Essays on Matching Processes and Effects of Institutional Changes on Regional and Occupational Labour Markets

Stops, Michael

Institut für Arbeitsmarkt- und Berufsforschung

Die Forschungseinrichtung der Bundesagentur für Arbeit

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I dedicate this work to my parents and my grand-parents.

Chapter 1

Introduction

This thesis consists of three essays that are organised in the following three chapters and either refer to mechanisms of creating new employment or selected changes of labour market institutions and their impact. Particularly, chapter 2 focusses on the structure and dynamic of matching processes and considers mobility on occupational labour markets – from my knowledge for the first time – in a search and matching framework. Chapters 3 and 4 deliver analyses of effects of important institutional changes; chapter 3 contributes new and more differentiated details about the effects of the German labour market reforms 2003–2005 on the matching efficiency. Chapter 4 provides a study of the effects of the introduction and the adjustments of the National Minimum Wage in the United Kingdom 1999–2010 that faces up some methodological issues in previous work. Beside others, this chapter explicitly considers interdependencies of local areas for the first time in a study for a nation wide minimum wage.

Each of the analyses considers aspects of labour market structure and functioning under the following common assumption: from a workers perspective, the decisions to search for jobs, to change jobs, to live in a certain local area or to work in another area are made taking, beside others, the situation on relevant partial labour markets as well as the institutional setting into account. Firms consider the same aspects when they decide about the location, the kind of their economic activities, where to search for workers, and which workers should be hired. The resulting behaviour can be observed as a number of key descriptive measures in relevant regional and/or occupational labour markets[1].

The analyses in the three chapters are based on different data sets. The commonality of these data is the panel structure that reveals to be a good basis for answering the addressed research questions (for the following, see also Hsiao, 2007). One reason for this is the gain of variation compared with pure time series or cross sectional data. E.g., in chapter 2 the methodology refers to groups of cross-sectional units in terms of jobs that are assumed to be alternatives in recruitment and job search processes and the repeated observations for each cross-sectional unit over time are used to derive robust inference. In chapters 3 and 4, a period before the institutional change is compared with the period after the change and the variation in the cross-sectional units is utilised for the identification of the effects. Another advantage of panel data, in order to get unbiased estimates of the impact of interesting variables, is that it is relatively

1 Here, occupations are understood as partial labour markets comprising jobs that share extensive commonalities in terms of requirements, skills and tasks.

easy to control for unobservable cross-sectional and time series heterogeneity by dummy coding or by using within estimators, respectively.[2]

The theoretical basis for the analyses of the matching processes in chapters 2 and 3 is the job matching function that relates the number of new hires to the number of job searchers and the number of vacancies. It is a central element of a theory to explain unemployment equilibria (compare Pissarides, 1979, 1985; Diamond, 1982a, b; Mortensen, 1982). This basis allows, beside others[3], to describe the efficiency of job matching processes. Lots of studies deal with the estimation of macroeconomic matching functions (compare the surveys by Petrongolo and Pissarides, 2001; Rogerson et al., 2005; Yashiv, 2007). A greater part of these studies is based on the assumption of homogeneous job searchers and worker searching firms in the whole labour market. Relaxing this assumption allows straightforwardly analyses whether and how the parameters of the matching function differ in partial labour markets. The literature refers to sectors (Broersma and Ours, 1999), regions (Burda and Wyplosz, 1994; Anderson and Burgess, 2000; Kangasharju et al., 2005; Lottmann, 2012), skill levels and occupations (Entorf, 1994; Fahr and Sunde, 2004; Mora and Santacruz, 2007; Stops and Mazzoni, 2010) as relevant and delimitable partial labour markets. Regarding occupational labour markets, Fahr and Sunde (2004) and Stops and Mazzoni (2010) showed that the matching efficiencies are notifiable different on these markets. Both studies are based on the assumption of separated occupational labour markets. This means that, generally, workers would not change their occupation during working life.

Based on the same administrative data sources used for the analyses in Stops and Mazzoni (2010), it is shown in chapter 2 that, on average, one third of all flows from one certain job to other jobs are associated with a change of the occupation. This clearly deteriorates the separation assumption for occupational labour markets. Chapter 2 discusses theoretically and empirically the implications of a relaxation of this assumption. It gives arguments that predictable or systematic relationships between new hires in a certain occupation and vacancies and unemployed in another occupation should be only observed for groups of occupations that can be regarded as alternatives to each other in recruiting decisions from the firms perspective or in job search decisions from the workers perspective, respectively (compare also with Gathmann and Schönberg, 2010).

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2 Naturally, panel data also reveal – like the other data structures – certain issues depending on the specific analyses and the assumptions the employed methodology is based on. Thus, also this data has to be tested and the adequate methodology has carefully to be selected. This is, where necessary, further discussed in the following chapters.

3 E.g., it allows also to model the observable negative relationship between unemployed and vacancies during the business cycle (represented by the Beveridge curve, compare with Blanchard and Diamond, 1989) or the observable (positive) correlation of the labour market tension, in terms of the ratio of the number of vacancies and the number of unemployed, and the probability that unemployed find a new job.

Following this idea, chapter 2 shows theoretically the relevance of occupational changes for the job search intensity and matching efficiency. This is based on a model structure firstly described by Burda and Profit (1996) to explain the influence of regional distances between job searchers and jobs on matching elasticities. The empirical assessment of the derived hypotheses is conducted with a model framework that is formally equivalent to panel data models containing spatial lags of exogenous regressors (SLX models, as described in LeSage and Pace, 2009, S. 179). The model follows the idea that an observation of a dependent variable in a certain cross-sectional unit like regions or occupations does not only depend on exogenous variables in the same cross-sectional unit but also in other – selected – units. One very often used selection criteria for regions is Waldo Tobler's first law of geography: "Everything is related to everything else, but near things are more related than distant things." (Tobler, 1970, p. 236). This principle can be easily modelled with information about topology of the regions because in this case information about distances or contiguity of regions is available. Chapter 2 adopts this idea for occupational groups whereas it is distinguished between groups that are similar to each other from groups that are not. This information stems from the study by Matthes et al. (2008) in which groups of occupations are described that can be considered as alternatives for recruiting or job search processes. The SLX model can easily be implemented in more established model frameworks like the ordinary least squares (OLS), the within estimator or the Pooled-Mean-Group model that was firstly applied by Stops and Mazzoni (2010) to estimate matching elasticities. The latter model revealed to be more adequate for the used data; it is based on the assumption that a long-term relationship between the variables of interest exists, thus the relationship of new hires on the one side and unemployed and vacancies on the other. Finally, this model does not only allow implications for the (different) matching elasticities in different partial labour markets. Since the long-term relationship is modelled as error-correction term, the coefficient of this term allows implications for the question whether there is dynamics in the data that adjusts short term deviations to an equilibrium. The results of chapter 2 are compared with previous studies and, by using information criteria, the quality of the models considering occupational changes in matching models are compared with models that do not consider these changes.

In chapter 3 the effects of the German labour market reforms 2003–2005 are analysed taken the whole labour market and occupational labour markets into account. The reforms are a topic of unchanged importance for Germany (well documented in recent studies by Dustmann et al., 2014; Gartner and Fujita, 2014; Krebs and Scheffel, 2013; Rinne and Zimmermann, 2013, 2012; Hertweck and Sigrist, 2012; Burda and Hunt, 2011; Möller, 2010; Fitzenberger, 2009). Considering that one of the main objectives of the reforms was to improve the matching process on the labour market, this chapter presents new details regarding the development of job-matching performance before, during, and after the reform years. Thus, it complements previous studies like these from Fahr and Sunde (2009); Hillmann (2009); Klinger and Rothe (2012); Klinger and Weber (2014), who found evidence for a better job matching after the reform years. The analysis in chapter 3 is conducted on the basis of a highly frequent administrative panel data set with a huge variation of detailed observations for occupations in local areas. The data set allows to control for local temporal shocks, e.g. induced by different economic situations in the German Federal States, and for time fixed effects in the same model. This allows a precise estimation of the pure time effect on the matching productivity for the whole economy but also for groups of occupations. Therefore, the chapter provides new details about the development of the matching productivity for the whole labour market, for occupational labour markets before and after the reform years, with and without considering the economic situation and it informs about the further development during the financial crisis and afterwards. Robustness checks are provided that are, beside others, based on the stock-flow matching approach proposed by Coles (1994); Coles and Smith (1998).

Finally, chapter 4 deals with the employment effects of the introduction and adjustment of the National Minimum Wage (NMW) in the United Kingdom (UK). The identification of these and other effects, e.g. on the wage distribution, is of general interest, particularly for Germany: here a nationwide minimum wage was recently introduced and its effects are widely discussed, though it is apparent that it is not possible to empirically assess its effects shortly after the introduction due to data availability and because firms are expected to react with a certain lag of time. From a theoretical perspective the direction of the effects depends on the minimum wage level and the assumptions about the type of the product market and the labour market. Theory based on the assumption of perfect competition on product and labour markets predicts negative employment effects of minimum wage rates that lie above the market clearing wage level, the equilibrium wage: A minimum wage at this level would raise the cost of labour and, therefore, the marginal cost of production. Firms would face higher output prices that lead to a decreasing demand for this products and the production will be downsized (the "scale effect"). The firms would further tend to substitute labour by capital (the "substitution effect") due to higher wages. Thus, due to both effects the demand on labour diminishes, firms lay off or do not recruit other workers with relative lower productivity, and generally these workers would face worse employment prospects (compare this neoclassic textbook approach with, e.g., Neumark and

Wascher, 2008). However, according to alternative theoretic approaches based on monopsony market types, a minimum wage can reduce recruitment and retention costs. In case of high turnover rates, like in low wage sectors, these costs could be substantial (compare with Card and Krueger, 1995). Considering a formal version of this model for a "single monopsonist", Manning (2003) argues that there is always a minimum wage at a certain level that would increase employment. But this is not necessarily the case in oligopsonistic labour markets, beside others due to firm heterogeneity and interdependencies between these firms. That is why the same author concludes that theory can only give an orientation but no answer in evaluating the effects of minimum wage schemes and that "[an] openminded empirical approach is appropriate for investigating the impact of minimum wages on employment" (Manning, 2003, p. 27).

With this in mind, the starting point of the analyses in chapter 4 are the empirical studies by Stewart (2002) and Dolton et al. (2012).[4] The latter study proposes an estimator that considers employment adjustments on the long run as well as short term adjustments due to the yearly changes of the NMW. The analysis in chapter 4 is based on two panel data sets for different geographies, one data set for 138 travel to work areas and one for 140 Unitary Authorities and Counties. As already mentioned, our empirical strategy addresses the main critics on previous studies. Firstly, the analysis takes the spatial dependence of local labour markets into account by estimating models that explicitly consider spatial dependencies of the error terms (SEMP models, compare, e.g., with Elhorst, 2010c). This is the most general case to consider spatial dependence, given a spatial dependency structure. In the chapter, it is assumed that commuting patterns and the contiguity structure of regions can represent this dependency structure and the advantages and disadvantages of these approximations are discussed. Not least because recent studies formulated some concerns regarding the identification of spatial lag effects, compare the study by Gibbons and Overman (2012) as an excellent summary, the baseline results for the standard errors are compared with the results of a methodology of computing standard errors considering spatial relatedness in the sense of the mentioned first law of geography by Tobler. This

4 The number of existing studies dealing with nation wide minimum wages is naturally quite larger, see the surveys by Brown et al. (1982); Card and Krueger (1995); Brown (1999); Neumark and Wascher (2008). There is also an increasing number of literature which attempts to identify the effects of a minimum wage on employment by using geographical variation in the bite of the MW in spatially separated markets, see Card (1992); Neumark and Wascher (1992, 2007); Card and Krueger (1994, 2000); Burkhauser et al. (2000); Dube et al. (2007, 2010); Baskaya and Rubinstein (2012); Neumark et al. (2014) for the United States; Baker et al. (1999) for Canada; Bosch and Manacorda (2010) for Mexico; Stewart (2002, 2004a, b); Dolton et al. (2009, 2012) for the UK. Studies for Germany are not explicitly considered in this analysis because they refer to minimum wages in certain sectors or branches, compare with König and Möller (2009) for the construction sector or Aretz et al. (2013) for the roofing sector to name two important examples. As already mentioned, an explicit German nation wide minimum wage did not exist before 2015.

methodology is described by Conley (1999). Secondly, the analysis implements regional demand side shocks for the first time; particularly the financial crisis lead to the concern of the UK Low Pay Commission how to adjust the minimum wage in times of (heavy) recessions without the risk of huge employment losses. Previous studies considered only rough measures for times of recessions (Dickens and Dolton, 2010; Dolton et al., 2011; Dolton and Rosazza-Bondibene, 2012). Thirdly, possible endogeneity of the Minimum Wage variable and the dynamic structure of the employment rate are discussed and addressed by estimating a further model class that belongs to the System General Methods of Moments (SGMM) estimators, as it is described by Roodman (2009b).

Each of the following chapters 2–4 starts with an abstract, ends with detailed conclusions, and is complemented by comprehensive appendices that make each analysis step transparent. The final chapter 5 draws some general conclusions.

Chapter 2

Job matching across occupational labour markets[1]

1 The contents of this chapter are published in the journal "Oxford Economic Papers" (Stops, 2014).

The analysis in this chapter refers to job matching processes in occupational labour markets in terms of jobs that share extensive commonalities in their required qualifications and tasks. To date, all studies in this field have been based on the assumption that matching processes only transpire within distinct occupational labour markets and that no occupational changes occur. I present theoretical and empirical arguments that undermine the validity of this assumption. I construct an "occupational topology" based on information about the ways in which occupational groups may be seen as alternatives in searches for jobs or workers. I then use different empirical models that consider cross-sectional dependency to test the hypothesis that job search and matching occur across occupational labour markets. The results support my hypothesis. The findings suggest that an augmented empirical model should be utilized that considers job and worker searches across occupational labour markets in estimating job matching elasticities.

2.1 Introduction

The determinants of matching labour demand and labour supply to create new jobs are of continual interest for both labour market researchers and politicians. In part, because it is difficult to observe the individual search processes that underlie this type of matching on the micro level, studies in this field typically refer to the analytical results obtained using macroeconomic matching functions that model the empirical dependency of the number of new hires on the number of job-seekers and vacancies in a particular context of interest; for an overview of the foregoing, compare the surveys of Petrongolo and Pissarides (2001), Rogerson et al. (2005), and Yashiv (2007). These studies help elucidate the efficiency of matching processes both in aggregated and partial labour markets. Therefore, studies examined particular sectors (Broersma and Ours, 1999), regions (Anderson and Burgess, 2000; Kangasharju et al., 2005), or occupational groups, which are classes of jobs that share extensive commonalities in their qualification requirements and tasks (Entorf, 1994; Fahr and Sunde, 2004; Mora and Santacruz, 2007; Stops and Mazzoni, 2010). The central assumption of most studies in this field is that partial labour markets are completely separated from each other; in other words, there are no flows of job-seekers from one partial labour market to another partial labour market, and no correlations exist between different labour markets with respect to newly created jobs or numbers of job vacancies. This central assumption is not presumed by studies of regional labour markets (e.g., Burda and Profit, 1996; Fahr and Sunde, 2006; Lottmann, 2012; Dauth et al., 2014) that consider the penetrability of partial labour markets. However, to date, no study of occupational labour markets has considered the dependencies between these partial labour markets. In investigations by Entorf (1994); Fahr and Sunde (2004); Mora and Santacruz (2007); Stops and Mazzoni (2010), the number of new jobs in a given occupational group is explained by the number of unemployed workers and vacancies in same occupational group.

In this paper, I use both theoretical and empirical arguments to demonstrate that the assumption of separate occupational labour markets is not appropriate. I test my hypotheses using pooled ordinary least squares, fixed effects and pooled mean-group models that include cross-sectional dependency lags of regressors. Therefore, the estimators take into account interactions between cross-sectional units. To achieve this purpose, I construct an empirically based "occupational topology" – as analogon to the spatial order of regions – in terms of a matrix that contains information about occupations that either are assumed to be substitutes for recruitment and employment or are not assumed to be substitutes following the considerations by Gathmann and Schönberg (2010) and Matthes et al. (2008). I discuss empirically and theoretically if job matching models that consider job searchers and vacancies in other occupational substitutes as explaining variables for new matches should be preferred. If that applies these models adjust and complement the well known (direct) matching elasticities of vacancies and job searchers in the occupational labour markets of interest with (indirect) matching elasticities of vacancies and job searchers in occupational groups that are considered to be substitutes to one another.

In the following section, I describe the motivation and theoretical framework of my estimation approach to the matching function. In section 2.3, I present the data used in this study, and the empirical estimates are subsequently provided in section 2.4. Section 2.5 summarizes the main results of the investigation.

2.2 Motivation and theoretical framework

The standard model of the matching function assumes the existence of a homogeneous pool of unemployed workers and a homogeneous pool of vacancies. The search activities of both sides of the market can be described as a matching technology. The processes underlying this matching procedure are not explicitly modelled;[2] instead, the matching process can be regarded as a black box (Petrongolo and Pissarides, 2001). The variables U, V and M may be used to represent the numbers of unemployed workers, vacancies and new hires (matches), respectively. The matching function $f(U, V)$ is frequently specified using a Cobb-Douglas functional form:

2 Examples of these processes include job and worker search decisions, job searches, and negotiations of wages.

$$M = AU^{\beta_U} V^{\beta_V} \tag{2.1}$$

where A describes the "augmented" matching productivity (e.g., Fahr and Sunde, 2004). The coefficients β_U and β_V represent the matching elasticities of unemployed and vacancies, respectively. In accordance with standard matching theory, both elasticities are positive. Furthermore, the theoretical model assumes constant returns to scale, which implies that $\beta_U + \beta_V = 1$ with $\beta_U, \beta_V > 0$.

In the following, the assumption of homogeneous pools of vacancies and unemployed workers will be relaxed. It is reasonable to assume that occupation-specific differences exist with respect to the matching processes due to differences in job requirements, apprenticeships and other factors (for empirical evidence, see Fahr and Sunde, 2004; Stops and Mazzoni, 2010). In Germany, in particular, occupations are more suitable units than regions or economic sectors for analyses of matching processes (compare with Fahr and Sunde, 2004), because occupations include specific qualification requirements, tasks, and other characteristics. Furthermore, individuals in Germany acquire occupation-specific knowledge over the courses of their careers. Typically, firms with vacancies attempt to hire workers with certain qualifications, whereas job searchers seek jobs in certain occupations. The aforementioned studies (Fahr and Sunde, 2004; Stops and Mazzoni, 2010) assume that the number of new jobs in an occupational group does not depend on the number of unemployed workers and vacancies in other occupational groups. Fahr and Sunde (2004) propose the existence of partial occupational labour markets that are aggregates of specific occupational groups. These labour markets should be separated from each other; no flows of workers between different occupational labour markets should occur, and no correlations should exist between different labour markets with respect to newly created jobs or numbers of job vacancies, but this may be the case within these markets. Both Fahr and Sunde (2004) and Stops and Mazzoni (2010) use data on occupational groups that are assigned to each occupational labour market to estimate matching elasticities for these markets. However, these researchers do not explicitly engage in either empirical or theoretical considerations of the flows or correlations between different occupations. Therefore, they assume that partial labour markets in terms of occupational groups are completely separate.

However, occupational labour markets could certainly interact with each other with respect to the matching process. One argument for the existence of these interactions is that both unemployed and employed persons change their occupations during their employment careers (Fitzenberger and Spitz, 2004; Seibert, 2007; Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010; Schmillen and Möller, 2012). An observation of the flows of individuals into employment between 1982 and 2007 reveals that the shares of these flows that involve occupational changes is rather in certain industries. In particular, these shares range from 16 per cent (the occupational changes of former foresters and huntsmen) to 75 per cent (the occupational changes of polymer processors).[3] These empirical examples show clearly that assumption of no mobility between occupational labour markets is even too strict for Germany. Furthermore, this should also apply a fortiori to countries such as the UK and the USA, both of which have labour markets that are less structured by well defined job titles.

From a theoretical point of view, the incorporation of flows between occupational labour markets causes analyses of the matching process to become considerably more complex: job searchers must decide on their search strategy with respect to their optimal numbers of job interviews in several different occupational labour markets.

In the following discussion, I utilize a theoretical matching model that offers deeper insights into the implications for the matching elasticities for unemployed workers and vacancies that derive from the fact that job and worker searches occur not only within occupational labour markets but also across these markets. Although the structure of this model is based on a paper by Burda and Profit (1996), the interpretation of the model has been widely modified. According to the model and under certain assumptions[4], the optimal search intensity N^*_{ij} of an individual with (former) occupation i in a job search in the new or same occupation j depends negatively on the costs of the job search $c + a_u D_{ij}$ with a fixed component c and a component associated with searching in other occupational groups that consists of a cost rate a_u and a dissimilarity measure D_{ij} for occupations i and j, positively on returns for a successful job search in terms of wages adjusted by the interest rate w/r, and negatively on the probability of obtaining a job after completing a job application p_j in the case in which the expected gain from job search highly exceeds the costs; in the opposite case N^*_{ij} would be zero:

$$N^*_{ij} = \begin{cases} \frac{1}{p_j}\ln(\frac{(w/r)p_j}{c+a_u D_{ij}}) & \text{for } \frac{w}{r}p_j \geq (c+a_u D_{ij}) \\ 0 & \text{for } \frac{w}{r}p_j < (c+a_u D_{ij}) \end{cases} \tag{2.2}$$

The negative relationship between optimal job search intensity and the probability of obtaining a job after applying arises from the assumption that the search costs

3 See appendix 2.A.1 for more detailed information.

4 The formal considerations for this model are presented in appendix 2.A.2.

are linear and should be significantly smaller than the expected revenues from the job search; thus, $(w/r)\,p_j >> c + a_u D_{ij}$.[5]

In their analysis of regional labour markets Burda and Profit (1996) complement fixed search costs c from standard search models with the variable element $a_u D_{ij}$, which depends positively on the distance D_{ij} between the region i in which a job searcher is located and the region j in which this individual is searching for a job. With respect to permeability, occupational labour markets may resemble regional labour markets.

In particular, workers and vacancies are typically associated with particular occupational groups. Nevertheless, workers and firms often do not limit their search to a single occupational labour market. With respect to regional labour markets, various metrics – such as geographic distances or commuting flows – should represent the strength of the interdependencies (and causal relationships) between economic activities in different regions. In many instances, the topology of the regions of interest provides a good indicator of the relationships that must be analysed: In occupational labour markets, the resulting "topology" becomes more complex because there are no physical restrictions on the numbers of borders and neighbours of particular occupational groups. Thus, metrics are required that represent similarities among occupational groups with respect to their property as alternatives for both job searchers and firms that are seeking workers.

In the following analyses, I differentiate only between the case of two or more occupations that are similar because they are plausible alternatives in the job search and matching process and the opposite case that consists of dissimilar occupations. Therefore, in the model, I assume that the variable portion of search costs might be zero if a job searcher is searching in his former occupational labour market ($D_{ij} = 0$), positive but moderate for a job search in similar occupational markets ($D_{ij} = d$; $0 < d << \infty$), or prohibitively high for a job search in dissimilar occupational labour markets ($D_{ij} \rightarrow \infty$). Thus, in the case of job searches in dissimilar occupational labour markets, the optimal search intensity should be low or even zero.

5 This finding contradicts the standard assumption of the discouraged worker hypothesis (Pissarides, 2000). According to this hypothesis, workers increase their job search intensity when the probability of obtaining a job increases but give up their search when the expected revenues from the search are relatively low. The hypothesis is derived from a model that assumes that search costs increase exponentially with job search intensity. Under the conditions of this model, optimal job search intensity depends positively on the job finding probability. The framework of the model is rather controversial; in particular, Shimer (2005) reveals that this model "[...] cannot generate business-cycle-frequency fluctuations in unemployment and job vacancies in response to shocks of a plausible magnitude [...]". One reason for this deficiency in the model could be that workers do not behave in accordance with the model's predictions. In a recession, the expected revenues of job searches may become quite low because of the decreased wages and smaller number of vacancies (which decrease the probability of finding a job); nonetheless, it could be reasonable for workers to increase their efforts to find a job under these difficult economic conditions. By contrast, in an economic upswing, workers may decrease their job search intensity because they know that a high search intensity is not required to obtain a job.

This approach implies directly that the number of matches in a certain occupation is determined not only by the number of unemployed workers and vacancies in the occupation itself but also by the number of unemployed workers and vacancies in similar occupations. Therefore, the empirical matching function should be augmented accordingly. The observed occupational market and similar occupational markets may be differentiated with respect to vacancies and unemployed workers. The following general modified matching function may thus be derived:

$$M_i = A_i U_i^{\beta_U} V_i^{\beta_V} U_{is}^{\gamma_U} V_{is}^{\gamma_V} \tag{2.3}$$

where M_i, A_i, U_i and V_i represent matches, "augmented" matching productivity, unemployed workers and vacancies in occupational group i, respectively. The terms U_{is} and V_{is} represent the number of unemployed and vacancies in occupational groups that are similar to occupational group i. Therefore, in addition to the well-known matching elasticities β_V and β_U, two further matching elasticities, γ_V and γ_U, must be considered because the latter represent the effects of dependencies on similar occupational labour markets.

Based on a quasi-reduced form of the matching model,[6] the sign of these matching elasticities are determined by two mechanisms. The number of matches in a certain occupation decreases with a decreasing probability, that a worker will receive a job offer in the same occupation, due to an increase in the number of unemployed workers in similar occupations. Simultaneously, this decreased probability of receiving a job offer leads to a higher optimal job search intensity, assuming that the expected gain from a job search is significantly higher than the search (and travel) costs and that the latter costs are small and increase linearly with the number of job applications; such an increase in search intensity tends to produce a higher number of job matches. An increase in the stock of vacancies, cet. par., would cause more matches – due to a higher job finding rate – but would also have indirect negative effects caused by the tendency towards lower optimal search intensities. For example, positive matching elasticities of vacancies in similar occupational groups would ensue if the decrease in the optimal search intensity is not too large. To sum up, the matching elasticities of the unemployed and vacancies in similar occupations might have positive signs if the (optimal) job search elasticity of the job finding rate is negative and lies in a certain range less than zero[7].

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6 The matches depend directly only on the number of unemployed and the job finding rate. The latter depends also on the number of vacancies.

7 See appendix 2.A.2.

2.3 Data

I construct a panel data set that is similar in its structure but larger in its time dimension than the data set that was used by Stops and Mazzoni (2010); Fahr and Sunde (2004). This data set consists of 81 occupational groups as cross-section units over the course of 26 time periods (1982 to 2007). The units are obtained from the German occupational classification scheme from 1988 (KldB 88[8]). Information about the unemployed and (registered) vacancies is provided by rich operative data from the Statistics of the German Federal Employment Agency. These data are only available at the required level of disaggregation for the reference date of September 30th of each year. To calculate new hires for each sampled year, I used the data from the IAB Sample of the Integrated Labour Market Biographies 1975–2008 (SIAB 1975–2008) from October 1st of each year to September 30th of the following year. The SIAB 1975–2008 is a representative 2% sample of an individual's history of unemployment and employment that is subject to social insurance contributions (Dorner et al., 2010). The number of new hires in the occupational groups is equal to the sum of flows to employment in each occupational group for each examined period (which ranges from October 1st of a year to September 30th of the following year). I calculated the number of new hires in the national economy using a ratio estimator that was suggested by Cochran (1977, pp. 150) and applied by Stops and Mazzoni (2010). In particular, the number of new hires is divided by the employment levels from the SIAB 1975–2008 data, and the resulting quotient is then multiplied by the employment levels[9] from the employment statistics of the Federal Employment Agency. This ratio estimator is more accurate than a simple extrapolation because the level of employment and the number of new hires are highly positively correlated. Because there are only 40 occupational sections in the employment statistics of the Federal Employment Agency, I assign the 81 occupational groups of this study to the 40 occupational sections.[10]

$$M_{i,t} = \frac{E_{o|i \in o,t}}{e_{o|i \in o,t}} \cdot m_{i,t} \tag{2.4}$$

where the variables have following definitions:

- $M_{i,t}$ is the interpolated number of new hires by the occupational groups $i = 1, \ldots, 81$ for the time period t,

8 *Klassifizierung der Berufe* 1988; see table 2.5 in appendix 2.A.3.

9 Employees who are subject to social insurance contributions are measured.

10 See table 2.6 in appendix 2.A.3.

- $m_{i,t}$ is the number of new hires m from the SIAB 1975–2008 data by occupational groups i = 1, ..., 81 for the year t,
- $e_{o|i\in o,t}$ is the number of employed persons from the SIAB 1975–2008 data in the occupational group $i \in o$ that has been assigned to the occupational sectors o = 1, ..., 40 on September 30th of each year t, and
- $E_{o|i\in o,t}$ is the level of employment on September 30th of each year t in the occupational group $i \in o$ that has been assigned to the occupational sector o = 1, ..., 40 on September 30th of each year t.

