Labour Market Institutions and Employment

Dissertation

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Introduction

1.1 Labour market institutions

Income is not only necessary to satisfy basic needs such as food, shelter and health care. Increasing income, on average, also leads to higher subject well-being (Easterlin 2001). Labour market participation is the major source of income for most individuals. As pointed out by the International Monetary Fund (2017), the share of income paid in wages amounted to approximately 50% in advanced economies as of 2014.[1] The distribution of capital, the other major source of income, is rather unequal. In the United States, the bottom-share of the wealth distribution (60%) owns less than 2.5% (Germany 2014: 6.5%) of household wealth (OECD 2018c). These figures imply that capital income is therefore de facto irrelevant for the majority of the population.

These individuals' economic fortune is hence largely determined by their labour market experiences; that is, the evolution of wages and (un)employment spells is of crucial importance for most people. Yet, labour markets outcomes (employment and wages) may be perceived as unsatisfactory (or unfair) by some participants or are perhaps even suboptimal. For example, the harmonised unemployment rate in the OECD countries averaged more than 8% after the Financial crisis (2009 –

[1]The difference between the labour share of income with and without self-employment is small. It corresponds to approximately 10% of total income (O'Higgins and Moscariello 2017).

2013) (OECD 2018a). The unemployment rate is usually found to be higher among low-skilled workers (OECD 2018b). Furthermore, an increase in wage inequality has been observed over the past decades, especially for those at the lower end of the wage distribution (e.g., Juhn et al. 1993 or Acemoglu and Autor 2011).

The purpose of labour market institutions is typically to protect the more vulnerable participants (O'Higgins and Moscariello 2017). Boeri (2011, p. 1182) defines a labour market institution as "a system of laws, norms or conventions resulting from a collective choice, and providing constraints or incentives which alter individual choices over labour and pay." That is, labour market institutions are policy interventions which affect the extent to which labour markets can freely adjust towards changes in the economic environment. Hence, labour market institutions affect labour market outcomes in terms of quantities and prices (employment and wages).

Because labour markets are complex, it is not always straight forward whether or not labour market institutions accomplish their objectives; they can also have side effects (Saint-Paul 2000). Economists are therefore naturally interested in studying how labour market institutions affect labour market outcomes. The *employment effects* of several labour market institutions are analysed in the literature. Frequently discussed are the following institutions (e.g., Neumark and Wascher 2004, Boeri 2011 or Holmlund 2014):

1. Active labour market policy:

   Active labour market policies are intended to improve the functioning of labour markets and are directed towards the unemployed; they aim to help unemployed workers to find a job (Calmfors 1994) and may include job training, subsidised employment, search assistance, and others (Card et al. 2010). In meta-analyses, Card et al. (2010, 2018) find that search assistance and training programs are generally favourable (with respect to employment) while the impact of subsidised employment programs is questionable.

2. Employment protection legislation:

   According to Skedinger (2010), employment protection legislation restricts the employer's ability to lay off employees to protect them from (unjust) firings, and hence, decreases job destruction. At the same time, employment protection legislation also reduces job creation because employers are more reluctant to hire additional staff since the ability to dismiss an (unproductive) worker is reduced. Skedinger (2010) argues that the literature does not reach consensus regarding the employment effects of employment protection legislation.

3. Minimum wages:

   Minimum wages typically aim to improve the economic situation of rather unproductive, low-wage employees (Neumark and Wascher 2007). However, if a low-wage worker's productivity is very low such that paying the minimum wage implies a loss for the employer, the worker may loose her job. Hence, the minimum wage may worsen low-productivity employees' economic situation. Neumark and Wascher (2007) point out that the empirical literature on the employment effects of minimum wages is inconclusive.

4. Unemployment benefits:

   The purpose of unemployment benefits is to protect workers against income losses during spells of unemployment (Moffitt 2014). Schmieder and von Wachter (2016) argue that the majority of studies agrees upon the employment effects of unemployment benefits. Generous employment benefits (level and duration) are typically found to have a negative impact on labour supply due to workers higher outside option and thus, have a negative effect on employment.

Other labour-market policies, such as collective-bargaining rules (e.g., Aidt and Tzannatos 2002), restrictiveness of labour standards (e.g., Neumark and Wascher 2004), short-time work (e.g., Balleer et al. 2016), or the tax wedge (e.g., Boeri 2011) are likely to effect labour market outcomes as well. However, even briefly discussing every policy goes beyond the scope of this chapter due to the amount of different institutions.

In this dissertation, I focus on the employment effects of minimum wages and employment protection legislation for two reasons. First, the impact on employment of these two labour market institutions remains subject to debates among scholars despite extensive research (e.g., Holmlund 2014). Second, Neumark and Wascher (2007) argue that minimum wages and employment protection legislation can have sizeable effects on labour market outcomes.

This thesis consists of three individual chapters and a conclusion. In the following subsections, I discuss how each chapter fits into and contributes to the relevant literature.

1.2 Chapter overview

1.2.1 Minimum wages and employment

Increasing wage inequality between skilled and unskilled labour has been observed for decades (Acemoglu 2002). Minimum wages are typically viewed as a tool to mitigate this inequality and aim to improve the economic situation of rather unproductive (unskilled), low-wage employees (Neumark and Wascher 2007). However, some jobs may be destroyed due to minimum-wage induced increases in labour cost and hence, worsen affected workers' situations. From a distributional point of view, it is therefore important to understand the effects of minimum wages on employment.

Contrary to a neoclassical textbook model (e.g., Ehrenberg and Smith, 2012) the employment effects of minimum wages in more realistic, complex models, e.g. an efficiency-wage model (Yellen 1984), a monopsony model (Dickens et al. 1999), a search model with endogenous contact rates (Flinn 2006), or a two-sided flow model (A. Brown et al. 2014) are ambiguous. The early empirical (mostly time-series) literature on the employment effects of minimum wages in the U.S. is thoroughly reviewed by C. Brown et al. (1982). In line with the neoclassical model, their main finding is that employment tends to decrease for those workers who are affected by the minimum wages.

According to Neumark and Wascher (1992), the nationwide time-series studies regress the employment-to-population ratio on a minimum wage variable and controls. The construction of the minimum wage variable typically includes the minimum and the average (or median) wage. Because the minimum wage does not change frequently, variation in the minimum wage variable is largely driven by changes in the average wage. Hence, the estimated effect reflects changes of the average instead of the minimum wage. Furthermore, most of the studies discussed by Neumark and Wascher (1992) use data on the federal minimum wage but neglect geographical differences. Instead, they employ a panel-data approach with state-level variables as the cross-sectional dimension. Their results suggest a negative effect of the minimum wage on employment.

A second branch of the literature exploits natural experiments. For example, Card (1992) investigate the raise of the minimum wage in California in July 1988 employing a difference-in-difference approach and does not detect negative employment effects. Other examples of methodologically comparable studies (e.g., Katz and Krueger 1992, Card and Krueger 1994, or Machin and Manning 1994 (UK)) draw similar conclusions.

The empirical literature does not conclusively answer whether minimum wages have positive, negative or, no effects on employment (Neumark and Wascher 2007). Dube et al. (2010) conclude that case studies typically do not find a negative employment effect whereas panel-data approaches indicate negative effects. However, both approaches may result in misleading estimates because they fail to account for unobserved heterogeneity. Instead, Dube et al. (2010) generalise the case-study method by considering all local differences in minimum-wage policies between 1990 and 2006. Their study does not speak in favour of negative employment effects.

Because a statutory minimum wage was not introduced until 2015 in Germany, relatively few papers study the effect of minimum wages on employment in Germany. For example, Bossler and Gerner (2016) or Caliendo et al. (2018) find (small) negative effects while others, such as Schubert et al. (2016), do not detect statistically significant effects or even positive effects on regular employment (Garloff 2016). As in the international case, the results on the employment effects of the German minimum-wage introduction are ambiguous. An overview of existing studies is given by Caliendo et al. (2019).

Chapter 2, *Employment Effects of Introducing a Minimum Wage: The Case of Germany*[*], written jointly with Oliver Holtemöller, contributes to the existing empirical literature by supplying new evidence on the employment effects of minimum wages analysing the introduction of a statutory minimum wage in Germany in January 2015. We construct two variables that measure the effect of the minimum wage on the wage distribution for approximately 190 state-industry combinations and

[*]This chapter is based on joint work with Oliver Holtemöller. It has been published as O. Holtemöller and F. Pohle. "Employment Effects of Introducing a Minimum Wage: The Case of Germany". *Economic Modelling* (forthcoming). Only minor revisions were made to the published version. A previous version has been published as O. Holtemöller and F. Pohle. 2017. "Employment Effects of Introducing a Minimum Wage: The Case of Germany". *IWH Discussion Papers* 2017 (28).

estimate panel models with cross-section and time-fixed effects and cross-section specific time trends. The results indicate a negative effect on marginal employment (67,000 – 129,000 destroyed jobs) and a positive effect on regular employment (47,000 – 74,000 created jobs). We also study whether marginal employment was converted into regular employment but do not find evidence.

1.2.2 Minimum wages, labour mobility, and native employment

In general, labour mobility is important to achieve an efficient allocation of labour because it is what forces firms to pay the equilibrium wage; that is, labour mobility is fundamental in market economies (e.g., Ehrenberg and Smith 2012). In a neoclassical model of labour mobility (e.g., Borjas 1999), voluntary mobility can be regarded as an investment by individuals who expect to obtain a return in the future. It is costly because mobility involves direct (e.g. moving), opportunity, and psychic (e.g. leaving family members) costs. Future returns are expected, e.g. due to wage differentials between the place of origin and the potential destination. If the benefits exceed the cost, the net present value of mobility is positive and hence, people are willing to decide in favour of mobility. This is usually confirmed by empirical studies (e.g., Clemente et al. 2016 or Dustmann et al. 2017).

In case of international migration, positive effects for the domestic economy as a whole can be expected (Lucas 2005). In a neoclassical model of the labour market, however, an increase in labour supply due to migration should put competing workers at the destination under pressure in terms of wages and employment opportunities (Borjas 1999, 2003). In case of international migration, this implies that foreigners and natives compete for jobs and/or that foreigners put wages of natives under pressure. Despite the simplicity of this argument, the empirical evidence in this regard is mixed (e.g., Friedberg and Hunt 1995 or Okkerse 2008). Borjas (2003) points towards the importance of skills in this discussion as a potential explanation for the ambiguity. According to Dustmann et al. (2007), three different approaches are frequently used in the empirical literature: the spatial correlation approach (e.g., Altonji and Card 1991), the simulation based approach (e.g., Borjas et al. 1997), and the skill cell approach advanced by Borjas (2003). Dustmann et al. (2007) discuss these methods as well as their strengths and weaknesses in detail.

In addition to these approaches, natural experiments are useful to analyse the impact of migration on native employment. Glitz (2012) argues that very few papers exploit natural experiments. Card (1990) studies the impact of the Marial Boatlift and the resulting inflow of Cuban workers into Florida on natives' wages and the unemployment rate. He does not detect negative effects on either variable. Kugler and Yuksel (2008) analyse the inflow of Central Americans into the U.S. after a hurricane in 1998. They do not detect substantial negative effects on native employment and wages. However, Kugler and Yuksel (2008) also show that a subgroup of earlier migrants suffered from the surge of Latin American immigration. Glitz (2012) exploits the fall of the Berlin Wall which allowed ethnic Germans in eastern Europe and the former Soviet Union to migrate to Germany. His findings suggest that this inflow of immigrants had a negative effect on native employment but no effect on relative wages. Dustmann et al. (2017) analyse a change in a commuting policy in the early 1990s in Germany. They conclude that the inflow of Czech workers resulted in negative effects on natives' labour market outcomes.

Chapter 3, *Labour Mobility and Native Employment: Evidence from the German Minimum-Wage Introduction*[†], contributes to the empirical immigration literature. I exploit the quasi-natural experiment of the German minimum-wage introduction in 2015 and analyse whether or not the policy-induced increase in wage differentials between Germany and low-wage neighbouring countries (the Czech Republic and Poland) increased labour mobility from these countries using an event-study model. I find a positive effect on labour supply from the Czech Republic and Poland in the respective German border regions. I subsequently use distance to the border as an instrument for the inflow of foreign workers to determine the effects on German employment in an instrumental variable approach. The results do not speak in favour of negative effects on native employment.

1.2.3 Employment (protection) and technology shocks

As in the case of minimum wages, the employment effects of employment protection legislation are ambiguous, too. Economic theory suggests that employment protec-

[†]This chapter is partially based on joint, unpublished work with Daniel Fackler. I also wish to thank Michael Barkholz for his support with the distance computations.

tion legislation favours incumbent employees because their dismissal becomes more difficult. At the same time, it reduces firm's propensity to hire because the ability to reduce their workforce is restricted. Hence, the total employment effect depends on which channel dominates (Bertola 1999). The empirical literature is inconclusive, too. In a seminal paper, Lazear (1990) shows that employment protection legislation has a negative effect on employment. On the contrary, Miles (2000) does not detect negative effects on aggregate employment. Autor et al. (2007) even suggest that employment protection can have positive effects. A thorough review of the empirical literature is provided by Skedinger (2011).

The Search-and-Matching (henceforth: SAM) approach to the labour market, advanced by Mortensen and Pissarides (1994, 1999), allows to model these two channels explicitly.[2] Employment protection legislation is modelled in the form of firing costs and reduces both job creation and job destruction and hence, the overall effect is analytically ambiguous (Pissarides 2000). The SAM approach is furthermore superior to a frictionless, neoclassical model in various dimensions, such as explaining equilibrium unemployment, the duration of unemployment spells etc. (e.g., Rogerson et al. 2005 or Yashiv 2007).

Dynamic stochastic general equilibrium (henceforth: DSGE) models have become a standard tool for academic research, forecasting, and policy analysis (Herbst and Schorfheide 2016). However, standard DSGE models (e.g., Rotemberg and Woodford 1997 or King and Rebelo 1999) usually apply a frictionless, neoclassical approach to model the labour market. Hence these models cannot account for equilibrium unemployment etc.

It therefore seems reasonable to embed such a labour market specification into DGSE models. For example, Merz (1995) and Andolfatto (1996) combine a real-business-cycle (henceforth: RBC) model with SAM (i.e. search frictions). Den Haan et al. (2000) extend this work by incorporating search frictions with endogenous separations into a New-Keynesian (henceforth: NK) model. Zanetti (2011) builds on den Haan et al. (2000) and explicitly studies the impact of firing costs on aggregate variables. Among other things, he finds that a moderate firing tax increase reduces both the level of employment and the volatility of employment over the business

[2]Notice that there are other models which allow studying the effects of employment protection legislation (e.g., Bentolila and Bertola 1990).

cycle. At the same time, the model proposed by Zanetti (2011) fails to replicate an important empirical observation. As shown by Galí (1999), employment drops after a technology shock.[3] The ability to explain this observation is one of the key features that distinguishes NK from RBC models. Therefore, the NK-SAM model proposed by Zanetti (2011) has a shortcoming in this regard. This is especially worrisome because this shortcoming is related to a key variable the model seeks to explain (employment). Hence, the incorporation of a powerful approach to model the labour market (SAM) worsens the model's empirical performance with respect to labour market outcomes.

In chapter 4, *Employment, Technology, and Hiring Costs in a NK-SAM Framework*, I propose an extension to Zanetti's model to address this shortcoming. I follow Mandelman and Zanetti (2014), who embed technology-dependent hiring costs along the lines of Blanchard and Galí (2010) in a RBC-SAM model without endogenous separations, and enrich the model proposed by Zanetti (2011) (NK-SAM model with endogenous separations) with technology-dependent hiring costs. The extension reduces both job creation (direct effect) and job destruction (indirect effects). For reasonable levels of hiring costs, the latter effect dominates the former and thus, the extended model does not replicate Galí's (1999) observation. However, once I abstract from endogenous separations, the model's empirical performance in this regard improves.

[3]The interested reader is referred to Ramey (2016) for a thorough review on the ongoing discussion of the effects of technology shocks on employment.

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Chapter 2

Employment Effects of Introducing a Minimum Wage: The Case of Germany*

Abstract

Income inequality has been a major concern of economic policy makers for several years. Can minimum wages help to mitigate inequality? In 2015, the German government introduced a nationwide statutory minimum wage to reduce income inequality by improving the labour income of low-wage employees. However, the employment effects of wage increases depend on time and region specific conditions and, hence, they cannot be known in advance. Because negative employment effects may offset the income gains for low-wage employees, it is important to evaluate minimum-wage policies empirically. We estimate the employment effects of the German minimum-wage introduction using panel regressions on the state-industry level. We find a robust negative effect of the minimum wage on marginal and a robust positive effect on regular employment. In

*This chapter is based on joint work with Oliver Holtemöller. It has been published as O. Holtemöller and F. Pohle. "Employment Effects of Introducing a Minimum Wage: The Case of Germany". *Economic Modelling* (forthcoming). Only minor revisions were made to the published version. A previous version has been published as O. Holtemöller and F. Pohle. 2017. "Employment Effects of Introducing a Minimum Wage: The Case of Germany". *IWH Discussion Papers* 2017 (28).

terms of the number of jobs, our results imply a negative overall effect. Hence, low-wage employees who are still employed are better off at the expense of those who have lost their jobs due to the minimum wage.

2.1 Introduction

Wage inequality has been increasing in Germany since the mid-1990s. In particular, real wages decreased in the low-wage sector by about 2% between 1992 and 2010 (Felbermayr et al. 2014). This trend can also be observed in other countries (Hammar and Waldenström 2017). Moreover, wage inequality between skilled and unskilled labour has increased over the past few decades (Acemoglu 2002). Technological progress may be a driver of increasing wage inequality (e.g., Mallick and Sousa 2017). In January 2015, the German government introduced a nationwide statutory minimum wage in Germany as a tool to mitigate the increasing wage inequality and to improve the economic situation of unskilled low-wage employees (BMWi 2014). However, while the new minimum wage has increased wages for the vast majority of employees who earned less than the new minimum wage before 2015 and who are still employed, there may also be employees who have lost their jobs due to the minimum-wage induced increase in labour costs. From a distributional point of view, it is therefore important to understand the employment effects of minimum wages.[4]

The employment effects of minimum wages are ambiguous. In a monopsony model (Dickens et al. 1999), in a search model with endogenous contact rates (Flinn 2006), in a circular matching model (Gavrel et al. 2010), or in a two-sided labour market flow model (Brown et al. 2014) there may be positive employment effects while employment effects are negative in a neoclassical labour market model. The empirical literature, which focuses on the U.S., is also inconclusive (Neumark and Wascher 2007). Dolado et al. (1996) study the impact in European countries and conclude that the evidence is mixed. More recent studies do also detect mixed evidence. For example, Dolton et al. (2012) show that the overall effect is neutral in the UK while Lindner and

[4] Gorostiaga and Rubio-Ramirez (2007) show that minimum wages can be an optimal redistribution policy.

Harasztosi (2019) find small negative effects in Hungary. Abowd et al. (2000) detect strong negative employment effects in France. Christl et al. (2018) point out that level of the minimum wage is a crucial determinant of the employment effects; that is, high minimum wages reduce employment. While some European countries may have set minimum wages that are too high, other countries are at the edge of the turning point or even below it. The employment effects of minimum wages depend on the specific conditions and the institutional framework of the respective labour market.

We add to the existing literature by supplying new empirical evidence on the employment effects of minimum wages. We study the introduction of a nationwide statutory minimum wage in Germany on January 1, 2015. Because there were only industry-specific minimum wages in place prior to 2015[5], the German minimum wage introduction is a rare event that allows us to study the introduction of a minimum wage rather than an increase of existing minimum wages. That is, the quasi-natural experiment analysed in this study differs from most of the literature which focuses on minimum wage increases. However, the fact that we study the introduction of a nationwide minimum wage complicates the analyses because it implies that there is neither variation of the minimum wage across regions nor over time which could be used to identify the employment effects. Instead, we use cross-sectional variation (state-industry combinations) in the bite of minimum wage (i.e. a variable which measures to what extent the minimum wage affects the wage distribution) to estimate the effects of the minimum wage on marginal employment ("mini-jobs") and on employment subject to social security contributions ("regular employment").[6]

Because no measure of the bite corresponding to our cross-sectional dimension is available yet, we compute the share of affected workers (SAW) and the average minimum-wage induced percentage average wage change (AWC) for each cross section. State-industry pairs are the cross-sectional dimension in the dataset. To identify the minimum-wage effect, we employ a panel model with cross-section and time-fixed effects and cross-section specific time trends. This approach allows for a-priori differences between the cross sections. The two bite variables lead to similar qualitative but differing quantitative results. We find a significant negative effect on

[5]According to Bispinck (2015), approximately 4.6 million employees (i.e. approximately 15% of total employment) were covered by industry-specific minimum wages.

[6]We explain the difference between marginal and regular employment in Section 2.2.

marginal employment. The introduction of the minimum wage in Germany resulted in the loss of about 67,000 (AWC) to 129,000 (SAW) mini-jobs. Meanwhile, we estimate that between 47,000 (AWC) and 74,000 (SAW) additional regular jobs have been created due to the minimum wage. We test whether marginal employment has been converted into jobs subject to social security contributions but do only find insignificant evidence.

The rest of this paper is organized as follows. We briefly discuss the German minimum wage and the related literature in Section 2.2. We then describe the data including the derivation of the two bite variables in Section 2.3. Section 2.4 is devoted to the estimation of the minimum-wage effect on marginal employment and on regular employment, as well as to the analysis of the relationship between both types of employment. In Section 2.5, we provide robustness analyses. The paper finishes with a conclusion in Section 2.6.

2.2 The minimum wage in Germany

In April 2014, the German government decided to introduce a nationwide statutory minimum wage. The corresponding law ("Tarifautonomiestärkungsgesetz") passed the German parliament on July 3, 2014 and became effective as of January 1, 2015. The minimum wage initially amounted to 8.50 Euro per hour and equally applies to all states and to all but very few industries (see Section 2.3 for details). Notice that higher sector-specific minimum wages are in place in some industries (e.g. in the construction sector) while transitional regulations applied to other sectors (e.g. agriculture). Bossler and Gerner (2016) report that the nationwide statutory minimum-wage regulation applies to approximately 98% of all employees. The initial level of the minimum wage was set by the German parliament, a minimum-wage commission is in charge of adjustments.[7]

It is important to distinguish between marginal and regular employment. Marginal employment describes jobs with a maximum monthly salary of 450 Euro, these jobs are not subject to social security contributions of employees. Only the employer

[7]The commission consists of a chair person, six members and two advising, non-voting researchers. The chair is jointly suggested by the corresponding umbrella organizations of employers and employees. They also propose the members and advisers. The federal government appoints the commission.

contributes to social security systems, albeit not to the full extent. If the threshold of 450 Euro is exceeded, then the mini-job turns into a job subject to social security contributions. Of the 30.4 million employees in 2014 (December), 5.2 million belonged to the mini-job group. As pointed out by Henzel and Engelhardt (2014), 40% of all mini-jobbers (i.e. more than 2 million employees) work more than 53 hours per month and, hence, received less than 8.50 Euro per hour in 2014. The wage increases for these workers imply that their monthly wage exceeds 450 Euro after the minimum-wage introduction and, therefore, the match is no longer eligible to be a mini-job. Accordingly, the introduction of the minimum wage was expected to reduce the number of mini-jobs for two reasons (Projektgruppe Gemeinschaftsdiagnose 2014). First, the increase in labour cost makes some matches unprofitable and, therefore, they vanish. Second, due to the 450 Euro cap in combination with minimum-wage induced pay rises, a fraction of marginal employment is expected to be converted into regular employment, tending to further decrease marginal employment. We refer to this phenomenon as the transformation effect or transformation hypothesis. The increased labour cost due the minimum wage is also likely to affect regular employment through the first channel. However, the affectedness is assumed to be significantly lower than for marginal employment and, therefore, the consequences are expected to be smaller. Through the lens of one of the theoretical models mentioned above, even positive effects on both forms of employment are possible.

Several papers analyse the employment effects of the German minimum-wage introduction. An overview of existing studies is given in Caliendo et al. (2019). Bossler and Gerner (2016) analyse the minimum-wage effect on employment with a difference-in-difference model that uses establishment-level affectedness as distinguishing feature (control group: unaffected establishments, treatment group: affected establishments). They find a small negative employment effect. Caliendo et al. (2018) exploit regional variation in the treatment intensity (the bite) in a difference-in-difference framework and find a small negative overall effect on employment, largely driven by marginal employment. Both studies crucially hinge on a common trend assumption. In contrast to these studies, our approach explicitly takes cross-section specific linear trends into account. Thus, we do not rely on a common-trends assumption. The method used in Garloff (2016) is closely related to our own. However, he uses region-age-sex combinations as a cross-sectional dimension while we rely on state-industry combinations. Bossler (2017) estimates a reduction in employment growth expectations of firms. Furthermore, he argues that there is a positive and stable relationship between expected growth and observed employment adjustments. Additionally, several studies have analysed the employment effects of the minimum-wage introduction with a regional focus. For example, Brautzsch and Schultz (2018) analyse the impact of the minimum wage in the skilled crafts sector in Saxony-Anhalt and do not detect evidence for employment effects.

Overall, our approach fills an important gap in the existing literature. We estimate the aggregated employment effects of the minimum-wage introduction in Germany and discuss region- and industry-specific heterogeneity in the minimum-wage effect on employment. Furthermore, we also explicitly test the transformation hypothesis on the regional and at the industry level.

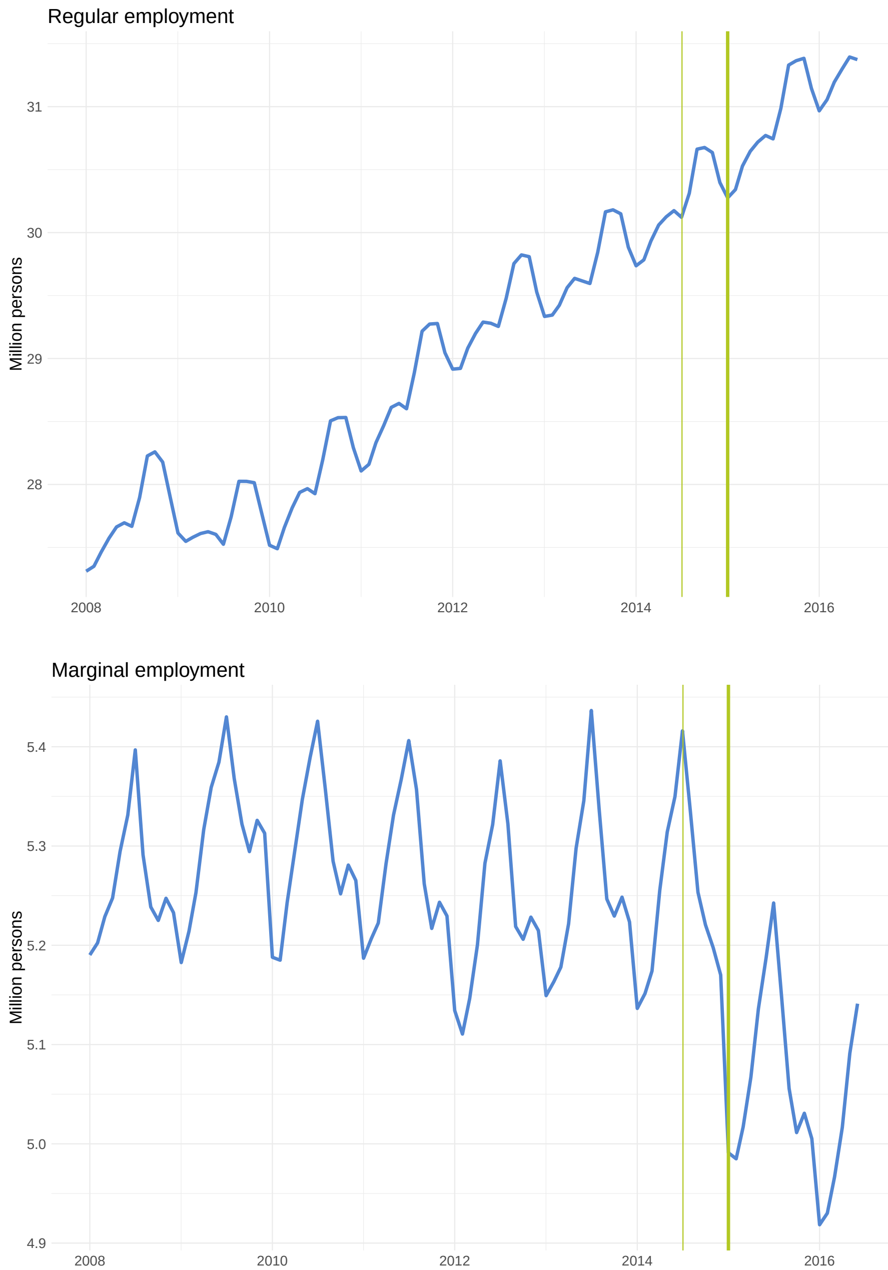
2.3 Data

2.3.1 Regular and marginal employment

The number of regularly and marginally employed persons for each cross section (state-industry combination) at a monthly frequency was obtained from the Federal Employment Agency (2016). The two types of employment show different patterns before the introduction of the minimum wage, see Figure 2.1. While regular employment has exhibited a stable upward trend since 2010, marginal employment was rather constant, abstracting from seasonal fluctuations. However, the increase in regular employment and the decline in marginal employment after the introduction of the minimum wage has not been equally distributed within Germany, see Figure 2.2. The relative increase in regular employment has been particularly large in the city states (Berlin, Bremen, and Hamburg) and in the West German states and much smaller in the East German states, whereas the decline in marginal employment has been particularly large in East Germany (see Table 2.6 in Appendix A for an overview of the German states). In Brandenburg, for example, marginal employment declined by almost 10% between mid-2015 and mid-2014.

