2003) show that firing costs internalize a quitting externality, which arises because firms discount the value of general human capital at a higher rate than society. Similarly, Belot, Boone, and Ours (2007) and Wasmer (2006) argue that EPL provides an incentive for workers to invest in firm-specific capital.

Another strand of the literature investigates how EPL affects innovation. Koeniger (2005) develops a model to analyze the effect of EPL on innovation in the context of product market competition. As EPL makes exit more costly and more advanced firms endogenously exit with smaller probability, EPL provides a dynamic incentive to innovate. Saint-Paul (2000) analyzes EPL and innovation through the lens of international specialization. He shows that countries with strict EPL tend to specialize in improving existing products, rather than introducing new products. Acharya, Baghai, and Subramanian (2014) exploit the staged adoption of wrongful dismissal laws in the U.S. to show that EPL spurs innovation and new firm creation. To explain these empirical findings Acharya, Baghai, and Subramanian (2014) argue that EPL limits employers' ability to hold up innovating employees and in turn encourages employees to innovate. Chapter 1 of this dissertation develops an alternative theoretical model to explain the empirical findings of Acharya, Baghai, and Subramanian (2014). In this model, EPL increases firm's willingness to pay for new product innovations. This shifts economic activity towards firms specializing in innovation and triggers entry of start-ups. In turn, innovation, measured by the number of new products per period, increases.

There already exists substantial literature on the labor market effects of technological change. Most empirical evidence indicates that higher productivity is not harmful for aggregate employment: for example, van Ark, Frankema, and Duteweerd (2004) found a strong correlation between per capita income, productivity, and employment at least in the medium term. Other papers (see Basu, Fernald, and KimKimball (2006) and Kim, Lim, and Park (2010)) find that positive technology shocks cause lower employment only in the very short run, but higher employment in the medium run. Using the label skill-biased technological change (SBTC), many authors argue that technological change often has very heterogeneous effects on different kinds of workers. Dustmann, Ludsteck, and Schönberg (2009) find that technological change is an important explanation for the widening of the wage distribution in Germany during the 1980s and 1990s. El-Sahli and Upward (2015) find that the introduction of containerization in the UK port industry has caused the decline of some occupations (e.g. stevedores). Autor and Dorn (2013) point out that SBTC is not monotonic across wage percentiles: many low-paid jobs done by unskilled workers can be classified as service type jobs, which are hardly automatable. In fact, real wages and employment in such jobs have strongly grown relative to higher paid jobs with high degrees of routinization. The associated decline in middle-paid jobs has been labeled labor market polarization. The latter is strongly connected to the idea, that technological change actually is not skill-biased but task biased. Using Norwegian data Akerman, Gaarder, and Mogstad (2015) find that well-educated workers performing abstract, non-routine tasks seem to benefit disproportionately from broadband internet adoption by firms. In contrast, low-skilled workers performing repetitive tasks suffer wage and employment losses. The third chapter of this dissertation empirically investigates whether similar effects can be found using German data.

In the following, I briefly outline the research questions analyzed in each of the three chapters and highlight their key results and contributions. The first chapter is motivated by the empirical finding that EPL lowers productivity and employment (see Autor, Donohue, and Schwab (2006)), but boosts innovation (see Acharya, Baghai, and Subramanian (2014)). As noted above Acharya, Baghai, and Subramanian (2014) explain the positive innovation effect by arguing that EPL incentivizes workers to innovate. The main contribution of our model is to provide a novel mechanism of how employment protection stimulates innovation consistent with empirical evidence. To do so, we develop a search and matching model in which EPL increases firms willingness to pay for innovations (product ideas). The intuition goes as follows: with EPL, firms do not layoff their workforce after an adverse idiosyncratic productivity shock. Hence, they employ more workers when searching for a trading partner in the innovation market. With many unproductive workers employed, the marginal benefit of obtaining a new product idea is large and thus is the willingness to pay for a new product idea. The latter stimulates new entry of research firms and thus triggers a higher equilibrium level of innovation. In a nutshell, our argument is based on EPL changing industrial composition instead of EPL changing incentives for individual workers within organizations.

The second chapter addresses the classical question whether EPL increases or decreases unemployment. This is done by using the concept of rationing unemployment, which was recently popularized by the seminal paper of Michaillat (2012). The chapter first develops a small search and matching model with rigid wages, diminishing returns to labor and firing costs. Rationing unemployment (defined as the level of unemployment, which prevails even in the absence of search frictions) arises once the marginal product of the least productive worker falls short of the real wage. The difference between actual employment and the hypothetical employment level without search frictions is denoted as search unemployment. Search frictions are absent, if either vacancy posting costs are zero or matching efficiency is infinity. The model predicts that EPL increases the rationing but decreases the search component of unemployment. The latter happens as EPL lowers market tightness by lowering turnover. Lower market tightness reduces the time needed to match with a new worker which finally leads to lower effective recruiting costs. Hence, the total effect of EPL depends crucially on unemployment composition. If unemployment is mainly driven by job rationing, EPL strongly increases unemployment. In contrast, if search frictions are the main driver of unemployment, EPL may even lower unemployment. Note that the share of rationing unemployment is increasing in the total level of unemployment. This implies that for a given matching efficiency EPL entails adverse employment effects in particular if pre-treatment unemployment is already high.

The second part of the chapter empirically assesses the model's prediction. I exploit a natural experiment, which has occurred in the United States during the 1970s and 1980s (see Autor, Donohue, and Schwab (2006)). By the late 1970s, several U.S. state courts began to adopt wrongful-dismissal laws. Using this variation, I test whether the employment effect of different wrongful-dismissal laws depends on pre-treatment unemployment (employment) rates. Results indicate that for two of the three wrongful-dismissal laws investigated, pre-treatment unemployment rates are crucial for the induced employment effects. Under the assumption of a constant matching efficiency across U.S. states these results confirm the prediction of my theoretical model.

The third chapter empirically investigates whether broadband internet can be classified as skill-biased technological change (SBTC). Using German labor market data from the IAB, we analyze how broadband affects output elasticities and wages of different workers. Following the task-based interpretation of SBTC, we classify workers by job routinization. As a robustness check, we also group workers by formal education. Regarding identification, we argue that conditional on county and time fixed effects the variation in broadband is plausibly exogenous to our outcome variables (see Akerman, Gaarder, and Mogstad (2015)). In addition, we carefully outline the necessary conditions for consistent estimation of the interaction term between broadband and skill group (see Bun and Harrison (2014)) and explain how the interaction term should be interpreted if these conditions are not fully satisfied. In line with SBTC, we find that broadband lowers output elasticities of workers with low formal education / highly routinized jobs. When workers are classified by job routinization, these results pass through on individual wages. This holds in particular when censored wages are replaced by imputed wages. Besides investigating classical SBTC issues, we also provide evidence that broadband Internet mitigates the wage penalty of previously unemployed workers. Interestingly, this desirable effect is not present for workers in highly routinized occupations.

Chapter 1

Employment Protection and the Market for Innovations[1]

1.1 Introduction

Employment protection legislation (EPL) is thought to protect workers against temporary productivity shocks. While most negative productivity shocks to a firm are exogenous, like a drop in demand due to changes in taste or an increase in competition due to new production technologies of competitors, positive productivity shocks are usually the result of process or product innovations and are hence endogenous. Product or process innovations can either be done within a firm through own R&D investment or they can be bought in the market (e.g. new machinery or patent licensing). If we study the effects of employment protection we should therefore take into account that EPL may influence firms abilities to restore their productivity.

The academic literature has already documented multiple effects of EPL. One strand of the literature documented a negative effect of EPL on productivity through inefficient

[1]This chapter is based on joint work with Christian Holzner.

worker reallocation.[2] In addition, Pierre and Scarpetta (2004a) report that EPL particularly harms the growth prospects of medium sized firms. Despite the fairly robust negative effect on productivity, the literature has identified channels that work in the opposite direction. Pierre and Scarpetta (2004a), for example, also show that EPL incentivizes firms to invest more in training. Zoega and Booth (2003) show that firing costs internalize a quitting externality, which arises because firms discount the value of general human capital at a higher rate than society. Similarly, Belot, Boone, and Ours (2007) as well as Wasmer (2006) argue that EPL provides an incentive for workers to invest in firm-specific capital. As productivity decreases despite the positive effect on training, the increase in training investment is likely to reflect a second-best reaction of firms to the introduction of EPL.

Another strand of the literature investigates how EPL affects innovation. Acharya, Baghai, and Subramanian (2014) exploit the staged adoption of wrongful dismissal laws in the U.S. to show that EPL spurs innovation and new firm creation.[3]To explain these empirical findings, Acharya, Baghai, and Subramanian (2014) argue that EPL limits employers' ability to hold up innovating employees and in turn encourages employees to innovate. Koeniger (2005) develops a model to analyze the effect of EPL on innovation in the context of product market competition. As EPL makes exit more costly and more advanced firms endogenously exit with smaller probability, EPL provides a dynamic incentive to innovate.[4] Saint-Paul (2000) analyzes EPL and innovation through the lens

[2]Negative productivity effects from inefficient labor reallocation are found by Hopenhayn and Rogerson (1993), Griliches and Regev (1995), Olley and Pakes (1996), Foster, Haltiwanger, and Krizan (2001), Disney, Haskel, and Heden (2003), Baldwin and W.Gu (2006) and Bartelsman, Haltiwanger, and Scarpetta (2009) among others.

[3] Murphy, Siedschlag, and McQuinn (2012) find, based on OECD data, that EPL leads to lower innovation intensity in industries with a higher job reallocation propensity.

[4]Other authors also emphasize different positive aspects of EPL: Bertola (1994) shows that despite EPL lowers returns to irreversible investment and thus the speed of capital accumulation, it shifts the income distribution towards workers with no capital income. This explains why trade unions often favor stricter EPL. Kessing (2006) argues that firms facing EPL have a stronger average market position as they can credibly commit to fiercely defend their position against potential competitors, because

of international specialization. He shows that countries with strict EPL tend to specialize in improving existing products, rather than introducing new products.

Our paper employs an equilibrium matching model with imperfect labor and innovation markets to provide a novel explanation for why EPL lowers productivity while potentially boosting innovation. We do so by exploiting the interaction between employment protection and firms' ability to restore their productivity. An innovation is defined as a new process or product idea, which enables a producing firm to restore its productivity. Each new product replaces an old product whose life-cycle has ended, that is, each innovation has the same productivity. However, we could also allow product and process innovations to increase productivity and therefore induce long-run growth. The upward shift in innovation, which EPL generates in our model, would then shift the economy's growth rate.

We assume labor market frictions, because without labor market frictions laid-off workers could be reemployed immediately by other firms, which makes employment protection redundant. We assume frictions in the innovation market, because without frictions firms could immediately purchase the machinery (process innovation) or product idea (product innovation) necessary to restore productivity. We model both markets as matching markets, where the time to find an appropriate trading partner depends on the ratio of buyers to sellers in the market, and where prices are negotiated bilaterally. The interaction between labor and innovation markets has the following implication: Employment protection induces firms to keep workers employed even if productivity has dropped. This increases firms' willingness to pay for product or process innovations in order to restore productivity. This increases the price for innovations, triggers entry of start-ups and shifts economic activity towards firms specializing in process and product innovation. It hence increases the rate, at which firms that are hit by a negative productivity shock can purchase the (process or product) innovation necessary to restore their productivity.

We calibrate our model to match aggregate U.S. labor and product market statistics as

EPL makes market exit very costly.

well as aggregate firm exit and entry rates. We then take the calibrated model, introduce employment protection and show that the rate at which firms are able to restore their productivity increases. Our comparative static results are also in line with the estimated negative impact of wrongful dismissal laws on productivity found by D.Autor, W.Kerr, and A.Kugler (2007) and the positive effect on innovations shown by Acharya, Baghai, and Subramanian (2014). Both exploit the fact that from 1970 to 1999 13 U.S. states introduced wrongful dismissal laws by recognizing the so-called "good-faith" exception to the employment-at-will doctrine. Our calibration results are also consistent with the findings by Acharya, Baghai, and Subramanian (2014), who show that the adoption of wrongful dismissal laws increases the number of firms, especially start-ups. We also find evidence for a shift in economic activity. More precisely we find that the number of firms producing the final consumption good decreases while the number of firms specializing in producing machinery (process innovation) or product ideas (product innovation) increases. These results can reconcile the findings by D.Autor, W.Kerr, and A.Kugler (2007), who observe an increase in employment in the manufacturing sector, with the findings by Autor, Donohue, and Schwab (2006), who find a negative effect on state-level employment. To be able to analyze both the firm's entry as well as employment decision, we allow for multiple worker firms.

The papers that are most closely related to ours are Wasmer (2006) and Bartelsman, Gautier, and Wind (2016). Both papers investigate the effect of employment protection in an equilibrium matching model to explain differences between the United States and continental Europe. Wasmer (2006) investigates the effect employment protection has on the type of human capital investment undertaken in the economy. The main difference to our framework is that he models productivity shocks as exogenous, while we endogenize the rate at which firms are able to restore their productivity. Bartelsman, Gautier, and Wind (2016) consider an equilibrium matching model where, under employment protection, firms are less likely to adopt a high-risk and high-return technology and more likely to adopt a low-risk and safe technology. The main difference to our model is that they do not consider that employment protection can increase the returns to investment in innovation.

Section 1.2 is the theory part of this chapter, where we discuss key equations of our model. The details of the model are deferred to the Appendix. The calibration in Section 1.3 discusses the effects of the introduction of employment protection first with fixed and then with endogenous innovation price. Section 1.4 concludes.

1.2 Theory

1.2.1 Framework

The model has an infinite horizon, is set in continuous time and concentrates on steady states. All agents are risk neutral and discount the future at rate r. The economy is populated by a unit mass of homogenous workers and an endogenous mass m of firms.

Production of consumption goods requires labor $N_i \in R_0^+$ and the input $y_i \in \{0, y\}$, where y_i can be interpreted as the productivity of the capital, which the firm employs, or the profitability of the firm's product in the market.[5] The production function for consumption goods is given by $y_i F(N_i) = y_i N_i^{\alpha}$. All firms, which produce consumption goods, produce the same homogenous good with prices normalized to unity.

The input y, i.e., the product idea or the machinery, can be produced by each firm at its firm-specific innovation cost k_i. The per period cost k_i is drawn randomly from a distribution characterized by the pdf $\xi(k)$ and the cdf $\Xi(k)$ on the support $[0, k_{\max}]$. We will also refer to the input y as an innovation. It can be thought of both, a process innovation (machinery) or a product innovation. The research process underlying the production of the input y is stochastic and happens at the Poisson rate η. It requires no production workers. The innovation y is assumed to be destroyed by a productivity

[5]We use this binary productivity distribution in order to avoid the complications arising from a continuum of firm sizes, wages and innovation prices

shock at the exogenous rate δ. Thus, $1/\delta$ can be interpreted as a product's or machinery's life-cycle.

Firms choose to become one of the following types $t \in \{B, R, S\}$ depending on firm-specific innovation costs k_i. Type B and type R firms with $y_i = y$ produce the final consumption good. Type B firms, which have been hit by a productivity shock, i.e., $y_i = 0$, search the innovation market for a new product or process innovation to restore their y_i to y. The details of the innovation market are given below. Type R firms, which are hit by a productivity shock, do their own research to restore their y_i to y. The per-period research success rate is denoted by η and exogenously given. For simplicity, we assume that firms cannot innovate while producing consumption goods. Type S firms develop product ideas or produce capital goods (machinery), i.e., they produce the input y at rate η. Once they have produced the input y, they will sell it on the innovation market. Again, we assume for simplicity that they cannot produce y while they are busy with selling the input y in the innovation market.

The innovation market or market for new product ideas is characterized by matching frictions, with a constant return to scale matching function that satisfies the usual Inada conditions. Tightness in the innovation market is defined as the ratio of firms looking for a new machine or a product idea (B for buyers) to the firms that specialize in innovation and sell the input y on the innovation market (S for sellers), i.e., $\varphi = B/S$. Type S firms that sell the innovation y are matched at rate $\varphi g(\varphi)$ with buyers (type B firms) and type B firms contact sellers (type S firms) at rate $g(\varphi)$. The properties of the matching function are such that the matching probability of a seller (buyer) increases (decreases) with the ratio of buyers to sellers, i.e., $[\varphi g(\varphi)]' > 0$ and $g'(\varphi) < 0$. The innovation price is determined by Nash-bargaining where β denotes the bargaining power of sellers.

Innovation or research costs are firm-specific and set at the beginning of a firm's life. Formally, we assume that potential firms have to pay a cost F upon entry (sufficiently small to guarantee existence) in order to learn the per-period, firm-specific innovation cost k_i. For simplicity, we assume that new firms are born with input $y_i = y$ upon paying the entry cost F.

The interaction between the destruction of firms and the layoff decision for workers is modeled as follows. Type B and type R firms will consider laying off workers only if the firm was hit by a productivity shock δ. A firm that decides to lay off workers will have to pay a firing cost f per worker. Firms can be destroyed only if their current productivity is zero, i.e., if $y_i = 0$. Consumption good producers ($t = B$ or $t = R$) with $y_i = 0$ can be hit by a destruction shock at rate λ_d. If workers must be laid off, because a firm is insolvent and destroyed, no firing costs are due. Type S firms that specialize in innovation do not employ production workers and therefore are not affected by firing costs. They are hit by a destruction shock at rate λ_s. We assume $\lambda_s < \lambda_d$, in order to ensure that type S and type B and R firms are equally likely to be destroyed. The reason is that type S firms are not only in the "$y_i = 0$" state if they are hit by a productivity shock, but also when they are doing research in order to produce the innovation y. They are hence more often exposed to a destruction shock than type B and R firms.

The labor market for production workers is also modeled using matching frictions. Firms hire workers by posting vacancies at the per period cost c (sufficiently small to guarantee existence). The matching function for production workers has constant return to scale and satisfies the Inada conditions. Labor market tightness is denoted by $\theta = V/U$, where V equals the number of vacancies created by all firms and U the number of unemployed workers. The job finding rate of workers is given by $\theta\lambda_m(\theta)$ and the rate at which firms contact workers by $\lambda_m(\theta)$. The properties of the matching function are such that the matching probability of an unemployed worker (vacancy) increases (decreases) with the ratio of vacancies to unemployed, i.e., $[\theta\lambda_m(\theta)]' > 0$ and $\lambda_m'(\theta) < 0$. Wages are negotiated and renegotiated each time the productivity of a firm changes. The bargaining power of workers is denoted by γ. Unemployed workers receive unemployment benefits z. Employed workers receive a wage $w^t(y_i, N_i)$, which depends on $y_i \in \{0, y\}$, on the marginal product $y_i F'(N_i)$, and the type t of the firm.

1.2.2 Optimality Conditions and Equilibrium

Consumption good producers: Firms of the consumption goods sector, i.e., type $t \in \{B, R\}$ firms, choose their labor input by deciding on the number of vacancies V_i^t they want to post and the number of workers they want to lay off L_i^t. The equation governing the change in the number of workers employed at firm i that posts vacancies V_i^t and lays off L_i^t workers is given by,

$$\dot{N}_i^t = \lambda_m(\theta) V_i^t - L_i^t. \tag{1.1}$$

Firms, which want to start production, will immediately hire their optimal number of workers N_i^t, by posting $V_i^t = N_i^t / \lambda_m(\theta)$ vacancies. The following Bellman equation characterizes the expected profit of a type B or R firm with productivity $y_i = y$, innovation cost k_i, and workforce N_i^t, i.e.,

$$\begin{aligned} r\pi^{h,t}\left(N_i^t, y, k_i\right) &= y\left(N_i^t\right)^{\alpha} - w^{h,t}\left(y, N_i^t\right) N_i^t \\ &+ \delta\left(\max\left[\pi^{I,t}\left(N_i^t, 0, k_i\right), \pi^{O,t}(0,0,k_i) - fN_i^t\right] - \pi^{h,t}\left(N_i^t, y, k_i\right)\right), \end{aligned} \tag{1.2}$$

for $t \in \{B, R\}$. Note, that this equation holds for all type B or R firms regardless of whether they employ outsiders $h = O$ or have insiders $h = I$. Firms that decide not to layoff their workers once a productivity shock δ hits, i.e., $L_i^t = 0$, can renegotiate the wage with their current workforce (insiders), i.e., have a continuation value $\pi^{I,t}(N_i^t, 0, k_i)$. Firms that decide to layoff their workers, i.e., $L_i^t = N_i^t$, have to continue without workers, which implies a continuation value $\pi^{O,t}(0, 0, k_i)$ and the payment of firing costs to the amount of fN_i^t. Type B or R firms will post vacancies subject to equation (1.1) until the marginal value of an additional worker equals the expected cost of hiring a worker, i.e.,

$$\frac{\partial \pi^{O,t}(N_i^t, y, k_i)}{\partial N_i^t} = \frac{c}{\lambda_m(\theta)}. \tag{1.3}$$

Thus, if the marginal value of an additional worker for a type B firm is different than that of a type R firm, then the number of vacancies posted and the number of workers employed will be different too.

Wages in the labor market are determined by Nash-bargaining. We assume intra-firm bargaining as in Smith (1999), Cahuc and Wasmer (2001), and Cahuc, Marque, and Wasmer (2008), among others. The worker surplus equals the value of being employed minus the outside option of being unemployed. The firm's surplus depends on whether it bargains with outsiders (new workers) or with insiders. If a firm is bargaining with outsiders the surplus is given by the marginal value of an additional worker. If an old firm is renegotiating the wages of its current workforce (insiders), then the surplus of continuing the employment relationship is given by the marginal value of an additional worker plus firing cost f, since a bargaining agreement ensures that the firm does not have to pay the firing cost. The Nash-product in the event a firm negotiates with outsiders and insiders, respectively, is given by,

$$w^{O,t}\left(y_i, N_i^t\right) = \arg\max_w \left(W^{O,t}\left(w\right) - U\right)^{\gamma} \left(\frac{\partial \pi^{O,t}(N_i^t, y_i, k_i)}{\partial N_i^t}\right)^{1-\gamma}, \tag{1.4}$$

$$w^{I,t}\left(y_i, N_i^t\right) = \arg\max_w \left(W^{I,t}\left(w\right) - U\right)^{\gamma} \left(\frac{\partial \pi^{I,t}(N_i^t, y_i, k_i)}{\partial N_i^t} + f\right)^{1-\gamma}. \tag{1.5}$$

The marginal value of an additional worker for a firm with $y_i = y$ that wants to hire new workers ($h = O$) is given by differentiating equation (1.2). The marginal value of an additional worker for a firm, which has been hit by a productivity shock, i.e., $y_i = 0$, but retains its workers is given by,

$$\frac{\partial \pi^{I,t}\left(N_i^t, 0, k_i\right)}{\partial N_i^t} = \begin{cases} \dfrac{\eta}{r + \lambda_d + \eta}\left(\dfrac{c}{\lambda_m\left(\theta\right)} - \gamma f - \dfrac{w^{I,R}\left(0, N_i^R\right)}{\eta}\right) & \text{if } \ t = R, \\[2em] \dfrac{g\left(\varphi\right)}{r + \lambda_d + g\left(\varphi\right)\left(1-\beta\right)}\left(\left(1-\beta\right)\left(\dfrac{c}{\lambda_m\left(\theta\right)} - \gamma f\right) - \dfrac{w^{I,B}\left(0, N_i^B\right)}{g\left(\varphi\right)}\right) & \\ & \text{if } \ t = B. \end{cases} \tag{1.6}$$

In the absence of a product idea workers are not productive. Correspondingly, the firms loss during the spell without a product idea is larger if it employs more workers. Nevertheless, the marginal value of an additional worker is negative only if the wage payments over the expected duration until the firm obtains a new innovation, i.e., $1/\eta$ or $1/g\left(\varphi\right)$, are higher than the expected cost of hiring a worker $c/\lambda_m\left(\theta\right)$ minus the part of the firing cost that the firm would have to bear γf if it lays off a worker (the fraction $(1-\beta)$ for type B firms due to Nash-bargaining over innovation prices). If the rate at which a firm can restore its productivity, i.e., η or $g(\varphi)$, is sufficiently high, the marginal value of an additional worker is positive even though workers are not productive.

The marginal value of an additional worker for a firm, which has been hit by a productivity shock, also determines a firm's layoff decision. A firm will keep all its workers if the surplus is positive, that is, if the marginal value of a worker plus firing costs is positive, i.e.,

$$\frac{\partial \pi^{I,t}\left(N_i^t, 0, k_i\right)}{\partial N_i^t} + f \geq 0. \tag{1.7}$$

If the surplus is negative, workers will be laid off. If a firm wants to lay off workers, it will lay off all workers, since firing costs per worker are constant and the marginal revenue product equals zero after a productivity shock.

Innovation producers: Firms of the innovation sector, i.e., type S firms, specialize on producing and selling innovations, i.e., producing and selling the input y for consumption good produces. The expected discounted profit of a type S firm $\pi^S(0, y_j, k_j)$ depends on the prices $p\left(k_j, N_i^B\right)$ it receives for its innovation. Prices are determined by Nash-bargaining, i.e.,

$$\begin{aligned} p\left(k_j, 0\right) = \arg\max_p & \left(\pi^{O,B}\left(N_i^B, y, k_i\right) - \frac{c}{\lambda_m(\theta)} N_i^B - \pi^{O,B}\left(0, 0, k_i\right) - p\right)^{1-\beta} \\ & \times \left(p + \pi^S\left(0, 0, k_j\right) - \pi^S\left(0, y, k_j\right)\right)^{\beta}, \end{aligned}$$

$$\begin{aligned} p\left(k_j, N_i^B\right) = \arg\max_p & \left(\pi^{I,B}\left(N_i^B, y, k_i\right) - \pi^{I,B}\left(N_i^B, 0, k_i\right) - p\right)^{1-\beta} \\ & \times \left(p + \pi^S\left(0, 0, k_j\right) - \pi^S\left(0, y, k_j\right)\right)^{\beta}, \end{aligned}$$

The price $p\left(k_j, N_i^B\right)$ of the innovation will depend on the surplus that is generated by the innovation. The surplus will depend on the type S firm's own innovation cost k_j and on the number of workers employed at the buyer N_i^B. The surplus of a type B firm that buys an innovation is given by the increase in expected profits from restoring productivity y_i from 0 to y, which allows the firm either to bring its workforce back to productive use, if it has kept its workforce after the productivity shock, or to hire and productively employ new workers, if it has laid off its workforce following a productivity shock. The buyer's innovation cost k_i does not enter the surplus, since a firm that decided to buy the innovation y will also do so in the future, that is, it will never decide to do own research. The surplus of a type S firm that sells the innovation is given by the price plus the expected loss in profit $\pi^S(0,0,k_j) - \pi^S(0,y,k_j)$ from having to produce a new innovation. A type S firm will not be active on the labor market for production workers, i.e., $N_j^S = 0$, since innovation requires by assumption no production workers. Labor market conditions only enter a type S firm's expected discounted profit $\pi^S(0,y,k_j)$ via the number of workers employed by type B firms, which influences the price $p\left(k_j, N_i^B\right)$.

Specialization: We can now characterize which firms will enter the consumption goods sector and specialize on production of the final good without doing own research, type B firms, which firms will enter the innovation goods sector and specialize on innovation, type S firms, and which firms will do both produce consumption goods and do own research, type R firms. Given the innovation cost k_i each firm will choose its type t such that expected profits are maximized, i.e.,

$$\max_{t \in \{S,B,R\}} \pi^{O,t}\left(N_i^t, y, k_i\right) - \frac{c}{\lambda_m(\theta)} N_i^t,$$

where N_i^t denotes the optimal number of workers that the firm intends to hire following the optimal vacancy creation condition in equation (1.3).

Type B firms decide to buy an innovation when they are hit by a productivity shock. They therefore never innovate. Hence, their expected profits are independent of k_i. Thus, the minimum profit that each firm can obtain is given by the expected profit of type B firms (before they hire workers). In contrast, type R firms conduct their own research, when they are hit by a productivity shock. Type S firms specialize in innovation and do more research than type R firms. Their profits are therefore more sensitive to the cost of innovation k_i. In Appendix A.5 we formally show that the expected profit of type S firms decreases more in the cost of innovation k_i than the expected profit of type R firms, i.e.,

$$\frac{\partial \pi^S\left(0, y, k_i\right)}{\partial k_i} < \frac{\partial \pi^{O,R}\left(N_i^R, y, k_i\right)}{\partial k_i} < \frac{\partial \pi^{O,B}\left(N_i^B, y, k_i\right)}{\partial k_i} = 0.$$

This is also shown in the following Figure.

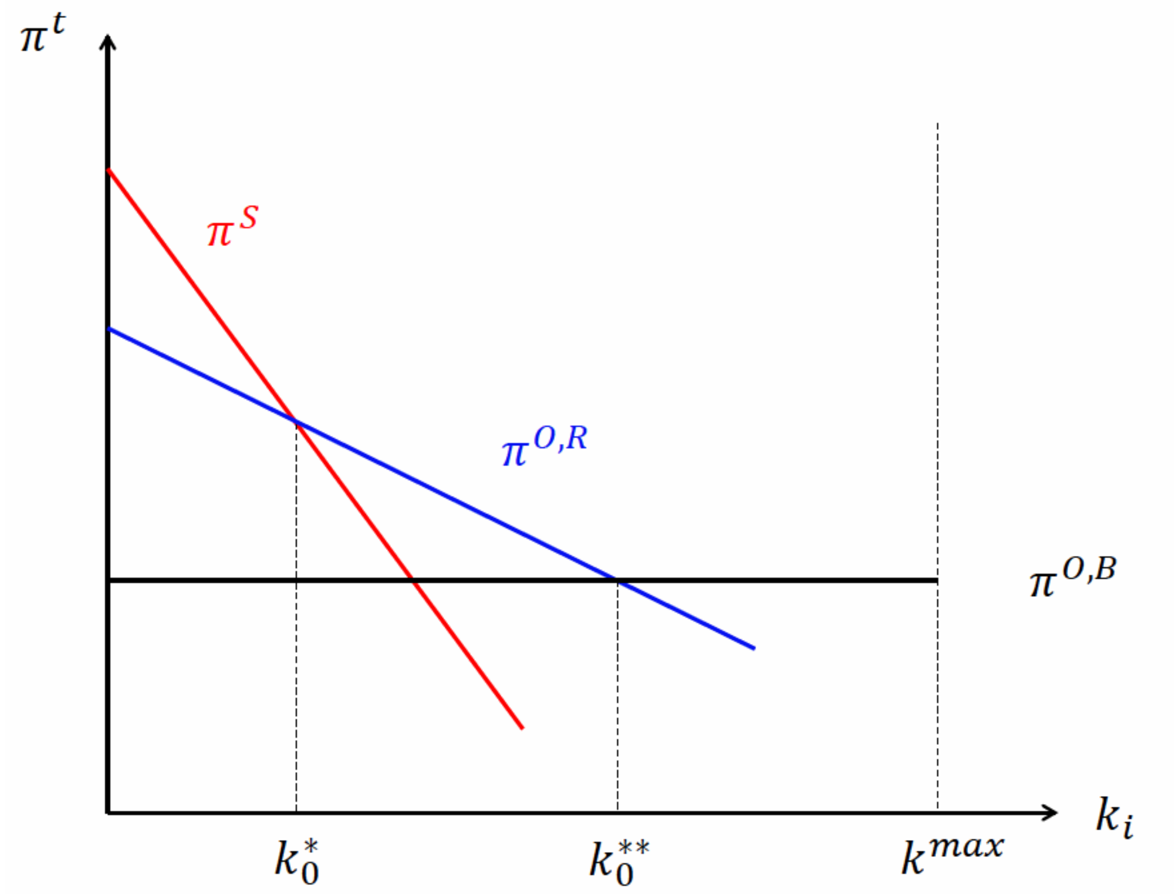

Figure 1.1 – Specialization decision of firms

Given this single crossing property we can define the innovation cost thresholds k^* and k^{**}. Firms with innovation cost $k_i \in [0, k^*]$ will specialize in innovation, firms with innovation cost $k_i \in (k^*, k^{**})$ will produce consumption goods and do their own research if they are hit by a productivity shock, and firms with innovation cost $k_i \in [k^{**}, k_{\max}]$ will produce consumption goods and buy a new innovation when they need one. The thresholds are formally defined by the following indifference conditions for type S and type R firms (thresholds k^*) as well as for type R and type B firm (thresholds k^{**})

respectively,

$$\pi^S(0, y, k^*) = \pi^{O,R}\left(N_i^R, y, k^*\right) - \frac{c}{\lambda_m(\theta)} N_i^R, \tag{1.8}$$

$$\pi^{O,R}\left(N_i^R, y, k^{**}\right) - \frac{c}{\lambda_m(\theta)} N_i^R = \pi^{O,B}\left(N_i^B, y, k^{**}\right) - \frac{c}{\lambda_m(\theta)} N_i^B. \tag{1.9}$$

Remember that the appropriate equations for expected profits depend on whether firms lay off workers, when a productivity shock hits.

Firm entry: The expected profit of a new firm before it draws its innovation cost k_i determines the number of active firms m in the economy. Since expected profits $\pi^S(0, y, k_i)$ and $\pi^{O,R}\left(N_i^R, y, k_i\right)$ are linear in k_i and $\pi^{O,B}\left(N_i^B, y, k_i\right)$ independent of k_i, we can write expected profit as,

$$\begin{aligned} F = {} & \varXi(k^*)\,\pi^S\left(0, y, \overline{k}\right) \\ & + \left(\varXi(k^{**}) - \varXi(k^*)\right)\left(\pi^{O,R}\left(N_i^R, y, \overline{\overline{k}}\right) - \frac{c}{\lambda_m(\theta)} N_i^R\right) \\ & + \left(1 - \varXi(k^{**})\right)\left(\pi^{O,B}\left(N_i^B, y, k_i\right) - \frac{c}{\lambda_m(\theta)} N_i^B\right), \end{aligned} \tag{1.10}$$

where average innovation cost $\overline{k}$ among type S firms and $\overline{\overline{k}}$ among type R firms are given by,

$$\overline{k} = \int_0^{k^*} k_i \frac{\xi(k_i)}{\varXi(k^*)} dk_i \text{ and } \overline{\overline{k}} = \int_{k^*}^{k^{**}} k_i \frac{\xi(k_i)}{\varXi(k^{**}) - \varXi(k^*)} dk_i.$$

Given the entry cost F, firms will enter until the expected profit is equal to the cost of entry. The parameter m for the number of firms is not directly visible in the entry condition (1.10), but it enters the expected profit indirectly via labor market tightness θ. Steady state labor market tightness is determined using the steady state flow equations analyzed next.

Steady state flows: We denote the measure of unemployed workers by u and the measure of type t firms with N_i^t employed workers and with productivity $y_i \in \{0, y\}$ by $m^t(y_i, N_i^t)$, where the number of firms must sum up to m. The respective worker- or firm-level flow measures evolve according to the difference between in- and outflows as shown in Appendix A.5.1. We focus on the steady state.

Steady state unemployment is given by,

$$u = \begin{cases} \dfrac{\lambda_d}{\theta\lambda_m(\theta)} \left(m^B\left(0, N_i^B\right) N_i^B + m^R\left(0, N_i^R\right) N_i^R\right) & \text{if } L_i^t = 0, \\ \\ \dfrac{\delta}{\theta\lambda_m(\theta)} \left(m^B\left(y, N_i^B\right) N_i^B + m^R\left(y, N_i^R\right) N_i^R\right) & \text{if } L_i^t = N_i^t. \end{cases}$$

If all R and B type firms retain their workers once they are hit by a productivity shock, the inflow into unemployment is given by the rate λ_d at which consumption good producers, which have been hit by a productivity shock, are destroyed times the number of workers that are employed at these firms, i.e., $m^B\left(0, N_i^B\right) N_i^B + m^R\left(0, N_i^R\right) N_i^R$. If all firms lay off their workers once they are hit by a productivity shock, the inflow into unemployment is given by the rate δ, at which a productivity shock hits, times the number of workers employed at firms producing consumption goods with $y_i = y$, i.e., $m^B\left(y, N_i^B\right) N_i^B + m^R\left(y, N_i^R\right) N_i^R$. The outflow is given by the matching probability of unemployed workers times the number of unemployed workers $\theta\lambda_m(\theta)\, u$.

Firm-level flow equations allow us to write the ratio of the steady state measures of type B firms $m^B\left(0, N_i^B\right)$ to the measure of type S firms $m^S(y, 0)$, which determines innovation market tightness φ and hence the meeting probability of buyers and sellers, i.e.,

$$\varphi = \frac{m^B\left(0, N_i^B\right)}{m^S(y, 0)} = \frac{\lambda_s}{\lambda_s + \eta} \frac{\delta + \varphi g(\varphi)}{\lambda_d} \frac{1 - \Xi\left(k^{**}\right)}{\Xi\left(k^*\right)}. \tag{1.11}$$

This equation implicitly determines innovation market tightness φ. Innovation market tightness φ decreases with both innovation cost thresholds k^* and k^{**}, since, in the case of k^*, more firms decide to specialize in innovation and, in case of k^{**}, fewer firms decide to buy a new innovation when they are hit by a productivity shock.

Equilibrium: The equilibrium in this economy is characterized by the market tightness in the innovation market φ and the labor market θ, the layoff decisions of type B and R firms L_i^B and L_i^R, the threshold values k^* and k^{**} that determine the fraction of type S,

B, and R firms, as well as the number of active firms in the economy m, i.e., by the set of variables $\{\varphi, \theta, L_i^B, L_i^R, k^*, k^{**}, m\}$. We concentrate on an equilibrium in which all three types exist. Of course, there are parameter values where only S and B type firms exist (for η sufficiently small), and parameter values where only type R firms exist (for η sufficiently high). In Appendix A.6 we show that the equilibrium can be solved sequentially.

1.3 Calibration

In this section, we show that our model is able to reconcile the empirical findings that the introduction of wrongful dismissal laws in the U.S. lead to a decrease in productivity as shown by D.Autor, W.Kerr, and A.Kugler (2007) and an increase in the number of active firms and the number of patents as shown by Acharya, Baghai, and Subramanian (2014).

1.3.1 Baseline Calibration

Parameters and targets: The model consists of 17 exogenous parameters (see Table 1.1). In the calibration we choose the time period to represent one quarter and set the quarterly discount rate to $r = 0.012$ (equivalent to an annual discount factor of 0.953).

The parameters to target aggregate labor market statistics are taken from Shimer (2005) and Kaas and Kircher (2011) among others. We use a standard Cobb-Douglas type matching function, i.e., $M(U, V) = \kappa_l U^{\psi} V^{1-\psi}$. Like Shimer (2005) we target a job finding rate $\theta\lambda_m(\theta)$ of 1.36. Moreover, we target an unemployment rate in line with the long run U.S. average (4.5% to 5%). To do so, we set the labor market matching efficiency parameter to $\kappa_l = 2$ and the vacancy posting costs to $c = 0.0352$. The matching elasticity on the labor market ψ is set at a medium value of 0.5. As workers in our model are all production workers unemployment benefits are set at a fairly high value $z = 0.575$, implying a replacement rate of 85%, which is close to Hagedorn and Manovskii (2008). Finally, workers' bargaining power γ is set at 0.72 (see Shimer (2005)). To specify the parameters of the production function for large firms, we follow Kaas and Kircher (2011). We normalize the productivity parameter to $y = 1$ and set the labor elasticity parameter of the production function α equal to the labor share of 0.7. Bauer and Lingens (2014), who also calibrate a matching model with large firms, take a value of 0.8 for the labor elasticity parameter. They motivate their choice by targeting realistic mark-up values. Taking a value of 0.8 instead of 0.7 for labor elasticity would change our results quantitatively but not qualitatively.

Table 1.1 – Exogenous Parameter Values

Parameter	**Value**	**Source / Target**
δ	0.100	Target: Average product cycle length, see Magnier, Kalaitzandonakes, and Miller (2010).
λ_d	0.250	Target: Average firm life expectancy of 50 quarters, see Burns (2010).
λ_s	0.010	Set to equal $25\lambda_d = \lambda_s$.
η	0.356	Set to equal the ratio of average product life cycle length to time to market of 3.56, see Griffin (2002).
y	1.000	Normalisation.
α	0.700	Set to equal the labor share, see Kaas and Kircher (2011).
ψ	0.500	Set to the medium value, see Mortensen and Pissarides (1994).
κ_l	2.000	Target: Average job-finding rate of 1.36 (Shimer (2005)) and unemployment rate of about 5%.
ν	0.500	Set due to computational constraints.
κ_p	0.180	Set to get a product idea finding rate of $g(\varphi) = \eta$.
γ	0.720	See to an conventional value Shimer (2005).
β	0.500	Set to equal the elasticity of the innovation market matching function.
z	0.575	Target: Replacement rate of 85%.
c	0.035	Target: Average job-finding rate of 1.36 (Shimer (2005)) and unemployment rate of about 5%.
r	0.012	Compare Shimer (2005).
f	1.000	Set to equal 4.5 months of wages, see Bartelsman, Gautier, and Wind (2016).
F	2.88	Set to get an average of 2.58 production workers per establishment(see U.S. Census (2007)).