The data set includes information about the German labour market since the early 1980s; however, data for Eastern Germany are only available since 1992. Thus, only the information for Western Germany can be used in this study, and neither Western German job seekers who obtained employment in Eastern Germany nor Eastern German unemployed workers were considered by this investigation. The numbers of Western German unemployed workers and registered vacancies are the explanatory variables used in this investigation to explain the dependent variable of the flows in employment in Western Germany. Another constraint of this study relates to the frequency of its time series. It has frequently been noted that information about the dynamic changes in the numbers of unemployed workers and vacancies is lost if yearly data are used; consequently, the estimation results could be biased (Petrongolo and Pissarides, 2001, for a broader discussion, see). However, I am forced to neglect this issue because data with greater frequencies are not available for the observed period.

Table 2.1 presents descriptive statistics for the aggregated stocks and flows from the data.

2.4 Empirical strategy and results

2.4.1 An occupational "topology"

The empirical approach of this work is based on the idea that cross-sectional units interact with others; this interaction effect implies that the average behaviour in a group influences the behaviours of those who comprise the group (Manski, 1993; Elhorst, 2010a). Analogously to a regional topology, which depends on region adjacency, I derive an "occupational group topology" that relies on the similarities between occupational groups, in accordance with Matthes et al. (2008).[11]

11 See table 2.7 in appendix 2.A.3.

Table 2.1: Descriptive statistics

		Average 1982–2007 (in numbers)	Share (in per cent)
Labour market stocks			
Labour force	$E+U$	25,436,839	100.00%
Employed	E	23,172,935	91.10%
Unemployed	U	2,263,904	8.90%
Registered Vacancies	V	277,831	1.09%
Flows in employment	M	5,595,605	

Note: The averaged stocks by year were calculated during the course of this study.
Source: The data centre of the statistics department of the Federal Employment Agency and the SIAB 1975–2008.

The approach in Matthes et al. (2008) is to aggregate occupational groups that are somewhat "similar" or "homogeneous" according to the *KldB 88* into occupational segments (*Berufssegmente*), following the concept outlined in an earlier version of Gathmann and Schönberg (2010). In accordance with this approach, occupational groups at the 3-digit level[12] are assumed to be similar if they are alternatives in recruitment decisions by firms or in job search decisions by potential employees. This information is available from the Federal Employment Agency and its Central Occupational File (Federal Employment Agency, 2010, *Zentrale Berufedatei*). To identify the similarities among given occupational groups, the Federal Employment Service has analysed not only the specific skills, licences, certificates, and knowledge requirements but also the typical tasks and techniques that are involved in each occupational group (Matthes et al., 2008).[13]

I transform the results for occupational groups at the 3-digit level into occupational groups on the 2-digit level; this transformation is possible due to the hierarchical structure of the occupational classification scheme.[14] Based on this information, I construct a symmetric 81 × 81 first-order contiguity weight matrix $\mathbf{W}$ in which a value of one reflects correlations between similar occupational groups. The diagonal elements are set to zero since it cannot be assumed that a occupational group is neighboured to itself; – furthermore – each occupational

12 The German occupational classification scheme 88 (KldB 88) code is a hierarchical construction that incorporates the following levels (from lowest to highest): occupational classes, which have a 4-digit code; occupational orders, which have a 3-digit code; occupational groups, which have a 2-digit-code; and occupational ranges, which have a 1-digit code. Under this classification scheme, a given occupational range consists of certain occupational groups, each of which in turn consists of certain occupational orders, where each of the latter in turn consists of certain occupational classes.

13 More details about the methodology can be found in appendix 2.A.4.

14 As mentioned, the results of this procedure are summarized in table 2.7 in appendix 2.A.3.

group is considered separately from other similar occupational groups in the empirical model. Finally, after the weight matrix is row-normalized, it can be used to calculate weighted averaged numbers of unemployed and vacancies in similar occupational groups. Thus, U_{is} (V_{is}) is the product of the i^{th} 1×81 row vector $\mathbf{w_i}$ of the weight matrix $\mathbf{W}$ and the 81×1 column vector of the numbers of unemployed $\mathbf{U}$ (vacancies $\mathbf{V}$) in each occupational group:

$$U_{is} \equiv \mathbf{w_i U} = \sum_{j=1}^{81} (w_{ij} U_j), \text{ and } V_{is} \equiv \mathbf{w_i V} = \sum_{j=1}^{81} (w_{ij} V_j)$$

One restriction of this approach must be noted. Some 2-digit groups are not assigned to only one occupational segment because they contain particular 3-digit groups that belong to one segment and other 3-digit groups that belong to another segment[15]. However, these occupational groups may be regarded as occupations that are similar to more than one segment (e.g., segment A and segment B) because they include certain tasks or qualifications that are only found in segment A and other tasks or qualifications that are only found in segment B. Therefore, though segments A and B are linked by an occupational group, they are not necessarily similar.

2.4.2 Estimation approach and results

To examine the influences of exogenous regressors in other occupational groups, I use the logarithmic version of the model in equation (2.3) considering a panel data structure with observation periods t:

$$\log M_{i,t} = \log A_i + \beta_U \log U_{i,t} + \beta_V \log V_{i,t} + \gamma_U \log U_{is,t} + \gamma_V \log V_{is,t} \tag{2.5}$$

At this stage, I present the model, assuming the availability of perfect information about job searchers, vacancies, and new hires. Subsequently, to overcome several shortcomings of the available data, like stationarity issues and a lack of information about non-registered vacancies, I complement the model with a recession and a time trend variable. In the first step of model construction, I apply a pooled ordinary least squares (pooled OLS) estimation. This model is used as a reference for previous studies, such as those of Fahr and Sunde (2004) or Stops and Mazzoni (2010). This estimator is based on two further important assumptions: (i) equality of the matching function parameters across all occupational groups and (ii) the stationarity of the time series used. In the second step of the estimation, I relax the

15 For example, consider occupational group 63, “technical specialist”, in table 2.7 in appendix 2.A.3. This group is assigned to “Miner/chemical occupations”; “Glass, ceramic, paper production”; and “Construction”.

assumption of equality of the intercept by applying a fixed effects (FE) estimator. Finally, I relax assumption (ii) by applying a pooled mean-group model, which is an approach that was introduced by Pesaran et al. (1999, S. 623).

2.4.3 Pooled OLS and FE estimators

The pooled OLS and FE models can be expressed, respectively, using the following regression equation with additional control variables and i.i.d. error terms $\varepsilon_{i,t}$:

$$\begin{aligned} \log M_{i,t} = A_i + \beta_U \log U_{i,t} + \beta_V \log V_{i,t} + \gamma_U \log U_{is,t} + \gamma_V \log V_{is,t} + \ldots \\ \ldots + \omega t + \zeta GDP_{cyc,t} + \epsilon_{i,t} \end{aligned} \tag{2.6}$$

In accordance with the literature (LeSage and Pace, 2009, p. 180), β_V and β_U can be interpreted as direct effects on the number of matches, and γ_V and γ_U can be interpreted as indirect effects (of the average number of unemployed workers in similar occupational groups) on the number of matches. With respect to the field of labour market theory, it is important not only to compare the impacts of vacancies and unemployed workers on the matching process but also to analyse returns to scale in terms of the sum of the matching elasticities. LeSage and Pace (2009, pp. 34) demonstrate that for the simple case of models with cross-sectional dependence regressors ("SLX" models), such as those presented in this paper, the (average) total elasticity is simply the sum of the (direct) elasticities, β_V and β_U, and the indirect elasticities, γ_V and γ_U. Therefore, to analyse the returns to scale of the estimated matching functions, I provide a Wald test with the null hypothesis that the sum of all direct and indirect elasticities is unity[16]. Among others, Berman (1997) argues that (monthly) numbers of the unemployed and vacancies are reduced by every hiring, eventually producing a downward bias in the estimated elasticities. Several studies for different countries based on elasticity estimations without restrictions on returns to scale empirically confirm this conjecture (see, e.g., Burda and Wyplosz, 1994; Fahr and Sunde, 2004; Stops and Mazzoni, 2010). In fact, in this paper, a further potential source of underestimated elasticities is addressed, namely, the omission of job searchers and vacancies in similar occupational groups.

In the pooled OLS version of the model, the "augmented" productivity coefficient A_i is equal across the occupational groups, whereas the value of this coefficient may vary in the FE version of the model. Furthermore, the model contains a trend coefficient, ω, that may be interpreted as an indicator of the average development of matching productivity during the observation period.

16 H_0: $\beta_U + \beta_V + \gamma_U + \gamma_V = 1$ vs. H_a: $\beta_U + \beta_V + \gamma_U + \gamma_V \neq 1$

Table 2.2: The results for the matching equation

dep. variable	(1) $\log M$ Pooled OLS i	(2) $\log M$ Pooled OLS ii	(3) $\log M$ FE i	(4) $\log M$ FE ii	(5) $\Delta\log M$ PMG i	(6) $\Delta\log M$ PMG ii
β_U	0.440***	0.458***	0.192**	0.189***	0.411***	0.493***
	(0.025)	(0.022)	(0.080)	(0.071)	(0.045)	(0.038)
β_V	0.389***	0.377***	0.210***	0.236***	0.238***	0.255***
	(0.020)	(0.017)	(0.049)	(0.041)	(0.027)	(0.019)
γ_U	0.187***		-0.014		0.358***	
	(0.038)		(0.076)		(0.075)	
γ_V	-0.059		0.077		0.133***	
	(0.036)		(0.066)		(0.039)	
Trend	-0.013***	-0.012***	-0.010***	-0.008**	-0.044***	-0.032***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
GDP_{cyc}	4.746***	2.932**	1.658***	2.248***	12.212***	9.757***
	(1.243)	(1.198)	(0.500)	(0.807)	(1.419)	(1.139)
φ					-0.240***	-0.263***
					(0.020)	(0.023)
Constant	2.218***	3.552***	6.725***	7.002***	0.130***	1.112***
	(0.276)	(0.127)	(0.967)	(0.760)	(0.016)	(0.089)
Observations	2,106	2,106	2,106	2,106	1,944	1,944
log-likelihood	-1,747	-1,770	-303.3	-311.1	1,874	1,865
AIC	3,507	3,549	618.6	630.2	-3,721	-3,708
BIC	3,547	3,578	652.5	652.8	-3,649	-3,647
Wald test (Prob > F) H(0): constant returns to scale	0.132	0.000	0.000	0.000	0.086	0.000
Wald test (Prob > χ^2) H(0): γ_U and γ_V are simultaneously zero	0.000		0.503		0.000	

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

Notes: (1) Pooled OLS and FE model: Robust standard errors in parentheses. Akaikes Information Criteria (AIC), Bayesian Information Criteria (BIC) on the base of the log-likelihood derived by the estimation results.
(3) FE and PMG model: Constant = average of fixed effects
(4) PMG model: Short-run coefficients are not reported here; further results can be found in table 2.3. Akaikes Information Criteria (AIC), Bayesian Information Criteria (BIC) on the base of the log-likelihood.

Note that the observable numbers of vacancies and unemployed are proxies for all job searchers and vacancies in the labour market. The use of these proxies could produce biased estimates (Broersma and Ours, 1999; Anderson and Burgess, 2000; Fahr and Sunde, 2005; Sunde, 2007). Therefore, Anderson and Burgess (2000) propose interpreting the empirical matching elasticities as quantities obtained from a "reduced" model. However, the total number of vacancies might be found if the ratios of observable vacancies[17] to total vacancies were known. These ratios are occasionally

17 These observable vacancies are those registered by the Federal Employment Service; employers are not obliged to register vacancies.

reported (Heckmann et al., 2009), but data for the entire observation period are not available. However, Franz (2006) reports that these ratios exhibit partially counter-cyclical characteristics. This finding can be used to obtain the unbiased coefficient of the matching elasticity of vacancies. Therefore, I complement the model by incorporating the cyclical component of the logarithm of German real gross domestic product GDP_{cyc} calculated using the Hodrick-Prescott filter (Hodrick and Prescott, 1997)[18]. In accordance with the work of Franz (2006), the coefficient of the GDP_{cyc} is expected to be positive.

In columns (1) to (4) of table 2.2, I present the results for the pooled OLS and FE models including one version of each model containing cross-sectional lags of exogenous regressors and one version of each model that does not include these lags to allow comparisons between those specifications.

Robust standard errors are calculated in accordance with Huber and White. Information criteria are reported, including the Akaike information criterion (AIC, Akaike, 1974) and the Bayesian information criterion (BIC, Schwarz, 1978). According to the AIC and BIC, models with the cross-sectional lags of the exogenous regressors should be preferred over models without such lags.

The matching elasticities of the unemployed workers and vacancies are significantly positive in all variations of the model; however, these elasticities are rather small in the FE models. The positive coefficient of the cyclical component of the real GDP and the negative parameter of the trend are robust for all of the models except for the pooled OLS estimation.

The parameters measuring the impact of the unemployed from other occupational groups, γ_U, are significant, positive, and robust in the pooled OLS model but not in the FE model, in which γ_U is small and insignificant. The coefficients measuring the impact of vacancies in other occupational groups, γ_U, are also quite small and insignificant in both the pooled OLS model and the FE model.[19] Accordingly, the null of the Wald test that both coefficients are simultaneously zero must be rejected for the pooled OLS model but not for the FE model. The results of the pooled OLS estimations indicate a positive relationship between new hires in an occupational group and unemployed workers in similar occupational groups. There is no robust indication that vacancies in similar occupational groups have an impact. The FE model does not reveal any impact from vacancies and unemployed in similar occupational groups. Moreover, the null of the Wald test for constant returns to scale must be rejected for all of the variants of the Pooled OLS and FE models.

18 Detailed considerations are provided in appendix 2.A.5.

19 Some variations of both models corroborate these results, compare with tables 2.11 and 2.12 in appendix 2.A.6.

2.4.4 Stationarity and the pooled mean-group model

The properties of the panel variables used are important to ensure that the correct estimator is applied. Blanchard and Diamond (1989, pp. 55) report the results of augmented Dickey-Fuller tests that reject the null of non-stationarity. However, these researchers could not show the existence of cointegration in the observed data. Entorf (1998, p. 79) confirmed that unit roots are seldom found in panel time series for certain metrics such as new hires, vacancies and unemployed workers. Fahr and Sunde (2004) use a stationarity test of Hadri (2000) with a null of stationarity and find that the null could not be rejected for their data. Stops and Mazzoni (2010) employ the same test for similar data with more observation timepoints and demonstrate that the null must be rejected.

I apply the same test and the results indicate again that the assumption of stationarity should not be maintained. The null of stationarity must therefore be rejected for all time series of new hires, vacancies, and unemployed workers. By contrast, the null could not be rejected for the first-order difference series because of the possibility of homoscedastic standard errors[20]. Thus, the time series are likely to be integrated of order 1. Furthermore, from a theoretical perspective, there is a long-run linear relationship between the logarithm of new hires and both unemployed workers and vacancies, and it can be reasonably assumed that these variables are co-integrated. Therefore, I apply the pooled mean-group model (PMG) proposed by Pesaran et al. (1999). The basis of the PMG estimator is an autoregressive distributive lag (l, q_1, q_2, ..., q_k) model (ARDL model) with $q = q_1 = q_2 = \ldots = q_k$. This model is reparameterized in a error correction form. In this study, I use a reparameterized ARDL(1,1,1) model as follows:

$$\begin{aligned}\Delta\log M_{i,t} = \phi_i[\log M_{i,t-1} - (\beta_U \log U_{i,t} + \beta_V \log V_{i,t} + \ldots \\ \ldots + \gamma_U \log U_{is,t} + \gamma_V \log V_{is,t})] + \delta_i^U \Delta\log U_{i,t} + \delta_i^V \Delta V_{i,t} + A_i + \epsilon_{i,t}\end{aligned} \tag{2.7}$$

In addition to the pooled OLS and FE estimators, the following variables are now implemented:

- $\Delta\log M_{i,t}$ are the first-order backward differences of the logarithm of the flow in employment,
- $\Delta\log U_{i,t}$ and $\Delta\log V_{i,t}$ are the first-order backward differences of the logarithm of unemployed persons and vacancies, and
- δ_i^U and δ_i^V are the regression coefficients of these differences.

20 This conclusion is also true with respect to heteroscedasticity of the residuals, with an exception for unemployed workers at a significance level of 10 per cent. Please compare the results in table 2.13 in appendix 2.A.7.

There is an adjustment process for $\log M_{i,t}$; the error-correction term φ_i on the right-hand side of equation (2.40) denotes the speed of adjustment, whereas the term in the square brackets represents deviations from the long-run equilibrium. If φ_i is equal to the null, then there is no long-run equilibrium between the dependent and independent variables. A significant negative parameter indicates that the variables tend to a long-run steady state.

The PMG estimator includes the FE and short-run dynamics of the variables for each occupational group i and requires the long-term coefficients to be equal across all occupational groups i. The PMG model in equation (2.40) is non-linear in its parameters φ_i and (β_U, β_V). Therefore, a maximum likelihood estimator is applied (Pesaran et al., 1999, p. 465).[21] Columns (5) and (6) of table 2.2 presents the results for the long-run coefficients and the averaged error-correction term for two variations of the model, one version with cross-sectional lags of the exogenous regressors and one version without. In addition, for these two models, the null hypothesis of the Wald test, stating that γ_U and γ_V are simultaneously equal to zero, must be rejected. Given the information criteria examined, the model with the cross-sectional lags of regressors should be preferred to the model without such lags. Table 2.3 contains all the results of the model including the following (additional) covariables: the lagged first-order difference of new hires, $\varsigma_1^{\Delta M_{-1}}$; variations in te trend, ω; the cyclical component of the real gross domestic product GDP_{cyc}, and the cross sectional regressors as long-term parameters in the error-correction term.

The long-run elasticities of vacancies and unemployed workers, the exogenous regressors, the cyclical component of real GDP, and the trend can be found in the upper part of table 2.3. At the bottom of the table, the following quantities appear: the error-correction term φ, the averages of the estimated short-term parameters for each occupational group and the average fixed effect A (denoted as *Constant*, Pesaran et al., 1999, p. 626).

The error-correction term φ is significant and negative for all variants of the model. This result indicates the existence of movements against deviations from the long-run equilibrium and therefore implies the existence of stable relationships between matches and both unemployed workers and vacancies.

21 See appendix 2.A.8.

Table 2.3: The results of the PMG estimations that use $\Delta \log M$ as the dependent variable

	(1) PMG 1	(2) PMG 2	(3) PMG 3	(4) PMG 4	(5) PMG 5	(6) PMG 6
		Long-run coefficients				
β_U	0.411***	0.420***	0.500***	0.493***	0.381***	0.680***
	(0.045)	(0.044)	(0.039)	(0.038)	(0.030)	(0.055)
β_V	0.238***	0.282***	0.211***	0.255***	0.296***	-0.036
	(0.027)	(0.021)	(0.025)	(0.019)	(0.017)	(0.033)
γ_U	0.358***	0.306***			0.026	-0.359***
	(0.075)	(0.072)			(0.044)	(0.073)
γ_V	0.133***		0.072**		0.053**	0.017
	(0.039)		(0.032)		(0.025)	(0.043)
Trend	-0.044***	-0.039***	-0.033***	-0.032***	-0.028***	
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	
GDP_{cyc}	12.212***	11.971***	10.444***	9.757***		15.494***
	(1.419)	(1.387)	(1.189)	(1.139)		(1.934)
φ	-0.240***	-0.244***	-0.257***	-0.263***	-0.329***	-0.180***
	(0.020)	(0.021)	(0.022)	(0.023)	(0.035)	(0.015)
		Short-run coefficients				
$\varsigma_1^{\Delta M-1}$	-0.107***	-0.097***	-0.096***	-0.088***	-0.040	-0.095***
	(0.022)	(0.022)	(0.023)	(0.023)	(0.025)	(0.024)
$\delta_0^{\Delta U}$	-0.172***	-0.180***	-0.171***	-0.180***	-0.226***	-0.079***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.034)	(0.028)
$\delta_{-1}^{\Delta U}$	-0.061***	-0.065***	-0.055**	-0.058**	-0.065***	0.002
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
$\delta_0^{\Delta V}$	0.044***	0.043***	0.051***	0.046***	0.024	0.118***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)	(0.015)
$\delta_{-1}^{\Delta V}$	0.040***	0.041***	0.046***	0.044***	0.040**	0.103***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.012)
Constant	0.130***	0.416***	1.004***	1.112***	1.398***	1.346***
	(0.016)	(0.030)	(0.077)	(0.089)	(0.144)	(0.105)
Observations	1,944	1,944	1,944	1,944	1,944	1,944
log-likelihood	1,874	1,870	1,867	1,865	1,826	1,789
AIC	-3,721	-3,716	-3,709	-3,708	-3,628	-3,554
BIC	-3,649	-3,649	-3,642	-3,647	-3,561	-3,487
Wald test (Prob > F)	0.0857	0.906	0.000	0.000	0.000	0.000
H(0): constant returns to scale						

Standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1
Constant = average of fixed effects.

The long-term coefficients β_U, β_V, γ_U, γ_V and GDP_{cyk} are positive, and the trend T is negative and significantly different from zero; the latter result implies that, on average, the augmented matching productivity decreased during the observation period. These results are robust for all estimated model variations[22]. The impact of unemployed workers on matches is larger than the impact of vacancies, even after accounting for the 95%-confidence intervals of β_V and β_U. This finding is in accordance with other studies for Germany (Stops and Mazzoni, 2010; Fahr and Sunde, 2004; Burda and Wyplosz, 1994). The indirect effects of unemployed and vacancies in similar occupational groups (γ_U, γ_V) are each smaller than the direct impacts of their counterparts (β_U, β_V). This implies for each occupational group that changes in the number of unemployed or vacancies in the same occupational group have a greater impact on new hires in that occupational group than do changes in the number of unemployed or vacancies in similar occupational groups.[23] For all of the examined model variations, there is a significant positive relationship between changes in the number of new hires and changes in the number of vacancies, in addition a significant negative relationship between changes in the number of new hires and changes in the number of unemployed workers.

The positive relationships between new hires in an occupational group and vacancies and unemployed workers in similar occupational groups have important implications for estimations of the matching efficiencies of unemployed workers and vacancies. In particular, this result indicates that these efficiencies are determined not only by the numbers of unemployed workers and vacancies in the same occupational group but also by the numbers of unemployed workers and vacancies in similar occupational groups.

2.5 Conclusions

This paper analyses matching processes in occupational labour markets in terms of classes of jobs that share commonalities in required qualifications and tasks. All previous studies in this field have been based on the assumption that job search and job matching processes occur separately in each occupational labour

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22 There is one exception γ_U takes a negative sign after excluding the trend T. However, this model specification would at least preferred according to the information criteria reported.

23 At this stage, it may be beneficial to enquire about the empirical impact of changes in non-similar occupational groups, and it may be expected that there is no impact. However, such a direct falsification test appears to be inadequate because the resulting estimates may partially reveal only common trends or shocks to the single occupational unemployment and vacancy time series. Furthermore, the results should instead be interpreted as correlations rather than elasticities, because the utilized weight matrices of non-similar occupational groups are neither theoretically nor empirically based. Considering that I provide an indirect falsification test that utilizes the same model framework but compares shock-adjusted correlations of the unemployed and vacancies in similar occupational groups and new hires with those of randomly selected non-similar occupational groups. The results show that the estimated correlations for the empirically based selection of similar occupational groups are higher than those for the non-similar occupational groups. Details can be found in appendix 2.A.9.

market, but this assumption is theoretically and empirically unreasonable. From the perspectives of both potential workers and employers, optimal search intensities in each occupational labour market are weighted against the expected gains and costs of searching, the latter of whom could be the (additional) financial burden of the training that is required for a change from one occupation to another. Therefore, workers who are prepared to work in a certain occupation may decide to search for a job in other occupations if the resulting search costs are not too high relative to the expected gains; similarly, firms with vacancies in a certain occupation may decide to search for workers currently in other occupations, if such workers might be viable alternatives. This reasoning implies that the processes of job search and matching occur not only in each occupational labour market but also across certain occupational labour markets. I support this prediction through observations of occupational changes that are obtained from German microdata.

I argue that these findings have important implications for estimating the macroeconomic matching function because an explanation of matches (in terms of new hires) in a given occupation requires consideration not only of vacancies and unemployed workers in the occupation of interest but also vacancies and unemployed workers in other relevant occupations. I use information regarding similarities of occupational groups with respect to their capacities to function as alternatives in the processes of worker and job search to construct an "occupational topology". Based on this topology, it is possible to calculate, for each occupational group, average vacancies and unemployed in similar occupations. Finally, I estimate an augmented matching function using pooled ordinary least squares, fixed effects and pooled mean-group models that include cross-sectional dependency lags of regressors in terms of vacancies and unemployed workers in similar occupational groups.

The results of this study indicate considerable dependencies between similar occupational groups in the matching process. I show that there are significant and positive matching elasticities of vacancies and unemployed in similar occupational groups, which is a finding that has important implications for estimating the matching elasticities of unemployed workers and vacancies; such elasticities are determined not only by the number of unemployed workers and vacancies in the occupational group of interest but also by the number of unemployed workers and vacancies in other occupational groups. Furthermore, the results reveal that returns to scale that are implied by the estimation results for the pooled mean-group model – which considers cross-sectional dependency – are constant on a significance level of 5 per cent. In sum, the findings of this study suggest that an augmented empirical matching function that considers job and worker searches across different occupational labour markets should be employed to obtain unbiased elasticity estimates.

2.A Appendix to chapter 2

2.A.1 Observing occupational changes in administrative data

I use the SIAB data set[24] to count the flows of either unemployment or employment in one occupational group to employment in other occupational groups. To obtain this count, certain restrictions must be employed. (1) The first observed employment sequence of every individual is not considered because no information about the (unobserved) employment status and any related occupation of the individual is available prior to the first observation. Therefore, I disregard these initial employment sequences in this study. (2) Cases of flows from unemployment to employment are treated as flows in employment with an occupational change if the occupation of the employment sequence before the unemployment period differs from the occupation in the employment sequence after unemployment. These flows are treated as flows in employment without an occupational change if the occupation for the employment sequence prior to the unemployment period is the same as the occupation for the employment that occurred after the unemployment period. If there was no employment sequence prior to the unemployment period, then the flow from unemployment to subsequent employment is not considered by this study. The results of this study demonstrate that the averaged percentages of all flows in employment with occupational changes ranged from 16 per cent (forester and huntsman) to 75 per cent (polymer processor; see table 2.4).