We use monthly data from January 2010 onwards. We do not use earlier data to avoid the disturbances due the financial crisis. For a discussion of the German

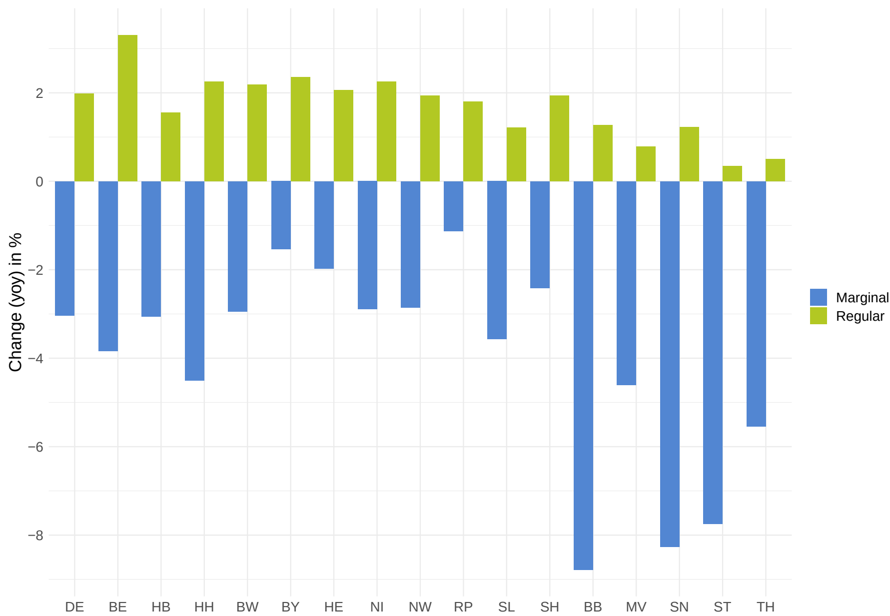
Figure 2.1: Employment in Germany



Notes: Vertical lines indicate the passing of the minimum wage law (July 2014) and the introduction of the minimum wage (January 2015).
Source: Federal Employment Agency (2016) and own exhibition.

labour market during the financial crisis, see, for example, Gehrke et al. (2019). The observation period ends in December 2015, one year after the minimum-wage law

Figure 2.2: Percentage change of employment between June 2015 and June 2014



Source: Federal Employment Agency (2016) and own calculations.

became effective.

Industries are classified according to the NACE 2 classification of economic activities, see Table 2.7 in Appendix A. As of January 2015, some industries were exempted from the statutory minimum wage. Because exceptions for agriculture and forestry were in place, we exclude "Agriculture, Forestry and Fishing". Furthermore, the sector-specific minimum wage for temporary employment was in place prior to 2015 and, therefore, the industries "Temporary Employment Agency & Other Human Resources Provision" are excluded from the sample. The meat industry, the textile industry, horticulture, laundry service and hairdressing were exempted from the statutory minimum wage as well. However, they only make up a small fraction of the respective sector and, therefore, remain in the sample.[8] A high sector-specific minimum wage (>10 Euro) applies to construction workers. Yet, not every employee

[8]The meat and textile industries are part of "Production of largely domestically consumed goods". Horticulture is included in "Administrative and Support Service Activities". Hairdressing and laundry services are included in "Arts, Entertainment and Recreation, Other Service Activities, Activities Of Households As Employers, Undifferentiated Goods- and Services-Producing Activities of Households for Own Use".

in the industry "Construction" is a construction worker and, therefore, the minimum wage affectedness in this industry is not zero. Accordingly "Construction" remains in our sample.

In our baseline scenario, we exclude the city states Berlin, Bremen, and Hamburg because their economic structure is not directly comparable to the other states. Finally, we exclude "Mining, Quarrying, Electricity etc." (industries B, D, E) in Saarland from our sample due to missing data. In total, we have 194 cross-sections and 72 months in our panel.

2.3.2 Bite of the minimum wage

Our econometric approach requires a measurement of the minimum-wage bite; that is, a variable which measures the minimum-wage induced change of the wage distribution. Because no such variable corresponding to our cross-sectional dimension is available, we calculate the share of affected workers (SAW) and the minimum-wage induced percentage average wage change (AWC). Because the minimum-wage regulation specifies an hourly minimum wage, the measure must also be an hourly measure. We propose a method, similar to Garloff (2016), that allows us to compute the bite based on aggregated monthly wage data.

Number of affected workers

For both the share of affected workers and the percentage average wage change due to the minimum wage, the number of affected workers in each cross section is of crucial importance. To find the latter, we require hourly wage data whose availability is rather unsatisfactory. We therefore use monthly income data for full-time workers; that is, we deduce the number of workers who receive less than 8.50 Euro per hour (i.e. affected workers) from monthly wages. The first step is to find a condition that determines, based on monthly income, whether or not a *single worker* receives more or less than the minimum wage. We proceed by pinning down *how many workers* fulfill this condition.

Define a threshold monthly income in industry i and state j, TMI_{ij}:

$$TMI_{ij} = 8.50 \times WH_{ij} \times 4.35 \tag{2.1}$$

where WH_{ij} denotes the average weekly working hours in each state-industry combination. These numbers can be obtained from Federal Statistical Office of Germany (2015), but not for each industry and, thus, we use aggregated values for industries.[9] Because we use weekly working hours, we scale it by factor 4.35 to obtain monthly working hours. This procedure allows us to pin down a condition which determines whether or not a worker is affected by the minimum wage. For any income $w_{month,ij} < TMI_{ij}$, a worker's hourly wage is below 8.50 Euro.

We use monthly wage data for full-time employees provided upon request by the Federal Employment Agency (2015) to pin down the number of affected workers.[10] This dataset contains the number of employees n_{ij} in $k \in \{1, .., 18\}$ intervals of increasing income (see Table 2.8 in Appendix A for details) with upper (lower) bound UB_k (LB_k) for every state-industry pair. We assume a piecewise linear distribution of workers within each interval. We define l_{ij} as the cross-section specific interval in which the threshold income, TMI_{ij}, is located:[11]

$$l_{ij} =_k (UB_k > TMI_{ij}).$$

This allows us to determine the number of employees with income $x < TMI_{ij}$ as follows:

$$n_{ij}^{x<TMI_{ij}} = \sum_{k=1}^{l} n_{ij}^{k} + n_{ij}^{l+1} \frac{TMI_{ij} - LB_{l+1}}{UB_{l+1} - LB_{l+1}}. \tag{2.2}$$

The first part of this equation is the sum of all workers in all intervals from $k = 1$ to $k = l$. The second term is the number of employees in interval $l + 1$ who receive less than the threshold income TMI_{ij}. Because we only have the total number of employees in interval $l + 1$, we need to scale it with the fraction in $l + 1$ that receives less than TMI_{ij}.

[9] In fact, there are values for three (aggregated) industries for each state (industries A, B-F, G-S). A state's average value replaces an industry's value if it is missing.

[10] The dataset was shared with us by Alfred Garloff.

[11] Notice that l varies over cross sections. For the sake of readability, we skip the index from this point onwards.

Share of affected workers (SAW)

The share of affected workers, SAW, describes the fraction of workers who received less than the minimum wage prior to its introduction in January 2015. Because we already know the number of affected workers, we simply need to divide this figure by the number of employees in the corresponding cross section, N_{ij}, to obtain SAW_{ij}:

$$SAW_{ij} = \frac{n_{ij}^{x<TMI_{ij}}}{N_{ij}} \tag{2.3}$$

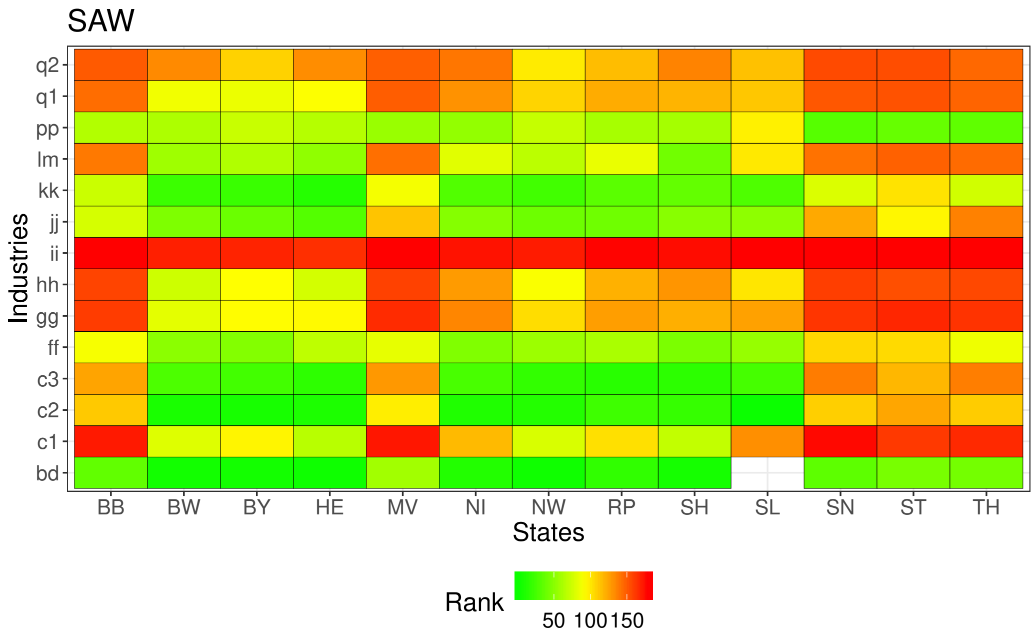
The results are depicted in Figure 2.3 (a) and summary statistics are presented in Tables 2.9 & 2.10 in Appendix A. Low-wage industries, such as "Accommodation and Food Service Activities", are significantly more exposed to the minimum wage than other industries. Furthermore, for quite a few industries, the minimum wage de facto does not play a role. From a spatial perspective, there seems to be a significant East-West gap. However, within both regions, the differences across states are less severe. The heterogeneity in the bite is largely driven by industries and, to smaller extent, by regions (East/West) rather than states. Notice that the purpose of the minimum-wage variable is to have a measure that quantifies the relative differences regarding the affectedness across cross sections. Therefore, we are not ultimately interested in the absolute value of the share of affected workers.

Percentage average wage change (AWC)

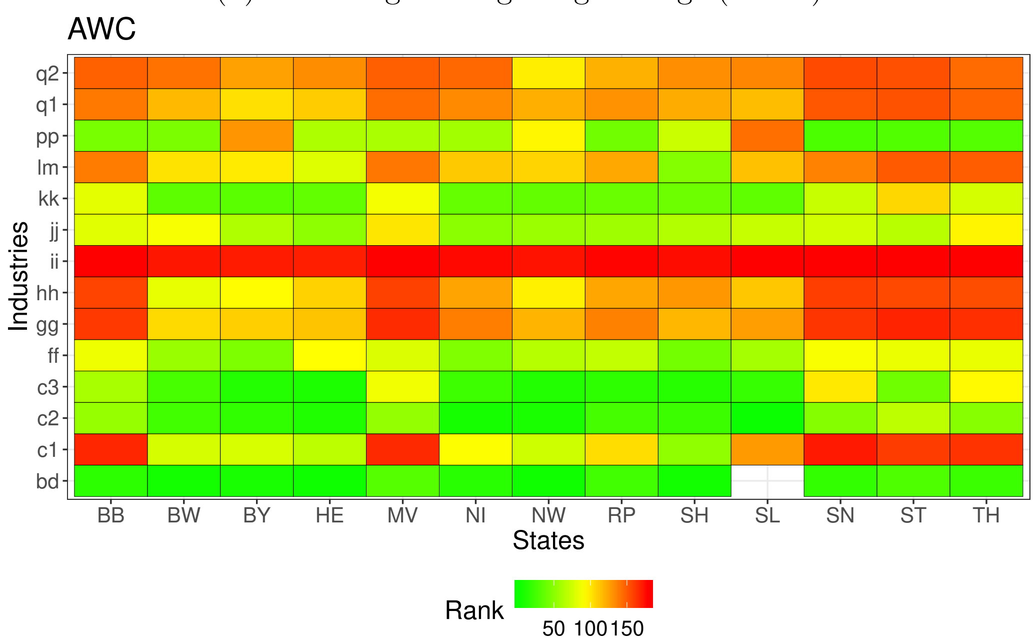
The share of affected workers does not account for the distance of a worker's wage to the minimum wage. Two cross sections could be exposed in a similar fashion in terms of the share of affected workers. However, no differentiation is made regarding the intensity of the bite. Suppose we find comparable values for some cross sections A and B ($SAW_A \approx SAW_B$). They may, however, be totally different regarding the average wage of affected workers (e.g. $\overline{w}_A = 8.40\,\text{Euro}$ and $\overline{w}_B = 5.00\,\text{Euro}$). To control for that possibility, we construct an alternative measure of the bite, the minimum-wage induced percentage average wage change. We build on the number of affected workers and the income data explained earlier to compute the average wage prior to the minimum wage as follows:

Figure 2.3: Bite of the minimum wage

(a) Share of affected workers (SAW)



(b) Percentage average wage change (AWC)



Notes: The heat map shows the rank (low to high affectedness) of a state-industry pair for the two bite indicators share of affected workers (SAW) and average percentage wage change (AWC).
Source: Agency (2015), Federal Statistical Office (2015), and own calculations.

$$\overline{w}_{ij}^{prior} = \frac{\sum_{k=1}^{l} \overline{w}^k n_{ij}^k + \frac{TMI_{ij} - LB_{l+1}}{UB_{l+1} - LB_{l+1}} n_{ij}^{l+1} \overline{w}_{ij}^{LB_{l+1} < w_{ij} < TMI_{ij}}}{n_{ij}^{x < TMI_{ij}}} + \frac{\left(1 - \frac{TMI_{ij} - LB_{l+1}}{UB_{l+1} - LB_{l+1}}\right) n_{ij}^{l+1} \overline{w}^{TMI_{ij} < w_{ij} < LB_{l+2}} + \sum_{l+2}^{k=17} \overline{w}^k n_{ij}^k}{N_{ij} - n_{ij}^{x < TMI_{ij}}}, \tag{2.4}$$

where $\overline{w}_{ij}^k$ denotes the average wage in interval k. For $k = \{3 \ldots 17\}$ the average wage is simply set according to $\overline{w}^k = \frac{1}{2}(LB_k + UB_k)$. Because this approach is unlikely to be valid for larger intervals at the lower end of the distribution, we use micro data for $k = 1, 2$. Based on the SOEP (2015) dataset, we compute $\overline{w}^1 = \mathbf{E}[w^{k=1} \mid 1 \leq w_{month} \leq 500]$ and $\overline{w}^2 = \mathbf{E}[w^{k=2} \mid 500 < w_{month} \leq 1000]$.[12] Notice that the average wage, $\overline{w}^k$, does not differ across state-industry combinations for all intervals k. We exclude interval $k = 18$ because it has no upper bound and, thus, we cannot compute an average wage. Eq. (2.4) is a weighted average of affected and unaffected workers. We account for the fact that the threshold income TMI_{ij} splits interval $l + 1$ arbitrarily (i.e. not according to the defined boundaries of this interval) by applying the piecewise linear distribution assumption. Hence, we scale the average wage of affected workers in $l + 1$ with the corresponding fraction of workers in interval $l + 1$. The average wage of unaffected workers in $l + 1$ is weighted with the the counterpart of the fraction of affected workers in $l + 1$.

To compute the average wage after the minimum-wage introduction, $\overline{w}_{ij}^{post}$, we assign a value of 8.50 Euro to all affected workers, whereas we assume that the wages of unaffected workers do not change:

$$AWC_{ij} = \frac{\overline{w}_{ij}^{post} - \overline{w}_{ij}^{prior}}{\overline{w}_{ij}^{prior}} \tag{2.5}$$

For detailed results, see Figure 2.3 (b), Table 2.9, and Table 2.10 in Appendix A. The

[12] There is a trade-off between the number of observations and how well the SOEP income data match the Federal Employment Agency employment data (2016) . If we choose only full-time employees from the SOEP sample, then the number of individuals with very low wages is too low for valid inference. However, if we decide to include part-time and full-time employees, then we face the problem that the Federal Employment Agency data (2016) only reports the number of full-time employees. Hence, the comparison of the two datasets becomes somewhat problematic. It turns out that both approaches yield identical results up to the second decimal. The differences should thus be negligible.

results are qualitatively similar to those obtained for the share of affected workers. Notice that both variables can only be computed for one period because there is no variation of the minimum wage during the observation period. We therefore set the value of both bite variables to zero in all periods prior to the minimum-wage introduction. Afterwards, the bite variable assumes the same value from the procedure described earlier in each period.

One could argue that using income data for full-time regular employees, who are usually assumed to be less affected by low wages than part-time workers, may bias our results. The values for the share of affected workers computed by Brautzsch and Schultz (2013) as well as Knabe and Schöb (2014) are based on survey data and, therefore, their results do not suffer from the selection problem we face. We compare their findings for each industry-state combination available (i.e. large cross sections and states, respectively) with our estimates. We then compute the correlation between their values and our findings. The resulting correlation coefficients are 0.94 (Brautzsch and Schultz 2013) and 0.99 (Knabe and Schöb 2014). Thus, we conclude that our computation serves as a reasonable proxy for the bite.

2.4 Model and main results

2.4.1 Employment effects

An important feature of industry and sector-specific employment data is that the individual cross sections exhibit different time trends. Individually estimated time-trend parameters vary from −0.0041 to 0.0051 (median 0.0014) for regular employment and from −0.0273 to 0.0109 (median –0.0004) for marginal employment. The parallel-trend assumption is hence violated and, thus, a simple difference-in-difference model is not appropriate.

To account for different time trends, we use a panel model with cross-section and time-fixed effects and cross-section specific time trends to estimate the effect of the minimum-wage introduction on regular and marginal employment:

$$\ln E_{ij,t} = \beta_{0,ij} + \lambda_t + \beta_{1,ij} \times t + \gamma \times BITE_{ij,t} + \varepsilon_{ij,t}, \tag{2.6}$$

where E refers to (regular or marginal) employment, t to a linear time trend, and

$BITE$ to the two bite measures SAW and AWC, respectively. $\varepsilon_{ij,t}$ is an error term. To identify the minimum-wage effect, we assume that the introduction was exogenous with respect to the cross sections. This assumption is reasonable given the institutional background discussed in Section 2.2. Furthermore, our identification assumption is in line with the literature (e.g., Neumark and Wascher 2007). We estimate this model in first differences[13] and add cross-section specific seasonal dummies (SD):

$$\Delta \ln E_{ij,t} = \beta_{1,ij} + \gamma \times \Delta BITE_{ij,t} + \Delta\lambda_t + \sum_{m=2}^{12} \beta_{ij,m} SD_{m,t} + \Delta\varepsilon_{ij,t}. \qquad (2.7)$$

The estimated parameters are shown in Table 2.1. Autocorrelation and heteroscedasticity robust standard errors are calculated using the Newey-West approach. In addition to the two calculated bite measures, we also run a regression with a simple minimum-wage dummy (DUM), which is zero until December 2014 and one afterwards (in this case, time-fixed effects cannot be included in the regression). Columns (1) and (4) reveal that there was a statistically significant increase in regular employment growth and a significant decrease in marginal employment growth in January 2015 in comparison to the other periods. The two bite measures yield significant effects on both regular and marginal employment. As expected, the effect on regular employment is positive, while the effect on marginal employment is negative.

Using the estimated coefficients and aggregate values of the bite (SAW and AWC), we can calculate the effects of the minimum-wage introduction on regular and marginal employment, respectively. Counterfactual employment without minimum-wage effects is given by:

$$\tilde{E}_{ij,t} = \exp(\ln E_{ij,t} - \gamma \times BITE_{ij,t}) \qquad (2.8)$$

for $t =$January 2015. The minimum-wage effect on employment is therefore given by $E_{ij,t} - \tilde{E}_{ij,t}$. We use $\widehat{\gamma}$ for SAW and AWC together with their 95% confidence intervals (± 1.96 standard errors) to derive intervals for the corresponding effects. The magnitude of the effects depends on the respective measure of the bite (Table

[13] Recall that the bite variables only assume two different values for each cross section throughout the observation period. Hence, $\Delta BITE_{ij,t}$ is zero in each period except in January 2015.

Table 2.1: Regression results for employment effects

	Dependent variable:					
	ΔRegular Employment			ΔMarginal Employment		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔDUM	0.003***			−0.028***		
	(0.001)			(0.003)		
ΔSAW		0.031***			−0.054**	
		(0.004)			(0.026)	
ΔAWC			0.137***			−0.196***
			(0.014)			(0.070)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Seas.Dum.	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Observations	13,774	13,774	13,774	13,774	13,774	13,774
Adjusted R^2	0.786	0.732	0.732	0.452	0.400	0.400

Notes: Dependent variable: ln-difference of employment (regular and marginal, respectively). Numbers in parentheses are Newey-West autocorrelation and heteroscedasticity robust standard errors. Calculations conducted in R using plm (Croissant and Millo 2008), regression output using stargazer (Hlavac 2018).*p<0.1; **p<0.05; ***p<0.01.
Source: Federal Employment Agency (2015, 2016), Federal Statistical Office (2015), and own calculations.

2.2). The effects are larger if the share of affected workers is used as measure of the bite. However, for both measures, the negative effect on marginal employment is about twice as large as the positive effect on regular employment. This implies, that the total effect of the minimum-wage introduction on both regular and marginal employment has been negative.

Brown et al. (2014) develop a two-sided labour market flow model featuring job offer and job acceptance decisions. In their model, higher (minimum) wages decrease job offers but increase job acceptances. The overall effect depends on which channel dominates. Brown et al. (2014) show that for sufficiently low minimum wages, the effect on job acceptances may dominate the effect on offers, implying a positive overall effect. The German minimum wage equally applies to all forms of employment. Suppose however, that marginal employment, on average, exhibits a lower productivity than regular employment. In that case, the minimum wage may be too

Table 2.2: Employment effects of the minimum-wage introduction

	SAW	*AWC*
Regular employment	73,521 [56,402; 90,630]	46,815 [37,344; 56,284]
Marginal employment	−128,943 [−252,557; −5,829]	−66,883 [−113,633;−20,206]

Notes: Numbers in brackets represent 95% confidence intervals. *SAW* and *AWC* refer to the two measures of the bite, share of affected workers and average minimum-wage induced change in wage, respectively.
Source: Federal Employment Agency (2016) and own calculations using estimates from Table 2.1.

high for mini-jobs (marginal employment) but reasonable for regular employment. The model would then predict a positive effect on regular employment but a negative effect on marginal employment. Thus, our findings are in line with the theoretical model proposed by Brown et al. (2014).

2.4.2 Transformation effect

To analyse whether regular employment rose in those state-industry pairs in which marginal employment decreased, we estimate the following regression:

$$\begin{aligned}\Delta \ln E_{ij,t}^{regular} \quad = \quad & \beta_0 + \beta_1 \times \Delta \ln E_{ij,t}^{marginal} + \Delta\lambda_t + \sum_{m=2}^{12} \beta_{ij,m} SD_{m,t} \\ & + \gamma_1 \times \Delta BITE_{ij,t} + \gamma_2 \times \Delta BITE_{ij,t} \times \Delta \ln E_{ij,t}^{marginal} + \varepsilon_{ij,t}.\end{aligned} \tag{2.9}$$

While β_1 captures the general relationship between changes in regular and marginal employment, which is expected to be positive, γ_1 describes again the effect of the minimum wage on regular employment, and γ_2 characterizes the relationship between changes in regular and marginal employment in January 2015, when the minimum wage became effective.

Table 2.3 shows that in general the correlation between the logarithmic change in regular and in marginal employment is positive. During periods in which additional marginal employment is built up, regular employment also increases. The interaction

Table 2.3: Transformation effect

	Dependent variable: $\Delta \ln E_{it}^{regular}$		
	(1)	(2)	(3)
$\Delta \ln E^{marginal}$	0.008***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)
$DUM \times \Delta \ln E^{marginal}$	−0.022		
	(0.020)		
$SAW \times \Delta \ln E^{marginal}$		−0.043	
		(0.089)	
$AWC \times \Delta \ln E^{marginal}$			−0.108
			(0.547)
DUM	0.003***		
	(0.001)		
SAW		0.028***	
		(0.007)	
AWC			0.131***
			(0.044)
Individual FE	Yes	Yes	Yes
Individual Seas.Dum.	Yes	Yes	Yes
Time FE	No	Yes	Yes
Observations	13,774	13,774	13,774
Adjusted R^2	0.787	0.732	0.732

Notes: Dependent variable: ln-difference of regular employment. Numbers in parentheses are Newey-West autocorrelation and heteroscedasticity robust standard errors. Calculations conducted in R using plm (Croissant and Millo 2008), regression output using stargazer (Hlavac 2018). $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.
Source: Federal Employment Agency (2015, 2016), Federal Statistical Office (2015), and own calculations.

coefficients indicate that in January 2015 the relationship has been negative. Additional regular employment has been built up while marginal employment declined. This could be used as evidence in favour of the transformation effect. However, the estimates are not significantly different from zero. This means that we cannot reject the hypothesis that the additional increase in regular employment in January 2015 is unrelated to the decline in marginal employment due to the minimum-wage introduction. This is compatible with the first visual impression from Figure 2.2 which revealed that additional regular employment was mainly not created in those regions in which the negative effect on marginal employment was particularly large.

Our interpretation of this finding is as follows. The main driver of the increase in regular employment and decrease in marginal employment is indeed the transmission channel discussed in the previous subsection instead of a transformation of marginal into regular employment. However, the negative sign of the estimated coefficient might be an indicator that indeed some jobs were transformed.

Vom Berge and Weber (2017) argue, based on micro data, that twice as many mini-jobs were transformed into employment subject to social security contributions in January 2015 as in January 2014. However, they also find that for every 100 transformed jobs, 58 (full and part-time) jobs in regular employment were destroyed and, hence, the net effect on regular employment that we are looking at is not equal to the increase in individual transformed jobs.

2.5 Robustness

2.5.1 Controlling for demographic change

In our baseline regressions in Section 2.4, we have neglected demographic changes. However, local demographic trends are important for the development of local employment. Intra-German migration and ageing of the population could potentially also be responsible for cross-regional differences in employment. Therefore, we have tested whether our results are robust with respect to the inclusion of population into the regression equations. The Federal Statistical Office (2017) provides monthly population data on the state level. Table 2.4 shows that population is indeed significant in all regressions. However, comparing the estimates for the bite measures to those from Table 2.1 indicates that these coefficients are not affected by the inclusion of population. Our baseline results are therefore robust to the inclusion of population as a control variable in the regressions.

2.5.2 Results by sector and by state

As a further robustness check, we have estimated the baseline regression for regular and marginal employment for individual sub-samples. Figure 2.5 in Appendix

Table 2.4: Regression results for employment effects: controlling for population

	Dependent variable:					
	ΔRegular employment			ΔMarginal employment		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔDUM	0.003***			−0.027***		
	(0.001)			(0.003)		
ΔSAW		0.031***			−0.054**	
		(0.004)			(0.026)	
ΔAWC			0.137***			−0.196***
			(0.014)			(0.070)
$\Delta \ln POP$	0.287***	0.662***	0.659***	−1.232***	−2.716**	−2.708**
	(0.092)	(0.247)	(0.247)	(0.332)	(1.137)	(1.137)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Seas.Dum.	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Observations	13,774	13,774	13,774	13,774	13,774	13,774
Adjusted R^2	0.786	0.732	0.732	0.452	0.400	0.400

Notes: Dependent variable: ln-difference of employment (regular and marginal, respectively). Numbers in parentheses are Newey-West autocorrelation and heteroscedasticity robust standard errors. Calculations conducted in R using plm (Croissant and Millo 2008), regression output using stargazer (Hlavac 2018). $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.
Source: Federal Employment Agency (2015, 2016), Federal Statistical Office (2015), and own calculations.

A shows a graphical representation of the estimated coefficients. In general, the variation of coefficients and the individual standard errors are quite large. Point estimates of the effect of the minimum-wage introduction on regular employment are positive in all states and most of the industries. However, due to the smaller sample size, many of the estimates are not significant as the corresponding confidence intervals include zero. For marginal employment, the picture is similar: we mostly find negative estimates of the minimum-wage effect, but in many cases the individual coefficients are not significantly different from zero. These results imply that the minimum-wage effect is indeed driven by the bite instead of industries or states. Thus, the disaggregate analysis supports our main findings.

2.5.3 Results for East and West Germany

Average wages in East Germany are considerably lower than in West Germany and the share of employees earning less than 8.50 Euro per hour before the introduction of the minimum wage was much higher. While the corresponding share was less than 10% in West Germany, it amounted to slightly more than 20% in East Germany (Mindestlohnkommission 2018). In this subsection, we test whether the effect of the minimum wage on employment is different for East and West Germany. We augment the baseline model by a dummy interaction term $EAST$, which is zero for observations from West German states and one for those from East Germany. The regression equation is:

$$\begin{aligned}\Delta \ln E_{ij,t} \quad = \quad & \beta_{1,ij} + \gamma_1 \times \Delta BITE_{ij,t} + \gamma_2 \times \Delta BITE_{ij,t} \times EAST_{ij} \\ & + \Delta\lambda_t + \sum_{m=2}^{12} \beta_{ij,m} SD_{m,t} + \Delta\varepsilon_{ij,t}. \end{aligned} \tag{2.10}$$

The baseline results are confirmed by the results (Table 2.5), although the inclusion of the $EAST$-Dummy leads to non-significant estimates in some cases. However, regressions (1) and (4) confirm that the change in employment has been significantly larger for regular and significantly smaller for marginal employment in the beginning of the year 2015. In line with the analysis of the transformation effect in Section 2.4.2, the positive minimum-wage effects on regular employment seem to be larger in West Germany and the negative minimum-wage effects on marginal employment appear to be larger in East Germany, albeit the difference is not significant.