We assume that research costs are uniformly distributed between zero and one. The support of the research cost distribution is chosen such that the threshold values for investment costs can be directly used to obtain the shares of the respective firm types. Using the uniform distribution on the $[0,1]$ support implies a R&D expenditure to GDP ratio of around 0.014, a value that is of the same magnitude as the 2% of GDP reported in Eurostat (2011) for private sector R&D expenditure in the U.S. . The productivity shock rate δ is calibrated in order to reflect average product life-cycle length. Magnier, Kalaitzandonakes, and Miller (2010) find that on average products last for about 2.5 years, implying $\delta = 0.1$. In order to obtain a value for the research success rate η, we use a result by Griffin (2002), who finds that the ratio of product life cycle length to the time to market for the development of a new product is 3.56 in almost all industries (i.e., product life cycle length and time to market are extremely highly correlated across industries with $\rho = 0.99$). Given the ratio of product life cycle length to the time to market of 3.56 we set the research success rate at $\eta = 0.356$.

There is less information in the literature that we can use in order to pin down the parameters for the innovation market. We also use a Cobb-Douglas type matching functions for the innovation market, i.e., $P(S,B) = \kappa_p(S)^{\nu}B^{1-\nu}$. We set the exponent of the innovation market matching function to $\nu = 0.5$ in order to derive an explicit expression for the innovation market tightness, which is done to reduce the computer capacity necessary to solve the model numerically. The bargaining power of firms that sell their product ideas in the innovation market is also chosen to equal $\beta = 0.5$. We choose a matching efficiency in the innovation market of $\kappa_p = 0.18$ in order to obtain an innovation acquisition rate $g(\varphi)$ that is of roughly the same magnitude as the research success rate η for firms that do their own research.

Firing costs $f = 1$ are chosen to equal 4.5 month of production in the calibration with employment protection and zero otherwise. Given the fact that only 13 U.S. states have adopted the "good-faith" exception, the value $f = 1$ seem appropriate since it implies roughly an average value of one month of production for the U.S. as a whole.

The firm level destruction rates λ_d and λ_s are chosen such that the average life expectancy of firms lies somewhere around 50 quarters (see Burns (2010)). We set the destruction shock of producing firms to be much larger than the destruction shock of firms that specialize in innovation, i.e., $\lambda_d = 0.25$ and $\lambda_s = 0.01$, since type S firms are more often exposed to the "$y_i = 0$"-state then type R and type B firms given that $y_i = 0$ every time they sell their innovation.

Finally we set entry costs to $F = 2.88$, which leads to firm-level employment of 2.58 production workers at type R and type B firms. Since we do not include non-production workers, we chose a value that is significantly smaller than the average U.S. firm size of around 4.18 employees (production and non-production workers) documented by U.S. Census (2007).

Baseline calibration of the U.S. economy: The first column of Table 1.2 below shows the baseline calibration of the U.S. economy without employment protection. Given the normalization of the number of workers in the economy and the productivity parameter to one, final consumption output[6] without employment protection is equal to 0.717. The total measure of innovations per quarter equals 0.048 and can be decomposed into the innovations done by existing firms 0.032 (innovations within), and innovations done by firms, which enter the economy 0.016 (innovations upon entry).[7] The private sector R&D

[6]Final output of consumption goods is given by all type R and type B firms with productivity $y_i = y$, i.e.,

$$Y = m^R\left(y, N_i^R\right) y \left(N_i^R\right)^{\alpha} + m^B\left(y, N_i^B\right) y \left(N_i^B\right)^{\alpha}.$$

[7]In our model, there are two ways in which new innovations are created. All firms that enter the economy, i.e., m^e, are assumed to start with an innovation. Additionally, research is done by all type S and type R firms with $y_i = 0$. These firms produce a new innovation at the research success rate η. The number of patents and patent citations in our framework is therefore measured by the number of innovations created each period, i.e.,

$$I = m^e + \eta\left(m^R(0, N_i^R) + m^S(0,0)\right)$$

expenditure to GDP ratio equals 0.014. Firms that acquire an innovation are willing to pay an average innovation price of 1.027. The rate, at which type B firms are able to acquire a new product idea y in the market for innovations, equals 0.307. Taking the weighted average over type B and type R firms, the average duration in which a firm remeins in the low productivity state $y_i = 0$, is slightly above 9.2 months.

In steady state, the free entry condition ensures that average expected profits exactly offset entry costs F. This pins down the number of firms in the economy at $m = 0.614$, out of which 0.369 produce the final consumption goods. The remaining firms either conduct own research 0.089 or search for a trading partner in the innovation market 0.155. The unemployment rate among production workers equals 0.048.

1.3.2 Introducing Employment Protection

In order to shed light on the interaction of employment protection and the innovation market we first keep the innovation price fixed at the level without employment protection. Later, we endogenize the price to demonstrate the role of the innovation market.

Fixed innovation price: Table 1.2 compares the baseline model without employment protection with a situation in which employment protection is in place. However, the average innovation price is kept constant at 1.027, the level in the baseline calibration. In order to understand the effect on profits, we first kept the number of firms in the economy constant at 0.614. This is shown in the second column of Table 1.2.

The introduction of employment protection implies that firms continue to employ their workers, if they are hit by a productivity shock. This increases the number of firms with employment by 14%. Although there are more firms, which employ workers, the number of firms producing the final consumption good decreases, because keeping and paying unproductive workers decreases profits, especially profits of type R and type B firms, and makes it more attractive to specialize in innovation. Higher labor costs also imply that firm-level employment drops on average by 10.5%. Both negative effects lead to a drop

Table 1.2 – Results: Employment Protection with Fixed Idea Price

Variable	**Baseline without EPL**	**With EPL m-fixed**	**With EPL m-flexible**
Final consumption output (Y)	0.717	0.637	0.604
Total innovations (I)	0.048	0.048	0.043
Total R&D costs / GDP	0.014	0.014	0.014
Seller-researcher threshold (k^*)	0.039	0.043	0.040
Researcher-buyer threshold (k^{**})	0.402	0.366	0.388
Innovation acquisition rate ($g(\varphi)$)	0.307	0.315	0.307
Innovation price (p)	1.027	1.027	1.027
Unemployment rate (u)	0.048	0.043	0.075
Job finding rate ($\theta g(\theta)$)	1.998	0.822	0.456
Job destruction rate	0.100	0.037	0.037
Firm-level employment			
Type R firms (N_i^R)	2.581	2.394	2.550
Type B firms (N_i^B)	2.581	2.221	2.350
Total number of firms (m)	0.614	0.614	0.545
Type S with $y_i = y$	0.115	0.125	0.105
Type S with $y_i = 0$	0.065	0.069	0.059
Type R with $y_i = y$	0.147	0.126	0.124
Type R with $y_i = 0$	0.024	0.021	0.021
Type B with $y_i = y$	0.222	0.231	0.200
Type B with $y_i = 0$	0.040	0.041	0.036
Firms with employment	0.369	0.419	0.370
Average firm destruction rate	0.027	0.026	0.027
Average profit	2.882	2.758	2.880

in final consumption output.

Unemployment falls (slightly) as job destruction decreases even more than job creation. The effect on job destruction emerges because under employment protection not only those type R and type B firms, which have not been hit by a productivity shock, but all type R

Table 1.3 – Results: Employment Protection with Endogenous Idea Price

Variable	**Baseline without EPL**	**With EPL m-fixed**	**With EPL m-flexible**
Final consumption output (Y)	0.717	0.601	0.632
Total innovations (I)	0.048	0.048	0.053
Total R&D costs / GDP	0.014	0.013	0.013
Seller-researcher threshold (k^*)	0.039	0.064	0.064
Researcher-buyer threshold (k^{**})	0.402	0.344	0.337
Innovation acquisition rate ($g(\varphi)$)	0.307	0.400	0.397
Innovation price (p)	1.027	1.365	1.323
Unemployment rate (u)	0.048	0.079	0.045
Job finding rate ($\theta g(\theta)$)	1.998	0.396	0.722
Job destruction rate	0.100	0.034	0.034
Firm-level employment			
Type R firms (N_i^R)	2.581	2.568	2.444
Type B firms (N_i^B)	2.581	2.544	2.416
Total number of firms (m)	0.614	0.614	0.670
Type S with $y_i = y$	0.115	0.169	0.185
Type S with $y_i = 0$	0.065	0.084	0.092
Type R with $y_i = y$	0.147	0.088	0.095
Type R with $y_i = 0$	0.024	0.015	0.016
Type B with $y_i = y$	0.222	0.223	0.246
Type B with $y_i = 0$	0.040	0.034	0.038
Firms with employment	0.369	0.361	0.394
Average firm destruction rate	0.027	0.021	0.021
Average profit	2.882	2.996	2.882

and type B firms employ workers. The drop in the unemployment rate shown in the second column does not yet take the negative effect of employment protection on firm entry and the respective (additional) negative effect on vacancy creation into account. The second column of Table 1.2 also shows that the share of type S firms slightly increases, as these firms are not affected by firing costs.

The adoption of employment protection laws decreases average profits by roughly 4.4% implying that the total number of firms in the economy with employment protection decreases by about 11.3%. This can be seen by looking at the third column of Table 1.2, which keeps the innovation prices constant, but allows for adjustment of the number of firms. The number of innovations also decreases with the number of firms by about 10%. Unemployment significantly increases (from 4.8% to 7.5%) once the additional effect of lower firm entry is taken into account.

Thus, without the innovation market channel (flexible innovation price) our model is not able to replicate the empirical findings by Acharya, Baghai, and Subramanian (2014), who find a positive effect of employment protection on the number of patents and an increase in the number of firms. In addition, the model is at odds with the empirical evidence showing that employment protection has only mild effects on unemployment.

Endogenous innovation price: Until now we fixed the innovation price at its baseline value in order to disentangle the innovation market effect from the conventional profit depressing effects of employment protection. We now compare the baseline calibration with the model with employment protection under flexible innovation prices. Again, the second column of Table 1.3 keeps the number of firms in the economy at the baseline calibration level in order to understand the effects of employment protection on profits.

The introduction of employment protection increases labor costs during the period in which a firm keeps its workers, despite a productivity shock. This increases the willingness of firms, which have been hit by a productivity shock, to pay for an innovation. This leads to an increase in the innovation price from 1.027 in the baseline calibration to 1.365. Correspondingly, profits of firms that specialize in innovation increase relative to profits of final consumption good producers. The associated shift in the composition of firms increases the number of innovations by type S and type R firms, by around 10%. The total number of innovations does not change, becasue we kept the number of firms fixed, which implies that we exclude all innovations that are attached to the entry of new firms.[8]

The change in the composition of firms mainly increases the number of type S firms that specialize in innovation. This increase is much larger compared to a situation with fixed innovation price (see Table 1.2) implying that the change in the innovation price is the main driver of the sectorial shift. At the same time the number of type R and type B firms that produce consumption goods decreases from 0.369 to 0.312. Although the reduction in the number of producing firms leads to lower hiring costs and higher profits, firm-level employment slightly decreases as firing costs effectively increase the marginal costs of employing a worker. Accordingly unemployment strongly increases (from $0,048\%$ to 0.079%) whereas total production decreases by around 16.2%.

In stark contrast to the calibration in Table 1.2 with fixed product idea prices, average profits increase by around 4%. This triggers firm entry and increases in the number of firms in the new steady state from 0.614 to 0.670. The increase in the number of firms of around 9.1% is well in line with the 8.7% to 12.4% increase estimated by Acharya, Baghai, and Subramanian (2014).

The increase in the total number of firms has a counteracting effect on the average innovation price, which decreases from 1.365 in the calibration with the fixed number of firms to 1.323. However, the above mentioned shift in the composition of firms towards a higher fraction of firms that specialize in innovation is still present and leads in combination with the innovations generated by newly created firms, to an increase in total innovations of around 8.3%. This increase is slightly below the one estimated by Acharya, Baghai, and Subramanian (2014), which lies between 12.2% and 18.8%. The shift in economic activity towards firms that specialize in innovation also increases the innovation acquisition rate $g(\varphi)$, at which type B firms can restore their productivity, from 0.307 in the baseline calibration to 0.397. Taking the weighted average over type B and type R

[8] As $\lambda_s \leq \lambda_d$ the change in the composition of firms towards more sellers leads to less exits per period and accordingly to less entries per period.

firms, the average duration, in which a firm remains in the low productivity state $y_i = 0$, equals 7.8 months. This implies a decrease of 15.7% compared to the average duration without employment protection of 9.2 months.

The higher number of firms m and the higher innovation acquisition rate dampen the decrease in the number of firms producing consumption goods. Nevertheless it is still lower than in the calibration without employment protection (0.340 instead of 0.369). Together with the decrease in firm-level employment of around 6% on average, this still leads to a substantial decline in the production of final consumption goods by 11.8%. In contrast to final consumption output, unemployment fully recovers from its high value in the calibration with fixed firm numbers once the increase in m is taken into account. Indeed, as unemployment falls to 4.5% it is even slightly below its original value, which was 4.8%. The model is therefore well in line with the empirical fact that employment protection can have ambiguous effects on unemployment. Since the decrease in final consumption output goes along with an increase in total employment, an increase in the number of firms, and an increase in the number of innovations our calibration is also able to explain the decrease in labor and total factor productivity due to employment protection observed by D.Autor, W.Kerr, and A.Kugler (2007).

1.4 Conclusion

We study the effects of employment protection taking into account that firms are able to restore their productivity. We develop an equilibrium matching model with imperfect labor and innovation markets. We model both markets as matching markets, where the time to find an appropriate trading partner depends on the ratio of buyers to sellers in the market, and where prices are negotiated bilaterally. The interaction between labor and innovation market has the following implication. Employment protection induces firms to keep workers employed even if productivity has dropped. This increases firms' willingness to pay for product or process innovations in order to restore productivity. This increases the price for innovations, triggers entry of start-ups and shifts economic activity towards firms specializing in process and product innovation. It hence increases the rate, at which firms that are hit by a negative productivity shock can purchase the (process or product) innovation necessary to restore their productivity.

We calibrate our model to match aggregate U.S. labor and product market statistics as well as aggregate firm exit and entry rates. We then take the calibrated model, introduce employment protection and show that the rate, at which firms are able to restore their productivity increases. Our comparative static results are also in line with the estimated negative impact of wrongful dismissal laws on productivity, the positive effect on innovations and the number of firms, especially start-ups. We also find evidence for a shift in economic activity towards firms specializing in producing machinery (process innovation) or product ideas (product innovation).

Chapter 2

Does the Effect of Employment Protection Depend on the Composition of Unemployment?

2.1 Introduction

Beginning in the 1970s many countries have introduced employment protection laws (EPL). Policy makers typically consider EPL as a way to prevent unjust dismissals and to provide income security to workers (see Clark (2005)). Scientist also emphasize the possibility that EPL may increase productivity and innovation by giving workers incentives to invest in firm-specific human capital[1] or by inducing a structural shift in the economy.[2] Finally, the question whether EPL may enhance aggregate employment is of great interest for both academics and policy makers. In this paper, I argue that taking

[1]See Akerlof (1984), Soskice (1997), Zoega and Booth (2003), Belot, Boone, and Ours (2007), Pierre and Scarpetta (2004b), Wasmer (2006) and Acharya, Baghai, and Subramanian (2014).

[2]The first chapter of this dissertation develops an equilibrium matching model in which employment protection increases the willingness-to-pay for new ideas and thus shifts economic activity towards more innovation.

into account unemployment composition (rationing vs. frictional) is crucial for answering this fundamental question.

In standard search models with endogenous layoffs (see Pissarides (2000)) EPL lowers turnover while the sign of the employment effect remains ambiguous. Consequentially, there exists a large literature trying to investigate the effect empirically. Lazear (1990) uses European data to find that severance pay requirements reduce employment. International organizations found a negative impact on the participation rate, but a positive effect on the employment rate for prime age men (see OECD (1994)). Several studies have supported the view that EPL can at least be associated with high youth unemployment rates. [3] Despite this emerging consensus, recent studies (e.g. Noelke (2011)) challenge the conventional view. Using OECD data Noelke (2011) founds no robust evidence whatsoever linking EPL to inferior youth labor market performance. He notes that although there is a strong positive correlation between regulations on temporary contracts and youth unemployment, this correlation is completely wiped out by country fixed effects.

In order to minimize endogeneity problems, several studies[4] exploited a natural experiment which has occurred in the United States during the 1970s and 1980s. As the U.S. has a long tradition of employment-at-will, EPL was almost non-existent until the mid twentieth century. However, beginning in the late 1970s, several U.S. state courts began to adopt wrongful-dismissal laws. The most prominent ones are the implied-contract, the public-policy and the good-faith exception.

Exploiting this variation MacLeod and Nakavachara (2007) argue that the effect of EPL differs between educational groups. They argue that the implied-contract and the good-faith exception raise employment of high skilled workers but have detrimental effects

[3]See Esping-Andersen and Regin (2000), Heckman, Pags-Serra, Edwards, and Guidotti (2000), Bertola, Blau, and Kahn (2002), Kahn (2007), Addison and Texeira (2003), Botero, Djankov, Porta, Silanes, and Shleifer (2004), Breen (2005), Allard and Lindert (2006), Cahuc and Zylberberg (2004)

[4]SeeAutor, Donohue, and Schwab (2006),D.Autor, W.Kerr, and A.Kugler (2007), Acharya, Baghai, and Subramanian (2014) and MacLeod and Nakavachara (2007).

on employment of low skilled workers. Autor, Donohue, and Schwab (2006) find significant negative employment effects only for the implied-contract exception, whereas the public-policy and the good-faith exception do not significantly alter employment. Moreover, they found that the detrimental effect is more pronounced for production workers. As production workers have a lower level of formal education compared to non-production workers, these findings are in line with MacLeod and Nakavachara (2007). Using the same natural experiment D.Autor, W.Kerr, and A.Kugler (2007) conclude that EPL reduces total factor productivity, while Acharya, Baghai, and Subramanian (2014) note that EPL has the potential to raise innovation.

The existing literature has not yet considered that the effect of employment effect of EPL may depend on unemployment composition. In fact, the idea of composing unemployment into different components felt somewhat out of fashion for a while. Popular labor search models building on the pioneering work of Mortensen and Pissarides (1994) focus on frictional labor markets as the only source of unemployment. In these models workers and jobs are heterogeneous which makes it necessary to invest real resources in search activities. Search models have vastly improved the understanding of labor market flows and provide a natural explanation for the co-existence of unemployed workers and job vacancies. However, these models predict that in the absence of search frictions unemployment converges to zero, which is not convincing.

A popular alternative is the job rationing model proposed by Michaillat (2012). Rationing unemployment occurs naturally in a model with diminishing marginal returns to labor and some sort of real wage rigidity. In such an environment, it is possible that the marginal product of the least productive worker falls short of the real wage, implying that firms do not further extend employment even in the absence of recruiting costs. Michaillat defines the unemployment level that prevails without search frictions as rationing unemployment.[5]

[5]Note, that the term rationing unemployment as it defined by Michaillat (and also used in the present paper) should not be confused with mutually binding rationing constraints on the product and labor market as proposed by Keynesian disequilibrium models (see Barro and Grossman (1971).

In the presence of (real) wage rigidities the marginal value of a worker is decreasing in firing costs.[6] Frictionless employment is determined purely by comparing the wage to the marginal value of a worker. Hence, it decreases in firing costs, which directly implies that rationing unemployment has to unambiguously increase in firing costs. However, an increase in rationing unemployment also increases total unemployment and thus leads to lower market tightness. Lower market tightness in turn causes lower recruitment costs, which implies that the additional unemployment caused by search frictions has to be smaller. The pro-cyclical[7] behavior of the search component has been extensively discussed in Michaillat (2012). In the context of EPL, there is a second effect: EPL reduces job destruction rates. Thus, firms need to post less vacancies in order to maintain the same employment level over time. This second effect additionally lowers market tightness, recruiting costs and finally frictional unemployment. The theoretical model developed in the next section even shows that frictional unemployment is monotonically decreasing in firing costs.

The prediction of the theoretical model is simple: if EPL is introduced in a labor market where jobs are already heavily rationed, EPL will aggravate the situation. In contrast, if the same laws are introduced in a labor market characterized by search frictions, aggregate employment will barely decrease or even increase. In the empirical part, I use data on the adoption of wrongful-dismissal laws by U.S. state courts in order to test this hypothesis. Under the assumption that differences in matching efficiency are negligible[8], search unemployment matters most in labor markets with low unemployment, while rationing unemployment is key in labor markets with high unemployment. Accordingly, average pre-treatment unemployment is used as a proxy for the composition of unemployment.

Empirical results suggest that the employment effects of the public-policy and good-faith exception significantly depend on pre-treatment unemployment. In contrast, pre-

[6] I use the terms "firing costs" and "EPL" interchangeably as the purpose of EPL is to make layoffs costly.

[7] Pro-cyclical in the sense of being positively correlated with the business cycle.

[8] This assumption is discussed in detail in section B.3 in the Appendix.

treatment unemployment does not significantly influence the way the implied-contract exception impacts employment. A possible explanation for this result could be that firms quickly adapt to the implied-contract exception by updating their recruitment process.[9] In this way, the implied-contract exception acts more as a law that imposes additional recruiting costs. Correspondingly, the labor market effect of the implied-contract exception does not depend on the composition of unemployment.

The rest of the chapter is organized as follows: Section 2.2 first outlines the theoretical and then proceeds by quantitatively illustrating the main insights from the model. Section 2.3 presents some background information on wrongful-dismissal laws, outlines the empirical model and discusses the results. Finally, Section 2.4 concludes.

2.2 Theory

2.2.1 Framework

Basic Assumptions The model is a variant of the classical search-and-matching model in the tradition of Mortensen and Pissarides (1994). It deviates from the basic textbook model by allowing for large firms, endogenous layoffs and real wage rigidities. The assumption of large firms with diminishing marginal returns combined with real wage rigidities opens up the possibility of rationing unemployment in the sense of Michaillat (2012), whereas endogenous layoffs are needed to study the effects of firing costs. Agents are risk neutral and infinitely lived. The model is written down in discrete time with labor as the only factor of production. Households consume the entire production in each period. The model is populated by a unity mass of firms and workers, each of which supplies one unit of labor. As the model is meant to capture the medium- to long-run impact of EPL, I

[9] Such an update may include a careful revision of new employment contracts and policy handbooks to rule out the danger that an implicit contract is established.

focus on the model's steady state equilibrium.[10]

Idiosyncratic Productivity Shock Firms exhibit two different idiosyncratic states: A low productivity state L and a high productivity state H. Firms in the H state produce according to the production function $y_i^H = N_{i,t}^{\alpha}$. Productivity in the L state is scaled down by a constant factor γ (where $0 < \gamma < 1$), that is, $y_i = \gamma N_{i,t}^{\alpha}$. The transition probability from state H to state L is given by δ, whereas the probability of returning to state H is given by η. I denote the number of workers employed by a firm in the H, respectively L state as $N_{i,t}^{H}$ and $N_{i,t}^{L}$.

Labor Market Flows If firms exhibit an unfavorable transition ($H \Rightarrow L$) they adjust their workforce from $N_{i,t}^{H}$ to $N_{i,t}^{L}$. To do so they have to pay firing costs f per worker. Layoffs occurring after the idiosyncratic productivity shock are the only source of job destruction. In order to hire workers firms must post vacancies. If a firm posts a vacancy, it incurs per-period costs c. Unemployed workers and vacancies are matched using a standard constant returns to scale matching function (see Pissarides and Petrongolo (2001)). Market tightness, defined as the ratio between vacant jobs and unemployed workers, is denoted as x_t, the job-finding rate as $m(x_t)$ and the worker-finding rate as $x_t m(x_t)$.

2.2.2 Profit Functions and Optimality Conditions

Profits of a firm in the high productivity state are given by:

$$\pi_{i,t}^{H}(N_{i,t}^{H}) = \max_{V_{i,t}^{H}, L_{i,t}^{H}} (N_{i,t}^{H})^{\alpha} - W_t^H N_{i,t}^{H} - cV_{i,t}^{H} - fL_{i,t}^{H} + \beta \left(\delta \pi_{i,t+1}^{L}(N_{i,t}^{H}) + (1-\delta)\pi_{i,t+1}^{H}(N_{i,t}^{H})\right) \tag{2.1}$$

[10]The steady state assumption implies that the model cannot be used to assess the economies behavior in the transition period between one steady state (e.g. low firing costs) and another (e.g. high firing costs). Due to the same reason the model can also not be used to investigate whether EPL amplifies or attenuates temporary shocks (e.g. technology shock) to the economy.

Similarly, profits of a firm in the low productivity state read:

$$\pi^L_{i,t}(N^L_{i,t}) = \max_{V^L_{i,t}, L^L_{i,t}} \gamma(N^L_{i,t})^\alpha - W^L_t N^L_{i,t} - cV^L_{i,t} - fL^L_{i,t} + \beta\left((1-\eta)\pi^L_{i,t+1}(N^L_{i,t}) + \eta\pi^H_{i,t+1}(N^L_{i,t})\right) \tag{2.2}$$

Given firm-level employment, profits only differ due to the productivity difference implied by $\gamma < 1$. In both states firms have to decide on the number of vacancies they post and the number of workers they wish to layoff. As the paper has a steady state focus, time indexes are dropped subsequently. In the steady state we have $V^L_i = L^H_i = 0$, that is, low productivity firms never hire, whereas high productivity firms never fire workers.[11] The intuition is straight forward: each firm entering the low productivity state has been in the high productivity state before and thus already employs $N^H_{i,t}$ workers. As both states are identical except of the productivity difference, it holds that $N^H_{i,t} \geq N^L_{i,t}$, implying that low productivity firms never have an incentive to post vacancies. Instead, these firms will layoff workers until their desired employment level $N^L_{i,t}$ is reached. Similarly, firms just entering the high productivity state will hire $N^H_{i,t} - N^L_{i,t}$ workers by posting the appropriate number of vacancies and keep employment constant until they face an adverse shock again. As firm-level employment does not exceed $N^H_{i,t}$, firms never have an incentive to layoff workers as long as they stay in the high productivity state.

Accordingly, solving the right hand side problem for a firm in the high productivity state is equivalent to finding the optimal number of vacancies, whereas for a firm in the low productivity state it is equivalent to finding the optimal number of layoffs. Setting the respective derivatives to zero and rearranging yields the following optimality conditions:

$$\frac{c}{m(x)} = \frac{\partial \pi^H_i}{\partial N^H_i} \tag{2.3}$$

$$-f = \frac{\partial \pi^L_i}{\partial N^L_i} \tag{2.4}$$

Equation (2.3) states that firms in the high productivity state post vacancies until the

[11]This result relies on the assumption that there is no exogenous job separation rate. Separations only occur if a firm explicitly decide to layoff a worker.

marginal value of an additional worker is exactly offset by marginal hiring costs (which depend on labor market tightness), whereas equation (2.4) reveals that firms in the low productivity state layoff workers until the marginal value of an additional layoff is exactly offset by marginal firing costs (which are exogenously given by f).

The marginal values of an additional worker can be computed directly from equations (2.1) and (2.2) by taking the derivative with respect to $N_H^{i,t}$ or $N_{i,t}^L$, respectively[12]. Combining the marginal values with equations (2.3) and (2.4) and rearranging yields:

$$\frac{c}{m(x)} = \alpha (N_i^H)^{\alpha-1} - W^H + \beta \left(-\delta f + (1-\delta) \frac{c}{m(x)} \right) \tag{2.5}$$

$$-f = \gamma \alpha (N_i^L)^{\alpha-1} - W^L + \beta \left(-(1-\eta) f + \eta \frac{c}{m(x)} \right) \tag{2.6}$$

Equations (2.5) and (2.6) determine N_i^H and N_i^L for given market tightness and wages.

2.2.3 Wage Setting

Most search models with endogenous layoffs assume that wages can be renegotiated[13] after an idiosyncratic productivity shock occurs. Layoffs happen only voluntarily, that is, if the joint surplus has become negative. The exclusion of involuntary layoffs is popular in the literature since Robert Barros famous critique of sticky wage / sticky price models (see Barro (1977)).

In the context of the present model some kind of wage rigidity is needed. This rigidity could be established by a fairly high value of the outside option z (see Hagedorn and Manovskii (2008)) which would trigger voluntary separations after the idiosyncratic productivity shock has occurred. Hence, a high value of z is enough for obtaining positive

[12]Note that when taking the derivative $V_{i,t}^H$ and $L_{i,t}^H$ can be treated as constant due to the envelope conditions.

[13]Typically one assumes that wages satisfy the Nash bargaining solution with symmetric bargaining weights. In models with large firms the corresponding assumption is intra-firm wage bargaining as proposed by Stole and Zwiebel (1996), which is also known as generalized Nash bargaining.

rationing unemployment[14]. Instead of explicitly modeling the wage bargaining game, I assume that wages are determined by an exogenous wage constant, which does not differ across productivity states:

$$W^H = W^L = \omega \tag{2.7}$$

This simple wage setting scheme serves the purpose of the paper better than assuming a rather complicated wage bargaining game, because wages are not always bargained individually and layoffs are not always voluntarily. Collective wage agreements dominate large parts of U.S. and in particular European labor markets. Minimum wage laws and efficiency wages further contribute to downward wage rigidity. Although, a simplistic wage setting scheme as posted above is only a rough approximation of reality, flexible wage bargaining is just as well far from capturing all institutional and social intricacies that determine wages in reality.[15] As the presence of an outside option z greater than the marginal product of labor (evaluated at full employment) is a realistic feature of most labor markets, rationing unemployment would be present even with endogenous wages. Hence, endogenizing wages would not qualitatively alter results.

Combining the wage setting schedule with (2.5) and (2.6) and rearranging implies:

$$N_{i,t}^H(x) = \left(\frac{\alpha}{\frac{c}{m(x)}(1-\beta(1-\delta)) + \omega + \beta\delta f} \right)^{\frac{1}{1-\alpha}} \tag{2.8}$$

[14]With Stole and Zwiebel (1996) bargaining wages are given as a linear combination between the workers outside option z and a term that depends on recruiting costs and the marginal product of labor. When recruiting costs go to zero, the corresponding term vanishes and wages simply become a linear combination between z and a term proportional to the marginal product of labor. This guarantees full employment in the limit of no recruiting costs as long as z is below the marginal product evaluated at full employment. Reversely, high values of z provide a mechanism which renders full employment unprofitable even in the absence of recruiting costs.

[15] Michaillat and Saez (2015) find that a fix-price equilibrium describes observed data better than a competitive equilibrium as market tightness (ob both the product and the labor market) fluctuates a lot.

$$N_{i,t}^{L}(x) = \left(\frac{\gamma\alpha}{\omega - (1-\beta(1-\eta))f - \eta\beta\frac{c}{m(x)}} \right)^{\frac{1}{1-\alpha}} \tag{2.9}$$

It is useful to investigate the relationship between firm-level employment and market tightness implied by equations (2.8) and (2.9). Market tightness enters the optimality conditions via recruiting costs. Intuitively, higher market tightness lowers the worker-finding rate and thus causes higher recruiting costs $\frac{c}{m(x)}$. However, optimal firm-level employment in the two states depends very differently on recruiting costs. Firm-level employment in the high productivity state is decreasing in recruiting costs (and thus in market tightness) as higher recruiting costs require the marginal value of a worker to increase (see (2.3))which can only be done by downward adjusting employment. In contrast, firm-level employment in the low productivity state is increasing in recruiting costs. Firms entering the low productivity state chose to layoff less workers if recruiting costs are high in order to save future hiring costs.

2.2.4 Rationing Unemployment

Rationing unemployment occurs if total labor demand in the absence of recruiting costs falls short of labor supply (unity). This limiting case can easily be analyzed by letting matching efficiency go to infinity [16] or setting vacancy posting costs to zero. By doing so market tightness drops out of equations (2.8) and (2.9). Solving both equations for firm-level employment yields firm-level labor demand $N_i^{H,R}$ and $N_i^{L,R}$, which would occur in a frictionless labor market:

$$N_i^{H,R} = \left(\frac{\alpha}{\omega + \beta\delta f} \right)^{\frac{1}{1-\alpha}} \tag{2.10}$$

$$N_i^{L,R} = \left(\frac{\alpha\gamma}{\omega - f(1-\beta(1-\eta)} \right)^{\frac{1}{1-\alpha}} \tag{2.11}$$

[16] In this case vacancies and workers get matched instantaneously. Correspondingly the worker finding rate $m(x)$ goes to infinity which implies that recruiting cost go to zero.

$N_i^{H,R}$ and $N_i^{L,R}$ depend only on the labor elasticity of output α, the wage constant ω as well as on firing costs f. Note that $N_i^{H,R}$ is decreasing in firing costs, while $N_i^{L,R}$ is increasing . This is intuitive: firms entering the high productivity state hire less workers as the marginal value of employing a worker is decreasing in firing costs. In contrast, firms entering the low productivity state keep more workers in order to save firing costs. To facilitate intuition, solve equations (2.10) and (2.11) for the marginal product of labor:

$$\alpha(N_i^{H,R})^{\alpha-1} = \omega + \beta\delta f \tag{2.12}$$

$$\alpha\gamma(N_i^{H,L})^{\alpha-1} = \omega - [1-\beta(1-\eta)]f \tag{2.13}$$

Equations (2.12) and (2.13) demonstrate that firing costs make it optimal for firms in the high productivity state to chose an employment level which guarantees that the marginal product of labor exceeds the real wage, whereas firms in the low productivity state choose an employment level at which the marginal product of labor is below the real wage. Firing costs reduce the gap between employment levels in the high- and low productivity states. Hence, EPL reallocates workers to low productive firms.

It is total and not firm-level labor demand what matters for determining rationing unemployment. In the job rationing model proposed by Michaillat (2012) rationing occurs when the marginal product of labor evaluated at full employment falls short of the real wage. It is not possible to make an analogous statement for the present model as there is no marginal product of labor for the whole economy, but two different marginal products for each productivity state. Nevertheless, as in the standard model, rationing occurs if the wage compared to marginal productivity (corrected for firing costs) is high.

To calculate rationing unemployment, it is necessary to calculate aggregate labor demand, which is given by:

$$N_R = m_H N_i^{H,R} + m_L N_i^{L,R} \tag{2.14}$$

Rationing unemployment immediately follows as $u^R = 1 - N^R$. It depends not only on firm-level employment in both sectors but also on the (exogenous) distribution of firms across productivity states. Negative values of u^R indicate that without recruiting costs labor demand would exceed labor supply, that is, there would be a shortage of labor. Allowing for negative values of u^R is useful to highlight the crucial economic mechanism of the model. Clearly, observable unemployment is entirely caused by search frictions, if rationing unemployment is below zero.

2.2.5 Equilibrium with Frictional Labor Market

If search frictions are present, labor market flows have to be taken into account explicitly. As I restrict attention to stationary equilibria, labor market flows must be balanced:

$$qN = xm(x)U$$

where $U = (1 - (1 - q)N)$ measures the pool of jobless individuals available for hiring. U is also referred to as beginning-of-period unemployment(see Blanchard and Gali (2010)), that is, unemployment before hiring has taken place. In contrast u measures within-period unemployment. Rearranging yields an Beveridge curve like expression:

$$N^{SS} = \frac{xm(x)}{q + xm(x)(1 - q)} \tag{2.15}$$

where N^{SS} denotes the employment level consistent with balanced labor market flows as a function of the job finding rate $xm(x)$ and the job destruction rate q. In contrast, to the standard search and matching model, q is endogenous and given by:

$$q = \delta m_H \frac{N_i^H(x) - N_i^L(x)}{N} \tag{2.16}$$

where $m_H = \frac{\eta}{\eta+\delta}$ and $m_L = \frac{\delta}{\eta+\delta}$ denote the number of firms in the high-, respectively low productivity state.

The second relationship between aggregate employment and market tightness can be obtained from firm-level optimality conditions discussed in the previous section. Using the definition of aggregate employment one obtains:

$$N^{FOC} = m_H N_i^H(x) + m_L N_i^L(x) \tag{2.17}$$

Equilibrium market tightness is determined by the intersection of equation(2.15) and(2.17), that is

$$N^{SS}(x) \stackrel{!}{=} N^{FOC}(x) \tag{2.18}$$

It is easy to show that N^{SS} is increasing in market tightness. High market tightness implies that workers find jobs quickly, which increases the outflow out of unemployment for a given number of unemployed workers. In the present model, there is an additional effect working in the same direction: higher market tightness leads to lower q, that is, the inflow rate into unemployment is lower. Correspondingly, the number of unemployed workers has to be low in order to ensure that labor market flows balance out.

As $\frac{\partial N_i^H(x)}{\partial x} < 0$ and $\frac{\partial N_i^L(x)}{\partial x} > 0$ the sign of $\frac{\partial N^{FOC}}{\partial x}$ is generally ambiguous. A necessary and sufficient condition for $\frac{\partial N^{FOC}}{\partial x} \leq 0$ is given by

$$f[\epsilon\beta\delta + \Theta_B(1-\beta(1-\eta))] + \frac{c}{m(x)}[\epsilon(1-\beta(1-\delta)) + \Theta_B\eta\beta] \leq (\Theta_B - \epsilon)\omega \tag{2.19}$$

where $\Theta_B = \left(\frac{\epsilon(1-\beta(1-\delta))}{\delta\beta}\right)^{\frac{1-\alpha}{2-\alpha}} < 1$. Thus, for a given set of exogenous variables, there exists a $\bar{x}$, such that for each x smaller (larger) than $\bar{x}$ it holds that $\frac{\partial N^{FOC}}{\partial x}$ is negative (positive). Moreover, the denominator of equation (2.9) goes to zero if x becomes large, implying that the slope of N^{FOC} goes to infinity. Thus, there exist two intersections of the N^{FOC} and the N^{SS} curves in (N, x)-space, reflecting two potential candidates for equilibrium market tightness, which I denote as x^* (low market tightness equilibrium) and x^{**} (high market tightness equilibrium).

Let me first consider the second equilibrium candidate. As $x^{**} > \bar{x}$, it holds that $\left.\frac{\partial N^{FOC}}{\partial x}\right|_{x=x^{**}} > 0$. Note, that $\frac{\partial N^{FOC}}{\partial x}$ has always the same sign as $\frac{\partial N^{FOC}}{\partial \frac{c}{m(x)}}$, as market tightness only matters for labor demand via recruiting costs. Correspondingly, labor demand in this equilibrium would be increasing in recruiting costs, implying that an increase in search frictions (measured by c) reduces unemployment. Clearly, such an equilibrium is not compatible with empirical evidence.

Requiring labor demand to be decreasing in recruiting costs is equivalent to imposing an equilibrium refinement condition[17]

$$\left.\frac{\partial N^{FOC}}{\partial \frac{c}{m(x)}}\right|_{x=x^{\text{Equilibrium}},\ c>0} < 0 \tag{2.20}$$

which directly implies $\left.\frac{\partial N^{FOC}}{\partial x}\right|_{x=x^{\text{Equilibrium}},\ c>0} \leq 0$. This allows me to rule out the second equilibrium candidate. Correspondingly, the unique market tightness, which satisfies equation (2.18) and the refinement condition (2.20), is given by x^*.[18] In addition, Section B.1 in the Appendix shows that the high market tightness equilibrium is not stable, while the low market tightness equilibrium is. Focusing on x^*, firm level employment is immediately given by equations (2.8) and (2.9). As $N = m_H N_i^H + m_L N_i^L$ one can also calculate aggregate employment and, correspondingly, unemployment ($u = 1 - N$).