24 See section 2.3 for further details.

Table 2.4: Percentages of flows in employment with occupational changes on all flows

Code (KldB 88)		Percentages of flows in employment with change of occupation (1982–2007)		
		average	min.	max.
1	farmer, fisher	0.48	0.36	0.67
3	agricultural administrator	0.60	0.36	0.83
4	helper in the agricultural sector, agricultural workers, stockbreeding professions	0.56	0.46	0.66
5	gardener, florist	0.38	0.31	0.47
6	forester and huntsman	0.16	0.10	0.41
7	miner and related professions	0.21	0.07	0.50
8	exhauster of mineral resources	0.34	0.26	0.54
9	mineral rehasher, mineral burner	0.56	0.33	1.00
10	stone processor	0.30	0.20	0.45
11	producer of building materials	0.40	0.24	0.59
12	ceramicist, glazier	0.68	0.41	0.79
13	glazier, glass processor, glass refiner	0.68	0.17	0.89
14	chemical worker	0.66	0.30	0.83
15	polymer processor	0.75	0.37	0.86
16	paper producer	0.73	0.56	0.84
17	printer	0.49	0.36	0.60
18	woodworker, wood processor	0.57	0.40	0.77
19	metal worker	0.63	0.36	0.87
20	moulder, caster, semi-metal cleaner	0.71	0.49	0.84
21	metal press workers, metal formers	0.72	0.53	0.85
22	turner, cutter, driller, metal polisher	0.54	0.39	0.66
23	metal burnisher, galvanizer, enameler	0.71	0.54	0.89
24	welder, solderer, riveter, metal gluter	0.54	0.41	0.65
25	steel smith, copper smith	0.69	0.54	0.91
26	plumber, plant locksmith	0.36	0.28	0.45
27	locksmith, fitter	0.47	0.37	0.57
28	mechanic	0.42	0.34	0.53
29	toolmaker	0.49	0.34	0.64
30	metal precision-workers, orthodontists, opticians	0.27	0.16	0.41
31	electricians	0.30	0.23	0.39
32	assemblers and metal related professions	0.74	0.60	0.82
33	spinner, ropemaker	0.63	0.25	0.85
34	weaver, other textile producer	0.55	0.21	0.78
35	tailor, sewer	0.40	0.28	0.58
36	textile dyer	0.64	0.39	0.81
37	leather and fur manufacturers, shoemaker	0.48	0.33	0.63
39	baker, confectioner	0.36	0.26	0.49
40	butcher, fishworkmansip and related	0.39	0.27	0.52
41	cooks, convenience food preparatory	0.45	0.39	0.53
42	brewer, manufacturer for tobacco products	0.65	0.45	0.75
43	milk/fat processor, nutriments producer	0.65	0.45	0.78

Code (KldB 88)		Percentages of flows in employment with change of occupation (1982–2007)		
		average	min.	max.
44	bricklayer, concrete builder	0.26	0.18	0.36
45	carpenter, roofer, spiderman	0.34	0.24	0.45
46	road/track constructors, demolisher, culture structurer	0.42	0.28	0.55
47	helper in the construction sector	0.60	0.48	0.68
48	plasterer, tiler, glazier, screedlayer	0.41	0.27	0.55
49	interior designer, furniture supplier	0.56	0.38	0.68
50	joiner, modeler, cartwright	0.36	0.26	0.43
51	painter, varnisher and related professions	0.27	0.20	0.39
52	goods tester, consignment professions	0.74	0.63	0.80
53	unskilled worker	0.72	0.60	0.86
54	machinist and related professions	0.42	0.28	0.63
60	engineer, architect	0.41	0.37	0.46
61	chemist, physicist	0.52	0.36	0.64
62	technician	0.47	0.39	0.56
63	technical specialist	0.39	0.28	0.51
68	merchandise manager	0.41	0.35	0.50
69	banking professional, insurance merchant	0.32	0.21	0.42
70	merchant/specialist in conveyance, tourism, other services	0.55	0.46	0.65
71	conductor, driver, motorist	0.38	0.27	0.46
72	navigator, ship engineer, water/air traffic professions	0.25	0.14	0.42
73	mail distributer	0.61	0.40	0.75
74	storekeeper, worker in storage and transport	0.68	0.60	0.73
75	manager, consultant, accountant	0.52	0.47	0.56
76	member of parliament, association manager	0.69	0.57	0.77
77	accounting clerk, cashier, data processing expert	0.54	0.45	0.61
78	clerk, typist, secretary	0.38	0.32	0.45
79	plant security, guard, gate keeper, servant	0.65	0.55	0.76
80	other security related professions, health caring professions	0.44	0.26	0.64
81	law related professions	0.63	0.52	0.81
82	publicist, translator, librarian	0.51	0.43	0.60
83	artist and related professions	0.34	0.20	0.46
84	physician, dentist, apothecaries	0.23	0.11	0.41
85	nurse, helper in nursing, receptionist and related	0.27	0.23	0.35
86	social worker, care taker	0.35	0.29	0.42
87	professor, teacher	0.53	0.36	0.62
88	scientist	0.65	0.52	0.73
89	helper for cure of souls and cult	0.66	0.47	0.83
90	beauty culture	0.20	0.14	0.30
91	guest assistant, steward, barkeeper	0.46	0.38	0.62
92	domestic economy, housekeeping	0.61	0.56	0.72
93	cleaning industry related professions	0.54	0.43	0.64
	Total	0.50	0.07	1.00

Source: SIAB 1975–2008. Own calculations.

2.A.2 Theoretical model

Job search and matching on non-separated occupational labour markets

The following paragraphs are based on the work of Burda and Profit (1996), which provide a spatial extension of the "bulletin board" matching process model that was conceived by Hall (1979) and Pissarides (1979). Although I use the structure of this model, its interpretation is modified to apply to the context of the current study.

Assume an economy with J occupational labour markets, which are denoted by $j = 1, \ldots, J$. There are U_j identical unemployed job searchers in each occupational labour market and V_j identical firms, each of which is searching for one worker in occupation j. All of the prospective workers reach decisions about their search intensity in two separate dimensions. Assuming that these workers choose to engage in a search for employment, they can decide to search in more than one occupational group, and they fix the number of jobs that they apply for in each occupation. In accordance with Burda and Profit (1996), I assume that the return on an effective search in terms of the wage w is equal over all potential occupations. An application or a job interview costs $c + a_u D_{ij}$ and can be regarded as a random draw. The terms c and a_u are constants, and D_{ij} is a measure for the dissimilarity of the occupations i and j[25]. Thus, D_{ij} refers to the capacity of occupations to be alternatives to each other in the search and matching process. The term $a_u D_{ij}$ denotes additional costs for job searches in other occupational groups. These costs result from the financial burden of the additional training that would be required to change from one occupation to another. Generally, these costs will be greater for occupations that are less similar to each other.

The job searchers decide on their search intensities for each occupation, which can be denoted by their optimal number of job interviews N^*_{ij} in occupation j. To keep the model simple, workers' search costs are assumed to be relatively small. This assumption implies that income effects from searches for jobs in other similar occupations can be ignored. Therefore, optimal search intensities can be analysed within each occupation j. The probability of obtaining a job after an interview within occupation j is provided by p_j for each occupation $j = 1, \ldots, J$. The job searcher is assumed to maximise the (net) utility of the job search, which is equal to the difference between the revenue from the job search and the costs of this search:

25 Because every pair of occupations is separated by a certain distance D_{ij}, the model allows for the implementation of a continuous distance measure or a contiguity measure as well, as I use it in section 2.2.

$$\max_{N_{ij}} \{[1-(1-p_j)^{N_{ij}}]\frac{w}{r} - N_{ij}(c + a_u D_{ij})\} \tag{2.8}$$

In the above equation, $\{[1 - (1 - p_j)^{N_{ij}}]w/r\}$ denotes the expected revenue to a job searcher who is currently in occupation i from realising N_{ij} interviews in occupation j, given p_j, the probability of obtaining a job, and the assumption that a worker cannot hold more than one job at any given time. I also assume that the expected income of unemployment is zero. It can be shown that the first-order condition of the optimisation problem in (2.8) can be expressed as follows:

$$-(1-p_j)^{N_{ij}} \ln(1-p_j)\frac{w}{r} - (c + a_u D_{ij}) = 0 \tag{2.9}$$

with the following solution:

$$N_{ij}^* = \frac{1}{\ln(1-p_j)} \ln(-\frac{c + a_u D_{ij}}{\frac{w}{r}\ln(1-p_j)}) \tag{2.10}$$

For small p_j, I obtain the following approximation:

$$N_{ij}^* = \begin{cases} \frac{1}{p_j}\ln(\frac{(w/r)p_j}{c+a_u D_{ij}}) & \text{for } \frac{w}{r}p_j \geq (c + a_u D_{ij}) \\ 0 & \text{for } \frac{w}{r}p_j < (c + a_u D_{ij}) \end{cases} \tag{2.11}$$

Therefore, optimal job search intensity depends positively on the ratio of the gains to the costs of a particular job search. A higher wage w has positive effects on job search intensity, whereas higher search costs and higher interest rates have negative effects on this intensity. The effects of a change in p_j, the probability of obtaining a job, are not clear; a higher probability leads to higher expected revenues of the job search, but this increased probability also implies that less intensive job searching will be required to obtain a given level of expected benefits. The differentiation of the upper case on the right-hand side of equation (2.11) leads to the following expression:

$$\frac{\partial N_{ij}^*}{\partial p_j} = \frac{1}{p_j^2}(1 - \ln\frac{(w/r)p_j}{c + a_u D_{ij}}) \tag{2.12}$$

Equation (2.12) implies that a higher p_j has negative effects on the optimal search intensity if the expected gain from a job search is significantly larger than the search costs ($(w/r)p_j >> c + a_u D_{ij}$). Given the assumption of low search costs, an increase of p_j will, cet. par., reduce the search intensity. Furthermore, the optimal choice of search intensity determines the range of the job search. Because the job search intensity must be positive, a maximum measure of similarity of occupational groups is present; this result can be derived from equation (2.11):

$$D_i^* = \frac{1}{a_u}(\frac{w}{r}p^{max} - c) \text{ with } p^{max} \equiv \sup p_j \tag{2.13}$$

An increasing maximum of the job-finding probabilities over p_j leads to a higher optimal range D_i. Furthermore, this range decreases with increasing dissimilarity costs a_u and increasing search costs c.

In the next step of the analysis, the unconditional job finding probabilities in any occupation can be derived from the optimal number of interviews in occupation j in which job searchers from occupation $i \in 1, ..., J$ have participated. I assume that there is no information exchange between job searchers. Therefore, it is reasonable that certain vacancies could attract many applicants, whereas other vacancies do not attach strong applicant interest. Furthermore, I assume that all vacancies in all occupations $V_j = V$ are known by all job searchers (in other words, a "bulletin board" of potential jobs exists). Consequently, the decision of job searchers in a certain occupation to search in other occupations depends on the competitive contexts among all of the job searchers in that occupation. By defining $U_j \equiv \sum_i P_i N_{ij}{}^* u_i$ as the sum of applications by unemployed workers, I approximately derive the probability that a vacancy will not be considered as follows:

$$\prod_{i=1}^{J}[\prod_{k=1}^{N_{ij}^*}(1 - \frac{1}{V_j - k + 1})]^{u_i} \approx \prod_{i=1}^{J}[\prod_{k=1}^{N_{ij}^*} e]^{-\frac{u_i}{V_j}} = \exp(-\frac{U_j}{V_j}) \tag{2.14}$$

The job finding probability, p_j, can now be derived. This probability will be equal to the ratio of the number of vacancies considered $(V_j - V_j \exp(-\frac{U_j}{V_j}))$ to U_j, the number of applications that were submitted by unemployed workers:

$$p_j = \frac{V_j}{U_j}[1 - \exp(-\frac{U_j}{V_j})] \tag{2.15}$$

Finally, in accordance with Burda and Profit (1996), a matching function that returns the number of flows from unemployment to employment in an occupation i can be formulated:

$$M_i(\mathbf{u},\mathbf{v}) = u_i P_i = u_i[1 - \prod_{j=1}^{J}(1 - p_j)^{N_{ij}^*}] \tag{2.16}$$

In the equation above, $\mathbf{u}$ and $\mathbf{v}$ denote the vectors of the number of unemployed workers and vacancies in each occupation, P_i represents the probability that a job searcher in occupation i will receive at least one job offer. This probability is equal to 1 minus the probability of receiving no job offer from all occupations.

The matching function above relates exits from unemployment to employment in a certain occupation to the labour market situation in every occupation. From an empirical perspective, a problem arises, namely, the optimal search intensity cannot be observed. To address this issue, according to Burda and Profit (1996), this matching function could be addressed in a quasi-reduced form that regards vacancies and wages as given quantities. This approach renders it possible to study the effects of the changes in the number of unemployed workers and vacancies on the number of matches:

$$\frac{\partial M_i}{\partial u_i} = P_i + u_i \frac{\partial P_i}{\partial u_i} \tag{2.17}$$

$$\frac{\partial M_i}{\partial u_j} = u_i \frac{\partial P_i}{\partial u_j}, \; j \neq i \tag{2.18}$$

$$\frac{\partial M_i}{\partial v_j} = u_i \frac{\partial P_i}{\partial v_j}, \text{ for all } j = 1, \ldots, J \tag{2.19}$$

The first term in equation (2.17) is positive, implying that an increase in the number of unemployed workers in occupation i leads to more matches M_i given a particular (constant) probability P_i. The sign of the second term could be either negative or positive. This term represents the external effect of additional unemployed workers on the job-finding probabilities of workers who are already unemployed in occupation i.

Burda and Profit (1996) showed that, in theory, for the second terms in equations (2.18) and (2.19), both positive and negative external effects are plausible:

$$\frac{\partial P_i}{\partial u_\tau} = \sum_{j=1}^{J} \{ [\frac{N_{ij}^*}{1 - p_j} - \frac{\partial N_{ij}^*}{\partial p_j} \ln(1 - p_j)] \frac{\partial p_j}{\partial u_\tau} \prod_{k=1}^{J} (1 - p_k)^{N_{ik}^*} \} \tag{2.20}$$

Analogously to (2.20), the first derivative of the job-finding probability P_i with respect to the vacancies v_τ is expressed as follows:

$$\frac{\partial P_i}{\partial v_\tau} = \sum_{j=1}^{J} \{ [\frac{N_{ij}^*}{1 - p_j} - \frac{\partial N_{ij}^*}{\partial p_j} \ln(1 - p_j)] \frac{\partial p_j}{\partial v_\tau} \prod_{k=1}^{J} (1 - p_k)^{N_{ik}^*} \} \tag{2.21}$$

The effect on the job-finding probability P_i induced by an increase either in unemployment or in the vacancies in occupation τ results from the weighted average of the effects on the (unconditional) job finding probabilities in all occupations $\partial p_j/\partial u_\tau$. Therefore, these results represent the net effect of variation in p_j for $j=1, ..., J$. A change in p_j directly affects the job-finding probability for unemployed workers in occupation *i* given a search intensity of $[N^*_{ij}/(1-p_j)]\partial p_j/\partial u_\tau$ in a situation involving the variation of u_τ and a search intensity of $[N^*_{ij}/1-p_j)]\partial p_j/\partial v_\tau$ in a situation involving the variation of v_τ. This change indirectly affects the optimal search intensity in all occupations and the employment prospects of the unemployed workers in occupation i, $(\partial N^*_{ij}/\partial p_j)\ln(1-p_j)(\partial p_j/\partial u_\tau)$. Therefore, the sign of $\partial P_i/\partial u_\tau$ in a situation involving a cet. par. change of u_τ depends on the spillover effects, $\partial p_j/\partial u_\tau$, which provide feedback to P_i by affecting search intensity. The same argument holds for $\partial P_i/\partial v_\tau$ in a situation involving a cet. par. change of v_τ and the spillover effects of $\partial p_j/\partial v_\tau$.

This model structure allows for the conditions for positive (or negative) external effects of job searches across different occupations to be defined. The starting point of this model is the total differential of the job-finding probability in equation (2.15) for occupation j.

The matching elasticities of unemployed workers

To obtain a prediction for the matching elasticities of unemployed workers, only the unemployment in occupation τ should be allowed to vary:

$$dp_j = \kappa_j N^*_{\tau j} du_\tau + \kappa_j \sum_{k=1}^{J} (u_k \frac{\partial N^*_{kj}}{\partial p_k}) dp_k \tag{2.22}$$

with

$$\kappa_j \equiv \frac{1}{U_j}[\exp(-\frac{U_j}{V_j}) - p_j] \tag{2.23}$$

In the above equation, as discussed by Burda and Profit (1996), κ_j is assumed to be smaller than zero[26]. The change in the unconditional finding rate dp_j of occupation j reacts to du_τ via two channels. First, for $\kappa_j<0$, there is a negative direct effect due to the dilution of job-finding prospects. The second indirect effect of a change in u_τ results from the shift in the search intensit y of the unemployed who are searching in occupation j; this shift is caused by the implications of the change in

26 Given equation (2.15) for p_j, this assumption holds true for $\frac{U_j}{V_j} > 0.806$, which should represent the real situation in the most occupational labour markets.

u_τ on their job-finding probabilities $p_k(\partial N^*_{kj}/\partial p_k$, for $k = 1, \ldots, J$, including $k = j$). In accordance with equation (2.11), it must be concluded that the optimal search intensity N^*_{kj} for occupation j of an unemployed worker in occupation k depends only on the job-finding probability in occupation j and does not depend on this probability in occupation k, which implies that $\partial N^*_{kj}/\partial p_k = 0$ except for $k = j$[27].

Therefore, equation 2.22 can be simplified to the following form:

$$dp_j = \kappa_j N^*_{\tau j} du_\tau + \kappa_j u_j \frac{\partial N^*_{jj}}{\partial p_j} dp_j \tag{2.24}$$

After several simple transformations, I obtain the following expression:

$$\frac{dp_j}{du_\tau} = \frac{\kappa_j N^*_{\tau j}}{1 - \kappa_j u_j (\partial N^*_{jj}/\partial p_j)} \tag{2.25}$$

The sign of $\partial p_j/\partial u_\tau$ depends on the sign and the absolute value of $\kappa_j u_j (\partial N^*_{jj}/\partial p_j)$. The standard situation in job matching theory is $\partial N^*_{jj}/\partial p_j = 0$. This situation would lead to a negative external effect[28]. According to equation (2.20), the condition of $\partial P_i/\partial u_\tau > 0$, which represents a positive external effect, results in the following range for the elasticity $\eta_{N_{ij},p_j} \equiv (\partial N^*_{ij}/\partial p_j)/(N^*_{ij}/p_j)$:

$$-\frac{1}{1-p_j} < \eta_{N_{ij},p_j} < \frac{p_j}{\kappa_j N^*_{ij} u_j} \tag{2.26}$$

The matching elasticities of vacancies

In contrast to the previous subsection, the number of vacancies in occupation τ should be allowed to vary, cet. par.; in this situation, the total differential of equation (2.15) is as follows:

$$dp_j = -\frac{U_j}{V_j}\kappa_j dv_\tau + \kappa_j \sum_{k=1}^{J} (u_k \frac{\partial N^*_{kj}}{\partial p_k}) dp_k \tag{2.27}$$

Again, κ_j is assumed to be smaller than zero. Analogously to the previous finding, I find once again that a change in the number of vacancies in occupation τ has effects on the job-finding probability via two channels; these effects are different and merit further consideration. In particular, an increase in the vacancy stock

27 This holds only under the strong assumption of small costs and no substitution effects between occupational labour markets, which would be important in the case of budget constraints and income effects. However, a theoretical treatment of this case is left for further research.

28 I obtain the same result if $\partial N^*_{jj}/\partial p_j > 0$. A positive external effect is induced by $\partial N^*_{jj}/\partial p_j > \frac{1}{\kappa_j u_j}$, given κ_j, $\partial N^*_{jj}/\partial p_j < 0$.

produces a direct and positive effect on job-finding probabilities because of the change in the supply of vacancies. The second indirect effect can be ascribed to changes in the optimal search strategy. As discussed above, equation (2.11) implies that $\partial N^*_{kj}/\partial p_k = 0$ except for $k = j$; therefore, equation (2.27) may be simplified as follows:

$$dp_j = -\frac{U_j}{V_j}\kappa_j dv_\tau + \kappa_j u_j \frac{\partial N^*_{jj}}{\partial p_j} dp_j \tag{2.28}$$

allowing me to obtain the following equation:

$$\frac{dp_j}{dv_\tau} = \frac{-\frac{U_j}{V_j}\kappa_j}{1 - \kappa_j u_j (\partial N^*_{jj}/\partial p_j)} \tag{2.29}$$

In either the standard case ($\partial N^*_{jj}/\partial p_j = 0$) or the situation in which $\partial N^*_{jj}/\partial p_j < \frac{1}{\kappa_j u_j}$, given $\kappa_j < 0$, I would obtain a positive external effect. Using equation (2.21), I can derive the condition for $\partial P_i/\partial v_\tau > 0$, which results in the following range for the elasticity η_{N_{ij}, p_j}:

$$-\frac{1}{1-p_j} < \eta_{N_{ij},p_j} < 0 \tag{2.30}$$

Conclusions for the matching elasticities

The absolute values of η_{N_{ij}, p_j} will vary with the similarity of the occupations i and j. In particular, workers will not seek interviews in occupations that are not similar to their original occupation; therefore, the condition above will not hold for all combinations of occupations j and i. In the model mechanisms conceived by Burda and Profit (1996), it can be demonstrated that both positive and negative external effects are conceivable. Within a certain range of η_{N_{ij}, p_j}, the external effects of vacancies and unemployed can both be positive.[29]

29 $-\frac{1}{1-p_j} < \eta_{N_{ij},p_j} < \frac{p_j}{\kappa_j N^*_{ij} u_j}$

2.A.3 Additional information tables

Table 2.5: Occupational groups according to the German occupational classification scheme *(KldB 88)*

Code (KldB 88)	Occupational group
1	farmer, fisher
3	agricultural administrator
4	helper in the agricultural sector, agricultural workers, stockbreeding professions
5	gardener, florist
6	forester and huntsman
7	miner and related professions
8	exhauster of mineral resources
9	mineral rehasher, mineral burner*
10	stone processor
11	producer of building materials
12	ceramicist, glazier
13	glazier, glass processor, glass refiner
14	chemical worker
15	polymer processor
16	paper producer
17	printer
18	woodworker, wood processor
19	metal worker
20	moulder, caster, semi-metal cleaner
21	metal press workers, metal formers
22	turner, cutter, driller, metal polisher
23	metal burnisher, galvanizer, enameler
24	welder, solderer, riveter, metal gluter
25	steel smith, copper smith
26	plumber, plant locksmith
27	locksmith, fitter
28	mechanic
29	toolmaker
30	metal precision-workers, orthodontists, opticians
31	electricians
32	assemblers and metal related professions
33	spinner, ropemaker
34	weaver, other textile producer
35	tailor, sewer
36	textile dyer
37	leather and fur manufacturers, shoemaker
39	baker, confectioner
40	butcher, fishworkmansip and related
41	cooks, convenience food preparatory
42	brewer, manufacturer for tobacco products

Code (KldB 88)	Occupational group
43	milk/fat processor, nutriments producer
44	bricklayer, concrete builder
45	carpenter, roofer, spiderman
46	road/track constructors, demolisher, culture structurer
47	helper in the construction sector
48	plasterer, tiler, glazier, screed layer
49	interior designer, furniture supplier
50	joiner, modeler, cartwright
51	painter, varnisher and related professions
52	goods tester, consignment professions
53	unskilled worker
54	machinist and related professions
60	engineer, architect
61	chemist, physicist
62	technician
63	technical specialist
68	merchandise manager
69	banking professional, insurance merchant
70	merchant/specialist in conveyance, tourism, other services
71	conductor, driver, motorist
72	navigator, ship engineer, water/air traffic professions
73	mail distributer
74	storekeeper, worker in storage and transport
75	manager, consultant, accountant
76	member of parliament, association manager
77	accounting clerk, cashier, data processing expert
78	clerk, typist, secretary
79	plant security, guard, gate keeper, servant
80	other security related professions, health caring professions
81	law related professions
82	publicist, translator, librarian
83	artist and related professions
84	physician, dentist, apothecaries
85	nurse, helper in nursing, receptionist and related
86	social worker, care taker
87	professor, teacher
88	scientist
89	helper for cure of souls and cult
90	beauty culture
91	guest assistant, steward, barkeeper
92	domestic economy, housekeeping
93	cleaning industry related professions

*Note: Occupational group 9 contains some missing values for vacancies. That's why it has to be dropped out for the estimations.

Table 2.6: Assignment of the occupational groups to the occupational section of the employment statistics of the Federal Employment Agency

	Occupational groups in data i = 1, …, 82	Occupational section in employment statistics o = 1, …, 40	Name of the occupational section
1, 3	-5	1	Plant cultivator/stockbreeding/fisher
6		2	Forester/huntsman
7	-9	3	Miner/exhauster of mineral resources
10	-11	4	Stone processor/producer of building materials
12	-13	5	Ceramicist/glazier
14	-15	6	Chemical worker/polymer processor
16		7	Paper producer
17		8	Printer
18		9	Woodworker/wood-processor
19	-24	10	Metal worker
25	-30	11	Locksmith/mechanic
31		12	Electrician
32		13	Assembler/metal-related professions
33	-36	14	Textile-related professions
37		15	Leather and fur manufacturer
39	-43	16	Nutrition-related professions
44	-47	17	Construction-related professions
48	-49	18	Interior designer/furniture supplier/upholsterer
50		19	Carpenter/modeller
51		20	Painter/varnisher/related professions
52		21	Goods tester/consignment professions
53		22	Unskilled worker
54		23	Machinist/related professions
60	-61	24	Engineer/chemist/physicist/mathematician
62		25	Technician
63		26	Technical specialist
68		27	Merchandise manager
69	-70	28	Service merchants
71	-73	29	Transportation-related professions
74		30	Storekeeper/worker in storage and transport
75	-78	31	Organization-/management-/office-related professions
79	-81	32	Security service-related professions
82		33	Publicist/translator/librarian
83		34	Artists and related professions
84	-85	35	Health care-related professions
86	-89	36	Social worker/pedagogue/science careers
90		37	Beauty culture
91		38	Guest assistant/steward/barkeeper
92		39	Domestic economy/housekeeping
93		40	Cleaning industry-related professions

Table 2.7: Assignment of the occupational groups to the occupational segments (Matthes et al., 2008)

Occupational segment Code	Name	Occupational group (KldB 88) Code	Name
101	Agricultural occupations	1	farmer, fisher
		3	agricultural administrator
		4	helper in the agricultural sector, agricultural workers, stockbreeding professions
		5	gardener, florist
		6	forester and huntsman
		42	brewer, manufacturer for tobacco products
201	Miner/chemical occupations	7	miner and related professions
		8	exhauster of mineral resources
		9	mineral rehasher, mineral burner
		14	chemical worker
		15	polymer processor
		46	road/track constructors, demolisher, culture structurer
		54	machinist and related professions
		60	engineer, architect
		62	technician
		63	technical specialist
202	Glass, ceramic, paper producer	11	producer of building materials
		12	ceramicist, glazier
		13	glazier, glass processor, glass refiner
		16	paper producer
		17	printer
		51	painter, varnisher and related professions
		63	technical specialist
		83	artist and related professions
203	Textile, leather producer	33	spinner, ropemaker
		34	weaver, other textile producer
		35	tailor, sewer
		36	textile dyer
		37	leather and fur manufacturers, shoemaker
		54	machinist and related professions
		62	technician
		93	cleaning industry related professions
204	Metal producer	19	metal worker
		20	moulder, caster, semi-metal cleaner
		21	metal press workers, metal formers
		22	turner, cutter, driller, metal polisher
		23	metal burnisher, galvanizer, enameler
		24	welder, solderer, riveter, metal gluter
		25	steel smith, copper smith
		26	plumber, plant locksmith
		27	locksmith, fitter

Occupational segment		Occupational group (KldB 88)	
Code	Name	Code	Name
		28	mechanic
		29	toolmaker
		30	metal precision-workers, orthodontists, opticians
		32	assemblers and metal related professions
		50	joiner, modeler, cartwright
		60	engineer, architect
		62	technician
		68	merchandise manager
205	Electricians	31	electricians
		32	assemblers and metal related professions
		60	engineer, architect
		62	technician
		77	accounting clerk, cashier, data processing expert
206	Wood occupations	18	woodworker, wood processor
		30	metal precision-workers, orthodontists, opticians
		48	plasterer, tiler, glazier, screed layer
		50	joiner, modeler, cartwright
		51	painter, varnisher and related professions
207	Construction occupations	11	producer of building materials
		44	bricklayer, concrete builder
		45	carpenter, roofer, spiderman
		46	road/track constructors, demolisher, culture structurer
		47	helper in the construction sector
		48	plasterer, tiler, glazier, screed layer
		49	interior designer, furniture supplier
		51	painter, varnisher and related professions
		54	machinist and related professions
		60	engineer, architect
		62	technician
		63	technical specialist
		71	conductor, driver, motorist
		83	artist and related professions
301	Hotel/restaurant occupations	39	baker, confectioner
		40	butcher, fishworkmansip and related
		41	cooks, convenience food preparatory
		43	milk/fat processor, nutriments producer
		70	merchant/specialist in conveyance, tourism, other services
		80	other security related professions, health caring professions
		91	guest assistant, steward, barkeeper
		92	domestic economy, housekeeping
		93	cleaning industry related professions

Occupational segment		Occupational group (KldB 88)	
Code	Name	Code	Name
302	Storage/transport occupations	52	goods tester, consignment professions
		70	merchant/specialist in conveyance, tourism, other services
		71	conductor, driver, motorist
		72	navigator, ship engineer, water/air traffic professions
		73	mail distributer
		74	storekeeper, worker in storage and transport
303	Merchandise occupations	68	merchandise manager
		69	banking professional, insurance merchant
		70	merchant/specialist in conveyance, tourism, other services
		77	accounting clerk, cashier, data processing expert
		85	nurse, helper in nursing, receptionist and related
		90	beauty culture
304	White collar worker	70	merchant/specialist in conveyance, tourism, other services
		73	mail distributer
		75	manager, consultant, accountant
		76	member of parliament, association manager
		77	accounting clerk, cashier, data processing expert
		78	clerk, typist, secretary
		81	law related professions
		86	social worker, care taker
		88	scientist
305	Security occupations	60	engineer, architect
		62	technician
		79	plant security, guard, gate keeper, servant
		80	other security related professions, health caring professions
306	Social/care occupations	86	social worker, care taker
		89	helper for cure of souls and cult
307	Medical occupations	85	nurse, helper in nursing, receptionist and related
308	Physicians	84	physician, dentist, apothecaries
309	Teaching professions	87	professor, teacher
310	Artists/Athlets	10	stone processor
		83	artist and related professions
		87	professor, teacher
311	Natural scientists	60	engineer, architect
		61	chemist, physicist
		84	physician, dentist, apothecaries
		88	scientist
312	Humanists	82	publicist, translator, librarian
		88	scientist
999	Unskilled worker	53	unskilled worker

2.A.4 Construction of the occupational segments (in addition to the following subsection, please consult Matthes et al., 2008, pp. 13 ff.)