2.5.4 Dynamic adjustment

Firms may not have immediately adjusted to the wage increase in January 2015 but have adjusted slowly over several months. Such a behavior could be motivated by fixed-term contracts which end a few months after the introduction of the minimum wage. In such cases, firms might keep the employee but refrain from hiring a successor. On the other hand, the effects found for January 2015 could also be only of temporary nature. The introduction of a new minimum wage brings some uncertainty about the new legal environment and its consequences. This may lead to postponing new

Table 2.5: Regression results for employment effects: East and West Germany

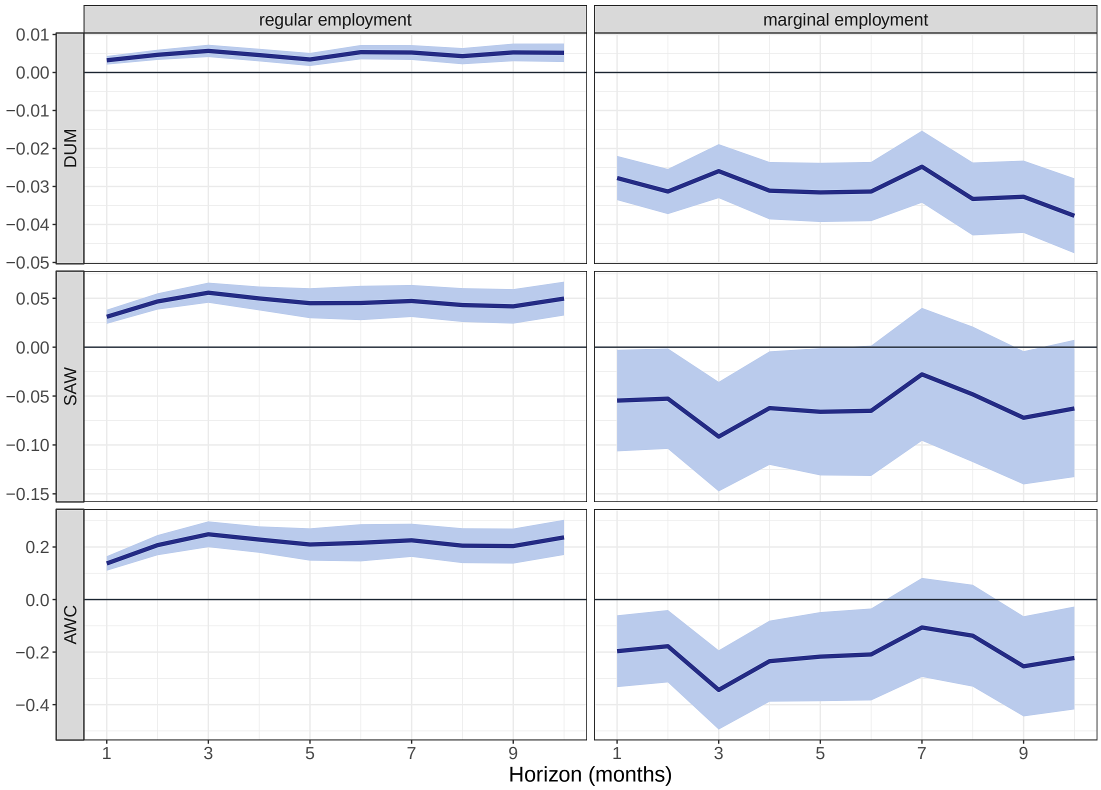
	Dependent variable:					
	ΔRegular employment			ΔMarginal employment		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔDUM	0.003***			−0.023***		
	(0.001)			(0.002)		
$\Delta DUM \times EAST$	0.002			−0.015*		
	(0.001)			(0.008)		
ΔSAW		0.038***			−0.017	
		(0.005)			(0.024)	
$\Delta SAW \times EAST$		−0.011**			−0.056	
		(0.005)			(0.042)	
AWC			0.170***			−0.021
			(0.021)			(0.121)
$\Delta AWC \times EAST$			−0.050**			−0.266
			(0.022)			(0.171)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual Seas.Dum.	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Observations	13,774	13,774	13,774	13,774	13,774	13,774
Adjusted R^2	0.786	0.732	0.732	0.452	0.400	0.400

Notes: Dependent variable: ln-difference of employment (regular and marginal, respectively). Numbers in parentheses are Newey-West autocorrelation and heteroscedasticity robust standard errors. Calculations conducted in R using plm (Croissant and Millo 2008), regression output using stargazer (Hlavac 2018). $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.
Source: Federal Employment Agency (2015, 2016), Federal Statistical Office (2015), and own calculations.

hires. In this case, there would be a negative effect in January 2015 which would be compensated in the following months.

To estimate the dynamic effects of the minimum-wage introduction, we use local projections (Jordà 2005, Jordà and Taylor 2016). The dynamic effect after h periods, γ^h, can be inferred from the following regression using the same dataset as in the previous sections:

Figure 2.4: Dynamic minimum-wage effects on employment



Notes: Dependent variable: h-period ln-difference of employment (regular and marginal, respectively) see eq. (2.11). Calculations conducted in R using plm (Croissant and Millo 2008). Shaded areas represent ±1.96 Newey-West standard errors.
Source: Federal Employment Agency (2015, 2016), Federal Statistical Office (2015), and own calculations.

$$\ln E_{ij,t} - \ln E_{ij,t-h} = \beta^h_{1,i,j} + \gamma^h \times BITE_{ij,t-h} + \alpha^h \Delta E_{ij,t-h} + \lambda^h_t + \sum_{m=2}^{12} \beta^h_{ij,m} SD_{m,t} + \Delta\varepsilon^h_{ijt}, \quad (2.11)$$

$h = 1, 2, \ldots, H$. The results of the local projections support our baseline findings. The effects on regular employment are positive and persistent, while the effects on marginal employment are negative and persistent (Figure 2.4). For regular employment, there seems to be a small lag in adjustment, the estimated coefficients increase until $h = 3$. However, they then remain stable for further horizons.

2.6 Conclusions

In this paper, we have estimated the effects of the introduction of a nationwide statutory minimum wage in Germany on marginal and regular employment exploiting cross-sectional variation in the bite of the minimum wage. First, we contribute to the literature by computing two treatment variables that measure the bite of the minimum wage for about 190 state-industry combinations based on aggregate monthly income data. Second, we estimate panel models that do not rely on a parallel-trend assumption. Our identifying assumption is that the minimum-wage introduction was exogenous with respect to the cross sections. The results for both measures of the bite indicate a negative effect of the minimum wage on marginal employment and a positive effect on regular employment and are robust to several modifications. Our estimates imply that 67,000 (AWC) to 129,000 (SAW) mini-jobs were destroyed while 47,000 (AWC) to 74,000 (SAW) regular jobs were created due to the minimum wage. This is well within the range of estimates in the literature, such as Garloff (2016) and Caliendo et al. (2018). Third, and despite opposing signs on both forms of employment, we do not find evidence to support the transformation hypothesis. Regular employment mainly increased in states and industries in which marginal employment also increased or did not decrease as strongly as regular employment increased.

A shortcoming of our study is that is uses the number of employees as a dependent variable instead of working hours. Unfortunately, sufficiently disaggregated data on working hours are not readily available. Using working hours would also be helpful to study the income effects of the minimum wage and the question whether the minimum wage fulfilled its purpose; that is, mitigated wage inequality.

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Appendix A

Table 2.6: German states

Abbreviation	State	Region
BW	Baden-Württemberg	West
BY	Bavaria	
HB	Bremen	
HH	Hamburg	
HE	Hesse	
NI	Lower Saxony	
NW	North Rhine-Westphalia	
RP	Rhineland-Palatinate	
SL	Saarland	
SH	Schleswig-Holstein	
BE	Berlin	
BB	Brandenburg	East
MV	Mecklenburg-Western Pomerania	
SN	Saxony	
ST	Saxony-Anhalt	
TH	Thuringia	

Table 2.7: List of industries (Chapter 2)

NACE 2 Code	Industry	Abbreviation
B,D, E	Mining, Quarrying, Electricity, Gas, Steam and Air Conditioning Supply, Water Supply, Sewerage, Waste Management and Remediation Activities	bd
C (10-15, 18, 21, 31)	Production of largely domestically consumed goods	c1
C (16, 17, 19, 20, 22, 23)	Production of Intermediate Goods, especially Chemical and Plastic Products	c2
C (24-30, 32, 33)	Metal and Electrical Industry, Steel Industry	c3
F	Construction	ff
G	Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles	gg
H	Transportation and Storage	hh
I	Accommodation and Food Service Activities	ii
J	Information and Communication	jj
K	Financial and Insurance Activities	kk
L, M	Real Estate Activities, Professional, Scientific and Technical Activities	lm
N (excl. 78.2 & 78.3)	Administrative and Support Service Activities	nn
O, U	Public Administration and Defence, Compulsory Social Security, Activities of Extraterritorial Organisations and Bodies	ou
P	Education	pp
Q (86)	Human Health Activities	q1
Q (87,88)	Residential Care Activities, Social Work Activities without Accommodation	q2
R, S, T	Arts, Entertainment and Recreation, Other Service Activities, Activities Of House- holds As Employers, Undifferentiated Goods- and Services-Producing Activities of Households for Own Use	rs

Source: Eurostat (2008).

Table 2.8: Income intervals for monthly incomes

Interval k	Monthly income in Euro w_{month}
1	1 – 500
2	501 – 1000
3	1001 – 1200
4	1201 – 1300
⋮	⋮
12	2001 – 2500
13	2501 – 3000
⋮	⋮
17	4501 – 4900
18	$>$ 4900

Source: Federal Employment Agency (2015).

Table 2.9: Summary statistics of the bite (by industry)

	SAW							*AWC*						
Industry	**Mean**	**S.D.**	**Min.**	Q^{25}	**Median**	Q^{75}	**Max.**	**Mean**	**S.D.**	**Min.**	Q^{25}	**Median**	Q^{75}	**Max.**
bd	1.47	0.83	0.87	1.14	1.44	2.69	4.31	0.21	0.04	0.15	0.20	0.23	0.26	0.36
c1	9.79	8.79	4.81	6.19	7.59	27.17	37.32	1.36	1.27	0.64	0.87	1.06	3.60	5.63
c2	2.03	1.95	0.77	1.33	1.58	7.28	8.11	0.28	0.14	0.11	0.22	0.26	0.62	0.78
c3	2.80	2.79	1.46	1.55	1.88	8.23	11.01	0.32	0.22	0.21	0.23	0.26	0.69	1.03
ff	4.40	1.29	3.16	3.67	4.58	6.45	7.11	0.73	0.14	0.55	0.66	0.78	0.92	0.95
gg	9.48	5.85	6.23	7.07	8.38	23.22	27.48	1.51	0.87	1.06	1.17	1.40	3.44	4.48
hh	8.99	4.96	5.98	6.63	8.54	18.14	21.74	1.25	0.48	0.90	1.08	1.23	2.11	2.50
ii	35.19	11.71	24.43	30.31	38.54	58.34	68.45	7.81	3.35	4.99	6.69	8.69	14.47	18.92
jj	3.35	1.59	2.37	3.01	3.64	6.67	9.90	0.74	0.12	0.63	0.66	0.76	0.90	1.03
kk	2.17	1.26	1.39	1.81	2.52	5.98	6.96	0.48	0.13	0.43	0.43	0.53	0.87	1.07
lm	5.70	2.58	3.05	4.67	6.41	11.64	14.62	1.09	0.21	0.58	1.04	1.13	1.49	1.85
nn	16.84	7.91	11.72	12.49	17.84	30.74	35.66	2.72	0.92	1.98	2.35	2.98	4.34	4.99
pp	4.62	1.02	2.50	3.87	4.45	4.68	6.74	0.80	0.33	0.28	0.55	0.67	0.84	1.62
q1	8.39	3.07	6.42	7.16	8.04	14.23	16.55	1.27	0.25	1.05	1.15	1.33	1.62	2.02
q2	9.69	3.46	6.76	7.58	9.75	14.75	17.97	1.39	0.33	1.00	1.35	1.56	1.75	2.08

Note: In percent.
Source: Federal Employment Agency (2015), Federal Statistical Office (2015), and own calculations.

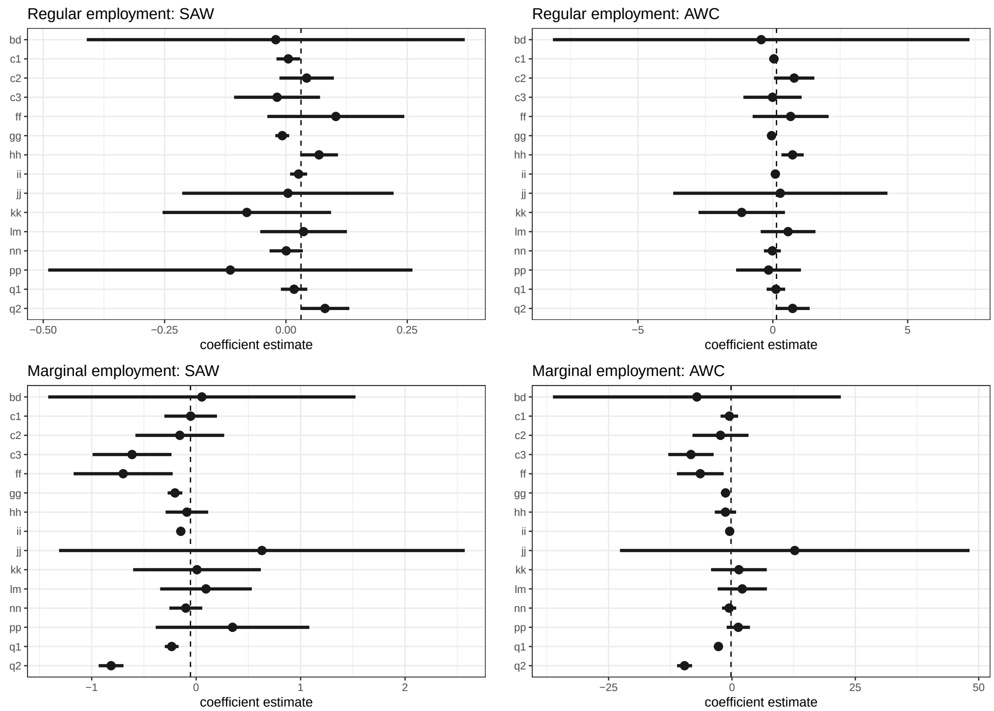
Table 2.10: Summary statistics of the bite (by state)

	SAW							*AWC*						
State	**Mean**	**S.D.**	**Min.**	Q^{25}	**Median**	Q^{75}	**Max.**	**Mean**	**S.D.**	**Min.**	Q^{25}	**Median**	Q^{75}	**Max.**
BB	17.12	12.14	2.56	6.28	11.12	20.49	57.60	2.53	2.94	0.24	0.79	1.49	2.71	14.47
BW	5.77	5.87	1.07	2.59	4.65	6.37	29.89	1.09	1.28	0.20	0.50	0.90	1.11	6.64
BY	6.00	5.83	1.17	2.24	5.71	6.66	28.75	1.07	1.11	0.21	0.50	0.96	1.16	5.54
HE	6.03	4.96	0.87	1.95	4.81	6.64	24.43	1.10	0.98	0.15	0.53	0.89	1.11	4.99
MV	19.99	14.46	3.96	6.64	12.43	23.28	58.34	2.89	2.77	0.36	0.91	1.53	3.12	11.42
NI	8.09	6.98	1.33	2.80	6.22	9.18	33.35	1.37	1.49	0.21	0.53	0.94	1.41	7.33
RW	6.48	5.82	0.88	2.25	5.37	6.92	30.31	1.17	1.27	0.17	0.55	0.98	1.12	6.69
RP	7.77	7.95	1.46	2.76	6.41	7.99	38.54	1.42	1.81	0.24	0.54	1.06	1.28	8.69
SH	8.21	7.39	1.19	2.81	4.32	8.33	33.39	1.36	1.49	0.19	0.55	0.74	1.26	6.83
SL	7.61	8.21	0.77	3.77	6.85	8.11	40.58	1.37	1.84	0.11	0.70	1.14	1.36	9.35
SN	18.03	13.64	2.50	7.19	11.64	22.48	61.96	2.67	3.16	0.25	0.84	1.38	2.97	15.27
ST	18.41	13.83	2.65	7.02	14.62	19.95	68.45	2.85	3.65	0.29	0.77	1.85	2.54	18.92
TH	16.36	12.65	2.53	6.90	13.51	21.08	64.03	2.46	3.22	0.25	0.89	1.64	2.84	16.72

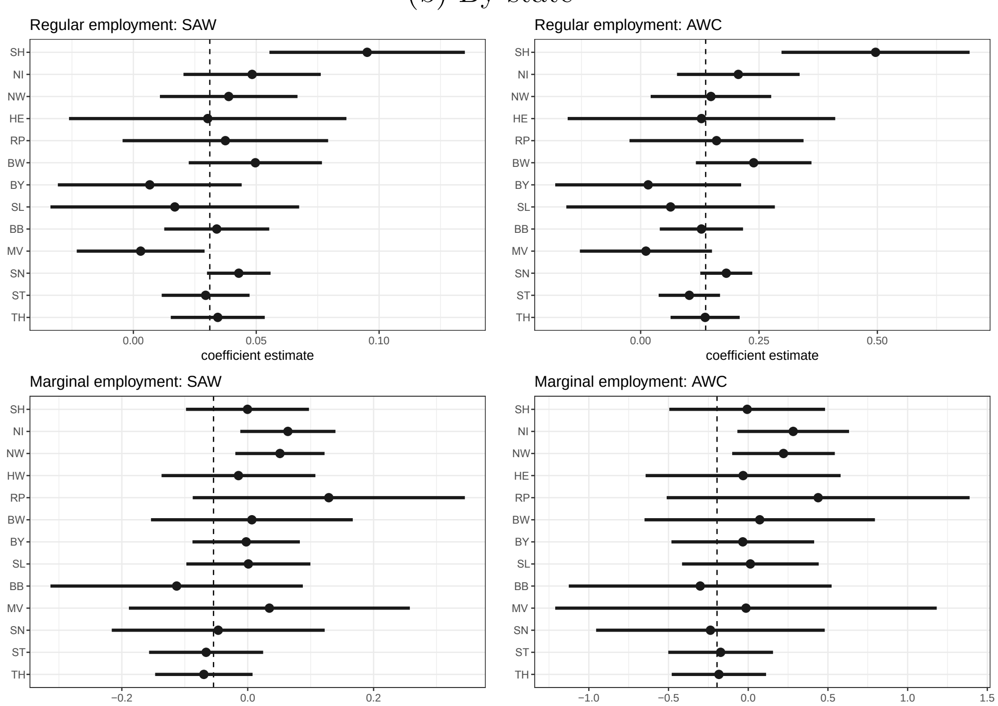
Note: In percent.
Source: Federal Employment Agency (2015), Federal Statistical Office (2015), and own calculations.

Figure 2.5: Disaggregated employment effects for regions and industries

(a) By industry



(b) By state



Notes: Dependent variable: ln-difference of employment (regular and marginal, respectively). Calculations conducted in R using plm (Croissant and Millo 2008). Horizontal lines represent ±1.96 OLS standard errors. Dotted lines indicate the baseline estimates using aggregate models.
Source: Federal Employment Agency (2015, 2016), Federal Statistical Office (2015), and own calculations.

Chapter 3

Labour Mobility and Native Employment: Evidence from the German Minimum-Wage Introduction†

Abstract

I exploit the nationwide statutory German minimum-wage introduction in 2015 as a quasi-natural experiment to investigate whether increases in wage differentials foster labour mobility from low-wage neighbouring countries. Employing an event-study approach, I find positive effects of the minimum wage on the inflows of Czech and Polish workers in the respective German border regions. I further analyse whether the minimum-wage induced increase in labour mobility comes along with negative effects on native employment. I use distance to the border as an instrument for the inflow of foreign workers in an instrumental-variable approach. The results suggest that there is no crowding-out of native

†This chapter is partially based on joint, unpublished work with Daniel Fackler. I also wish to thank Michael Barkholz for his support with the distance computations.

employment after the minimum-wage induced inflow of foreign workers.

3.1 Introduction

International migration and foreign labour supply has been the subject of controversial discussions in the public for decades. On the one hand, labour migration typically has positive effects for the domestic economy as a whole and it may help to overcome labour shortages (e.g., Lucas 2005). On the other hand, there is the fear that foreign labour supply has negative effects on native workers in terms of employment and wages (e.g., Friedberg and Hunt 1995).

In a competitive, neoclassical model of labour mobility (e.g., Borjas 1999), mobility is an investment (cost of migration) by individuals who expect to obtain a return in the future (wage differentials). Higher wages in the host country ceteris paribus increase the net present value of mobility and will therefore induce more labour supply from other countries, a result that is usually confirmed by empirical studies (e.g., Dustmann et al. 2017).

Such a theoretical model implies that an increase in foreign labour supply leads to negative effects on native employment and/or wages if foreign and native workers are substitutes; that is, have the same skills. Despite that intuitive argument, the empirical literature on the effects of immigration on native employment (and wages) in general is inconclusive (e.g., Friedberg and Hunt 1995 or Okkerse 2008). Borjas (1999, 2003) points out that skills of immigrants are a key determinant of the effects of immigration on native labour market outcomes. Hence, different skills of immigrants relative to natives may be an explanation for the lack of clear empirical evidence. One could also think of market imperfections as another theoretical explanation why native employment not necessarily drops after immigration. Consider for example a downward wage rigidity due to a binding minimum wage. In that case, wages cannot fully absorb the increase in labour supply leading to negative effects on native employment.[14] However, minimum wages may prevent natives from leaving the labour force (or even increase it) and hence, counteract the previous effect (Edo and

[14] In addition to potential negative employment effects of minimum wages. See, e.g. Neumark and Wascher (2007), for a review on the topic in general and Caliendo et al. (2019) for the employment effects of the German minimum wage in particular.

Rapoport 2018). Furthermore, because low-wage jobs are rather unattractive for natives (Constant 2014), foreigners may just fill vacancies and thus, the employment effects are theoretically unclear.

This paper contributes to the immigration literature by making use of the nationwide statutory German minimum-wage introduction in 2015 as a quasi-natural experiment. I address two related research questions. First, I investigate whether the minimum-wage shock increases labour supply from low-wage neighbouring countries, the Czech Republic and Poland, in border regions. In light of Lucas' (2005) argument, this could help to mitigate the shortage of labour in several industries, e.g. in the care sector (Schulz 2012 or Federal Employment Agency 2019). Second, I study whether the minimum-wage induced increase in foreign labour supply comes along with negative effects on native employment in the respective region.

In the empirical analyses, I use a large panel dataset to estimate the effect of the minimum wage introduction on foreign worker inflows, applying an event-study approach. Because the minimum wage equally applies to all German regions, the separation of the "treatment groups" from the "control group" is based on distance to the border. I find a positive, significant and robust effect of the minimum wage on foreign worker inflows in regions very close to the border compared to regions that are further away. In order to shed light on the question whether or not the inflow has a negative effect on native employment in Germany, I closely follow Dustmann et al. (2017) and use distance to the border as an instrument for the foreign worker inflow to tackle potential endogeneity issues. The results do not indicate negative effects on native employment.

As pointed out by Glitz (2012), very few studies exploit natural experiments in this context.[15] A particular interesting feature of this paper is the fact that it allows to analyse international migration due to an exogenous wage shock without any legal restrictions regarding labour market access. Closely related to the setting analysed in this paper is a recent study by Dustmann et al. (2017) who also make use of a natural experiment. They analyse the impact of a commuting policy change in the early 1990ies in Germany. This policy made it significantly easier for Czech workers to seek employment in Germany. The authors find that regions close to the border

[15] Examples that exploit natural experiments include Card (1990), Kugler and Yuksel (2008), Glitz (2012), and Dustmann et al. (2017).

experience significant inflows of Czech workers due to the commuting policy change. To analyse the impact of these inflows on native employment and wages, they use distance to the border as an instrument and find negative employment and wage effects on natives in the corresponding regions. The setting in this study thus differs largely in three dimensions from that in Dustmann et al. (2017): Policy change (minimum wage vs commuting), affected workers (mostly low-wage vs all workers), timing (2010s vs 1990s). My findings therefore do not contradict those obtained by Dustmann et al. (2017). Instead they highlight the role of the specific conditions and the institutional framework of the respective labour market and thus, the necessity to evaluate each occurrence empirically.

The remainder of this paper is organized as follows. In Section 3.2, I briefly discuss the institutional background and describe the dataset used in the econometric analysis in Section 3.3. This section is devoted to the estimation of the inflow of foreign workers and subsequently to the estimation of the impact on German employment. In Section 3.4, I apply several robustness checks. The paper closes with a conclusion in Section 3.5.

3.2 Institutional background and data

The introduction of the nationwide statutory German minimum wage became official with the coalition agreement of the future government in November 2013, the German government decided in April 2014 to introduce a nationwide statutory minimum wage amounting to 8.50 Euro per hour as of January 1, 2015. The regulation equally applied to all states and to all but few industries, it covered approximately 98% of all employees (Bossler and Gerner 2016). See Holtemöller and Pohle (forthcoming) for further details.

I use monthly panel data which cover the period from January 2012 to June 2017. District-industry combinations are the cross-sectional dimension in the dataset. Industries are classified according to NACE 2 classification of economic activities (Eurostat 2008). A list of the industries and districts which are used in the econometric analyses is provided in Table 3.4 and Table 3.5, respectively, in Appendix B. The dataset contains the number of German, Czech and Polish employees subject to social security contribution (i.e. regular employment without marginal employment)

Table 3.1: Average annual and minimum wages in Germany, the Czech Republic and Poland

	Germany	Czech Republic	Poland
Average annual wage (2015)	43,000 USD	14,000 USD	12,000 USD
Minimum wage (2015)	8.5 Euro	1.8 Euro	2.25 Euro

Notes: US Dollar in 2017 US Dollar, Conversion of Krone and Zloty into Euro based on the average Euro reference rate 2018.
Source: Average annual wages (OECD 2019), minimum wages (WSI 2019).

for each cross section and is provided by the Federal Employment Agency (2018) upon request. The data are generally available further back in time, but the free movement of workers in the European Union did not unrestrictedly apply for workers from Poland and the Czech Republic until May 2011. To ensure that the analyses are not distorted by other policy changes and to allow for an adjustment period, I set the beginning of the observation period to January 2012. Because the number of Czech and Polish workers is rather small in some cross sections, data privacy issues may arise. If the number of workers in a cross section at a certain point in time is one or two or if the value can be inferred from other information, the corresponding observation is anonymized. For that reason, I do not use a finer classification of industries or smaller regional units (e.g. municipalities).

Notice that the data do not contain information on the place of living of the individuals. In the light of the research questions raised above, it is, however, not important whether foreign workers commute or migrate.

The analysis focuses on the low-wage neighbouring countries Czech Republic and Poland. Both, averages annual wages and minimum wages in these countries are substantially lower than in Germany, see Table 3.1. The impact of the German minimum wage on the wage distribution substantially differs between East and West Germany (Holtemöller and Pohle forthcoming). Several indicators support this statement, see Table 3.2.

Table 3.2: Bite of the minimum wage: East vs. West Germany

	East Germany	West Germany
Increase of minimum-wage affected wages (04/2014 to 04/2016)	~21%	~12%
Affectedness (average per state)	17.8% – 21.4%	7.6% – 11%

Source: Increase of minimum-wage affected wages (Mindestlohnkommission 2018), affectedness (Knabe and Schöb 2014).

Bavaria is the only West German state that shares a border with the Czech Republic, the other West German states do not have a common border with either of the two low-wage countries. Therefore, three separate cases are to be considered:

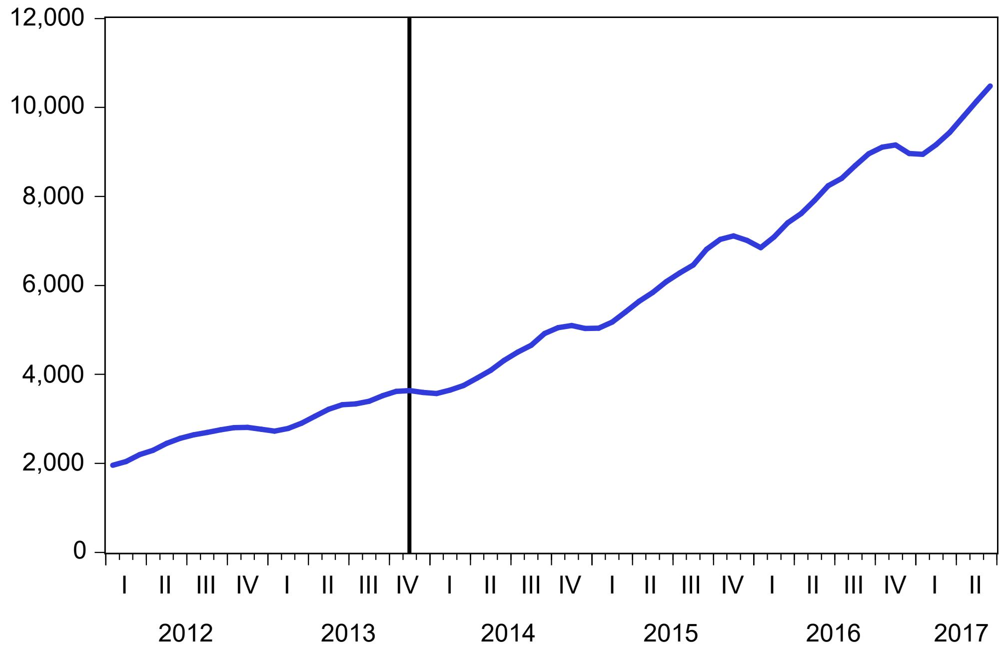
1. East German-Czech border
2. East German-Polish border
3. West German-Czech border.