The primary goal of the illustrative model is to shape intuition about how frictional and rationing unemployment react to changes in firing costs. Computing $\frac{\partial N^R}{\partial f}$ and rearranging reveals that N^R is falling in firing costs if and only if

$$f < \frac{\Theta_A - \epsilon}{\Theta_A(1-\beta(1-\eta)) + \beta\delta\epsilon}\omega \stackrel{!}{=} f^{R,max} \tag{2.21}$$

where $\Theta_A = \left(\frac{\epsilon\eta\beta}{1-\beta(1-\eta)}\right)^{\frac{1-\alpha}{2-\alpha}}$. Thus, if the ratio of firing cost to the wage is sufficiently low, an increase in firing costs unambiguously lowers hypothetical labor demand N^R and thus leads to higher rationing unemployment. The reason why $\frac{\partial N^R}{\partial f}$ changes its sign at

[17] The refinement condition is closely related to excluding the case of negative search unemployment. However, it is somewhat stronger as there exist equilibria which do not satisfy the refinement condition but still exhibit positive search unemployment ($N^R - N > 0$). Why is that? Search unemployment is being computed as difference in labor demand between an equilibrium with $c = 0$ and $c > 0$, where c is not infinitesimally small. Thus the difference between the two equilibria involves a discrete jump (!) in recruiting costs. As the derivative of labor demand with respect to recruiting costs itself depends positively (!) on recruiting costs, a positive derivative does not imply that search unemployment is negative. However, if the derivative is negative one can conclude that search unemployment is positive. Correspondingly, all equilibria satisfying the refinement condition (2.20) exhibit positive search unemployment.

[18] Even if one does not require equation (2.20) to be satisfied it can be shown numerically that (for reasonable parameter values) x^{**} violates the plausibility constraint $N_i^H \geq N_i^L$ independent of the level of firing cost or the wage regime.

very high levels of f lies in the convex shape of $N^{R,L}$. Appendix B shows that a sufficient condition for frictional unemployment to be decreasing in firing costs is given by

$$\frac{\partial N^{FOC}(x,f)}{\partial f} < 0 \tag{2.22}$$

Hence, under the assumption that equations (2.21) and (2.22) are satisfied, the following proposition holds:

Proposition 1. *An increase in firing costs causes a decrease in frictional unemployment (as defined as $N^R - N$), while at the same time rationing unemployment increases. In contrast the effect on total unemployment is ambiguous.*

2.2.6 Equilibrium Characterization

As the overall effect of a change in firing costs on employment is ambiguous, the next step is to numerically explore the model's reaction to changes in firing costs in different economic regimes.[19] Like in Michaillat (2012), the model is calibrated at a weekly frequency to fit U.S. data. I use a standard Cobb-Douglas specification of the matching function (see Pissarides and Petrongolo (2001)), that is, $H = \tau U^{\eta} V^{1-\eta}$, where τ denotes matching efficiency. Accordingly, the worker-finding-rate reads $m(x) = \tau x^{-\eta}$ and the job-finding-rate reads $xm(x) = \tau x^{1-\eta}$.

Table 2.1 – Exogenous Parameter Values

Variable	Value	Source/Target
Matching Efficiency: τ	0.233	Michaillat (2012)
Discount Factor: β	0.999	Michaillat (2012)
Matching Elasticity w.r.t. Unemployment: Ψ	0.700	Shimer (2005)
Vacancy Posting Costs: c	0.214	Michaillat (2012)
Output Elasticity of Labor: α	0.666	Michaillat (2012)
Firing Costs: f	0.270	Bartelsman et. al (2010)
Wage Constant: ω	0.615	Unemployment Rate 4.5
Probability High $\Rightarrow$ Low: δ	0.020	Target: Job Destruction Rate of 0.01
Probability Low $\Rightarrow$ High: δ	0.080	Target: Vacancy Filling Rate of 0.325
Low productivity parameter: γ	0.500	Target: Market Tightness of 1

[19] A side effect of numerically calibrating the model is the possibility to graphically display the key results of the model which vastly improves intuition.

The baseline calibration consists of the following ten values for exogenous variables: matching efficiency is set to $\tau = 0.233$. The discount rate is set to $\beta = 0.99$, vacancy posting costs are set to $c = 0.214$ and the output elasticity of labor is set to $\alpha = 0.66$ (all values correspond to Michaillat (2012)). The matching elasticity with respect to unemployment is set to $\Psi = 0.7$ (see Shimer (2005)). Firing costs f are set to 0.27 reflecting that firing costs in the U.S. roughly equal one month of production (see Bartelsman, Gautier, and Wind (2016)).

All former variables are pinned down using direct empirical evidence, while the remaining variables are set to ensure that outcome variables satisfy specific target values. First, the wage constant ω is set to 0.615 to target an unemployment rate of 4.5%. The transition probabilities between the high and low productivity state are set to $\delta = 0.02$ and $\eta = 0.08$ targeting a job destruction rate of 0.01 as well as a vacancy filling rate of 0.325 (see Michaillat (2012)[20]). Finally, I target market tightness to equal unity (as in Shimer (2005)[21], which pins down the productivity shifter to $\epsilon = 0.5$.

To illustrate different labor market responses, the model is simulated not only for the baseline value of firing costs, but instead for the whole range of potential firing cost values. In specific, I calculate the models equilibrium for all $f \in (0, 2.5)$. This range covers the laissez-faire ($f = 0$) equilibrium, the baseline specification ($f = 0.27$) as well as European levels of firing costs ($f = 1.89$).[22]

[20]Michaillat estimates the job destruction and finding rates from the seasonally adjusted monthly series for total separations and hirings in all non-farm industries constructed by the Bureau of Labor Statistics (BLS) from the Job Openings and Labor Turnover Survey (JOLTS) for the December 2000-June 2009 period.

[21]In Shimers model targeting a market tightness of unity is a normalization as market tightness is intrinsically meaningless in his model. Although this is not the case in my model, I follow Shimers calibration because an equalized vacancy-unemployment ratio represents a natural benchmark while also being an empirically plausible value in a rather tight labor market.

[22]Empirically firing costs range between one (U.S.) and seven months of production (see Bartelsman, Gautier, and Wind (2016)). Taken purely mechanically, this translates into values for the firing cost parameter f ranging from $f = 3.6$ to $f = 25.2$ (weekly output in the model is roughly 0.9). However, taken into account the setup of the model this is not sensible. In the model each separation in-

To investigate whether firing costs impact the labor market differently depending on the initial labor market state, the model is simulated using 4 different values $\omega \in [0.60, 0.615, 0.63, 0.645]$ for the wage constant. As aggregate productivity remains constant, these differences translate into differences in the wage-to-productivity ratio, hence representing four different states of the labor market. With a high real wage, the labor market is sluggish, which is reflected in severe job rationing, whereas search frictions do not play an important role. The opposite is true if the real wage is low: competition for workers is high, which makes search frictions the main driver of unemployment (see Michaillat (2012)).

Table 2.2 – Calibration Results

Unemployment	$f=0$	$f=2.5$
	$\omega = 0.6$	
Total	2.19	2.00
Frictional	14.96	-0.11
Rationing	-12.77	2.18
	$\omega = 0.615$	
Total	4.14	9.18
Frictional	8.888	0.09
Rationing	-4.74	9.09
	$\omega = 0.63$	
Total	6.68	15.38
Frictional	4.12	0.03
Rationing	2.55	15.35
	$\omega = 0.645$	
Total	10.68	21.05
Frictional	1.50	0.02
Rationing	9.18	21.03

Notes: The Table displays total, frictional and rationing unemployment in % for four different wage regimes with and without firing costs. Source: Own simulations.

Table 2.2 shows total, frictional and rationing unemployment in percent for each wage

volves paying firing costs. In reality two thirds of job separations happen by mutual agreement (for job sorting, life cycle or personal reasons). In addition, half of the remaining separations are due to discontinuing temporary jobs. Only about 15% of all layoffs can be attributed to retrenchments (see D'Arcy, Gustafsson, Lewis, and Wiltshire (2012)). Retrenchments may be either a job closure or a dismissal. If firing costs have to be paid for 50% of all retrenchments (which seems to be a sensible proxy) this implies that only 7.5% of all dismissals are associated with paying firing costs. Taking this into account implies an empirically plausible range for f between 0.27 and 1.89 which fits well into the range used in the simulation.

regimes either with very high ($f = 2.5$) or without firing costs ($f = 0$). For a graphical illustration of all equilibria between $f = 0$ and $f = 2.5$, see Figure B.4 in the Appendix.

If the wage is very low ($\omega = 0.6$), unemployment equals 2.19% before firing costs are introduced. Remarkably, rationing unemployment is highly negative -12.77%. Hence, there would be a shortage of labor in the absence of search frictions. With search frictions, such a shortage never occurs, as market tightness and thus recruiting costs approach infinity once unemployment goes to zero. Even if the wage-to-productivity ratio is extremely low, there is always positive unemployment in an economy with search frictions. Correspondingly, search unemployment, measured as the drop in labor demand caused by recruiting cost, equals 14.96%. [23] With increasing firing costs, the expected pattern materializes: rationing unemployment picks up, as the cost of employing a worker rises, but remains negative until about $f = 1.8$. Conversely, frictional unemployment monotonically decreases and reaches zero at $f = 2.5$. Most interestingly, total unemployment is left nearly unaffected: it decreases from 2.19% (at $f = 0$) to 2% (at $f = 2.5$). The independence of total unemployment from firing costs hides that firing cost massively change the composition of unemployment from being entirely driven by search frictions to being entirely driven by job rationing. This heavily affects the effectiveness of other labor market policies. For example, if policy makers somehow manage to eliminate recruiting cost ($c = 0$) unemployment would completely vanish in the equilibrium without firing cost, while being not affected in the equilibrium with very high firing costs ($f = 2.5$).

Despite the slight increase in employment, firing costs lower output from 0.92 to 0.9 (see Figure B.6) as more workers are employed in low productive firms. From a welfare point of view, it is not output, which is most relevant, but net output as defined as output minus sunk costs. Recruiting expenditures definitely belong to sunk costs. Whether firing costs are also sunk is not clear per se. If they consist of a severance payment, firing costs, are simply a transfer between workers and firms (in the same way as the wage) and do not belong to sunk costs. Instead, if firing costs mainly consist of legal costs or bureaucracy

[23] If, for example, $N_R = 1.02$, we have $u_R = -0.02$. With a total unemployment rate of 4% the drop in labor demand (search unemployment) caused by search friction is 6%.

costs they are lost for workers and firms and correspondingly have to be counted as sunk. I measure net output using both interpretations of firing costs.[24] If firing costs are interpreted as severance payment, net output is almost unaffected by them. Lower gross output is compensated by lower recruiting expenditures. Instead, if firing cost are sunk, net output decreases in firing costs as long as $f < 2$. At $f = 2$, net output reaches a minimum and then slightly increases again. The latter happens as turnover heavily declines at very high levels of firing costs. Lower turnover implies less firings and thus lower total firing cost. Overall, EPL performs remarkably well in a labor market with low wage-to-productivity ratio: employment is marginally positively affected, output decreases only slightly, while net output even stays constant (if firing costs are severance payments). Apparently EPL benefits like higher job security and longer employment spells[25] can be obtained at no costs.

Turning to the high wage labor market ($\omega = 0.645$) completely reverses this impression. In this scenario, unemployment before introducing firing costs equals 10.68%. With increasing firing costs, unemployment heavily increases and reaches 21.03% at $f = 2.5$. In this economy, search frictions do not matter much: only 1.5% can be attributed to them before firing costs are introduced. At $f = 2.5$, frictional unemployment is again zero. Hence, the decrease in frictional unemployment is quantitatively small (compared to total unemployment) as search frictions do not matter much in the first place. As rationing unemployment strongly increases (similarly as it does in the low wage setup), EPL has a strong adverse effect on employment. The positive effect via lower turnover is only small as turnover is not very costly due to low market tightness (see Figure B.5 in the Appendix).

The negative employment effect directly passes through on output: compared with the low wage equilibrium, gross output decreases far more steeply in firing costs, because lower aggregate employment reinforces the negative effect of decreasing average productivity.

[24] Note that the models equilibrium is unaffected by the specific type of firing costs, as wages and labor supply are fixed.

[25] Note that, although important in reality, these benefits are not explicitly valued in the model.

Net output defined as output minus recruiting costs very closely resembles the course of output as market tightness and, thus, recruiting expenditures are low for the whole range of firing costs. Correspondingly, savings in recruiting cost caused by lower turnover can not even closely make up for the loss in gross output. Quantitatively, net output decreases by around 9%, when firing costs increase from $f = 0$ to $f = 2.5$. If firing costs are counted as sunk costs, the negative effect on net output even increases to about 11%.

If $\omega = 0.615$ and $\omega = 0.63$ outcomes range between the previously discussed results, ensuring that unemployment composition matters in a continuous way when assessing the effects of firing costs. The observed decrease in search unemployment is key for understanding why the composition of unemployment matters. This decrease occurs, because market tightness is monotonically decreasing in firing costs throughout all wage regimes (see Figure B.5 in the Appendix). Appendix B.1 provides a theoretical proof for this relationship. Intuitively, market tightness decreases primarily because firing costs suppress labor turnover, implying that less vacancies are needed for a given level of employment. In most equilibria, there is a second effect working in the same direction: a higher level of total unemployment implying lower market tightness.[26] The latter causes lower recruiting costs per worker $\left(\frac{c}{m(x)}\right)$, which in turn decrease frictional unemployment.[27]

2.3 Empirical Evidence

2.3.1 Outline

The empirical analysis in this paper builds on the difference-in-difference approach used by Autor, Donohue, and Schwab (2006). Currently, they provide the most reliable estimates regarding general labor market effects of EPL. Specifically, they measure the

[26]This is the same channel which causes the negative dependency of frictional unemployment and the wage-to-productivity ratio.

[27]Except for the case where labor demand is increasing in recruiting costs. These equilibria, however, do not satisfy the equilibrium refinement condition (see equation (2.20))

effects on employment and wages of wrongful-dismissal laws adopted by U.S. state courts during the 1970s till the 1990s. As heterogeneity between U.S. states is smaller than between countries, the common-trend assumption used in their difference- in-difference[28] identification strategy is more likely to be satisfied compared to a cross country study. Basically, Autor, Donohue, and Schwab (2006) assume that the systematic difference in employment over time between adopting and non-adopting states can be attributed to the introduction of wrongful-dismissal laws. Identification is discussed in greater detail in section 2.3.4. The present paper uses the same dataset[29], but augments the analysis by taking into account the composition of steady state unemployment before EPL is introduced.

As the components of unemployment are not directly observable, Proposition 1 cannot be tested directly. The prediction of the model depends on whether differences in unemployment are driven by differences in the wage-to-productivity ratio or by differences in matching efficiency (see section B.3 in the Appendix for details). As regional differences in matching efficiency within a country are likely to be small (see Sunde and Fahr (2002)), I restrict matching efficiency to be constant across counties. [30] Given this assumption, rationing unemployment matters most if total unemployment is high, while unemployment is driven by search frictions, if total unemployment is low. This leads to the following testable hypothesis:

Hypothesis 1. *The higher the unemployment rate before EPL is introduced (before treatment), the more adverse is the employment effect of EPL.*

[28] Autor, Donohue, and Schwab (2006) implement the difference-in-difference design by using a two-way fixed effects regression model which includes state- as well as time fixed effects.

[29] Using the same data increases comparability of our results to those obtained by Autor, Donohue, and Schwab (2006).

[30] To take into account differences in matching efficiency, state level vacancy data would be necessary. Unfortunately, there is no regional vacancy data available for the relevant time period in the U.S.

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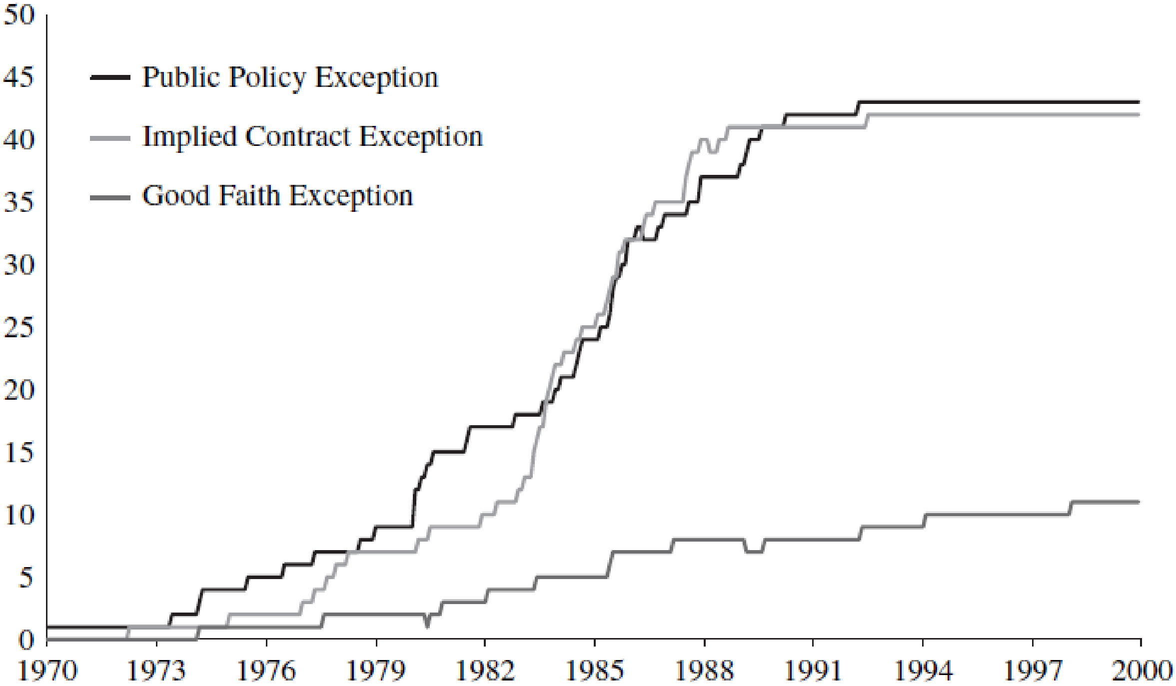

Figure 2.1 – The Figure shows the staged adoption of wrongful-dismissal laws by U.S. state courts between the mid 1970s and the mid 1990s. Source: Autor, Donohue, and Schwab (2006)

2.3.2 Wrongful-Dismissal Laws

The United States have a long tradition of employment at will, that is, both parties (employer and employee) have the right to terminate the employment relationship at any time. However, during the 1970s and 1980s the majority of U.S. state courts adopted one or more common-law exceptions to the employment-at-will doctrine. These wrongful-dismissal laws protect workers from being laid off in different ways, which are briefly discussed below. The three distinct wrongful-dismissal laws used in the analysis are (i) the public-policy exception, (ii) the good-faith exception and (iii) the implied-contract exception.

The public policy exception (PP) prohibits firing a worker for an act that is consistent with public policy[31] and at the same time for refusing an act that is inconsistent with

[31] Take a worker who knows that his employer violates safety standards. Laying off a worker, be-

public policy.[32] The public-policy exception was widely recognized. By 1999, 43 U.S. states had adopted the policy. However, courts restrict the application of the public-policy exception to violations of law instead of violations of public-policy in a broader sense. Thus, its direct economic importance is limited.

As suggested by its name, the good-faith exception (GF) requires employers to layoff workers only with just cause. The interpretation of the good faith exception is vague. Broadly applied, its economic impact could be very far-reaching. It could be used as general device against any layoff that is not due to economic necessity or poor performance. However, courts normally limit the application to timing cases, in which the employer fires a worker just before a large payment (bonus, pension benefits, etc.) is due. In contrast, to the public-policy exception, the good-faith exception was only adopted by 11 state courts.

The implied-contract exception (IC) rules out layoffs without "just cause" if the employer raises the expectation that it is regular policy of the company to restrict layoffs to situations of just cause.[33] According to U.S state courts raising such expectations establishes an implicit contract between the employer and its employees. This is the case, for example, if an internal personnel policy handbook states that it is the company's policy to terminate employment relationships only for just cause, or if the employee has a long history of service or promotion. By 1999, the implied-contract exception was adopted by 41 U.S. state courts. Although, employers can evade the implied-contract exception by simply checking personnel handbooks, it can be very important as a judgement based on the implied-contract exception potentially impacts a large fraction of an employer's workforce. For a more elaborated discussion of the institutional details see Autor, Donohue, and Schwab (2006), Edelman, Abraham, and Erlanger (1992) and Schwab (1993).

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cause he reports the information to the inspecting authority violates the public-policy exception.

[32]It violates the public policy-exception if the employer fires a worker, because the latter refuses to commit perjury or to conduct industrial spying.

[33]Examples for "just cause" layoffs are redundancies due to business operations or layoffs due to serious misbehavior of the employee.

2.3.3 Data

The dataset used by Autor, Donohue, and Schwab (2006) is available on David Autors webpage.[34] The dataset contains detailed information about when and by which state a particular wrongful-dismissal law was adopted. Note that it is not always completely clear when a particular wrongful-dismissal law was adopted by a certain state. Autor, Donohue, and Schwab (2006) consider a wrongful-dismissal law as adopted once a major appellate-court signals adoption. In particular, this excludes lower court decisions that have been reversed on appeal. To increase the usable variation in the adoption of wrongful-dismissal laws (and thus precision of estimation), data is coded at monthly frequency. Most wrongful-dismissal laws were adopted already in the early 1980s, whereas in the 1990s there is only little variation. State level unemployment data is taken from the Current Population Survey (CPS). I use the employment-to-population ratio (as done by Autor, Donohue, and Schwab (2006)) and the unemployment rate as outcome variable.

2.3.4 The Empirical Model

Regression Equation

I adopt the empirical model estimated by Autor, Donohue, and Schwab (2006) extended by an interaction term between the treatment indicator $post_{i,t}$ and the pre-treatment average unemployment rate.[35] The latter can be thought of as a proxy for steady state unemployment before introduction of the WDL. Formerly, the model reads:

$$Y_{i,t} = \gamma_i + \gamma_s * treat_{i,t} + \delta_t + Region * Year + \tag{2.23}$$

$$\theta_1 * post_{i,t} + \theta_2(\bar{U}_i * post_{i,t}) + \theta_3 * postpost_{i,t} + \epsilon_{i,t} \tag{2.24}$$

[34] The full dataset and all corresponding Stata files can be found here: http://economics.mit.edu/faculty/dautor/data/autdonschw06.

[35] Note that the main effect of the average pre-treatment unemployment rate is perfectly co-linear with state dummies, as it does not contain any variation over time.

where $Y_{i,t}$ is the log of the employment-to-population ratio, δ_t represents a full set of time fixed effects, whereas γ_s represents a full set of state fixed effects. $Region$ and $Year$ are sets of dummy variables representing calendar years and the four major regions of the U.S.

$treat_{i,t}$ is one for a particular observation if the observation belongs to the treatment group. Like Autor, Donohue, and Schwab (2006) I use a five year pre-post interval implying that $treat_{i,t}$ is one if state i has adopted the specific wrongful-dismissal law $1-24$ month after or $12-36$ month before the current date. Observations from the year directly following treatment are excluded from the treatment group in order to allow for an adjustment interval just after treatment.

The control group contains all observations stemming from states that did not adopt any of the three doctrines during the relevant pre[36]- or post[37]-treatment interval. If there is not a single state that had adopted the doctrine within the relevant time-span around the current date, all observations from that date are dropped. This happens most often, when analyzing the good-faith exception as it was adopted by only 11 states.

In contrast to $treat_{i,t}$, $post_{i,t}$ is one only for treatment group observations after treatment, but not before treatment. $postpost_{i,t}$ is one for observations belonging to a state that had introduced the wrongful-dismissal law more than 36 month ago.

Time dummies absorb variation over time, which is identical across all states, whereas state dummies absorb variation across states, which is constant over time. By using such a two-way fixed effects setup it is possible to control for both time constant heterogeneity across states and nationwide differences across time (e.g. business cycle fluctuations). Additionally, the setup partially absorbs differences in the variation over time: first, the interaction between state dummies and the treatment group indicator allows for systematic differences between treatment and control group states, that is, the estimated state dummy is allowed to be different for the same state during the time when the state belongs

[36] The pre-treatment period contains the 24 months before treatment

[37] The post-treatment period contains the time-span $12-36$ month after treatment

to the treatment group. Region by year dummies control for business cycle differences across the four major U.S. regions. *postpost* dummies are meant to capture systematic differences between control observations stemming from states which were treated in the past and those, which were not.

Identification Strategy

In order to identify the causal effect of a wrongful-dismissal law, one has to assume that all remaining systematic differences in variation over time between treatment and control group observations are either directly caused by the introduction of the wrongful-dismissal law or by (temporary) shocks, which are not correlated with the adoption of wrongful-dismissal laws. This is identical to assume that there are no state-specific temporary shocks, which are correlated with treatment status. Without the interaction term ($\bar{U}_i * post_{i,t}$) this assumption is enough to identify the models parameters.[38]

The inclusion of the interaction term, however, creates an additional threat to identification. Estimating equation (2.23) without the interaction term (which corresponds exactly to the specification used in Autor, Donohue, and Schwab (2006)) reveals that residuals are strongly autocorrelated. [39] It is exactly this autocorrelation, which makes the interaction term likely to be endogenous.

To see this, assume state i introduces a wrongful-dismissal law in period $t = \tau$ and let $\bar{U}_i$ denote the average unemployment rate in the pre-treatment period. As unemployment is strongly correlated with the outcome variable,[40] it follows that $\bar{U}_i$ is directly correlated with the error terms from all pre-treatment periods, that is, $\epsilon_{i,\tau-24}$ to $\epsilon_{i,\tau-1}$. That alone would not be a problem, but as error terms are highly autocorrelated this translates

[38] If the assumption is violated, estimation would suffer from an omitted variable bias.

[39] Autor, Donohue, and Schwab (2006) use Huber-White standard errors clustered by state in order to be able to compute consistent standard errors despite the presence of strong serial autocorrelation.

[40] The outcome variable is either the employment-to-population ratio, or the unemployment rate itself.

immediately into a significant correlation between $\bar{U_i}$ and $\epsilon_{i,t}$ for $t = \tau + 12$ until $t = \tau + 36$. Correspondingly, the interaction term is potentially $\bar{U_i^*} post_{i,t}$ correlated with the contemporaneous error term that causes an endogeneity bias.[41]

As a solution I use an instrumental variable (IV) approach. A valid instrument has to be correlated with the endogenous variable but not with the error term. This is the case if the instrument impacts the outcome variable via the endogenous variable, but is not correlated with any of the variables omitted in the error term. To derive such an instrument I estimate equation (2.23) without the interaction term and with (log) unemployment as the dependent variable ("auxiliary regression") and collect the fitted values. The fitted values directly translate into estimated values for the level of unemployment, which are then used to construct estimated values for the pre-treatment unemployment rate.

The estimated values are by construction uncorrelated with empirical residuals. Given the validity of the identifying assumptions used by Autor, Donohue, and Schwab (2006) they are also asymptotically[42] uncorrelated with the true error term . This implies that the average pre-treatment unemployment rate constructed from fitted values can be used as an instrument for the actual average pre-treatment unemployment rate. The instrument is valid as it is correlated with the endogenous variable, but as outlined above, uncorrelated with the model's error term.

In general, using an estimated regressor renders standard errors to be wrong, because estimated regressors only proxy the regressors of interest. However, this is not the case

[41] In general it is possible to consistently estimate an interaction term even if one of the involved regressors is endogenous. This is the case if the correlation of that variable with the error term does not depend on hte other variable involved in the interaction. In this case, the correlation of $\bar{U_i}$ and the error is not allowed to depend on $post_{i,t}$. However, we do not rely on this assumption but instead using an instrumental variable approach to prevent endogeneity in the first place. For a detailed description of the necessary conditions for consistent estimation of interaction terms see section 3.4.2 of this Dissertation.

[42] It is safe to rely on asymptotic arguments as there are at least 7000 in any regression performed in the paper

here. Note that asymptotically the predicted value equals the systemic part $(X\beta)$ of the actual value, which is exactly the desired instrument. The predicted value is not a proxy for the true value, but it is the actual variable of interest (i.e. the desired instrument). This implies that the variance of the true error term of the auxiliary regression (differences between predicted and actual value which are not due to differences between the true β and $\widehat{\beta}$) does not matter. A problem would only arise if $\widehat{\beta} \neq \beta$. In this case, the predicted value would not be exactly equal to the systemic part, implying that the systemic part could only be observed with an error. However, as $plim\ \widehat{\boldsymbol{\beta}} = \boldsymbol{\beta}$ this is relevant only in small samples.

2.3.5 Results

Table 2.3 – Interaction Term Results

Dep. Variable	(1) IC	(2) PP	(3) GF	Region
$ln(epop)$	-0.128	-0.602	-2.264	Yes
	(0.479)	(0.050)	(0.002)	
$ln(epop)$	-0.426	-0.833	-2.026	No
	(0.133)	(0.039)	(0.012)	
$ln(unemprate)$	-1.642	4.839	18.789	Yes
	(0.368)	(0.078)	(0.001)	
$ln(unemprate)$	0.963	7.042	22.242	No
	(0.882)	(0.051)	(0.003)	

Notes: The Table displays coefficients on the interaction term between $post_i, t$and pre-treatment average unemployment $\bar{U}_i$. Each coefficient stems from a different regression. Models are weighted by each state's share of national population aged 16-64 (in each month) using CPS sampling weights. P-values in parentheses are computed using Huber-White standard errors which allow for unrestricted error correlation within states. The column "Region" refers to whether or not region-by-year dummies are included. Region here means one of the four major regions in the U.S.

I estimate equation (2.23) for all three wrongful-dismissal laws. I choose the employment-to-population ratio and the unemployment rate as dependent variable. In the former case, empirical results confirm my theoretical proposition if the coefficient on the interaction term is significantly negative, whereas in the latter case it should be significantly positive. Table 2.3 shows all estimated interaction term coefficients as well as the corresponding p-values. Beside testing the paper's main hypothesis, the section also evaluates the marginal effect of EPL on the two outcome variables at different values of average pre-treatment unemployment. [43]

Interaction Term

First, consider the implied-contract exception. When the employment-to-population ratio is used as dependent variable, point estimates are in line with theory (that is, negative), however p-values indicate that the estimated coefficients are not significantly different from zero. The insignificance is particularly striking once regional dummies are included. Turning to unemployment as dependent variable reveals that the point estimate even changes its sign depending on whether regional dummies are included or not. Without regional dummies it is positive (and thus in line with theory), while turning negative once regional dummies are included. Overall results suggest that the pre-treatment unemployment rate does not significantly influences the way the labor market is affected by an adoption of the implied-contract exception.

Regarding the public-policy exception results draw a fairly different picture. First, all signs are now in line with theory regardless whether the employment-to-population ratio or the unemployment rate is chosen as dependent variable. Using the employment-to-population ratio leads to a point estimate for the interaction term coefficient of -0.833 without regional dummies. Regional dummies slightly decrease the absolute value of the estimated coefficient to -0.602, however, the coefficient remains significant at the 5% confidence level. Economically, these results imply that an increase in the average pre-treatment unemployment rate by 1 percentage point boosts the negative effect of EPL by 0.6% to 0.8% percentage points. Replacing the dependent variable with unemployment reveals that results are remarkably robust: Still the sign of all coefficients are well in line with theory, that is, a higher pre-treatment unemployment rate amplifies the positive effect of EPL. Quantitatively, I find that the increase in the unemployment rate due

[43] Note that, as the marginal effect consists of a combination between the coefficient on $post_{i,t}$ and the coefficient on the interaction term, it is necessary to employ the *Delta*-method to obtain correct standard errors. When using the STATA command *margins* the *Delta*-method is used by default.

to the adoption of the public-policy exception is between 4.8% (with regional dummies) and 7% (without regional dummies) higher when the pre-treatment average unemployment rate increases by 1 percentage point. The corresponding p-values are between 0.05 (without regional dummies) and 0.08 (with regional dummies) indicating significance at conventional confidence levels.

Results for the good-faith exception provide even stronger evidence in favor of the papers main proposition: invariably all point estimates are well in line with theory and highly significant (at the 1% confidence level). Correspondingly, the estimated coefficients are larger than in case of the public-policy exception. In case of the employment-to-population ratio (unemployment rate), the adverse effect of EPL is strengthened by about 2 (20) percentage points for every percentage point the pre-treatment unemployment rate is higher.[44]

Marginal Effects

The second quantity of interest is the marginal employment effect of introducing a specific wrongful-dismissal law. These marginal effects are shown in Tables B.1 to B.3 in Appendix section B.4 . In the absence of an interaction term the marginal effect is simply given by the coefficient on $post_{i,t}$ which is θ_1. Once the interaction term is taken into account the the marginal effect reads $\theta_1 + \theta_2 \bar{U}_i$. As already pointed out above, it is the sign of θ_2 that determines whether the marginal effect is increasing or decreasing in average pre-treatment unemployment. Although marginal effects can be directly obtained using the formula stated above, computation of consistent standard errors requires us-

[44]Note that coefficients on both the main effect and the interaction term are naturally higher when the unemployment rate and not the employment-to-population ratio is chosen as dependent variable. The reason is simple: First, the model is written down in semi-log form, implying that coefficients measure the percentage change in the outcome variable due to an one unit increase of the explanatory variable. Second, the absolute level of the unemployment is far smaller than the absolute level of the employment-to population-ratio. Thus, the same change in absolute numbers gives rise to a far larger percentage change if the unemployment rate is the dependent variable.

ing the *Delta* method.[45] Note that estimated standard errors increase in the absolute distance between the current value of pre-treatment unemployment and its mean. Thus, it is possible that a specific marginal effect is less significant for some extreme value of pre-treatment unemployment. Marginal effects are evaluated at the mean as well as for values two and four units above and below.

Implied-Contract Exception Again I start by considering the implied-contract exception (see Table B.1). With employment-to-population as dependent variable and pre-treatment unemployment evaluated at its mean, marginal effects approximately coincide with the results from Autor, Donohue, and Schwab (2006)[46]. The small, negative interaction term coefficient implies that the marginal effect is somewhat smaller for low values and somewhat larger for high values of pre-treatment unemployment. As standard errors go up when evaluating marginal effects far off the mean, marginal effects become insignificant when evaluated at a very low value of pre-treatment unemployment (4 units below its mean). In contrast, if it is evaluated at a high pre-treatment unemployment rate, the marginal effects are large enough to stay significant despite larger estimated standard errors. Turning to unemployment as dependent variable reveals that marginal effects are less significant compared to the model with employment-to-population. If pre-treatment unemployment is evaluated at its mean the marginal effect still remains significant. This holds in particular, if regional dummies are included (p-value 0.023). However, as the coefficient on the interaction term is very small (compared to the main effect), larger standard errors lead to insignificance once marginal effects are evaluated for high or low values of pre-treatment unemployment.

Public-Policy Exception One more time the public-policy exception reveals a rather different picture (see Table B.2). Marginal effects are highly insignificant when evaluated at the mean of average pre-treatment unemployment. This is inline with the result

[45]The *Delta* method can easily be implemented by using the STATA command *margins*.

[46]Clearly, results do not exactly coincide as the inclusion of an additional regressor (the interaction term) lowers estimation precision leading to somewhat different point estimates.

of Autor, Donohue, and Schwab (2006) who does not find any significant effect of the public policy exception. However, marginal effects become significant when being evaluated at very low or very high values of the moderator. This holds true no matter whether the employment-to-population or the unemployment rate is chosen as dependent variable.[47] If average pre-treatment unemployment takes on a value two units below its mean, the employment-to-population ratio (the unemployment rate) significantly increases (decreases) when the public-policy exception is introduced. This corresponds to the case in which the positive effect of a lower job destruction rate outweighs the negative effect of a lower job finding rate. Spoken differently, the decrease in frictional unemployment is larger than the increase in rationing unemployment. The story reverses, once the marginal effect is evaluated at a very high value of the moderator (two units above its mean). This case corresponds to an sluggish economy with rationing unemployment contributing the main part to total unemployment. Now, adopting the public-policy exception has a detrimental effect on labor market performance. It lowers the employment-to-population ratio and increases the unemployment rate. Significance is somewhat lower compared to the case of a low moderator value, although p-values remain around 0.1, indicating at least weak significance. Note that in both cases the estimated are significant despite large estimated standard errors, which arise because the marginal effects are evaluated far off the mean of average pre-treatment unemployment. Marginal effects clearly reflect the large and significant coefficients on the interaction term, discussed above.

Good-Faith Exception Table B.3 reveals that marginal effects of the good-faith exception draw a similar pattern to those of the public-policy exception. They are insignificant when evaluated at the mean of average pre-treatment unemployment, which again corresponds to the result of Autor, Donohue, and Schwab (2006). When marginal effects are evaluated at very high and very low levels of average pre-treatment unemployment, the large coefficient on the interaction term unfolds its impact: for low values of the moder-

[47] Again significance levels are somewhat higher if the dependent variable is given by the employment-to-population ratio.

ator (one unit below the moderators mean), adopting the public-policy exception leads to a significant improvement of labor market conditions. The employment-to-population ratio increases by about 3.5%, whereas the unemployment rate drops by around 30% (with regional dummies) to 40% (without regional dummies). In contrast, for high levels of average pre-treatment unemployment (one unit above its mean), the public-policy exception has a strong detrimental effect on both the employment-to-population ratio and the unemployment rate. The effect on the former is between 4 to 5%, while the effect on the latter is about 45-50%. Clearly, all coefficients are highly significant (at the 1% confidence level)[48]

Interpretation

Overall, results draw a somewhat mixed picture. Regarding the public-policy and the good-faith exception, the analysis provides strong evidence in favor of the papers main proposition. The estimated coefficients on the interaction term are significant and have the desired sign throughout (almost) all specifications. Correspondingly, marginal effects behave as expected: the insignificance results reported in Autor, Donohue, and Schwab (2006) vanish when marginal effects are evaluated at low or high values of average pre-treatment unemployment. The economic message behind these results is clear: although the public-policy and good-faith exception do not affect the employment-to-population ratio and the unemployment rate in a typical U.S. state, they do have strong effects when being introduced in a notably strong or weak labor market. Adopting the public-policy or good-faith exception has positive labor markets effects in states with low unemployment, while adverse effects dominate in labor markets with high unemployment. This provides strong evidence for the mechanism proposed in the theory section: EPL lowers frictional unemployment, but increases rationing unemployment. Thus, it has adverse effects in markets driven by job rationing, but favorable effects in markets driven by search frictions.

[48]Note that due to the very large interaction term coefficients marginal effects evaluated two units below or above of the mean cannot be reliably estimated, as the model specification abstracts from second order effects. In order to avoid confusion, the corresponding results are omitted from Table B.3.

As rationing is likely to occur in sluggish labor markets, EPL widens the gap between strong and weak markets. Many states adopted wrongful-dismissal laws during the 1970s and 1980s. Interestingly, one can observe a sharp rise in U.S. income inequality during the same time period. [49]

The promising results for the public-policy and good-faith exception do not translate to the implied-contract exception. Data does not sufficiently support the proposition that pre-treatment unemployment (and thus unemployment composition) has a significant impact on the way the implied-contract exception influences the labor market. Instead, the implied contract exception seems to have detrimental labor market effects in any case (although less significant in labor markets with low pre-treatment unemployment).

There are two possible explanations for the observed pattern: first, the implied-contract exception could be structurally different from the other two wrongful-dismissal laws. This perception is supported by the fact that it is the only wrongful-dismissal law for which Autor, Donohue, and Schwab (2006) found significant effects on labor market performance. One explanation is that firms quickly adapt to the implied-contract exception by updating their recruitment process including a careful revision of new employment contracts and policy handbooks. The complication of the recruitment process may not be limited to the initial adoption as continuous effort is needed to safely prevent the formation of implicit contracts. In this way, the implied-contract exception act more as a law which imposes additional recruiting costs instead of firing costs. An increase in recruiting costs unambiguously leads to lower employment / higher unemployment independent of the composition of unemployment. If this mechanism is true, obtained results are well in line with theoretical predictions. Alternatively, insignificance results from a downward bias caused by omitting matching efficiency (see section B.3 in the Appendix).

[49] The Gini-Index for the U.S. rose from about 39 at the beginning of the 1970s to about 45 at the beginning of the 1990s.

2.4 Conclusion

This paper studies the effects of EPL on labor market performance taking into account the composition of unemployment. The paper outlines a stylized equilibrium matching model, which features diminishing marginal returns to labor and real wage rigidities. The model suggests that EPL unambiguously increases rationing unemployment while having a favorable effect on frictional unemployment. The first effect arises due to a lower marginal value of employing a worker (net of hiring costs), while the second effect is caused by lower recruiting costs, which arise due to lower labor market tightness.