With the Central Occupational File (Zentrale Berufedatei) – a rich data set with detailed information about occupations and tasks – Matthes et al. (2008) construct occupational segments based on the following criteria: (a) occupational segments must contain job titles that are employment and recruiting substitutes; (b) job titles in different occupational segments must not be employment and recruiting substitutes; and (c) occupational segments must be clearly linked to the 3-digit occupational orders of the German Occupational Classification System 1988 (KldB 88). In the following, I provide more details about the data base and the steps involved in the construction of the occupational segments (Source: Matthes et al., 2008, pp. 13 ff.).

The Central Occupational File (Zentrale Berufedatei) is an administrative expert's data base of the German Federal Employment Agency that contains all professional education titles, job titles, and task titles in Germany that are certified, substantially defined, or comparable. Therefore, it contains all occupations that are based on regulated professional education or advanced training. If a title cannot be linked to regulated training, the experts assess the relevance of the title to the labour market. Titles are considered to be relevant to the labour market if they are explicitly mentioned in collective agreements, if there is a certain number of employees with such title, or if they are subject to specific educational requirements. Thus, one can conclude that the data base contains virtually all job titles used in Germany. Titles are linked to substantial quantities of information, regarding work tasks, work equipment, conditions of work, required qualifications, and regulations. Each title is assigned to "systematic numbers" (*Systematiknummern*) with 7 digits. The first four digits are equivalent to the German occupational classification scheme 88 (KldB 88), and the 5th digit signifies whether the title refers to professional education or to a job. The last two digits are randomly assigned, so that each title has its own "systematic number". The data base contains information about direct employment or placement alternatives for each systematic number. This information is based on an analysis of the skills typically required for a give job title, typical areas of deployment (e.g., customer care), tasks, and particular techniques or required licenses (e.g., languages, IT qualifications, software training). This information is used to compute a preliminary similarity matrix. The matrix is considered to be preliminary because the dimensions are not weighted yet. Thus, similarities might arise when two completely different jobs require identical qualifications. Such similarities might be useful to study aggregate qualification issues but not to study issues related to occupational mobility or job matching, which is the subject matter of this paper. Thus, at the base of the preliminary similarity matrix, data base experts assign jobs of interest a value based on an ordinal scale, using the following criteria:

- Employment and recruiting substitutes for jobs that do not involve initial training (value: 0.95): The competence profiles (skills and experiences) of such job titles are virtually identical (e.g., original job – qualified dental employee; new job – dental assistant).
- Employment and recruiting substitutes for jobs that involve brief initial training (value: 0.90): The competence profiles (skills and experiences) of such job titles are nearly identical; brief industry specific, task specific, or product specific initial training is required (e.g., original job – property assistant; new job – management assistant in real estate).
- Employment and recruiting substitutes for job groups that involve brief initial training (value: 0.85): Employees in such jobs have competencies in a basic qualification or task (e.g., original job – management assistant in retail shoe business; new job – management assistant in retail cosmetics business).
- Employment and recruiting substitutes for parts of job tasks and forms of specialisation of original job with or without initial training (value: 0.75): Such jobs are forms of specialisation or are linked to specific tasks related to the original job. Brief initial training might be necessary (e.g., original job – gardener/cultivator of ornamental plants; new job – cemetery gardener – or – original job – baker; new job – bread-baker).
- Employment and recruiting substitutes for "adjacent" occupations (value: 0.70): Employees have valuable skills and experiences from the original job, and are thus able to perform partial tasks after initial training in certain new jobs (e.g., original job – mason; new job – steel fixer or prefabricated house constructor).
- Employment and recruiting substitutes in lower qualification level (value: 0.65): These are jobs related to original jobs but with a lower qualification level (e.g., origin job – master precision machinist; new job – lathe operator).
- Job titles that do not meet the above criteria are generally assigned to the similarity level of 0.00.

On the basis of these definitions, an additional similarity matrix is computed. An extract of the similarity matrix can be found in table 2.8 for 7-digit job titles within the occupational group of turners (221). The rows specify each job-title and indicate original jobs. The columns specify the same job titles in the same order and indicate the new jobs. The numbers in each cell correspond to the assigned values of the similarity levels.

Table 2.8: Similarity matrix for the occupational order 221 (turners)

Job title	Systematic no. 221 …	-0100	-0102	-0103	-0104	-0105	-0111	-1100	-1101	-1102	-1103	-2101	-2102	-2103	-2104	-2106	-2107	-3100	-4100	-4101	-4102	-5100	-5101	-7100
CNC Turner	-0100	1.00	0.90	0.75	0.00	0.00	0.00	0.90	0.90	0.90	0.90	0.90	0.00	0.00	0.00	0.00	0.00	0.90	0.00	0.00	0.00	0.75	0.00	0.00
Turner (turning)	-0102	0.75	1.00	0.75	0.75	0.00	0.00	0.95	0.90	0.90	0.95	0.70	0.75	0.65	0.00	0.00	0.00	0.75	0.75	0.75	0.75	0.75	0.75	0.00
Engine lathe fitter	-0103	0.90	0.90	1.00	0.90	0.00	0.00	0.90	0.90	0.90	0.90	0.90	0.00	0.00	0.00	0.90	0.90	0.90	0.00	0.00	0.00	0.00	0.00	0.00
Foreman turnery	-0104	0.00	0.90	0.90	1.00	0.00	0.00	0.90	0.90	0.90	0.90	0.90	0.00	0.00	0.00	0.00	0.00	0.90	0.00	0.00	0.00	0.00	0.00	0.00
Machine tool cutter (turning/cutting)	-0105	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Master turner	-0111	0.00	0.65	0.00	0.65	0.00	1.00	0.65	0.00	0.00	0.00	0.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cutting machine operator (turning technology)	-1100	0.75	0.95	0.75	0.75	0.00	0.00	1.00	0.90	0.90	0.95	0.70	0.75	0.65	0.00	0.00	0.00	0.75	0.75	0.75	0.75	0.75	0.75	0.00
Qualified cutting machine operator (turning machines)	-1101	0.75	0.95	0.75	0.75	0.00	0.00	0.95	1.00	0.95	0.95	0.70	0.75	0.65	0.00	0.00	0.00	0.75	0.75	0.75	0.75	0.75	0.75	0.00
Skilled worker for machine tools (turning)	-1102	0.75	0.95	0.75	0.75	0.00	0.00	0.95	0.95	1.00	0.95	0.70	0.75	0.00	0.00	0.00	0.00	0.75	0.75	0.75	0.75	0.75	0.75	0.00
Cutting machine operator	-1103	0.75	0.85	0.75	0.75	0.00	0.00	0.85	0.85	0.85	1.00	0.85	0.75	0.65	0.85	0.85	0.85	0.75	0.75	0.75	0.75	0.75	0.75	0.00
Cutting machine operator (CNC turning technology)	-2101	0.75	0.70	0.75	0.75	0.00	0.00	0.70	0.00	0.00	0.95	1.00	0.75	0.65	0.00	0.90	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Long automatic machine turner	-2102	0.90	0.90	0.00	0.00	0.00	0.00	0.90	0.90	0.90	0.90	0.90	1.00	0.00	0.00	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Turret lathe turner	-2103	0.00	0.00	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.70	1.00	0.00	0.70	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.65
Automatic machine fitter (forming)	-2104	0.75	0.70	0.75	0.75	0.00	0.00	0.70	0.00	0.00	0.95	0.95	0.75	0.65	1.00	0.95	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Qualified cutting machine operator (automatic machine tools)	-2106	0.75	0.70	0.75	0.75	0.00	0.00	0.70	0.00	0.00	0.95	0.95	0.75	0.65	0.00	1.00	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CNC tuning machine fitter	-2107	0.75	0.70	0.75	0.75	0.00	0.00	0.70	0.00	0.00	0.95	0.95	0.75	0.65	0.00	0.95	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Roll turner	-3100	0.75	0.90	0.75	0.75	0.00	0.00	0.95	0.90	0.90	0.90	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.75	0.75	0.00	0.00	0.00	0.00
Turner (screw-cutting lathe)	-4100	0.00	0.90	0.00	0.00	0.00	0.00	0.90	0.90	0.90	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.90	1.00	0.00	0.00	0.00	0.00	0.00
Turner (contouring lathe)	-4101	0.00	0.90	0.00	0.00	0.00	0.00	0.90	0.90	0.90	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.90	0.00	1.00	0.00	0.00	0.00	0.00
Turner (center lathe)	-4102	0.00	0.90	0.00	0.00	0.00	0.00	0.90	0.90	0.90	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.90	0.00	0.00	1.00	0.00	0.00	0.00
Turner (NC vertical turning and boring machine)	-5100	0.90	0.90	0.00	0.00	0.00	0.00	0.90	0.90	0.90	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.95	0.00
Turner (vertical turning and boring machine)	-5101	0.90	0.90	0.00	0.00	0.00	0.00	0.90	0.90	0.90	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.75	1.00	0.00
Helper turning	-7100	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Source: Matthes et al. (2008, p. 16), Central occupational file

Thus, the job title of cutting-machine operator (systematic number 221–2102) has a similarity (ordinal) value level of 0.75 to the CNC turner (221-0100) and 0.85 to turner (221-0102). An employer searching for a turret lathe turner, therefore, could decide to recruit a CNC turning machine fitter because of the relatively high similarity level of 0.90. As a first step, Matthes et al. (2008) used this matrix to calculate the degree of homogeneity within occupational orders (the 3-digit level of the German occupational classification scheme KldB 88) by computing the averages of the similarity levels of each job title on the 7-digit level that belong to those occupational orders[30]. The following examples are illustrative: The degree of homogeneity is 0.370 for turners (221), 1.000 for printer helper (177), 0.019 for "other" production engineers (606), and 0.144 for qualified office employee (781). Compare for the computation table 2.9. In the second step, Matthes et al. (2008) summarized the occupational orders into occupational segments: they construct another similarity matrix of the occupational orders based on degrees of homogeneity. On the main diagonal are degrees of homogeneity for each occupational order. In the other cells are degrees between pairs of occupational orders, calculated as in the first step. Thus, the degree of homogeneity in a given cell refers to both the original occupational order belonging to the i^{th} row and the new occupational order belonging to the j^{th} column.

Table 2.9: Calculation of degrees of (within) homogeneity for various occupational orders

Occupational order		Similarity level								
		1.00	0.95	0.90	0.85	0.75	0.70	0.65	0.00	Sum
Turners (221)	Frequency	23	25	76	8	74	14	13	296	529
	Frequency x Similarity level	23.00	23.75	68.40	6.80	55.50	9.80	8.45	0.00	195.70
		Grade of homogeneity: 195.70/529 = 0.370								
Printer helper (177)	Frequency	1	0	0	0	0	0	0	0	1
	Frequency x Similarity level	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
		Grade of homogeneity: 1.00/1 = 1.000								
Other production engineers (606)	Frequency	125	17	37	23	120	10	0	15293	15625
	Frequency x Similarity level	125.00	16.15	33.30	19.55	90.00	7.00	0.00	0.00	291.00
		Grade of homogeneity: 291.00/15,625 = 0.019								
Qualified office employee (781)	Frequency	17	7	6	0	15	0	2	242	289
	Frequency x Similarity level	17.00	6.65	5.40	0.00	11.25	0.00	1.30	0.00	41.60
		Grade of homogeneity: 41.60/289 = 0.144								

Source: Matthes et al. (2008, p. 17)

30 Thus, Matthes et al. (2008) implicitly assume that the values levels are measured on a cardinal scale. This is not problematic because the averages are used only to compare the degrees of homogeneity of occupational orders. Thus, the decisions described below are based on whether a degree of homogeneity within an occupational order is higher, lower, or equal to others – and not on an assessment of differences of several degrees of homogeneity.

Figure 2.1: Extract of the similarity matrix for the occupational orders

	011	012	021	022	031	032	041	042	043	044	051	052	053	061	062	071	072	...
011	0.326	0.018	0.011		0.044	0.027	0.063	0.022		0.002	0.042	0.003						
012	0.015	0.772			0.025	0.030	0.010											
021	0.016		0.071	0.023	0.039	0.015	0.014	0.045		0.020				0.001				
022			0.028	0.262														
031	0.004				0.195	0.005	0.004											
032	0.012	0.021	0.004		0.038	0.068	0.002				0.000	0.005			0.001			
041	0.050		0.016		0.009	0.008	0.082	0.021		0.002								
042	0.026		0.051		0.038	0.017	0.018	0.663		0.016								
043									–									
044	0.004		0.031		0.007	0.003	0.010	0.036		0.093								
051	0.031					0.005					0.151	0.027	0.005		0.008			
052	0.002				0.007	0.006					0.029	0.136						
053											0.004		0.340					
061			0.001											0.144	0.010			
062						0.004					0.012			0.016	0.229			
071																0.371	0.135	
072																0.128	0.333	
...																		...

Source: Matthes et al. (2008, p. 19)

Figure 2.1 shows an extract of the similarity matrix. Cells coloured in dark grey are cells contain degrees of homogeneity above 0.1. Cells coloured in light grey contain degrees of homogeneity with values between 0.01 and 0.1, and cells coloured in white contain degrees of homogeneity of 0.01 or less. In the third step, occupational order pairs with highest degrees of homogeneity (degrees of homogeneity for 7-digit job titles that are outside the main diagonal of the matrix) and above a certain threshold value are summarized as occupational aggregates. The aim of the procedure is to obtain occupational segments with similar degrees of homogeneity. Therefore, the threshold value is determined as the lowest value of the degree of homogeneity of the 3-digit occupational orders, specifically, 0.019. As one example, the occupational orders of farmers (011) and farm labourers (041) were aggregated because the sum of the degrees of homogeneity outside the diagonal of the matrix has the highest value (0.050 from row [041] and column [011] and 0.063 from row [011] and column [041]; compare with figure 2.1). After aggregation of these occupational orders, the new aggregate has a degree of homogeneity of 0.118 (for computation, see table 2.10). Thus, the grade of homogeneity even exceeds the sum of the individual degrees of homogeneity because there are additional similar 7-digit job titles between these two occupational orders. Thus, there is a new similarity table with the new occupational aggregates, and the third step is repeated until the degrees of homogeneity does not come below the threshold value of 0.019. As noted above, the degrees of homogeneity between pairs of aggregates should be ideally zero. Matthes et al. (2008) defined the following criteria for a sufficient separation of two occupational aggregates: the degree of homogeneity of all 7-digit job titles in one occupational aggregate should be higher than the degree of homogeneity of the 7-digit job titles and 7-digit job titles of the other occupational aggregate.

Table 2.10: Computation of the grade of homogeneity of the occupational orders farmers (011) and farm labourer (041)

Origin occupational order	New occupational order	Similarity levels								
		1.00	0.95	0.90	0.85	0.75	0.70	0.65	0.00	Sum
011	011	17	11	33	3	20	16	13	176	289
011	041	0	0	0	0	22	0	9	326	357
041	041	21	13	3	0	0	0	0	404	441
041	011	0	0	20	0	0	0	0	337	357
Frequencies		38	24	56	3	20	38	22	1,243	1,444
Similarity level x frequency		38.00	22.80	50.40	2.55	31.50	11.20	14.30	0.00	170.75
Grade of homogeneity: 170.75/1,444 = 0.118										

Source: Matthes et al. (2008, p. 20)

If two occupational aggregates do not meet this criterion, i.e., thus if they are not sufficiently separate from one another, they are summarized as one aggregate. For example, the occupational aggregate that could be labelled "metal extractors" (an aggregate that contains rollers (192), casters (202), and farriers (251)) and the aggregate for "metal workers" (turners (221), machine fitters (273), and precision mechanics (284)) do not show a strong separation. Therefore, those aggregates are summarized by the occupational segment "Metal producers".

2.A.5 Real GDP and the proportion of all vacancies that are registered vacancies (in addition to the following subsection, please consult Stops and Mazzoni, 2010)

Only vacancies V can be observed that are registered by the Federal Employment Service. To estimate the matching function, it would be ideal to know of all vacancies V_{ALL}. R_{BA} denotes the proportion of all vacancies V_{ALL} that are composed of registered vacancies V:

$$V = R_{BA} \cdot V_{ALL} \tag{2.31}$$

Employers register their vacancies if they expect that searches for workers via the Federal Employment Service will be successful. During economic booms, the number of registered job searchers decreases. This phenomenon is noticed by firms; therefore, it could be assumed that firms have more negative expectations about their abilities to find staff through the Federal Employment Service during prosperous economic times. In accordance with (vgl. Franz, 2006, S. 107 f.), R_{BA} decreases during economic recovery phases; in other words, this variable is anticyclical. Therefore, the (logarithm of) R_{BA} correlates negatively with the cyclical component of the real gross domestic product (GDP_{cyc}). This component could be interpreted as the deviation of the GDP from its long-term trend. Therefore, GDP_{cyc} is an indicator for the economic situation at a certain time; consequently, the rate R_{BA} could be regarded as a function of GDP_{cyc}:

$$R_{BA} = f(GDP_{cyc}) \tag{2.32}$$

Thus,

$$V = f(GDP_{cyc}) \cdot V_{ALL} \tag{2.33}$$

and after several simple rearrangements, I obtain

$$V_{ALL} = \frac{V}{f(GDP_{cyc})} \tag{2.34}$$

The matching function is specified by the following expression:

$$M = AV_{ALL}^{\beta_V} U^{\beta_U} \tag{2.35}$$

Taking the logarithm of both sides yields

$$\log M = \log A + \beta_V \log V_{ALL} + \beta_U \log U \tag{2.36}$$

The use of equation (2.34) allows this equation to be rewritten as follows:

$$M = \log A + \beta_V [\log V - \log f(GDP_{cyc})] + \beta_U \log U \tag{2.37}$$

The assumption $\log f(GDP_{cyc}) \cong (-\beta_{gdp} GDP_{cyc})$ permits the following simplification:

$$\log M = \log A + \beta_V \log V + \beta_{GDP} GDP_{cyc} + \beta_U \log U \tag{2.38}$$

where $\beta_{GDP} = (-\beta_V) \cdot (-\beta^{gdp})$.

Finally, the assumptions $\beta_V > 0$ and $\beta_{gdp} > 0$ imply that $\beta_{GDP} > 0$

2.A.6 Additional empirical results

The pooled OLS model

Table 2.11: The results of the pooled OLS estimations with $\log M$ as the dependent variable

	(1) Pooled OLS 1	(2) Pooled OLS 2	(3) Pooled OLS 3	(4) Pooled OLS 4	(5) Pooled OLS 5	(6) Pooled OLS 6
β_U	0.440***	0.450***	0.464***	0.458***	0.431***	0.445***
	(0.025)	(0.022)	(0.023)	(0.022)	(0.025)	(0.025)
β_V	0.389***	0.379***	0.370***	0.377***	0.395***	0.385***
	(0.020)	(0.017)	(0.019)	(0.017)	(0.020)	(0.020)
γ_U	0.187***	0.151***			0.158***	0.197***
	(0.038)	(0.027)			(0.036)	(0.038)
γ_V	-0.059		0.043		-0.031	-0.132***
	(0.036)		(0.026)		(0.035)	(0.033)
Trend	-0.013***	-0.015***	-0.014***	-0.012***	-0.013***	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
GDP_{cyc}	4.746***	4.051***	2.622**	2.932**		4.153***
	(1.243)	(1.199)	(1.191)	(1.198)		(1.256)
Constant	2.218***	2.115***	3.226***	3.552***	2.333***	2.480***
	(0.276)	(0.275)	(0.256)	(0.127)	(0.273)	(0.275)
Observations	2,106	2,106	2,106	2,106	2,106	2,106
ll	-1747	-1749	-1768	-1770	-1754	-1770
AIC	3507	3510	3548	3549	3520	3551
BIC	3547	3544	3581	3578	3554	3585
Wald test (Prob > F)	0.132	0.457	0.000	0.000	0.095	0.000
H(0): constant returns to scale						

Robust standard errors in parentheses
*** p < 0.01, ** p < 0.05, *p < 0.1

The fixed effects model

Table 2.12: The results of the fixed effects estimations with log$M$ as the dependent variable

	(1) FE 1	(2) FE 2	(3) FE 3	(4) FE 4	(5) FE 5	(6) FE 6
β_U	0.192**	0.189**	0.189**	0.189***	0.186**	0.218**
	(0.080)	(0.077)	(0.072)	(0.071)	(0.080)	(0.084)
β_V	0.210***	0.236***	0.211***	0.236***	0.212***	0.209***
	(0.049)	(0.041)	(0.048)	(0.041)	(0.049)	(0.048)
γ_U	–0.014	0.002			–0.041	–0.126
	(0.076)	(0.077)			(0.075)	(0.081)
γ_V	0.077		0.076		0.089	0.001
	(0.066)		(0.066)		(0.066)	(0.055)
Trend	–0.010***	–0.008**	–0.010***	–0.008**	–0.010***	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	
GDP_{cyc}	1.658***	2.260***	1.751**	2.248***		1.131**
	(0.500)	(0.707)	(0.696)	(0.807)		(0.505)
Constant	6.725***	6.985***	6.609***	7.002***	6.936***	8.084***
	(0.967)	(0.845)	(0.955)	(0.760)	(0.986)	(0.875)
Observations	2,106	2,106	2,106	2,106	2,106	2,106
Number of groups	81	81	81	81	81	81
ll	–303.3	–311.1	–303.4	–311.1	–306.5	–335.0
AIC	618.6	632.2	616.8	630.2	622.9	679.9
BIC	652.5	660.5	645.0	652.8	651.2	708.2
Wald test (Prob > F)	0.000	0.000	0.000	0.000	0.000	0.000
H(0): constant returns to scale						

Robust standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1 Constant = average of fixed effects

2.A.7 Hadri's LM test

Table 2.13: Results of the LM test by Hadri (2000) for the levels and the first-order differences of the logarithm of time series

Variable	Characteristics of Residuals	Model I (without trend)		Model II (with trend)	
		t-stat	P-value	t-stat	P-value
$log M$	Homoscedasticity	93.390	0.000	30.515	0.000
	Heteroscedasticity	66.107	0.000	34.453	0.000
$log U$	Homoscedasticity	46.723	0.000	44.480	0.000
	Heteroscedasticity	45.825	0.000	38.670	0.000
$log V$	Homoscedasticity	63.112	0.000	47.491	0.000
	Heteroscedasticity	52.905	0.000	42.465	0.000
$\Delta log M$	Homoscedasticity	-4.507	1.000	-6.010	1.000
	Heteroscedasticity	-1.303	0.904	-3.182	0.999
$\Delta log U$	Homoscedasticity	-0.919	0.821	-4.150	1.000
	Heteroscedasticity	7.357	0.000	3.490	0.000
$\Delta log V$	Homoscedasticity	-2.200	0.986	-1.759	0.9607
	Heteroscedasticity	0.483	0.315	1.699	0.045
H(0): Stationarity					

2.A.8 Maximum likelihood estimation

The likelihood equation that is used to estimate the model in equation (2.40) has the following form:[31]

$$l_T(\vartheta', \phi', \sigma') = -\frac{T}{2}\sum_{i=1}^{N} log(2\pi\sigma_i^2) - \frac{1}{2}\sum_{i=1} N\frac{1}{\sigma_i^2}[\Delta \log \mathbf{M_{h,i}} - \phi_i \xi_i(\vartheta)]'\mathbf{H}_i[\Delta \log \mathbf{M}_{h,i} - \phi_i \xi_i(\vartheta)] \quad (2.39)$$

where

$\xi_i(\vartheta)$ = $\log \mathbf{M}_{h,i,-1} - (\log \mathbf{U}_i, \log \mathbf{V}_i)(\beta_U, \beta_V)' - (\log(\mathbf{w}_i\mathbf{U}), \log(\mathbf{w}_i\mathbf{V}))(\gamma_U \mathbf{I}_N, \gamma_V \mathbf{I}_N)'$ with ϑ as the vector of the coefficients

$\mathbf{H}_i$ = $\mathbf{I}_T - \mathbf{L}_i(\mathbf{L}_i' \mathbf{L}_i)\mathbf{L}_i$ for an identity matrix $\mathbf{I}_T$, whereas

$\mathbf{L}_i$ = $(\log \mathbf{M}_{h,i,-1}, \ldots, \log \mathbf{M}_{h,i,-p+1}, \Delta\log\mathbf{U}_i, \Delta\log\mathbf{V}_i, \imath)$

φ = $(\varphi_1, \varphi_2, \ldots, \varphi_N)'$

σ = $(\sigma_1^2, \sigma_2^2, \ldots, \sigma_N^2)'$

The residuals $\xi_i(\vartheta) = \log \mathbf{M}_{h,i,-1} - (\log \mathbf{U}_i, \log \mathbf{V}_i)(\beta_U, \beta_V)' - (\log(\mathbf{w}_i\mathbf{U}), \log(\mathbf{w}_i\mathbf{V}))(\gamma_U \mathbf{I}_N, \gamma_V \mathbf{I}_N)'$ are included in the logarithm of the density function of the normal distribution.

31 The equation is expressed in terms of vectors and matrices (bold letters). Data for different observation times are staggered in the columns of the matrices or in the vectors; therefore, the index t becomes expendable.

2.A.9 Falsification test on the weight matrix

The empirical models utilized capture recessionary shocks through a measure of the cyclical component of real gross domestic product. In addition, the PMG model comprises short term deviations from the long run-trend of the macroeconomic matching function through 1^{st} difference time series of new hires, unemployed and vacancies. Thus, the estimated coefficients are solid measures of the matching elasticities of interest.

My strategy for a falsification test on the empirically based weight matrix is to construct randomly selected weight matrices in which occupational groups that are considered to be non-similar are treated as similar. I restricted the number of similar occupational groups to 11, because this is the average of the number of occupational groups that are similar, according to the occupational segments. This ensures that the sparsity of the randomly selected weight matrices equals the empirically based weight matrix. As consequence, I could theoretically construct $\frac{(81-11)!}{70-11!} \approx 86.374$ trillion different randomly selected weight matrices. I decided to re-estimate the PMG model specification based on 500 different randomly selected weight matrices. Under the assumption that occupational groups are either similar or not similar, the results should reveal no, or at least fewer significant matching elasticities of unemployed and vacancies in non-similar occupational groups.

However, it is not possible to specify exactly the same model because it may be reasonable that including randomly selected non-similar occupational groups in the weight matrix induces "matching elasticities" that are similar to those of the empirical based similar occupational groups. There are two reasons for this:

- First, although I obtain accurate information about similar occupational groups on the basis of the analysis of Matthes et al. (2008), it is not possible to construct a weight matrix that contains only "total" non-similar occupational groups because some of the non-similar occupational groups are somewhat more similar to the observed occupational group than other non-similar occupational groups[32]. Therefore, a somewhat significant impact might remain.
- Second, the observed occupational time series of unemployed and vacancies might be influenced not only by occupation specific determinants but by common shocks caused due to, e.g., institutional changes and other factors. Thus, estimations based on other (randomly) selected matrices than the empirical based weight matrix may reveal shocks that are not occupation specific.