I study the impact of the minimum wage on the inflow of foreign workers and the subsequent effect on native employment in all three cases. However, I use the first case as the baseline econometric analysis because I expect the strongest effect of the minimum wage in this case for two reasons. First of all, the impact of the minimum wage on the wage distribution is much stronger in East Germany. Second, I use the Czech Republic instead of Poland because minimum-wage differentials between Germany and the Czech Republic are larger than between Germany and Poland, and because of the comparably low density in economic activity in the German-Polish border region.[16] In total, the unbalanced panel dataset used in the baseline econometric analysis in Section 3.3 consists of 912 cross sections observed at 66 months.[17]

[16] While the (East) German - Czech border is mostly in Saxony, large parts of the German-Polish border are in Brandenburg. The ratio of GDP to the size of the state in Saxony is about three times as large as the ratio in Brandenburg (Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder 2018). At the same time GDP per capita in Saxony and Brandenburg are comparable (Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder 2018).

[17] Berlin is excluded from the sample because its economy is structurally different from the rest of East Germany, e.g., in terms of GDP per capita (Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder 2018) or the bite of the minimum wage (Statistisches Bundesamt 2019).

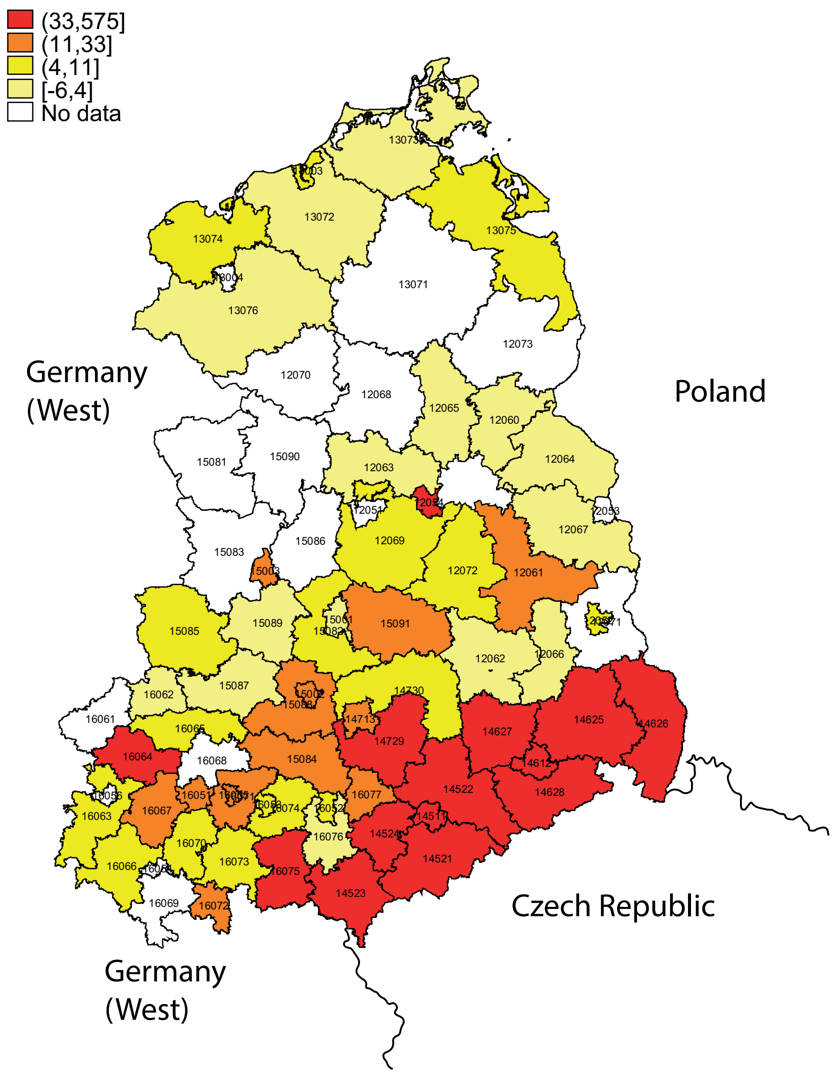
Figure 3.1: Number of Czech workers in East Germany



Note: Vertical line indicates the minimum-wage announcement (November 2013).
Source: Federal Employment Agency (2018) and own exhibition.

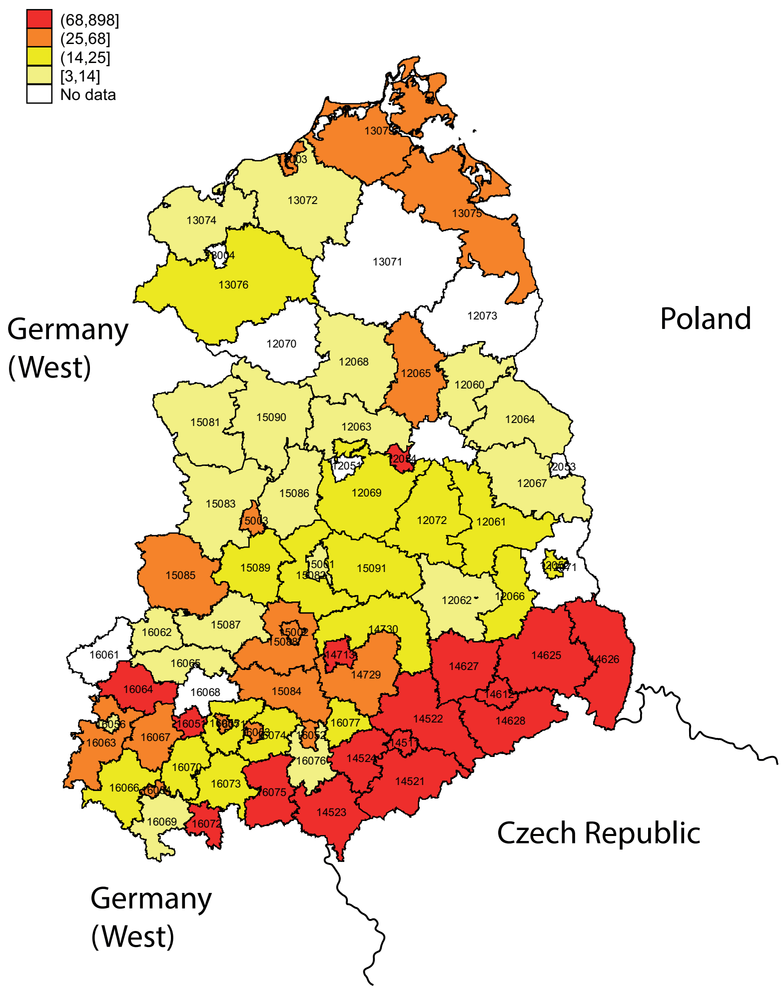
The total number of Czech workers over time in East Germany is depicted in Figure 3.1. I observe a modest increase in the number of Czech workers prior to the announcement of the minimum wage. However, the inflow of Czechs seems to accelerate after the minimum wage was announced. To get some idea regarding the geographic distribution of the increase in inflows, the absolute change in the number of Czech workers from June 2013 to June 2015 is depicted in Figure 3.2. Clearly, districts which are closer to the German-Czech border experienced higher inflows of Czech workers in comparison to districts that are further away from the border. However, as shown in Figure 3.3, these districts were also larger in terms of the number of Czech workers prior to the minimum-wage introduction. The question is whether or not the increase in inflows is caused by the minimum wage or simply a continuation of a trend.

Figure 3.2: Absolute change in the number of Czech workers in East Germany 06/2013 to 06/2015



Notes: Classification of districts according to quartiles of the inflows. Codes within districts denote the district identifier.
Source: Federal Employment Agency (2018) and own exhibition.

Figure 3.3: Stock of Czech workers in East Germany 06/2013



Notes: Classification of districts according to quartiles of the stock of Czech workers. Codes within districts denote the district identifier.
Source: Federal Employment Agency (2018) and own exhibition.

3.3 Econometric analysis

3.3.1 East German – Czech border

Impact of the minimum wage on labour mobility

In the following, I apply an event-study approach to compare the minimum-wage induced inflows of Czech workers in border regions with regions that are further away from the border. For this purpose, I classify all districts in East Germany into two "treatment groups" and a "control group" based on their proximity to the Czech border.[18] Hence, I assume that the minimum-wage induced increase in wage differentials between Germany and its neighbouring country is gradually offset by larger mobility cost if a region is further away from the border. Given that mobility costs increase in distance (e.g., Eliasson et al. 2003), this assumption is reasonable.

A district is classified as being in the treatment group if the district's centroid is located less than 75 kilometers from the next border crossing. I will refer to this treatment group as the treatment group A (TG A) from this stage onwards. A district belongs to the (second) treatment group B (TG B) if its centroid's distance is between 75 and 150 kilometers from the closest border crossing. The TG B can also be regarded as a buffer between the TG A and the control group (CG). Figure 3.4 depicts the assignment of the districts to these groups in the East German – Czech example (first case). Obviously, this classification is to some extent arbitrary. I therefore test several alternatives and briefly discuss them in Section 3.4.

The standard approach would be to apply a simple difference-in-difference model. It is well known that valid identification of causal effects in difference-in-difference models is only feasible if the parallel trend assumption is satisfied. The evolution of the district-industry-combinations average of the number of Czech workers in the control and treatment group is plotted in Figure 3.5. It can be seen that both the initial number of Czech workers per cross section and the development over time differ markedly. Given the pre-existing wage differential and the free movement of workers between the Czech Republic and Germany since 2011, these differences are not surprising. The parallel trend assumption is clearly violated.

Figure 3.5 further reveals that it is generally unclear at what point in time the minimum wage effect kicked in. Economic agents may have anticipated the wage increase and therefore, Czech employment may have gone up after the minimum-wage announcement (11/2013) but before its introduction (01/2015). At the same time, if agents did not fully anticipate these changes, the adjustment process may have taken some time because labour markets are often rather sluggish.

I therefore estimate a model which takes both cross-section specific trends and

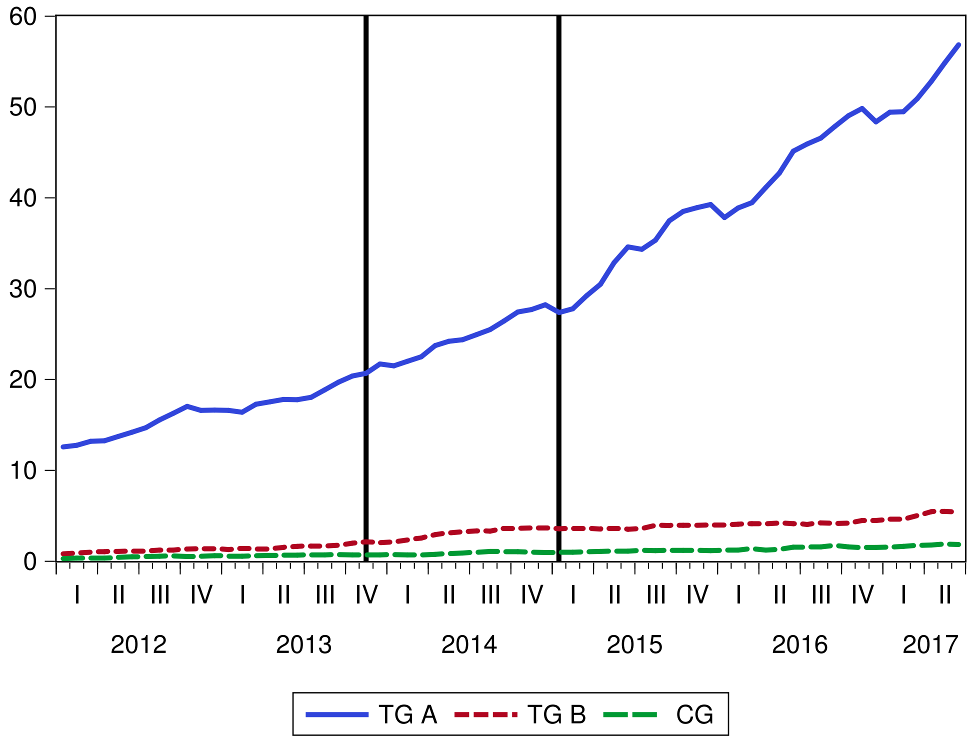
[18] Recall that the statutory minimum wage applies equally to all districts in Germany. Therefore, the decision whether a district belongs to the treatment or the control group cannot be based on the minimum-wage policy.

Figure 3.4: Classification of districts as control and treatment groups

Note: Codes within districts denote the district identifier.
Source: Distances were computed based on data from Bundesamt für Kartographie und Geodäsie (2017) and OpenStreetMap (2019) in QGIS, own exhibition.

dynamic adjustments of foreign labour supply due to the minimum wage-introduction into account:

Figure 3.5: Average number of Czech workers per cross section over time in the control and treatment groups



Note: Vertical lines indicate the minimum-wage announcement (November 2013) and the introduction (January 2015).
Source: Federal Employment Agency (2018) and own exhibition

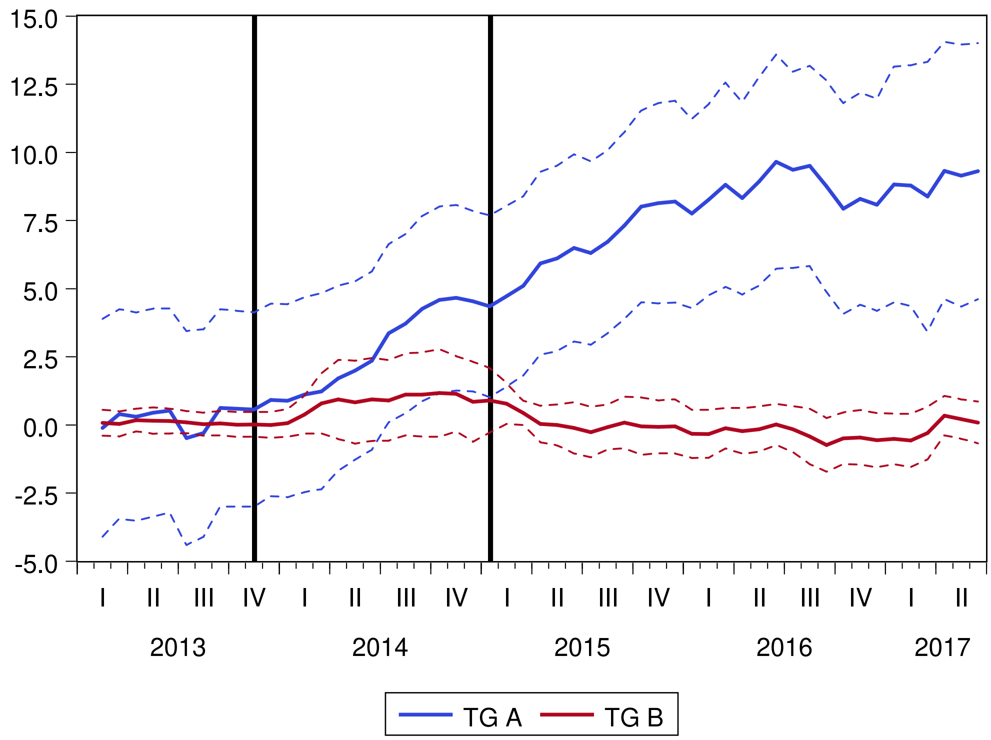
$$\Delta L^{CZ}_{ij,t} = \alpha_{ij} + \sum_{p=2}^{P} \delta_p D_{p,t} + \sum_{p=2}^{P} \gamma_p^{TG_A} D_{p,t} D_{ij}^{TG_A} + \sum_{p=2}^{P} \gamma_p^{TG_B} D_{p,t} D_{ij}^{TG_B} + \epsilon_{ij,t}, \tag{3.1}$$

where $\Delta L^{CZ}_{ij,t} = L^{CZ}_{ij,t} - L^{CZ}_{ij,t-12}$; that is, it denotes the change in the number of Czech workers in each cross section ij (industry i, district j) compared to the (respective month of the) previous year. α_{ij} is a cross-section fixed effect. They are included to control for initial difference in the change of the size of each cross section because the dependent variable is the change of levels (rather than relative changes). Because

I combine first differences with fixed effects, the fixed effects dummies estimate individual trends (e.g., Hendry and Doornik 2013). $D_{p,t}$ represents dummy variables indicating the month relative to the base period (2013M01). Time dummies control for a common development over time. Hence, δ_p is the coefficient that estimates the difference in period p relative to the base period. $D_{ij}^{TG_A}$ is a dummy for the TG A, and $D_{ij}^{TG_B}$ is a dummy variable for the TG B. In line with the literature (e.g., Neumark and Wascher 2007), I assume that the minimum-wage introduction is exogenous with respect to individual cross-sectional units.

The interesting terms are the interactions of the period and the treatment-groups dummies. The corresponding coefficients describe the difference of the change of the treatment groups in comparison to the control group in each period relative to 01/2013. That is, they describe the deviation of the treatment group developments from the evolution in the control group. The estimates for $\gamma_p^{TG_A}$ and $\gamma_p^{TG_B}$ in each period are depicted in Figure 3.6. The solid blue and red lines represent the point estimates for the districts very close to the border (TG A) and the districts relatively close to the border (TG B), respectively. The corresponding dotted lines mark the 95% pointwise confidence intervals around the point estimates based on robust standard errors. First of all, I observe that the approach successfully controls for differences in the trending behaviour depicted in Figure 3.5. Prior to the minimum-wage announcement in 11/2013, there are no differences in the pre-treatment trends between both treatment groups and the control group and thus, $\gamma_p^{TG_A}$ and $\gamma_p^{TG_B}$ solely capture post-treatment effects. After the announcement, the change in the number of workers in the TG A slowly increases in relation to the control group and is significantly larger than zero from 08/2014 onwards. Apparently, agents anticipated the wage increase and started to seek employment in Germany prior to the minimum wage introduction in districts very close to the border. This pattern is particularly interesting because it points to the importance of policy announcements regarding the behaviour of economic agents. This is in line with Bossler (2017) who finds that firms reacted to the minimum-wage introduction after its announcement but before it became active. After the introduction in 01/2015 a steady continuation of the increase in the number of Czech workers in the TG A can be observed. On the contrary, no statistically significant effect is visible in the TG B throughout the observation period. Overall, these results show that the introduction of the

Figure 3.6: Estimated coefficients over time



Notes: The solid lines are the point estimates for $\gamma_p^{TG_A}$ and $\gamma_p^{TG_B}$ from eq. (3.1). Dotted lines represent the corresponding 95% confidence interval based on robust standard errors. Vertical lines indicate the minimum-wage announcement (November 2013) and the introduction (January 2015). *Source:* Federal Employment Agency (2018) and own computation.

minimum wage had a positive effect on labour supply from the Czech Republic in border regions. It seems reasonable to assume that an increase in mobility costs (in distance) is more important for commuters in comparison to migrants because the costs have to be covered every working day in case of commuting. Given that assumption and the fact that foreign employment only increased in districts which are within a commuting distance, it seems likely that the inflow of Czech workers is rather due to commuting instead of migration.[19]

A potential driver of the results could be a larger minimum-wage induced wage-

[19]See Section 3.4 for a brief discussion of commuting distances.

increase in border regions. However, an analysis of the Kaitz-index[20] does not point to a higher bite of the minimum wage in border regions in East Germany (Statistisches Bundesamt 2019).

Impact on German employment

To analyse whether the inflow of Czech workers has an effect on native employment, I estimate the following relationship:

$$\Delta L_{ij,t}^{DE} = \alpha_{ij} + \sum_{p=2}^{P} \delta_p D_{p,t} + \lambda \Delta L_{ij,t}^{CZ} + \epsilon_{ij,t}, \tag{3.2}$$

where $\Delta L_{ij,t}^{DE}$ ($\Delta L_{ij,t}^{CZ}$) denotes change in the number of German (Czech) workers in each cross section compared to the (respective month of the) previous year. As in the previous section, time and cross-section fixed effects are included. Using the inflow of Czech workers, endogeneity issues may arise because Czech workers could sort themselves into prospering cross sections. However, it is also not unreasonable to believe that Czech workers sort themselves into cross sections which are heavily affected by the minimum wage and are not necessarily booming.[21] In the latter case, OLS would underestimate the true effect. I show in the previous section that the increase in Czech employment is driven by the distance to the border. Therefore, and as in Dustmann et al. (2017), I instrument the inflow of Czech workers with distance to the border in a two-stage least squares (2SLS) procedure. Because dummy variables are used to capture the distance to the border in the above exercise, I do not use a continuous distance measure (as in Dustmann et al. 2017) here but in the robustness section. Hence, I use $D_{ij}^{TG_A}$ in order to measure the distance to the border. Because this variable is time invariant, and it is desirable to take the full sample period into account, I interact the distance variable with the time dummies. That is, the inflow of Czech workers, $\Delta L_{ij,t}^{CZ}$, is instrumented by $\sum_{p=2}^{P} D_{p,t} \times D_{ij}^{TG_A}$.

[20] The Kaitz index is typically defined as the ratio of the minimum to the average (e.g., Burkhauser et al. 2000) or to the median wage (e.g., Hwang and Lee 2012).

[21] Mckenzie and Rapoport (2007) argue that networks reduce the cost of migration and thus, the concentration of long-time migrants may foster immigration. As argued above, however, the inflow in this study likely is due to commuting instead of migration and hence, network effects seem less important.

Table 3.3: Effects on German employment

	East G. – CZ	East G. – PL	West G. (Bavaria) – CZ
OLS	2.47***	1.98***	6.17***
OLS 95% CI	[1.32; 3.61]	[1.51; 2.44]	[2.39; 9.96]
2*SLS*	5.1*	3.71*	−0.11
2*SLS* 95% CI	[−0.36; 10.57]	[−0.09; 7.5]	[−16.75; 16.54]
Elasticity	0.002	0.009	0

Notes: Regression results from eq. (3.2), point estimates and confidence intervals (CI) for all cases (East Germany – Czech Republic, East Germany – Poland, West Germany (Bavaria) – Czech Republic). Confidence intervals are based on bootstrapped standard errors (500 replications). Elasticity based on the corresponding 2SLS point estimate. *p<0.1; **p<0.05; ***p<0.01.
Source: Federal Employment Agency (2018) and own calculations.

In order to be a valid instrument, distance to the border must be uncorrelated with evolution of German employment prior to the policy shock (Dustmann et al. 2017). That is, there must not be pre-treatment differences between the control and treatment group prior to the minimum-wage announcement. To verify this assumption, I use German employment in eq. (3.1) without the TG B. The results (Figure 3.7, Appendix B) are encouraging in a sense that there are no differences in the pre-treatment evolution of German employment between the TG A and the control group.

The regression results are reported in Table 3.3 (column 2). First of all, it is encouraging that both estimates have the same sign and therefore, the estimated qualitative effect is identical. The fact that the OLS estimate is smaller than the 2SLS estimate implies that Czech workers likely sort themselves into minimum-wage affected instead of prospering cross sections. Taking into account that the inflow of Czech workers is caused by the minimum wage, this result is what I expected. The F-statistic of the instrument is larger than 30 and thus, the instrument is strong (Staiger and Stock 1997). The positive signs do not speak in favour of negative effects on native employment. That is, foreign workers may indeed just fill vacancies which could otherwise not be filled. Because the OLS estimate likely underestimates the true effect, I focus on the 2SLS estimate ($\hat{\lambda}_{2SLS}$) to discuss the economic relevance of the coefficient, despite the fact that the 95% confidence interval of the 2SLS estimate includes zero. The estimated coefficient from eq. (3.2) corresponds to the marginal effect of Czech on German employment. It is therefore easy to compute the elasticity between German and Czech employment. This elasticity is close to zero ($\hat{\eta}_{DE,CZ} = 0.002$); that is, the inflow of Czech workers did not have an economically relevant effect on native employment. Using the estimated coefficient from the OLS regression leads to an even smaller value.

3.3.2 East German – Polish border

In this subsection, I repeat the previous analyses for Polish workers in Germany. The classification of the treatment groups is as in the baseline case and depicted in Figure 3.8 (Appendix B).

The estimates for the interesting coefficients from eq. (3.1) are depicted in Figure 3.9 (Appendix B). The qualitative results are very similar as to the case of Czech workers. After the minimum-wage announcement, I observe a slow but steady increase in the inflow of Polish workers in the TG A (PL). However, the effect is less pronounced and the corresponding confidence bands include zero in several periods. The effect of the minimum wage on districts further away from the border (TG B (PL)) is statistically not different from zero throughout the observation period. This finding is well in line with the results from the baseline analysis. Overall, the results for Polish workers confirm the previous results. The minimum wage has a positive effect on labour supply in border regions.

Repeating the instrumental-variable exercise (eq. 3.2), I obtain $\hat{\lambda}^{PL}_{2SLS} = 3.71$ (Table 3.3, column 3), a value slightly smaller than in the case of Czech workers. This is in line with smaller change of the inflow in the TG A (PL) in comparison to Czech border regions. The implied elasticity is again close to zero ($\hat{\eta}_{DE,PL} = 0.009$) and hence, the inflow of foreign workers essentially does not affect native employment. Even though the the estimated coefficients from eq. (3.2) are smaller in comparison to the Czech Republic, it is not surprising that the elasticity is larger than in case of Czech workers because of the larger stock of Polish workers in East Germany.[22] In general, the main result is confirmed, the inflow of foreign workers does not have a negative effect on native employment.

[22] In January 2013, approximately 9,000 Polish and 1,700 Czech workers are in employed in the sample used in the econometric exercise.

3.3.3 West German – Czech border

Bavaria is the only West German state that shares a border with the Czech Republic. The classification of treatment and control groups is exactly as in the previous two cases (Figure 3.10, Appendix B). A slight difference to the previous two cases arises because in this case, only one state is included in the regressions. Notice, however, that Bavaria is a fairly large state in terms of both size and population.

The relevant coefficients from eq. (3.1) are show in Figure 3.11 (Appendix B). The qualitative picture is similar to both East German cases. After the announcement of the minimum-wage introduction, Czech employment increases in the TG A (BY) but remains roughly unchanged in the TG B (BY) in comparison to the relevant control group. Yet, the coefficient is only significantly different from zero in some periods. It is worth to mention that the quantitative effect in the TG A (BY) is smaller than in the TG A besides a larger initial average size of the TG A (BY).[23] Given that the increase in wage differentials is substantially smaller in Bavaria in comparison to East Germany, this is what I expected. Furthermore, it is interesting to notice that the adjustment apparently kicked in earlier in Bavaria than in East Germany. One could think of the prospering labour market in Bavaria as a reason for this finding.[24] It might just be easier (and thus, require less time) for a Czech worker to find a job in Bavaria than in Saxony or than for a Polish worker in Brandenburg.

As in the previous two cases, I use distance to the border as an instrument for the inflow of Czech workers in eq. (3.2). The resulting estimate is $\hat{\lambda}^{BY}_{2SLS} = -0.11$ (see Table 3.3, column 4). Contrary to the above cases, however, the estimate is statistically unlikely to be different from zero. Hence, it is both statistically and economically ($\hat{\eta}_{BY,CZ} = 0$) irrelevant and thus, the inflow of foreign workers does not speak in favour of a negative effect on native employment.

[23] As of January 2013, the average cell-size amounts to approximately 15 workers in the TG A and to approximately 35 workers in the TG A (BY).

[24] Consider, for example, the unemployment rate as of January 2013: 4.4% in Bavaria, 10.6% in Saxony, and 11% in Brandenburg (Federal Employment Agency 2013).

3.4 Robustness

Fackler and Rippe (2017) show that the vast majority does not commute more than 60 kilometres. Using a 75 kilometres to specify the TG A thus implies that almost every commuter is in this treatment group. However, and as mentioned above, this classification is arbitrary. Fackler and Rippe (2017) furthermore provide evidence that 90% of commuters do not travel more than 44 kilometres. I therefore introduce the TG C (less than 44 kilometres from the districts centroid to the next border crossing) and TG D (between 44 and 88 kilometres). To cover approximately the same distance with all treatment groups as in the baseline specification, I also add a TG E (between 88 and 132 kilometres).[25] The results from eq. (3.1) using the three treatment groups described here are depicted in Figure 3.12 (Appendix B). The coefficient of the TG C, $\gamma_p^{TG_C}$ is larger than the coefficient of the TG A; that is, the results indicate that districts super close to the border (TG C) are the main driver of the baseline results. Hence, this classification is somewhat better suited to understand the role of the distances and thus, mobility cost. Using the TG C in eq. (3.2) leads to $\hat{\lambda}_{2SLS,3TG} = 4.92$, implying an equally small elasticity, $\hat{\eta}_{DE,CZ,3TG} = 0.002$. I also test further alternatives. For example, using four treatment groups in 25 kilometres intervals implies $\hat{\eta}_{DE,CZ,4TG} = 0.003$.[26] Hence, the results are robust to the classification choice. Foreign employment increased in districts very close to the border but this increase does not have a negative effect on native employment.

I have ignored the fact that Czech workers do likely not live at the border crossing an hence, the actual commuting distance is larger because they also have to travel from their place of living to the border crossing. This fact, and the finding that super close districts drive the results, speak in favour of a smaller distance given that the purpose of the TG A is to cover the majority of commuters. However, due to data reasons, the baseline classification of the treatment groups is preferred. For example, the TG C and the TG D only consist of six districts and are thus, sensitive to outliers.

Instead of using a binary variable, which captures whether or not a district is affected, one could also use distance to the border as a continuous variable. I therefore use

[25] Notice that adding a third treatment group has negligible effects on the results.

[26] For computational convenience, a district's minimum distance instead of the district's centroid's distance is used in this exercise. Detailed results are available upon request.

distance to the border in kilometres in the event-study specification. The results for the relevant coefficient are depicted in Figure 3.13 (Appendix B). They support the main finding, the minimum wage had a positive effect on labour supply from the Czech Republic in border regions. As in Dustmann et al. (2017), I also use distance to border (and the square of it) in the instrumental-variable setup. The resulting coefficient, $\hat{\lambda}_{2SLS,cont} = 4.66$, and the elasticity, $\hat{\eta}_{DE,CZ,cont} = 0.002$, confirm that the increase of Czech workers does not have a relevant effect on German employment.