Calibrating the model reveals that the overall effect of EPL crucially depends on initial unemployment composition. If unemployment is mainly driven by search frictions, the positive channel via lower recruiting costs is strong enough to offset the negative effect caused by a lower marginal value of employing a worker. In contrast, if rationing unemployment is the main contributor to overall unemployment, the reduction in recruiting costs is only negligible, causing EPL to unfold strong adverse labor market effects.

The empirical part of the paper tests this theoretical prediction using data on the adoption of wrongful-dismissal laws by U.S. state courts. Under the assumption of a constant matching efficiency, average pre-treatment unemployment is used as an indicator for the composition of unemployment. Results confirm the theoretical prediction for both the public-policy and the good-faith exception. In contrast, results regarding the implied-contract exception indicate that unemployment composition does not play a significant role in moderating labor market effects. A possible explanation for this phenomenon could be that firms adopt to the implied-contract exception, which complicates the recruiting process without actually affecting firing costs.

Overall, theoretical and empirical results indicate that taking into account the composition of unemployment is crucial when assessing aggregate labor market effects of EPL. Moreover, EPL is likely to act as an amplifier of regional differences in labor market performance.

Chapter 3

Labor Market Consequences of Increased Broadband Availability - Evidence from German Micro Data[1]

3.1 Introduction

Advances in information and communication technologies (ICT) have constituted the major technological change since 1980's. The first decades of the "IT Revolution" were marked by the penetration of computers, the more recent ICT changes relate to the availability of high-speed Internet enabled by the rapid expansion of broadband infrastructure. While policy-makers emphasize ICT benefits such as higher productivity and job creation, existing empirical evidence points toward factor non-neutrality of these technological changes. This phenomenon was labeled "skill biased technological change" (SBTC).[2] People of different educational and occupational groups appear to benefit unequally from

[1] This chapter is based on joint work with Nadzeya Laurentsyeva.

[2] Effect of Internet: Akerman, Gaarder, and Mogstad (2015); Atasoy (2013); Forman, Goldfarb, and Greenstein (2012). Older generations of IT: Katz and Autor (1999); Autor, Levy, and Murnane (2003); Autor, Donohue, and Schwab (2006).

the availability of ICT. Quantifying and understanding this bias has important policy implications. Public and private spending on broadband infrastructure may not reach the desirable welfare improvements if losses are not mitigated by designing appropriate compensation schemes or by providing complementary investments in necessary skills.

This project investigates the labor market effects of the development in broadband infrastructure. We link data on the gradual rollout of the broadband Internet in Germany to labor market and firm data from the German linked employer-employee dataset (LIAB) and the BIBB labor force survey. We analyze if the availability of broadband changes the output elasticities and wages of different workers. To that end, we classify workers according to their formal education or routinization of their job. Our results confirm the presence of a skill bias. Broadband upward shifts the output elasticity of skilled workers (workers in low-routine occupations), while lowering the output elasticity of low-skilled workers (workers in high-routine occupations). A 10 percentage point increase in broadband availability raises the output elasticity of non-routine workers by about 0.5-0.7 percentage points. At the same time, the output elasticity of workers in high-routine occupations drops by about 1 percentage point. The change in output elasticities partly passes through to workers' wages: we find a significant negative effect of broadband on the relative wage of workers in highly routinized occupations. A 10 percentage point increase in broadband decreases the relative wage of these workers by about 0.25-0.56%. In contrast, when workers are classified by formal education, we do not find corresponding wage effects.

We link these asymmetric labor market effects to changes in firm production processes, which are possible due to the availability of broadband. Cloud computing helps to standardize IT systems within and between firms, hence reducing the need to manually convert or transfer data between departments and establishments. Moreover, broadband allows firms to centralize some functions, such as quality assurance or product distribution. For example, complex machines become increasingly cross-linked and react autonomously to changes in the environment and to new requirements. Branch establishments (for instance, branch banks) become redundant due to the availability of centralized online services. All of these processes reduce the required amount of routinized labor (broadband substitutes routine labor). Economically, broadband increases the effective amount of routinized labor. In turn, the law of decreasing marginal returns implies a lower marginal productivity of routinized workers, which finally leads to lower demand for this type of labor.[3] In contrast, demand for non-routine workers, who *use* broadband to perform complementary tasks, increases. In addition, demand for some non-routine workers increases directly as broadband applications need to be implemented.

We complement the analysis by looking at the broadband effects that take place outside of firms. Specifically, we investigate whether broadband alters the wage penalty associated with past unemployment spells. With the widespread availability of broadband Internet, new communication methods like video conferences, web videos, or Voice over IP become feasible. This might facilitate job search, by enlarging the usual geographical or occupational labor markets and by enabling workers to approach more employers. Skype interviews and online assessment centers can further increase matching efficiency. Moreover, broadband Internet gives access to online labor markets and makes it easier to improve own human capital through various online-learning platforms. Hence, broadband slows down human capital deterioration during an unemployment spell. Do these improvements benefit different workers equally or is the access to these benefits also characterized by the skill bias? We find that a 10 percentage point increase in broadband availability lowers the penalty to unemployment (which is equal to 23%) by about one percentage point. In line with SBTC, we find that the effect is not present for workers in highly routinized occupations.

For the identification of the effects, we exploit the county-level variation in timing of the broadband expansion. In Germany, the biggest telecommunication company Deutsche Telekom started to roll out broadband infrastructure in 2000. By 2005, broadband coverage (at 384 kbit/s) has already constituted 60%. By 2010, it has reached 96%. Initially, the

[3] While firms may find some "useful" routinized task for their employees even when their original task gets automated the value added by performing those additional tasks is likely to be lower.

profit-maximizing behavior of telecommunication providers determined the geographical spread-out of broadband. Profitability depends almost exclusively on observable county characteristics, which do not vary much over time.[4] Consequently, endogeneity issues can be resolved by including county and time fixed effects. To increase confidence in our identification, we allow time dummies to depend on initial county characteristics. Given these controls, residual variation in broadband availability can be treated as exogenous to labor market outcomes and firm performance.

To measure the differential effect of broadband, we need to estimate the coefficients on *interaction* terms. Although interaction terms have played an important role in many empirical studies, most authors (including Akerman, Gaarder, and Mogstad (2015)) only try to convince the reader why their treatment variable is exogenous. The seminal paper by Bun and Harrison (2014), however, shows that consistent estimation of interaction terms requires further assumptions. Our paper discusses these assumptions, reveals potential biases and carefully explains how to interpret the estimated coefficients.

This paper contributes to the broad literature on technological change in general and on the effects of information and communication technologies (ICT) in specific. Empirical evidence indicates that higher productivity is not harmful for aggregate employment: for example, van Ark, Frankema, and Duteweerd (2004) found a strong correlation between per capita income, productivity, and employment at least in the medium term. Other papers (see Basu, Fernald, and KimKimball (2006) and Kim, Lim, and Park (2010)) find that positive technology shocks lead to lower employment only in the short run, but increase employment in the medium run. As shown by Chen, Rezai, and Semmler (2007) a similar relationship also holds when unemployment (instead of employment) is used to characterize the labor market state. Yet, some scholars are concerned that the previously found positive correlation between productivity, growth and employment does not hold anymore, a phenomenon called the great decoupling (Brynjolfsson and McAfee (2011) and Rotman (2013)).

[4]These characteristics include total population, population density as well as the employment-to-population ratio. See section 3.4.1 for details.

Besides aggregate labor market outcomes, factor non-neutrality of new technologies (SBTC) presents another major concern in the literature. Acemoglu (2003), Bond and Reenen (2007), and Goldin and Katz (2007) survey corresponding studies. Using German data, Spitz-Oener (2006) finds that skill requirements have increased most rapidly in occupations, which have experienced extensive computerization. Dustmann, Ludsteck, and Schönberg (2009) point out that technological change is an important explanation for the widening of the wage distribution in Germany during the 1980s and 1990s. Akerman, Gaarder, and Mogstad (2015) exploit the progressive rollout of broadband in Norway to compare its effects on wages, employment, and output elasticities of labor. Similarly to our results, they report that broadband increases the output elasticity of skilled versus unskilled workers. They also find corresponding effects on wages.

In using the degree of routinization to classify workers, our paper relates to the literature on job polarization, introduced by Autor, Levy, and Murnane (2003). The authors were the first to study the differential effect of computerization by looking directly at occupational tasks, rather than educational credentials. They provide evidence that computer technology substitutes routine tasks and thus decreases demand for jobs requiring the corresponding skills. As most of these jobs (for example, manual assemblers or clerks) are medium-paid, this leads to an asymmetric effect at the top and at the bottom of the wage distribution.[5] While ICT substitutes for routine tasks often performed at middle-paid jobs, it cannot easily replace low-skilled, service-type jobs, which often exhibit direct client interaction and, correspondingly, a low level of routinization. Autor and Dorn (2013) argue along these lines to explain the growth of low-skill service occupations in the U.S. since 1980. They hypothesize that workers performing routine task (like bookkeepers or administrative officers) reallocate into service occupations. Although formal education and routinization are correlated (in the sense that high formal education implies

[5]Feng and Graetz (2015) develop a model that distinguishes between a task's engineering complexity and its training requirements. When two tasks are equally complex, firms will automate the task that requires more training and in which labor is hence more expensive. Under quite general conditions this leads to job polarization, a decline in middle wage jobs relative to both high and low wage jobs.

lower routinization), the mapping is far from being one-to-one. For example, only about 39.72% of German low-skilled workers actually work in highly routinized occupations. Against this background, we expect our routine measure to be more precise in capturing task-biased technological change compared to rough measures of formal education.

The rest of the chapter is organized as follows: Section 3.2 presents the data as well as key descriptive statistics. Section 3.3 outlines some details on the institutional background of broadband Internet in Germany. Section 3.4 discusses key identifying assumptions. Section 3.5 and 3.6 outline our regression models and discuss empirical evidence for skill-biased technological change as well as for the relation between broadband and past unemployment spells. Finally, section 3.7 concludes.

3.2 Data and Descriptive Evidence

3.2.1 Data

LIAB Data

The core dataset in our analysis is the linked employer-employee data provided by the Institute for Employment Research (IAB) of the Federal Employment Agency called LIAB. The data combines survey information on German establishments with labor market biographies of matched employees. We use the Longitudinal Model, which spans the period 1993-2010.[6] The IAB Establishment Panel is an annual panel study of establishments in all branches and of all sizes with at least one employee covered by social security. Employee biography data stems from the administrative social security records and covers all employment spells and benefit receipts of matched workers throughout 1993-2010. For a more detailed description of LIAB, we refer to Heining, Scholz, and Seth (2013) and Fischer, Janik, Mueller, and Schmucker (2009). Table 3.1 summarizes the available

[6] The data after 2011 has become publicly available only in June 2016.

dataset.

Table 3.1 – Dataset Summary: Number of Observations

	(1)	(2)	(3)	(4)	(5)	(6)
	2000	2006	2007	2008	2009	2010
Individuals	1474395	1399295	1403499	1408574	1394541	1354048
Full-time	1005607	943311	963777	974875	956089	937558
Linked to firms	789665	649208	663951	684411	581751	486906
Firms	9489	9882	10112	10578	9837	8926

Source: LIAB dataset

For our analysis, we use LIAB data from 2006-2010 as well as from 2000.[7] We collapse the dataset to a person-year level. If an employee works at more than one establishment during a calendar year, we keep the establishment that paid the largest wage bill as the main employer and drop other observations for this individual-year. To the extent that most workers in the sample have only one employer during a year (the average number of employment spells is 1.1), this transformation should not affect our results. Prior to that, we calculate the annual wage income received from all employers, the annual number of days in unemployment, and the annual amount of obtained social-security money.

For the worker-level regressions LIAB provides information on daily wages, education, 3-digit occupation codes, unemployment spells as well as demographics. Wage data is right-censored at the highest level of earnings subject to social security; censoring applies to around 7.5% of all observations. We tackle the censoring problem using two different approaches: the first approach drops all censored observations, while the second uses an imputation procedure.[8] For the establishment-level regressions, we aggregate the individual-level dataset on the establishment level and merge it with the IAB Establish-

[7]Our broadband data covers years 2006-2010, and we use the fact, that in 2000 broadband coverage was zero in all counties.

[8]The imputation procedure follows Dustmann, Ludsteck, and Schönberg (2009).

ment Panel. Before the aggregation, we limit the sample to full-time workers only and calculate labor input by skill and routinization level for each establishment. Our dataset contains information on establishments' sales, capital[9], material inputs and firm age. We can also see the industry (5-digit level) and county, where the establishment operates.

Worker Classification

To classify workers in different skill groups, we adopt two approaches. First, we use information on formal education to assign workers to a low-skill group if their highest attainment is Volks/Haupt/Mittelschule; to a medium-skill - if they completed Abitur; and to a high-skill - if they have a University or a Fachhochschule degree.

As outlined in the introduction, education is only a very rough proxy of the actual tasks performed by different workers. Hence, we also classify workers using an index that captures the degree of routinization. To develop a measure for job routinization we follow Autor and Dorn (2013) who use job task requirements from the *Dictionary of Occupational Titles* (DOT) to measure routine, abstract and manual task content by occupation. Using this information Autor and Dorn (2013) calculate a routine intensity for each occupation by subtracting the manual and abstract task input from the routine task input.

We use the a labor force survey performed by the Federal Institute for Vocational Education and Training (BIBB) to construct an index of job routinization. The survey aggregates responses of approximately 20000 individuals regarding their job tasks and job skill requirements. It was carried in 2000, 2006 and 2012. We use the 2006 wave as it corresponds best to the LIAB sample. To construct the routine measure, we combine answers from four different questions, which measure standardization, repetitiveness, new tasks, and new procedures. The answers were codified using numbers 1 to 4, where 1 = often and 4 = never. Standardization and repetitiveness measures enter the index with

[9]Establishments do not directly report the value of capital assets. However, capital can be implicitly approximated from the available information on investment.

negative sign, while new tasks and new procedures enter with positive sign. Hence, the aggregate measure maps every occupation to a value between -6 and $+6$, where higher values imply that the corresponding occupation is more routinized. We assign the extent of job routinization (at a 3-digit occupation level) to every worker in the LIAB dataset. We then classify all workers as low-, medium-, or high-routine based on the tertiles of the index.

Internet Data

The German "Breitbandatlas" provides the data on broadband availability.[10] The "Breitbandatlas" uses the original broadband definition, that is, internet speed of at least 384 kbit/s. The annual data is available from year 2006 onwards.[11] For the period 2006-2010, the "Breitbandatlas" reports contain maps of broadband availability . These maps are based on representative household surveys.[12] Using ARCGIS software we calculated broadband coverage statistics per county. Since 2010, broadband definition has changed reflecting the ongoing technological progress. The 2010-2015 digitized broadband county-level data is available from the "Breitbandatlas" upon request.[13] In contrast to Falck, Gold, and Heblich (2014) who also uses German internet data, we do not exploit municipality-level broadband information, as LIAB does not contain municipality indicators.[14]

[10] See http://www.breitbandatlas.de.

[11] Knowing that the rollout of broadband infrastructure in Germany started in early 2000s, we assign zero broadband availability to all counties in 2000.

[12] Using different color intensities, the maps reflect broadband penetration rates according to the share of households with broadband access in a given municipality.

[13] We plan to repeat our analysis using data from 2010 onwards as soon as the latest waves of LIAB will be published.

[14] As we can identify location of firms and employees only on the county level, we cannot apply an identification strategy in the spirit of Falck, Gold, and Heblich (2014).

3.2.2 Descriptive Evidence

This subsection presents worker- and firm-level descriptives: we compare classifications of workers obtained with education and routine measures, track wage dynamics and unemployment statistics across different skill groups, and provide decompose the variation in key variables.

Table 3.2 shows the share of worker-year observations that belong to a certain skill (education) or routine type. Over 78% of all workers are either low-skilled or workers with missing skill. 22.33% of low-skilled workers perform non-routine jobs, this holds true for 42.52% of medium-skilled and 77.14% of high-skilled workers. When considering highly routinized occupations, the picture reverses: 36.28% of low-skilled workers are employed in such occupations compared to only 10.94% of medium-skilled and 2.29% of high-skilled workers. The overall correlation between the routine and the skill measure is -0.138. Nevertheless, there is an important asymmetry: while being high-skilled almost surely excludes the possibility of having a highly routinized job, being low-skilled is compatible with working in a low-routine environment. This notion was first popularized by Autor, Levy, and Murnane (2003) who pointed out that low-skilled workers often perform manual service task, which often involve direct client interaction and therefore are hardly automatable. Consequently, in the context of SBTC, low-skilled workers may perform better than than medium-skilled workers.

Table 3.3 tracks the evolution of daily wages in our dataset. We treat low-skilled workers respectively workers in high-routine occupations as reference groups. Wages of other types are normalized.[15] In that way, we can see how wage dispersion across skill or routine levels evolves over time. Note that the wage gap between medium- and low-skilled (medium- and high-routine) workers increases. The same holds true for relative wages of low-routine workers. Only relative wages of high-skilled workers stay roughly constant.

Besides investigating the classical SBTC hypothesis our paper analyzes whether broad-

[15]We divide the average group wages by the average wage of the corresponding reference group.

Table 3.2 – Share of Worker-Year Observations by Routine Group for each Skill Level

		(1)	(2)	(3)	(4)
		Skill (Formal Education)			
		0	1	2	Total
	0	22.33%	42.52%	77.15%	30.30%
Routine	1	31.14%	43.66%	20.13%	30.07%
	2	36.28%	10.93%	2.29%	30.14%
	Missing	10.24%	2.87%	0.44%	8.47%

Notes: The Table displays the share of worker-year oberservations belonging to a specific routine group separately for each skill group. Source: LIAB.

band affects the wage penalty caused by past unemployment spells. Table 3.4 shows the percentage of worker-year observations that have experienced an unemployment spell in the past five years by skill, respectively, by job routinization. The Table shows that workers in highly routinized occupations experience unemployment spells more often than workers in low- or medium-routine jobs. However, quantitatively the difference between the latter two categories is negligible (5.061% vs. 5.188%) while the difference between workers in medium and highly routinized jobs is substantial (5.188% vs. 8.777%). Classifying workers by skill reveals that low-skilled workers are most often (6.670%) affected by unemployment. Surprisingly, medium-skilled workers experience even less unemployment spells than high-skilled workers (3.567% vs. 4.678%). Table C.2 in the Appendix in addition summarizes the number of days in unemployment per year and skill (routine) group: Although this measure decreases over time for less-skilled workers (workers in high-routine occupations), the difference to other groups remains large. Less-skilled workers (workers in high-routine occupations) were also more vulnerable during the crisis in 2008-2009.

Tables 3.5 and 3.6 compare the SSE[16] within and between individuals (firms) with the SSE within and between counties for several key variables. Results indicate that county fixed effect absorb about 10% of total variance. In contrast, individual fixed

[16]SSE = Sum of Squared Errors.

Table 3.3 – Dynamics of Wages by Skill and Routine Groups

	(1) Low-skill	(2) Medium-skill	(3) High-skill	(4) High-routine	(5) Medium-routine	(6) Low-rotine
2000	64.34	0.95	1.65	51.57	1.22	1.56
2006	71.24	1.01	1.70	51.96	1.37	1.79
2007	73.22	1.01	1.67	53.93	1.36	1.76
2008	75.75	1.02	1.64	55.93	1.36	1.74
2009	76.89	1.04	1.64	55.88	1.40	1.77
2010	79.66	1.10	1.63	58.01	1.40	1.78

Note: LIAB dataset. The table shows average daily wage in Euro for low-skill workers and workers in high-routine occupations (reference groups). Wages of other groups of workers are divided by the values in the reference groups.

Table 3.4 – Frequency of Past Unemployment Spells by Skill / Routine Group

	(1) % Workers with past UE		(2) % Workers with past UE
Low Skilled	6.670	High Routine	8.777
Medium Skilled	3.567	Medium Routine	5.188
High Skilled	4.678	Low Routine	5.061

Notes: The Table displays the frequency of past unemployment spells by skill level as well as by job routinization for each year between 2006 and 2010. Source: LIAB.

effects absorb about 90% of total variation. In addition to the theoretical considerations outlined in section 3.4.2, these results guide us toward using county instead of individual fixed effects.[17]

[17]Loosing variation directly translates into a loss of precision. Hence, as long as there are no strong theoretical reasons requiring the inclusion of individual fixed effects, county fixed effects are favorable compared to individual fixed effects.

Table 3.5 – Variance Decomposition of Key Variables - Firm Level

	Firm		**County**	
	Between	Within	Between	Within
Variable	(1)	(2)	(3)	(4)
log(Value Added)	310114	13652	38832	284934
log(# Low Skilled Workers)	294419	15359	24887	284891
log(# Medium Skilled Workers)	102705	7158	7644	102219
log(# High Skilled Workers)	145299	6941	10944	141296
Broadband Availability	609	456	494	571

Notes: The table displays a decomposition of the sum of squared errors (SSE) between and within firm and county for each variable. Source: LIAB.

Table 3.6 – Variance Decomposition of Key Variables - Worker Level

	Person*Firm		**Person**		**County**	
	Between	Within	Between	Within	Between	Within
Variable	(1)	(2)	(3)	(4)		
log(Wage)	4903267	820375	5445110	1211752	780919	4942723
Skill	3163335	0	3208758	0	242104	2921231
Job Routinization	12020529	362633	11780539	602624	1325229	11057933

Notes: The table displays a decomposition of the sum of squared errors (SSE) between and within person*firm, person and county for each variable. Source: LIAB.

3.3 Details on rollout of Broadband Infrastructure in Germany

This section provides detailed information about the broadband rollout in Germany.[18] One of the key actors in the development of broadband infrastructure was Deutsche Telekom[19], which started its broadband offensive in 2000. At the time, it was the first

[18]We define broadband access as permanent access to the Internet at a speed of at least 384 kbit/s. This definition corresponds to the original definition used by the Deutsche Telekom. Due to technological progress the definition has changed over the years, however, in order to provide comparability we stick to the original definition.

[19]Deutsche Telekome had held the exclusive right to serve the German telecommunications market until 1996 when it was privatized via an IPO and had to give up its monopoly profits.

German telecommunication provider offering DSL access. Within five years (2005) broadband had been made available to more than 60% of German households. Clearly, there were substantial differences regarding the speed of broadband rollout between different geographical regions. Our paper exploits the resulting variation provided by this staged rollout.

To address potential endogeneity it is important to think of the economic incentives that guided telecommunication providers during the rollout: during the initial phase of broadband expansion there was no public promotion of broadband. Instead, Deutsche Telekom (and its competitors) made broadband available based on profit-maximizing behavior. The main driver of broadband profitability is population density. In counties with high population density one access point is able to serve many clients. Therefore, marginal cost of providing broadband to one potential client is higher in rural areas compared to densely populated areas. Other supply factors include topography and existing infrastructure (roads, buildings, railways). Important demand factors include income level, educational composition, as well as industry structure. In total, profit margins arising from broadband expansion differ substantially between counties leading to the observed pattern of a staged broadband installation. Importantly for our analysis, timing of broadband penetration is largely driven by observable, mostly time-constant characteristics.

The German government considers broadband as a key locational factor. To avoid increasing regional disparities, the government decided to actively stimulate broadband in rural areas. In practice this has happened via cooperation between municipalities and telecommunication providers. First, the municipality analyzes its broadband requirements. Second, the municipality awards the request. Third, the company winning the request commits to install the broadband infrastructure within a given time period, while the municipality covers the (potential) gap between costs and revenues. However, such cooperation between municipalities and telecommunication providers have not started before 2008. They do not pertain the first generation of broadband expansion. Hence, the role of public broadband initiatives in our sample is negligible.

The left panel of Figure C.1 shows the geographical distribution of broadband in the initial period of our sample. Although broadband had already reached high availability rates in some regions by 2006, the penetration is fairly low in other places, particularly in the North-East of Germany. The other two panels show broadband in 2007 and 2009. While broadband availability increases over time, the increase is far from being homogeneous across counties. There seems to be a convergence towards full broadband coverage at the end of our sample.[20]

In the main empirical specifications, we use the data from year 2000 (when we set broadband penetration in all counties to zero) and years 2006-2010. A potential concern is that the initial growth in broadband availability (from 0% in 2000 to 60% in 2006) has a different effect than during more mature stages of broadband expansion. We check the robustness of results by restricting the sample only to years 2006-2010.

3.4 Identification Strategy

This section derives the key identifying assumptions underlying our econometric models. Note that our goal is to identify the coefficient on the interaction term *Broadband X skill group*. First, we address the classical endogeneity issue: we provide evidence indicating that, conditional on fixed effects, broadband can be treated as exogenous to outcome variables. Next, we explicitly discuss the conditions under which the interaction term can be consistently estimated and propose an alternative interpretation.

[20]Note that broadband availability only refers to the original broadband definition (384 kbit/s). hence, the absence of large differences in broadband availability in later years does not imply that there are no substantial differences in the availability of high-speed broadband access. Unfortunately, information about the availability rates of higher bandwidths is only available for years 2010 and later, whereas LIAB data is available only until 2010.

3.4.1 Exogeneity of Broadband

Falck, Gold, and Heblich (2014) address potential endogeneity of broadband by exploiting regional and technological peculiarities of the preexisting voice telephony network that hindered the rollout of fixed-line infrastructure for high-speed Internet. Although appealing, their approach is not feasible in our setup, as LIAB data does not provide any information in which municipality a certain worker / firm resides due to data protection. Hence, we have to restrict our analysis to the county level, implying that we have to rely on controlling for potential confounders in order to guarantee exogeneity of broadband.[21]

As outlined, broadband availability is largely determined by observable economic and demographic variables, most of which vary little over time. Thus, conditional on county and year fixed effects, the variation in broadband can be treated as plausibly exogenous. To test this assumption and guide the inclusion of additional controls we perform two types of auxiliary regressions. First, we regress broadband availability on county and time fixed effects as well as on potential time-varying demand and supply factors (see Table C.3 in the Appendix).

$$BB_{k,t} = \eta_k + \theta_t + \beta Controls_{k,t} + \epsilon_{k,t} \tag{3.1}$$

where $Controls_{k,t}$ is a vector of time-varying control variables[22] and β is the corresponding coefficient vector. We report the regressions for 2000 + 2006-2010 sample; the full results including only 2006-2010 are available upon request. In our baseline sample, regressing on county and year effects only, yields a R^2 of 0.973 ensuring that broadband rollout was largely determined by time-invariant factors. The only significant time-varying factors are net migration, employment to population, and age structure. However, these controls explain less than 1% of the variation in broadband availability. We are reluctant to include these variables in our main regressions to avoid a "bad control" problem.[23]

[21] A similar approach has been taken by Akerman, Gaarder, and Mogstad (2015).

[22] Demographic factors, inputs and outputs, industry structure and skill composition.

[23] If part of the broadband-induced changes in labor market outcomes work through the above mentioned time-varying factors, keeping those factors constant by including them in the regression equation would not be appropriate.

As a second step, we check whether the timing of broadband rollout depends on pre-rollout county characteristics by regressing the change in broadband on county and time fixed effects where the latter is allowed to depend on initial county characteristics (see Figures C.4-C.5 in the Appendix):

$$\Delta BB_{k,t} = \eta_k + \theta_t + [\theta_t * \boldsymbol{Controls_{k,2005}}]'\boldsymbol{\Psi} + \epsilon_{k,t} \tag{3.2}$$

where $\boldsymbol{\Psi}$ is a vector that contains the estimated coefficients on $[\theta_t * \boldsymbol{Controls_{k,2005}}]'$ for each year and control variable. When only including fixed effects, the R^2 reads 0.54; allowing the time dummies to depend on pre-rollout county characteristics raises R^2 to 0.58. The coefficients on the interaction term can be interpreted as follows: if, for example, $\theta_{2007} * Income_{k,2005}$ is not significant, then pre-rollout average income does not predict the 2006-2007 change in broadband. If the same coefficient is significantly positive, counties with above average income in 2005 experience (on average) a specifically strong increase in broadband between 2006 and 2007.

The following initial county characteristics turn out to be significant determinants of broadband rollout: population density, total population, share of unemployed workers as well as age structure. To control for differential time trends in our main regressions (see equations (3.5) and (3.7)), we estimate models where time dummies are allowed to depend on the county characteristics that have proven to alter the timing of broadband rollout. This procedure mitigates the problem that variation in outcome variables caused by differences in (initial) county characteristics are spuriously related to changes in broadband availability. In what follows we call this procedure "allowing for heterogeneous time trends".

3.4.2 Consistent Estimation of the Interaction Term

The primary goal of our analysis is to find out how broadband availability affects output elasticities and wages of different workers. In our setup "different" means belonging to different educational or occupational classes. Technically, this may happen for two reasons: first, broadband directly alters the returns to belonging to a certain skill group.[24] The second effect arises due to unobserved worker ability. When workers' selection into skill groups depends on ability and the returns to ability depend on broadband, broadband affects (for example) non-routine workers differently, not only because they perform non-routine tasks, but also because they have high ability.

In this case, the interaction term coefficient measures not only how broadband changes the causal effect of skill / routine group on the outcome, but also to some extent how broadband alters the return to unobserved ability. Luckily, this does not prevent assessing the differential effects of broadband, which is the main goal of the paper. The economic importance and policy relevance of our results do not rely on assuming homogenous returns to ability. Notwithstanding, we outline the exact conditions under which the coefficient on the interaction term indeed captures how broadband changes the *causal* effect of skill groups. In what follows we refer to estimates that satisfy these conditions as "consistent".

Exogeneity of two variables, say x and w, is neither sufficient nor necessary for the interaction $x * w$ to be an exogenous regressor as well. Bun and Harrison (2014) show that the interaction term can be consistently estimated if and only if

$$\begin{aligned} E(x_{i,t}u_{i,t}|w_{i,t}) &= E(x_{i,t}u_{i,t}) \\ E(w_{i,t}u_{i,t}|x_{i,t}) &= E(w_{i,t}u_{i,t}) \end{aligned} \tag{3.3}$$

where $u_{i,t}$ is the error term of the regression model. Equation (3.3) says that the correlation between each regressor and the error term has to be independent of the other regressor. Exogeneity of x and w implies $E(x_{i,t}u_{i,t}) = E(w_{i,t}u_{i,t}) = 0$, which does neither imply nor contradict equation (3.3). This casts doubt on studies that claim to identify interaction terms solely based on exogeneity arguments. However, it also clarifies that consistent

[24]When workers are classified by formal education this means, for example, that broadband alters the return to education.

estimation of an interaction term may be possible if one of the involved regressors is not exogenous.

In our setup, we think of broadband availability as being exogenous once county and time fixed effects are included.[25] Whether or not the other variable can be treated as exogenous depends on the choice of fixed effects, the inclusion of controls and ultimately on the set of assumptions one is willing to make. For the sake of generality we denote the variable, which is supposed to be interacted with broadband as x. x can either be skill group or number of workers (of a certain type) employed.

In the absence of fixed effects, x is likely to be endogenous due to unobserved worker ability / firm productivity. This idea can be formalized by writing down the error term as $u_{i,t} = \beta_a a_i + u^*_{i,t}$ where $u^*_{i,t}$ is the white noise component of the error term, a_i is unobserved heterogeneity and β_a measures its return. With this conventional specification, individual fixed effects are able to remove the unobserved heterogeneity from the error term and therefore lead to consistent estimates.

However, once the returns to unobserved ability depend on broadband, the error term has to be written as:

$$u_{i,t} = \beta_a * x_i + \beta_{a,BB} * BB_{i,t} * a_i + u^*_{i,t} \tag{3.4}$$

Bun and Harrison (2014) show that equation (3.3) can only be satisfied if $\beta_{a,BB} = 0$. Correspondingly, it is not possible to consistently estimate the interaction term once the returns to unobserved ability depend on broadband. At the same time $\beta_{a,BB} \neq 0$ is perfectly compatible with broadband being exogenous[26] as long as unobserved ability and broadband are uncorrelated, i.e., $E(a_i|BB_{i,t}) = 0)$. Besides requiring $\beta_a w = 0$, Bun and Harrison (2014) show that consistent estimation of the interaction term also requires that the correlation between x and unobserved ability does not depend on broadband, i.e., $E(x_{i,t} * a_i|BB_{i,t}) = E(x_{i,t} * a_i)$.

[25] As we argued in section 3.4.1.

[26] Broadband is classified as exogenous if $E(u_{i_t}|BB_{i,t}) = 0$ which also implies $Cov(u_{i_t}, BB_{i,t}) = 0$. Hence, broadband is exogenous if it is unconditionally uncorrelated with the error term.

One cannot directly test whether the true data generating process satisfies these criteria. With x representing skill group, it seems unlikely that broadband availability directly affects the correlation between x and unobserved heterogeneity. Hence, we take this assumption as satisfied. In contrast, it cannot generally be excluded that the returns to unobserved ability depend (positively) on broadband. Given this notion, two questions arise: do individual fixed effects fix the problem and, if not, is it possible to characterize the potential bias?

To answer the first question, consider the case in which $\beta_{a,BB} = 0$. Then, equation (3.3) is satisfied. Nevertheless, the main effect of skill group exhibits an upward bias. The main effect of broadband is downward biased if broadband is a positive determinant of skill group. Using worker (instead of county) fixed effects eliminates this bias. The interaction term can be estimated consistently with both types of fixed effects as the correlation between skill group and the error term is independent of broadband. Once $\beta_{a,BB} > 0$ the situation is different. Using individual fixed effects absorbs only the time constant part of unobserved ability, i.e. $\beta_a * a_i$. Despite $\beta_{a,BB} > 0$, this drives down the (unconditional) correlation between skill group and the error term to zero.[27] In other words: skill group is exogenous. However, this is not sufficient for consistent estimation of the interaction term $x_{i,t} * BB_{i,t}$. Although the unconditional correlation between skill group and the (transformed) error term is zero, the same correlation *conditional* on broadband is not generally zero. Instead, with $\beta_{a,BB} > 0$, it is increasing in broadband. To appreciate this, note that the variance of $BB_{i,t} * a_i$ conditional on $BB_{i,t}$ is increasing in $BB_{i,t}$. Hence, the part of the error term with which skill group is correlated, contributes a larger portion to

[27] To see this, note that the time-varying part of the transformed error term reads $\beta_{a,BB} * [BB_{i,t} - \widehat{BB_i}] * a_i$ where $\widehat{BB_i}$ is average broadband availability over time for individual i and $BB_{i,t} - \widehat{BB_i} \equiv .BB^*_{i,t}$ the demeaned broadband availability. $BB^*_{i,t}$ and a_i are uncorrelated by construction as $BB^*_{i,t}$ varies only within workers (it has mean zero for every worker i), whereas a_i varies only between workers. In addition we have $E(BB^*_{i,t}) = E(a_i) = 0$. This implies that neither $BB_{i,t}$ nor a_i are correlated with $BB^*_{i,t} * a_i$. Hence, x is also not correlated with $BB^*_{i,t} * a_i$ (although it depends on a_i and potentially on $BB_{i,t}$) which directly implies that skill group is not correlated with the transformed error term and thus exogenous.

the variance of the compound error term if broadband is high. The correlation between skill group and the error term is large (small) for high (low) values of broadband. Thus, the estimated coefficient on the interaction term exhibits a bias even when using individual fixed effects.

Using county fixed effects eases the problem as the time constant component of unobserved heterogeneity is partly left in the error term. Thus, the part of the error term, with which the interaction term $x_{i,t} * BB_{i,t}$ is correlated, [28] contributes a smaller share to the overall error term variance thus attenuating the bias in the estimated interaction term coefficient. Hence, although time constant unobserved ability is problematic when estimating main effects, it can be even desirable when estimating interaction terms.

The next step is to characterize the potential bias. As the interaction term is positively correlated with the error term, the coefficient on the interaction term will be upward biased. Even though (on average) x and broadband are uncorrelated with the error term (when using individual fixed effect) both main effects will be downward biased. This happens because (on average) x and broadband (i) are unconditionally uncorrelated with the error term and (ii) (by construction) positively correlated with the interaction term. As the latter is positively correlated with unobserved ability, (on average) x and broadband are, for given values of the interaction term, negatively correlated with unobserved ability and thus with the error term.

The analysis yield the following implications: first, individual fixed effects do not add any value for estimating the interaction term coefficient. Instead using county fixed effects is appropriate. Second, if the interaction term coefficient shall be interpreted as measuring the change in the causal effect of skill group, assuming $\beta_{a,BB} = 0$ is necessary for consistent estimation. Third, in the more realistic case $\beta_{a,BB} > 0$, an upward bias will be present[29]. Fourth, as outlined above, reinterpreting the interaction term coefficient as

[28] As noted above this part reads $\beta_{a,BB} * [BB_{i,t} - \widehat{BB_i}] * a_i$

[29] A similar bias will also be present when estimating the model separately for each type of workers without including an interaction term. In this case, the difference in the estimated effect of broadband (on wages) between samples cannot be fully attributed to differences in skill group, but also to differ-

measuring how broadband changes the return to skill group plus (partially) to unobserved ability is sensible and does not harm the economic significance of our results.

3.4.3 Stable Unit Treatment Value Assumption (SUTVA)

The stable unit treatment value assumption (SUTVA) is another requirement for consistency. The SUTVA states that (i) treatment status of any unit does not affect outcomes of other units (non-interference) and (ii) treatments for all units are comparable (no variation in treatment). The second part is uncontroversial in our application: Providing broadband availability is technologically the same in all counties. The first part requires to assume that increasing broadband availability in one county does not directly influence outcomes of other counties. Although one could think of specific examples in which the assumption seems to be violated, we believe that these exceptions are rare. Hence, we take the SUTVA as generally satisfied. This notion is supported by Akerman, Gaarder, and Mogstad (2015) who find that broadband impacts the labor market only via firms broadband adoption and not via changes in the demand for goods. Broadband adoption by a firm in one county does not influence labor market outcomes in another county.

ences in average unobserved ability between samples. Consider an individual low-skilled worker with unobserved ability equal to the average ability of his class. The broadband coefficient of the "low skill sample" then correctly measures the expected wage change of this worker due to broadband. However, when the worker suddenly acquires high skill the "high skill sample" coefficient does not measure the expected broadband-associated wage change, because the workers ability is still lower than the average ability of high skilled workers. Hence, the reported difference between low-skilled and high-skilled coefficients overestimates the true difference caused by different skill groups.

3.5 Skill-Biased Technological Change

3.5.1 Empirical Model

To test the SBTC hypothesis, we estimate two types of models. The first model operates at the worker level and evaluates if broadband increases wage differences between workers of different types. The second model analyzes whether broadband changes output elasticities of different workers.

For the wage regression the empirical model reads[30]:

$$\begin{aligned} log(Wage)_{i,t} = \beta_0 + \beta_1 BB_{c,t} + \boldsymbol{\beta_2'} \boldsymbol{x_{i,t}} + \boldsymbol{\beta_3'}(\boldsymbol{x_{i,t}} BB_{c,t}) + \\ \boldsymbol{\beta_4'} \boldsymbol{Controls_{i,t}} + \boldsymbol{\beta_5'} * \boldsymbol{\xi_c} + \boldsymbol{\beta_6'} * \boldsymbol{\eta_I} + \boldsymbol{\beta_7'} * \boldsymbol{\tau_t} \\ \boldsymbol{\beta_8'} \boldsymbol{CountyChar_{c,2000}} \boldsymbol{\tau_t} + \epsilon_{i,t} \end{aligned} \tag{3.5}$$

where $log(Wage)_{i,t}$ is the log of the daily wage earned by worker i in period t, $\boldsymbol{x_{i,t}}$ is a vector of mutually-exclusive dummy variables representing either educational attainment or job-routinization, $BB_{c,t}$ is broadband availability in county c in period t. $\boldsymbol{Controls_{i,t}}$ is a vector containing baseline worker- or firm-specific control variables such as experience, firm age and whether the wage bargaining takes place individually or on a collective level. $\boldsymbol{\xi_c}$, $\boldsymbol{\tau_t}$ and $\boldsymbol{\eta_I}$ represent county, year, and industry fixed effects. Finally, $\boldsymbol{CountyChar_{c,2000}}$ is a vector containing year 2000-values of baseline county characteristics, which have turned out to be significant determinants of broadband. We report results with and without these heterogeneous time trends. Standard errors are clustered at the county level and are robust to heteroscedasticity[31].