32 Referring to section 2.2, this would correspond to a distance $d < D_{ij} << \infty$.

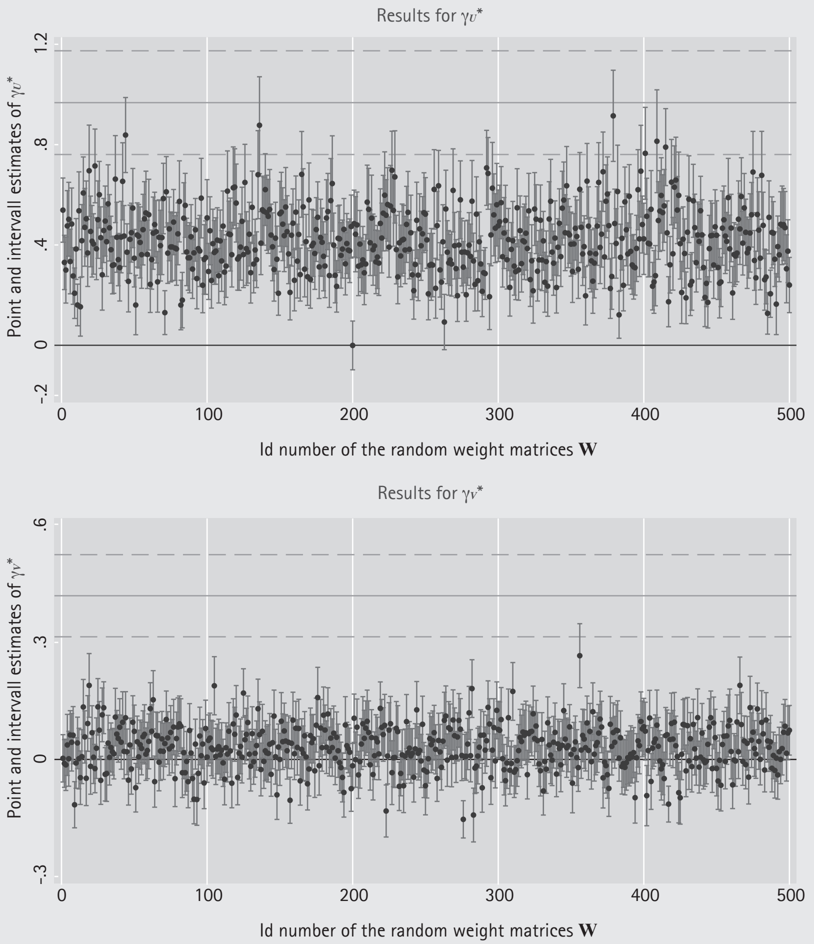
Whereas the model containing similar occupational groups allows me to estimate matching elasticities based on theoretical considerations and empirical evidence, the "matching elasticities" revealed by models containing non-similar occupational groups are spurious correlations. However, it can be shown that the empirically based computed averages of vacancies and unemployed in similar occupational groups have greater effects on new hires than randomly computed averages, if aggregate short term shocks on the occupational time series of unemployed and vacancies can be ruled out, which would isolate the effect of the "pure" occupational component of the times series. Although we have no explicit information about such common shocks, they should clearly influence the aggregate time series. Thus, the information from the aggregate time series can be used to generate a common shock component. This creates an opportunity to measure "matching elasticities" that are adjusted by common shocks other than recessionary shocks and, thus reveal the influence of the "pure" occupational component of the time series. I therefore complement the long-term part of the PMG model with the cyclical components U_{cyc}^{aggr} *and* V_{cyc}^{aggr} of the aggregated unemployed and vacancy times series, which is computed using the Hodrick-Prescott filter. Thus, the PMG model in equation (2.40) is modified to

$$\begin{aligned}\Delta\log M_{i,t} = \phi_i[\log M_{i,t-1} - (\beta_U \log U_{i,t} + \beta_V \log V_{i,t} + \dots \\ \dots + \gamma_U^* \log U_{is,t} + \gamma_V^* \log V_{is,t} + \dots \\ \dots + \psi_U U_{cyc,t}^{aggr} + \psi_V V_{cyc,t}^{aggr})] + \dots \\ \dots + \delta_i^U \Delta\log U_{i,t} + \delta_i^V \Delta V_{i,t} + A_i + \epsilon_{i,t}\end{aligned} \tag{2.40}$$

The "matching elasticities" computed by this model should not be confused with the matching elasticities of interest, as a common component of these measures is the shock coefficient. Thus, I refer to these "matching elasticities" as occupation related correlations γ_U^* and γ_V^*. This strategy should reveal whether occupational groups identified as similar exhibit larger occupational correlations than occupational groups identified as non-similar.

As only the occupational correlations of unemployed γ_U^* and vacancies γ_V^* in the empirically based selection of similar occupational groups with new hires compared to those of randomly selected occupational groups are of interest, I present point and interval estimates for those coefficients in figure 2.2. The horizontal lines in each figure represent the estimations based on the empirical weight matrix. The figures illustrate that the point estimates based on the empirical weight matrix are larger than those based on the randomly selected weight matrices. Indeed, the vast majority of them is significantly smaller. Furthermore, the vast majority of the occupational related correlations of matches and vacancies are not significantly unequal zero. That is not the case for the correlations of matches and unemployed. These results let me finally conclude that the empirically based weight matrix passes the indirect falsification test.

Figure 2.2: Point and 95%-interval estimates of the occupational correlations γ_U^* and γ_V^*



Notes: Estimates are based on the empirical weight matrix and 500 randomly selected weight matrices. The solid horizontal lines mark the point estimates and the dotted lines indicate the 95%-confidence interval estimates of the occupational correlations based on the empirically based weight matrix:
$\gamma_U^* = 0.967$; 95%-confidence interval (lower bound, upper bound): 0.761, 1.174.
$\gamma_V^* = 0.420$; 95%-confidence interval (lower bound, upper bound): 0.314, 0.525.
The dots and the vertical lines mark the point and 95%-interval estimates of the occupational correlations based on randomly selected weight matrices of non-similar occupational groups.

Chapter 3

Revisiting German labour market reform effects – a panel data analysis for occupational labour markets[1]

1 Parts of this chapter are intended to be published in the "IZA Journal of European Labour Studies".

There is an ongoing discussion that centres on the German labour market reforms (2003–2005) and the role of these reforms in boosting the German economy. Considering that one of the main objectives of the reforms was to improve the matching process on the labour market, I use rich, high-frequency, and recent administrative panel data to present new details regarding the development of job-matching performance before, during, and after the reform years. The results show that matching productivity increased during all reform stages and slightly deteriorated in 2009 (the year of the financial crisis), even after controlling for the recession. Furthermore, increases in matching productivity have become smaller in recent years. Beyond these findings, the results show detailed differences in the changes in matching productivity on occupational labour markets.

3.1 Introduction

The tenth anniversary of the German labour market reforms has been accompanied by a lively discussion regarding the contributions of these reforms to the development of the German labour market and the German economy as a whole (Dustmann et al., 2014; Gartner and Fujita, 2014; Krebs and Scheffel, 2013; Rinne and Zimmermann, 2013, 2012; Hertweck and Sigrist, 2012; Burda and Hunt, 2011; Möller, 2010; Fitzenberger, 2009). Whether the results of various studies imply that German labour market policy in the last decade can thus be regarded as a role model for other countries seems to depend on policy makers' expectations for these reforms. In particular, it is debatable whether the reforms were expected to boost the entire German economy and raise its competitiveness. However, it is clear that one of the main objectives of the reforms was explicit in its mandate to improve matching processes on the German labour market (Hartz et al., 2002) because Germany suffered from a high degree of structural unemployment in the early 2000s.

In this paper, I present comprehensive details regarding the development of the jobmatching function and its performance before and after the reforms took effect. The German labour market reforms were implemented in four stages and spanned the period from 2003 to 2005. The laws that were implemented are referred to as Hartz I to Hartz IV and were named after the head of the expert commission that worked out the substantial propositions for the German labour market reforms (Hartz et al., 2002). In January 2003, the first two reform stages were implemented (Hartz I and II). The third stage, Hartz III, followed in January 2004 and the last stage, Hartz IV, was implemented in January 2005. Few studies have shed light on the direction and structure of the reform's effects on job matching productivity. Fahr and Sunde (2009) reported better matching for the aggregated German labour market after the first three reform stages (Hartz I/II and Hartz III) had been implemented. Klinger and Rothe (2012) used newer and richer data, which enabled these authors to analyse the last reform stage (Hartz IV in 2005) and to distinguish between long- and short-term unemployed. Overall, these authors also found that the reforms had positive effects on matching efficiency, particularly after Hartz I/II (2003) and III (2004) were introduced. In addition, they found stronger reform effects for the long-term unemployed. However, the last reform stage (Hartz IV) – consisting of a fundamental change in the tax-financed and means-tested unemployment benefit scheme – did not lead to further positive effects. The same authors explain this finding using statistical effects because the number of unemployed increased sharply in 2005 due to the changes under Hartz IV. Hillmann (2009), who also used newer data, found that Hartz IV had positive effects; her analysis constructed the reform dummy differently for Hartz IV.[2] Finally, Klinger and Weber (2014) used data from 1979 to 2009 to analyse the inward shift of the Beveridge curve after the reform years and were able to generally confirm the positive effects of the reforms on matching efficiency, although these authors also found that the positive trend of matching efficiency came to an end in 2009. Clearly, these studies have shed light on the temporal and structural properties of the effects of these reforms.

However, until now, it has not been known whether the positive changes in matching efficiency can be observed for all jobs or how the matching efficiencies changed in the relevant partial labour markets and particularly in occupational labour markets. Another relevant question is whether the effects changed temporarily or permanently during (extreme) economic situations, such as the 2008/2009 financial crisis.

This paper complements previous research by estimating the parameters of a macroeconomic matching function on the basis of detailed, high-frequency, and more recent administrative data for the 2000–2011 period; thus, it includes the span of the 2008/2009 financial crisis. As this study's first step, I deliver a highly exact and detailed analysis of the evolution of the matching productivity. In the second step, I present an analyses of occupational labour markets because it is known that matching efficiency varies in different occupational labour markets, as shown in Stops and Mazzoni (2010) and Fahr and Sunde (2006). To distinguish occupational labour markets, I use the German occupational classification scheme according to Blossfeld (1983). It is possible to identify the temporal evolution of matching productivity by estimating yearly time fixed effects that can be interpreted as year-specific deviations from average matching productivity during

2 Klinger and Rothe (2012) generated a dummy variable that was valued at zero before 2005 and unity after 2005. Hillmann (2009) assumed an exponentially growing reform effect during the first 12 months after Hartz IV was implemented.

the observation period. To identify the temporal evolution of matching productivity in occupational labour markets, I complement the model with interaction dummy variables that combine yearly and occupational labour market effects.

My analysis corroborates the previous findings of positive changes in matching productivity during and after all the reform stages and clarifies that there are also positive changes after Hartz IV. Furthermore, these findings can be corroborated in all the occupational labour markets. However, there are some differences in later years. A (temporary and small) decrease in matching productivity is observable during the recession in 2009 ("crisis dip") in some occupational labour markets, even after controlling for the recession; in addition, there are differences in more recent changes of matching productivity.

The remainder of this paper is organised as follows. In section 3.2, I describe some relevant facts regarding the German labour market reforms and their (theoretical) implications for matching productivity. Then, I present the theoretical foundations of the macroeconomic matching function, the interpretation of its parameters, and, finally, information about the occupational labour market structure the analysis will be related to. Section 3.3 presents details about the data used for the analysis and certain descriptive key statistics. Section 3.4 explains the empirical strategy and reports and discusses estimation results. Robustness checks that generally confirm these results and that are based on both another theoretical perspective of job matching and higher aggregated data are reported in section 3.5. Section 3.6 contains the main conclusions.

3.2 Labour market reforms and job matching

3.2.1 *Hartz* reforms, organisational changes, and organisational outcomes

Empirical findings for the early 2000s in Germany reveal high and persistent unemployment that was independent of the business cycle (Klinger and Rothe, 2012). Furthermore, there were discussions regarding opportunities to measure the efforts of public job placement services and to make the job placement organisation more efficient. Therefore, the government stipulated four laws that were implemented in three waves. In particular, the government considered the working results of an expert commission, the so-called *Hartz* commission. Each of the *Hartz* I to IV reform laws consisted of various components that refer to the organisation and rules of the labour market. The reform laws consist of three elements that should influence the job-finding rate of unemployed workers (see, for instance, Ochel, 2005; Bieber et al., 2005; Jacobi and Kluve, 2007; Klinger and Rothe, 2012).

- Raising the effectiveness and efficiency of the Federal Employment Agency: Re-Organising the Federal Employment Agency, promoting competition between public and private placement services into the private sector, or identifying measures of active labour market policy that promised to be more effective. The Federal Employment Agency consists of three levels – the head office, regional directorates (Regionaldirektionen), and employment agencies (Agenturen für Arbeit) and job centres. Before the reform, the head office was primarily responsible for the operational business of the regional units. The reform clarified that the head office is in charge of targeting and strategy development and that the regional directorates are responsible for steering the employment agencies. The latter are in charge of operational business. The employment agencies are supposed to operate as branch offices and are responsible for their own work results. Labour market instruments, such as training and/or financial support for applications, are provided that are consistent with clear customer group definitions that distinguish customers who are near the labour market from customers with a need for counselling and from customers with one or more issues regarding labour market integration. In particular, the type of counselling and the usage of labour market instruments varies with different customer groups. Generally, the Federal Employment Service should invest in an unemployed person only when the investment is effective (and efficient), which implies that the customer group that is near the market and the group with one or more issues regarding labour market integration are hardly provided with instruments.
- More activation and higher self-responsibility of the unemployed (principle of "Promoting and demanding"[3]): new start-up subsidies, targets on reintegration efforts, reconfiguring the unemployment benefit and social assistance system towards lower or shorter benefit entitlement and higher claims of search effort.
- Easing of labour market policy: relaxing regulations for temporary agency work, fixed term contracts, and employment protection.

3.2.2 Random matching

It generally remains an empirical question whether and to what extent all the reform efforts affect labour market outcomes, such as the efficiency of matching. It is not possible to identify the total extent and variation in the described efforts within the different reform stages. Nevertheless, it is possible to evaluate

3 German expression *"Fördern und Fordern".*

changes in matching productivity before, during and after the reform years with a macroeconomic matching function framework.

The macroeconomic matching function and the matching process behind it were conceived by Pissarides (1979, 1985); Diamond (1982a, b); Mortensen (1982). The matching process begins with the decisions of firms to create a new job or to fill a vacancy (job creation decisions), and decisions of (unemployed) persons regarding how intensely to search for a new job (job search decisions) (Pissarides, 2000, p. xi). Firms spend time, financial, and personnel resources for job advertisements, screening, training, and vocational adjustments. Job seekers spend resources for job search and application procedures. Unemployed persons and firms are randomly matched and begin to bargain regarding wages.

The basic model assumes homogeneous unemployed persons and homogeneous jobs. The activities of both market sides are matching technologies. The processes behind these activities are not explicitly modelled, so the matching process can be compared with a black box (Petrongolo and Pissarides, 2001). The variables U, V and M represent the stock of unemployed, the stock of vacancies and the flows of new hires, respectively. The resulting matching function $f(U, V)$ is specified in a Cobb-Douglas form:

$$M_t = A_t U_t^{\beta_{Us}} V_t^{\beta_{Vs}} \tag{3.1}$$

where A describes the "augmented" matching productivity. Constant returns to scale imply $\beta_{Us} + \beta_{Vs} = 1$ with β_{Us}, $\beta_{Vs} > 0$. Another important assumption lies behind the approach – workers and firms are randomly matched and originate from the pool of existing unemployed workers and job vacancies.

My analysis refers to changes in the parameter A of the matching function that result of changes in the institutional framework of the labour market resulting from the reforms. The central question is whether this parameter changed after implementing the reforms. Therefore, I assume that this parameter varies over time; thus, A_t is different for different observation periods, whereas the elasticities remain constant during the entire observation period.

This model differs from Klinger and Rothe (2012) and Fahr and Sunde (2009), who both assumed that there is a constant augmented productivity for the observation period before the reforms were implemented and a (possibly) different augmented productivity after the reform was introduced[4]. In the model described above, this term differs from observation period to observation period. Therefore, it is possible to compare the temporal evolution of augmented productivity, which is similar to

4 Thus, they estimated an averaged augmented productivity term before and after the reforms' implementation.

Klinger and Weber (2014), who estimates an "extended matching function" that contains a time-varying matching efficiency parameter that is decomposed in a cyclical and a trend component. However, their identification strategy differs from the strategy utilised herein because it is based on a multivariate time series and correlated unobserved components model, whereas the identification made in this paper is based on variations in repeated observations in regional and occupational labour markets.

To analyse the reforms' effects on occupational labour markets, I use the occupational classification scheme derived by Blossfeld (1983), who divides the labour market into 12 broader occupational categories and a category "[0] Not assignable" (table 3.1). These categories can be roughly assigned to qualification levels and sectors. Thus, this classification can be understood as an approximation of occupational labour markets that are assumed to be separate from one another and as a good (exogenous) base for the analysis of changes in the matching efficiency of occupational labour markets.

Table 3.1: Occupational categories

[1]	AGR agrarian occupations
[2]	EMB simple manual occupations
[3]	QMB qualified manual occupations
[4]	TEC technicians
[5]	ING engineers
[6]	EDI simple service occupations
[7]	QDI qualified service occupations
[8]	SEMI semi-professions
[9]	PROF professions
[10]	EVB simple business and administrative occupations
[11]	QVB qualified business and administrative occupations
[12]	MAN manager
[0]	*Not assignable*

Source: Occupational categories are taken from Blossfeld (1983).

Again, I assume constant matching elasticities of unemployed and vacancies (stocks and flows) in the economy, but the augmented productivity term A_{tb} now varies with the occupational categories b and observation periods t:

$$M_{tb} = A_{tb} U_{tb}^{\beta_{U_s}} V_{tb}^{\beta_{V_s}} \tag{3.2}$$

3.3 Data

I use a unique administrative panel data set of 329 occupational orders in 402 NUTS3 regions with 138 observation periods from January 2000 to June 2011. The occupational orders are coded according to the German occupational classification scheme (three digits, KldB 88[5]). All the data stem from the Federal Employment Agency. The groups are assigned to the 13 occupational labour markets described in the previous section.[6]

I use monthly data regarding flows from unemployment to employment and stocks of unemployed and registered vacancies. Table 3.2 shows some descriptive statistics.

Table 3.2: Descriptive statistics

Measure	Monthly averages 2000–2011 (in1,000)			
	Mean	Minimum	Maximum	Standard deviation
Employment inflows M	259	144	412	51
Unemployment stock U	3,750	2,761	4,950	570
Registered vacancies stock V	332	173	460	79

Source: Own calculation based on the administrative data from the statistics department of the Federal Employment Agency 2000–2011.

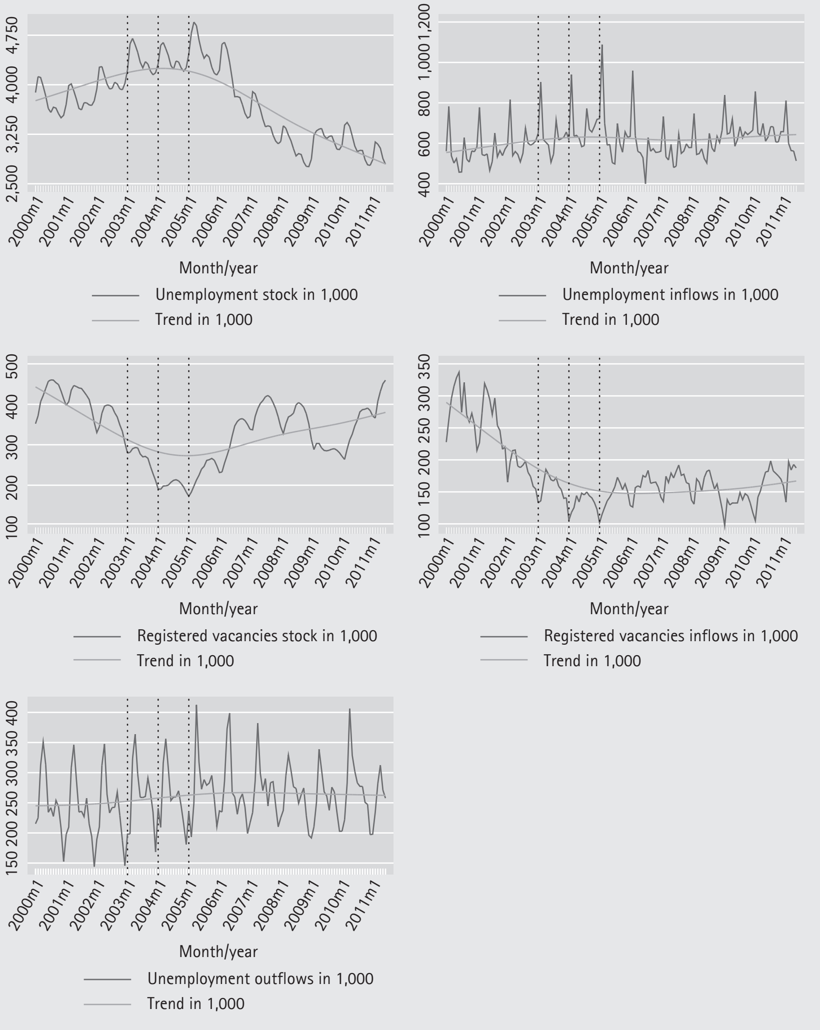
To get unbiased matching parameter estimations, I adjust the data set by observations for occupations and NUTS3 regions, respectively, in which vacancies, unemployed or flows into employment are zero, which leads to an unbalanced panel data structure with 2,394,250 observations.

Figure 3.1 shows the time series of unemployment stocks, unemployment inflows, vacancy stocks, vacancy inflows and flows from unemployment into employment and their trends. The trends are computed using the Hodrick Prescott filter (Hodrick and Prescott, 1997). It is clear that there is a change in the trends from 2003 to 2005, i.e., the reform years. Whereas the trends of the unemployment outflows and inflows and stock of registered vacancies decreased before and increased after the reform years, the stock and inflows of the unemployed increased before and decreased after the reform years. However, the strongest changes are shown in the unemployment and the vacancy stocks, whereas the outflows reveal only slight changes in the trend.

5 *Klassifizierung der Berufe* 1988.

6 Further information can also be found in appendix 3.A.1.

Figure 3.1: Time series of the key figures for the 2000–2011 analysis



Source: Statistics of the Federal Employment Agency, own computations. Trends are computed with the Hodrick Prescott filter (Hodrick and Prescott, 1997, smoothing parameter α = 129,600).

3.4 Empirical strategy and results

3.4.1 Aggregated estimations

At first, I estimate regression equations that are based on the logarithm version of equation (3.1) and complemented by further variables that are included stepwise:

$$\log M_{ijt} = a + \beta_{Us} \log U_{ijt} + \beta_{Vs} \log V_{ijt} + \mu_{ij} + \gamma GDP_{cyc,FS(i),year(t)} + d_t + \epsilon_{ijt} \quad (3.3)$$

Here, the term $\log M_{ijt}$ denotes the logarithm of the flows from unemployment to employment for region i, occupational order j and observation period t. The parameter a is a constant and thus a component of the logarithm of the average augmented matching productivity. The variables log U and log V are the logarithms of the unemployed and vacancy stocks, whereas β_{Us} and β_{Vs} denote the matching elasticities of the unemployed and vacancies, respectively. Furthermore, the regression equation contains a fixed effect, μ_{ij}, for each regional occupational labour market, ij, that can be interpreted as the occupational and local area specific augmented productivity. Finally, this basic specification includes also an i.i.d. error term, ε_{ijt}, for each observation.

In the next step, I include the cyclical component of real gross domestic product, $GDP_{cyc,\ FS(i),\ year(t)}$, for the federal state, FS, that region i belongs to and the year that the observation period, t, belongs to. The coefficient for this variable is γ. Then, I include monthly time fixed effects, d_t, that are – for the moment – the coefficients of interest. These variables are effect coded, and their coefficients can thus be directly interpreted as the monthly deviations from the average augmented matching productivity for the 2000 to 2011 observation period.[7] The reference period is January 2000.

Finally, I modify the regression above by including dummy variables $d_{q(t)}$ for the 1st, 2nd, or 3rd quarter of the year. Furthermore, I substitute the monthly observation period time fixed effects with year fixed effects $d_{year(t)}$. This variable is also effect coded[8], and the reference year is 2000. Thus, the latter variable can be interpreted as the yearly seasonal adjusted deviation from the average of augmented matching productivity during the 2001 to 2011 observation period. The regression equation is then as follows:

$$\begin{aligned}\log M_{ijt} = a + \beta_{Us} \log U_{ijt} + \beta_{Vs} \log V_{ijt} + \gamma GDP_{cyc,FS(i),year(t)} \\ + d_{q(t)} + d_{year(t)} + \mu_{ij} + \epsilon_{ijt}\end{aligned} \quad (3.4)$$

7 Compare details about effect coding in appendix 3.A.2.

8 See appendix 3.A.2.

The results of the estimations can be found in table 3.3. Column FE 1 of table 3.3 refers to the basic specification. As expected from the theoretical model, the matching elasticities of the unemployed and vacancy stocks are both significantly positive. Furthermore, the matching elasticity of the unemployed is higher than the matching elasticity of the vacancies. This result corroborates previous studies for Germany (Burda and Wyplosz, 1994; Entorf, 1998; Fahr and Sunde, 2004; Stops and Mazzoni, 2010; Klinger and Rothe, 2012).

The results in the second column, FE 2, belong to the same specification augmented with the cyclical component of the yearly gross domestic product for the 16 federal states ($GDP_{cyc,\ FS(i),\ year(t)}$). These results do not differ much from the results in the first column, FE 1.

The third column, FE 3, contains the results for the regression equation (3.3), including monthly time fixed effects. Compared with previous specifications, the matching elasticities of the unemployed are somewhat higher and the matching elasticities of the vacancies are lower. The monthly fixed effects are not presented in table 3.3; however, their graphical representation can be found in the left panel of figure 3.2. The right panel of this figure shows the evolution of the year fixed effects of column 4 in table 3.3.

As explained above, these variables can be interpreted as time specific deviations from the average augmented matching productivity, where the average is normalised to zero. Accordingly, from the beginning of the observation period until 2006, the monthly deviations might be negative or positive with a seasonal pattern. In addition, beginning with the reform years, 2003–2005, and continuing forward, the monthly deviations began to increase from year to year; from 2007 onwards, the deviations are all significantly positive. These results provide the first impression of how augmented matching productivity developed after the labour market reforms were implemented in 2003 to 2005. All in all, the volatile seasonal pattern gives only a rough first impression regarding the evolution of matching productivity.

In equation (3.4), the year dummies can be interpreted as yearly deviations from the averaged augmented matching productivity and should thus give a clearer picture.

Furthermore, seasonality patterns are adjusted by quarter dummies. The results of the estimations, including the yearly deviations, are reported in column 4 of table 3.3. The graphical representation of the year effects for the random matching model can be found in the right panel of figure 3.2. The yearly deviations are negative at the beginning of the observation period and begin to increase from 2002 with a sharper increase from 2005 onwards; they become significantly positive from 2007 onwards. This increase is interrupted in 2009 the year of the financial crisis (although I control for the business cycle), and after a small increase

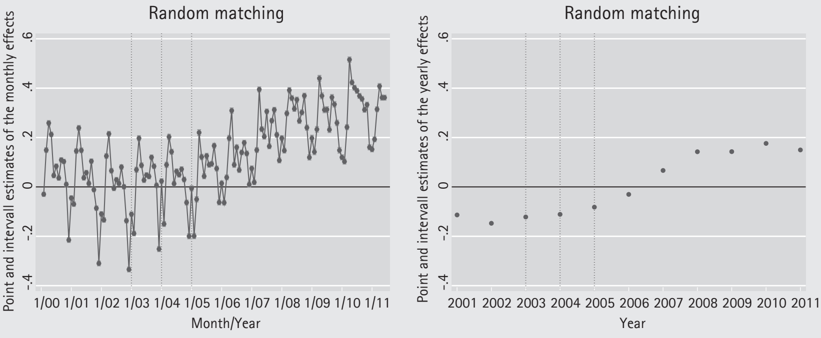
Table 3.3: Fixed effects estimation results based on the data set disaggregated by occupations and NUTS3 regions

	Dependent variable: $\log M$			
	FE 1	FE 2	FE 3	FE 4
β_{Us}	0.514*** (0.003)	0.519*** (0.003)	0.625*** (0.003)	0.626*** (0.003)
β_{Vs}	0.060*** (0.001)	0.056*** (0.001)	0.039*** (0.001)	0.044*** (0.001)
Year dummies, effect coded (reference: 2000):				
d_{2001}				–0.114*** (0.001)
d_{2002}				–0.147*** (0.001)
d_{2003}				–0.122*** (0.001)
d_{2004}				–0.111*** (0.001)
d_{2005}				–0.082*** (0.002)
d_{2006}				–0.030*** (0.001)
d_{2007}				0.067*** (0.002)
d_{2008}				0.143*** (0.002)
d_{2009}				0.143*** (0.002)
d_{2010}				0.176*** (0.001)
d_{2011}				0.150*** (0.002)
γ		0.985*** (0.021)	1.336*** (0.047)	1.352*** (0.047)
a	–0.428*** (0.013)	–0.443*** (0.013)	–0.990*** (0.014)	–0.919*** (0.012)
Monthly time dummies	no	no	yes	no
Quarter dummies	no	no	no	yes
Observations	2,394,250	2,394,250	2,394,250	2,394,250
R-squared	0.206	0.207	0.304	0.275
Number of groups	55,422	55,422	55,422	55,422

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Column FE 3 includes monthly time fixed effects with effect coding (reference period is January 2000); compare with figure 3.2, left panel.

in 2010, the deviation slightly decreases in 2011.[9] In general, this result leads me to conclude that there are positive changes in matching productivity during and after implementation of the reform; in recent years, there are only small changes.

Figure 3.2: Random matching: Monthly and yearly time fixed effects and 95 per cent confidence band



Notes: Specifications from table 3.3, left side, are FE 3; those from the right side are FE 4 – based on a data set disaggregated by occupations and NUTS3 regions. The dots and the vertical lines mark the point and 95% interval estimates, and the interval is very small in most cases. In the left panel, the dots are linked with a line to illustrate temporal development. Time fixed effects with effect coding (the reference period is January 2000 for month fixed effects or 2000 for year fixed effects, respectively).

Source: Statistics of the Federal Employment Agency, own computations.