As a placebo test, I use the number of Polish workers in the baseline specification; that is, in German districts close to the Czech border (TG A). As reported in Figure 3.14 (Appendix B), the evolution of Polish employment in the TG A does not differ from the evolution in the control group. Hence distance to the actual border is indeed the driver of the inflow of workers from the corresponding neighbouring country.

I also test if demographic changes are important for the results. I therefore use the annual change of the population in a district (Statistische Ämter des Bundes und der Länder 2019) as a control variable in eq. (3.1). Due to local government reorganizations in East Germany, the data are not readily available for this exercise. Therefore, this robustness test is conducted in the case of the Bavarian-Czech border. Because the data are only available at an annual frequency, I interpolate the series using a cubic spline to match the monthly frequency of the employment data. While the population coefficient is statistically significant, the coefficient of the TG A (BY) is nearly unaffected (see Figure 3.15, Appendix B), confirming the main findings.

3.5 Conclusions

In this paper, I exploit the quasi-natural experiment of the minimum-wage introduction in Germany in 2015 to address two research questions. First, I analyse if the exogenous wage shock has an impact on labour mobility from low-wage neighbouring countries. The minimum-wage introduction has a positive effect on labour supply from the Czech Republic and Poland in the corresponding German border regions; the effect is less pronounced in regions which are less affected by the minimum-wage introduction. However, districts which are not very close to the border are basically unaffected by changes in foreign labour mobility due to the minimum wage. Given this finding, it is likely that the vast majority of the additional foreign workers are commuters. Because commuting has several advantages over moving (Stark and Fan 2007), wage-differential increases must be substantially larger to induce foreign workers to move out of their country of origin. Hence, if policy makers wish to address the problem of labour shortage (e.g. in the care sector), induced wage-differential increases must be fairly large.

Second, I study if the inflow of foreign workers has an effect on native employment. Even though the estimated coefficient is positive in most specifications, the economic (and sometimes statistic) relevance on native employment is essentially zero in all cases. Hence, the fear that the inflow of foreign labour reduced employment prospects for natives is not justified. Because this is an empirical study, it is important to stress that this result need not hold in general. During the time of the minimum-wage introduction, the German labour market was a fairly good condition (Projektgruppe Gemeinschaftsdiagnose 2014). If the inflow of foreign workers occurred during a recession, foreign labour mobility could have had negative effects on native employment.

Taking into account that the inflow is caused by the introduction of a lower-wage floor, it seems unlikely that native's wages were negatively affected. However, to determine whether or not wages were indeed unaffected is left open for future research. I do not address this issue here because the dataset does not contain information on wages. The availability of wage data would also allow researchers to compute the elasticity of labour supply, another interesting topic for future research.

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Appendix B

Table 3.4: List of industries (Chapter 3)

NACE 2 Code	Industry
C	Manufacturing
G	Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles
H	Transportation and Storage
I	Accommodation and Food Service Activities
J, K	Information and Communication, Financial and Insurance Activities
L, M	Real Estate Activities, Professional, Scientific and Technical Activities
N (excl. 78.2 & 78.3)	Administrative and Support Service Activities
O, U	Public Administration and Defence, Compulsory Social Security, Activities of Extraterritorial Organisations and Bodies
P	Education
Q (86)	Human Health Activities
Q (87,88)	Residential Care Activities, Social Work Activities without Accommodation
R, S, T	Arts, Entertainment and Recreation, Other Service Activities, Activities Of House- holds As Employers, Undifferentiated Goods- and Services-Producing Activities of Households for Own Use

Source: Eurostat (2008).

Table 3.5: List of districts

District identifier	District	State
12051	Brandenburg an der Havel	Brandenburg
12052	Cottbus	(East Germany)
12053	Frankfurt (Oder)	
12054	Potsdam	
12060	Barnim	
12061	Dahme-Spreewald	
12062	Elbe-Elster	
12063	Havelland	
12064	Märkisch-Oderland	
12065	Oberhavel	
12066	Oberspreewald-Lausitz	
12067	Oder-Spree	
12068	Ostprignitz-Ruppin	
12069	Potsdam-Mittelmark	
12070	Prignitz	
12071	Spree-Neiße	
12072	Teltow-Fläming	
12073	Uckermark	
13003	Rostock	Mecklenburg-Western
13004	Schwerin	Pomerania
13071	Mecklenburgische Seenplatte	(East Germany)
13072	Rostock	
13073	Vorpommern-Rügen	
13074	Nordwestmecklenburg	
13075	Vorpommern-Greifswald	
13076	Ludwigslust-Parchim	

Table 3.5: List of districts (cont.)

District identifier	District	State
14511	Chemnitz	Saxony (East Germany)
14521	Erzgebirgskreis	
14522	Mittelsachsen	
14523	Vogtlandkreis	
14524	Zwickau	
14612	Dresden	
14625	Bautzen	
14626	Görlitz	
14627	Meißen	
14628	Sächsische Schweiz-Osterzgebirge	
14713	Leipzig	
14729	Leipzig	
14730	Nordsachsen	
15001	Dessau-Roßlau	Saxony-Anhalt
15002	Halle (Saale)	(East Germany)
15003	Magdeburg	
15081	Altmarkkreis Salzwedel	
15082	Anhalt-Bitterfeld	
15083	Börde	
15084	Burgenlandkreis	
15085	Harz	
15086	Jerichower Land	
15087	Mansfeld-Südharz	
15088	Saalekreis	
15089	Salzlandkreis	
15090	Stendal	
15091	Wittenberg	

Table 3.5: List of districts (cont.)

District identifier	District	State
16051	Erfurt	Thuringia
16052	Gera	(East Germany)
16053	Jena	
16054	Suhl	
16055	Weimar	
16056	Eisenach	
16061	Eichsfeld	
16062	Nordhausen	
16063	Wartburgkreis	
16064	Unstrut-Hainich-Kreis	
16065	Kyffhäuserkreis	
16066	Schmalkalden-Meiningen	
16067	Gotha	
16068	Sömmerda	
16069	Hildburghausen	
16070	Ilm-Kreis	
16071	Weimarer Land	
16072	Sonneberg	
16073	Saalfeld-Rudolstadt	
16074	Saale-Holzland-Kreis	
16075	Saale-Orla-Kreis	
16076	Greiz	
16077	Altenburger Land	
09161	Ingolstadt	Bavaria (West Germany)
09162	München	
09163	Rosenheim	
09171	Altötting	
09172	Berchtesgadener Land	
09173	Bad Tölz-Wolfratshausen	
09174	Dachau	
09175	Ebersberg	
09176	Eichstätt	
09177	Erding	
09178	Freising	
09179	Fürstenfeldbruck	
09180	Garmisch-Partenkirchen	
09181	Landsberg am Lech	
09182	Miesbach	

Table 3.5: List of districts (cont.)

District identifier	District	State
09183	Mühldorf a. Inn	Bavaria (West Germany)
09184	München	
09185	Neuburg-Schrobenhausen	
09186	Pfaffenhofen a.d. Ilm	
09187	Rosenheim	
09188	Starnberg	
09189	Traunstein	
09190	Weilheim-Schongau	
09261	Landshut	
09262	Passau	
09263	Straubing	
09271	Deggendorf	
09272	Freyung-Grafenau	
09273	Kelheim	
09274	Landshut	
09275	Passau	
09276	Regen	
09277	Rottal-Inn	
09278	Straubing-Bogen	
09279	Dingolfing-Landau	
09361	Amberg	
09362	Regensburg	
09363	Weiden i.d. OPf.	
09371	Amberg-Sulzbach	
09372	Cham	
09373	Neumarkt i.d. OPf.	
09374	Neustadt a.d. Waldnaab	
09375	Regensburg	
09376	Schwandorf	
09377	Tirschenreuth	
09461	Bamberg	
09462	Bayreuth	
09463	Coburg	
09464	Hof	
09471	Bamberg	
09472	Bayreuth	
09473	Coburg	
09474	Forchheim	

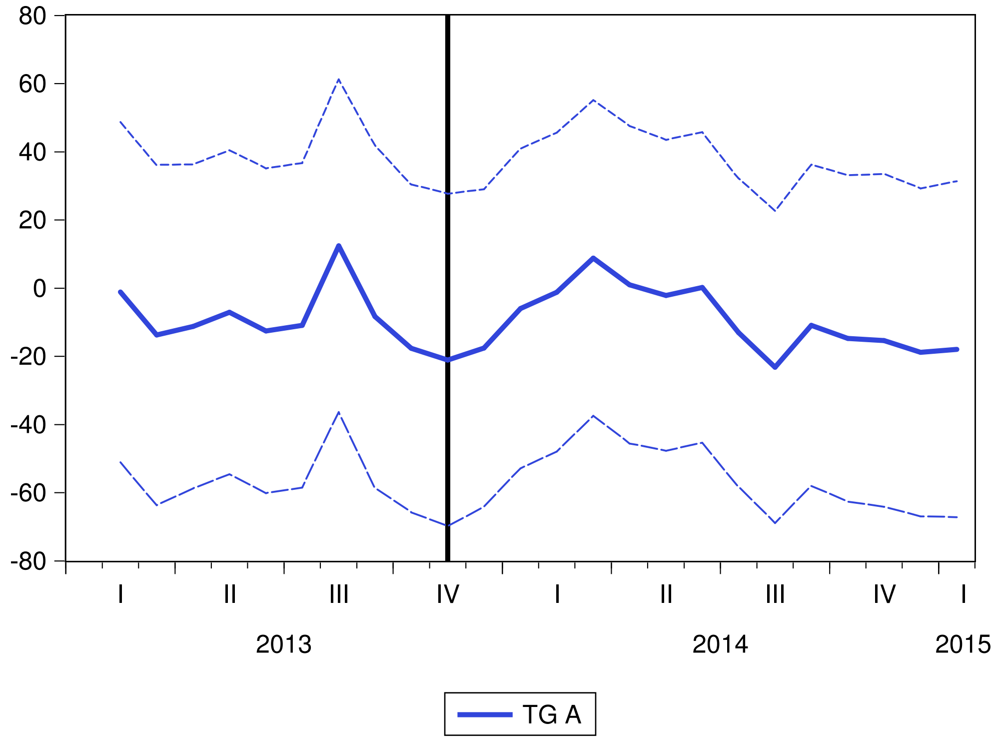
Table 3.5: List of districts (cont.)

District identifier	District	State
09475	Hof	Bavaria (West Germany)
09476	Kronach	
09477	Kulmbach	
09478	Lichtenfels	
09479	Wunsiedel i. Fichtelgebirge	
09561	Ansbach	
09562	Erlangen	
09563	Fürth	
09564	Nürnberg	
09565	Schwabach	
09571	Ansbach	
09572	Erlangen-Höchstadt	
09573	Fürth	
09574	Nürnberger Land	
09575	Neustadt a.d. Aisch-Bad Windsheim	
09576	Roth	
09577	Weißenburg-Gunzenhausen	
09661	Aschaffenburg	
09662	Schweinfurt	
09663	Würzburg	
09671	Aschaffenburg	
09672	Bad Kissingen	
09673	Rhön-Grabfeld	
09674	Haßberge	
09675	Kitzingen	
09676	Miltenberg	
09677	Main-Spessart	
09678	Schweinfurt	
09679	Würzburg	
09761	Augsburg	
09762	Kaufbeuren	
09763	Kempten (Allgäu)	
09764	Memmingen	
09771	Aichach-Friedberg	
09772	Augsburg	
09773	Dillingen a.d. Donau	
09774	Günzburg	
09775	Neu-Ulm	

Table 3.5: List of districts (cont.)

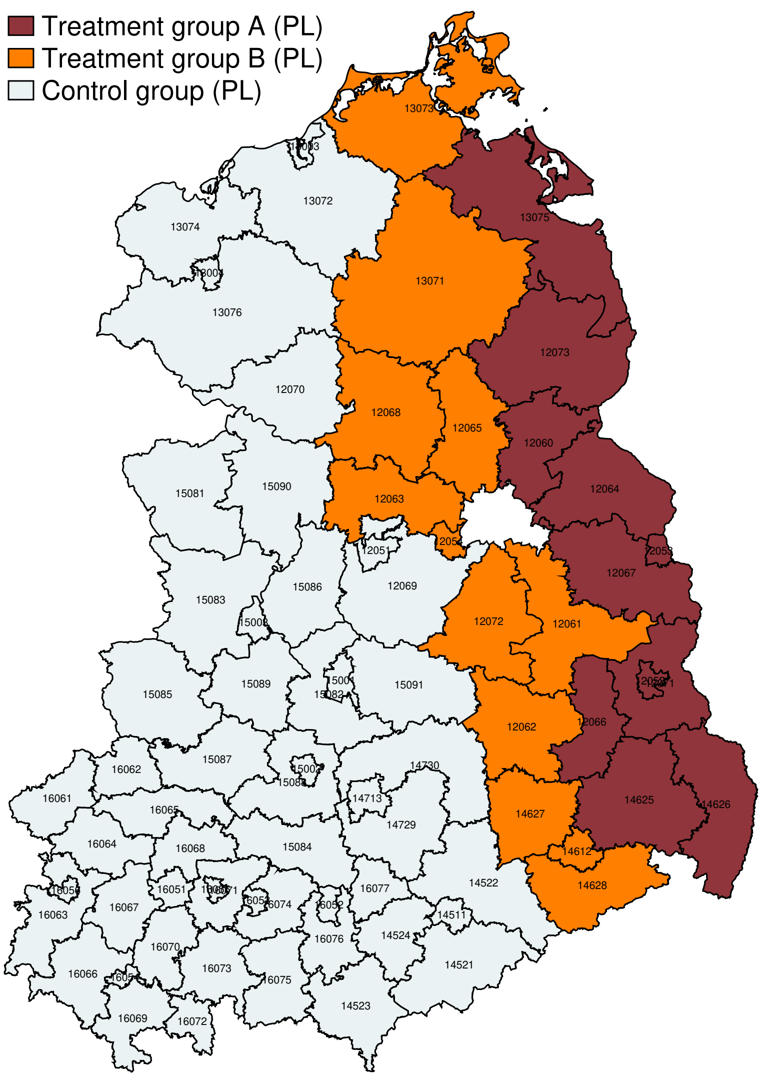
District identifier	District	State
09776	Lindau (Bodensee)	Bavaria (West Germany)
09777	Ostallgäu	
09778	Unterallgäu	
09779	Donau-Ries	
09780	Oberallgäu	

Figure 3.7: Pre-treatment evolution of German employment in the treatment group A



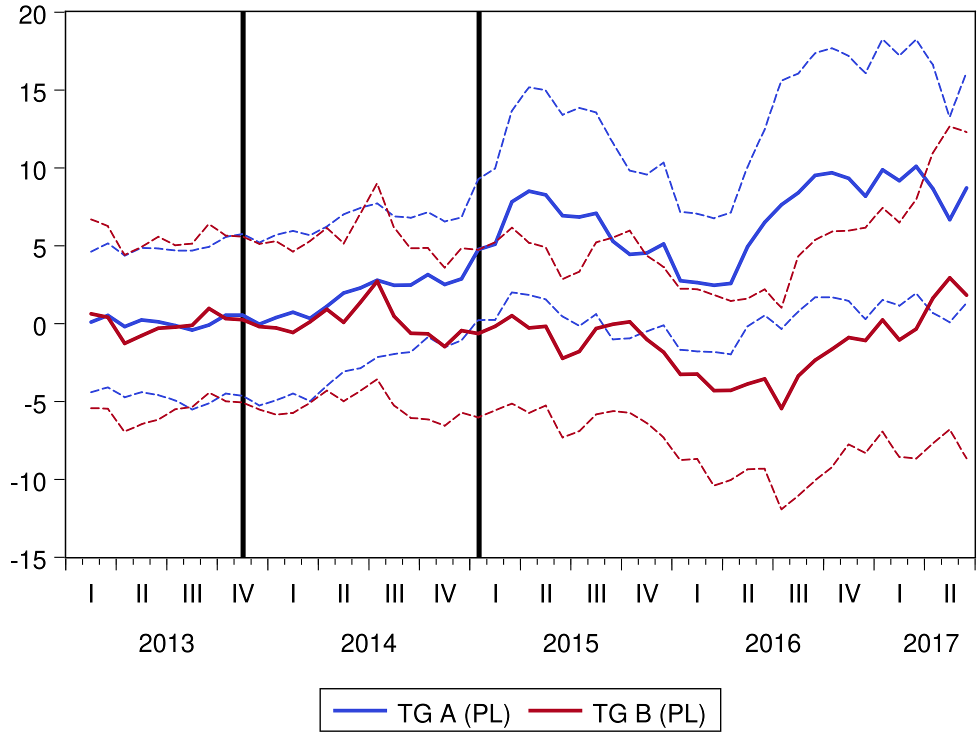
Notes: The solid line depicts the point estimates for $\gamma_t^{TG_A}$ from eq. (3.1) excluding the TG B. It represents the difference of German employment in the TG A relative to the CG: Dotted lines represent the corresponding 95% confidence interval based on robust standard errors. Vertical line indicates the minimum-wage announcement (November 2013).
Source: Federal Employment Agency (2018) and own computation.

Figure 3.8: Classification of control and treatment groups (Poland)



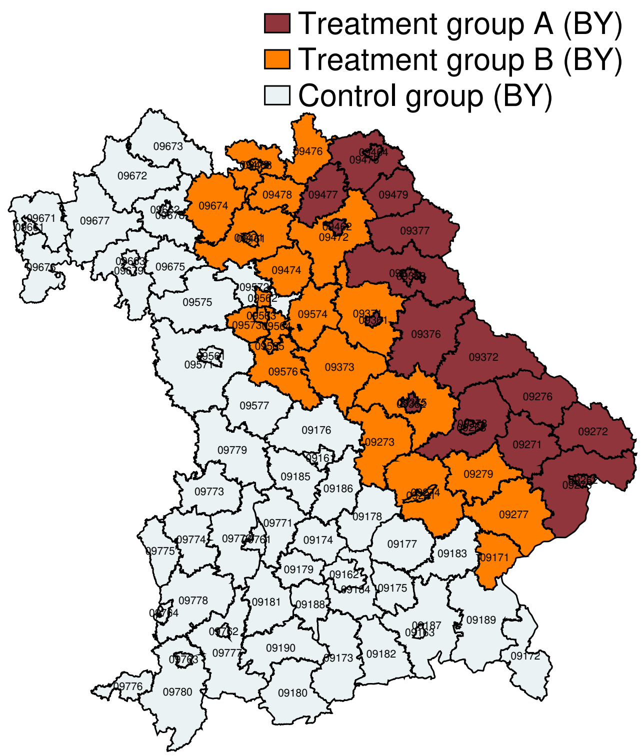
Note: Codes within districts denote the district identifier.
Source: Distances were computed based on data from Bundesamt für Kartographie und Geodäsie (2017) and OpenStreetMap (2019) in QGIS, own exhibition.

Figure 3.9: Estimated coefficients over time (Poland)



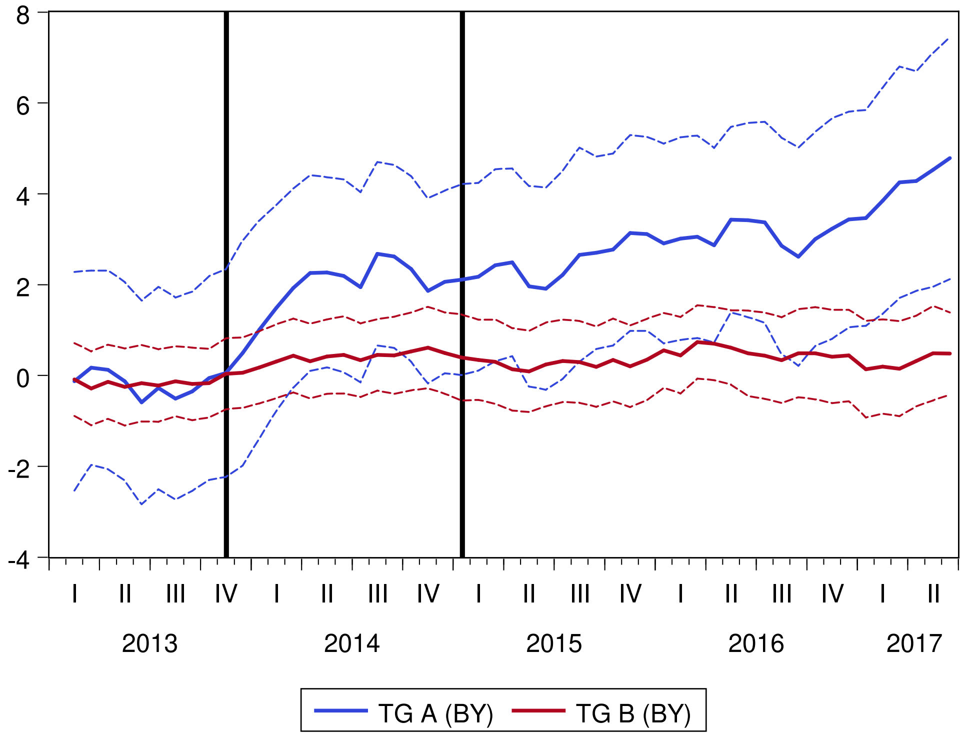
Notes: The solid lines are the point estimates for $\gamma_p^{TG_A^{PL}}$ and $\gamma_p^{TG_B^{PL}}$ from eq. (3.1). Dotted lines represent the corresponding 95% confidence interval based on robust standard errors. Vertical lines indicate the minimum-wage announcement (November 2013) and the introduction (January 2015). *Source:* Federal Employment Agency (2018) and own computation.

Figure 3.10: Classification of control and treatment groups (Czech Republic – Bavaria)



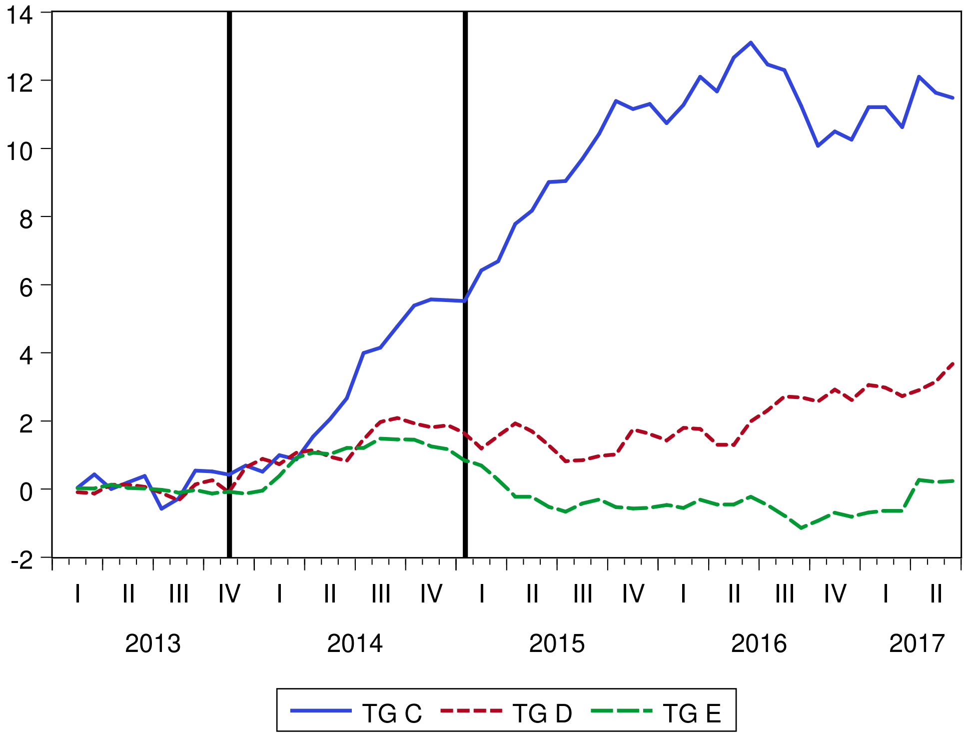
Note: Codes within districts denote the district identifier.
Source: Distances were computed based on data from Bundesamt für Kartographie und Geodäsie (2017) and OpenStreetMap (2019) in QGIS, own exhibition.

Figure 3.11: Estimated coefficients over time (Czech Republic – Bavaria)



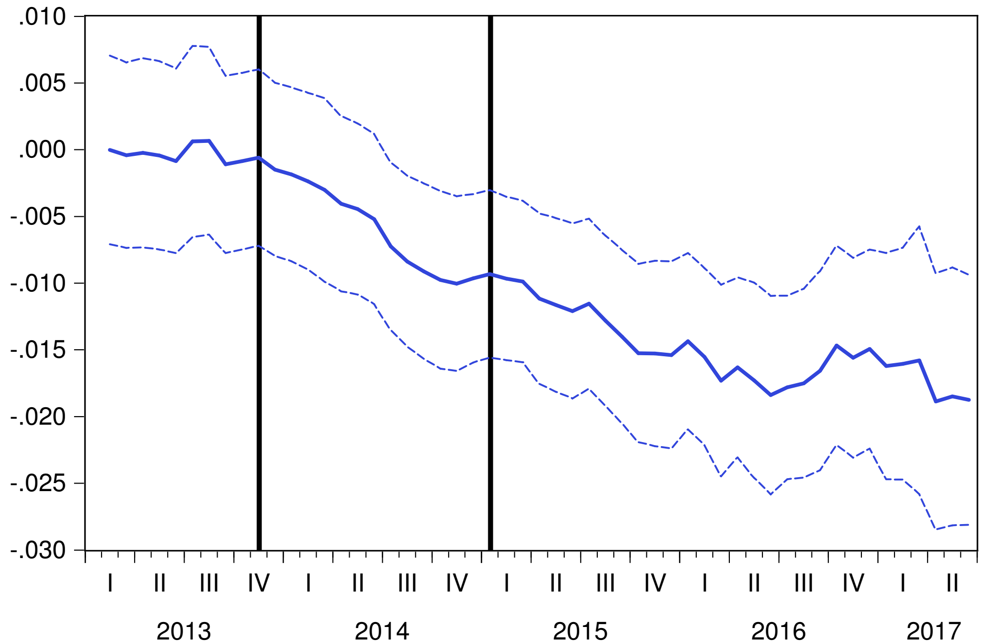
Notes: The solid lines are the point estimates for $\gamma_p^{TG_A^{BY}}$ and $\gamma_p^{TG_B^{BY}}$ from eq. (3.1). Dotted lines represent the corresponding 95% confidence interval based on robust standard errors. Vertical lines indicate the minimum-wage announcement (November 2013) and the introduction (January 2015). *Source:* Federal Employment Agency (2018) and own computation.

Figure 3.12: Estimated coefficients over time (three treatment groups)



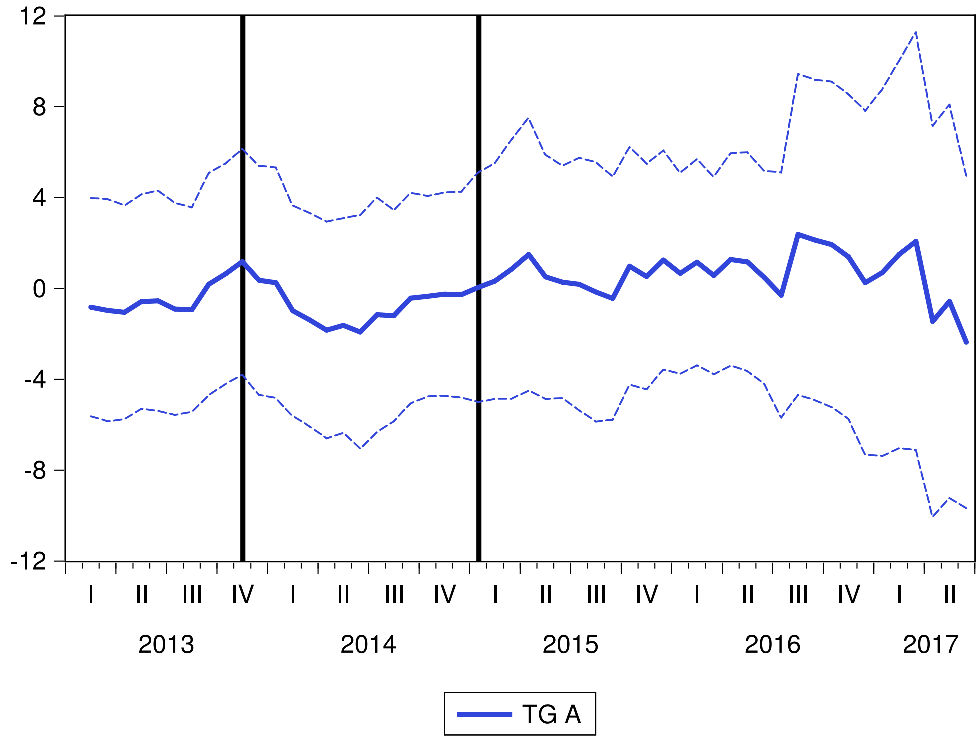
Notes: The solid lines are the point estimates for $\gamma_t^{TG_C}$, $\gamma_t^{TG_D}$, and $\gamma_t^{TG_E}$. For the sake of readability, I do not plot confidence intervals here. Vertical lines indicate the minimum-wage announcement (November 2013) and the introduction (January 2015).
Source: Federal Employment Agency (2018) and own computation.