Firm regressions are motivated by the notion that production takes place according to a conventional Cobb-Douglas production function. However, in contrast to the textbook

[30] Bold characters represent vectors

[31] We choose this level of clustering as our treatment variable, that is, broadband availability, varies on the county level.

model, we allow output elasticities to depend on broadband availability[32]:

$$
\begin{aligned}
ValueAdded_{f,t} =& e^{\beta_0+\beta_1*BB_{c,t}}K^{\beta_{2,K}+\beta_{3,K}BB_{c,t}} \\
& N_0^{\beta_{2,N_0}+\beta_{3,N_0}BB_{c,t}}N_1^{\beta_{2,N_1}+\beta_{3,N_1}BB_{c,t}} \\
& N_2^{\beta_{2,N_2}+\beta_{3,N_2}BB_{c,t}}e^{\epsilon_{f,t}}
\end{aligned}
\tag{3.6}
$$

where $ValueAdded_{f,t}$ is the value added by firm f in period t, K is the size of the capital stock, N_0, N_1 and N_2 denote the number of employees of a certain skill group. We also estimate production functions where we use total wage bills instead of employee counts. To the extent that wages capture quality of workers, this could be a more precise measure for labor input. Yet, it is also noisier due to wage dispersion across equally productive workers as well as due to wage censoring.

$e^{\beta_0+\beta_1*BB_{c,t}}$ is average TFP, whereas η_I and ξ_c represent a full set of county and industry fixed effects. Finally, $e^{\epsilon_{f,t}}$ is the firm- and time specific deviation from average TFP.[33]

Taking logs, adding fixed effects as well as additional controls yields the following linear model:

$$
\begin{aligned}
log(ValueAdded_{f,t}) = & \beta_0+\beta_1 BB_{c,t}+\boldsymbol{\beta_2'x_{f,t}}+\boldsymbol{\beta 3}'(\boldsymbol{x_{i,t}}BB_{c,t})+ \\
& \boldsymbol{\beta_4' Controls_{i,t}}+\boldsymbol{\beta_5'\xi_c}+\boldsymbol{\beta_6'\eta_I}+ \\
& \boldsymbol{\beta_7'\tau_t}+\boldsymbol{\beta_8' CountyChar_{c,2000}\tau_t}+\epsilon_{f,t}
\end{aligned}
\tag{3.7}
$$

where $Controls_{i,t}$ is a vector containing firm age (and its square) as well as a dummy for collective bargaining and the vector of log inputs $\boldsymbol{x_{i,t}'} = [log(K_i)\ log(N_{0,i})\ log(N_{1,i})\ log(N_{2,i})]$. Note that output elasticities are given by $\boldsymbol{\beta_2}+\boldsymbol{\beta_3}*BB$ and thus can be inferred directly from the estimated coefficients. If one of the elements in $\boldsymbol{\beta_3'} = [\beta_{3,K_i}\beta_{3,N_{0,i}}\beta_{3,N_{1,i}}\beta_{3,N_{2,i}}]$ is significantly different from zero, broadband has a significant impact on the output elasticity of the corresponding production factor. Conversely, if $\boldsymbol{\beta_3}$ is zero, output elasticities

[32]This specification is inspired by Akerman, Gaarder, and Mogstad (2015).

[33]In the linearized regression model this term corresponds to the error term.

are given by $\boldsymbol{\beta_2}$ alone.[34] $\beta_1 + \boldsymbol{\beta_3'} \boldsymbol{x_{i,t}}$ captures the main effect of broadband given a certain input factor combination.

The above specifications implicitly assume that the effects of higher broadband availability are already present in the year of its increase, whereas the firms may need some time to adjust to the new ICT opportunities. We complement the analysis with the event-study regressions. Within each county, we center the data around the year with the largest increase in broadband availability and denote it y_0. We keep the observations up to three years before and after y_0. To capture the change in output elasticities and wages due to the introduction of broadband, we pull the years in two groups: the dummy variable $after$ equals one for years bigger or equal to y_0, and zero otherwise. We then estimate similar models to (3.5) and (3.7) but instead of interacting employee types $x_{i,t}$ with the annual broadband measure, we interact them with the dummy variable $after$. In addition, we estimate the production function and the wage regression, separately for each year before and after y_0, to see how the corresponding coefficients evolve over time. We use the same set of controls, including year and county fixed effects. Such exercise allows to check for the presence of pre-trends and for the timing of the effect.

3.5.2 Results

We estimate equations (3.5) and (3.7) using time periods 2006 to 2010 throughout which broadband data is continuously available (baseline sample). In addition we exploit that in 2000 broadband availability was zero across all counties. Hence, the sample consists of year 2000 as well as 2006 - 2010 values. We have also estimated models which use only values from 2000 and 2006 as well as models relying on 2006 - 2010 values only. To keep tables parsimonious we only report results using the full sample. Results using the above-mentioned alternative sample selections are available upon request, but do not

[34] β_{2,N_0}, for example, measures the output elasticity of an low-skilled or low-routine worker if broadband availability is zero.

qualitatively differ from the results presented in the text.[35]. Workers are classified using either job routinization or formal education. [36]We consider classifying by routinization as economically more sensible. Hence we put a larger weight on results derived using this classification. Results using formal education are reported mainly for comparability reasons. All models are estimated with and without heterogeneous time trends.

Output Elasticity Regressions

Table C.4 in the Appendix summarizes results regarding output elasticities. Overall our results support SBTC. When workers are classified by job routinization (columns (1) to (4) of Table C.4) theory suggests that the output elasticity of low (high) routine workers increases (decreases) with broadband. Results largely confirm this theory: broadband decreases the output elasticity of highly routinized workers independent of whether heterogeneous time trends are included. When the number of workers employed is used as input factor, a 10 percentage point increase in broadband is associated with a decrease in the output elasticity of highly routinized workers by 1.2 percentage points.[37]

[35]In the output elasticity regressions we also present results from using the sum of wages paid (instead of numbers of workers employed) as input factors. We only show these additional results for the sake of comparability with other papers. Typically, "wages paid" are used in order to capture quality differences between workers. These quality differences, however, are already partially captured by distinguishing between three types of workers. On the other hand, wage bills include much additional noise, because very similar workers obtain potentially very different wages. This noise biases all estimated coefficients toward zero. Thus, our argumentation is based only on results obtained using "number of workers employed" as input factor.

[36]In both cases we group workers in three categories.

[37]We use the convention to measure output elasticities in percent. If the production function is given by $Y = K^{0.5}N^{0.5}$, both the output elasticity of capital and labor is 50%, implying that a 1% increase in labor (or capital) results in a 0.5% increase in output. In our analysis we are interested in how broadband *changes* these output elasticities. Stating that "broadband increases the output elasticity of labor by 1 percentage point" implies, for example, that the output elasticity of labor increases from 50% to 51%. We do so in order to provide an intuitive sense about the quantitative size of the effects associated with movements in broadband availability.

The expected beneficial effect for non-routine workers is also visible: a 10 percentage point increase in broadband increases the output elasticity of non-routine workers by 0.5 to 0.75 percentage points (depending on whether heterogeneous time trends are included). The estimated coefficient is somewhat smaller in absolute size compared to the one estimated for routine workers. Nevertheless, it remains significant at the 10% confidence level. Medium routinized jobs experience the smallest change due to broadband. The corresponding output elasticity is estimated to increase only slightly. Note that the effect is not statistically different from zero.

Classifying workers by formal education yields similar, yet not identical results (see columns (1) to (4) of Table C.4). The output elasticity of low-skilled workers significantly decreases while the output elasticity of high-skilled workers significantly increases. The latter increases by about 2.2 percentage points (for each 10 percentage point increase in broadband), while the former drops by about 0.65 percentage points. Both effects are statistically different from zero. Medium-skilled workers (like low-skilled workers) experience a decrease in their output elasticity. For each 10 percentage point increase in broadband the output elasticity of medium skilled workers decreases by 1.9 percentage points. These results are in line with the task based interpretation of SBTC if medium skilled workers work more often in highly routinized jobs compared to low skilled workers. Table 3.2 shows that only 22% of low-skilled workers work in non-routine jobs whereas 42% of medium skilled workers do. Correspondingly, the task-based interpretation cannot fully explain the observed results. As only about 8% of all workers are classified as medium-skilled workers we hypothesize that the striking results for medium skilled workers could be mainly driven by chance, and should not be over-interpreted. In total, our results support the SBTC hypothesis.

Wage Regressions

Table C.5 in the Appendix summarizes results from the wage regressions. Results are shown with and without heterogeneous time trends. Censored observations are either dropped from the sample (columns (1), (2), (5) and (6)) or imputed (remaining columns) using the wage imputing procedure by Dustmann, Ludsteck, and Schönberg (2009). The first four columns relate to models in which workers are classified by formal education, whereas the last four columns relate to job routinization models. SBTC suggests that broadband leads to increasing wages of high skilled / non -routine workers compared to wages of low skilled / routine workers. Overall, our results verify these expectations, in particular when using imputed wages.

Relative wages of routine workers (compared to non-routine workers) are significantly negatively affected by broadband. The effect is significant irrespective of whether censored wages are dropped from the sample (columns (5) and (6) of Table C.5) or whether they are replaced by imputed wages (columns (7) and (8) of Table C.5). However, the effect is estimated to be twice as large (0.5 percentage points for each 10 percentage point increase in broadband) when wages are imputed. In contrast, relative wages of medium skilled workers are left virtually unchanged. As the main effect of broadband is also not statistically different from zero, our result indicate that non-routine workers are not able to benefit from their increased output elasticity.

Columns (1) to (4) of Table C.5 display results when workers are classified by formal education. When censored observations are dropped, broadband internet significantly lowers the wage of medium skilled workers relative to low skilled workers. These results reflect that the output elasticity of these workers decreases not only in absolute terms, but also relative to low skilled workers. However, the effect becomes insignificant once censored wages are replaced by imputed wages.

Regarding high skilled workers results are somewhat puzzling. Although broadband internet clearly increases the output elasticities of high skilled workers there is no corresponding change in the relative wage. Instead our estimates indicate that broadband does not significantly change the wage premium high skilled workers earn compared to low skilled workers. Put together, we interpret our results as a confirmation of the SBTC change hypothesis. We can also partially confirm the job polarization effect in workers' wages.

Event-Study Results

To conduct the Event-study analysis, we center the data within each county around the year y_0, when the broadband growth was the largest. As the available broadband dataset starts in 2006, y_0 should be interpreted as the year with the largest broadband expansion during the period 2007-2010. In our dataset, for about 70% of counties $y_0 = 2007$; for 25% - $y_0 = 2008$; for 4%- $y_0 = 2009$; and for less than 1% $y_0 = 2010$.

We then pull the observations up to three years before y_0 in the pre-broadband group and the observations in or up to three years after y_0 in the post-broadband group. The Event-study specifications are similar to our baseline regressions, the only difference being that instead of the interaction with a broadband availability measure, we interact the skill groups with a dummy variable $After$, which is equal 1 for years $\geq y_0$. The interaction coefficients reflect the difference in output elasticities and in returns to skills between the periods before and after the introduction of broadband conditional on controls, year and county fixed effects. As before, effects are identified through different timing in broadband expansion across German counties.

In line with our baseline results, we expect to find evidence for the SBTC. In the wage regressions (Table C.7), we see that broadband increases the wage penalty for workers in highly routinized occupations. In the post-broadband period, wages of these workers decrease by about 3.06-4.21%. The results are robust, when we replace censored wages by imputed wages rather than dropping the corresponding observations from the sample. Similarly, Graph B in Figure C.6 illustrates that the wage penalty for highly-routinized work in the years following y_0 is growing.[38]

Results from the firm-level regressions (Table C.6), though, do not concord with our baseline specification: the interaction coefficients between the dummy $After$ and the

[38]The confidence interval is large, as we estimate the regressions separately for each time-period.

low-skill (high-routine) labor input are positive, contrary to our previous results and the SBTC hypothesis. One should note, however, several caveats regarding the Event-study approach due to the limitations of our dataset. First, we cannot precisely estimate the y_0 as broadband data is not available for years between 2001-2005. Median broadband availability in 2006 (the first year in our broadband dataset) was already above 70%, and it is likely that for most counties the year with the largest increase is within the time period we do not observe. Figure C.6 also illustrates that output elasticities are estimated with a lot of noise. Second, estimations suffer from a composition effect: the last year in our dataset is 2010, and for counties with $y_0 > 2007$, we cannot observe all three time periods after y_0. Given these limitations, we prefer to base our conclusions on the results obtained from the baseline specification.

3.6 Broadband and Past Unemployment

3.6.1 Theoretical Background

This section analyzes whether the effect of being unemployed on the reemployment wage depends on broadband availability. Nichols, Mitchell, and Lindner (2013) have identified several channels that can explain why past unemployment spells lower wages: (i) unemployment may lead to real deterioration of human capital; (ii) if workers are unsure about their own productivity (or if they expect potential employers to be), they may downward adjust their reservation wage when unemployment prolongs , even if there is no real human capital deterioration; (iii) with imperfect information, employers infer that workers with long unemployment spells are likely to be low productivity workers, even if a specific worker is unemployed only by chance; (iv) more productive workers find new employment more quickly, implying that being unemployed is spuriously correlated with being a low productivity worker. While channels (i)-(iii) constitute causal mechanisms through which unemployment lowers wages, (iv) leads merely to a statistical correlation. In our analysis, we do not claim to identify the causal effect of past unemployment spells on wages. Instead, we are interested in how broadband changes the wage difference between workers, which were previously unemployed and those who were not, independent of the causal origin of these differences.

Regarding identification, the theoretical considerations outlined in section 3.4.2 still apply. The interaction term can be estimated consistently even if $x_{i,t}$ is correlated with the error term as long as the return to unobserved worker ability does not depend on broadband. If the return to unobserved worker ability depends positively on broadband, the interaction term exhibits an upward bias. In this case, the estimated coefficient captures not only how broadband alters the return to past unemployment but also, to some extent, how it alters the return to unobserved ability.

We expect broadband to lower the unemployment wage penalty for several reasons: first, broadband potentially mitigates search frictions leading to shorter unemployment spells, which in turn mitigates effects (i) to (iii). Second, broadband may also increase the possibility for unemployed workers to keep in touch with their field as well as with former and potentially future co-workers. We test this hypothesis by using the model from section 3.5, where $\boldsymbol{x_{i,t}}$ (see equation (3.5)) now represents a dummy variable indicating whether or not a worker was unemployed within the past five years.

3.6.2 Results

We first discuss results obtained when including all workers in the sample. Afterwards we assess potential implications for SBTC by estimating the model separately for workers of different routine groups.

The upper panel of Table C.9 as well as Table C.8 in the Appendix shows the results from the unemployment regression using the sample containing all workers. The main effect reflects the wage difference between workers with and without unemployment spells if broadband availability fixed at zero. The estimated wage gap is remarkably robust: The quantitative values range between 0.2112 and 0.2322 depending on whether imputed wages and / or heterogeneous time trends are used, , implying that previously unemployed workers earn between 21 and 23% less compared to other workers. These estimates should be interpreted as the combination of self selection and effects directly caused by experiencing an unemployment spell (see channels (i)-(iii) above). The main coefficient of interest, i.e. the interaction between the past unemployment dummy and broadband is positive throughout all specifications, indicating that broadband indeed mitigates the wage penalty associated with past unemployment spells. A 10 percentage points increase in broadband reduces the wage penalty by 0.84 (with heterogeneous time trends) to 0.97% (without heterogeneous time trends) when observations with censored wages are dropped from the sample. Both coefficients are highly statistically significant. When imputed wages are used the coefficient is cut in half. Correspondingly, the estimated coefficients are only weakly significantly different from zero. Despite these weaker results, the overall conclusion remains that broadband internet significantly mitigates the wage penalty of previously unemployed workers.

In the context of SBTC, it is interesting to ask whether the wage penalty reduction differs between worker groups. The second panel of Table C.9 shows that when restricting the sample to workers performing non-routine tasks, the estimated coefficients on the interaction term are very similar compared to results obtained from the full sample. Medium routinized workers (third panel of Table C.9) experience the strongest reduction in the wage penalty. Coefficients are somewhat larger compared to the full sample and significant even when imputed wages are used. In stark contrast, the reduction of the wage penalty is completely absent for high routine workers[39] (fourth panel of Table C.9). Our results suggest that workers in highly routinized occupations have difficulties to use broadband as a tool to find new employers quicker and prevent human capital deterioration. In that way, our analysis uncovers another variety of SBTC.

Table C.8 presents results from repeating the same exercise with formal education as classification device. The beneficial effect is strongest for high skilled workers followed by

[39]This is particularly important as high routine workers experience past unemployment spells more often than other workers (see Table 3.4).

low skilled workers (which represent 75% of all workers in the sample). Similarly as for high routine workers, there is no significant change in the unemployment wage penalty for medium skilled workers.

3.7 Conclusion

In this paper, we empirically study the differential effects of increasing broadband availability on labor market outcomes. We do so by combining German data on broadband rollout with the linked employer-employee dataset provided by the Institute for Employment Research. To test the SBTC hypothesis, we classify workers using formal education and the degree of job routinization. In addition, we test whether broadband influences the wage penalty of previously unemployed workers.

Regarding the change in output elasticities our results largely confirm the SBTC hypothesis: output elasticities of low and medium skilled workers decline, while high skilled workers are able to realize higher output elasticities. Similarly, the output elasticity of workers performing non-routine (abstract) tasks increases, while high routine workers experience a lower output elasticity. The broadband effect on the output elasticity of workers in medium routinized jobs depends on sample selection. Using the full sample the effect is not significant. Overall, results regarding output elasticities definitely strengthen the task-biased interpretation of the SBTC hypothesis.

The documented changes in output elasticities partially pass-through on relative wages. In line with those results, relative wages of high routine workers drop significantly. Compared to the change in output elasticities, the effect on relative wages is smaller reflecting some form of wage rigidity. In contrast, we do not find an increasing wage premium for high skilled workers due to broadband. As we believe that classifying workers according to job routinization is more appealing than using formal education, we interpret our wage results as a confirmation of SBTC.

In addition to investigating classical SBTC issues, we found convincing evidence that broadband narrows the wage gap between workers who were previously unemployed and those who were not. Depending on the particular specification, a 10 percentage point increase in broadband lowers the wage penalty due to past unemployment spells by 0.8 to 1.4%. When using imputed wages, estimates drop by around a half. These results suggest that broadband either mitigates search frictions or slows down the loss of human capital by enabling unemployed workers to keep in touch with their profession. We also report that the documented beneficial effect is not present when restricting the sample to high routine workers.

Finally, we call attention to the problem that the returns to unobserved ability may depend on broadband. In this context, we explicitly outline the conditions necessary for consistent estimation of the interaction terms estimated in this paper. As similar problems were largely ignored by the existing literature and may well arise in a broad range of applications, we think of these remarks as of general interest. In addition, we provide guidance for appropriate interpretation of the estimated interaction terms.

Appendix A

Appendix to Chapter 1

A.1 Value Functions

Workers: Workers can become employed only at firms that produce consumption goods, since innovation firms will not be active on the labor market for production workers. Firms will post vacancies and hire unemployed workers. Denote the fraction of vacancies posted by type $t \in \{B, R\}$ firms with productivity y_i and N_i employed workers by $v^t(y_i, N_i)$. We therefore can write the value of being unemployed as,

$$rU = z + \theta\lambda_m(\theta) \sum_{t\in\{B,R\},y_i\in\{0,y\},N_i} \max\left[v^t(y_i, N_i) W^{O,t}\left(w^{O,t}(y_i, N_i)\right) - U, 0\right], \tag{A.1}$$

where the value of being employed at a type t firm as an outsider, that is, as a newly hired worker (indexed by O), at the wage $w^{O,t}(y, N_i)$ is given by,

$$rW^{O,t}\left(w^{O,t}(y, N_i)\right) = w^{O,t}(y, N_i) + \delta\left(\max\left[W^{I,t}\left(w^{I,t}(0, N_i)\right), U\right] - W^{O,t}\left(w^{O,t}(y, N_i)\right)\right). \tag{A.2}$$

Once a worker is employed, he becomes an insider, indexed by I, and has employment protection. This protection (manifested through firing costs) implies that insiders will receive a higher wage when wages are renegotiated. The value of being employed as an insider at a firm with $y_i = y$ is given by,

$$rW^{I,t}\left(w^{I,t}\left(y,N_i\right)\right) = w^{I,t}\left(y,N_i\right) + \delta\left(\max\left[W^{I,t}\left(w^{I,t}\left(0,N_i\right)\right),U\right] - W^{I,t}\left(w^{I,t}\left(y,N_i\right)\right)\right). \tag{A.3}$$

The value of being employed depends on whether the surplus of the match is negative if the firm is hit by a productivity shock. If it is negative, wage negotiations will fail and the worker will be laid off. However, if the surplus of a match is positive even if a productivity shock hits, then wages will be renegotiated and the value of being employed changes to,

$$rW^{I,R}\left(w^{I,R}\left(0,N_i\right)\right) = \begin{cases} w^{I,R}\left(0,N_i\right) + \eta\left(W^{I,R}\left(w^{I,R}\left(y,N_i\right)\right) - W^{I,R}\left(w^{I,R}\left(0,N_i\right)\right)\right) \\ +\lambda_d\left(U - W^{I,R}\left(w^{I,R}\left(0,N_i\right)\right)\right), \quad \text{if} \quad t = R, \end{cases} \tag{A.4}$$

$$rW^{I,B}\left(w^{I,B}\left(0,N_i\right)\right) = \begin{cases} w^{I,B}\left(0,N_i\right) + g\left(\varphi\right)\left(W^{I,B}\left(w^{I,B}\left(y,N_i\right)\right) - W^{I,B}\left(w^{I,B}\left(0,N_i\right)\right)\right) \\ +\lambda_d\left(U - W^{I,B}\left(w^{I,B}\left(0,N_i\right)\right)\right), \quad \text{if} \quad t = B. \end{cases} \tag{A.5}$$

The value of being employed at a firm with $y_i = 0$ depends on the wage, the type $t \in \{B, R\}$ of a firm, the respective rate at which the firm is able to restore y_i to y, that is, η for firms that do their own research and $g(\varphi)$ for firms that buy the innovation, and on the destruction rate λ_d.

Firms: Firms that specialize in innovation will not be active on the labor market for production workers, i.e., $N_i^S = 0$. Thus, labor market conditions only enter the expected profit of a selling firm via the prices it receives for its innovation. The expected profit of a type S firm that is doing research to obtain a new innovation is given by,

$$\left(r + \lambda_s\right)\pi^S\left(0,0,k_i\right) = -k_i + \eta\left(\pi^S\left(0,y,k_i\right) - \pi^S\left(0,0,k_i\right)\right). \tag{A.6}$$

The expected profit of a type S firm, which sells its innovation, is given by,

$$\begin{aligned} r\pi^S\left(0,y,k_i\right) = {} & \varphi g\left(\varphi\right)\max\left[E_{N_j}\left[p\left(k_i,N_j^B\right)\right] + \pi^S\left(0,0,k_i\right) - \pi^S\left(0,y,k_i\right),0\right] \\ & + \delta\left(\pi^S\left(0,0,k_i\right) - \pi^S\left(0,y,k_i\right)\right), \end{aligned} \tag{A.7}$$

where the price $p\left(k_i, N_j^B\right)$ that is negotiated on the innovation market will depend on the surplus that is generated. The surplus will depend on the innovation cost k_i of the seller and the number of workers employed at the buyer N_j^B. The buyer's innovation cost does not enter the surplus, since a firm that decided to buy the input y will also do so in the future, that is, it will never decide to do own research. Sellers only sell their innovation when the surplus is positive.

The Bellman equation (1.2) characterizes the expected profit of a type B or R firm with productivity $y_i = y$, innovation cost k_i, and N_i^t workers. The Bellman equations for a type R firm that decides to do own research when it was hit by a productivity shock are given by,

$$(r+\lambda_d)\,\pi^{O,R}(0,0,k_i) = -k_i + \eta\left(\pi^{O,R}\left(N_i^R, y, k_i\right) - \frac{c}{\lambda_m(\theta)}N_i^R - \pi^{O,R}(0,0,k_i)\right), \tag{A.8}$$

$$(r+\lambda_d)\,\pi^{I,R}\left(N_i^R,0,k_i\right) = -w^{I,R}\left(0,N_i^R\right)N_i^R - k_i + \eta\left(\pi^{I,R}\left(N_i^R,y,k_i\right) - \pi^{I,R}\left(N_i^R,0,k_i\right)\right), \tag{A.9}$$

with and without laying off workers, respectively. A type B firm that decides to acquire an innovation when it is without one has the following expected profit,

$$(r+\lambda_d)\,\pi^{O,B}(0,0,k_i) = g(\varphi)\int_0^{k_{\max}} \max\left[S^B,0\right]h(k_j)\,dk_j, \tag{A.10}$$

$$(r+\lambda_d)\,\pi^{I,B}\left(N_i^B,0,k_i\right) = -w^{I,B}\left(0,N_i^B\right)N_i^B + g(\varphi)\int_0^{k_{\max}} \max\left[S^B,0\right]h(k_j)\,dk_j, \tag{A.11}$$

with and without laying off workers, respectively, where the surplus for the buyer is given by,

$$S^B = \begin{cases} \pi^{O,B}\left(N_i^B,y,k_i\right) - \dfrac{c}{\lambda_m(\theta)}N_i^B - \pi^{O,B}(0,0,k_i) - p(k_j,0) \text{ if } L_i^B = N_i^B, \\ \\ \pi^{I,B}\left(N_i^B,y,k_i\right) - \pi^{I,B}\left(N_i^B,0,k_i\right) - p\left(k_j,N_i^B\right) \text{ if } L_i^B = 0. \end{cases}$$

The decision whether to do own research or, instead, acquire an innovation depends on the rate η or $g(\varphi)$ at which the firm can restore its productivity level, on the level of firm-specific innovation cost k_i, and on the expected price of the innovation. Since a firm can buy an innovation only from firms that decide to sell their innovations, we denote by $h(k_j)$ the pdf of those firms that are willing to sell their innovations and that have innovation cost k_j (in equilibrium $h(k_j) = \gamma(k_j)/\Xi(k^*)$, since all firms with k_j below some threshold k^* prefer to specialize in innovation and are willing to sell their innovations). The maximum operator in the integral guarantees that firms will buy an innovation only when the surplus is positive.

The marginal value of an additional worker for a firm with $y_i = y$ that wants to hire new workers ($h = O$) is given by differentiating equation (1.2). The value depends on whether a firm lays off workers when it is hit by a productivity shock, i.e.,

$$\frac{\partial \pi^{O,t}(N_i^t, y, k_i)}{\partial N_i^t} = \begin{cases} \dfrac{\alpha y \left(N_i^t\right)^{\alpha-1} - w^{O,t}\left(y, N_i^t\right) - \dfrac{\partial w^{O,t}\left(y, N_i^t\right)}{\partial N_i^t} N_i^t + \delta \dfrac{\partial \pi^{I,t}(N_i^t, 0, k_i)}{\partial N_i^t}}{r+\delta} & \text{if } L_i^t = 0, \\ \dfrac{\alpha y \left(N_i^t\right)^{\alpha-1} - w^{O,t}\left(y, N_i^t\right) - \dfrac{\partial w^{O,t}\left(y, N_i^t\right)}{\partial N_i^t} N_i^t - \delta f}{r+\delta} & \text{if } L_i^t = N_i^t, \end{cases} \tag{A.12}$$

The third term in the marginal value of an additional worker $\left(\partial w^{O,t}\left(y, N_i^t\right)/\partial N_i^t\right) N_i^t$ captures the fact that each time a new worker is hired, the wages of all workers are renegotiated and adjusted to the new marginal revenue product.

The marginal value of an additional worker for a firm, which has been hit by a productivity shock but retains its workers can be obtained by differentiating equations (A.9) and (A.11) and using equation (A.14) to substitute out the price for an innovation (see Appendix A.4 below). Substituting the vacancy creation condition (1.3) implies equation (1.6).

A.2 Wage Equations

Let us first consider the wages paid in type R firms. Wage bargaining according to equations (1.4) and (1.5) implies the following surplus splitting rule for outsiders in firms with $y_i = y$, for insiders in firms with $y_i = y$ and for insiders in firms with $y_i = 0$,

$$(1-\gamma)\left(W^{O,R}\left(w^{O,R}\left(y, N_i^R\right)\right) - U\right) = \gamma\left(\frac{\partial \pi^{O,R}(N_i^R, y, k_i)}{\partial N_i^R}\right),$$
$$(1-\gamma)\left(W^{I,R}\left(w^{I,R}\left(y, N_i^R\right)\right) - U\right) = \gamma\left(\frac{\partial \pi^{I,R}(N_i^R, y, k_i)}{\partial N_i^R} + f\right),$$
$$(1-\gamma)\left(W^{I,R}\left(w^{I,R}\left(0, N_i^R\right)\right) - U\right) = \gamma\left(\frac{\partial \pi^{I,R}(N_i^R, 0, k_i)}{\partial N_i^R} + f\right),$$

where firms only have to pay firing costs f, if they do not continue to employ an insider. Substituting the marginal value of a worker in the respective situation from equations (A.12) and (1.6), i.e.,

$$\frac{\partial \pi^{O,R}(N_i^R, y, k_i)}{\partial N_i^R} = \frac{\alpha y \left(N_i^R\right)^{\alpha-1} - w^{O,R}\left(y, N_i^R\right) - \dfrac{\partial w^{O,R}\left(y, N_i^R\right)}{\partial N_i^R} N_i^R + \delta \dfrac{\partial \pi^{I,R}(N_i^R, 0, k_i)}{\partial N_i^R}}{(r+\delta)},$$
$$\frac{\partial \pi^{I,R}(N_i^R, y, k_i)}{\partial N_i^R} = \frac{\alpha y \left(N_i^R\right)^{\alpha-1} - w^{I,R}\left(y, N_i^R\right) - \dfrac{\partial w^{I,R}\left(y, N_i^R\right)}{\partial N_i^R} N_i^R + \delta \dfrac{\partial \pi^{I,R}(N_i^R, 0, k_i)}{\partial N_i^R}}{(r+\delta)},$$
$$\frac{\partial \pi^{I,R}(N_i^R, 0, k_i)}{\partial N_i^R} = \frac{-w^{I,R}\left(0, N_i^R\right) - \dfrac{\partial w^{I,R}\left(0, N_i^R\right)}{\partial N_i^R} N_i^R + \eta \dfrac{\partial \pi^{I,R}(N_i^R, y, k_i)}{\partial N_i^R}}{(r+\lambda_d+\eta)},$$

and the workers' surplus from employment using equations (A.2) and (A.4), i.e.,

$$\left[W^{O,R}\left(w^{O,R}\left(y, N_i^R\right)\right) - U\right] = \frac{w^{O,R}\left(y, N_i^R\right) - rU + \delta\left[W^{I,R}\left(w^{R}\left(0, N_i\right)\right) - U\right]}{(r+\delta)},$$
$$\left[W^{I,R}\left(w^{I,R}\left(y, N_i^R\right)\right) - U\right] = \frac{w^{I,R}\left(y, N_i^R\right) - rU + \delta\left[W^{I,R}\left(w^{R}\left(0, N_i\right)\right) - U\right]}{(r+\delta)},$$
$$\left[W^{I,R}\left(w^{I,R}\left(0, N_i^R\right)\right) - U\right] = \frac{w^{I,R}\left(0, N_i\right) - rU + \eta\left[W^{I,R}\left(w^{i,R}\left(y, N_i\right)\right) - U\right]}{(r+\eta+\lambda_d)},$$

and rearranging using again the surplus splitting rules in the equations above, leads to the following set of differential wage equations,

$$w^{O,R}\left(y,N_i^R\right) = (1-\gamma)\,rU + \gamma\left(\alpha y\left(N_i^R\right)^{\alpha-1} - \frac{\partial w^{O,R}\left(y,N_i^R\right)}{\partial N_i^R}N_i^R\right) - \gamma\delta f,$$
$$w^{I,R}\left(y,N_i^R\right) = (1-\gamma)\,rU + \gamma\left(\alpha y\left(N_i^R\right)^{\alpha-1} - \frac{\partial w^{I,R}\left(y,N_i^R\right)}{\partial N_i^R}N_i^R\right) + \gamma r f,$$
$$w^{I,R}\left(0,N_i^R\right) = (1-\gamma)\,rU - \gamma\frac{\partial w^{I,R}\left(0,N_i^R\right)}{\partial N_i^R}N_i^R + \gamma\left(r+\lambda_d\right)f,$$

Solving the differential equations for $w^{O,R}\left(y,N_i^R\right)$ and $w^{I,R}\left(y,N_i^R\right)$ following Cahuc and Wasmer (2001) and Cahuc, Marque, and Wasmer (2008) gives the above wage equations. If we substitute the value of being unemployed by $(1-\gamma)\,rU = (1-\gamma)\,z + \gamma\theta c$, we obtain wages as a function of labor market tightness. The differential wage equation for $w^{I,R}(0,N_i)$ is independent of N_i^R and is therefore given by setting $\partial w^{I,R}\left(0,N_i^R\right)/\partial N_i^R = 0$.

Now consider wages paid by type B firms. The surplus splitting rules are given by,

$$(1-\gamma)\left(W^{O,B}\left(w^{O,B}\left(y,N_i^B\right)\right) - U\right) = \gamma\left(\frac{\partial\pi^{O,B}(N_i^B,y,k_i)}{\partial N_i^B}\right),$$
$$(1-\gamma)\left(W^{I,B}\left(w^{I,B}\left(y,N_i^B\right)\right) - U\right) = \gamma\left(\frac{\partial\pi^{I,B}(N_i^B,y,k_i)}{\partial N_i^B} + f\right),$$
$$(1-\gamma)\left(W^{I,B}\left(w^{I,B}\left(0,N_i^B\right)\right) - U\right) = \gamma\frac{r+\lambda_d+g(\varphi)(1-\beta)}{r+\lambda_d+g(\varphi)}\left(\frac{\partial\pi^{I,B}(N_i^B,0,k_i)}{\partial N_i^B} + f\right),$$

where the surplus splitting rule for the case with $y_i = 0$ takes into account that innovation price bargaining implies that part of the marginal value of continuing the employment relationship (the fraction β) is going to the seller. This causes the additional term in the last equation. The marginal values of employing a worker are given by,

$$\frac{\partial\pi^{O,B}(N_i^B,y,k_i)}{\partial N_i^B}=\frac{\alpha y\left(N_i^B\right)^{\alpha-1}-w^{O,B}\left(y,N_i^B\right)-\dfrac{\partial w^{O,B}\left(y,N_i^B\right)}{\partial N_i^B}N_i^B+\delta\dfrac{\partial\pi^{I,B}(N_i^B,0,k_i)}{\partial N_i^B}}{(r+\delta)},$$

$$\frac{\partial\pi^{I,B}(N_i^B,y,k_i)}{\partial N_i^B}=\frac{\alpha y\left(N_i^B\right)^{\alpha-1}-w^{I,B}\left(y,N_i^B\right)-\dfrac{\partial w^{I,B}\left(y,N_i^B\right)}{\partial N_i^B}N_i^B+\delta\dfrac{\partial\pi^{I,B}(N_i^B,0,k_i)}{\partial N_i^B}}{(r+\delta)},$$

$$\frac{\partial\pi^{I,B}(N_i^B,0,k_i)}{\partial N_i^B}=\frac{-w^{I,B}\left(0,N_i^B\right)-\dfrac{\partial w^{I,B}\left(0,N_i^B\right)}{\partial N_i^B}N_i^B+g\left(\varphi\right)\left(1-\beta\right)\dfrac{\partial\pi^{I,B}(N_i^B,y,k_i)}{\partial N_i^B}}{\left(r+\lambda_d+g\left(\varphi\right)\left(1-\beta\right)\right)},$$

and the workers' surplus from employment by,

$$\left[W^{O,B}\left(w^{O,B}\left(y,N_i^B\right)\right)-U\right]=\frac{w^{O,B}\left(y,N_i^B\right)-rU+\delta\left[W^{I,B}\left(w^{I,B}\left(0,N_i^B\right)\right)-U\right]}{(r+\delta)},$$

$$\left[W^{I,B}\left(w^{I,B}\left(y,N_i^B\right)\right)-U\right]=\frac{w^{I,B}\left(y,N_i^B\right)-rU+\delta\left[W^{I,B}\left(w^{I,B}\left(0,N_i^B\right)\right)-U\right]}{(r+\delta)},$$

$$\left[W^{I,B}\left(w^{I,B}\left(0,N_i^B\right)\right)-U\right]=\frac{w^{I,B}\left(0,N_i^B\right)-rU+g\left(\varphi\right)\left[W^{I,B}\left(w^{I,B}\left(y,N_i\right)\right)-U\right]}{\left(r+\lambda_d+g\left(\varphi\right)\right)}.$$

Substituting implies the following differential wage equations,

$$\begin{aligned}
w^{O,B}\left(y,N_i^B\right)&=\left(1-\gamma\right)rU+\gamma\alpha y\left(N_i^B\right)^{\alpha-1}-\gamma\frac{\partial w^{O,B}\left(y,N_i^B\right)}{\partial N_i^B}N_i^B-\delta\gamma f\\
&\quad+\delta\frac{\beta g\left(\varphi\right)}{r+\lambda_d+g\left(\varphi\right)}\gamma\left(\frac{\partial\pi^{I,B}(N_i^B,0,k_i)}{\partial N_i^B}+f\right),\\
w^{I,B}\left(y,N_i^B\right)&=\left(1-\gamma\right)rU+\gamma\alpha y\left(N_i^B\right)^{\alpha-1}-\gamma\frac{\partial w^{I,B}\left(y,N_i^B\right)}{\partial N_i^B}N_i^B+\gamma rf\\
&\quad+\delta\frac{g\left(\varphi\right)\beta}{r+\lambda_d+g\left(\varphi\right)}\gamma\left(\frac{\partial\pi^{I,B}(N_i^B,0,k_i)}{\partial N_i^B}+f\right),\\
w^{I,B}\left(0,N_i^B\right)&=\left(1-\gamma\right)rU-\gamma\frac{\partial w^{I,B}\left(0,N_i^B\right)}{\partial N_i^B}N_i^B+\gamma\left(r+\lambda_d\right)f\\
&\quad-\beta g\left(\varphi\right)\gamma\left(\frac{\partial\pi^{I,B}(N_i^B,y,k_i)}{\partial N_i^B}+f\right),
\end{aligned}$$

where the last term in each line, i.e., a fraction of firms' surplus, appears due to innovation price bargaining. Since wages of outsiders and insiders at a firm with $y_i=y$ only differ by a constant, we know that the $\partial w^{O,B}\left(y,N_i^B\right)/\partial N_i^B=\partial w^{I,B}\left(y,N_i^B\right)/\partial N_i^B$. This allows us to write the differences in wages between outsiders and insiders as,

$$w^{I,B}\left(y,N_i^B\right)-w^{O,B}\left(y,N_i^B\right)=\gamma\left(r+\delta\right)f.$$

Substituting allows us to write the difference in the marginal values of employing an outsider and an insider as,

$$\frac{\partial \pi^{O,B}(N_i^B, y, k_i)}{\partial N_i^B} - \frac{\partial \pi^{I,B}(N_i^B, y, k_i)}{\partial N_i^B} = \frac{w^{I,B}\left(y, N_i^B\right) - w^{O,B}\left(y, N_i^B\right)}{(r+\delta)} = \gamma f.$$

Given the vacancy creation condition, we can write the marginal value of employing an insider as

$$\frac{\partial \pi^{I,B}(N_i^B, y, k_i)}{\partial N_i^B} = \frac{\partial \pi^{O,B}(N_i^B, y, k_i)}{\partial N_i^B} - \gamma f = \frac{c}{\lambda_m(\theta)} - \gamma f.$$

This allows us to determine the wage for an insider at a firm with $y_i = 0$,

$$w^{I,B}\left(0, N_i^B\right) = (1-\gamma) rU + \gamma (r + \lambda_d) f - \beta g(\varphi) \gamma \left(\frac{c}{\lambda_m(\theta)} + (1-\gamma) f\right)$$

where we used the fact that the differential equation is independent of N_i^B.