3.4.2 Occupational labour markets

Figure 3.3 describes the development of the trends of our key figures – flows from unemployment to employment, unemployment stocks, and the registered vacancy stocks – as normalised measures with index 1 first in January 2000 (left panels) and second for January 2005 (right panels).

Generally, these figures show that there is a certain heterogeneity in the development of the key figures in different occupational labour markets, which leads me to conclude that I can expect different results regarding the analysis of the changes of the matching elasticity in these markets. Thus, I separately estimate the deviations of the averaged augmented productivity for the occupational labour markets, $b(j)$, that the occupational order j is assigned to. The regression is equivalent to the logarithm version of equation (3.2). Again, this specification is stepwise complemented by additional variables:

9 The changes are small, but I can observe a significant "crisis dip" in 2009 and larger elasticity and productivity coefficients based on regression equations without the recession variable as a control variable; compare with columns 1 to 3 of table 3.9 and the left panels of figures 3.9 and 3.10 in appendix 3.A.3.

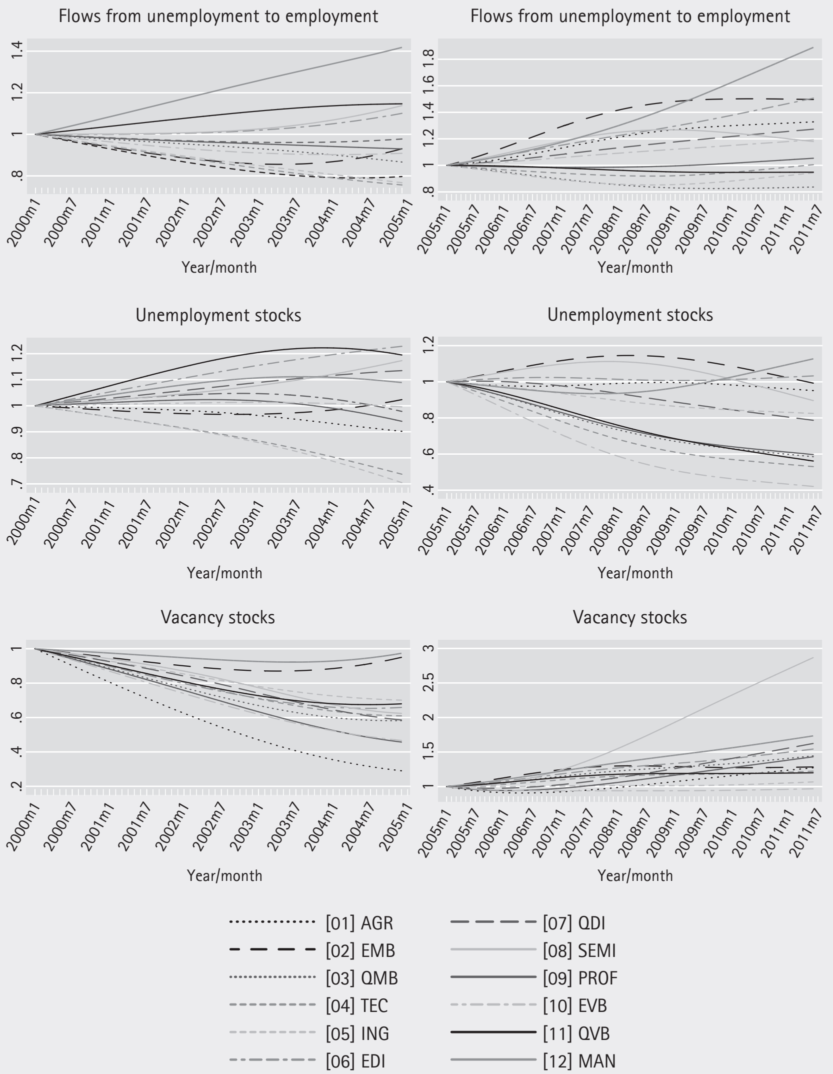
$$\log M_{ijt} = a+\beta_{Us}\log U_{ijt}+\beta_{Vs}\log V_{ijt}+GDP_{cyc,FS(i),year(t)} \\ +d_i+d_{q(t)}+d_{year(t)}+d_{b(j)}+d_{b(j),year(t)}+\epsilon_{ijt} \tag{3.5}$$

Here, it is not possible to separate the occupational and regional fixed effects and the occupational labour market effects, $b(j)$, related to occupation j. Therefore, I exclude the fixed effects μ_{ij} and I estimate an ordinary least squares (OLS) model. The model is augmented by local area effects d_i, quarter dummy variables ($d_{q(t)}$), and year dummies (yearly observation period fixed effects, $d_{year(t)}$) with reference to year 2000 and thus the yearly specific deviations from the average augmented productivity. Furthermore, it contains dummy variables for 11 occupational categories with reference to the "agrarian and not assignable occupations" ($d_{b(j)}$) categories. The coefficients of these variables are equivalent to the occupational labour market's specific deviations from average matching productivity. Finally, the model contains interaction dummies for the yearly and occupational labour market-specific deviations $d_{b(j),\ year(t)}$. Formally, the latter variable is the interaction term of the year dummies and the occupational labour market dummy variables. Again, dummy variables are effect coded with the exception of the quarter dummy (the 4th quarter is the reference period).

The results can be found in table 3.4. Column OLS 1 contains the OLS estimation of a pure matching model without the recession variable or further dummy variables. As expected, the coefficients for the matching elasticities are again significantly positive. After including the recession variable (OLS 2), the coefficients hardly change. Column OLS 3 of table 3.4 shows the results for the specifications, including dummy variables for year effects, quarters and occupational labour markets. In particular, the year fixed effects coefficients have a similar pattern as the results of the fixed effects estimations. Thus, the main conclusions of the previous section are unaffected. Finally, column OLS 4 reports the results of the full specification, including year- and occupational-specific interaction effects. Due to space constraints, I do not report the latter coefficients, but I show the point and interval estimations graphically in figures 3.4 and 3.5.

Columns OLS 3 and OLS 4 reveal another finding: the occupational labour market specific deviations from the augmented productivity for the observation period are significantly negative for occupations that are assignable to a lower skill level (EMB, EDI, EVB), and for technicians (TEC), engineers (ING), and qualified business and administrative occupations (QVB). The deviations for the remaining occupational labour markets are significantly positive. In the following, I discuss the results for the year- and occupational-specific

Figure 3.3: Key figures by occupational groups, normalised trends, 2000–2004 (January 2000 = 1, left panel) and 2005–2011 (January 2005 = 1, right panel)



Abbreviations: [01] AGR agrarian occupations; [02] EMB simple manual occupations; [03] QMB qualified manual occupations; [04] TEC technicians; [05] ING engineers; [06] EDI simple service occupations; [07] QDI qualified service occupations; [08] SEMI semi professions; [09] PROF professions; [10] EVB simple business and administrative occupations; [11] QVB qualified business and administrative occupations; [12] MAN manager.

Source: Statistics of the Federal Employment Agency. Trends are computed with the Hodrick Prescott filter (Hodrick and Prescott, 1997, smoothing parameter α = 129,600).

interaction effects. Figures 3.4 and 3.5 show 95 per cent interval estimate sums of the yearly dummy and the yearly interaction effects dummy variables in 11 panels for each occupational labour market ($d_{year(t)} + d_{b(j),\ year(t)}$), with the exception of the reference category "[AGR] agrarian and not assignable occupations"). These sums represent the yearly deviations from average occupational labour market-specific augmented productivity ($d_{b(j)}$); thus, they show how the augmented productivity in a certain occupational labour market is changed based on a "pure" time effect.

The common finding is that there is a positive change in the deviation from occupational labour market-specific augmented productivity after the reform years, which can be understood as an indicator that the reform had effects on the entire labour market. However, there are certain differences regarding the timing of the change and the further development of matching efficiency. In addition, differences arise during the years of the financial crisis in 2008/2009.

Regarding the structure of the time effects after the crisis, there are significantly positive effects observable from 2007 onwards, at the latest. Information regarding the timing of the effects complements previous studies that only compared matching productivity before or during the reform years and after the reform years (part., Fahr and Sunde, 2009; Klinger and Rothe, 2012). This allows an analysis without an assumption that consequences of each reform stage came immediately into effect or – at least – within one year.[10] This can not be corroborated by the results in this study.[11] Overall, the view on the year effects in the different occupational labour markets corroborate that the development of the matching efficiency is rather different in different labour markets; thus, the timing of the effects is also different.

10 In addition, the identification might also be difficult due to possible anticipation effects, which would be the case when firms or the unemployed changed their search decisions after the reform plans were published but before these plans were realised.

11 If I base this analysis on the assumption that the estimated average matching productivity (the constant in all models) for the 2000–2011 observation period is equivalent to long-term augmented productivity and should not change after varying the observation periods in the estimation, I might even conclude that the reform effects arise with a certain delay. However, this assumption can hardly be tested because it must be expected that a sample with fewer observation periods would reveal another value for the long-term augmented productivity and that massive short-term shocks on the labour market based on the Hartz reforms or the financial crisis would explain that more than "invalid" data. This analysis implies that when there are substantial concerns about the value of the estimated augmented productivity, the observed positive or negative deviations from that productivity might be different based on the true value. However, the relative size of those time effects and a comparison of their year-to-year differences reveal that in seven of 11 occupational categories, the highest positive change was from 2006 to 2007 (in addition to the figures 3.4 and 3.5, which is shown in table 3.12 in appendix 3.A.3). For the simple manual occupations (EMB) and the simple service occupations (EDI), this is one year earlier (2005/2006); for the professions, this is from 2003 to 2004; and for the qualified manual occupations, this is from 2002 to 2003.

Table 3.4: OLS estimation results based on data set disaggregated by occupations and NUTS3 regions

	Dependent variable: log M			
	OLS 1	**OLS 2**	**OLS 3**	**OLS 4**
β_{Us}	0.577***	0.579***	0.634***	0.633***
	(0.000)	(0.000)	(0.000)	(0.000)
β_{Vs}	0.141***	0.139***	0.117***	0.118***
	(0.000)	(0.000)	(0.000)	(0.000)
Year dummies, effect coded (reference: 2000):				
d_{2001}			–0.129***	–0.142***
			(0.001)	(0.001)
d_{2002}			–0.155***	–0.164***
			(0.001)	(0.001)
d_{2003}			–0.111***	–0.124***
			(0.001)	(0.001)
d_{2004}			–0.079***	–0.079***
			(0.001)	(0.002)
d_{2005}			–0.059***	–0.051***
			(0.001)	(0.002)
d_{2006}			–0.023***	–0.027***
			(0.001)	(0.001)
d_{2007}			0.057***	0.070***
			(0.001)	(0.002)
d_{2008}			0.132***	0.148***
			(0.001)	(0.002)
d_{2009}			0.150***	0.168***
			(0.002)	(0.002)
d_{2010}			0.170***	0.172***
			(0.001)	(0.001)
d_{2011}			0.132***	0.139***
			(0.001)	(0.002)
Dummies for occupational categories, effect coded (reference: [1] AGR):				
[02] EMB			–0.038***	–0.040***
			(0.001)	(0.001)
[03] QMB			0.153***	0.152***
			(0.001)	(0.001)
[04] TEC			–0.038***	–0.036***
			(0.002)	(0.002)

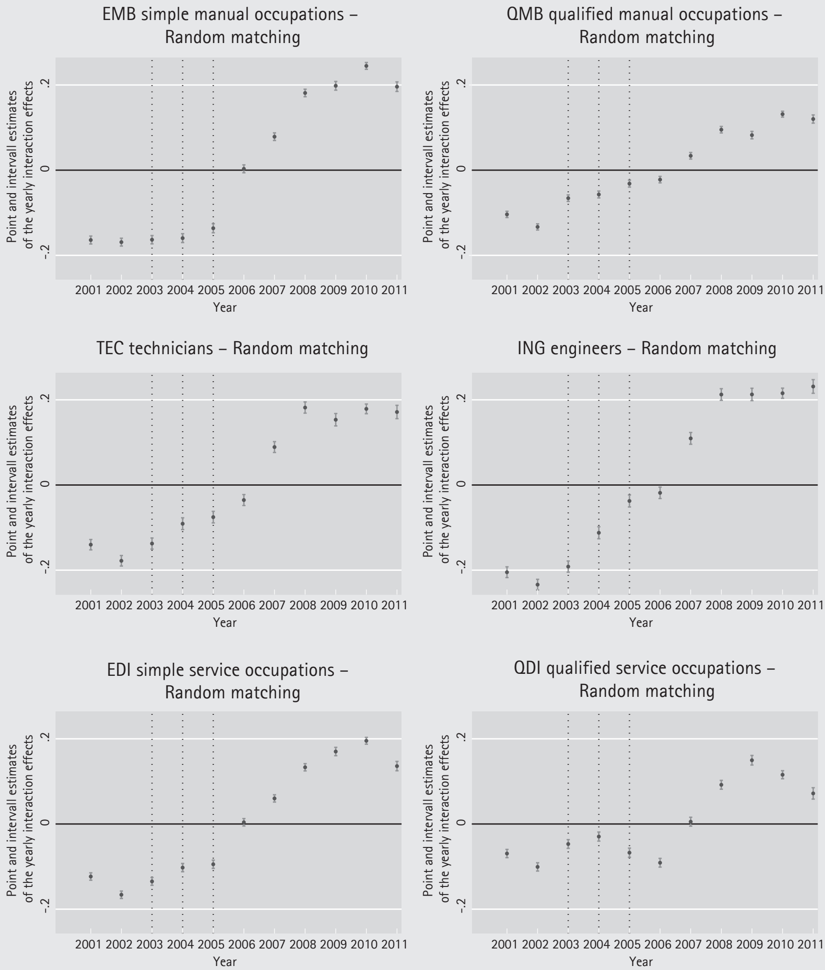
	Dependent variable: $\log M$			
	OLS 1	OLS 2	OLS 3	OLS 4
[05] ING			−0.033***	−0.024***
			(0.002)	(0.002)
[06] EDI			−0.178***	−0.178***
			(0.001)	(0.001)
[07] QDI			0.007***	0.005***
			(0.001)	(0.001)
[08] SEMI			0.037***	0.034***
			(0.001)	(0.001)
[09] PROF			0.252***	0.257***
			(0.002)	(0.002)
[10] EVB			−0.233***	−0.231***
			(0.001)	(0.001)
[11] QVB			−0.012***	−0.012***
			(0.001)	(0.001)
[12] MAN			0.046***	0.043***
			(0.002)	(0.002)
γ		0.667***	1.378***	1.345***
		(0.018)	(0.041)	(0.041)
a	-0.923***	-0.925***	-1.161***	-1.162***
	(0.007)	(0.007)	(0.007)	(0.007)
Local area effects	yes	yes	yes	yes
Occupational yearly interaction dummies	no	no	no	yes
Quarter dummies	no	no	yes	yes
Observations	2,394,250	2,394,250	2,394,250	2,394,250
R-squared	0.684	0.684	0.718	0.720

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Columns OLS 4 includes yearly time and occupational category interaction effects (reference year is 2000, reference category is "[01] AGR Agrarian and not assignable occupations"), and all dummy variables are effect coded; compare appendix 3.A.2.
Abbreviations: [01] AGR agrarian and not assignable occupations; [02] EMB simple manual occupations; [03] QMB qualified manual occupations; [04] TEC technicians; [05] ING engineers; [06] EDI simple service occupations; [07] QDI qualified service occupations; [08] SEMI semi professions; [09] PROF professions; [10] EVB simple business and administrative occupations; [11] QVB qualified business and administrative occupations; and [12] MAN manager.

Regarding the further evolution of the time fixed effects, the results reveal that the effects differ between the occupational labour markets in recent years, e.g., in the qualified service occupations (QDI), the semi-professions (SEMI), and the professions (PROF), the positive deviations decreased in at least the last years, i.e., 2009 to 2011.

Figure 3.4: Estimated sums of the yearly dummy and the yearly interaction effects and 95 per cent confidence band by occupational categories (part 1/2)

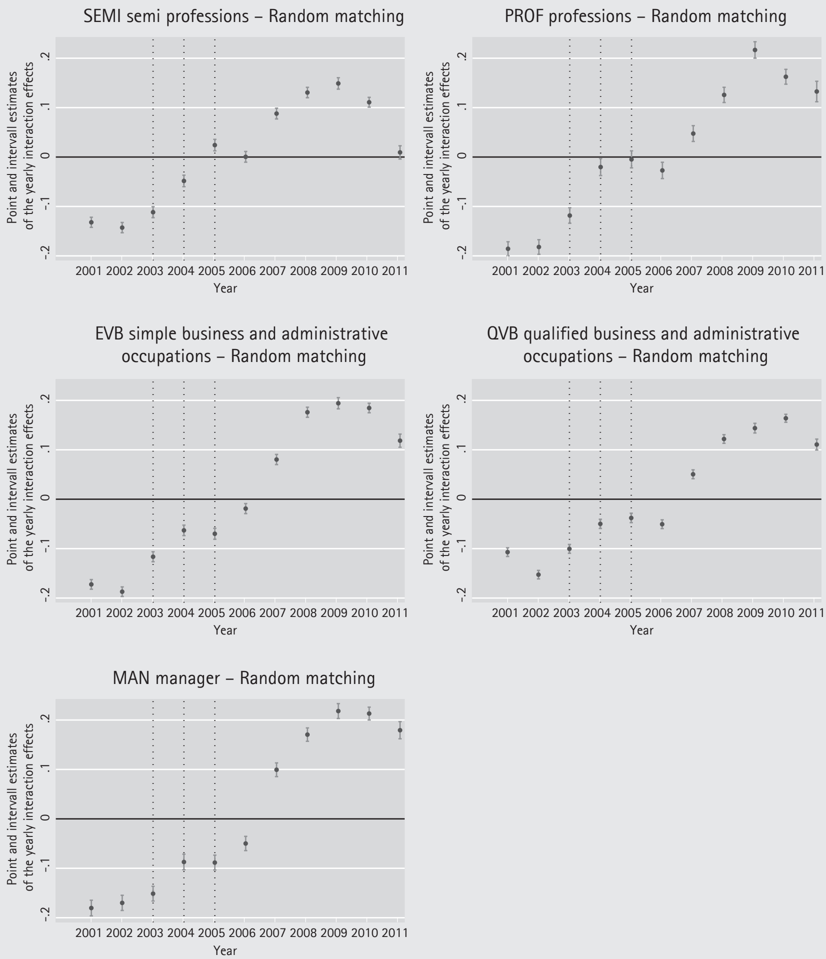


Notes: Graphs refer to results in column OLS 4 in table 3.4, based on the data set disaggregated by occupations and NUTS3 regions. The dots and the vertical lines mark the point and 95% interval estimates.

Source: Statistics of the Federal Employment Agency, own computations.

For the other occupational labour market the development moves more "sideward". Generally, the results suggest that there were further positive changes with respect to the augmented (occupational specific) matching productivities one or two years after the last reform stage. In the years following, smaller positive or even negative changes were observed.

Figure 3.5: Estimated sums of the yearly dummy and the yearly interaction effects and 95 per cent confidence band by occupational categories (part 2/2)



Notes: Graphs refer to results in column OLS 4 in table 3.4, based on the data set disaggregated by occupations and NUTS3 regions. The dots and the vertical lines mark the point and 95% interval estimates.

Source: Statistics of the Federal Employment Agency, own computations.

Finally, the results in figures 3.4 and 3.5 suggest that there is a "crisis dip" in 2009 but only in the occupational labour markets of qualified manual occupations (QMB) and technicians (TEC), which illustrates that the German labour market was not generally invulnerable during the crisis, at least regarding matching productivity, even after considering the recession variable.

3.5 Validity and robustness checks

3.5.1 Another theoretical perspective: selective search

Gregg and Petrongolo (2005) state that the unstable results of papers that study the parameters of matching functions result in a certain misspecification of the matching function due to the assumption of (completely) random search. These authors propose to utilise a stock-flow matching model framework, originally derived by Coles (1994) and Coles and Smith (1998). This approach considers job searching that is not completely random. However, for this, it must state an assumption that might be understood as a further restriction of the random matching approach: the assumption is made that the agents on both sides of the market are able to sample the entire relevant part of the stocks of the other side with no friction due to the availability of quite efficient information channels. Following that, the agents who didn't find adequate offers and, therefore, remain in the unemployed or vacancy stocks, respectively, only select further offers on the other market side from those that have just arrived. However, Gregg and Petrongolo (2005) concluded that the true (single) matching process is equivalent to one that is somewhere between the random matching approach and the stock-flow matching approach. Whereas random matching assumes a search process that consumes time to sample and assess all available and relevant (stocks of) offers from the other market side, the stock-flow matching approach is assumed to minimise the required time to check the stocks of the other market side to zero. These concepts offer me a good opportunity to discuss the robustness of the focussed efficiency parameter estimates on the basis of two different matching functions.

Therefore, the matches are determined, on the one hand, by the stocks of the unemployed and the inflows of vacancies and, on the other hand, by the stocks of vacancies and the inflows of the unemployed. Technically, the matching function in equation (3.1) is complemented by the inflows of the unemployed u and vacancies v with their matching elasticities β_{Uf} and β_{Vf}:

$$M_t = A_t U_t^{\beta_{Us}} u_t^{\beta_{Uf}} V_t^{\beta_{Vs}} v_t^{\beta_{Vf}} \tag{3.6}$$

The model that considers the variation of the augmented productivity term with occupational labour markets *b*, compared with equation (3.2), is then modified to:

$$M_{tb} = A_{tb} U_{tb}^{\beta_{Us}} u_{tb}^{\beta_{Uf}} V_{tb}^{\beta_{Vs}} v_{tb}^{\beta_{Vf}} \tag{3.7}$$

Table 3.5: Further descriptive statistics

Measure	Monthly averages 2000–2011 (in 1,000)			
	Mean	Minimum	Maximum	Standard deviation
Unemployment inflows u	616	400	1,088	101
Registered vacancies inflows v	177	97	337	52

Source: Own calculation based on the administrative data from the statistics department of the Federal Employment Agency 2000–2011.

Table 3.5 shows some descriptive statistics for the aggregated flows from the data set. The logarithm versions of the stock-flow models are equivalent to the regression equations (3.3) and (3.4) for the random matching model complemented by parameters and variables of the logarithm of the flow measures:

$$\log M_{ijt} = \quad [\textit{Right side of equation (3.3) or (3.4)}] + \beta_{Uf} \log u_{ijt} + \beta_{Vf} \log v_{ijt} \qquad (3.8)$$

Thus, the variables $\log u$ and $\log v$ are the logarithms of the unemployed and vacancy inflows whereas β_{Uf} and β_{Vf} denote the matching elasticities of the inflows of the unemployed and vacancies, respectively.

The results of the estimations of the stock-flow matching parameters can be found in table 3.6. Compared with table 3.3, the columns contain the results of the same specifications augmented with the inflow measures for registered vacancies and the unemployed. The graphic representation for the month fixed effects (FE 3) and year fixed effects (FE 4) can be found in figure 3.6. Overall, the results do not reveal fundamental differences with those that are based on the random matching approach. The foregoing is also true for the regressions' estimates without the recession variable, compare with columns 4 to 6 of table 3.9 and the right panels of figures 3.9 and 3.10 in appendix 3.A.3. Again, the "crisis dip" becomes larger after excluding the recession variable.

The results of the analysis for the occupational labour markets can be found in table 3.7. The columns contain the results of specifications analogous to table 3.4, augmented with the flow measures. Again, the results are quite similar to those based on the random matching approach.

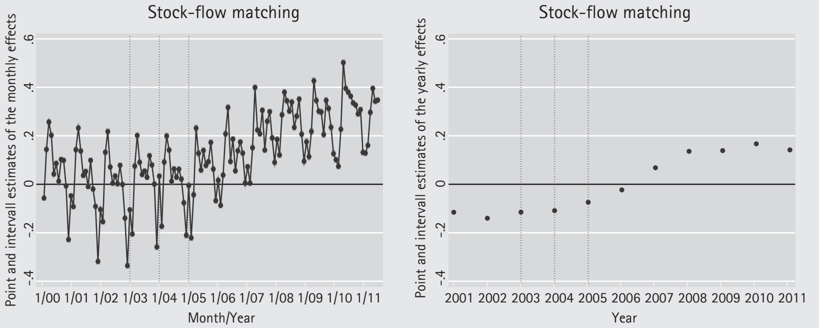
Table 3.6: Robustness check: Fixed effects estimation results based on the stock-flow matching model and data set disaggregated by occupations and NUTS3 regions

	Dependent variable: $\log M$			
	FE 1	FE 2	FE 3	FE 4
β_{Us}	0.453***	0.457***	0.565***	0.584***
	(0.003)	(0.003)	(0.003)	(0.003)
β_{Uf}	0.085***	0.087***	0.071***	0.049***
	(0.002)	(0.002)	(0.001)	(0.001)
β_{Vs}	0.041***	0.037***	0.020***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)
β_{Vf}	0.029***	0.029***	0.031***	0.035***
	(0.001)	(0.001)	(0.001)	(0.001)
Year dummies, effect coded (reference: 2000):				
d_{2001}				-0.115***
				(0.001)
d_{2002}				-0.140***
				(0.001)
d_{2003}				-0.115***
				(0.001)
d_{2004}				-0.109***
				(0.001)
d_{2005}				-0.074***
				(0.002)
d_{2006}				-0.023***
				(0.001)
d_{2007}				0.068***
				(0.002)
d_{2008}				0.136***
				(0.002)
d_{2009}				0.139***
				(0.002)
d_{2010}				0.167***
				(0.001)
d_{2011}				0.142***
				(0.002)
γ		1.094***	1.375***	1.413***
		(0.021)	(0.045)	(0.045)
a	-0.381***	-0.395***	-0.909***	-0.867***
	(0.012)	(0.012)	(0.014)	(0.012)
Monthly time dummies	no	no	yes	no
Quarter dummies	no	no	no	yes
Observations	2,394,250	2,394,250	2,394,250	2,394,250
R-squared	0.213	0.215	0.309	0.278
Number of id	55,422	55,422	55,422	55,422

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Column FE 3 includes monthly time fixed effects with effect coding (reference period is January 2000), compare with figure 3.6, left panel.

Figure 3.6: Stock-flow matching: Monthly and yearly time fixed effects and 95 per cent confidence band



Notes: Specifications from table 3.6, left side: FE 3; right side: FE 4, based on the data set disaggregated by occupations and NUTS3 regions. The dots and the vertical lines mark the point and 95% interval estimates; in most cases, the interval is very small. In the left panel, the dots are linked with a line to illustrate temporal development. Time fixed effects with effect coding (reference period is January 2000 for month or year 2000 for year fixed effects).

Source: Statistics of the Federal Employment Agency, own computations.

Only the yearly deviations from average augmented productivity are mainly less volatile in the stock-flow matching approach than in the random matching model. Thus, the main conclusions of the previous section are unaffected. Finally, column OLS 4 reports the results of the full specification, including the year- and occupational-specific interaction effects. Again, I do not report the results for the specification, including year- and occupational-specific interaction effects (OLS 4), but I graphically show the point and interval estimations in figures 3.7 and 3.8.

There is one difference between the results based on the stock-flow matching model compared with the random matching model for the the occupational labour market– specific deviations of the qualified service occupations (QDI) and the engineers (ING): the signs of the deviations differ between the stock-flow matching and the random matching model. However, the magnitude of these deviations are quite small in both models. Considering the results for the year- and occupational-specific interaction effects, there are only minor differences regarding the timing of the change and the further development of the matching efficiency. Furthermore, there are differences during the years of the financial crisis in 2008/2009.