Figure 3.13: Estimated coefficient over time (continuous distance measure)



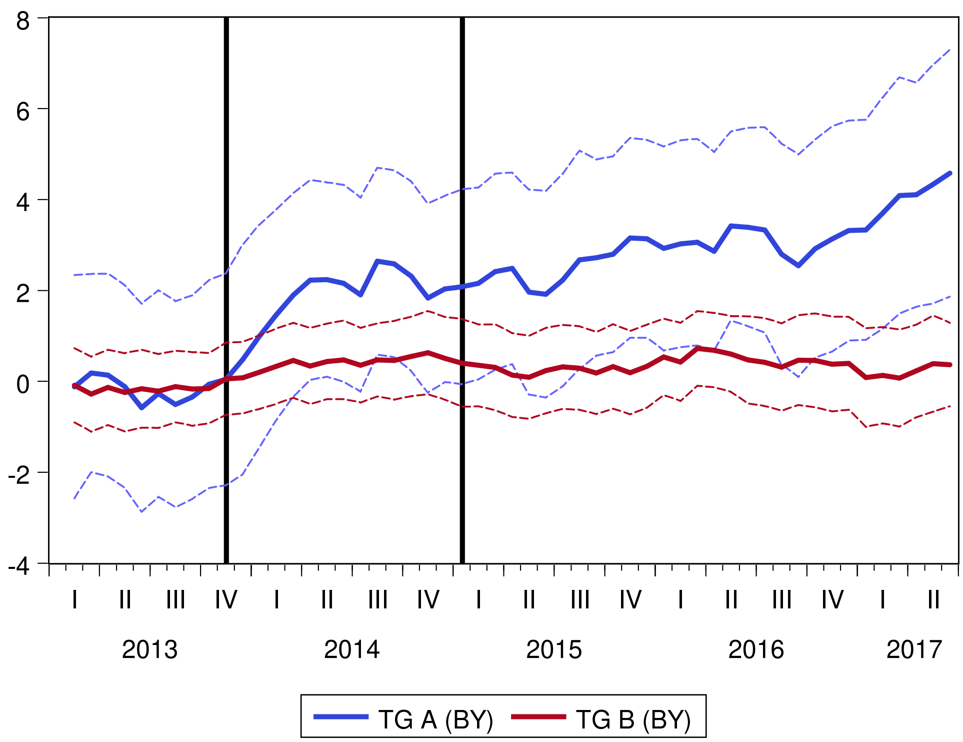
Notes: The solid line represents the point estimates for distance to the border (continuous variable) from eq. (3.1). Dotted lines represent the corresponding 95% confidence interval based on robust standard errors. Vertical lines indicates the minimum-wage announcement (November 2013) and the introduction (January 2015).
Source: Federal Employment Agency (2018), Bundesamt für Kartographie und Geodäsie (2017), OpenStreetMap (2019), and own computation.

Figure 3.14: Estimated coefficients over time (placebo test)



Notes: The solid line is the point estimates for $\gamma_t^{TG_A}$ from eq. (3.1) using Polish workers in the TG A. Dotted lines represent the corresponding 95% confidence interval based on robust standard errors. Vertical lines indicates the minimum-wage announcement (November 2013) and the introduction (January 2015).
Source: Federal Employment Agency (2018) and own computation.

Figure 3.15: Estimated coefficients over time (Bavaria, controlling for demography)



Notes: The solid lines are the point estimates for $\gamma_p^{TG_A^{BY,pop}}$ and $\gamma_p^{TG_B^{BY,pop}}$ from eq. (3.1) including population growth. Dotted lines represent the corresponding 95% confidence interval based on robust standard errors. Vertical lines indicate the minimum-wage announcement (November 2013) and the introduction (January 2015).
Source: Federal Employment Agency (2018) and own computation.

Chapter 4

Employment, Technology, and Hiring Costs in a NK-SAM Framework

Abstract

Galí (1999) provides empirical evidence that hours worked decline after a technology shock, an observation which is consistent with the predictions of a textbook New-Keynesian model. However, several New-Keynesian Search-and-Matching models fail to replicate this stylized fact. In this paper, I propose an extension to a standard New-Keynesian Search-and-Matching with endogenous job separations by enriching it with technology-dependent training costs. I show that, for reasonable levels of training costs, it is not possible to replicate Galí's observation in the presence of endogenous job separations. However, once I solely rely on exogenous job separations, the extension improves the empirical relevance of the augmented model; that is, employment drops after a technology shock.

4.1 Introduction

In a seminal paper, Galí (1999) shows that technology shocks have contractionary employment effects. While this finding is inconsistent with the predictions of the standard real business-cycle (henceforth: RBC) model, a simple New-Keynesian (henceforth: NK) model replicates it well. Hence, this observation calls the empirical relevance of the real RBC model into question and gives an important motivation for the NK model.

Both RBC and NK models usually employ a standard, frictionless labour market paradigm of supply and demand. However, it is well known that this approach has some shortcomings. First of all, there is no explanation for equilibrium unemployment in these models (e.g., Rogerson et al. 2005). Furthermore, the ability of a supply and demand model to embed labour market institutions (e.g. employment protection legislation) is limited. On the contrary, the Search-and-Matching (henceforth: SAM) paradigm, advanced by Mortensen and Pissarides (1994, 1999), is a rigorous tool to analyse equilibrium unemployment, labour market institutions, the in- and outflows into employment, etc. It therefore seems reasonable to embed a labour market with search frictions (i.e. with SAM) in DSGE models if one wants to study labour market properties or the impact of labour market institutions over the business cycle.

However, this potentially promising incorporation of search frictions into a NK model may produce some side effects. Some New-Keynesian Search-and-Matching (henceforth: NK-SAM) models fail to replicate Galí's (1999) observation, e.g. Zanetti (2011). He studies the impact of labour market institutions (unemployment benefits and employment protection legislation) on aggregate fluctuations. Among other things, Zanetti (2011) finds that employment protection legislation (in the form of firing costs) decreases the volatility of output and employment over the business cycle. Furthermore, his numerical exercise reveals that a moderate firing costs increase lead to higher employment levels. At the same time, his exercise does not replicate Galí's (1999) empirical observation (negative response of employment towards a technology shock), questioning the relevance of the model. I propose an extension to address this shortcoming to improve Zanetti's model such that it replicates this empirical observation.

Mandelman and Zanetti (2014) embed technology-dependent hiring costs similar to

Blanchard and Galí (2010) in an RBC-SAM model without endogenous separations and show that this generates a negative response of employment to a technology shock. I build on Mandelman and Zanetti' s (2014) idea and introduce technology-dependent hiring costs into the model proposed by Zanetti (2011), a NK-SAM model with endogenous separations. I ask the following research question: Do technology-dependent training costs generate a negative response of employment after a positive technology shock? Because Mandelman and Zanetti's (2014) approach replicates Galí's observation in an RBC model, there is good reason to assume that it also works in the model I develop below. Surprisingly, incorporating technology-dependent training costs does the opposite, employment further rises after a technology shock. The economic reason for this finding is the indirect effect of training costs on decreasing job destruction which outweighs the direct effect on job creation. Once I abstract from endogenous separation, technology-dependent training costs flip the sign of the impulse response function (henceforth: IRF). However, certain labour market institutions, e.g. employment protection legislation, crucially hinge on endogenous separations.

The remainder of this paper is organized as follows. In Section 4.2, I repeat Galí' s (1999) exercise with more recent data, discuss the empirical findings and compare them with Zanetti's (2011) theoretical result. Section 4.3 develops the model and derives the equilibrium conditions. The subsequent Section 4.4 is devoted to the calibration of the model. I begin by thoroughly analysing Zanetti's strategy and subsequently propose an alternative calibration. Section 4.5 is dedicated to the results. Business cycle properties and the dynamic responses of the economy to a technology shock are presented. To isolate the effect of endogenous separations, I also study the dynamics in a model without endogenous separations. The paper closes with a conclusion in Section 4.6.

4.2 Employment and technology

In order to illustrate the inconsistency of the model proposed by Zanetti (2011) and the empirical evidence obtained by Galí (1999), I repeat both exercises in this section and briefly discuss the underlying economic mechanisms.[27]

Because Zanetti (2011) calibrates his model to U.K. data, I focus on the United Kingdom in the subsequent analysis. Notice that the evidence provided in Galí (1999) holds for several countries (e.g. UK, USA and Germany). As a robustness test, I show that the main results also hold for the model if I calibrate it to the German economy. I use Germany instead of the USA as a robustness test because the German labour market is subject to higher employment protection (Riphahn 2004).

The observation period in Galí's baseline bivariate vector autoregression (henceforth: VAR) model (log productivity, defined as log hours subtracted from log GDP, and log hours) ends in 1994. I therefore repeat the exercise with more recent data using the same identification strategy and assume that only technology shocks can have a permanent effect on productivity. The series used are "Total actual weekly hours worked" (YBUS) for hours worked and "Gross Domestic Product: chained volume measures" (ABMI) for output provided by the Office for National Statistics.[28] Both time series are seasonally adjusted and cover the period 1971Q1 – 2017Q4. Based on the 5% significance level of an ADF test, I conclude that both series are difference-stationary instead of stationary. Standard lag-length selection criteria (AIC, HQC and SIC) lead to a specification with four (instead of eight) lags.[29] The IRFs of employment to a technology shock for both Galí' s original and more recent data are depicted in Figure 4.1. Even though there are some differences between the estimated responses based on the different data, the pattern is roughly comparable. Most importantly, employment drops after a technology shock. After about five quarters both trajectories slightly diverge before they remain roughly unchanged until the end of the IRF horizon.

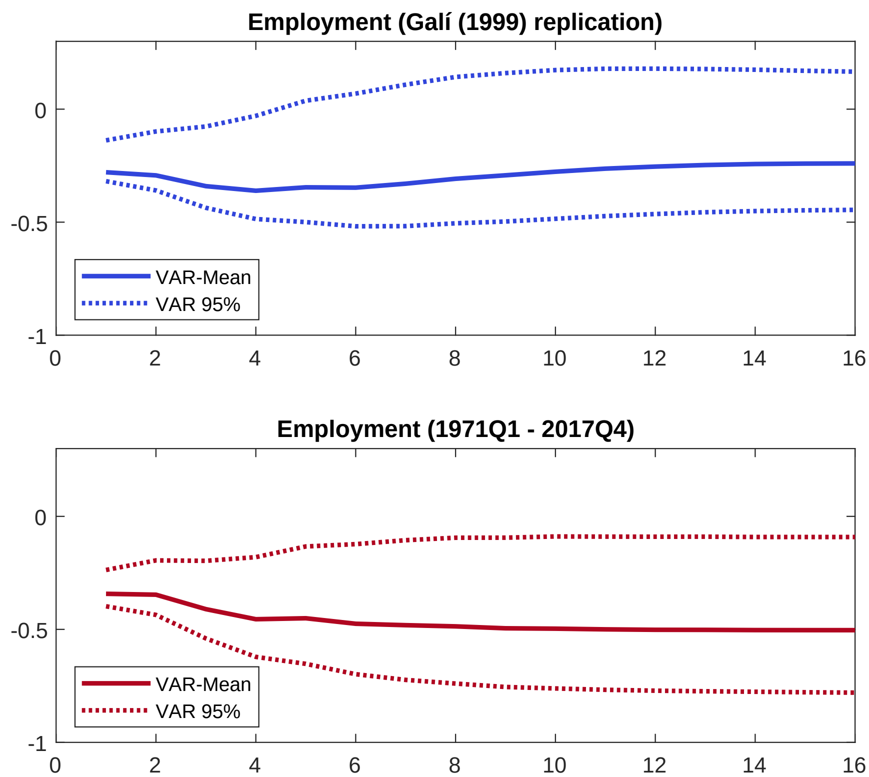
Notice that this exercise is carried out in order to illustrate the matter. I do not intend to resolve the dispute in the literature which analyses whether technology

[27] Notice that Galí studies the impact of technology shocks on hours worked; that is, a combination of the extensive and intensive margin. However, the model I develop only features the extensive margin with constant hours worked (i.e. there is no intensive margin). Hence, under the assumption of no adjustments along the intensive margin, a reduction in employment is equivalent to a reduction in hours worked in the model developed here.

[28] All series from the Office for National Statistics can be obtained using the series identifier on the respective website `https://www.ons.gov.uk/`.

[29] For a discussion of unit-root tests and lag-length selection criteria in VAR models, see, e.g., Kilian and Lütkepohl (2017).

Figure 4.1: Estimated impulse response functions to a technology shock (UK)



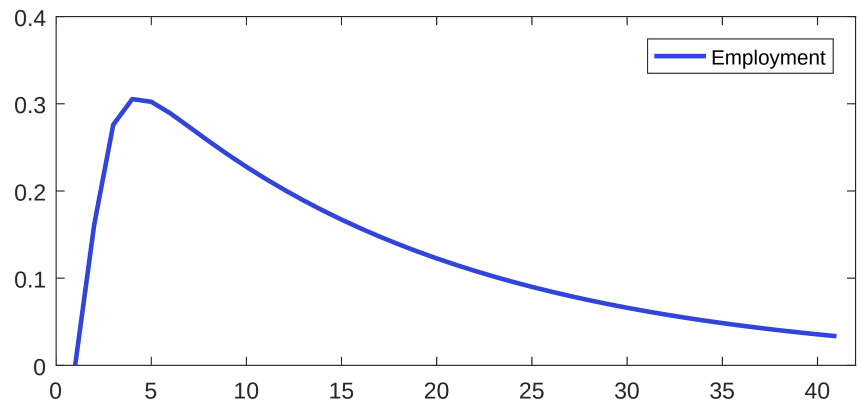
Notes: Estimated impulse response functions to a technology shock from a bivariate model (Galí 1999) with bootstrapped confidence bands, U.K. Data, different observation periods.
Source: Galí (1999) and the references therein (upper panel), Office of National Statistics, Series: YBUS (hours worked) and ABMI (Y) (lower panel), and own computation.

shocks have expansionary or contractionary effects on employment.[30] Instead, I take a firm stand in this discussion and follow the Galí strand of the literature; that is, the empirical evidence speaks in favour of contractionary employment effects.

This empirical result is important for the motivation of NK models. In these theoretical models, the replication of Galí's empirical observation either stems from price stickiness (Calvo 1983) or from the assumption of quadratic price-adjustment costs (Rotemberg 1982). Through different transmission channels of the two mechanisms, demand rises proportionally less than productivity after a TFP shock[31] and hence,

[30]The interested reader is refereed to Ramey (2016) for a thorough review on the ongoing discussion.
[31]The terms technology shock, productivity shock, and TFP shock do not necessarily have the

Figure 4.2: Impulse response functions to a technology shock (Zanetti 2011)



Notes: Impulse response function (percentage deviation from the steady state) to a one-percentage-point technology shock.
Source: Own computation based on Zanetti (2007, 2011).

employment drops due to market clearing. The ability to explain Galí' s observation is one of the key features that distinguishes NK from RBC models. Hence, especially NK models should replicate the drop in employment to justify their empirical relevance.

The NK-SAM proposed by Zanetti (2011) does not do so. As depicted in Figure 4.2, employment increases after a technology shock.[32] In other words, the incorporation of a rigorous approach to model the labour market into a textbook NK model worsens its empirical performance regarding the labour-market dynamics. Because the sticky-price transmission channel in Zanetti (2011) is identical to a textbook NK model, the result is due to the impact of a technology shock on job creation and job destruction; that is, it arises as a consequence of SAM.

In the neoclassical model of labour demand and supply, optimizing behaviour implies that the marginal job does not yield a profit for the firm because the marginal product of labour equals the marginal costs (the wage). The presence of search frictions, however, implies a surplus at the margin, there is a gap between a worker's wage and

same meaning. However, in the context discussed in this paper, these terms refer to an increase in output while input (i.e. labour) does not change. Therefore, the terms are used interchangeably.

[32]Notice that I use a calibration largely based on the working paper (Zanetti 2007) because I fail to replicate the Zanetti (2011) calibration in Figure 4.2. See Section 4.4 and Appendix C for a detailed discussion of this matter. The IRF depicted above is identical to the IRF in Zanetti (2011) from a visual inspection.

her productivity (Pissarides 2000).[33] The technology shock increases the surplus of every match and hence, the firm seeks to increase the number of matches and thus, to expand employment after a TFP shock. In the model developed below, it can either increase vacancy posting and/or decrease the number of jobs destroyed. Both job creation and (a reduction in) job destruction work in the same direction (employment increase), outweighing the employment decline caused by price stickiness after a TFP shock in Zanetti (2011).

I intend to resolve the issue and to improve the model proposed by Zanetti (2011) such that it generates a negative employment response after a TFP shock and thus, is consistent with the empirical evidence provided by Galí (1999) and by the more recent example above. Mandelman and Zanetti (2014) embed hiring costs along the lines of Blanchard and Galí (2010) in an RBC-SAM model and show that this works in the sense discussed above. The Mandelman and Zanetti (2014) model differs from Zanetti (2011) mainly in two aspects. First of all, they use an RBC instead of a NK framework. Since the extension proposed by Mandelman and Zanetti (2014) flips the sign of the IRF of employment after a TFP shock in an RBC-SAM model, it is likely to work into the same direction in a NK-SAM model.[34] Second, Mandelman and Zanetti (2014) use an approach which relies solely on exogenous job destruction. This difference may be crucial as it allows firms to adjust to a shock through two channels (job creation and job destruction). The costs proposed by Blanchard and Galí (2010) and generalized in Mandelman and Zanetti (2014) are likely to reduce job creation after a TFP shock but may also decrease job destruction resulting in an ambiguous overall effect with respect to employment. The purpose of embedding SAM into a DSGE framework is to have a more realistic approach to model the labour market. Abstracting from endogenous separation implies that a firm only adjusts through hirings, only job creation has an impact on aggregate variables. It therefore seems far more realistic to open a second adjustment channel and build on endogenous job destruction, besides its complexity. Recall that several labour market institutions, e.g. employment protection legislation in the form of firing costs, cannot be modelled without endogenous separations. Furthermore, Fujita and Ramey (2012)

[33] The firm decides to stop hiring if the expected costs of recruiting a new worker are larger than the expected gain from a new match, see Section 4.3 for details.

[34] Recall that a textbook NK model without SAM already generates a negative employment response to a TFP shock while a textbook RBC model does not.

argue that endogenous separations are superior to exogenous separations in various dimensions.

There are several other NK-SAM models which generate a positive response of employment after a technology shock. A non-exhaustive list with examples can be found in Table 4.3 (Appendix C). Should the extension sketched above turn out to improve the model proposed by Zanetti (2011), it may be worth to analyse whether these other models can benefit from this approach, too.

4.3 Model

The model I develop is an extension of the model proposed by Zanetti (2011). The economy consists of a large number of identical households that maximize expected lifetime utility. Intermediate-goods producing firms use labour, which is traded in a market subject to frictions, as the only input in production. Intermediate production is sold in a fully competitive market to a continuum of retail firms. Without any costs, the retail firms differentiate the intermediate goods into final output. Households purchase final output in a market characterized by monopolistic competition and staggered price setting as in Calvo (1983). The central bank conducts monetary policy according to a Taylor rule.

4.3.1 The labour market

The general labour market setup in Zanetti (2011) builds on den Haan et al. (2000), which in turn is based on Mortensen and Pissarides (1994, 1999). A worker can either work or search for a job (be unemployed) while a firm can be matched or unmatched. For convenience, the labour force is normalized to one $n_t = 1 - u_t$, where n_t and u_t denote employment and unemployment, respectively. The labour market at time t depends on the flows into and out of employment.

Inflows are captured through the matching function $m(u_t, v_t) = \chi u_t^{\xi} v_t^{1-\xi}$, where χ is a scale parameter (matching technology), $0 < \xi < 1$ denotes the match elasticity with respect to unemployment, and v_t is the number of vacancies. The ratio of vacancies over unemployment is defined as (labour market) tightness, $\theta_t = v_t/u_t$. The constant returns to scale property allows to compute the probability that a firm finds a worker $q(\theta_t) = m(u_t, v_t)/v_t = \chi\theta_t^{-\xi}$ and the probability that a worker finds a job $p(\theta_t) = m(u_t, v_t)/u_t = \chi\theta_t^{1-\xi}$. Once a firm and worker are matched, production starts in the following period which is equivalent to lagged (as opposed to immediate) hiring. New matches start with productivity α^N which is always above some threshold productivity $\tilde{\alpha}_t$.[35]

During each period, the flow into unemployment is due to two shocks. First, an exogenous separation shock with constant probability ρ^x, this is the case of exogenous separations. Second, a shock to the idiosyncratic (match specific) productivity α_t, which is a random draw in each period. When the idiosyncratic productivity α_t falls below the threshold productivity $\tilde{\alpha}_t$, the match is destroyed. This is the case of endogenous separations because the threshold productivity $\tilde{\alpha}_t$ is an endogenous variable of the model. It occurs with probability $\rho_t^n = F(\tilde{\alpha}_t)$, where $F(\cdot)$ denotes the cumulative distribution function (henceforth: CDF) of a log-normal distribution with support $\alpha \in (0, +\infty)$. In case of endogenous separation, the firm has to pay the firing costs $T = \rho_T w$, where ρ_T is a parameter that pins down the fraction of firing costs to the average wage w.[36] Total job separation is therefore $\rho_t = \rho^x + (1 - \rho^x)\rho_t^n$. The evolution of employment is hence:

$$n_t = (1 - \rho_t)n_{t-1} + \chi\, u_{t-1}^{\xi}\, v_{t-1}^{1-\xi}. \tag{4.1}$$

Employment equals the surviving stock of employment plus the number of new matches from the previous period.

[35]Assume, for the sake of simplicity that α^N is a fixed value (e.g. as in Pissarides 2000).

[36]Notice that the firing costs T leave the system (e.g. payment for layers); that is, there are no severance benefits. See, for example, Burda (1992) for a discussion of firing tax and severance benefit.

4.3.2 Households

The representative infinitely-living household maximizes expected-discounted utility with constant relative risk aversion of the form[37]:

$$E_t \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma} - 1}{1-\sigma} \right], \tag{4.2}$$

where E_t is the expectational operator, β is the discount factor, and σ denotes the coefficient of relative risk aversion. The consumption basket, C_t, is a Dixit-Stiglitz consumption aggregator $C_t = \left(\int_0^1 C_t(i)^{\frac{\gamma-1}{\gamma}} di \right)^{\frac{\gamma}{\gamma-1}}$, where γ denotes the elasticity of substitution between different goods i. Final output (or income) Y_t can be decomposed in consumption C_t or risk-free bonds B_t which yields the following budget constraint:

$$P_t C_t + \frac{B_t}{R_t} = B_{t-1} + P_t Y_t, \tag{4.3}$$

where R_t denotes the gross nominal interest rate and P_t the price level. The household solves its problem by choosing $\{C_t, B_t\}_{t=0}^{\infty}$ subject to eq. (4.3) and a no Ponzi-Game condition. The result is a standard Euler consumption equation which relates present to future consumption:

$$C_t^{-\sigma} = \beta R_t E_t [\Pi_{t+1}^{-1} C_{t+1}^{-\sigma}], \tag{4.4}$$

where $\Pi_t = P_t / P_{t-1}$ is the gross inflation rate defined in terms of the ratio of the price levels P_t between two periods. It is useful to define the stochastic discount factor between two periods at this stage: $Q_{t,t+1} = \beta \frac{C_t^{-\sigma}}{C_{t+1}^{-\sigma}}$.

Notice that I assume full labour market participation and therefore, dis-utility from work (or utility from leisure) does not appear in the household's problem. Instead, the workers are assumed to assign a value to each state of employment (unemployed, new job and continuous job). Let U_t denote the present-discounted value of expected income of an unemployed worker:

$$U_t = b + E_t \, Q_{t,t+1} [p(\theta_t) W_{t+1}^N + (1 - p(\theta_t)) U_{t+1}], \tag{4.5}$$

[37]Notice that is a simplification with respect to the utility function in Zanetti (2011) who also incorporates money holdings. However, because the central bank conducts monetary policy according to a Taylor-rule instead of a money supply rule, I do not require a money demand function to derive the equilibrium.

where b denotes the return on unemployment and W_t the value of a new job. Following Pissarides (2000) and Zanetti (2011), I assume that $b = h + \rho_R w$. Thereby, h stands for the value of leisure or home production and $0 < \rho_R < 1$ for the replacement ratio for unemployment. The second part of the equation above is the expected gain from the two states in the subsequent period.

As argued by Zanetti (2011), the presence of firing costs implies that the wage offered by the firm differs for new jobs, w_t^N, and continuing matches, $w_t(\alpha_t)$. Additionally, training costs only affect the wage for new matches, another source of different wages for new and continuing matches. Therefore, the present-discounted value of new matches, W_t^N, differs from the value of continuing matches, $W_t(\alpha_t)$,:

$$W_t^N = w_t^N + E_t\, Q_{t,t+1} \left[(1-\rho^x) \int_{\tilde{\alpha}_{t+1}}^{\infty} W_{t+1}(\alpha_{t+1}) dF(\alpha_{t+1}) + \rho_{t+1} U_{t+1} \right], \tag{4.6}$$

and

$$W_t(\alpha_t) = w_t(\alpha_t) + E_t\, Q_{t,t+1} \left[(1-\rho^x) \int_{\tilde{\alpha}_{t+1}}^{\infty} W_{t+1}(\alpha_{t+1}) dF(\alpha_{t+1}) + \rho_{t+1} U_{t+1} \right], \tag{4.7}$$

Eqs. 4.6 and 4.7 state that the value of a job is made up of the corresponding wage and the expected discounted gain from the two alternative states in the subsequent period.

4.3.3 Intermediate goods

The representative intermediate-goods producing firm has a continuum of jobs. Each filled job produces intermediate output according to $y_t = A_t \alpha_t$, where α_t is the idiosyncratic (match specific) productivity and is a random draw from the distribution $F(\cdot)$ in every period. The level of technology, A_t, is subject to common, exogenous shocks. The technology shock process evolves according to the stationary AR(1) process $\ln(A_t) = \beta_A \ln(A_{t-1}) + \iota_A$ with white noise innovations. The firm further searches for workers by posting vacancies at costs c per vacancy. Hence, the firm's choice variable is the number of vacancies v_t. Up to this point, the model is largely identical to the model proposed by Zanetti (2011).

As in Mandelman and Zanetti (2014), I adopt Blanchard and Galí's (2010) idea that hiring costs are associated with the state of technology and make the adjustments necessary to fit them into this model. In addition to vacancy posting costs, I assume that there are technology-dependent training costs for new matches. Therefore, hiring costs in the model are the sum of ex-ante (search or vacancy posting) and ex-post (training) costs, a plausible differentiation. Blanchard and Galí's (2010) formalization implies that hiring costs increase in tightness and technology.

In this model, search costs enter the value of a vacancy, V_t, while training costs enter the value of a new job, J_t^N. The value of a vacancy reads:

$$V_t = -c + E_t\, Q_{t,t+1} \left[q(\theta_t) J_{t+1}^N + (1 - q(\theta_t)) V_{t+1} \right]. \tag{4.8}$$

It depends on the costs of posting a vacancy, c, and the expected gain in the next period. Contrary to Blanchard and Galí (2010) hiring is uncertain in this model.[38] However, indicated by the job filling rate, $q(\theta_t) = \chi \theta_t^{-\xi}$, the hiring probability decreases in tightness. Hence, search (and thus, total hiring) costs are increasing in tightness, a feature similar to the specification in Blanchard and Galí (2010).

Once a firm and worker are matched, the firm pays the training costs. This leads to the following value of a new job:

$$J_t^N = \epsilon_t A_t \alpha^N - w_t^N - \kappa\, A_t^\delta + E_t\, Q_{t,t+1} (1 - \rho^x) \left[\int_{\tilde{\alpha}_t}^{\infty} J_{t+1}(\alpha_{t+1}) dF(\alpha_{t+1}) - F(\tilde{\alpha}_{t+1}) T \right], \tag{4.9}$$

where ϵ_t reflects the real marginal costs of the intermediate good.[39] Hence, the first term on the RHS is the revenue. The value of a new hire also depends on the wage for new matches, w_t^N, technology related training costs, $\kappa\, A_t^\delta$, and the expected match value in the next period. As in Mandelman and Zanetti (2014), δ governs the extent of the convexity of the technology dependence of training costs whereas κ is a simple scale parameter. In line with Blanchard and Galí (2010), the training (and thus, hiring) costs are increasing in technology.

Following Aghion and Howitt (1994) and Mortensen and Pissarides (1998), Michelacci and Lopez-Salido (2007) argue that only newly created jobs embody the most advanced technologies. This translates into the calibration of the rather high productivity of new matches, α^N (see Section 4.4 for details). For these reasons,

[38] In Blanchard and Galí (2010), the firm simply pays the costs of hiring to employ a worker.

[39] Due to perfect competition it is also the price of the good. Recall that the production function is linear.

technology-dependent training costs are only applicable to new matches. Once a new worker has been trained, the training costs are sunk. Therefore, technology-dependent training costs do not enter the value of a continuing match $J_t(\alpha_t)$:

$$J_t(\alpha_t) = \epsilon_t A_t \alpha_t - w_t(\alpha_t) + E_t\, Q_{t,t+1}(1-\rho^x) \left[\int_{\tilde{\alpha}_t}^{\infty} J_{t+1}(\alpha_{t+1}) dF(\alpha_{t+1}) - F(\tilde{\alpha}_{t+1})T \right]. \tag{4.10}$$

4.3.4 Final goods and central bank

The retail sector consists of a continuum of monopolistically competitive retail firms indexed by $i \in [0,1]$ subject to staggered price setting à la Calvo (1983). Retail firms buy intermediate goods at price ϵ_t (intermediate firm's marginal costs), transform them into final output y_t without any costs and sell them to the household. This service is not free of charge for the consumer, the retailer charges a mark-up. This intermediate production-retailer firms construction allows to model search frictions and price stickiness separately.

Optimal consumer behaviour combined with this market structure leads to the standard NK price setting rule (e.g., Galí 2015):

$$\sum_{j=0}^{\infty} \nu^j E_t \left\{ \frac{Q_{t,t+j}}{P_{t+j}} Y_{t+j}(i) \left(p_t^* - \mu \pi_{t,t+j} \epsilon_{t+j} \right) \right\} = 0, \tag{4.11}$$

where $\mu = \gamma/(\gamma-1)$ is the frictionless markup, $p_t^* = P_t^*/P_t$ the real optimal price, $\pi_{t,t+j} = P_{t+j}/P_t$ inflation between t and $t+j$ and ν the Calvo parameter.