Substituting implies that the marginal value of employing an insider with $y_i = 0$ is independent of the number of employed workers, i.e.,

$$\frac{\partial \pi^{I,B}(N_i^B, 0, k_i)}{\partial N_i^B} = \frac{g(\varphi)(1-\beta)\left(\frac{c}{\lambda_m(\theta)} - \gamma f\right) - w^{I,B}\left(0, N_i^B\right)}{(r + \lambda_d + g(\varphi)(1-\beta))}.$$

This allows us to write the wage equation for an outsider and an insider at a firm with $y_i = y$ as,

$$\begin{aligned}
w^{O,B}\left(y, N_i^B\right) &= (1-\gamma) rU + \gamma \frac{\alpha}{1-\gamma(1-\alpha)} y \left(N_i^B\right)^{\alpha-1} - \delta\gamma f \\
&\quad + \delta\beta g(\varphi)\gamma \frac{g(\varphi)(1-\beta)\left(\frac{c}{\lambda_m(\theta)} - \gamma f\right) - w^{I,B}\left(0, N_i^B\right)}{(r+\lambda_d + g(\varphi))(r + \lambda_d + g(\varphi)(1-\beta))}, \\
w^{I,B}\left(y, N_i^B\right) &= (1-\gamma) rU + \gamma \frac{\alpha}{1-\gamma(1-\alpha)} y \left(N_i^B\right)^{\alpha-1} + \gamma r f \\
&\quad + \delta\beta g(\varphi)\gamma \frac{g(\varphi)(1-\beta)\left(\frac{c}{\lambda_m(\theta)} - \gamma f\right) - w^{I,B}\left(0, N_i^B\right)}{(r+\lambda_d + g(\varphi))(r + \lambda_d + g(\varphi)(1-\beta))},
\end{aligned}$$

If we substituted the value of being unemployed by $(1-\gamma) rU = (1-\gamma) z + \gamma\theta c$, then we get wages as a function of labor market tightness.

A.3 Innovation Price

The vacancy creation and firing conditions (1.3) and (1.7) imply that in a given steady state, all type B firms have either 0 or N_j^B employees. This simplifies the analysis and implies that the expected price of an innovation charged by a firm with innovation cost k_i is given by $p(k_i, 0)$ or $p\left(k_i, N_j^B\right)$. Since we concentrate on parameter sets that guarantee the existence of an innovation market, we know that all type S firms are willing to sell to any type B firm, that is, all matches in the innovation market will generate a positive surplus.

The innovation price is given by the surplus splitting rule,

$$\begin{aligned} p(k_j, 0) = {} & \beta\left(\pi^{O,B}\left(N_i^B, y, k_i\right) - \frac{c}{\lambda_m(\theta)} N_i^B - \pi^{O,B}(0, 0, k_i)\right) \\ & + (1-\beta)\left(\pi^S(0, y, k_j) - \pi^S(0, 0, k_j)\right), \end{aligned} \tag{A.13}$$

$$\begin{aligned} p\left(k_j, N_i^B\right) = {} & \beta\left(\pi^{I,B}\left(N_i^B, y, k_i\right) - \pi^{I,B}\left(N_i^B, 0, k_i\right)\right) \\ & + (1-\beta)\left(\pi^S(0, y, k_j) - \pi^S(0, 0, k_j)\right). \end{aligned} \tag{A.14}$$

The closed form expressions for the expected profit of type S firms that sell their innovations and of type B firms that buy innovations are as follows. Given the fact that the price that a type S firm with innovation cost k_i is given by $p(k_i, 0)$ or $p\left(k_i, N_j^B\right)$, respectively, and using equations (A.7) and (A.6) the expected profit with $y_i \in \{0, y\}$ can be written as,

$$\pi^S(0, y, k_i) = \frac{(r + \lambda_s + \eta)\varphi g(\varphi)\, p(k_i, N) - (\delta + \varphi g(\varphi))\, k_i}{r(r + \lambda_s + \eta) + (\delta + \varphi g(\varphi))(r + \lambda_s)}, \tag{A.15}$$

$$\pi^S(0, 0, k_i) = \frac{\eta\varphi g(\varphi)\, p(k_i, N) - (r + \delta + \varphi g(\varphi))\, k_i}{r(r + \lambda_s + \eta) + (\delta + \varphi g(\varphi))(r + \lambda_s)}. \tag{A.16}$$

where $N = N_j^B$ if $L_j^B = 0$ and $N = 0$ if $L_j^B = N_j^B$. Using equations (1.2) and (A.11) the expected profit for firms that do not lay off their workers if they are hit by a productivity shock can be written as,

$$\pi^{I,B}\left(N_i^B, y, k_i\right) = \frac{\left(r+\lambda_d+g\left(\varphi\right)\right)\left(y\left(N_i^B\right)^\alpha - w^{I,B}\left(y, N_i^B\right)N_i^B\right)}{\left(r+\lambda_d\right)\left(r+\delta\right)+g\left(\varphi\right)r} - \delta\frac{w^{I,B}\left(0, N_i^B\right)N_i^B + g\left(\varphi\right)E_{k_j}\left[p\left(k_j, N_i^B\right)\right]}{\left(r+\lambda_d\right)\left(r+\delta\right)+g\left(\varphi\right)r}, \tag{A.17}$$

$$\pi^{I,B}\left(N_i^B, 0, k_i\right) = \frac{g\left(\varphi\right)\left(y\left(N_i^B\right)^\alpha - w^{I,B}\left(y, N_i^B\right)N_i^B\right)}{\left(r+\lambda_d\right)\left(r+\delta\right)+g\left(\varphi\right)r} - \left(r+\delta\right)\frac{w^{I,B}\left(0, N_i^B\right)N_i^B + g\left(\varphi\right)E_{k_j}\left[p\left(k_j, N_i^B\right)\right]}{\left(r+\lambda_d\right)\left(r+\delta\right)+g\left(\varphi\right)r}. \tag{A.18}$$

If workers are laid off in case of a productivity shock, the expected profits are given by,

$$\pi^{O,B}\left(N_i^B, y, k_i\right) = \frac{\left(r+\lambda_d+g\left(\varphi\right)\right)\left(y\left(N_i^B\right)^\alpha - w^{O,B}\left(y, N_i^B\right)N_i^B - \delta f N_i^B\right)}{\left(r+\lambda_d\right)\left(r+\delta\right)+g\left(\varphi\right)r} - \frac{\delta g\left(\varphi\right)}{\left(r+\lambda_d\right)\left(r+\delta\right)+g\left(\varphi\right)r}\left(\frac{c}{\lambda_m\left(\theta\right)}N_i^B + E_{k_j}\left[p\left(k_j, 0\right)\right]\right), \tag{A.19}$$

$$\pi^{O,B}\left(0, 0, k_i\right) = \frac{g\left(\varphi\right)\left(y\left(N_i^B\right)^\alpha - w^{O,B}\left(y, N_i^B\right)N_i^B - \delta f N_i^B\right)}{\left(r+\lambda_d\right)\left(r+\delta\right)+g\left(\varphi\right)r} - \frac{\left(r+\delta\right)g\left(\varphi\right)}{\left(r+\lambda_d\right)\left(r+\delta\right)+g\left(\varphi\right)r}\left(\frac{c}{\lambda_m\left(\theta\right)}N_i^B + E_{k_j}\left[p\left(k_j, 0\right)\right]\right). \tag{A.20}$$

To determine the price that type B firms expect to pay for an innovation, we first focus on the average seller that has innovation cost $\overline{k}$ such that its price equals the expected price, i.e.,

$$p\left(\overline{k}, N_i^B\right) = E_{k_j}\left[p\left(k, N_i^B\right)\right] \text{ or } p\left(\overline{k}, 0\right) = E_{k_j}\left[p\left(k, 0\right)\right].$$

Computing the differences in expected profits using equations (A.15) to (A.20) and plugging the results into the innovation price equations (A.13) and (A.14) leads to

$$E_{k_j}\left[p\left(\overline{k}, N_i^B\right)\right] = \frac{K_2\beta\left(r+\lambda_d\right)\left(y\left(N_i^B\right)^\alpha - w^B\left(y, N_i^B\right)N_i^B\right) + K_2\beta r w^{I,B}\left(0, N_i^B\right)N_i^B}{K_1K_2 - K_1\left(1-\beta\right)\left(r+\lambda_s\right)\varphi g\left(\varphi\right) - K_2\beta r g\left(\varphi\right)} + \frac{K_1\left(1-\beta\right)r\overline{k}}{K_1K_2 - K_1\left(1-\beta\right)\left(r+\lambda_s\right)\varphi g\left(\varphi\right) - K_2\beta r g\left(\varphi\right)}, \tag{A.21}$$

$$E_{k_j}\left[p\left(\overline{k}, 0\right)\right] = \frac{K_2\beta\left(r+\lambda_d\right)\left(y\left(N_i^B\right)^\alpha - w^{O,B}\left(y, N_i^B\right)N_i^B - \delta f N_i^B - \left(r+\delta\right)\frac{c}{\lambda_m\left(\theta\right)}N_i^B\right)}{K_1K_2 - K_1\left(1-\beta\right)\left(r+\lambda_s\right)\varphi g\left(\varphi\right) - K_2\beta r g\left(\varphi\right)} + \frac{K_1\left(1-\beta\right)r\overline{k}}{K_1K_2 - K_1\left(1-\beta\right)\left(r+\lambda_s\right)\varphi g\left(\varphi\right) - K_2\beta r g\left(\varphi\right)}, \tag{A.22}$$

where

$$K_1 = (r+\delta)(r+\lambda_d) + rg(\varphi),$$
$$K_2 = (r+\delta+\varphi g(\varphi))(r+\lambda_s) + r\eta.$$

Given the expected price in equation (A.21) or (A.22) the innovation price $p\left(k_j, N_i^B\right)$ or $p(k_j, 0)$ for a seller with innovation cost k_j is given by substituting the expected price in the respective expected profit functions (A.15) to (A.20) and inserting them into the innovation price equations (A.13) and (A.14). Rearranging implies,

$$\begin{aligned}
p\left(k_j, N_i^B\right) &= \frac{K_2\beta(r+\lambda_d)\left(y\left(N_i^B\right)^\alpha - w^{I,B}\left(y, N_i^B\right)N_i^B\right) + K_2\beta r w^B\left(0, N_i^B\right)N_i^B}{K_1K_2 - K_1(1-\beta)(r+\lambda_s)\varphi g(\varphi)} \\
&+ \frac{K_1(1-\beta)rk_j + K_2\beta rg(\varphi)p\left(\overline{k}, N_i^B\right)}{K_1K_2 - K_1(1-\beta)(r+\lambda_s)\varphi g(\varphi)}, \\
p(k_j, 0) &= \frac{K_2\beta(r+\lambda_d)\left(y\left(N_i^B\right)^\alpha - w^{O,B}\left(y, N_i^B\right)N_i^B - \delta f N_i^B - (r+\delta)\frac{c}{\lambda_m(\theta)}N_i^B\right)}{K_1K_2 - K_1(1-\beta)(r+\lambda_s)\varphi g(\varphi)} \\
&+ \frac{K_1(1-\beta)rk_j + K_2\beta rg(\varphi)p\left(\overline{k}, 0\right)}{K_1K_2 - K_1(1-\beta)(r+\lambda_s)\varphi g(\varphi)}.
\end{aligned}$$

A.4 Vacancy Creation Conditions

Using the respective marginal values of a worker from section A.2 and the fact that,

$$\frac{\partial\pi^{O,t}(N_i^t, y, k_i)}{\partial N_i^t} - \frac{\partial\pi^{I,t}(N_i^t, y, k_i)}{\partial N_i^t} = \frac{w^{I,t}\left(y, N_i^t\right) - w^{O,t}\left(y, N_i^t\right)}{(r+\delta)} = \gamma f,$$

where

$$\frac{\partial \pi^{I,R}(N_i^R, y, k_i)}{\partial N_i^R} = \frac{\frac{(1-\gamma)\alpha}{1-\gamma(1-\alpha)} y \left(N_i^R\right)^{\alpha-1} - (1-\gamma) rU - \gamma r f + \delta \frac{\partial \pi^{I,R}(N_i^R, 0, k_i)}{\partial N_i^R}}{(r+\delta)}$$

$$= \frac{\frac{(1-\gamma)\alpha}{1-\gamma(1-\alpha)} y \left(N_i^R\right)^{\alpha-1} - (1-\gamma) rU - \gamma r f}{(r+\delta)}$$

$$+ \frac{\delta}{(r+\delta)} \frac{\eta\left(\frac{c}{\lambda_m(\theta)} + (1-\gamma) f\right) - w^{I,R}\left(0, N_i^R\right) - \eta f}{(r+\lambda_d+\eta)}$$

$$= \frac{\frac{(1-\gamma)\alpha}{1-\gamma(1-\alpha)} y \left(N_i^R\right)^{\alpha-1} - (1-\gamma) rU - \gamma r f}{(r+\delta)}$$

$$+ \frac{\delta}{(r+\delta)} \frac{\eta \frac{c}{\lambda_m(\theta)} - (1-\gamma) rU - \gamma (r+\lambda_d+\eta) f}{(r+\lambda_d+\eta)}$$

and using the fact that

$$\frac{\partial \pi^{O,t}(N_i^t, y, k_i)}{\partial N_i^t} = \frac{\partial \pi^{I,t}(N_i^t, y, k_i)}{\partial N_i^t} + \gamma f = \frac{c}{\lambda_m(\theta)}$$

implies

$$\frac{c}{\lambda_m(\theta)} = \frac{\frac{(1-\gamma)\alpha}{1-\gamma(1-\alpha)} y \left(N_i^R\right)^{\alpha-1} - (1-\gamma) rU}{(r+\delta)}$$

$$+ \frac{\delta}{(r+\delta)} \frac{\eta \frac{c}{\lambda_m(\theta)} - (1-\gamma) rU}{(r+\lambda_d+\eta)}$$

$$\frac{c}{\lambda_m(\theta)} = \frac{(r+\lambda_d+\eta) \frac{(1-\gamma)\alpha}{1-\gamma(1-\alpha)} y \left(N_i^R\right)^{\alpha-1} - (r+\delta+\lambda_d+\eta)(1-\gamma) rU}{(r+\delta)(r+\lambda_d) + r\eta}$$

Similarly for type B firms, i.e.,

$$\frac{\partial \pi^{I,B}(N_i^B, y, k_i)}{\partial N_i^B} = \frac{\alpha y \left(N_i^B\right)^{\alpha-1} - w^{I,B}\left(y, N_i^B\right) - \frac{\partial w^{I,B}\left(y, N_i^B\right)}{\partial N_i^B} N_i^B + \delta \frac{\partial \pi^{I,B}(N_i^B, 0, k_i)}{\partial N_i^B}}{(r+\delta)}$$

$$= \frac{\frac{(1-\gamma)\alpha}{1-\gamma(1-\alpha)} y \left(N_i^B\right)^{\alpha-1} - (1-\gamma) rU - \gamma (r+\delta) f - \delta (1-\gamma) f}{(r+\delta)}$$

$$+ \frac{\delta}{(r+\delta)} \frac{r+\lambda_d+g(\varphi) - g(\varphi)\gamma\beta}{r+\lambda_d+g(\varphi)} \left(\frac{\partial \pi^{I,B}(N_i^B, 0, k_i)}{\partial N_i^B} + f\right).$$

Using the fact that

$$\frac{\partial \pi^{O,t}(N_i^t, y, k_i)}{\partial N_i^t} = \frac{\partial \pi^{I,t}(N_i^t, y, k_i)}{\partial N_i^t} + \gamma f = \frac{c}{\lambda_m(\theta)},$$

implies

$$\begin{aligned}
\frac{c}{\lambda_m(\theta)} &= \frac{\frac{(1-\gamma)\alpha}{1-\gamma(1-\alpha)} y \left(N_i^B\right)^{\alpha-1} - (1-\gamma) rU - \delta(1-\gamma) f}{(r+\delta)} \\
&\quad + \frac{\delta}{(r+\delta)} \frac{r+\lambda_d+g(\varphi)-g(\varphi)\gamma\beta}{r+\lambda_d+g(\varphi)} \left(\frac{\partial \pi^{I,B}(N_i^B, 0, k_i)}{\partial N_i^B} + f\right),
\end{aligned}$$

$$\begin{aligned}
\frac{c}{\lambda_m(\theta)} &= \frac{\frac{(1-\gamma)\alpha}{1-\gamma(1-\alpha)} y \left(N_i^B\right)^{\alpha-1} - (1-\gamma) rU - \delta(1-\gamma) f}{(r+\delta)} \\
&\quad + \frac{\delta}{(r+\delta)} \frac{r+\lambda_d+g(\varphi)-g(\varphi)\gamma\beta}{(r+\lambda_d+g(\varphi))} \frac{g(\varphi)(1-(1-\gamma)\beta)\frac{c}{\lambda_m(\theta)} - (1-\gamma) rU}{(r+\lambda_d+g(\varphi)(1-\beta))} \\
&\quad + \frac{\delta}{(r+\delta)} \frac{r+\lambda_d+g(\varphi)-g(\varphi)\gamma\beta}{r+\lambda_d+g(\varphi)} \frac{r+\lambda_d+g(\varphi)(1-\beta)+g(\varphi)\gamma\beta}{r+\lambda_d+g(\varphi)(1-\beta)} (1-\gamma) f, \\
&= \frac{\frac{(1-\gamma)\alpha}{1-\gamma(1-\alpha)} y \left(N_i^B\right)^{\alpha-1}}{(r+\delta)} \\
&\quad - \left(1 + \delta \frac{(r+\lambda_d+g(\varphi)-g(\varphi)\gamma\beta)}{(r+\lambda_d+g(\varphi))(r+\lambda_d+g(\varphi)(1-\beta))}\right) \frac{(1-\gamma) rU}{(r+\delta)} \\
&\quad + \frac{\delta}{(r+\delta)} \frac{(r+\lambda_d+g(\varphi)-g(\varphi)\gamma\beta) g(\varphi)(1-(1-\gamma)\beta)}{(r+\lambda_d+g(\varphi))(r+\lambda_d+g(\varphi)(1-\beta))} \frac{c}{\lambda_m(\theta)} \\
&\quad + \frac{g(\varphi)\beta(1-\gamma) g(\varphi)\gamma\beta}{(r+\lambda_d+g(\varphi))(r+\lambda_d+g(\varphi)(1-\beta))} \frac{\delta}{(r+\delta)} (1-\gamma) f,
\end{aligned}$$

Rearranging implies,

$$\begin{aligned}
\frac{c}{\lambda_m(\theta)} &= \frac{C_2}{C_1} \left(\frac{(1-\gamma)\alpha}{1-\gamma(1-\alpha)} y \left(N_i^B\right)^{\alpha-1} - (1-\gamma) rU\right) \\
&\quad - \frac{r+\lambda_d+g(\varphi)-g(\varphi)\gamma\beta}{C_1} \delta(1-\gamma) rU \\
&\quad + \frac{g(\varphi)\beta(1-\gamma) g(\varphi)\gamma\beta}{C_1} \delta(1-\gamma) f
\end{aligned}$$

with

$$C_1 = C_2(r+\delta) - (r+\lambda_d+g(\varphi)-\gamma\beta g(\varphi))\,\delta(1-(1-\gamma)\beta)\, g(\varphi)$$

$$C_2 = (r+\lambda_d+g(\varphi))(r+\lambda_d+g(\varphi)(1-\beta))$$

The first-order condition for the optimal number of posted vacancies in equation (1.3) shows that vacancy posting costs always exceeds the marginal value of an additional worker for a firm that has been hit by a productivity shock, i.e.,

$$\frac{\partial \pi^t(N_i^t, 0, k_i)}{\partial V_i^t} = \frac{\partial \pi^t(N_i^t, 0, k_i)}{\partial N_i^t} \lambda_m(\theta) - c < 0,$$

as one can easily verify by substituting the marginal value of an additional worker using equation (1.6). Thus, firms that have been hit by a productivity shock never post vacancies.

A.5 Type Choice

We show

$$\frac{\partial \pi^S(0, y, k_i)}{\partial k_i} < \frac{\partial \pi^{O,R}\left(N_i^R, y, k_i\right)}{\partial k_i} < \frac{\partial \pi^{O,B}\left(N_i^B, y, k_i\right)}{\partial k_i} = 0.$$

Note first that $\pi^{O,B}\left(N_i^B, y, k_i\right)$ is independent of k_i as shown in equation (A.19), which implies $\partial \pi^{O,B}\left(N_i^B, y, k_i\right)/\partial k_i = 0$.

The closed form expression for the expected profit of type R firms is obtained by rearranging equations (A.8), (A.9) and (1.2), i.e.,

$$\pi^{O,R}\left(N_i^R, y, k_i\right) = \begin{cases} \dfrac{(r+\lambda_d+\eta)\left(y\left(N_i^R\right)^\alpha - w^{O,R}\left(y, N_i^R\right)N_i^R\right) - \delta k_i}{((r+\lambda_d)(r+\delta)+r\eta)} \\ \qquad -\delta \dfrac{w^{I,R}\left(0, N_i^R\right)N_i^R + \eta\gamma f N_i^R}{((r+\lambda_d)(r+\delta)+r\eta)} \quad \text{if } L_i^R = 0, \\ \dfrac{(r+\lambda_d+\eta)\left(y\left(N_i^R\right)^\alpha - w^{O,R}\left(y, N_i^R\right)N_i^R - \delta f N_i^R\right) - \delta k_i}{(r+\lambda_d)(r+\delta)+r\eta} \\ \qquad - \dfrac{\delta\eta}{(r+\lambda_d)(r+\delta)+r\eta}\dfrac{c}{\lambda_m(\theta)}N_i^R \quad \text{if } L_i^R = N_i^R, \end{cases}$$

The expected profit is strictly decreasing in k_i, which makes it less attractive for high innovation cost firms to do own research if they are hit by a productivity shock.

Type S firms that only innovate in order to sell their innovations obtain the expected profit $\pi^S(0,y,k_i)$, where substituting the price $p(k_i,N)$ implies,

$$\begin{aligned}
\pi^S(0,y,k_i) &= \frac{(r+\lambda_s+\eta)\varphi g(\varphi)\beta(r+\lambda_d)\left(y\left(N_j^B\right)^\alpha - w^B\left(y,N_j^B\right)N_j^B\right)}{((r+\lambda_d)(r+\delta)+g(\varphi)r)((r+\lambda_s)(r+\delta+\beta\varphi g(\varphi))+r\eta)} \\
&+ \frac{(r+\lambda_s+\eta)\varphi g(\varphi)\beta\left(rw^B\left(0,N_j^B\right)N_j^B + rg(\varphi)p\left(\overline{k}_i,N_j^B\right)\right)}{((r+\lambda_d)(r+\delta)+g(\varphi)r)((r+\lambda_s)(r+\delta+\beta\varphi g(\varphi))+r\eta)} \\
&- \frac{(\delta+\beta\varphi g(\varphi))}{(r+\lambda_s)(r+\delta+\beta\varphi g(\varphi))+r\eta}k_i \quad \text{if} \quad L_j^B = 0\ , \\
\pi^S(0,y,k_i) &= \frac{(r+\lambda_s+\eta)\varphi g(\varphi)\beta(r+\lambda_d)\left(y\left(N_j^B\right)^\alpha - w^B\left(y,N_j^B\right)N_j^B - \delta f N_j^B\right)}{((r+\delta)(r+\lambda_d)+rg(\varphi))((r+\delta)(r+\lambda_s)+\beta\varphi g(\varphi)(r+\lambda_d)+r\eta)} \\
&+ \frac{(r+\lambda_s+\eta)\varphi g(\varphi)\beta\left(-(r+\lambda_d)\left((r+\delta)\frac{c}{\lambda_m(\theta)}N_j^B\right)+rg(\varphi)p\left(\overline{k}_j,0\right)\right)}{((r+\delta)(r+\lambda_d)+rg(\varphi))((r+\delta)(r+\lambda_s)+\beta\varphi g(\varphi)(r+\lambda_d)+r\eta)} \\
&- \frac{(\delta+\beta\varphi g(\varphi))}{(r+\lambda_s)(r+\delta+\beta\varphi g(\varphi))+r\eta}k_i \quad \text{if} \quad L_j^B = N_j^B\ ,
\end{aligned}$$

The expected profit $\pi^S(0,y,k_i)$ is strictly decreasing in k_i. Comparing how the expected profit of type S and R firms change with the innovation cost k_i reveals,

$$\begin{aligned}
&\frac{\partial\pi^S(0,y,k_i)}{\partial k_i} - \frac{\partial\pi^{O,R}\left(N_i^R,y,k_i\right)}{\partial k_i} \\
&= \frac{\delta}{(r+\delta)(r+\lambda_d+\eta)}\left(1+\frac{\eta\delta}{((r+\lambda_d)(r+\delta)+r\eta)}\right) - \frac{(\delta+\beta\varphi g(\varphi))}{(r+\lambda_s)(r+\delta+\beta\varphi g(\varphi))+r\eta} \\
&= \frac{\delta}{(r+\lambda_d)(r+\delta)+r\eta} - \frac{(\delta+\beta\varphi g(\varphi))}{(r+\lambda_s)(r+\delta+\beta\varphi g(\varphi))+r\eta} \\
&= \frac{(\lambda_s-\lambda_d)(r\delta+\delta)-(r+\lambda_d+\eta)r\beta\varphi g(\varphi)}{((r+\lambda_d)(r+\delta)+r\eta)((r+\lambda_s)(r+\delta+\beta\varphi g(\varphi))+r\eta)} < 0,
\end{aligned}$$

since $\lambda_s < \lambda_d$ by assumption.

A.5.1 Steady State Measures

Firm Flows and Innovation Market Tightness: Denote the measure of firms that exit the economy each period by m^e, where the assumptions regarding the destruction of firms imply,

$$m^e = \lambda_s m^S(0,0) + \lambda_d\left(m^R\left(0,N_i^R\right) + m^B\left(0,N_i^B\right)\right).$$

In a steady state the measure of firms that exit the economy is equal to the measure of new firms that enter, i.e., $m^e = m^n$. The respective measure of firms evolve according to the difference between in- and outflows, i.e.,

$$\dot{m}^S(0,0) = (\delta + \varphi g(\varphi))\, m^S(y,0) - (\lambda_s + \eta)\, m^S(0,0) \tag{A.23}$$

$$\dot{m}^S(y,0) = \Xi(k^*)\, m^n + \eta m^S(0,0) - (\delta + \varphi g(\varphi))\, m^S(y,0) \tag{A.24}$$

$$\dot{m}^R\left(0, N_i^R\right) = \delta m^R\left(y, N_i^R\right) - (\lambda_d + \eta)\, m^R\left(0, N_i^R\right) \tag{A.25}$$

$$\dot{m}^R\left(y, N_i^R\right) = (\Xi(k^{**}) - \Xi(k^*))\, m^n + \eta m^R\left(0, N_i^R\right) - \delta m^R\left(y, N_i^R\right) \tag{A.26}$$

$$\dot{m}^B\left(0, N_i^B\right) = \delta m^B\left(y, N_i^B\right) - (\lambda_d + g(\varphi))\, m^B\left(0, N_i^B\right) \tag{A.27}$$

$$\dot{m}^B\left(y, N_i^B\right) = (1 - \Xi(k^{**}))\, m^n + g(\varphi)\, m^B\left(0, N_i^B\right) - \delta m^B\left(y, N_i^B\right) \tag{A.28}$$

We focus on the steady state, where the measures of the different firm types do not change, i.e., $\dot{m}^t(y_i, N_i^t) = 0$. The above flow equations allow us to write the ratio of the steady state measures of type B firms $m^B\left(0, N_i^B\right)$ to the measure of type S firms $m^S(y,0)$ as written in equation (1.11). Note, that the Inada conditions guarantee that the RHS of equation (1.11) increases in the innovation market tightness φ at a decreasing rate. Since in addition the RHS at $\varphi = 0$ exceeds the LHS, i.e., RHS(0) > 0, equation (1.11) determines the unique innovation market tightness φ for given innovation cost thresholds k^* and k^{**}.

Worker Flows and Labor Market Tightness: We denote the measure of unemployed workers by u. Unemployment evolves according to the difference between inflows and outflows, i.e.,

$$\dot{u} = \begin{cases} \theta\lambda_m(\theta)\, u - \lambda_d\left(m^B\left(0, N_i^B\right) N_i^B + m^R\left(0, N_i^R\right) N_i^R\right) & \text{if } L_i^t = 0, \\ \\ \theta\lambda_m(\theta)\, u - \delta\left(m^B\left(y, N_i^B\right) N_i^B + m^R\left(y, N_i^R\right) N_i^R\right) & \text{if } L_i^t = N_i^t. \end{cases} \tag{A.29}$$

We denote the measure of employed workers by l. Let us first consider the case when all firms keep their workers if they are hit by a productivity shock. We can determine the steady state measure of employed workers by equating the in- and outflow from unemployment, i.e.,

$$\begin{aligned} \theta\lambda_m(\theta)\, u &= \lambda_d\left(m^B\left(0, N_i^B\right) N_i^B + m^R\left(0, N_i^R\right) N_i^R\right), \\ &= \lambda_d\left(N_i^B + \frac{\Xi(k^{**}) - \Xi(k^*)}{1 - \Xi(k^{**})} N_i^R\right) m^B\left(0, N_i^B\right). \end{aligned}$$

The level of employment l can be obtained by summing over all type B and R firms, i.e.,

$$
\begin{aligned}
l &= \left(m^B\left(0, N_i^B\right) + m^B\left(y, N_i^B\right)\right) N_i^B + \left(m^R\left(0, N_i^R\right) + m^R\left(y, N_i^R\right)\right) N_i^R, \\
&= \left(\frac{\delta + \lambda_d + g\left(\varphi\right)}{\delta} N_i^B + \frac{\delta + \lambda_d + \eta}{\delta} \frac{\Xi\left(k^{**}\right) - \Xi\left(k^*\right)}{1 - \Xi\left(k^{**}\right)} N_i^R\right) m^B\left(0, N_i^B\right),
\end{aligned}
$$

where the flow equations for firms in equations (A.23) to (A.28) imply,

$$
\begin{aligned}
\frac{1}{m^B\left(0, N_i^B\right)} = &\left(\frac{1}{\varphi} + \frac{\delta + \varphi g\left(\varphi\right)}{(\lambda_s + \eta)\varphi} + \frac{\delta + \lambda_d + g\left(\varphi\right)}{\delta}\right) \frac{1}{m} \\
&+ \frac{\delta + \lambda_d + \eta}{\delta} \frac{\Xi\left(k^{**}\right) - \Xi\left(k^*\right)}{1 - \Xi\left(k^{**}\right)} \frac{1}{m}.
\end{aligned}
\tag{A.30}
$$

Using the fact that the number of unemployed and employed workers have to add up to one, i.e., $l = 1 - u$, allows us to write labor market tightness θ as a function of the number of workers employed at type B and R firms N_i^B and N_i^R, as well as of $\{\varphi, k^*, k^{**}, m\}$, i.e.,

$$
\begin{aligned}
&\left(\frac{\lambda_d}{\delta} \frac{\delta + \theta\lambda_m\left(\theta\right)}{\theta\lambda_m\left(\theta\right)} + \frac{\delta + g\left(\varphi\right)}{\delta}\right) N_i^B + \left(\frac{\lambda_d}{\delta} \frac{\delta + \theta\lambda_m\left(\theta\right)}{\theta\lambda_m\left(\theta\right)} + \frac{\delta + \eta}{\delta}\right) \frac{\Xi\left(k^{**}\right) - \Xi\left(k^*\right)}{1 - \Xi\left(k^{**}\right)} N_i^R \\
&= \left(\frac{1}{\varphi} + \frac{\delta + \varphi g\left(\varphi\right)}{(\lambda_s + \eta)\varphi} + \frac{\delta + \lambda_d + g\left(\varphi\right)}{\delta} + \frac{\delta + \lambda_d + \eta}{\delta} \frac{\Xi\left(k^{**}\right) - \Xi\left(k^*\right)}{1 - \Xi\left(k^{**}\right)}\right) \frac{1}{m},
\end{aligned}
\tag{A.31}
$$

The vacancy creation conditions at type B and R firms can then be used to substitute out N_i^B and N_i^R to get an equation that solely determines θ as a function of $\{\varphi, k^*, k^{**}, m\}$.

Let us now consider the case when all firms lay off workers if they are hit by a productivity shock. Equating in- and outflow into employment defines steady state employment as,

$$
\begin{aligned}
\frac{\theta\lambda_m\left(\theta\right)}{\delta + \theta\lambda_m\left(\theta\right)} = l &= \left(m^B\left(y, N_i^B\right) + m^R\left(y, N_i^R\right)\right) N_i^t, \\
&= \left(\frac{\lambda_d + g\left(\varphi\right)}{\delta} + \frac{\Xi\left(k^{**}\right) - \Xi\left(k^*\right)}{1 - \Xi\left(k^{**}\right)} \frac{\lambda_d + \eta}{\delta}\right) m^B\left(0, N_i^B\right) N_i^t,
\end{aligned}
$$

where $1/m^B\left(0, N_i^B\right)$ is given by equation (A.30). Substituting $m^B\left(0, N_i^B\right)$ again implies,

$$
\begin{aligned}
&\left(\frac{1}{\varphi} + \frac{\delta + \varphi g\left(\varphi\right)}{(\lambda_s + \eta)\varphi} + \frac{\delta + \lambda_d + g\left(\varphi\right)}{\delta} + \frac{\delta + \lambda_d + \eta}{\delta} \frac{\Xi\left(k^{**}\right) - \Xi\left(k^*\right)}{1 - \Xi\left(k^{**}\right)}\right) \frac{1}{m} \\
&= \left(\frac{\lambda_d + g\left(\varphi\right)}{\delta} + \frac{\Xi\left(k^{**}\right) - \Xi\left(k^*\right)}{1 - \Xi\left(k^{**}\right)} \frac{\lambda_d + \eta}{\delta}\right) \frac{\delta + \theta\lambda_m\left(\theta\right)}{\theta\lambda_m\left(\theta\right)} N_i^t.
\end{aligned}
\tag{A.32}
$$

This again allows us to write labor market tightness θ as a function of the number of workers N_i^t employed at type B and R firms with $y_i = y$, as well as $\{\varphi, k^*, k^{**}, m\}$. Again we can use the vacancy creation conditions for productive firms under $L_i^t = N_i^t$ to substitute out N_i^t.

If only type B or only type R firms lay off workers, if they are hit by a productivity shock, steady state unemployment and the respective employment level are given by,

$$\theta\lambda_m(\theta)\, u = \begin{cases} \lambda_d m^B\left(0, N_i^B\right) N_i^B + \delta m^R\left(y, N_i^R\right) N_i^R & \text{if } L_i^B = 0 \text{ and } L_i^R = N_i^R, \\ \lambda_d m^R\left(0, N_i^R\right) N_i^R + \delta m^B\left(y, N_i^B\right) N_i^B & \text{if } L_i^B = N_i^B \text{ and } L_i^R = 0, \end{cases}$$

$$l = \begin{cases} \left(m^B\left(0, N_i^B\right) + m^B\left(y, N_i^B\right)\right) N_i^B + m^R\left(y, N_i^R\right) N_i^R & \text{if } L_i^B = 0 \text{ and } L_i^R = N_i^R, \\ m^B\left(y, N_i^B\right) N_i^B + \left(m^R\left(0, N_i^R\right) + m^R\left(y, N_i^R\right)\right) N_i^R & \text{if } L_i^B = N_i^B \text{ and } L_i^R = 0. \end{cases}$$

The flow equations (A.23) to (A.28) then determine the respective measures for the number of firms of type B and R. Using the fact that all workers have to add up to one, i.e., $l = 1-u$, allows us again to write the labor market tightness θ as a function of the number of workers employed at type B and R firms N_i^B and N_i^R, as well as of $\{\varphi, k^*, k^{**}, m\}$, i.e., for $L_i^B = N_i^B$ and $L_i^R = 0$,

$$\begin{aligned} &\left(\frac{1}{\varphi} + \frac{\delta + \varphi g(\varphi)}{\varphi(\lambda_s + \eta)} + \frac{\delta + \lambda_d + g(\varphi)}{\delta} + \frac{\delta + \lambda_d + \eta}{\delta} \frac{\Xi(k^{**}) - \Xi(k^*)}{1 - \Xi(k^{**})}\right) \frac{1}{m} \\ &= \left(\frac{\lambda_d + g(\varphi)}{\theta\lambda_m(\theta)} + \frac{\lambda_d + g(\varphi)}{\delta}\right) N_i^B + \left(\frac{\lambda_d}{\theta\lambda_m(\theta)} + \frac{\delta + \lambda_d + \eta}{\delta}\right) \frac{\Xi(k^{**}) - \Xi(k^*)}{1 - \Xi(k^{**})} N_i^R, \end{aligned} \tag{A.33}$$

and for $L_i^B = 0$ and $L_i^R = N_i^R$,

$$\begin{aligned} &\left(\frac{1}{\varphi} + \frac{\delta + \varphi g(\varphi)}{\varphi(\lambda_s + \eta)} + \frac{\delta + \lambda_d + g(\varphi)}{\delta} + \frac{\delta + \lambda_d + \eta}{\delta} \frac{\Xi(k^{**}) - \Xi(k^*)}{1 - \Xi(k^{**})}\right) \frac{1}{m} \\ &= \left(\frac{\lambda_d}{\theta\lambda_m(\theta)} + \frac{\delta + \lambda_d + g(\varphi)}{\delta}\right) N_i^B + \left(\frac{\lambda_d + \eta}{\theta\lambda_m(\theta)} + \frac{\lambda_d + \eta}{\delta}\right) \frac{\Xi(k^{**}) - \Xi(k^*)}{1 - \Xi(k^{**})} N_i^R. \end{aligned} \tag{A.34}$$

Keeping the variables $\{\varphi, k^*, k^{**}, m\}$ constant, equations (A.31) to (A.34) determine the respective increasing functions of the number of workers employed at the respective firms, i.e., $\theta\left(N_i^R, N_i^B\right)$ with $\partial\theta\left(N_i^R, N_i^B\right)/\partial N_i^t > 0$.

A.6 Equilibrium

An equilibrium is characterized by the market tightness in the innovation and the labor markets, the layoff decision of type B and R firms L_i^B and L_i^R, the threshold values k^* and k^{**} of the innovation cost k_i that determine the fraction of type S, B, and R firms and the number of active firms in the economy m, i.e., by the set of variables $\{\varphi, \theta, L_i^B, L_i^R, k^*, k^{**}, m\}$.

The innovation market tightness φ is determined by equation (1.11). Comparative statics using the implicit function theorem imply that innovation market tightness φ decreases with both innovation cost thresholds k^* and k^{**}, since, in the case of k^*, more firms decide to specialize in innovation and, in case of k^{**}, fewer firms decide to buy a new innovation when they are hit by a productivity shock.

The layoff decision for firm types B and R are given by substituting the respective values of an additional worker into the firing condition (1.7). Workers are laid off, i.e., $L_i^t = N_i^t$, if the marginal value of continuing an employment relationship plus the firing cost is negative, i.e., if and only if,

$$\frac{g(\varphi)(1-\beta)\left(\dfrac{c}{\lambda_m(\theta)} - \gamma f\right) - w^{I,B}\left(0, N_i^B\right)}{(r + \lambda_d + g(\varphi)(1-\beta))} + f < 0,$$

$$\frac{\eta\left(\dfrac{c}{\lambda_m(\theta)} - \gamma f\right) - w^{I,R}\left(0, N_i^R\right)}{(r + \lambda_d + \eta)} + f < 0,$$

These firing conditions for type R and type B firms are derived as follows. We know that workers are laid off if,

$$\frac{\partial \pi^{I,R}(N_i^R, 0, k_i)}{\partial N_i^R} + f < 0, \text{ and } \frac{\partial \pi^{I,B}(N_i^B, 0, k_i)}{\partial N_i^B} + f < 0.$$

Using the respective marginal values of a worker from section A.2 and the fact that,

$$\frac{\partial \pi^{O,t}(N_i^t, y, k_i)}{\partial N_i^t} - \frac{\partial \pi^{I,t}(N_i^t, y, k_i)}{\partial N_i^t} = \frac{w^{I,t}(y, N_i^t) - w^{O,t}(y, N_i^t)}{(r + \delta)} = \gamma f,$$

and that the vacancy creation condition,

$$\frac{\partial \pi^{O,t}(N_i^t, y, k_i)}{\partial N_i^t} = \frac{c}{\lambda_m(\theta)},$$

gives the above equations.