Table 3.7: Robustness check: OLS estimation results based on stock-flow matching model and data set disaggregated by occupations and NUTS3 regions

	Dependent variable: log M			
	OLS1	**OLS2**	**OLS3**	**OLS4**
β_{Us}	0.347***	0.348***	0.440***	0.441***
	(0.001)	(0.001)	(0.001)	(0.001)
β_{Uf}	0.247***	0.249***	0.196***	0.193***
	(0.001)	(0.001)	(0.001)	(0.001)
β_{Vs}	0.063***	0.060***	0.049***	0.049***
	(0.001)	(0.001)	(0.001)	(0.001)
β_{Vf}	0.075***	0.074***	0.076***	0.078***
	(0.001)	(0.001)	(0.000)	(0.000)
Year dummies, effect coded (reference: 2000):				
d_{2001}			-0.117***	-0.127***
			(0.001)	(0.001)
d_{2002}			-0.123***	-0.133***
			(0.001)	(0.001)
d_{2003}			-0.082***	-0.096***
			(0.001)	(0.001)
d_{2004}			-0.070***	-0.072***
			(0.001)	(0.002)
d_{2005}			-0.028***	-0.025***
			(0.001)	(0.002)
d_{2006}			0.005***	-0.003*
			(0.001)	(0.001)
d_{2007}			0.061***	0.072***
			(0.001)	(0.002)
d_{2008}			0.099***	0.114***
			(0.001)	(0.002)
d_{2009}			0.110***	0.126***
			(0.002)	(0.002)
d_{2010}			0.124***	0.130***
			(0.001)	(0.001)
d_{2011}			0.093***	0.103***
			(0.001)	(0.002)
Dummies for occupational categories, effect coded (reference: [0]/[1] AGR):				
[02]EMB			-0.045***	-0.047***
			(0.001)	(0.001
[03] QMB			0.113***	0.112***
			(0.001)	(0.001)
[04] TEC			-0.019***	-0.018***
			(0.002)	(0.002)

	Dependent variable: log M			
	OLS1	OLS2	OLS3	OLS4
[05] ING			0.006***	0.013***
			(0.002)	(0.002)
[06] EDI			−0.176***	−0.177***
			(0.001)	(0.001)
[07] QDI			−0.022***	−0.024***
			(0.001)	(0.001)
[08] SEMI			0.017***	0.013***
			(0.001)	(0.001)
[09] PROF			0.245***	0.250***
			(0.002)	(0.002)
[10] EVB			−0.210***	−0.208***
			(0.001)	(0.001)
[11] QVB			−0.008***	−0.009***
			(0.001)	(0.001)
[12] MAN			0.062***	0.059***
			(0.002)	(0.002)
γ		0.985***	1.400***	1.368***
		(0.017)	(0.040)	(0.040)
a	−0.498***	−0.499***	−0.790***	−0.791***
	(0.007)	(0.007)	(0.007)	(0.007)
Local area effects	yes	yes	yes	yes
Occupational yearly interaction dummies	no	no	no	yes
Quarter dummies	no	no	no	yes
Observations	2,394,250	2,394,250	2,394,250	2,394,250
R-squared	0.704	0.705	0.731	0.732

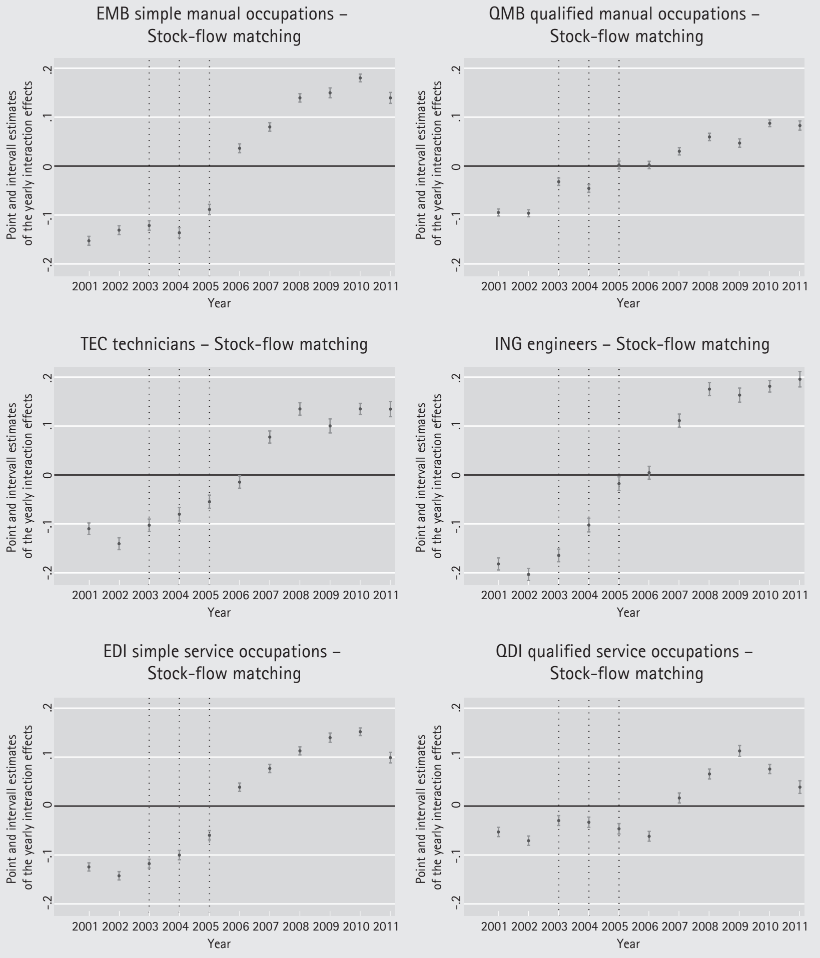
Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Column OLS 4 includes yearly time and occupational category interaction effects (reference year is 2000, reference category is "[01] AGR Agrarian and not assignable occupations"), all dummy variables are effect coded, compare appendix 3.A.2.

Abbreviations: [01] AGR agrarian and not assignable occupations; [02] EMB simple manual occupations; [03] QMB qualified manual occupations; [04] TEC technicians; [05] ING engineers; [06] EDI simple service occupations; [07] QDI qualified service occupations; [08] SEMI semi professions; [09] PROF professions; [10] EVB simple business and administrative occupations; [11] QVB qualified business and administrative occupations; [12] MAN manager.

Regarding the largest absolute changes of the yearly time fixed effects from year to year, table 3.13 in appendix 3.A.3 shows hardly any differences compared with the results based on the random matching model (table 3.12) with the exception of the semi-professions and professions. For these occupational categories, the largest absolute changes in the yearly time fixed effects based on the stock-flow matching model was measured from 2004 to 2005 for the semi professions and from 2008 to 2009 for the professions.

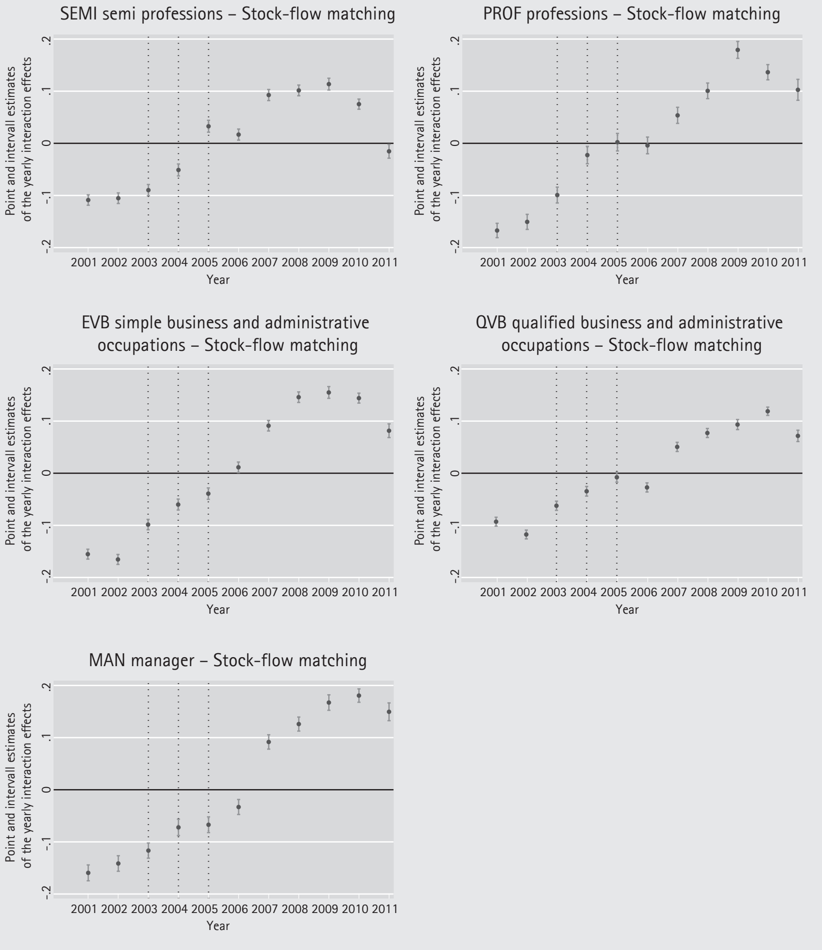
Figure 3.7: Estimated sums of the yearly dummy and the yearly interaction effects and 95 per cent confidence band by occupational categories (part 1/2)



Notes: Graphs refer to results in column OLS 4 in table 3.7, based on the data set disaggregated by occupations and NUTS3 regions. The dots and the vertical lines mark the point and 95% interval estimates.

Source: Statistics of the Federal Employment Agency, own computations.

Figure 3.8: Estimated sums of the yearly dummy and the yearly interaction effects and 95 per cent confidence band by occupational categories (part 2/2)



Notes: Graphs refer to results in column OLS 4 in table 3.7, based on the data set disaggregated by occupations and NUTS3 regions. The dots and the vertical lines mark the point and 95% interval estimates.

Source: Statistics of the Federal Employment Agency, own computations.

3.5.2 Aggregated data

Most of the estimates presented are highly significant with very small standard errors and are also significantly different from one another. The reason for this result is the enormous variation of the data set the study is based on. From my knowledge, this study is the first to deliver such exact evidence. However, one shortcoming of such a detailed data set is that the probability of measurement errors at the small local area level or occupational level increases. In aggregated data sets, those measurement errors could be "compensated" for, and the prize are higher standard errors. Because I am interested in the effects on partial labour markets, it is important to see whether the results would change after aggregating the data set. Therefore, I aggregated the data sets by NUTS3 regions over occupations and vice versa. As expected, the results show less precision, but the main conclusions remain stable. Compare further results in appendix 3.A.3, table 3.10 with figures 3.11 and 3.12 for the data set with NUTS3 regions as well as table 3.11 with figures 3.13 and 3.14 for the data set with occupations.

3.6 Conclusions

In this paper, I present analyses of changes in the job matching productivity before, during, and after the German labour market reforms of 2003 to 2005, which are also known as the Hartz reforms. Although one of the main objectives of the German labour market reforms was to improve the matching processes on the labour market, there are only a few studies that elucidate the direction and structure of the reform effects on job matching. Previous studies confirm positive effects, but there are different conclusions regarding the effects of the different reform stages. Furthermore, it was not known whether the reform effects covered the entire labour market or only parts of it. Another question is how the effects change during extreme economic situations like the financial crisis of 2008/2009.

The paper closes some of these gaps by estimating (unrestricted) macroeconomic matching function parameters on the basis of detailed, high-frequency, and recent administrative panel data for the 2000–2011 period. To identify effects for occupational labour markets, I utilise an occupational category scheme that distinguishes between simple manual occupations, qualified manual occupations, technicians, engineers, simple service occupations, qualified service occupations, semi-professions, professions, simple business and administrative occupations, qualified business and administrative occupations, and managers.

The results complement previous findings and show significant differences in the changes of matching productivity in different occupational labour markets. In general, six important new conclusions can be derived: (1) matching productivity increased during all reform stages, including Hartz IV; (2) even after controlling for the recession, matching productivity was (slightly) deteriorated in 2009, the year of the financial crisis; (3) the positive changes become smaller in recent years; (4) the reform reached all occupational labour markets, as suggested, in particular, by the results of the analysis for occupational labour markets; (5) the result of smaller positive effects in recent years is not true for all occupational groups; and (6) a (rather small) "crisis dip" during 2009 can be observed in the occupational labour markets of technicians and qualified manual occupations.

The results complement studies that find that the German reforms had positive effects on the labour market. It can be stated that a more efficient job matching contributes to a more successful realisation of companies' activity plans and, therefore, this higher efficiency should boost – rather than weaken – the standing of firms in their relevant markets.

3.A Appendix to chapter 3

3.A.1 Occupational labour markets

Table 3.8: Assignment of Blossfelds occupational categories to the 3-digit code of the German occupational classification scheme 1988 *(KldB 88)*

	KldB 88 – occupational orders	
Occupational category	**Code**	**Title**
[01] AGR agrarian occupations	11	Farmers
	12	Winegrowers
	21	Livestock farmer
	22	Fish farmer
	41	Mixed crop and livestock farm labourers
	42	Livestock and dairy producers
	44	Pet groomers, animal care workers and related occupations
	51	Gardeners, horticultural and nursery growers
	53	Florists
	61	Forestry production managers, foresters and huntspersons
	62	Forestry labourers
[02] EMB simple manual occupations	71	Miners
	72	Mining shot firers and blasters
	81	Stone crushers
	82	Earth, gravel and sand quarry workers
	83	Gas and crude oil quarry workers
	91	Mineral and stone processing plant operators
	101	Stone splitters, cutters and carvers
	102	Precious-stone workers, jewel preparers
	111	Brickmakers and other stoneware makers
	112	Cement and concrete block makers
	121	Ceramics plant operators
	131	Frit makers, glass vitrifiers
	132	Hollow glassware makers
	133	Flat glass makers
	135	Glass cutters, grinders and refiners
	141	Chemical products, plant and machine operators
	143	Rubber products machine operators
	151	Plastic products machine operators
	161	Pulp and cellulose plant operators
	162	Packaging makers
	164	Other paper products machine operators
	176	Hecto- and mimeo-graphers
	177	Printer's hands
	181	Wood-processing plant operators

	KldB 88 – occupational orders	
Occupational category	Code	Title
	182	Woodworking machine setters and setter-operators, and appropriate occupations
	183	Wood products, brush- and cork-maker
	184	Basketry weavers and wicker worker
	191	Ore and metal furnace operators, metal melters
	192	Rolling-mill operators
	193	Metal drawers and extruders
	203	Casters of semi-finished products and other mould casters
	211	Sheet metal pressers, drawer and puncher
	212	Wire moulder, cable splicers
	213	Other metal moulders non cutting deformation
	222	Metal milling cutters
	223	Metal planers
	224	Metal borers
	225	Metal grinders
	226	Other metal-cutting occupations
	231	Metal polishers
	232	Engravers, chasers
	233	Metal finishers
	234	Galvanisers, metal colourers
	235	Enamelers, zinc platers and other metal surface finishers
	241	Welder, oxy-acetylene cutters
	242	Solderers
	243	Riveters
	244	Metal bonders and other metal connectors
	263	Pipe and tube fitters
	301	Precious fitters otherwise undisclosed
	313	Electric motor, transformer fitters
	321	Electrical appliance and equipment assemblers
	322	Metal, rubber, plastic, paperboard, textile and related products assemblers
	323	Metal plant operators no further specification
	332	Spoolers, twisters, rope makers
	341	Weaving- and knitting-machine preparers
	342	Weavers and weaving-machine operators
	343	Tufted textile-, fur- and leather-products makers
	344	Knitters and knitting-machine operators
	345	Felt and hat body makers
	346	Textile braiders
	352	Sewers and sewing-machine operators
	353	Lingerie tailors and sewers
	354	Embroiderers

	KldB 88 – occupational orders	
Occupational category	Code	Title
	355	Hatters and cap makers
	356	Sewer and sewing-machine operators otherwise undisclosed
	357	Other textile-products makers
	361	Textile dyer and dyeing-machine operators
	362	Textile bleaching-, cleaning-machine operators and other finishers
	371	Tanners, catgut string makers and other leather-preparing machine operators
	373	Shoemaking-machine operators
	375	Purse, hand bag and other fine-leather products makers
	376	Leather garment makers and other leather-products machine operators
	377	Leather glove makers
	402	Meat- and sausage-processing machine operators
	403	Fish-processing machine operators
	412	Ready-made meal-, fruit- and vegetable-processing machine operators
	424	Tobacco preparers, product makers
	431	Dairy-products machine operators, butter, lard and margarine makers
	432	Grain- and spice-milling machine operators
	433	Sugar-production machine operators, chocolate, sweets and ice-cream makers
	442	Steel fixers, concrete workers
	452	Roofers
	453	Scaffolders
	461	Pavers
	462	Road building experts
	463	Track building experts
	465	Land improvement, maintenance and hydraulic structure building experts
	466	Well, duct and other civil engineering building experts
	471	Earth-moving labourers
	472	Building construction labourers and other construction and maintenance labourers otherwise undisclosed
	482	Insulators and proofers
	486	Composition floor and terrazzo layers
	504	Other wood-products makers, Boat-, glider- and wooden sports-equipment building experts
	512	Goods painters and varnishers
	513	Wood surface finishers, veneers
	514	Glass, ceramics and related decorative painters, glass engravers and etchers
	521	Products testers, sorters otherwise undisclosed

Occupational category	KldB 88 – occupational orders Code	Title
	522	Product packagers, balers, wrappers, qualifiers and other loading agents
	531	Labourers not further specified
	543	Pump-, compressor-, assembly line-, boring and other machines operators
	544	Crane and hoist plant operators
	545	Earth-moving and related plant operators
	546	Construction plant operators
	547	Machine maintenance operators, machinists' assistants
	548	Boiler persons, incinerators and related plant operators
	549	Machine-tool setters and setter-operators no further specified
[03] QMB qualified manual occupations	134	Gaffer
	142	Chemical laboratory workers
	144	Tyre vulcanisers
	163	Bookbinding workers
	171	Type setters, pre-press workers
	173	Book printers, letterpress
	174	Flat screen, gravure and intaglio printers
	175	Special, silk-screen printers
	201	Moulders and core makers
	202	Casters
	221	Metal lathe operators
	251	Steel-, black-, hammersmiths and forging press workers
	252	Tank and container builders, coppersmiths and related occupations
	261	Tinsmiths
	262	Plumbers
	270	Locksmiths and fitters, not further specified
	271	Building fitters
	272	Sheet metal worker, plastics fitters
	273	Engine fitters
	274	Plant and maintenance fitters
	275	Steel construction fitters, steel ship builders
	281	Motor vehicle repairers
	282	Agricultural machinery repairers
	283	Aircraft mechanics
	284	Precision mechanics
	285	Other mechanics
	286	Watch-, clockmakers
	291	Toolmakers, instrument mechanics
	302	Precious metal smiths
	305	Musical instrument makers
	306	Doll, model makers, taxidermists

Occupational category	KldB 88 – occupational orders Code	Title
	311	Electrical fitters, mechanics
	312	Telecommunications mechanics, craftsmen
	314	Electrical appliance fitters
	315	Radio, sound equipment mechanics
	331	Spinner, fibre-preparer
	351	Tailors and dressmakers
	372	Shoe-makers
	374	Saddlers, truss makers and other coarse-leather-products makers
	378	Pelt dressers, furriers and other fur-products makers
	391	Bakers and baked-goods, cereal- and chocolate-products machine operators
	392	Pastry-cooks and confectionery makers
	401	Butchers and stickers
	411	Cooks
	421	Wine coopers and other wine-processing operators
	422	Brewers, maltsters and other brewer machine operators
	423	Other beverage makers, coffee-processing-machine operators, tasters and graders
	441	Bricklayers and masons
	451	Carpenters
	464	Shot firers and blasters except mining shot firers
	481	Stuccoers, plasterers
	483	Tile setters
	484	Stove setters and air heating fitters
	485	Glaziers
	491	Interior decorators, carpet and parquet layers
	492	Upholsterers, mattresses makers
	501	Cabinetmakers, carpenters and joiners
	502	Pattern and mold carpenters
	503	Cartwrights, wheelwrights, coopers and tubbers
	511	Construction painters, wallpaperers, varnishers
	541	Power production plant operators
	542	Winding-, conveyor- and ropeway-machine operators
[04] TEC technicians	32	Agricultural engineers and advisors
	52	Garden and landscape architects and administrators
	303	Dental technicians
	304	Ophthalmic opticians
	601	Mechanical and automotive engineers
	602	Electrical and electronics engineers
	603	Architects, civil and structural engineers
	604	Cartographers and survey engineers
	605	Mining, metallurgy, foundry engineers

	KldB 88 – occupational orders	
Occupational category	Code	Title
	606	Other production engineers
	607	Industrial and other operating engineers
	611	Chemists, chemical engineers
	612	Physicists, physics engineers, mathematicians
	621	Mechanical engineering technicians
	622	Electrical, electronics and telecommunications engineering technicians
	623	Civil engineering technicians
	624	Survey engineering technicians
	625	Mining, metallurgy, foundry engineering technicians
	626	Chemical and physical engineering technicians
	627	Other production technicians
	628	Industrial and other operating technicians
	629	Forepersons and other operations managers
	631	Agronomy, forestry and life science technicians
	632	Physical and mathematical science technicians
	633	Chemical science technicians
	634	Photo laboratory technicians
	635	Draftspersons
	721	Navigators, nautical ships' officers and pilots
	722	Technical ship's officers, engineers, technicians and machinists
	726	Aircraft pilots, flight engineers and other air traffic occupations
	733	Radio operators
	857	Medical technical, laboratory, radiological assistants
	883	Biologists, geographers, meteorologists and other natural scientists, otherwise undisclosed
[06] EDI simple service occupations	685	Chemist's assistants in pharmacies
	686	Filling station attendants
	706	Cashiers, ticket agents, Debt- and vending-machine money collectors and ticket inspectors
	713	Other brake, signal and switch operators, transport guides and conductors, fleet managers
	714	Car, taxi, bus, (heavy) truck and other motor vehicle drivers
	715	Cabby
	716	Construction and maintenance labourers: roads, dams, bridges and similar constructions
	723	Seagoing ships' deck crews
	724	Inland boatmen and related ships' decks crews
	725	Ferrymen, lockmasters, coastguards and other water traffic occupations
	741	Stocks administrators and clerks
	742	Lift, lifting-trucks and other materials handling equipment operators

Occupational category	KldB 88 – occupational orders Code	Title
	743	Longshoremen, furniture removers
	744	Stock, loading and other transport workers
	791	Factories security offices, store, hotel and other detectives
	792	Watchpersons, custodians, attendants and related workers
	793	Door-, gatekeepers and caretakers
	794	Menials, bellmen, ushers and groundkeepers
	805	Disinfectors, morticians, meat and and other health inspectors
	838	Clowns, magicians, acrobats, professional sportspersons, mountain guides and models
	911	Hoteliers, innkeepers, restaurateurs and management assistants in hotels and restaurants
	912	Waiters, waitresses, stewards, stewardesses and buspersons
	913	Porters, bartenders and other hotel and restaurant attendants
	923	Valets, chambermaids and other housekeeping attendants
	931	Launderers and ironers
	932	Textile cleaner, dyers, chemical purifiers
	933	Dishwashers, room and domestic cleaners
	934	Windows, frontages and buildings cleaners
	935	Sweepers, streets and sewerages cleaners, dustmen and other waste disposal workers
	936	Car washers, vehicle cleaners, car and vehicle carers
	937	Machinery, plant, tube and container cleaners
[07] QDI qualified service occupations	172	Stereotypers and electrotypers
	684	Chemists in drugstores
	704	Finance, stock, trade, ship, real estate, insurance brokers
	705	Landlords, hirers, agents, bookers, auctioneers
	711	Locomotive engine, tram and subway drivers
	712	Railway brake, signal and switch operators, shunters and railway guards and conductors
	801	Soldiers, border guards, police officers
	802	Firefighters
	803	Safety inspectors, trade controllers, gauging, and environmental protection officers
	804	Chimney sweepers
	812	Law officers
	814	Executory officers, prison guards
	831	Composers, music directors and musicians
	832	Film, stage and related directors, actors, singers and dancers
	833	Sculptors, painters, graphic and related artists
	834	Decorators, sign painters
	835	Set designer, light board, image and sound recording engineers, technicians and operators

Occupational category	KldB 88 – occupational orders Code	Title
	836	Interior architects, visual merchandiser
	837	Photographers, camera and retouching operators
	851	Non-medical practitioners, psychotherapists
	852	Masseurs, physiotherapists and health care professionals
	854	Paramedics and nursing auxiliary workers
	855	Dieticians, nutritionists and pharmacy technicians
	856	Doctor's receptionists and assistants
	892	Nuns, friars and other religious associate professionals
	893	Sextons, cantors and other religious assistants
	901	Hairdressers, barbers, wigmakers and related workers
	902	Beauticians, manicurists, pedicurists and related workers
	921	Housekeepers and related workers
	922	Energy and other consumer advisors
[08] SEMI semi professions	821	Authors, journalists, editors and announcers
	822	Interpreters, translators
	823	Librarians, archivists, documentalists, curators, library and filing clerks
	853	Nurses, midwifes, nursing and midwifery associate professionals
	861	Social work, welfare, health care professionals and workers; geriatric nurses
	862	Housemasters, social pedagogue, deacons
	863	Employment, vocational training, study, careers advisors
	864	Kindergarten teachers, child care workers and paediatric nurses
	873	Primary, secondary school, special education teachers and related teaching professionals
	874	Vocational, professional college teachers and related teaching professionals
	875	Art, music and voice teachers and related teaching professionals, otherwise undisclosed
	876	PE teachers, related teaching professionals, skiing and other sports instructors
	877	Driving, flying, hygienic and other instructors, otherwise undisclosed
[09] PROF professions	811	Judges and prosecutors
	813	Lawyers, notaries, legal representatives, advisors and other legal professionals
	841	Medical doctors
	842	Dentists
	843	Veterinaries
	844	Pharmacists
	871	University, college professors and related teaching professionals
	872	Grammar school teacher and related teaching professionals

Occupational category	KldB 88 – occupational orders Code	 Title
	881	Economists, psychologists, sociologists, political scientists, statisticians
	882	Philologists, historians, philosophers and other humanities scientists, otherwise undisclosed
	891	Bishops, pastors, chaplains and other religious professionals
[10] EVB simple business and administrative occupations	682	Shop, stall and market salespersons and demonstrators
	687	Commercial sales representatives and sales agents
	732	Mail carriers, sorting clerks, porters and deliverers
	734	Telephone switchboard operators
	773	Cashiers and ticket clerks
	782	Secretaries, stenographers and typists
	783	Data entry operators
	784	Scribes and other office hands
[11] QVB qualified business and administrative occupations	31	Agricultural production manager
	681	Wholesaler, retail salespersons and buying agents
	683	Publishers, management assistants in publishing and booksellers
	691	Banking experts including tellers, finance clerks as well as finance dealers and brokers
	692	Building society experts including representatives as well as clerks
	693	Health insurance experts including representatives as well as clerks, not social security
	694	Life, property insurance experts including representative as well as clerks
	701	Logistics managers and transport clerks
	702	Travel agency clerks, attendants, stewards, consultants, organisers and guides
	703	Advertising and public relations experts
	771	Calculators, calculating and counting clerks
	772	Bookkeepers
	774	Computer scientists, equipment operators, computing and data processing professionals
	781	Office clerks, otherwise undisclosed
[12] MAN manager	751	Entrepreneurs, managing directors and division managers
	752	Management personnel and other business consultants
	753	Financial, tax accountants and accounting clerks
	762	Senior and administrative state officials
	763	Senior and administrative officials of humanitarian and other special-interest organisations
[00] not assignable	982	Interns, volunteer with occupation remaining to be specified
	983	Job-seekers with occupation remaining to be specified
	991	Labourers not further specified

3.A.2 Effect coding

The time dummy variables, the occupational labour market dummy variables, and the interaction variables that are used in the regression equation to analyse occupational and time-specific changes in matching productivity are effect coded. The advantage of effect coding is that the coefficients can be directly interpreted as deviations from the general, the time or the occupational specific intercept in the model. This intercept can be interpreted as the average overall, time specific or occupational matching productivity.