Aggregate output is $y_t = n_t A_t \bar{\alpha}_t - c\, v_t - \kappa\, m_t A_t^\delta - T \rho_t^n n_t$, total production is reduced by total vacancy posting costs cv_t, total training costs $\kappa m_t A_t^\delta$ (where $m_t = m(u_t, v_t)$ is the number of new matches in period t), and total firing costs $T\rho_t^n n_t$.[40]

The central bank conducts monetary policy according to a modified Taylor rule, it gradually adjusts the nominal interest rate in response to deviations from the steady

[40]Notice that this is a deviation from Zanetti (2011) who does not subtract total firing costs from aggregate output. However, this difference is quantitatively negligible because only a very small fraction of existing matches are destroyed due to endogenous separations.

state values[41] of the interest rate, output and inflation with different weights:

$$\ln(R_t/R) = \phi_r \ln(R_{t-1}/R) + \phi_y \ln(y_t/y) + \phi_\pi \ln(\pi_t/\pi) + \iota_{Pt}, \tag{4.12}$$

where ϕ_r is the degree of interest rate smoothing, ϕ_y and ϕ_π denote the extent to which the central bank reacts to deviations of inflation and output (from the their steady-state values), respectively. ι_{Pt} is a zero-mean serially uncorrelated policy shock which is normally distributed with standard deviation σ_P.

4.3.5 Equilibrium

To derive the conditions describing the equilibrium for employment, the average wage, the number of posted vacancies and the threshold productivity, I largely follow Pissarides (2000).

As argued above, the presence of frictions implies a surplus of a match at the margin. A Nash bargained wage is the argument which maximizes this surplus. Recall that the model implies different wages for new and old matches and thus, different problems:

$$w_t^N = \arg\max \left[\left(W_t^N - U_t\right)^\eta \left(J_t^N - V_t\right)^{1-\eta} \right], \tag{4.13}$$

and

$$w_t(\alpha_t) = \arg\max \left[\left(W_t(\alpha_t) - U_t\right)^\eta \left(J_t(\alpha_t) - V_t + T\right)^{1-\eta} \right]. \tag{4.14}$$

Free market entry drives the profit of vacancies to zero ($V_t = 0$), leading to the solutions:

$$\eta J_t^N = (1-\eta)(W_t^N - U_t), \tag{4.15}$$

and

$$\eta \left(J_t^N(\alpha_t) + T\right) = (1-\eta)(W_t(\alpha_t)^N - U_t). \tag{4.16}$$

In order to find explicit wage rules, I substitute eqs. (4.5), (4.6), (4.7), (4.9), and (4.10) into eqs. (4.15) and (4.16), and use the zero profit condition for vacancies.

[41] Variables without subscript t refer to the steady state values of the corresponding variable.

After some algebra, I find the rules for new and continuing matches:

$$w_t^N = \eta[\epsilon_t A_t \alpha^N + c\,\theta_t - \kappa\, A_t^{\delta} - \zeta_t T] + (1-\eta)b, \tag{4.17}$$

and

$$w_t(\alpha_t) = \eta[\epsilon_t A_t \alpha_t + c\,\theta_t + (1-\zeta_t)T] + (1-\eta)b, \tag{4.18}$$

where $\zeta_t = E_t\, Q_{t,t+1}(1-\rho^x)$. A new worker receives a share of the total revenue plus a reward on saving vacancy posting costs (firm's outside option) but bears a fraction of the training costs. Because the firm eventually pays the firing tax, a worker's wage is also reduced by the latter. The wage increases in unemployment benefits because the worker's outside option is higher. Wages for new and incumbent workers differ through different productivities for new (fixed) and incumbent (random draw) workers. Training costs do not enter eq. (4.18) because they are sunk and thus, are completely internalized in the first period (new match). The firing tax has two opposing effects: a reward on saving the tax (current period) and a penalty for eventually paying the tax (future periods). Because ζ_t is by construction smaller than one, the reward unambiguously exceeds the penalty and thus, the overall effect of the tax on the wage for incumbent workers is always positive. Let ω_t denote the weight for continuing matches and combine eqs. (4.17) and (4.18) to find the average wage, w_t:

$$w_t = \eta[\epsilon_t A_t \bar{\alpha}_t + c\,\theta_t + (\omega_t - \zeta_t)T - (1-\omega_t)\kappa\, {A_t}^{\delta}] + (1-\eta)b, \tag{4.19}$$

where $\bar{\alpha}_t = \omega_t\, H(\tilde{\alpha}_t) + (1-\omega_t)\alpha^N$ is the average productivity and $H(\tilde{\alpha}_t)$ denotes the conditional expected productivity; that is, the probability that a worker's productivity exceeds the threshold.

To pin down the number of vacancies and the threshold productivity, I need to derive the job-creation condition (henceforth: JC) and the job-destruction condition (henceforth: JD). Due to the presence of the firing tax, the firm wishes to terminate the match if its value plus the firing tax is negative. The threshold therefore satisfies $J(\tilde{\alpha}_t) + T = 0$ (Zanetti 2011). This fact combined with eqs. (4.9) and (4.17), and the zero profit condition for vacancies leads to the JC:

$$\frac{c}{q(\theta_t)} = (1-\eta)E_t Q_{t,t+1}[\epsilon_{t+1} A_{t+1}(\alpha^N - \tilde{\alpha}_{t+1}) - T - \kappa\, A_{t+1}^{\delta}]. \tag{4.20}$$

The firm's choice variable is the number of vacancies. This number affects eq. (4.20) through the job filling rate $q(\theta_t)$. The JC states that the expected costs of posting a vacancy equals the firm's expected gain from a new match. Notice that the effect of a TFP shock on the number of posted vacancies is ambiguous. On the one hand, such a shock increases vacancy posting through the effect on the difference between the productivity of a new match and the threshold productivity. On the other hand, it decreases posting through training costs, which are increasing in κ and δ. Given the functional form of training costs, sufficiently large values for κ and δ imply that the latter effect dominates the former, and TFP shocks therefore reduce vacancy posting.

To find the JD, I exploit the fact that $J(\tilde{\alpha}_t) + T = 0$, eqs. (4.10) and (4.18):

$$\begin{aligned} &\epsilon_t A_t \tilde{\alpha}_t - b - \frac{\eta}{1-\eta} c\theta_t + (1-\zeta_t)T \\ &+ E_t Q_{t,t+1}(1-\rho_{t+1})\epsilon_{t+1}A_{t+1}\left[H(\tilde{\alpha}_{t+1}) - \tilde{\alpha}_{t+1}\right] = 0. \end{aligned} \tag{4.21}$$

The threshold productivity, $\tilde{\alpha}$, is explicitly determined via eq. (4.21). In contrast to the JC, the reservation productivity unambiguously falls after a TFP shock because it makes every match more profitable. Job destruction increases in tightness and unemployment benefits through higher wages. The firing tax naturally decreases the reservation productivity because firings are expensive. Therefore, a job which would have been destroyed in the absence of the tax survives in this case. The option value of the match lowers the threshold productivity because in subsequent periods, the match productivity may increase and production can take place immediately without the necessity of a costly new hire; that is, there is some labour hoarding in the economy (Pissarides 2000). Notice that training costs do not directly affect job destruction because they are sunk.

The derivation of the remaining equilibrium conditions is rather standard and therefore, skipped. Instead, a complete list of (linearised) equilibrium conditions can be found in Appendix C.

4.4 Calibration

Because the model developed in the previous Section nests the model proposed by Zanetti (2011) for $\kappa = 0$ and the fact that I intend to improve that model, it seems reasonable to stick as closely as possible to Zanetti's model and thus, use his calibration whenever possible. However, he does not state all parameter values in his paper and therefore, the computation of some values is necessary. This attempt is rather unsuccessful; I cannot replicate Zanetti's calibration and his results (Subsection 4.4.1). I therefore propose an alternative calibration in Subsection 4.4.2 including a value for κ. The parameter governing the convexity of training costs δ is discussed in the Subsection 4.4.3.

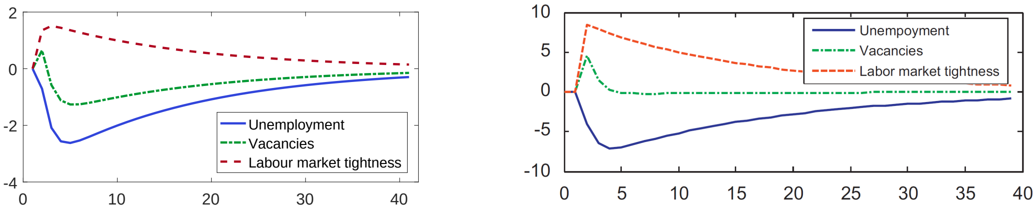
4.4.1 Replication Zanetti (2011)

Zanetti (2011) uses the steady-state job creation and job destruction condition to pin down the value for vacancy posting costs, c, and the value of leisure, h, respectively, but does not state the value for c in the paper. I therefore follow his computational procedure to find a value for c. Notice that this procedure determines a value for c and h simultaneously. Unfortunately, the value for h I obtain contradicts Zanetti's. I thoroughly investigate this issue in Appendix C and conclude that there are some inconsistencies in Zanetti's (2011) calibration.

One could argue that the parameter/steady-state values do not ultimately matter because I focus on the dynamic consequences of a technology shock. I therefore use the parameter values from the unsuccessful replication exercise to compute the IRFs. However, the resulting IRF of vacancies only qualitatively mimics the response in Zanetti (2011) in the first periods and follows a different pattern afterwards, see Figure 4.3. Apparently, the differences in the parameter values[42] have a severe impact on the dynamic consequences of shocks. Given that the response of vacancies is different, it is not surprising that unemployment (and hence employment) and tightness follow different trajectories. However, if I want to understand whether training costs help to flip the sign of the IRF of employment, I need to obtain similar results in the absence of training costs ($\kappa = 0$), especially for vacancies and

[42] I suspect that the driver of the differences is the value for c which I cannot compare with the value from Zanetti 2011.

Figure 4.3: Comparison of impulse response functions



Own computation based on Zanetti (2011) — Zanetti (2011)

Notes: Comparison of the impulse response functions of vacancies (percentage deviation from the steady state) to a one-percentage-point technology shock.
Source: Own computation based on Zanetti (2011) and Zanetti (2011).

unemployment because my extension directly affects the job-creation condition.

4.4.2 Calibration – baseline model

Because I fail to replicate the calibration used in Zanetti (2011), I introduce an alternative calibration. Since the focus of this paper is on the impact of technology-dependent training costs, I also propose a value for the scale parameter κ while the parameter governing the convexity of technology-dependent training costs is set to zero ($\delta = 0$) in this subsection. From this stage onwards, I will refer to this calibration (or model) as baseline model.

If possible, I still follow Zanetti (2011) and the references therein and thus, calibrate the model based on UK data. The parameters describing the household's discount factor, the elasticity of substitution between goods, the Calvo parameter, the worker's bargaining strength, the matching elasticity, the firing-tax and the unemployment-benefit parameters, the vacancy filling rate at steady state, the AR coefficients of the technology shock, the monetary policy shock standard deviation, and the autoregression coefficients of the central bank's response function are taken from Zanetti (2011). The household's risk-aversion parameter is set to $\sigma = 1$ (log-utility function).

Following Elsby et al. (2013), the steady-state unemployment rate is set to $u = 0.077$. These authors also provide a monthly separation rate. I convert this value into a quarterly rate as in Blanchard and Galí (2010) and set $\rho = 0.03$. The split between exogenous and endogenous separations follows den Haan et al. (2000), i.e.

$\rho^x = 1.5\rho^n \approx 0.02$. These values imply a job finding rate of $p(\theta) = 0.36$.

To closely match key business cycle properties (Subsection 4.5.1), I set the parameters of the idiosyncratic productivity distribution to $\mu_{LN} = 0$ and $\sigma_{LN} = 0.092$; the standard error of the technology shock is set to $\iota_A = 0.007$ for the same reason. The productivity of a new match equals the 95th percentile of the distribution. As in Zanetti (2011), the value of leisure and the vacancy posting costs are inferred from the steady-state job destruction condition and job creation condition, respectively, implying that $h = 0.63$ and $c = 0.021$. Muehlemann and Leiser (2018) show that the costs to fill a vacancy are made up to 21% of recruitment (search) costs and to 79% of adoption costs. I split total hiring costs accordingly and obtain $\kappa = 0.09$. In this calibration, total hiring costs at steady state account for roughly 0.34% of output, which is below the value (0.49%) obtained by Christiano et al. (2016) but well within the corresponding 95% probability interval.

The baseline calibration and implied steady-state values of selected variables are summarized in Table 4.1.

4.4.3 Calibration – extended model

So far, I ignored the parameter determining the convexity of training costs, δ.[43] As argued by Silva and Toledo (2009), the evidence on labour turnover costs is scarce. This is even more true for the convexity of training costs with respect to technology. Instead of assigning the "correct" value, I therefore choose a variety of plausible parameter values and repeat the following numerical exercise for each value. From this stage onwards, I will refer to the resulting model as the extended model and explicitly state the value of δ whenever necessary.

In general, the formulation of training costs in this paper allows for positive and negative co-movements of training costs and technology. However, I assume that there is a positive relationship between both variables and therefore, $\delta \geq 0$. It implies that advances in technology make it more complex and thus, it requires more training to operate new machinery such as information technology. This idea is, e.g., in line with Greenwood and Yorukoglu (1997). Hall and Khan (2003) also argue

[43] Notice that the choice of δ does not have an impact on the model's steady state because the level of technology equals one in that case.

Table 4.1: Baseline calibration/steady-state values of selected variables

Parameter/steady-state	Value
Coefficient of relative risk aversion, σ	1
Degree of interest rate smoothing, ϕ_r	0.32
Discount factor, β	0.99
Elasticity of substitution between goods, γ	11
Exogenous job separation rate, ρ^x	0.02
Firing costs parameter, ρ_T	0.3
Match elasticity, ξ	0.7
Matching technology, χ	0.47
Mean of $F(\cdot)$, $\mu_{\ln}$	0
Price stickiness, ν	0.75
Replacement ratio, ρ_R	0.3
Responsiveness to inflation, ϕ_π	1.5
Responsiveness to output deviations, ϕ_y	0.5
Standard deviation of $F(\cdot)$, $\sigma_{\ln}$	0.092
Standard deviation of a policy shock, ι_p	0.001
Standard deviation of a technology shock, ι_A	0.007
Technology shock persistence, τ_A	0.94
Training costs parameter, κ	0.09
Total separations, ρ	0.029
Unemployment rate, u	0.077
Vacancy filling rate, $q(\theta)$	0.9
Vacancy posting costs, c	0.021
Value of leisure, h	0.63
Worker's bargaining power, η	0.5

that technological progress may lead to significant costs for training, justifying my assumption.

To get some intuition, let us briefly discuss what different values of δ imply. Setting $\delta = 0$ means that technology shocks do not affect training costs at all. Values between zero and one imply that training costs increase by less than the level of technology. If δ is set to one, the percentage increase in training costs equals the increase in technology, while larger values of δ imply convex training costs.

Mandelman and Zanetti (2014) use Bayesian methods to estimate the parameter based on a rather uninformative prior. The resulting posterior mean is approximately 10, the 95% probability interval of the point estimate ranges from roughly 6 to 15. It therefore seems reasonable to use these values in the following exercise. Furthermore, a linear and a quadratic relationship between both variables are investigated. Notice that $\delta = 0$ resembles the baseline model. Hence, the numerical exercise is conducted for the following values: $\delta = \{0, 1, 2, 6, 10, 15\}$.

4.5 Results

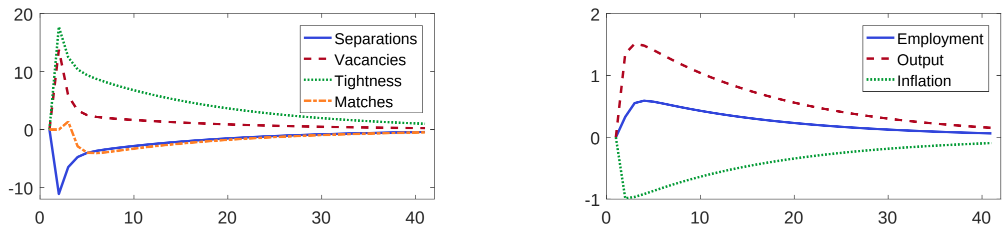
I begin the discussion of the results with the baseline model. While the focus is on the dynamic consequences of a technology shock, especially the impact on employment, I also analyse if the baseline model replicates observed business cycle statistics. I subsequently turn to the extended model and study the dynamic properties of the model for different values of δ. Since the results are rather unsatisfactory, I reduce the complexity of the (extended) model by abstracting from endogenous separations. I then analyse whether convex training costs flip the sign of the impulse response function of employment after a technology shock in a model which solely relies on exogenous separations.

Notice that the modelling choice of training costs only has an effect if the level of technology changes. Hence, the economy's response to a monetary policy shock does not depend on the model extension. I therefore do not study the effects of a monetary policy shock.

4.5.1 Baseline model

The IRFs of the baseline model to a one-percentage-point technology shock are depicted in Figure 4.4. Because workers only receive a fraction of the technology-shock induced increase of the surplus of an existing match, every existing match becomes more profitable for the firm. Thus, separations fall via the job destruction condition (eq. 4.21), leading to an immediate increase in employment because inflows to employment occur with a delay of one period. Notice that the magnitude of the effect on separations is comparable to the response in Zanetti (2011) and Krause and Lubik (2007). Additionally, the firm wants to take advantage of the increased gain from a new job. Transmitted through the job creation condition (eq. 4.20), vacancy

Figure 4.4: Impulse response function to a technology shock (baseline model)



Notes: Impulse response function (percentage deviation from the steady state) to a one-percentage-point technology shock, baseline model ($\delta = 0$).

posting therefore goes up.[44] Due to the surge of tightness, the positive effect (of vacancies) on new matches is rather small. Because vacancies swiftly return to their initial level and tightness remains large for a prolonged period, the number of new matches even falls below the steady state. Since separations initially exhibit a huge drop and new matches only fall below the steady state after about two quarters, employment remains above its steady state for quite some time. The baseline model hence exhibits the same shortcoming as the model proposed by Zanetti (2011), both models contradict Galí's (1999) empirical observation. As labour is the only input in production, output also increases. Caused by Calvo-pricing, inflation falls below the zero-inflation steady state.

To further evaluate the baseline model, I compare the business cycle statistics of the variables of interest in the data with those generated by the model. Following Zanetti (2011), I restrict this exercise to the standard deviation. The results are summarized in Table 4.2. Most importantly, I observe that the volatility of the baseline model is considerably close to the volatility in the data. Notice that the standard deviation relative to output generated by the model is slightly larger for unemployment, vacancies, and employment in comparison to the data. On the contrary, the volatility of employment, in- and outflows into employment relative to output is a bit larger in the data than in the model. It is worth to mention that the difference of the in- and outflows between the data and the model is significantly smaller than in Zanetti (2011). The correlation of vacancies and unemployment in the data equals, $\rho^D_{vu} = -0.87$; that is, the data exhibit a Beverdige curve. This

[44]Contrary to response shown in Figure 4.3, this is in line with Zanetti (2011).

Table 4.2: Business cycle statistics

Variable	UK economy (SD)	Baseline model (SD)	UK economy (relative SD)	Baseline model (relative SD)
Output	0.014	0.014	1	1
Employment	0.007	0.005	0.45	0.38
Unemployment	0.078	0.066	5.45	4.57
Vacancies	0.083	0.085	5.78	5.94
Flows into unemployment	0.087	0.074	6.08	5.13
Flows into employment	0.061	0.042	4.25	2.95

Notes: Business cycle statistics (standard deviation and standard deviation relative to output), observed data (UK economy) and baseline model. All series are seasonally adjusted and transformed into logarithms and subsequently HP filtered (one-sided). Simulation statistics are based on 10,000 (3,000 burnin drops) quarter horizon and HP filtered (one-sided). Observation period: 2001Q4 (availability of X02) – 2018Q2.
Source: Office for National Statistics; Series: ABMI (Y), A02 SA (N), VACS01 (U & V), X02 (Flows), and own computation.

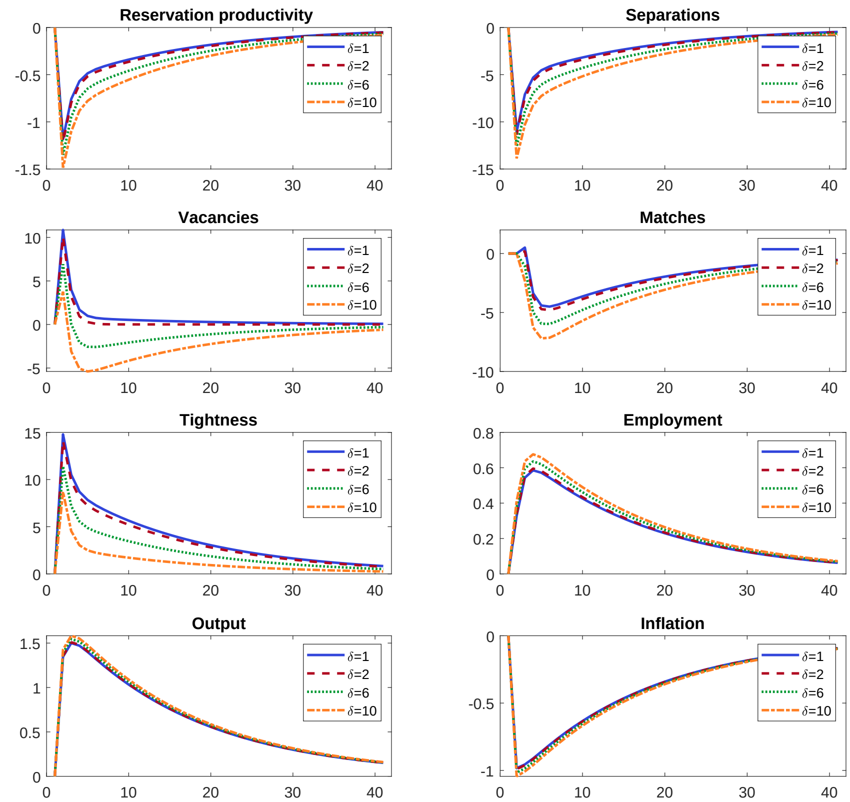
correlation is $\rho_{vu}^{BM} = -0.42$ in the baseline model. Hence, the model also generates a Beverdige curve. Because some NK-SAM models fail to generate a Beverdige curve (e.g., Krause and Lubik 2007), I regard this result as encouraging, despite the fact that the correlation in the model is not as high as in the data.

Some recent studies (e.g., Kohlbrecher et al. 2016) assume immediate hiring. I therefore repeat the previous exercise with immediate hiring. This change increases the impact of a TFP shock on vacancies (and thus, tightness) since the firm can instantly take advantage of the new state of technology. The response of employment is almost identical to the case depicted above. Furthermore, the effects on the business cycle statistics and the correlation between unemployment and vacancies are negligible.

4.5.2 Extended model

Similar to the results in Zanetti (2011), I show in the previous Subsection that the baseline model generates reasonable business cycle statistics but fails to replicate Galí's empirical observation. To study the effects of the extension, I now repeat the

Figure 4.5: Impulse response functions to a technology shock (extended model)



Notes: Impulse response function (percentage deviation from the steady state) to a one-percentage-point technology shock, extended model ($\delta = \{1, 2, 6, 10\}$).

exercise with different values for δ as discussed above.

Figure 4.5 depicts the impulse response functions to a technology shock for different values of $\delta = \{1, 2, 6, 10\}$.[45] As discussed in Subsection 4.3.5, the reservation productivity is not directly affected by training costs. However, through indirect effects (e.g. the option value on an occupied job), the reservation productivity is decreasing in δ and hence, total separations further fall. As expected, the increase in

[45]Notice that the difference between $\delta = 0$ and $\delta = 1$ is very small and the response of $\delta = 0$ is shown and discussed in the previous subsection. Furthermore, it is obvious in what direction increasing values of δ work. In order to avoid overloading the Figures, I therefore do not plot the IRFs for $\delta = \{0, 15\}$ here.

training costs exceeds the benefit from a new match for sufficiently large values of δ and thus, sharply decrease vacancy posting. This drop in vacancies after a TFP shock is in line with recent empirical evidence (Christiano et al. 2016) and leads to a reduction of new matches despite decreasing effects of δ on tightness. The numerical exercise reveals that, for increasing values of δ, firings decrease proportionally more than hirings. Therefore, the response of employment to a TFP shock depends positively on technology-dependent training costs; that is, the positive dynamic response of employment is amplified by the convexity of training costs. I further observe that the effect of δ on output and inflation is rather small.

As argued above, search frictions imply some labour hoarding due to the option value of an existing match. Increasing training costs raise the option value of a match because the costs to create a new match go up. If hiring becomes more and more expensive, there is no reason for the firm to fire a worker and hire a new worker instead. At some point, it is optimal for the firm to even keep very unproductive workers. This unproductive worker has the same probability to draw an average idiosyncratic productivity as every other (highly productive) worker in the next period. The firm anticipates that a low-productivity worker's idiosyncratic productivity may increase in the subsequent period and hence, the reservation productivity in the current period is very low.

It seems reasonable to consider an alternative to the assumption of random productive draws in each period. For example, one could think of modelling the idiosyncratic productivity as an $AR(1)$ process. However, if all idiosyncratic productivities were an $AR(1)$ process, the reservation productivity would be unaffected because both low and high-productive workers likely remain in the vicinity of their previous productivity. Instead, it would be necessary to incorporate some sort of stickiness to low-productive matches such that only they exhibit some persistence. However, this would require the introduction of heterogeneity (e.g. as in Krause and Uhlig 2012) which significantly complicates the analysis and goes beyond the scope of this paper.

The main finding is robust to several modifications. A potential source for the sharp drop in the job destruction discussed above is the firing tax. I therefore repeat the exercise with varying firing tax parameters. I furthermore calibrate alternative idiosyncratic productivity distributions. In fact, I use different parameters of the log-normal distribution and try a different distribution (log-logistic distribution) such that I still mimic the shape of the wage distribution depicted in Jolivet et al. (2006). I also test the calibrations based on Zanetti (2007) and Zanetti (2011). Instead of using a ratio of training costs to total hiring costs in order to pin down a value for κ, one could assume that hiring costs must not exceed a certain fraction of GDP. For example, Blanchard and Galí (2010) calibrate total hiring costs such that they do not exceed one percent of GDP. This approach leads to significantly higher values for this parameter (κ). Furthermore, I also use immediate hiring. All these variations have (mostly adverse) effects on the business cycle statistics, but do not change the ultimate results. I also analyse the impact of a technology shock in an RBC framework. Unsurprisingly, employment further increases (in comparison to the baseline model) because the sticky-price effect is not present.

Additionally, I calibrate the model to the German economy. For details of the calibration and the corresponding IRFs, see Table 4.7 and Figure 4.9a in Appendix C, respectively. The main results do not change, the reduction of separations outweighs the reduction of new matches for increasing values of δ and hence, employment further increases after a TFP shock with increasing training costs.

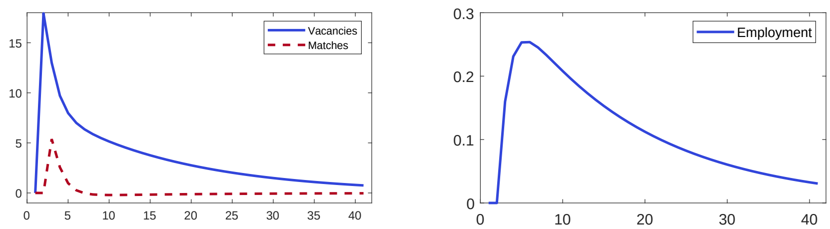
Given the research question, the results are rather unsatisfactory. I therefore regard it as futile to further evaluate the model (e.g. compare business cycle statistics).

4.5.3 Model without endogenous separations

The firm has two adjustment channels in both the baseline and the extended model (hirings and firings). It turns out that firms rather use the firing margin to adjust to technology shocks in case of increasingly convex training costs. As a result, the extension I propose does not flip the sign of the employment IRF. However, for sufficiently large values of δ, firms decrease vacancy posting after a TFP shock and hence, the extended model is in line with recent empirical evidence (Christiano et al. 2016) in this regard. I therefore proceed by analysing whether the extension flips the sign of the IRF (employment) in a model without endogenous separations; that is, the firm has only one adjustment channel. Because the model in general nests a model without endogenous separations, only minor adjustments are necessary to conduct this exercise.

To isolate the effect of convex training costs, I begin by looking at the dynamics of

Figure 4.6: Impulse response functions to a technology shock (exogenous separations)



Notes: Impulse response function (percentage deviation from the steady state) to a one-percentage-point technology shock, model without endogenous separations or technology-dependent training costs.

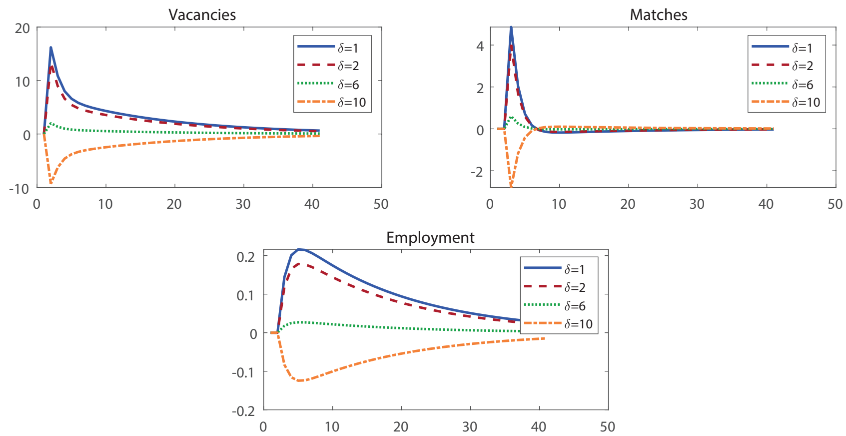
the model without endogenous separations or technology-dependent training costs focusing on the employment dynamics (Figure 4.6). As in the cases above, the firm wishes to expand employment after a TFP shock to take advantage of the new state of technology.[46] In a world without endogenous separations, firms can only achieve that by increasing vacancy posting, leading to a positive impact on the number of new matches.[47] Consequently, employment increases after a technology shock; that is, the shortcoming of the baseline model is independent of the modelling choice with respect to separations.