Bargained wages are given in Appendix A.2. The vacancy creation conditions are given in Appendix A.4. All vacancy creation curves define the number of employed workers as a decreasing function of labor market tightness, i.e., $N_i^t(\theta)$ with $\partial N_i^t(\theta)/\partial\theta < 0$. Substituting the respective functions $N_i^t(\theta)$ into the respective steady-state equations (A.31) to (A.34) determines labor market tightness as a function of $\left\{\varphi, L_i^B, L_i^R, k^*, k^{**}, m\right\}$. The property $\partial N_i^t(\theta)/\partial\theta < 0$ together with $\partial\theta\left(N_i^R, N_i^B\right)/\partial N_i^t > 0$, guarantees that the equilibrium market tightness is unique for a given set of variables $\left\{\varphi, L_i^B, L_i^R, k^*, k^{**}, m\right\}$. The comparative static result that a higher number of firms m leads to higher labor market tightness θ ensures that the free entry condition (1.10) is well defined.

The innovation cost thresholds k^* and k^{**} are determined by comparing the expected profits of the different types of firms as defined in equations (1.8) and (1.9). The single crossing property of the expected profits guarantees a unique pair of innovation cost thresholds k^* and k^{**} for a given set of variables $\{\varphi, \theta, m\}$. Thus, firms with low innovation costs specialize in innovation, firms with high innovation costs buy innovations when they are hit by a productivity shock and firms with medium innovation costs do own research if they are hit by a productivity shock.

The final equation that determines the number of firms m in equilibrium is the free entry condition (1.10), where the number of firms enters indirectly via labor market tightness θ. A higher number of firms m increases, ceteris paribus, labor market tightness θ. A higher labor market tightness increases the recruitment cost of workers and thus decreases the expected profit of type B and R firms. Thus, the free entry condition is decreasing in the number of firms.

Appendix B

Appendix to Chapter 2

B.1 Equilibrium Stability

The models steady equilibrium is determined by equating $N^{SS}(x)$ and $N^{FOC}(x)$ (see equation (2.18)). In the main text I outlined that equation (2.18) is satisfied by two distinct values of x, denoted as x^* and $x^{*}*$. The equilibrium characterized by x^{**} was ruled out, as it requires unemployment to be locally decreasing in firing costs. In this section I augment this argument by showing that the equilibrium associated with x^{**} is not stable, while the equilibrium associated with x^* is. As a full-blown out of steady-state analysis under rational expectations is not feasible, I rely on a simplified, yet intuitive, graphical analysis, which relies on the assumption that firms behave according to (2.8) and (2.9) even if market tightness is off its steady state value. Put differently, I assume that firms expect market tightness to remain constant at any given point in time.

Figure B.1 shows the adjustment process resulting from a (small) deviation from the *low* market tightness equilibrium denoted by x^* in the main text. First note that the N^{FOC} curve is downward sloping (in an environment around x^*) as $\partial N^{FOC} \partial x \Big|_{x=x^*} < 0$. If $x = x' < x^*$ and N is below the N^{FOC} line firms find it optimal to hire workers until $N = N^{FOC}(x')$. However, the new employment level can only be held constant, if firms continuously hire many workers from a small pool of unemployed which. Correspondingly the N^{SS} line indicates a high level of market tightness $x = x'' > x^*$. Firms react to the increase in market tightness by reducing employment to $N = N^{FOC}(x'')$, which again leads to a decrease in steady state market tightness. However, as long as the negative slope of the N^{FOC} line is smaller in absolute value than the positive slope of the N^{SS} line this decrease does not fully offset the initial increase in market tightness. Hence, after one adjustment step market tightness is in between x' and x^*. The same process repeats itself until x^* is reached, that is, the low market tightness equilibrium x^* is stable. If the slope of N^{FOC} evaluated at $x = x^*$ is larger in absolute value than the slope of N^{SS} evaluated at $x = x^*$, the adjustment process would not fully converge. In this case the economy oscillates around $x = x^*$. However, as N^{FOC} becomes flatter (and eventually upward sloping) when x increases the magnitude of the oscillation process is bounded. Hence, a divergent behavior can be excluded. Consequentially, describing the equilibrium associated with x^* is economically meaningful in any case.

In contrast, Figure B.1 shows that the high market tightness equilibrium x^{**} is not stable (knife-edge equilibrium). If market tightness is slightly below x^{**} (at x', point A) firms will downward adjust employment to $N^{FOC}(x')$. To maintain the lower level of employment firms continuously hire less workers from a larger pool of unemployed, leading to lower market tightness as indicated by the N^{SS} line. As $N^{FOC}(x)$ is upward sloping (around $x = x''$) firms react to the lower market tightness with an further decrease in employment, followed once again by a decrease in market tightness. The economy diverges away from x^{**}. Analogous arguments hold true, if market tightness is slightly above x^{**}. In fact, the high market tightness equilibrium turns out to be a modeling artifact and is not of economic importance. Neglecting it does not harm the generality of my analysis.

B.2 Proof of Proposition 1

Computing $\frac{\partial N^R}{\partial f}$ and rearranging reveals that N^R is falling in firing costs if and only if

$$f < \frac{\Theta_A - \epsilon}{\Theta_A(1-\beta(1-\eta)) + \beta\delta\epsilon}\omega \overset{!}{=} f^{R,max} \tag{B.1}$$

where $\Theta_A = \left(\frac{\epsilon\eta\beta}{1-\beta(1-\eta)}\right)^{\frac{1-\alpha}{2-\alpha}}$. If the ratio between firing costs and wages is sufficiently low, an increase in firing costs unambiguously lowers hypothetical labor demand N^R and thus leads to higher rationing unemployment. The reason why $\frac{\partial N^R}{\partial f}$ changes its sign at very high levels of f is rooted in the convex shape of $N^{R,L}$.

The next step is to infer the impact of introducing firing costs on frictional unemployment. The frictional component is defined as the drop in labor demand caused by recruiting cost, that is, $N^R - N$. Equation (2.20) implies that the frictional component is always greater zero and positively linked to market tightness (via recruiting costs). Hence, showing that higher firing costs lead to lower frictional unemployment boils down to showing that firing costs lead to lower market tightness. To do so rewrite equation (2.18) as:

$$G(x,f) = xm(x) - N^{FOC}(x,f) * (q(x,f) + xm(x)(1-q(x,f))) \tag{B.2}$$

The implicit function theorem implies that $\frac{dx^*}{df} = -\frac{\frac{\partial G(x,f)}{\partial f}}{\frac{\partial G(x,f)}{\partial x}}$, that is, market tightness is decreasing in firing costs if G_x and G_f have the same sign. Correspondingly, the next step is to compute the partial derivatives. It holds that:

$$\begin{aligned} G_x = \quad & (xm(x))'(1-N^{FOC}(x,f)) - \frac{\partial N^{FOC}(x,f)}{\partial x}[q(x,f) + xm(x)(1-q(x,f))] \\ & -N^{FOC}(x,f)[(1-xm(x))\frac{\partial q(x,f)}{\partial x} - (xm(x))'q(x,f)] \\ = \quad & (xm(x))'(1-N^{FOC}(x,f)) - (1-xm(x))\delta m_H\left(\frac{\partial N_i^H(x,f)}{\partial x} - \frac{\partial N_i^L(x,f)}{\partial x}\right) \\ & +N^{FOC}(x,f)(xm(x))'q(x,f) - \frac{\partial N^{FOC}}{\partial x}xm(x) \end{aligned} \tag{B.3}$$

$$
\begin{aligned}
G_f &= -\frac{\partial N^{FOC}(x,f)}{\partial f}[q(x,f) + xm(x)(1-q(x,f))] - (1-xm(x))N^{FOC}(x,f)\frac{\partial q(x,f)}{\partial f} \\
&= -\frac{\partial N^{FOC}(x,f)}{\partial f}xm(x) - (1-xm(x))\delta m_H\left(\frac{\partial N_i^H(x,f)}{\partial f} - \frac{\partial N_i^L(x,f)}{\partial f}\right)
\end{aligned}
\tag{B.4}
$$

Under the restriction of the refinement condition (see equation (2.20)), equation (B.3) reveals that G_x is always positive. A sufficient condition for $G_f > 0$ (and thus for $\frac{dx}{df} < 0$) is given by $\frac{\partial N^{FOC}(x,f)}{\partial f} < 0$. The latter is is equivalent to:

$$
f[\epsilon\beta\delta + \Theta_A(1-\beta(1-\eta))] + \frac{c}{m(x)}[\epsilon(1-\beta(1-\delta)) + \Theta_A\eta\beta] < (\Theta_A - \epsilon)\omega \tag{B.5}
$$

where Θ_A is already known from equation (2.21). Unfortunately, equation (B.5) is harder to satisfy than equation (2.19) as $\Theta_A < \Theta_B$. Thus the refinement condition does not automatically imply $G_f > 0$[1].

Let $\overline{x}$ and $\overline{\overline{x}}$ denote the maximum market tightness for which equation (B.5), respectively (2.19) are just satisfied (for a given set of exogenous parameters). As the left hand side of equation (B.5) is increasing in x, equation (B.5) is (by definition) strictly satisfied for all $x^* < \overline{x}$. Hence, focusing on equilibria with $x^* < \overline{x}$ is sufficient to ensure that equilibrium market tightness is declining in firing costs. Note that this is equivalent to assume $\frac{\partial N^{FOC}(x,f)}{\partial f} < 0$, therefore labor demand is required to be decreasing in firing costs for given market tightness. This is not a strong assumption as the primary channel through which firing costs can positively influence employment is via lowering market tightness (as less vacancies are needed for a given level of employment) and thus recruiting costs.

Moreover, note that the difference between $\frac{\partial N^{FOC}(x,f)}{\partial f} < 0$ and the refinement condition (2.20) is quantitatively negligible. The difference between equations (B.5) and (2.19) is entirely due to the difference between Θ_A and Θ_B. Note that, independent of any other parameter values, $\Theta_A = \Theta_B$ if the discount factor β is set to unity. For reasonable values

[1]Equations(2.19) and (B.5) share the feature that market tightness cannot be directly substituted out, because no closed form solution for x can be derived. The latter results from the non-linearity of the matching function.

of β (for example $\beta = 0.999$) Θ_A is only marginally smaller than Θ_B[2]. Correspondingly, assuming $\frac{\partial N^{FOC}(x,f)}{\partial f} < 0$ is only a very small additional assumptions once the refinement condition (see equation (2.20)) is accepted (see Figure B.3).

Although equilibria satisfying the above mentioned conditioned are necessarily characterized by an inverse relationship between firing costs and frictional unemployment this does not imply that other equilibria do not exhibit this relationship. In the calibration frictional unemployment is be decreasing in f even if $f > f^{max}$ [3].

To facilitate intuition the models limiting behavior can be investigated. Assume that firing costs are raised to the highest level (denoted as f^*) consistent with the plausibility constraint $N_i^H - N_i^L \geq 0$. By definition it holds that $\lim_{f \to f^*} N_i^H - N_i^L = 0$. Correspondingly the job destruction rate q converges against zero as well. As labor market flows have to be balanced in steady state, this requires that either market tightness or unemployment converges against zero. However, as long as $\lim_{f \to f^*} N < 1$ one can conclude that market tightness converges to zero. Hence $\lim_{f \to f^*} x^* = 0$, which also implies $\lim_{f \to f^*} (N - N^R) = 0$, that is, frictional unemployment vanishes when firing costs are raised to the maximum value.

B.3 The Role of Matching Efficiency

In the main text average pre-treatment unemployment proxies the steady state composition of unemployment before treatment. However, relatively high unemployment can only be attributed to a large (small) share of rationing (search) unemployment, if matching efficiency is constant across observations. As no data on matching efficiency is available, it is necessary to assume that matching efficiency does not vary across states. This section

[2] In the calibration it holds that $\Theta_A = 0.8381$ and $\Theta_B = 0.8510$.

[3] For each set of exogenous parameters (excluding f) there exist an f for which $x^* = \overline{\overline{x}}$, that is, equilibrium market tightness equals the maximum market tightness for which the refinement condition is just satisfied. I denote this value as f^{max}, as it is the maximum level of firing cost which yields an equilibrium compatible with the refinement condition.

analyzes how a violation of this assumption might change results.

If matching efficiency is not constant, estimation potentially suffers from an omitted variable bias. Luckily, it is possible to determine the sign of the resulting bias. Once matching efficiency is available, one can compute average pre-treatment matching efficiency $\bar{\tau}_i$ for every state and append equation (2.23) by an additional interaction term $\bar{\tau}_i * post_{i,t}$. If matching efficiency is high, the share of frictional unemployment is low (for a given unemployment rate). Correspondingly, the theoretical model implies that in this case the employment effect of EPL should be more adverse. Put differently, the expected sign of the coefficient on $\bar{\tau}_i * post_{i,t}$ is negative [4]. Remember also, that theory implies that the coefficient on $\bar{U}_i * post_{i,t}$ should be negative as well. At the same time, observations with high pre-treatment average matching efficiency should, on average, have low levels of pre-treatment unemployment. Hence, $\bar{\tau}_i * post_{i,t}$ and $\bar{U}_i * post_{i,t}$ are likely to be negatively correlated.

Consider an observation with high pre-treatment unemployment rate . This observation is likely to have low pre-treatment matching efficiency. The latter causes the employment effect of EPL to be rather favorable. Correspondingly, omitting $\bar{\tau}_i * post_{i,t}$ causes the coefficient on $\bar{U}_i * post_{i,t}$ to be less negative compared to a model which includes $\bar{\tau}_i * post_{i,t}$. Hence, differences in matching efficiency bias the estimated coefficient on $\bar{U}_i * post_{i,t}$ towards zero.

Hence, it is not possible that untruly significant results occur. Accordingly, including matching efficiency is very unlikely to change conclusions in case of the public-policy and good-faith exception. In contrast, taking into account differences in matching efficiency is likely to strengthen the presented empirical evidence. In addition, the bias may provide an alternative explanation for the lack of significance when evaluating the implied-contract exception[5].

[4] The argumentation reverses if the unemployment rate is used as dependent variable.

[5] In the main text the lack of significance is explained by structural differences between the implied-contract exception and the other two wrongful-dismissal laws.

B.4 Tables

Table B.1 – Implied Contract Exception

			Marg. Eff. at $icUbar_i = \overline{icUbar_i}$ plus					
Dep. Variable	**Variable**	**Coefficient**	**-4**	**-2**	**0**	**2**	**4**	Region
$ln(epop)$	$icpost_{i,t}$	-1.573	-1.063	-1.318	-1.573	-1.828	-2.083	Yes
		(0.000)	(0.236)	(0.031)	(0.000)	(0.001)	(0.009)	
	$icpost_{i,t} * icUbar_i$	-0.128						
		(0.479)						
$ln(epop)$	$icpost_{i,t}$	-1.639	-0.066	-0.787	-1.639	-2.492	-3.344	No
		(0.004)	(0.956)	(0.292)	(0.004)	(0.003)	(0.012)	
	$icpost_{i,t} * icUbar_i$	-0.426						
		(0.133)						
$ln(unemprate)$	$icpost_{i,t}$	8.714	15.281	11.997	8.714	5.430	2.147	Yes
		(0.023)	(0.108)	(0.055)	(0.023)	(0.186)	(0.751)	
	$icpost_{i,t} * icUbar_i$	-1.642						
		(0.368)						
$ln(unemprate)$	$icpost_{i,t}$	10.303	6.452	8.377	10.303	12.229	14.155	No
		(0.090)	(0.687)	(0.408)	(0.090)	(0.112)	(0.277)	
	$icpost_{i,t} * icUbar_i$	0.963						
		(0.771)						

Notes: Models are weighted by state's share of national population aged 16-64 in each month using CPS sampling weights. P-values in parentheses are computed using Huber-White standard errors which allow for unrestricted error correlation within states. $icUbar_i$ equals state $i's$ average unemployment rate in the 24 months before the introduction of the Implied Contract Exception.

Table B.2 – Public Policy Exception

			Marg. Eff. at $icUbar_i = \overline{icUbar_i}$ plus					
Dep. Variable	**Variable**	**Coefficient**	**-4**	**-2**	**0**	**2**	**4**	Region
$ln(epop)$	$pppost_{i,t}$	-0.039	2.371	1.166	-0.039	-1.243	-2.448	Yes
		(0.947)	(0.033)	(0.070)	(0.947)	(0.221)	(0.120)	
	$pppost_{i,t} * ppUbar_i$	-0.602						
		(0.050)						
$ln(epop)$	$pppost_{i,t}$	-0.160	3.172	1.506	-0.160	-1.825	-3.491	No
		(0.836)	(0.023)	(0.056)	(0.836)	(0.181)	(0.097)	
	$pppost_{i,t} * ppUbar_i$	-0.833						
		(0.039)						
$ln(unemprate)$	$pppost_{i,t}$	1.770	-17.587	-7.909	1.770	11.448	21.127	Yes
		(0.712)	(0.081)	(0.164)	(0.712)	(0.183)	(0.120)	
	$pppost_{i,t} * ppUbar_i$	4.839						
		(0.078)						
$ln(unemprate)$	$pppost_{i,t}$	2.878	-25.289	-11.205	2.878	16.961	31.045	No
		(0.668)	(0.038)	(0.093)	(0.668)	(0.165)	(0.100)	
	$pppost_{i,t} * ppUbar_i$	7.042						
		(0.051)						

Notes: Models are weighted by state's share of national population aged 16-64 in each month using CPS sampling weights. P-values in parentheses are computed using Huber-White standard errors which allow for unrestricted error correlation within states. $ppUbar_i$ equals state $i's$ average unemployment rate in the 24 months before the introduction of the Public Policy Exception.

Table B.3 – Good Faith Exception

			Marg. Eff. at $icUbar_i = \overline{icUbar_i}$ plus					
Dep. Variable	**Variable**	**Coefficient**	**-4**	**-2**	**0**	**2**	**4**	Region
$ln(epop)$	$gfpost_{i,t}$	-0.949		3.579	-0.949	-5.478		Yes
		(0.288)		(0.008)	(0.288)	(0.008)		
	$gfpost_{i,t} * gfUbar_i$	-2.264						
		(0.002)						
$ln(epop)$	$gfpost_{i,t}$	-0.551		3.501	-0.551	-4.603		No
		(0.381)		(0.024)	(0.381)	(0.015)		
	$gfpost_{i,t} * gfUbar_i$	-2.026						
		(0.012)						
$ln(unemprate)$	$gfpost_{i,t}$	7.961		-29.615	7.961	45.538		Yes
		(0.274)		(0.001)	(0.274)	(0.006)		
	$gfpost_{i,t} * gfUbar_i$	18.789						
		(0.001)						
$ln(unemprate)$	$gfpost_{i,t}$	4.196		-40.288	4.196	48.680		No
		(0.505)		(0.003)	(0.505)	(0.010)		
	$gfpost_{i,t} * gfUbar_i$	22.242						
		(0.003)						

Notes: Models are weighted by state's share of national population aged 16-64 in each month using CPS sampling weights. P-values in parentheses are computed using Huber-White standard errors which allow for unrestricted error correlation within states. $gfUbar_i$ equals state $i's$ average unemployment rate in the 24 months before the introduction of the Good Faith Exception.

B.5 Figures

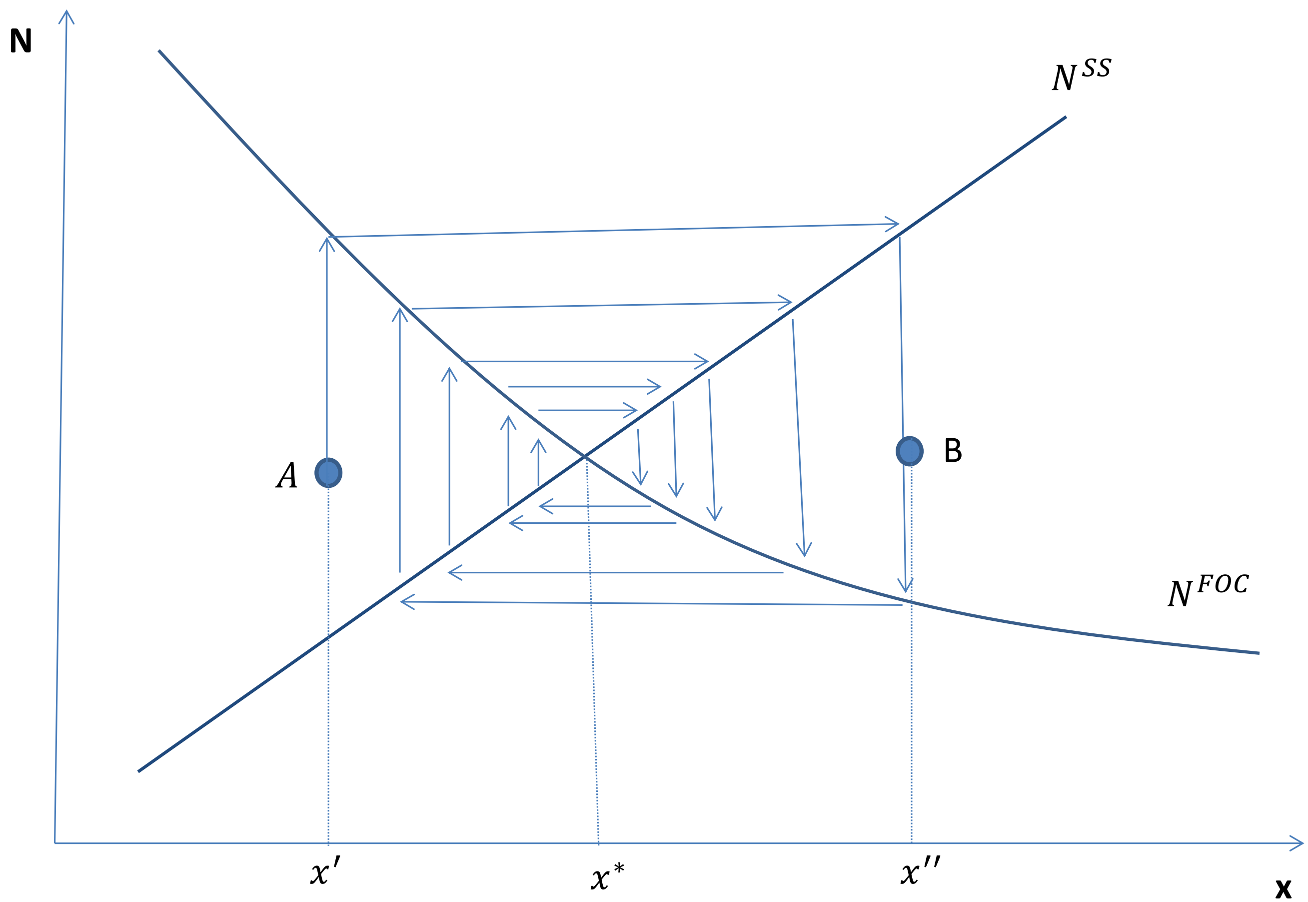


Figure B.1 – The Figure shows the adjustment process resulting from a small deviation from the *low* market tightness equilibrium. Source: Own Simulations.

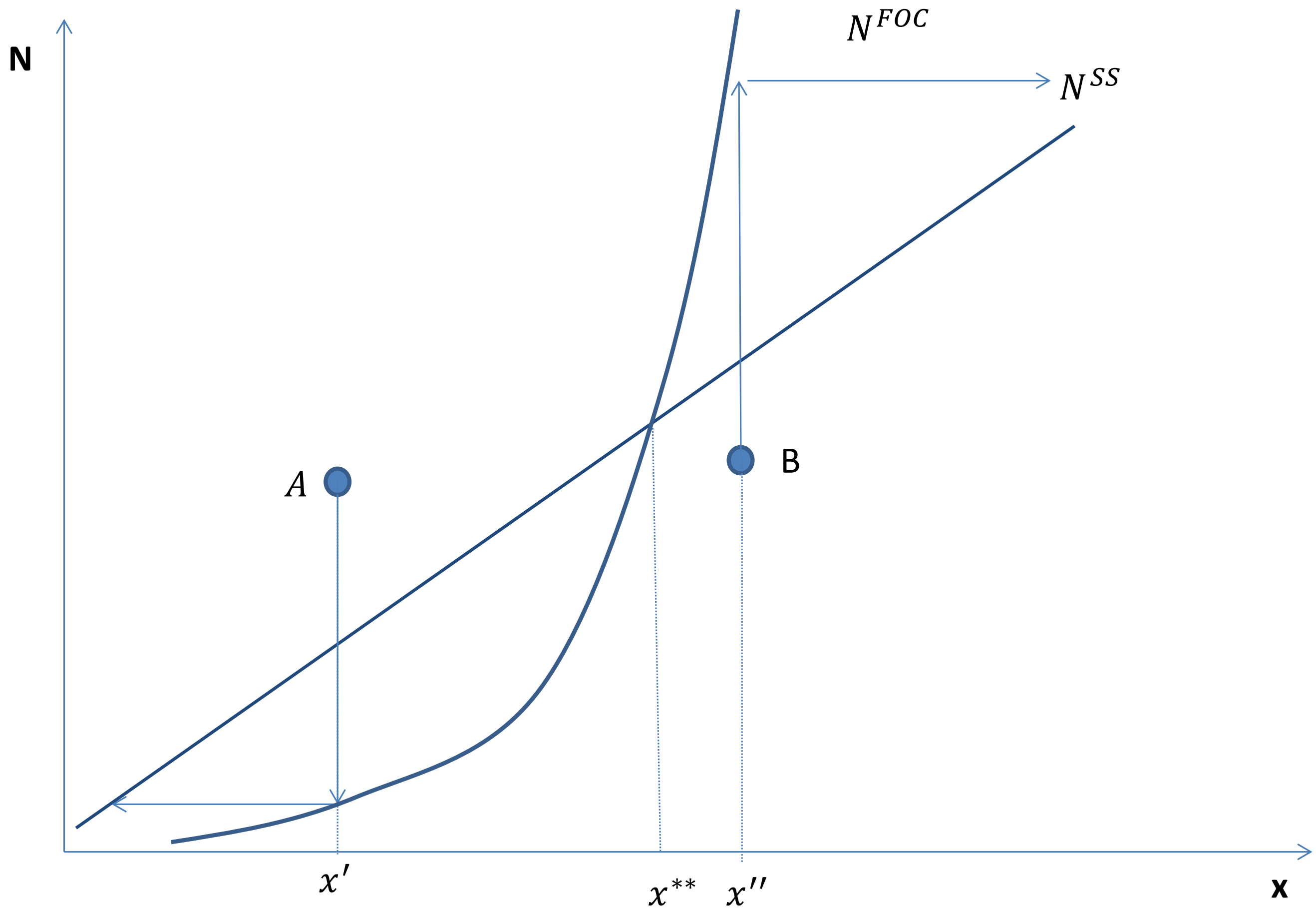


Figure B.2 – The Figure shows the adjustment process resulting from a small deviation from the *high* market tightness equilibrium. Source: Own Simulations.

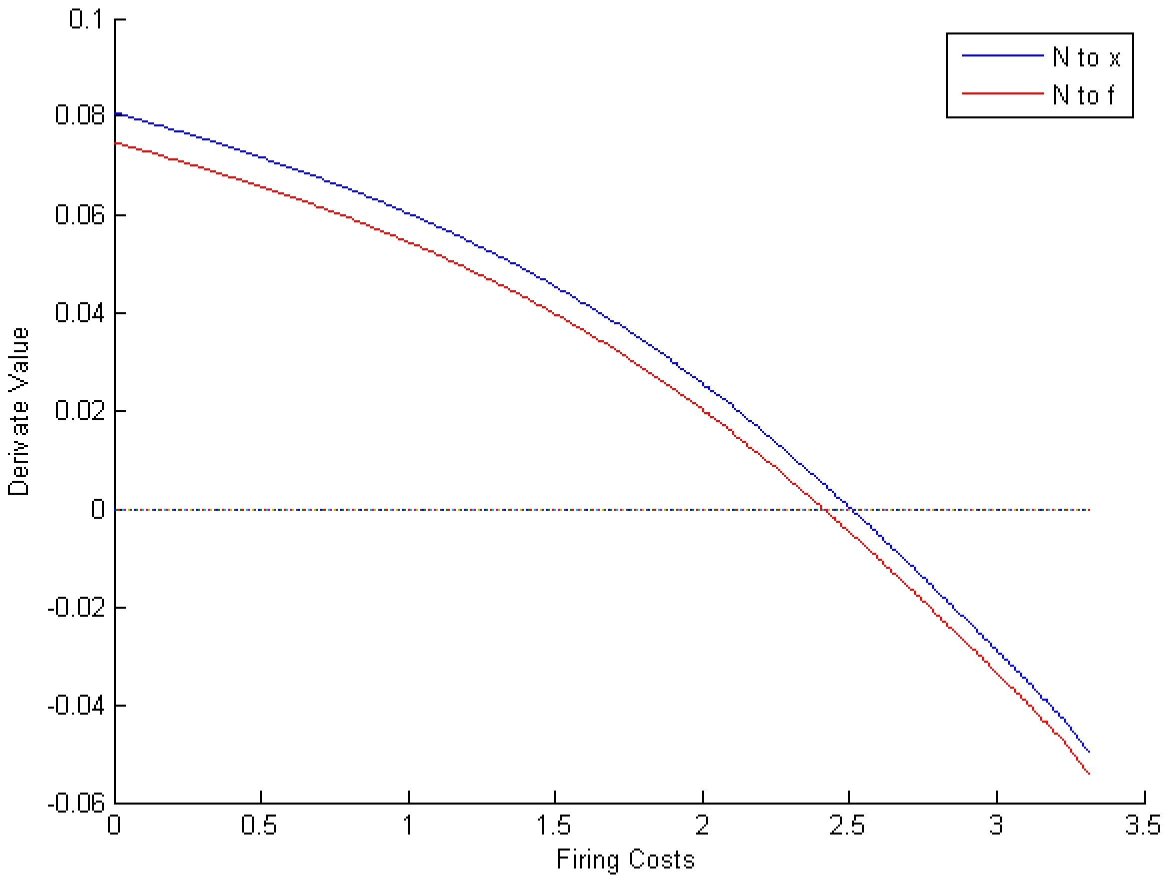


Figure B.3 – The Figure shows the value of $\frac{\partial N^{FOC}}{\partial x}$ (blue line) and $\frac{\partial N^{FOC}}{\partial f}$ (red line) as functions of firing costs f. Source: Own Simulations.

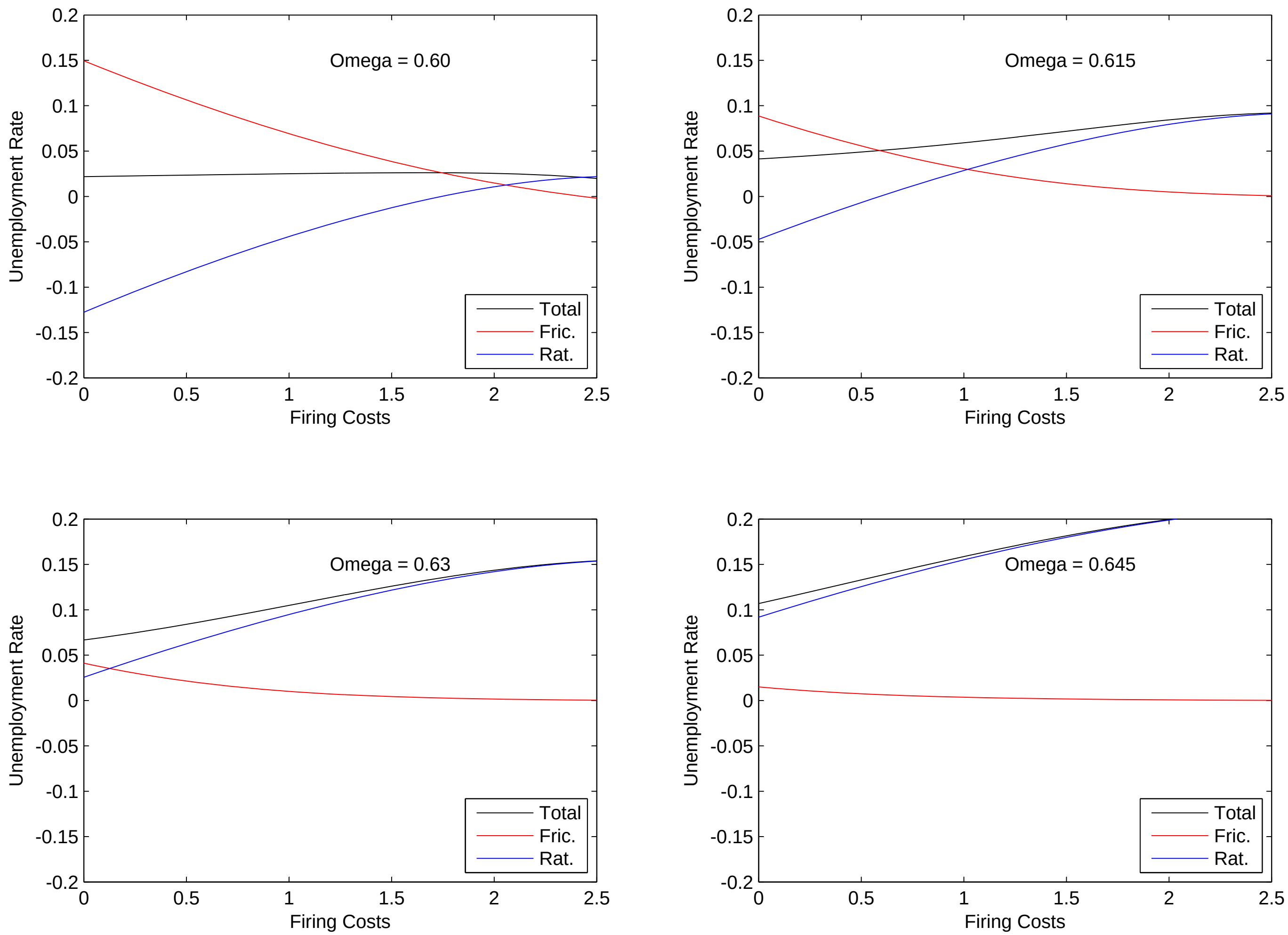


Figure B.4 – The figure shows total, frictional and rationing unemployment as a function of firing costs. Each graph results from a simulation using the exact same set of parameter values except of the wage parameter. Source: Own simulations.

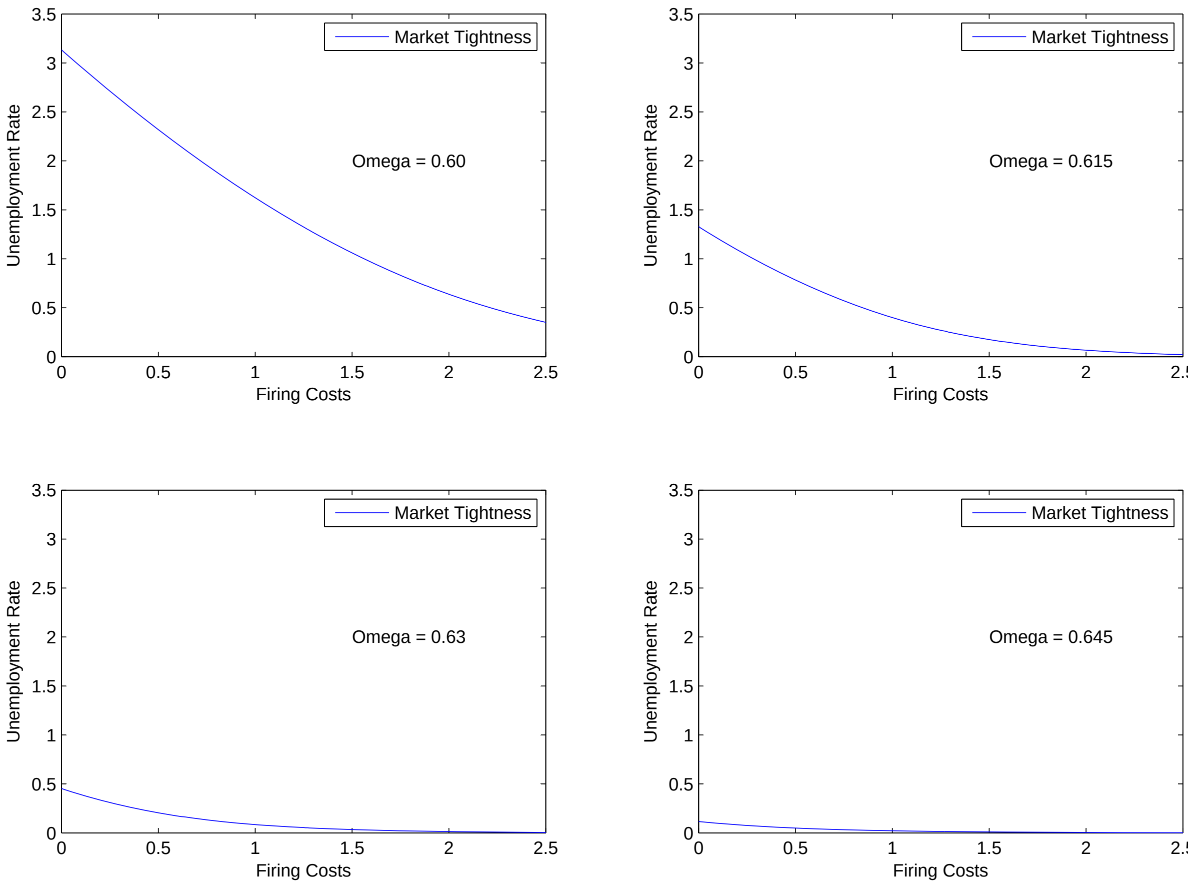


Figure B.5 – The figure shows equilibrium market tightness as a function of firing costs. Each graph results from a simulation using the exact same set of parameter values except of the wage parameter. Source: Own simulations.

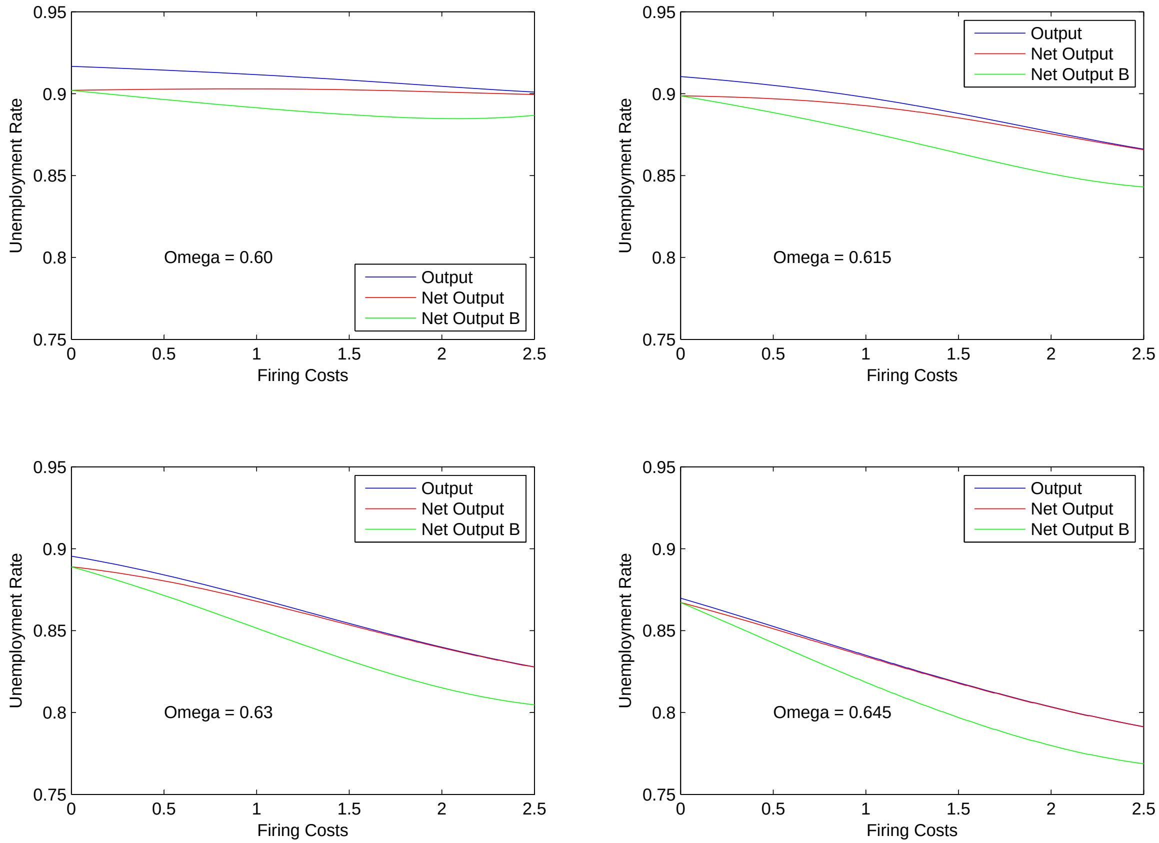


Figure B.6 – The figure shows total output and two definitions of net output as functions of firing costs. Net Output is calculated as total output net of recruiting expenditures, while Net Output B is calculated as Net Output minus total firing costs. Each graph results from a simulation using the exact same set of parameter values except of the wage parameter. Source: Own simulations.