I continue by studying the results of different values of δ in the model without endogenous separations. The effect of technology-dependent training costs on vacancy posting (Figure 4.7) is exactly as in the case of endogenous separations (Figure 4.5). Once the convexity of training costs is sufficiently large, vacancy posting and thus, the number of matches decreases upon impact of a TFP shock. Because firms do not have another adjustment margin, this implies an employment reduction. Hence, in a model without endogenous job separations, reasonably convex training costs flip the sign of the impulse response function of employment to a technology shock such that the prediction of the model is in line with the empirical evidence provided by Galí (1999). Furthermore, it qualitatively replicates the response of vacancies upon impact as in Christiano et al. (2016). The results for the German calibration are

[46]Notice that I still maintain the assumption of different productivities for new and existing matches. However, the result is independent of this assumption.

[47]Notice that it is not desirable for the firm (exogenous separation) to post as many vacancies as necessary to achieve the same level of employment (endogenous separators) because of diminishing marginal returns of posting vacancies on the number of matches ($\frac{\partial^2 m(v_t,u_t)}{\partial v_t^2} < 0$).

Figure 4.7: Impulse response functions to a technology shock (exogenous separations & training costs)



Notes: Impulse response function (percentage deviation from the steady state) to a one-percentage-point technology shock, model without endogenous separations ($\delta = \{1, 2, 6, 10\}$).

similar (Figure 4.9b, Appendix C).

Notice that the choice of κ crucially affects what levels of convex training costs flip the sign of the IRF. In the calibration used above, the value for κ is relatively small. I could have set total hiring costs such that they amount to a certain fraction of GDP. This implies substantially higher values for κ.[48] In this case, even quadratic training costs reverse the impact of a TFP shock on employment. Although not in the sense of technology-dependent training costs, quadratic labour adjustment costs are frequently assumed in recent studies, e.g. Christiano et al. (2011) or Furlanetto and Groshenny (2016). This assumption is supported by the empirical evidence provided in Yashiv (2016).

4.6 Conclusions

The model proposed by Zanetti (2011) (and other NK-SAM models) generate(s) a positive dynamic response of employment to a technology shock. This result is a stark contradiction to the empirical observation made by Galí (1999). I aim at

[48] Recall that my calibration implies that 0.34% of output are spend on hiring at steady state, which is below values in Blanchard and Galí (2010) or estimated in Christiano et al. (2016).

improving Zanetti's model such that it replicates Galí's finding. To do so, I enrich the model (Zanetti 2011) with training costs which are allowed to be convex in technology based on Blanchard and Galí (2010) and Mandelman and Zanetti (2014). I use a range of plausible values describing the convexity of these costs. The precise determination of the convexity of training costs is left open for future research.

The contribution of this paper to the literature is threefold. First, I show that the calibrated baseline model is a valuable extension of the model proposed by Zanetti (2011) by means of the business cycle properties.

Second, the extended model does not generate the desired response of employment for reasonable degrees of the convexity of training costs. In fact, the extension amplifies the positive reaction of employment after a TFP shock. If hiring becomes more and more expensive, firms more than proportionally reduce firings, offsetting the dampening effect of hirings on employment. This result partially stems from the positive option value of an occupied job. Hence, further research could focus on lowering the option value of a match which exhibits a low productivity in a certain period. The incorporation of heterogeneity, e.g. based on Krause and Uhlig (2012), potentially allows modelling this feature.

Third, I show that reasonably convex training costs offset the benefit from a new match and thus, lower vacancy posting below the steady-state level such that the model replicates recent empirical evidence obtained by Christiano et al. (2016). In a model without endogenous separation, this implies that employment drops after a TFP shock. It would be a useful exercise to incorporate convex training costs in a NK-SAM without endogenous separations which generate a positive response of employment after a TFP shock, e.g. Thomas (2008).

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Appendix C

Examples

Table 4.3: Examples of NK-SAM models

Study	Response employment/unemployment
Cooleya and Quadrini (1999)	Employment increases
Gertler et al. (2008)	Initial drop of employment (app. 3 periods) → positive afterwards
Krause and Lubik (2007)	Unemployment decreases
Thomas (2008)	Unemployment increases after a *negative* TFP shock
Thomas and Zanetti (2009)	Employment increases
Zanetti (2011)	Employment increases

Notes: Responses of employment or unemployment upon impact of a technology shock in several studies.

(Linearised) equilibrium conditions

The system of equations is approximated by first-order approximations. Hence, the dynamic responses of all endogenous variables to exogenous shocks are percentage deviations from their steady state. A variable with a "hat" denotes that deviation.

1. Market clearing

$$Y_t = C_t \tag{4.22}$$

$$\hat{Y}_t Y = \hat{C}_t C \tag{4.23}$$

2. Euler equation

$$Y_t^{-\sigma} = \beta R_t E_t[\pi_{t+1}^{-1} Y_{t+1}^{-\sigma}], \tag{4.24}$$

$$\sigma E_t \hat{Y}_{t+1} = \sigma \hat{Y}_t + \hat{R}_t - E_t \hat{\pi}_{t+1}. \tag{4.25}$$

3. Inflation dynamics, using the definition of the price index and eq. (4.11), one

can show that:

$$\hat{\pi}_t = \kappa_\pi \hat{\epsilon}_t + \beta E_t \hat{\pi}_{t+1}, \tag{4.26}$$

where $\kappa_\pi = (1-\nu)(1-\nu\beta)/\nu$.

4. Taylor rule

$$\ln(R_t/R) = \phi_r \ln(R_{t-1}/R) + \phi_y \ln(Y_t/Y) + \phi_\pi \ln(\pi_t/\pi) + \iota_{Pt}, \tag{4.27}$$

$$\hat{R}_t = \phi_r \hat{R}_{t-1} + \phi_y \hat{Y}_t + \phi_\pi \hat{\pi}_{t,t+1} + \iota_{Pt}. \tag{4.28}$$

5. Stochastic discount factor

$$E_t Q_{t,t+1} = E_t \beta \frac{Y_{t+1}^{-\sigma}}{Y_t^{-\sigma}}, \tag{4.29}$$

$$E_t \hat{Q}_{t,t+1} = \sigma(\hat{Y}_t - E_t \hat{Y}_{t+1}). \tag{4.30}$$

6. Number of employed workers

$$u_t = (1 - n_t), \tag{4.31}$$

$$\hat{u}_t u = -\hat{n}_t n. \tag{4.32}$$

7. Labour market tightness

$$\theta_t = v_t/u_t, \tag{4.33}$$

$$\hat{\theta}_t = \hat{v}_t - \hat{u}_t. \tag{4.34}$$

8. Law of motion of employment

$$n_t = (1-\rho_t) n_{t-1} + \chi u_{t-1}^{\xi} v_{t-1}^{1-\xi}, \tag{4.35}$$

$$\hat{n}_t = (1-\rho)\hat{n}_{t-1} - \hat{\rho}_t \rho + \rho \left[\xi \hat{u}_{t-1} + (1-\xi)\hat{v}_{t-1}\right]. \tag{4.36}$$

9. Separation rate

$$\rho_t = \rho^x + (1-\rho^x)\rho_t^n, \tag{4.37}$$

$$\hat{\rho}_t = \frac{1-\rho^x}{\rho}\hat{\rho}_t^n \rho^n. \tag{4.38}$$

10. Endogenous separation

$$\rho_t^n = F(\tilde{\alpha}_t), \tag{4.39}$$

$$\hat{\rho}_t^n = f(\tilde{\alpha})\frac{\hat{\tilde{\alpha}}_t \tilde{\alpha}}{\rho^n}. \tag{4.40}$$

11. Job creation condition

$$\frac{c}{q(\theta_t)} = (1-\eta)E_t Q_{t,t+1}[\epsilon_{t+1}A_{t+1}(\alpha^N - \tilde{\alpha}_{t+1}) - T - \kappa\, A_{t+1}{}^{\delta}], \tag{4.41}$$

$$\begin{aligned} \xi\hat{\theta}_t = {} & (1-\eta)\beta\frac{q(\theta)}{c} \\ & \times E_t\Big\{\epsilon A\Big\langle \alpha^N(\hat{Q}_{t,t+1} + \hat{\epsilon}_{t+1} + \hat{A}_{t+1}) - \tilde{\alpha}_0(\hat{Q}_{t,t+1} + \hat{\epsilon}_{t+1} + \hat{A}_{t+1} + \tilde{\alpha}_{t+1})\Big\rangle \\ & - T\hat{Q}_{t,t+1} - \kappa\, A^{\delta}(\delta\hat{A}_{t+1} + \hat{Q}_{t,t+1})\Big\} \end{aligned} \tag{4.42}$$

12. Job destruction condition[49]

$$\begin{aligned} & \epsilon_t A_t \tilde{\alpha}_t - b - \frac{\eta}{1-\eta}c\theta_t + (1-\zeta_t)T \\ & + E_t Q_{t,t+1}(1-\rho_{t+1})\epsilon_{t+1}A_{t+1}\left[H(\tilde{\alpha}_{t+1}) - \tilde{\alpha}_{t+1}\right] = 0, \end{aligned} \tag{4.43}$$

$$\begin{aligned} & \epsilon A\tilde{\alpha}(\hat{\epsilon}_t + \hat{A}_t + \hat{\tilde{\alpha}}_t) - \frac{\eta}{1-\eta}c\hat{\theta}_t\theta - T\zeta E_t\hat{Q}_{t,t+1} \\ & + \beta(1-\rho)\epsilon A[H(\tilde{\alpha}) - \tilde{\alpha}]E_t\left[\hat{Q}_{t,t+1} + \hat{\epsilon}_{t+1} + \hat{A}_{t+1} - \frac{\hat{\tilde{\alpha}}_{t+1}\tilde{\alpha}}{H(\tilde{\alpha}) - \tilde{\alpha}}\right] = 0. \end{aligned} \tag{4.44}$$

[49]Notice that:

$$\frac{\partial H(\tilde{\alpha})}{\partial \tilde{\alpha}} = \frac{f(\tilde{\alpha})}{1-F(\tilde{\alpha})}[H(\tilde{\alpha}) - \tilde{\alpha}].$$

13. Average wage

$$w_t = \eta[\epsilon_t A_t \bar{\alpha}_t + c\,\theta_t + (\omega_t - \zeta_t)T - (1-\omega_t)\kappa\, {A_t}^{\delta}] + (1-\eta)b, \tag{4.45}$$

$$\begin{aligned} w_0 \hat{w}_t = \eta \Big\{ & \epsilon A \bar{\alpha} \left(\hat{\epsilon}_t + \hat{A}_t + \hat{\bar{\alpha}}_t\right) + c\hat{\theta}_t \theta \\ & + T\left(\omega\hat{\omega}_t - \zeta E_t \hat{Q}_{t,t+1}\right) + \kappa\, A\left(\omega(\delta\hat{A}_t + \hat{\omega}_t) - \delta\hat{A}_t\right)\Big\}. \end{aligned} \tag{4.46}$$

14. Average idiosyncratic productivity

$$\bar{\alpha}_t = \omega_t H(\tilde{\alpha}_t) + (1-\omega_t)\alpha_t^N, \tag{4.47}$$

$$\hat{\bar{\alpha}}_t \bar{\alpha} = -\alpha^N \hat{\omega}_t \omega + H(\tilde{\alpha})\omega\left[\frac{f(\tilde{\alpha})}{1-\rho^n}\left(H(\tilde{\alpha}) - \tilde{\alpha}\right)\frac{\tilde{\alpha}}{H(\tilde{\alpha})}\hat{\tilde{\alpha}}_t + \hat{\omega}_t\right]. \tag{4.48}$$

15. Fraction of continuing workers

$$\omega_t = (1-\rho_t)n_{t-1}/n_t, \tag{4.49}$$

$$\hat{\omega}_t = \hat{n}_{t-1} - \hat{\rho}_t \frac{\rho}{1-\rho} - \hat{n}_t. \tag{4.50}$$

16. Aggregate income

$$y_t = \bar{\alpha}_t A_t n_t - c v_t - \kappa m_t A_t^{\delta} - T\rho_t^n n_t = 0 \tag{4.51}$$

$$\hat{y}_t y = nA\bar{\alpha}(\hat{n}_t + \hat{A}_t + \hat{\bar{\alpha}}_t) - c\hat{v}_t v - \kappa A\bar{m}(\hat{m}_t - \delta\hat{A}_t) - Tn\rho^n(\hat{\rho}_t^n + \hat{n}_t). \tag{4.52}$$

17. Technology

$$\ln(A_t) = \tau_A \ln(A_{t-1}) + \iota_A, \tag{4.53}$$

$$\hat{A}_t = \tau_A \hat{A}_{t-1} + \iota_A. \tag{4.54}$$

Replication

Zanetti (2011)

Zanetti (2011) uses the steady-state job creation and job destruction condition to pin down the value for vacancy posting costs, c, and the value of leisure, h, respectively. For convenience, I state these equations at steady-state:

$$\epsilon A\tilde{\alpha} - b - \frac{\eta}{1-\eta}c\theta + (1-\zeta)T + \beta(1-\rho)\epsilon A\left[H(\tilde{\alpha}) - \tilde{\alpha}\right] = 0, \tag{4.55}$$

$$\frac{c}{\chi\theta^{-\xi}} = (1-\eta)\beta[\epsilon A(\alpha^N - \tilde{\alpha}) - T - \kappa\, A^{\delta}]. \tag{4.56}$$

To solve for the unknowns, I also need a value for T and b and thus, the steady-state wage, w:

$$T = \rho_T\, w, \tag{4.57}$$

$$b = \rho_R\, w + h, \tag{4.58}$$

$$w = \eta[\epsilon A\bar{\alpha} + c\theta + (\omega - \zeta)T - (1-\omega)\kappa A^{\delta}] + (1-\eta)b. \tag{4.59}$$

The system of five equations with five unknowns (c, h, T, b, w) implies a unique solution.[50] The value I find is $h = 1.83$, a stark contradiction to the value proposed by Zanetti ($h = 0.59$). Since he does not state a value for vacancy posting costs, c, I cannot compare it with my result ($c = 1.25$).

Interestingly, the value for h is exactly the same in two versions of the Zanetti model (2007 and 2011), despite a differently calibrated productivity distribution. This implies that the steady-state values of variables and parameters that are a directly linked to the productivity distribution ($\tilde{\alpha}$, $\bar{\alpha}$, $H(\tilde{\alpha})$, α^N) must clearly be different in both versions of the paper. Hence, the parameter values inferred from eqs. (4.55) – (4.59) should also be different (e.g. h). Yet, the value of leisure is found to be $h = 0.59$ in both versions of the paper. In other words, a worker's (nominal) value of leisure does not differ despite an entirely different (expected) output of that worker.

I subsequently analyse the steady states for selected variables. In particular, I compare output, wages and tightness with the values obtained by Zanetti (2011). As shown in the upper rows of Table 4.4, the values for output and wages clearly contradict

[50] I set $\kappa = 0$ in the computational procedure such that the model is identical to Zanetti (2011).

Zanetti's while tightness is almost identical. The latter result is encouraging in a sense that both values for the matching technology are probably (almost) identical. To get some intuition regarding the values for output and wages, I further look at

Table 4.4: Comparison of steady-state values

Variable	Zanetti (2011)	Own computation
Output, y	2.97	4.04
Wages, w	2.84	3.88
Employment, n	0.945	0.945
Tightness, θ	0.66	0.67
Costs of frictions, CoF	1.14	0.06
Costs of frictions relative to production	0.28	0.015

Notes: Comparison of steady-state values for selected variables, Zanetti (2011) vs. own computations. The CoF and the costs of frictions relative to production were computed based on the values in Zanetti (2011).

the productivity distribution and the costs of frictions (hiring and firing costs). The unconditional expectation of the calibrated distribution is $E[\alpha] = 4.23$, the average productivity is $\bar{\alpha} = 4.34$ and employment is $n = 0.945$. The last two values imply that total production is $nA\bar{\alpha} = 4.11$.[51] Hence, if there are no costs for hirings and firings, output would be $y \approx 4.1$. To quantify the costs of frictions[52] (CoF), I calculate the difference between production and output: $CoF = nA\bar{\alpha} - y$. I furthermore pin down the ratio of the costs of frictions over production: $CoF/nA\bar{\alpha}$ as a relative measure. In Zanetti's economy, almost 30% of total production are required for hiring and firing while it is approximately only 1.5% in my case (Table 4.4, bottom rows). From this perspective, the value I obtain is far more reasonable.

Zanetti (2007)

The strategy to pin down the values for h and c is identical in the 2007 and 2011 paper. Using the corresponding strategy and the values proposed in Zanetti (2007), I find that $h = 0.61$ and $c = 0.04$. The former value is very close to the original value $h = 0.59$ (Zanetti 2007), the latter cannot be compared. There are, however, some

[51]Notice that I need to compute production as it is not stated in Zanetti (2011).

[52]Notice that I additionally subtract firing costs from total production. See Subsection 4.3.4 for details. However, this difference is quantitatively negligible.

Table 4.5: Calibration based on Zanetti (2007, 2011)

Parameter/steady-state	Value
Coefficient of relative risk aversion, σ	2
Degree of interest rate smoothing, ϕ_r	0.32
Discount factor, β	0.99
Elasticity of inflation w.r.t. marginal costs, κ	0.09
Elasticity of substitution between goods, γ	11
Exogenous job separation rate, ρ^x	0.013
Firing costs parameter, ρ_T	0.3
Match elasticity, ξ	0.7
Matching technology, χ	0.68
Mean of $F(\cdot)$, μ_{ln}	0
Price stickiness, ν	0.75
Replacement ratio, ρ_R	0.3
Responsiveness to inflation, ϕ_π	1.5
Responsiveness to output deviations, ϕ_y	0.5
Standard deviation of $F(\cdot)$, σ_{ln}	0.1
Technology shock persistence, τ_A	0.94
Vacancy posting costs, c	0.04
Value of leisure, h	0.61
Worker's bargaining power, η	0.5

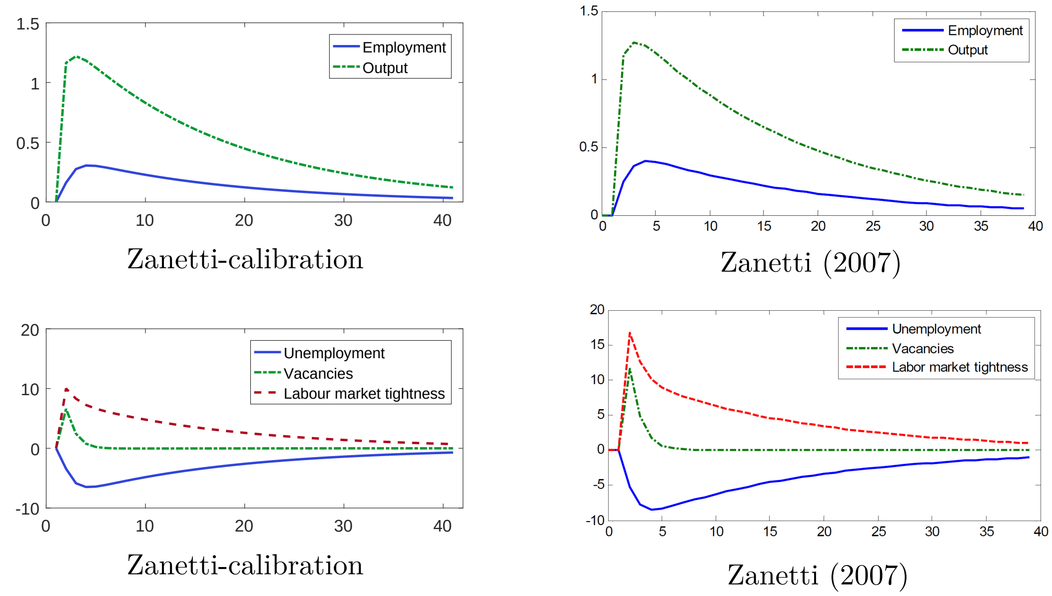
other problems with the calibration in Zanetti (2007). First of all, the values for total, exogenous, and endogenous job separation rates are not consistent in Zanetti (2007). He sets $\rho = 0.02$ and $\rho^x = 0.01$. The endogenous separation rate is consequently $\rho^N = (\rho - \rho^x)/(1 - \rho^x) \approx 0.01$ (instead of $\rho^N = 0.005$ as reported in Zanetti (2007)). Because I do not know which value is actually chosen, I split the total separation rate in line with Zanetti (2011) and den Haan et al. (2000): $\rho = 1.5\rho^x$; that is, $\rho^x = 0.013$ and $\rho^N = 0.007$.

Second, Zanetti (2007) ends up with different steady-state values for tightness and vacancies. It follows from the definition and the values of $p(\theta)$ and $q(\theta)$ that $\theta = 0.67$ instead of $\theta = 0.33$. This difference also implies another level of vacancies at steady state. Because both the job and vacancy filling rate are identical in the two versions of the paper and the resulting level of tightness is $\theta = 0.67$ in Zanetti (2011), I conclude that it is indeed $\theta = 0.67$. The resulting calibrated parameters (henceforth: Zanetti-calibration) are summarized in Table 4.5. The steady-state values of the

Table 4.6: Comparison of steady-state values (Zanetti-calibration)

Variable	Zanetti (2007)	Own computation
Output, y	0.96	0.96
Wages, w	0.91	0.92

Figure 4.8: Comparison of impulse response functions (Zanetti-calibration and Zanetti (2007))



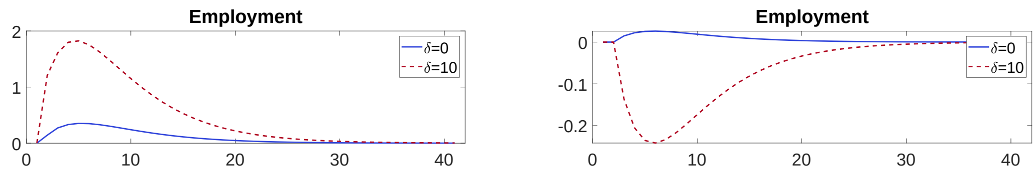
Notes: Comparison of the impulse response functions of vacancies (percentage deviation from the steady state) to a one-percentage-point technology shock, own computation based on Zanetti (2007, 2011) vs Zanetti (2011).

Zanetti-calibration for selected variables are listed in Table 4.6. This computation implies steady states very close to the values obtained by Zanetti (2007). The Zanetti-calibration furthermore allows me to match the pattern of the IRF of employment and vacancies to a technology shock (Figure 4.8).

I have employed the identical calibration strategy as used in Zanetti (2007) and Zanetti (2011). However, only using the parameter values from Zanetti (2007) allows to replicate the corresponding findings. Once I use the 2011 parameters values in the same computational procedure, the results (steady states and IRFs) differ from those depicted in Zanetti (2011). This observation, the unreasonable high costs of frictions in Zanetti's (2011) economy and the fact that he uses the same value for h in differently calibrated models, give rise to assume some inconsistencies regarding parameter calibration and steady-state value computations in Zanetti (2011). However, without further information from the author, it is futile to explore these issues in more detail.

German calibration

Figure 4.9: Impulse response functions to a technology shock (German calibration)



Extended model | Model without endogenous separations

Notes: Impulse response function (percentage deviation from the steady state) to a one-percentage-point technology shock, German calibration, extended model and model without endogenous separations ($\delta = \{0, 10\}$).

Table 4.7: German calibration/steady-state values of selected variables

Parameter/steady state	Value	Source
Coefficient of relative risk aversion, σ	1	Set (as above)
Degree of interest rate smoothing, ϕ_r	0.92	Drygalla et al. (2019)
Discount factor, β	0.99	Zanetti (2011)
Elasticity of substitution between goods, γ	11	Zanetti (2011)
Exogenous job separation rate, ρ^x	0.015	Gartner et al. (2012) and den Haan et al. (2000)
Firing costs parameter, ρ_T	0.5	Set (slightly higher than above)
Match elasticity, ξ	0.65	Kohlbrecher et al. (2016)
Mean of $F(\cdot)$, $\mu_{\ln}$	2.43	Based on the data from Jolivet et al. (2006)
Price stickiness, ν	0.75	Zanetti (2011)
Replacement ratio, ρ_R	0.3	Zanetti (2011)
Responsiveness to inflation, ϕ_π	1.5	Drygalla et al. (2019)
Responsiveness to output deviations, ϕ_y	0.125	Drygalla et al. (2019)
Standard deviation of $F(\cdot)$, $\sigma_{\ln}$	0.37	Based on the data from Jolivet et al. (2006)
Standard deviation of a policy shock, ι_p	0.001	Set (as above)
Standard deviation of a technology shock, ι_A	0.007	Set (as above)
Technology shock persistence, τ_A	0.82	Drygalla et al. (2019)
Tightness, θ	0.3	Based on Kohlbrecher et al. (2016)
Total separations, ρ	0.023	Gartner et al. (2012)
Traininc costs parameter, κ,	13.14	Implied
Unemployment rate, u	0.083	Elsby et al. (2013)
Vacancy filling rate $q(\theta)$	0.93	Implied
Vacancy posting costs, c,	2.96	Implied
Value of leisure, h,	6	Implied
Worker's bargaining power, η	0.65	Set to be in line with Hosios (1990)

Chapter 5

Concluding remarks

Labour market institutions aim to improve the outcome of labour markets in terms of employment and wages. However, it is not straight forward whether these institutions accomplish their objectives. Furthermore, they may come along with side effects. In this dissertation, I focus on two labour market institutions: minimum wages and employment protection legislation.

The purpose of minimum wages is to improve the economic situation of low-wage employees. However, negative effects on the employment opportunities of these workers are a potential side effect of a minimum wage policy. Neither economic theory nor empirical studies conclusively answer whether or not minimum wages have negative employment effects (e.g., Neumark and Wascher 2007). Apparently, the institutional background and the specific conditions are important. The second chapter of this dissertation, which is joint work with Oliver Holtemöller, analyses one particular institutional setting. We study the minimum-wage introduction in Germany in 2015. Our findings indicate small positive effects on regular employment and moderate negative effects on marginal employment. In general, the positive effect does not appear implausible through the lens of sophisticated models of the labour market (e.g., a monopsony model (Dickens et al. 1999), a search model with endogenous contact (Flinn 2006), or a two-sided flow model (Brown et al. 2014)) while the negative effects can be explained with a simple model of supply and demand. For a policy maker, the quantification of the negative effects is useful to evaluate whether or not the policy should be considered as successful. However, this evaluation furthermore requires evidence regarding the impact of the minimum wage on wages and hours worked, topics left open for future research, mainly due to data-availability issues.

A characteristic of the German labour market are shortages of skilled labour in certain industries (e.g. in the care sector, Schulz 2012). This phenomenon is expected to intensify in the future due to demographic dynamics. A potential resolution for this problem is migration. At the same time, (im)migration is often critically viewed in the public as it may lead to negative effects on natives' employment opportunities. In the third chapter of this dissertation, I exploit the natural experiment of the German minimum-wage to address this topic. I study if the increase in wage differentials between Germany and the Czech Republic/Poland induced an inflow of labour from these countries. The results suggest that an increase in wage-differentials indeed attracts foreign labour and are in line with a simple model of labour mobility (e.g., Borjas 1999). However, the results also indicate that this inflow is largely due to commuting instead of migration. Because the threshold for migration is larger than for commuting (Stark and Fan 2007), (moderate) policy-induced increases in wage differentials are not sufficient to tackle the problem of labour shortages on a larger scale. I also analyse the impact of the inflow on native employment but do not detect negative effects. One could think of different skill sets of native and foreign workers (Borjas 2003), effects of the minimum wage on (native) labour supply (Edo and Rapoport 2018), or perhaps foreign workers simply filling vacancies as a theoretical explanation for this result.

Another frequently discussed policy to improve labour market outcomes is employment protection legislation. It favours incumbent workers because it makes their dismissal less likely. At the same time, it reduces employer's propensity to hire and thus, the overall effect on employment is a-priori unclear. This is confirmed by the empirical ambiguity (Skedinger 2011). Both channels can be modelled in a search model with endogenous separations as proposed by Mortensen and Pissarides (1994, 1999). Because this approach to model the labour market is superior to a standard supply-and-demand approach (Rogerson et al. 2005), it appears reasonable to embed the search framework into a DSGE model to conduct policy analysis etc. However, this incorporation (e.g. as in Zanetti 2011) may produce some effects that worsen the empirical relevance of the augmented DSGE models. In the fourth chapter of this dissertation, I propose an extension to address this shortcoming. In the presence of endogenous separations, the extension does not improve the empirical relevance of the augmented model. This points towards the problems that come along with endogenous separations as they are currently modelled despite their advantages.[53] A potential reason for my result is the assumption of random productivity draws in each period and hence, future research could be direct towards that assumption.

Chapters two and three of this dissertation contribute to the empirical literature on the employment effects of minimum wages and to the empirical immigration literature, respectively. The studies are impact evaluations and hence, the results must not hold in general. However, the academic work and findings may serve as a reference for future research and may be useful for policy makers to evaluate the minimum-wage policy. On the contrary, the fourth chapter tackles an academic issue in general and addresses a shortcoming that some NK-SAM models exhibit. The approach I employ only improves these models' relevance under a restrictive assumption. I identify the underlying problem and propose a potential resolution for future research.

[53] See, for example, Fujita and Ramey 2012 for a discussion of exogenous and endogenous separations in search models.

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