Appendix C

Appendix to Chapter 3

C.1 Figures

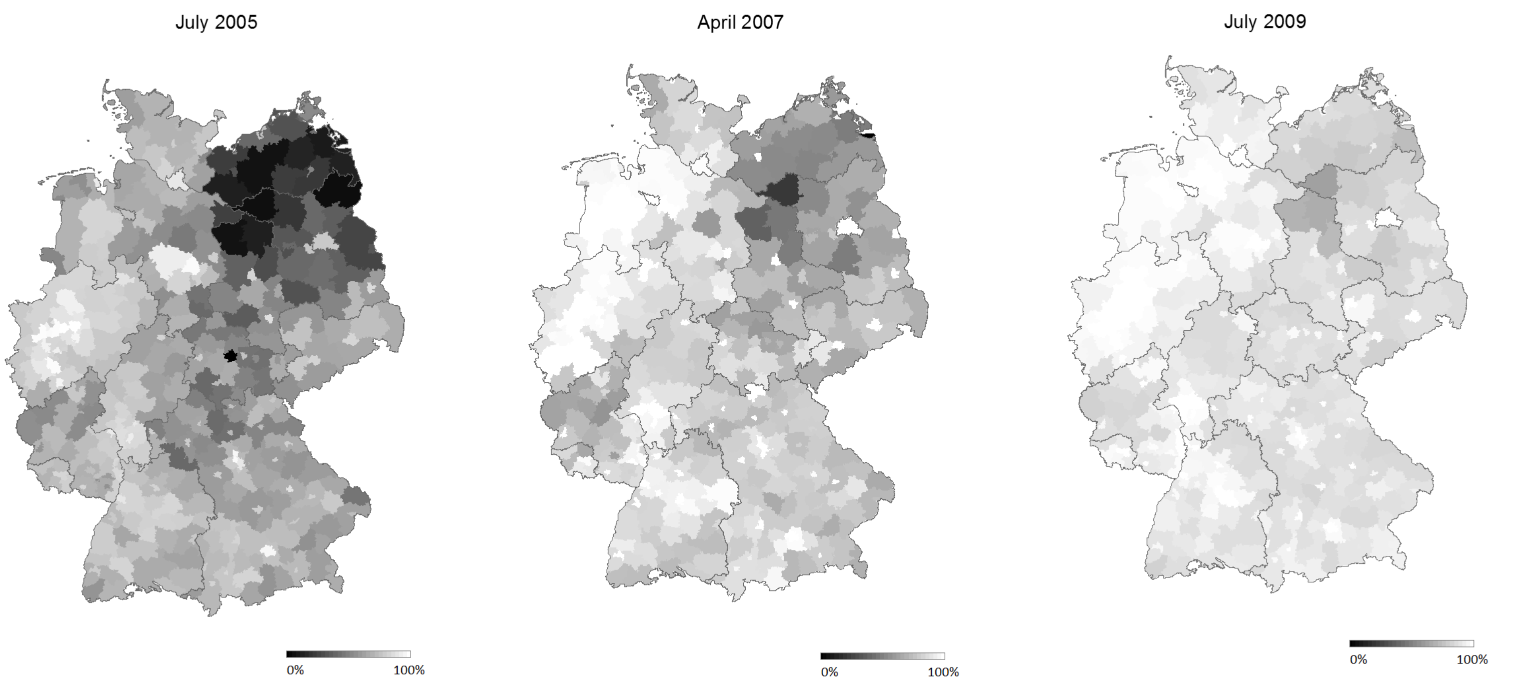
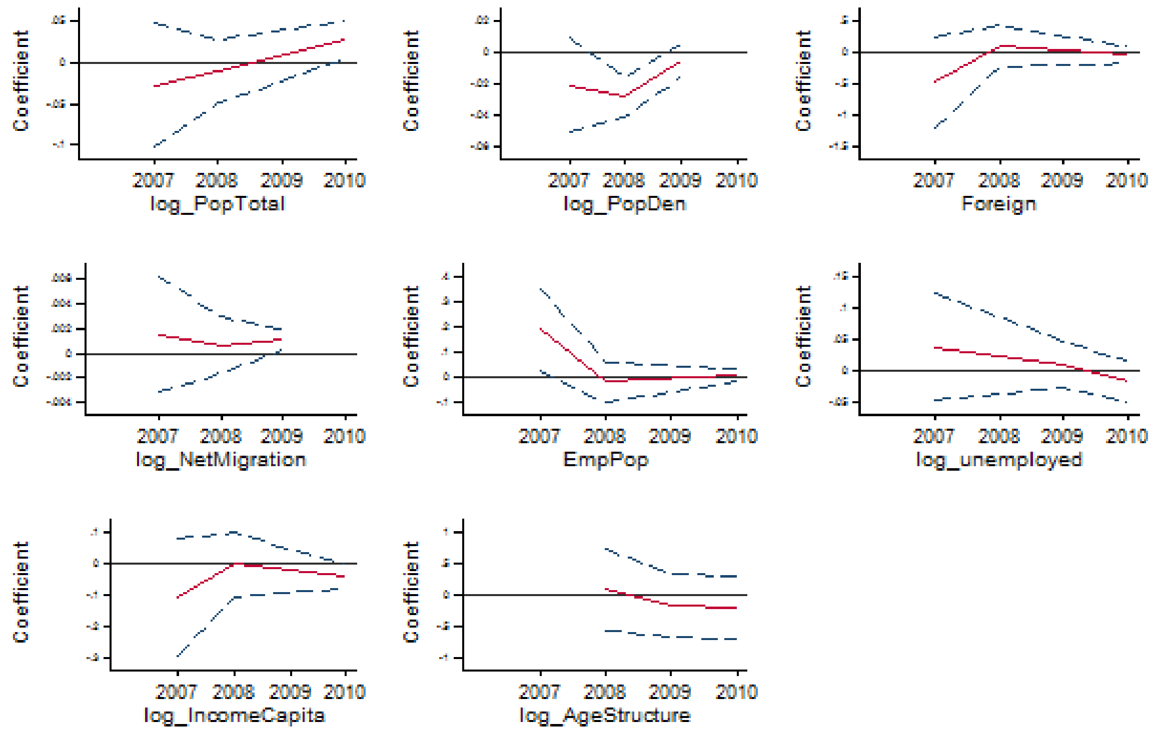


Figure C.1 – Geographical distribution of broadband availability across German counties in years 2005, 2007 and 2009. Source: Breitbandatlas

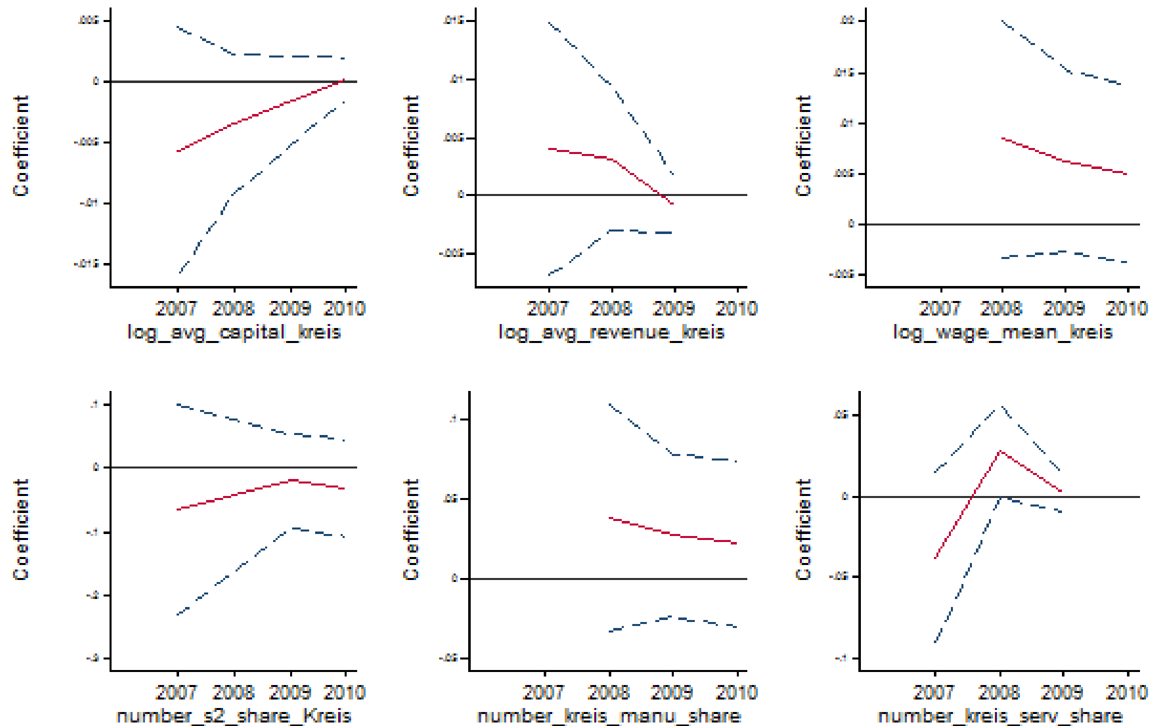
Figure C.2 – Timing of Broadband and Demographic Controls, 2006-2010



Note: Red solid line connects estimated coefficients; blue dashed lines connect upper and lower bounds (95% confidence level). The coefficients are estimated for the interactions of variables (value from 2005) with year dummies. Missing values for some years correspond to omitted interactions.

Source:LIAB

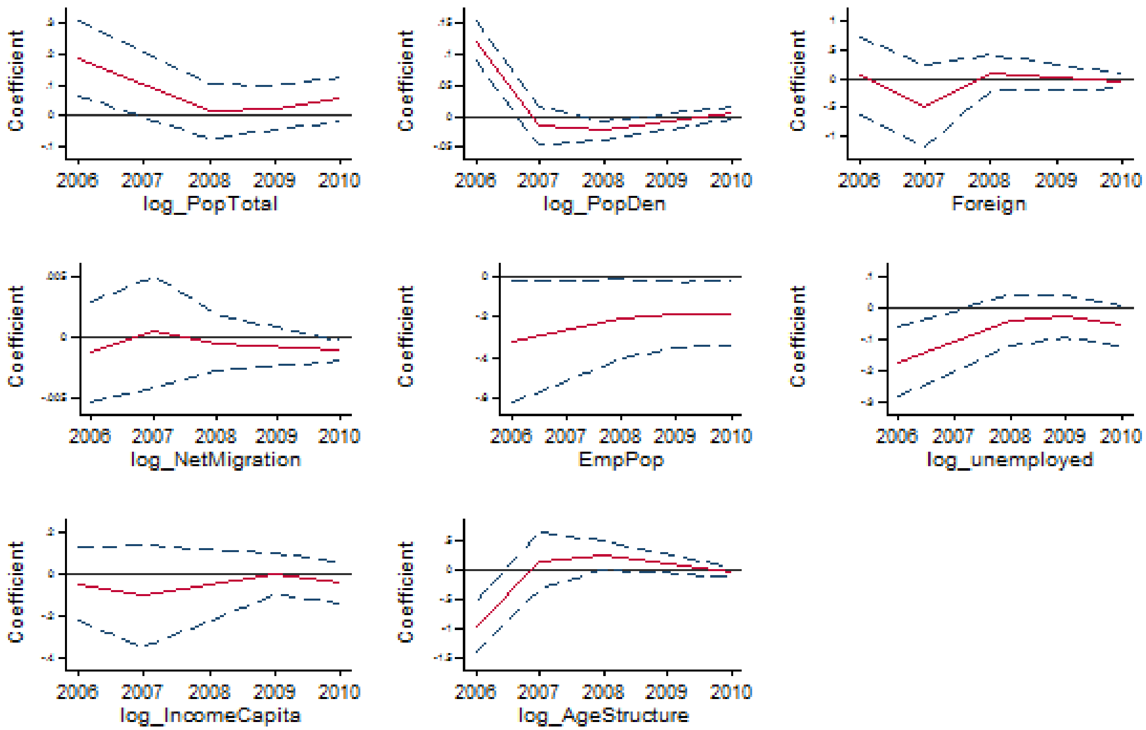
Figure C.3 – Timing of Broadband and Input/Output Controls, 2006-2010



Note: Red solid line connects estimated coefficients; blue dashed lines connect upper and lower bounds (95% confidence level). The coefficients are estimated for the interactions of variables (value from 2005) with year dummies. Missing values for some years correspond to omitted interactions

Source:LIAB

Figure C.4 – Timing of Broadband and Demographic Controls, 2000+2006-2010

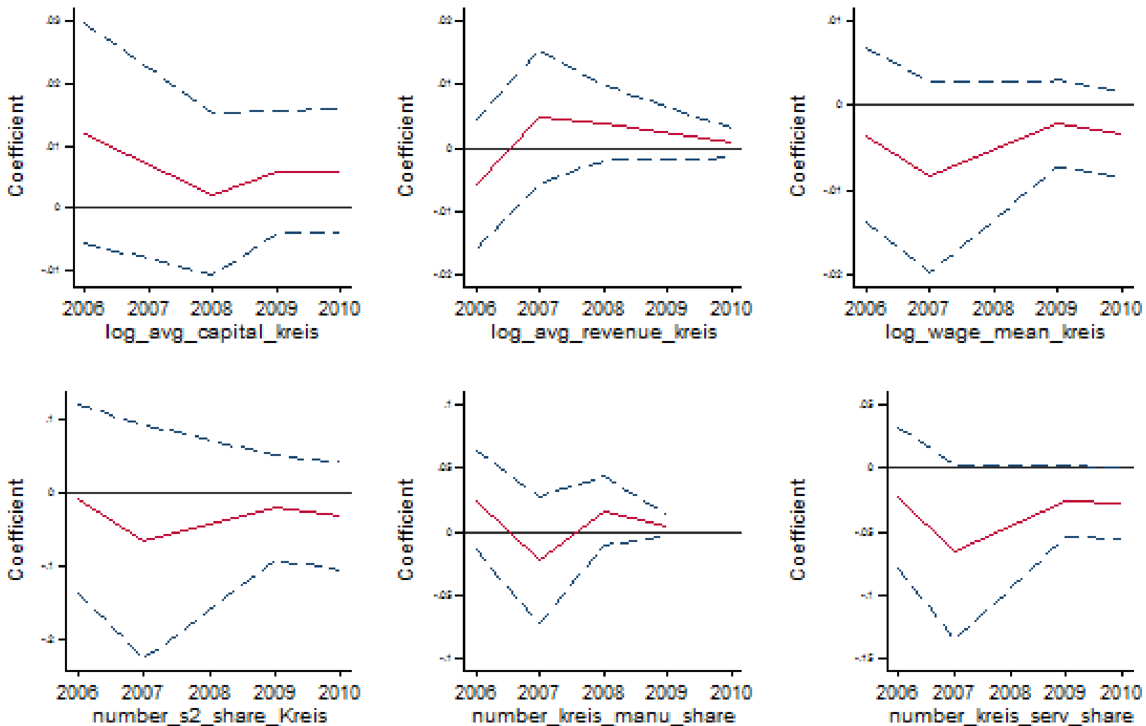


Note:Red solid line connects estimated coefficients; blue dashed lines connect upper and lower bounds (95% confidence level). The coefficients are estimated for the interactions of variables (value from 2000) with year dummies. Missing values for some years correspond to omitted interactions

Source:LIAB

Figure C.5 – Timing of Broadband and Input/Output Controls,

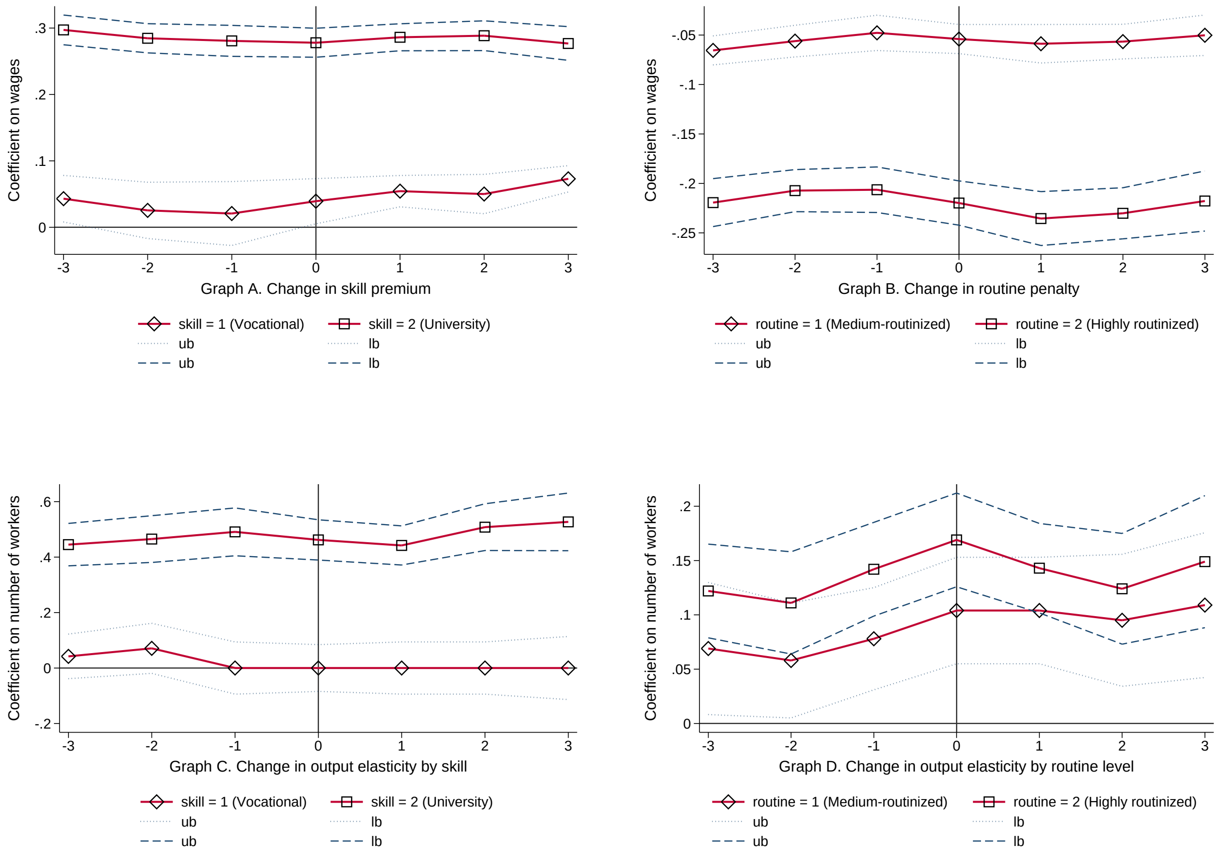
2000+2006-2010



Note: Red solid line connects estimated coefficients; blue dashed lines connect upper and lower bounds (95% confidence level). The coefficients are estimated for the interactions of variables (value from 2000) with year dummies. Missing values for some years correspond to omitted interactions

Source:LIAB

Figure C.6 – Event-Study Illustration



Note: Red solid lines connect estimated coefficients; blue dashed and dotted lines connect upper and lower bounds (95% confidence level). Year 0 is the year of the largest increase in broadband availability within a county. Wage and production function regressions are estimated separately for each period (including controls, year, industry, and county fixed effects). The plotted coefficients correspond to skill premium (Graph A), routine penalty (Graph B), output elasticity of skilled workers (Graph C), and output elasticity of workers in routine occupations (Graph D). Note: Red solid lines connect estimated coefficients; blue dashed and dotted lines connect upper and lower bounds (95% confidence level). Year 0 is the year of the largest increase in broadband availability within a county. Wage and production function regressions are estimated separately for each period (including controls, year, industry, and county fixed effects). The plotted coefficients correspond to skill premium (Graph A), routine penalty (Graph B), output elasticity of skilled workers (Graph C), and output elasticity of workers in routine occupations (Graph D).

Source:LIAB

C.2 Tables

Table C.1 – Frequency of Past Unemployment Spells by Skill / Routine Group

	(1) % Workers with past UE		(2) % Workers with past UE
		Year = 2006	
Low Skilled	7.347	Low Routine	5.702
Medium Skilled	4.021	Medium Routine	5.664
High Skilled	5.121	High Routine	9.949
		Year = 2007	
Low Skilled	7.459	Low Routine	5.444
Medium Skilled	3.822	Medium Routine	5.626
High Skilled	5.056	High Routine	9.905
		Year = 2008	
Low Skilled	7.159	Low Routine	5.188
Medium Skilled	3.447	Medium Routine	5.325
High Skilled	4.726	High Routine	9.376
		Year = 2009	
Low Skilled	6.3372	Low Routine	4.848
Medium Skilled	3.287	Medium Routine	4.965
High Skilled	4.398	High Routine	8.086
		Year = 2010	
Low Skilled	4.578	Low Routine	3.777
Medium Skilled	3.104	Medium Routine	4.033
High Skilled	3.943	High Routine	5.669
		Total	
Low Skilled	6.670	Low Routine	5.061
Medium Skilled	3.567	Medium Routine	5.188
High Skilled	4.678	High Routine	8.777

Notes: The table displays the frequency of past unemployment spells by skill level as well as by job routinization for each year between 2006 and 2010. Source: LIAB.

Table C.2 – Dynamics of Days in Unemployment by Skill and Routine Groups

	(1) Low-skill	(2) Medium-skill	(3) High-skill	(4) High-routine	(5) Medium-routine	(6) Low-rotine
2000	25.78	0.27	0.34	34.01	0.66	0.54
2006	12.06	0.41	0.48	15.25	0.75	0.60
2007	9.83	0.40	0.47	12.39	0.75	0.59
2008	9.83	0.37	0.45	13.51	0.65	0.51
2009	13.07	0.36	0.41	18.21	0.58	0.51
2010	8.85	0.45	0.52	11.94	0.69	0.59

Note: LIAB dataset. The table shows average annual number of days in unemployment for low-skill workers and workers in high-routine occupations (reference groups). Unemployment days for other groups of workers are divided by the values in the reference group.

Table C.3 – Variance Decomposition - Broadband Availability

	(1)	(2)	(3)	(4)
	full sample	full sample	2006-2010	2006-2010
Total Population		0.0649		-1.409***
		(0.130)		(0.524)
Population Density		0.0102		0.263
		(0.0948)		(0.313)
Share of Foreigners		-0.0722		4.002***
		(0.441)		(1.519)
Net Migration		0.00284***		-0.00114
		(0.000733)		(0.00101)
Employment-to-Population		0.0721***		0.0177
		(0.0205)		(0.0241)
Number of Unemployed		0.0630***		-0.0285
		(0.0204)		(0.0319)
Income per Capita		-0.0105		0.614***
		(0.0765)		(0.184)
Age Structure		-0.532**		-1.731***
		(0.267)		(0.553)
Average Revenue per County		-0.00182		0.00142
		(0.00200)		(0.00262)
High Skilled Share per County		0.0127		-0.0318
		(0.0574)		(0.0709)
Observations	2,408	2,180	1,971	1,835
R^2	0.973	0.976	0.795	0.825
FE	y kkz	y kkz	y kkz	y kkz
Controls	no	yes	no	yes
KKZ	465	396	412	396

Robust standard errors in parentheses

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

Note: LIAB dataset. Full sample includes year 2000, when broadband availability was equal 0 in all counties.

Table C.4 – Results - SBTC: Output Elasticity (2000 + 2006-2010)

	Formal Education					*Routine-Index*			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
	Number	Number	Wage bill	Wage bill		Number	Number	Wage bill	Wage bill
Low-skill	0.229***	0.226***	0.0625***	0.0621***	High-routine	0.227***	0.237***	0.0609***	0.0620***
	(0.0276)	(0.0261)	(0.0079)	(0.00815)		(0.0289)	(0.0280)	(0.00582)	(0.00566)
Medium-skill	0.178***	0.130**	0.0453***	0.0409***	Medium-routine	0.0630*	0.0655**	0.0270***	0.0272***
	(0.0552)	(0.0586)	(0.00705)	(0.00781)		(0.0324)	(0.0322)	(0.00616)	(0.00636)
High-sill	0.215***	0.224***	0.0609***	0.0619***	Low-routine	0.234***	0.214***	0.0570***	0.0556***
	(0.0423)	(0.0433)	(0.00640)	(0.00678)		(0.0295)	(0.0312)	(0.00619)	(0.00653)
Broadband	-0.0267	-0.236*	0.130	-0.0903	Broadband	-0.113	-0.323***	-0.136	-0.311
	(0.116)	(0.126)	(0.129)	(0.134)		(0.114)	(0.124)	(0.130)	(0.137)
L-skill*Broadband	-0.0638*	-0.0672**	-0.0133	-0.0137	H-routine*Broadband	-0.118***	-0.128***	-0.0109*	-0.0120*
	(0.0364)	(0.0316)	(0.00913)	(0.00891)		(0.0279)	(0.0267)	(0.00637)	(0.00611)
M-skill*Broadband	-0.199***	-0.163**	-0.00862	-0.00443	M-routine*Broadband	0.0146	0.00411	0.00415	0.00233
	(0.0591)	(0.0637)	(0.00777)	(0.00843)		(0.0314)	(0.0323)	(0.00415)	(0.00233)
H-skill*Broadband	0.220***	0.226***	0.0174**	0.0169**	L-routine*Broadband	0.0530*	0.0758*	0.00939	0.0105
	(0.0483)	(0.0489)	(0.00712)	(0.00734)		(0.0292)	(0.0313)	(0.00667)	(0.00709)
Collective	0.672***	0.682***	0.674***	0.686***	Collective	0.716***	0.727***	0.729***	0.739***
	(0.0352)	(0.0371)	(0.0345)	(0.0362)		(0.0365)	(0.0384)	(0.0359)	(0.0380)
Observations	26,510	24,232	26,510	24,232	Observations	25,510	24,232	25,510	24,232
R^2	0.664	0.667	0.667	0.671	R^2	0.657	0.660	0.659	0.662
FE	y i kkz	y i kkz	y i kkz	y i kkz	FE	y i kkz	y i kkz	y i kkz	y i kkz
HTT	no	yes	no	yes	HTT	no	yes	no	yes
Clusters	446	402	446	402	Clusters	446	402	446	402

Note: The table presents results of the standard production function estimation. Workers are classified by either formal education or job routinization. All regressions include year, industry, and county fixed effects. Unreported controls are firm capital stock, its interaction with Broadband, firm age (linear and squared). Specifications 2, 4, 6, 8 control for heterogeneous time trends. Robust standard errors in parentheses are clustered on the county level. In the skill regressions, $Low * Broadband$ represents the number (wage bill) of low-skilled workers employed by a firm. In the routine regressions, $Low * Broadband$ represents the number (wage bill) of workers employed in low-routine jobs. The same denotation holds for $Medium * Broadband$ and $High * Broadband$.

Table C.5 – Results - SBTC: Wage Regressions (2000 + 2006-2010)

	Formal Education					*Routine-Index*			
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
	Uncensored	Uncensored	Imputed	Imputed		Uncensored	Uncensored	Imputed	Imputed
Medium-skill	0.0664***	0.0645***	0.147***	0.149***	Medium-routine	-0.0678***	-0.0711***	-0.190***	-0.199***
	(0.0133)	(0.0140)	(0.0121)	(0.0123)		(0.00854)	(0.0104)	(0.0121)	(0.0129)
High-sill	0.270***	0.271***	0.533***	0.541***	High-routine	-0.190***	-0.187***	-0.368***	-0.370***
	(0.0149)	(0.0134)	(0.0123)	(0.0126)		(0.0132)	(0.0135)	(0.0162)	(0.0173)
Broadband	-0.00215	-0.0155	0.000997	-0.0189	Broadband	-0.00156	-0.00536	0.0190	0.0142
	(0.0167)	(0.0173)	(0.0179)	(0.0190)		(0.0172)	(0.0222)	(0.0201)	(0.0257)
M-skill*Broadband	-0.0435***	-0.0423***	-0.00509	-0.00786	M-routine*Broadband	0.00240	0.00497	-0.0134	-0.00597
	(0.0116)	(0.0125)	(0.0134)	(0.0148)		(0.00761)	(0.00987)	(0.0121)	(0.0130)
H-skill*Broadband	-0.0153	-0.0144	0.0171	0.0101	H-routine*Broadband	-0.0244**	-0.0287**	-0.0567***	-0.0578***
	(0.0115)	(0.0114)	(0.0156)	(0.0138)		(0.0109)	(0.0115)	(0.0102)	(0.0109)
Experience	0.204***	0.202***	0.162***	0.161***	Experience	0.225***	0.225***	0.240***	0.241***
	(0.0204)	(0.0211)	(0.0209)	(0.0216)		(0.0212)	(0.0220)	(0.0211)	(0.0217)
Collective	0.138***	0.135***	0.138***	0.135***	Collective	0.146***	0.143***	0.152***	0.148***
	(0.0106)	(0.0108)	(0.0118)	(0.0122)		(0.0110)	(0.0112)	(0.0132)	(0.0136)
Female	-0.105***	-0.105***	-0.159***	-0.160***	Female	-0.105***	-0.106***	-0.157***	-0.158***
	(0.00827)	(0.00877)	(0.00962)	(0.0101)		(0.00750)	(0.00794)	(0.0104)	(0.0109)
Observations	1,875,948	1,795,661	2,244,190	2,155,442	Observations	1,875,948	1,795,661	2,244,190	2,155,442
R^2	0.528	0.522	0.544	0.541	R^2	0.529	0.523	0.505	0.500
FE	y i kkz	y i kkz	y i kkz	y i kkz	FE	y i kkz	y i kkz	y i kkz	y i kkz
HTT	no	yes	no	yes	HTT	no	yes	no	yes
Clusters	459	406	459	406	Clusters	459	406	459	406

Note: The table presents results of the standard wage regressions. Workers are classified by either formal education or job routinization. All specifications include year, industry, and county fixed effects. Specifications 2, 4, 6, 8 control for heterogeneous time trends. Robust standard errors in parentheses are clustered on the county level. "Skill"("Routine") are indicator variables. We choose $Low - skill$ ($Low - routine$) as the base category. The reported interaction coefficients reveal how wages of medium- and high-skill (routine) workers change due to broadband compared to low-skill(routine) workers.

Table C.6 – Effect of Broadband on Output Elasticities, Event-Study

	Formal Education (1) Number	(2) Wage bill		*Routine Index* (3) Number	(4) Wage bill
Low-skill	0.143***	0.0452***	High-routine	0.123***	0.0501***
	(0.0191)	(0.00387)		(0.0155)	(0.00316)
Medium-skill	0.055***	0.0428***	Medium-routine	0.0739***	0.0323***
	(0.0305)	(0.00386)		(0.0200)	(0.00356)
High-skill	0.453***	0.0896***	Low-routine	0.316***	0.0739***
	(0.0317)	(0.00369)		(0.0201)	(0.00374)
After	-0.0850*	0.0100	After	-0.0435	-0.0787
	(0.0497)	(0.00881)		(0.0456)	(0.0507)
Low-skill*After	0.0667***	0.0127*	H-routine*After	0.0297**	0.00979***
	(0.0158)	(0.00405)		(0.0147)	(0.00313)
Medium-skill*After	-0.0977***	0	M-routine*After	0.0237	0.00575*
	(0.0298)	(0.00365)		(0.0165)	(0.00298)
High-skill*After	0.0295	0.00164	L-routine*After	-0.00106	0.00322
	(0.0246)	(0.00352)		(0.0155)	(0.00296)
Collective	0.808***	0.817***	Collective	0.845***	0.855***
	(0.0363)	(0.0351)		(0.0364)	(0.0366)
Constant	10.85***	10.61***	Constant	10.68***	10.17***
	(0.225)	(0.239)		(0.252)	(0.240)
Observations	37,412	37,412	Observations	37,412	37,412
R^2	0.591	0.598	R^2	0.582	0.586
FE	y i kkz	y i kkz	FE	y i kkz	y i kkz
HTT	no	no	HTT	no	no
Clusters	408	408	Clusters	408	408

Note: The table presents the results of the standard production function estimation. The dummy variable $After$ is equal 1 for years ≥ the year of the largest growth in broadband availability. All regressions include year, industry, and county fixed effects. Unreported controls are firm capital stock, its interaction with $After$, firm age (linear and squared). Robust standard errors in parentheses are clustered on the county level. In the skill regressions *Low* represents the number (wage bill) of low-skilled workers employed by a firm. In the routine regressions *Low* represents the number (wage bill) of workers employed in low-routine jobs. The same denotation holds for $Medium$ and $High$. The reported interaction coefficients reveal how output elasticities of high and medium-skilled (routine) workers change compared to low-skilled (routine) workers before and after the expansion of broadband.

Table C.7 – Effect of Broadband on Wages, Event-Study

	Formal Education			*Routine Index*	
	(1)	(2)		(3)	(4)
	uncensored	imputed		uncensored	imputed
Medium-skill	0.0467***	0.153***	Medium-routine	-0.0591***	-0.193***
	(0.0158)	(0.0153)		(0.00702)	(0.0156)
High-skill	0.284***	0.569***	High-routine	-0.205***	-0.403***
	(0.0101)	(0.0146)		(0.0111)	(0.0143)
After	0.00363	0.0100	After	0.0143	0.0278**
	(0.00745)	(0.00881)		(0.00881)	(0.0126)
Medium-skill*After	0.0107	0.0174**	M-routine*After	0.000475	-0.00773
	(0.00908)	(0.00768)		(0.00659)	(0.0132)
High-skill*After	-0.00495	-0.000527	H-routine*After	-0.0306***	-0.0421***
	(0.00905)	(0.0103)		(0.00880)	(0.0123)
Experience	0.225***	0.185***	Experience	0.249***	0.262***
	(0.0190)	(0.0188)		(0.0190)	(0.0178)
Experience2	-0.0190***	0.00248	Experience2	-0.0263***	-0.0208***
	(0.00350)	(0.00369)		(0.00336)	(0.00344)
Collective	0.149***	0.149***	Collective	0.164***	0.173***
	(0.0121)	(0.0134)		(0.0128)	(0.0151)
Female	-0.0935***	-0.146***	Female	-0.0978***	-0.150***
	(0.00848)	(0.00962)		(0.00725)	(0.00946)
Constant	2.926***	2.903***	Constant	3.042***	3.118***
	(0.0998)	(0.109)		(0.0993)	(0.118)
Observations	3,988,323	4,777,405	Observations	3,988,323	4,777,405
R^2	0.492	0.523	R^2	0.491	0.474
FE	y i kkz	y i kkz	FE	y i kkz	y i kkz
HTT	no	no	HTT	no	no
Clusters	465	465	Clusters	465	465

Note: The table presents the results of the standard wage regressions. The dummy variable $After$ is equal 1 for years $\geq$ the year of the largest growth in broadband availability. All regressions include year, industry, and county fixed effects. Robust standard errors in parentheses are clustered on the county level. "Skill" ("routine") are indicator variables. We choose $Low - skill$ ($Low - routine$) as the base category. The reported interaction coefficients reveal how wages of high- and medium-skilled (routine) workers change compared to low-skilled (routine) workers before and after the broadband expansion.

Table C.8 – Past Unemployment Penalty, Formal Education (2000+2006-2010)

	(1)	(2)	(3)	(4)
	Sample: All Workers			
	Uncensored		**Imputed**	
Variable	With HTT	Without HTT	With HTT	Without HTT
Past UE	-0.2112***	-0.2293***	-0.2184***	-0.2322***
	(0.000)	(0.000)	(0.000)	(0.000)
Past UE x Broadband	0.0839**	0.0969***	0.0435	0.0509
	(0.020)	(0.002)	(0.200)	(0.103)
R-squared	0.4713	0.4963	0.4010	0.4218
Worker - year Observations	1703865	1875948	2053684	2244190
	Sample: High-skilled Workers			
	Uncensored		**Imputed**	
Variable	With HTT	Without HTT	With HTT	Without HTT
Past UE	-0.1767***	-0.2200***	-0.2409***	-0.2909***
	(0.000)	(0.000)	(0.000)	(0.000)
Past UE x Broadband	0.1005**	0.1425***	0.0485	0.0951*
	(0.035)	(0.002)	(0.348)	(0.076)
R-squared	0.3545	0.3813	0.3759	0.3835
Worker - year Observations	135423	152902	305872	335092
	Sample: Medium-skilled Workers			
	Uncensored		**Imputed**	
Variable	With HTT	Without HTT	With HTT	Without HTT
Past UE	-0.0874	-0.1058	-0.0715	-0.0968
	(0.258)	(0.124)	(0.363)	(0.168)
Past UE x Broadband	0.0119	0.0256	-0.0692	-0.0492
	(0.882)	(0.718)	(0.405)	(0.508)
R-squared	0.4115	0.4113	0.4277	0.4278
Worker - year Observations	108575	115991	141179	149733
	Sample: Low-skilled Workers			
	Uncensored		**Imputed**	
Variable	With HTT	Without HTT	With HTT	Without HTT
Past UE	-0.1961***	-0.2129***	-0.1937***	-0.2086***
	(0.000)	(0.000)	(0.000)	(0.000)
Past UE x Broadband	0.061*	0.0727**	0.0401	0.0501*
	(0.068)	(0.011)	(0.206)	(0.070)
R-squared	0.5227	0.5457	0.4852	0.5089
Worker - year Observations	1459867	1607055	1606633	1759365

Notes: The table presents results of the unemployment wage penalty regressions using different samples. All specifications include year, industry and county fixed effects. Specifications 1 and 3 control for heterogeneous time trends. P-values in parentheses are computed using standard errors which are clustered on the county level. "Past UE" is an dummy variable, indicating whether a worker experienced an unemployment spell during the past five years.

Table C.9 – Past Unemployment Penalty, Routine Index (2000+2006-2010)

	(1)	(2)	(3)	(4)
	Sample: All Workers			
	Uncensored		**Imputed**	
Variable	With HTT	Without HTT	With HTT	Without HTT
Past UE	-0.2112***	-0.2293***	-0.2184***	-0.2322***
	(0.000)	(0.000)	(0.000)	(0.000)
Past UE x Broadband	0.0839**	0.0969***	0.0435	0.0509
	(0.020)	(0.002)	(0.200)	(0.103)
R-squared	0.4713	0.4963	0.4010	0.4218
Worker - year Observations	1703865	1875948	2053684	2244190
	Sample: Low-routine Workers			
	Uncensored		**Imputed**	
Variable	With HTT	Without HTT	With HTT	Without HTT
Past UE	-0.1905***	-0.2276***	-0.2573***	-0.2920***
	(0.000)	(0.000)	(0.000)	(0.000)
Past UE x Broadband	0.0906**	0.1239**	0.0800*	0.1097*
	(0.030)	(0.015)	(0.085)	(0.064)
R-squared	0.4706	0.5092	0.3756	0.4062
Worker - year Observations	160172	175489	254603	274187
	Sample: Medium-routine Workers			
	Uncensored		**Imputed**	
Variable	With HTT	Without HTT	With HTT	Without HTT
Past UE	-0.2668***	-0.2795***	-0.2620***	-0.2771***
	(0.000)	(0.000)	(0.000)	(0.000)
Past UE x Broadband	0.1434***	0.1513***	0.1163**	0.1257***
	(0.008)	(0.001)	(0.027)	(0.004)
R-squared	0.4608	0.4827	0.4393	0.4556
Worker - year Observations	604533	671548	684540	756025
	Sample: High-routine Workers			
	Uncensored		**Imputed**	
Variable	With HTT	Without HTT	With HTT	Without HTT
Past UE	-0.0894***	-0.1244***	-0.0867***	-0.1207***
	(0.003)	(0.000)	(0.004)	(0.000)
Past UE x Broadband	-0.0144	0.0189	-0.0223	0.010
	(0.634)	(0.462)	(0.466)	(0.697)
R-squared	0.5925	0.6134	0.5766	0.5988
Worker - year Observations	586751	636025	599203	648805

Notes: The table presents results of the unemployment wage penalty regressions using different samples. All specifications include year, industry and county fixed effects. Specifications 1 and 3 control for heterogeneous time trends. P-values in parentheses are computed using standard errors which are clustered on the county level. “Past UE” is an dummy variable, indicating whether a worker experienced an unemployment spell during the past five years.

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