Formally, the year dummy variable d_y with $y = [2001, ..., 2011]$ with reference year 2000 is coded as follows (t denotes the observed month/year):

$$d_y = \begin{cases} -1 & year(t) = 2000 \\ 0 & year(t) \neq y \\ 1 & year(t) = y \end{cases}$$

The occupational labour market dummy variables d_b with $b = [2, ..., 12]$ with reference category "Agrarian and not assignable occupations" (occupational category = 1) are coded as follows:

$$d_b = \begin{cases} -1 & \text{occupational category}(j) = 1 \\ 0 & \text{occupational category}(j) \neq b \\ 1 & \text{occupational category}(j) = b \end{cases}$$

To measure the occupational category specific reform effects, I use effect-coded interaction dummy variables with the occupational reference category "Agrarian and not assignable occupations" and the reference year 2000. This interaction effect variable $d_{b,y}$ with $y = [2001, ..., 2011]$ and $b = [2, ..., 12]$ is coded as follows:

$$d_{b,y} = \begin{cases} -1 & year(t) = 2000 \text{ and occupational category}(j) = 1 \\ 0 & year(t) \neq y \text{ and} \\ & \text{occupational category}(j) \neq b \\ 1 & year(t) = y \text{ and occupational category}(j) = b \end{cases}$$

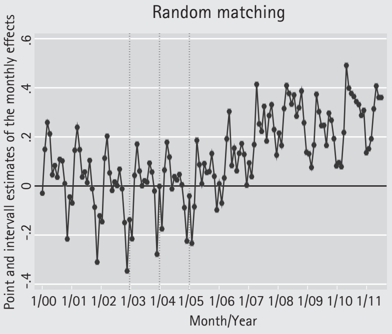
3.A.3 Further empirical results

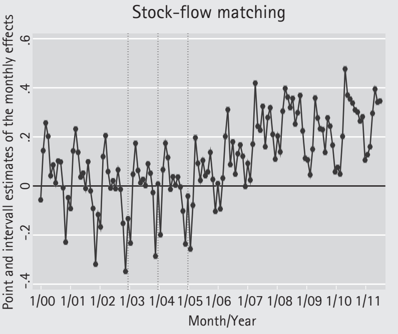
Table 3.9: Fixed effects estimation results based on data set disaggregated by occupations and NUTS3 regions, all specifications without recession variable

	Dependent variable: log M					
	FE 1	FE 2	FE 3	FE 4	FE 5	FE 6
β_{Us}	0.514***	0.623***	0.624***	0.453***	0.563***	0.582***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
β_{Uf}				0.085***	0.071***	0.049***
				(0.002)	(0.001)	(0.001)
β_{Vs}	0.060***	0.040***	0.044***	0.041***	0.021***	0.023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
β_{Vf}				0.029***	0.030***	0.034***
				(0.001)	(0.001)	(0.001)
Year dummies, effect coded (reference: 2000):						
d_{2001}			-0.100***			-0.101***
			(0.001)			(0.001)
d_{2002}			-0.146***			-0.139***
			(0.001)			(0.001)
d_{2003}			-0.135***			-0.129***
			(0.001)			(0.001)
d_{2004}			-0.123***			-0.121***
			(0.001)			(0.001)
d_{2005}			-0.103***			-0.096***
			(0.002)			(0.002)
d_{2006}			-0.023***			-0.016***
			(0.001)			(0.001)
d_{2007}			0.099***			0.102***
			(0.001)			(0.001)
d_{2008}			0.174***			0.169***
			(0.002)			(0.002)
d_{2009}			0.089***			0.083***
			(0.001)			(0.001)
d_{2010}			0.165***			0.155***
			(0.001)			(0.001)
d_{2011}			0.162***			0.155***
			(0.002)			(0.002)
a	-0.428***	-0.970***	-0.912***	-0.381***	-0.888***	-0.861***
	(0.013)	(0.014)	(0.012)	(0.012)	(0.014)	(0.012)
Monthly time dummies	no	yes	no	no	yes	no
Quarter dummies	no	no	yes	no	no	yes
Observations	2,394,250	2,394,250	2,394,250	2,394,250	2,394,250	2,394,250
R-squared	0.206	0.304	0.274	0.213	0.309	0.278
Number of groups	55,422	55,422	55,422	55,422	55,422	55,422

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Note: Columns FE 2 and FE 5 include monthly time fixed effects with effect coding (reference period is January 2000), compare with figure 3.9.

Figure 3.9: Monthly time fixed effects and 95 per cent confidence band

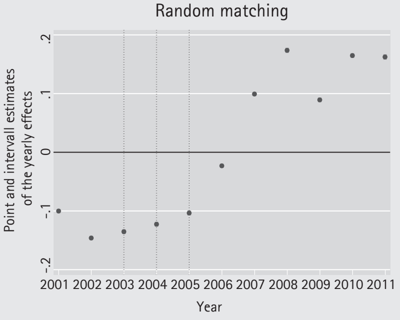


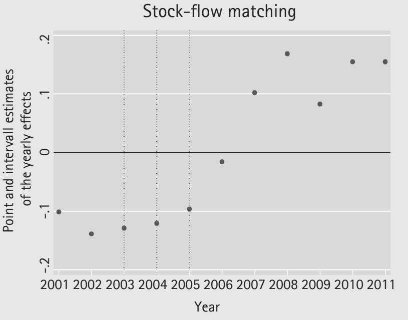


Notes: Specifications from table 3.9, left side: FE 2, right side: FE 5, based on data set disaggregated by occupations and NUTS3 regions, all regressions without recession variable. The dots and the vertical lines mark the point and 95% interval estimates; in most cases, the interval is very small. The dots are linked with a line to illustrate the temporal development. Monthly time fixed effects with effect coding (reference period is January 2000).

Source: Statistics of the Federal Employment Agency, own computations.

Figure 3.10: Yearly time fixed effects and 95 per cent confidence band





Notes: Specifications from table 3.9, left side: FE 3, right side: FE 6, based on a data set disaggregated by occupations and NUTS3 regions, all regressions without recession variable. The dots and the vertical lines mark the point and 95% interval estimates; in most cases, the interval is very small. Yearly time fixed effects with effect coding (reference period is 2000).

Source: Statistics of the Federal Employment Agency, own computations.

Table 3.10: Fixed effects estimation results based on data set disaggregated by NUTS3 regions

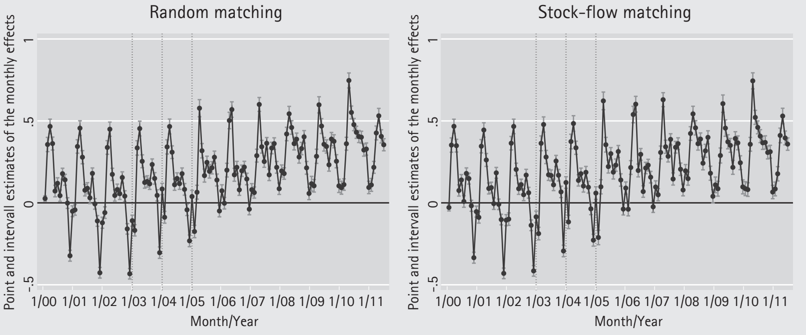
	Dependent variable: log M							
	FE 1	FE 2	FE 3	FE 4	FE 5	FE 6	FE 7	FE 8
β_{Us}	0.469***	0.469***	0.618***	0.690***	0.476***	0.476***	0.527***	0.745***
	(0.016)	(0.016)	(0.021)	(0.024)	(0.019)	(0.019)	(0.024)	(0.029)
β_{Vs}	0.123***	0.123***	0.061***	0.110***	0.074***	0.076***	0.026***	0.031***
	(0.009)	(0.009)	(0.007)	(0.008)	(0.012)	(0.012)	(0.008)	(0.009)
β_{Uf}					−0.056***	−0.058***	0.151***	−0.109***
					(0.015)	(0.016)	(0.016)	(0.014)
β_{Vf}					0.062***	0.063***	0.075***	0.141***
					(0.009)	(0.009)	(0.006)	(0.007)
Year dummies, effect coded (reference: 2000):								
d_{2001}				−0.143***				−0.195***
				(0.005)				(0.005)
d_{2002}				−0.165***				−0.171***
				(0.005)				(0.005)
d_{2003}				−0.099***				−0.096***
				(0.006)				(0.006)
d_{2004}				−0.066***				−0.057***
				(0.006)				(0.006)
d_{2005}				−0.025***				−0.021***
				(0.007)				(0.007)
d_{2006}				−0.003				−0.007
				(0.005)				(0.006)
d_{2007}				0.066***				0.065***
				(0.005)				(0.005)
d_{2008}				0.133***				0.149***
				(0.007)				(0.007)
d_{2009}				0.122***				0.177***
				(0.009)				(0.010)
d_{2010}				0.172***				0.201***
				(0.006)				(0.007)
d_{2011}				0.097***				0.114***
				(0.008)				(0.009)
γ		0.014	0.895***	0.921***		−0.203***	1.121***	1.266***
		(0.066)	(0.156)	(0.162)		(0.077)	(0.139)	(0.162)
a	1.285***	1.285***	0.181	−0.685***	1.568***	1.568***	−0.302	−0.701***
	(0.182)	(0.183)	(0.207)	(0.228)	(0.169)	(0.169)	(0.196)	(0.220)
Monthly time dummies	no	no	yes	no	no	no	yes	no
Quarter dummies	no	no	no	yes	no	no	no	yes
Observations	55,371	55,371	55,371	55,371	55,371	55,371	55,371	55,371
R-squared	0.144	0.144	0.666	0.426	0.151	0.151	0.675	0.446
Number of groups	402	402	402	402	402	402	402	402

Robust standard errors in parentheses.

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

Note: Columns FE 3 and FE 7 include monthly time fixed effects with effect coding (reference period is January 2000), compare with figure 3.11.

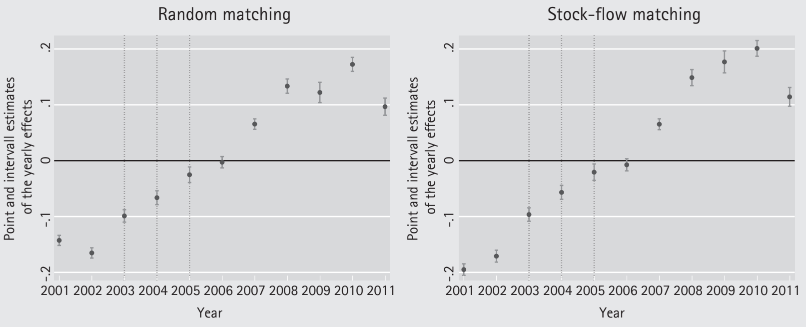
Figure 3.11: Monthly time fixed effects and 95 per cent confidence band



Notes: Specifications from table 3.10, left side: FE 3, right side: FE 7, based on data set disaggregated by NUTS3 regions. The dots and the vertical lines mark the point and 95% interval estimates; in the most cases the interval is very small. The dots are linked with a line to illustrate temporal development. Monthly time fixed effects with effect coding (reference period is January 2000).

Source: Statistics of the Federal Employment Agency, own computations.

Figure 3.12: Yearly time fixed effects and 95 per cent confidence band



Notes: Specifications from table 3.10, left side: FE 4, right side: FE 8, based on data set disaggregated by NUTS3 regions. The dots and the vertical lines mark the point and 95% interval estimates. Yearly time fixed effects with effect coding (reference period is 2000).

Source: Statistics of the Federal Employment Agency, own computations.

Table 3.11: Fixed effects estimation results based on data set disaggregated by occupations

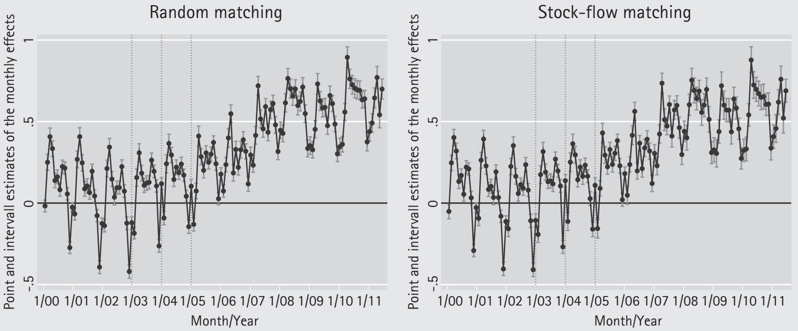
	Dependent variable: log M							
VARIABLES	FE 1	FE 2	FE 3	FE 4	FE 5	FE 6	FE 7	FE 8
β_{Us}	0.640***	0.645***	0.927***	0.928***	0.507***	0.505***	0.832***	0.940***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.028)	(0.028)	(0.043)	(0.039)
β_{Uf}					0.174***	0.188***	0.091**	–0.029
					(0.038)	(0.039)	(0.042)	(0.037)
β_{Vs}	0.138***	0.132***	0.087***	0.098***	0.092***	0.085***	0.031***	0.035***
	(0.011)	(0.011)	(0.008)	(0.008)	(0.013)	(0.013)	(0.010)	(0.010)
β_{Vf}					0.052***	0.048***	0.071***	0.083***
					(0.013)	(0.013)	(0.010)	(0.010)
Year dummies, effect coded (reference: 2000):								
d_{2001}				–0.260***				–0.281***
				(0.009)				(0.012)
d_{2002}				–0.282***				–0.282***
				(0.008)				(0.010)
d_{2003}				–0.209***				–0.214***
				(0.009)				(0.011)
d_{2004}				–0.141***				–0.149***
				(0.009)				(0.009)
d_{2005}				–0.075***				–0.084***
				(0.009)				(0.011)
d_{2006}				–0.043***				–0.042***
				(0.006)				(0.007)
d_{2007}				0.113***				0.126***
				(0.008)				(0.009)
d_{2008}				0.237***				0.254***
				(0.010)				(0.014)
d_{2009}				0.279***				0.292***
				(0.011)				(0.015)
d_{2010}				0.320***				0.330***
				(0.010)				(0.014)
d_{2011}				0.248***				0.265***
				(0.014)				(0.017)
γ		0.717***		1.800***		1.042***		1.624***
		(0.146)		(0.180)		(0.175)		(0.177)
a	–0.596***	–0.595***	–2.874***	–2.723***	–0.590***	–0.603***	–2.696***	–2.684***
	(0.158)	(0.159)	(0.148)	(0.139)	(0.145)	(0.145)	(0.162)	(0.152)
Monthly time dummies	no	no	yes	no	no	no	yes	no
Quarter dummies	no	no	no	yes	no	no	no	yes
Observations	42,053	42,053	42,053	42,053	42,053	42,053	42,053	42,053
R-squared	0.453	0.454	0.675	0.610	0.464	0.466	0.681	0.616
Number of groups	327	327	327	327	327	327	327	327

Robust standard errors in parentheses.

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

Note: Columns FE 3 and FE 7 include monthly time fixed effects with effect coding (reference period is January 2000), compare with figure 3.13. Specifications FE 3 and FE 7 without $GDP_{cyc,\ quarter(t)}$ due to collinearity.

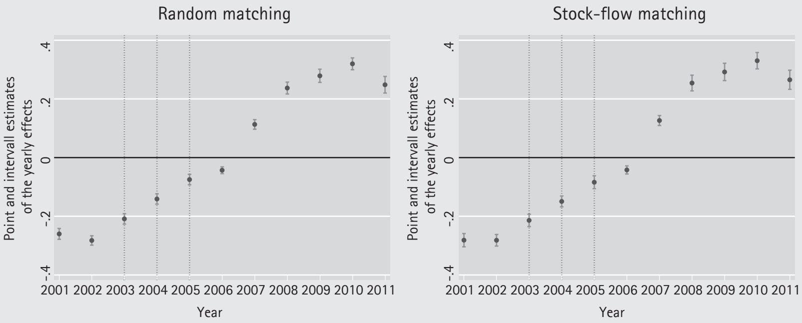
Figure 3.13: Monthly time fixed effects and 95 per cent confidence band



Notes: Specifications from table 3.11, left side: FE 3, right side: FE 7, based on data set disaggregated by occupations. The dots and the vertical lines mark the point and 95% interval estimates; in the most cases the interval is very small. The dots are linked with a line to illustrate the temporal development. Monthly time fixed effects with effect coding (reference period is January 2000).

Source: Statistics of the Federal Employment Agency, own computations.

Figure 3.14: Yearly time fixed effects and 95 per cent confidence band



Notes: Specifications from table 3.11, left side: FE 4, right side: FE 8, based on data set disaggregated by occupations. The dots and the vertical lines mark the point and 95% interval estimates; in most cases, the interval is very small. The dots are linked with a line to illustrate the temporal development. Monthly time fixed effects with effect coding (reference period is January 2000).

Source: Statistics of the Federal Employment Agency, own computations.

Table 3.12: Absolute year-to-year differences between the yearly time fixed effects sums from figures 3.4 and 3.5, based on the random matching model

Occupational category	2001/2002	2002/2003	2003/2004	2004/2005	2005/2006	2006/2007	2007/2008	2008/2009	2009/2010	2010/2011
[2] EMB	-0.005	0.006	0.004	0.023	**0.140**	0.075	0.103	0.017	0.047	-0.049
[3] QMB	-0.029	**0.067**	0.009	0.026	0.009	0.056	0.061	-0.013	0.049	-0.011
[4] TEC	-0.038	0.040	0.047	0.015	0.040	**0.124**	0.093	-0.029	0.025	-0.007
[5] ING	-0.029	0.042	0.079	0.075	0.019	**0.128**	0.103	0.000	0.003	0.016
[6] EDI	-0.043	0.031	0.032	0.008	**0.099**	0.056	0.073	0.037	0.025	-0.059
[7] QDI	-0.031	0.054	0.017	-0.038	-0.024	**0.096**	0.087	0.058	-0.034	-0.044
[8] SEMI	-0.011	0.031	0.063	0.073	-0.024	**0.087**	0.043	0.018	-0.038	-0.101
[9] PROF	0.004	0.064	**0.098**	0.016	-0.022	0.075	0.078	0.091	-0.054	-0.030
[10] EVB	-0.015	0.071	0.053	-0.007	0.051	**0.099**	0.096	0.018	-0.010	-0.066
[11] QVB	-0.046	0.052	0.051	0.012	-0.013	**0.101**	0.071	0.022	0.020	-0.053
[12] MAN	0.010	0.019	0.064	-0.001	0.039	**0.149**	0.071	0.048	-0.005	-0.034

Abbreviations: [01] AGR agrarian and not assignable occupations; [02] EMB simple manual occupations; [03] QMB qualified manual occupations; [04] TEC technicians; [05] ING engineers; [06] EDI simple service occupations; [07] QDI qualified service occupations; [08] SEMI semi professions; [09] PROF professions; [10] EVB simple business and administrative occupations; [11] QVB qualified business and administrative occupations; [12] MAN manager.

Source: Statistics of the Federal Employment Agency, own computations. Bold printed values denote the maximal positive absolute changes of the time fixed effects.

Table 3.13: Absolute year-to-year differences between the yearly time fixed effects sums from figures 3.7 and 3.8, based on the stock-flow matching model

Occupational category	2001/2002	2002/2003	2003/2004	2004/2005	2005/2006	2006/2007	2007/2008	2008/2009	2009/2010	2010/2011
[2] EMB	0.022	0.009	-0.015	0.048	**0.125**	0.044	0.059	0.010	0.030	-0.041
[3] QMB	-0.002	**0.064**	-0.014	0.048	0.000	0.028	0.029	-0.013	0.040	-0.005
[4] TEC	-0.031	0.038	0.023	0.026	0.040	**0.092**	0.057	-0.035	0.035	0.000
[5] ING	-0.021	0.039	0.062	0.085	0.022	**0.107**	0.064	-0.012	0.018	0.014
[6] EDI	-0.018	0.025	0.017	0.040	**0.098**	0.038	0.036	0.027	0.012	-0.053
[7] QDI	-0.018	0.041	-0.003	-0.013	-0.015	**0.078**	0.049	0.047	-0.037	-0.037
[8] SEMI	0.004	0.015	0.039	**0.084**	-0.016	0.076	0.009	0.012	-0.038	-0.090
[9] PROF	0.017	0.051	0.077	0.025	-0.006	0.058	0.047	**0.079**	-0.043	-0.034
[10] EVB	-0.010	0.067	0.038	0.021	0.051	**0.080**	0.055	0.009	-0.011	-0.063
[11] QVB	-0.025	0.055	0.028	0.027	-0.019	**0.078**	0.027	0.016	0.026	-0.047
[12] MAN	0.018	0.025	0.045	0.005	0.034	**0.125**	0.034	0.041	0.013	-0.031

Abbreviations: [01] AGR agrarian and not assignable occupations; [02] EMB simple manual occupations; [03] QMB qualified manual occupations; [04] TEC technicians; [05] ING engineers; [06] EDI simple service occupations; [07] QDI qualified service occupations; [08] SEMI semi professions; [09] PROF professions; [10] EVB simple business and administrative occupations; [11] QVB qualified business and administrative occupations; [12] MAN manager.

Source: Statistics of the Federal Employment Agency, own computations. Bold printed values denote the maximal positive absolute changes of the time fixed effects.

Chapter 4

Identifying the Employment Effect of Invoking and Changing the Minimum Wage: A Spatial Analysis of the UK[1]

1 The contents of this chapter were jointly worked out with Prof. Peter Dolton, Ph.D. (University of Sussex) and Chiara Rosazza-Bondibene, Ph.D. (National Institute of Economic and Social Research, London). The contents of this chapter are published in the journal "Labour Economics" (Dolton et al., 2015).

We assess the impact of the National Minimum Wage (NMW) on employment in the UK over the 1999–2010 period explicitly modelling the effect of the 2008–2010 recession. Identification of invoking a NMW is possible by reference to a pre-period (prior to 1999) without a NMW. Separate identification of the effect of incremental changes (and year interaction effects) in the NMW is facilitated by variation in the bite of the NMW across local labour markets. We address the issues of possible endogeneity and dynamic structure of employment rate changes, regional demand side shocks induced by the recession, and take account of the spatial dependence of local labour markets. Using System GMM, we conclude that there is no discernable effect of the NMW introduction or its uprating on employment but show how more naïve estimation may have revealed the various widely different positive and negative effects found in the literature.

4.1 Introduction

The introduction of a minimum wage (MW) could have important implications for employment levels in an economy. Likewise the uprating or changing of a MW on an annual basis could also have separate incremental effects on employment levels in the economy. Up to now, the literature rarely distinguishes between the imposition of a new MW and its uprating, simply because in most countries we do not observe the pre-period prior to the introduction of a MW to set a benchmark from which to measure the effect of the introduction. The introduction of a new National Minimum Wage (NMW) in Britain in 1999 and its subsequent annual uprating provide a unique opportunity to distinguish between these two effects.[2]

The important concern of how the MW should be changed in times of recession, when most wages are declining in real terms, is a current and pressing problem. The problem is compounded by the consideration of what effects the MW itself may have on employment during the biggest recession since the 1930s. Since inception, the UK NMW has been administered on a national basis, with both adult and youth rates applying to all parts of the country. However, the issue of whether a MW adequately reflects regional variation in the regional cost of living, the relative balance of industrial regional growth, and the growth and variation in regional productivity, is questionable. Clearly, longstanding geographic variation in wage rates across the UK have a direct effect on the 'bite' of the NMW in different areas, as the NMW reaches further up the wage distribution in poorer parts of the country than in others (Stewart, 2002). This study makes use of both this geographical

2 There is voluminous literature on the inequality and other effects of the NMW. These are referenced, e.g., in Dolton et al. (2012). In this article we focus exclusively on the econometric estimation of the employment effects of the MW.

variation and the variation in the real level that the NMW has been set at over time, in order to see how changes in the local area NMW incidence over several years of the minimum wage's existence are correlated with changes in local area performance. We are also concerned that all of our geographic locations are not independent labour markets but interconnected (contiguous) markets. The very fact that the comparative prosperity of the South East of the country is conditioned by the economic gravity that is induced by proximity to London means that we should not treat local labour markets as independent observations in any statistical model. As Dube et al. (2010) recognize, the likely consequences of erroneously doing so induces an underreporting of the standard error of the estimates and hence makes it likely that there will be mistaken positive or negative inferences regarding the relationship between the MW and employment.

This paper builds on that literature by examining the impact of the NMW in the UK over the period 1997–2010, comparing the period two years before its introduction with the subsequent history of the NMW and its up-ratings. This enables us to provide an additional insight by distinguishing between effects in a NMW policy off period compared to each incremental up-rating of the NMW in subsequent years. Hence, instead of using a simple policy on-policy off, difference-in-difference model, we examine a model in which each year's change in the NMW is considered as a separate interaction effect. This 'Incremental Diff-in-Diff' (IDiD) estimator (Dolton et al., 2012)[3] introduces a yearly interaction term for each change of the NMW, so that we may gauge the year-on-year impact of the uprating of the NMW on employment.

Most existing UK studies have focused on the impact of the introduction of the NMW, finding broadly that the aggregate employment effects of the introduction were zero or small and positive (Stewart, 2002, 2004b, a; Dolton et al., 2009, 2010; Dolton and Rosazza-Bondibene, 2012). Arguably, this counter-intuitive employment effect could be due to the fact that any long-run effects have not been captured by previous studies or that the problem of identifying the introduction of the NMW has not been separated from the effects of the annual uprating of the NMW. Clearly, the overall effect of having a MW in the labour market may induce a long run impact whereas small changes in the uprating of the level of the NMW in any given year may induce short run adjustment effects. In this paper, we take a medium to long run look at the impact of the NMW in the UK and its up-ratings and assess whether these two separate processes may have had a differential impact across heterogeneous geographical areas.

3 This IDiD estimator is a logical corollary of the econometric model suggested by Wooldridge (2002) and Bertrand et al. (2004).

There is a large literature on the employment effects of a Minimum Wage (see Brown et al., 1982; Card and Krueger, 1995; Brown, 1999; Neumark and Wascher, 2008, for extensive reviews of the literature). In recent years, there has been a growing literature attempting to identify the effects of a MW on employment by using geographical variation in the bite of the MW in spatially separated markets, see Card (1992); Lee (1999); Neumark and Wascher (1992, 2007); Card and Krueger (1994, 2000); Burkhauser et al. (2000); Dube et al. (2007, 2010); Baskaya and Rubinstein (2012) for the United States; Baker et al. (1999) for Canada; Bosch and Manacorda (2010) for Mexico; Stewart (2002, 2004a, b); and Dolton et al. (2009, 2010, 2012) for the UK. This literature has not concerned itself with what happens to employment effects of the MW in times of macro-economic recession. This paper focuses on the modern era in the UK from 1997 to 2010 with the introduction of the NMW in 1999 and then leading into the current 'Great' recession of 2008–2010. Hence, we focus on the important question of what impact the MW has in an era when the economy is contracting, unemployment is rising, and real incomes are falling for many people in the economy. We do this explicitly by controlling for regional demand shocks using data on Gross Value Added, which is a direct measure of the level and shocks to economic activity over time at a regional level.

A second feature of nearly all the literature on the MW to date which uses geographical variation to identify the impact of the MW is that it has made the assumption that the geographical units of observation are geographically separate and unrelated to one another[4]. This assumption is unwarranted for many important reasons – we focus on just two. Firstly, in reality, a job vacancy is never posted with the condition that nobody outside the immediate geographical vicinity need apply. Clearly, being able to travel to the job location is the problem of the individual and the resulting commute is never considered in whether someone gets the job. This means that labour markets are not independent units of observation that bear no relation to one another. Economists frequently consider local labour markets as if each geographical area consists only of people who both live and work in the same location. Accordingly they model all such areas as a set of independent, unrelated observations. In reality, such a notion is false as all geographical areas have people who live in them but work in other locations. This pattern of commuting is then, in some sense, the realized form of all the subtle interrelationships between different geographical locations. A second flaw with treating such geographical units as independent is that spatially located phenomena like plant closures have an effect not just in the geographical location it occurred in, but also in the immediate

4 One exception is the study by Dube et al. (2010), who consider cross-state border spillovers of the MW in the fast food industry in the US.

neighbouring areas. The degree of contiguity of neighbouring locations is therefore an important factor in the spread of unemployment, poverty, wage rises and other labour market phenomena. The extent of spillover effects from one location to another will depend on transport links, the spatial distribution of related industries and many other factors. It is well known that if we model an econometric relationship under the mistaken assumption that the units of observation are independent of one another (spherical) – when in reality they are not – then we may get biased and inconsistent estimates of the resulting economic relationships. This means that if we estimate a model of the effects of the MW using geographical data under the assumption of non-spatially related units, when they are indeed spatially related, then we will get estimates of the effects which are different from what they should be and also more or less statistically significant than they ought to be. Hence, the assumption of spatial independence is a very important one in this context which should be tested.

An important problem that has been a preoccupation with papers in this literature is how to capture the autoregressive process of employment determination. Many papers have adopted the practice of attempting to control for this by using unemployment or various lags of employment (see Neumark and Wascher, 1994; Burkhauser et al., 2000). Clearly, such variables are endogenous to the employment dependent variable. To overcome this problem, we adopt an Arellano Bond system GMM IV estimator which explicitly controls for the lagged value of employment by a carefully constructed set of lagged values as IVs. This paper is the first in the MW debate (to our knowledge) to adopt this more robust consistent estimation strategy of a dynamic panel model.

Furthermore, with the GMM approach we consider another difficult issue: the problem of the appropriate way to address the potential endogeneity of the controlling MW regressor–typically the Kaitz index.[5] Early papers in the literature just assumed that the wage regressor in the model was exogenous. More recently, some authors recognize the problem and use a variety of IV type strategies to solve it; Dube et al. (2010) considered different lag lengths regarding when the MW comes into effect and Dolton et al. (2011) considered temporal lags of different explanatory variables. In contrast, Baskaya and Rubinstein (2012) focus on the impact of federal minimum wages on state effective minimum wages where the latter have the property of being an external source of variation in state effective minimum wages. According to the authors, this impact varies depending on persistent cross-state disparities in the economic situation and political preferences regarding state specific minimum wage policy. By implementing the lagged employment variable

5 The problem is that the Kaitz index as a ratio is subject to change due to either the denominator, or the numerator, or both. This clearly means that it may shift as a result of the value of the MW (numerator) or as a result shifts in the wage distribution which changes the median of the wage distribution.

in our equation we explicitly control for a potential (partial) wage determination by employment levels in previous periods. Crucially, in this paper, we examine whether the definition of the geographical unit used for the analysis matters. Since the definition of what constitutes a 'local labour market' in Great Britain is still open to discussion, the analysis is undertaken at two different levels of geographical aggregation. Firstly, the data is divided into 140 areas comprising Unitary Authorities and Counties. Secondly we look at how the results change if we use the definition of 67% of people living and working in the same geography to capture a local labour market, as now used by the UK national statistics office to define a "travel-to-work area" (TTWA, 138 resulting areas). We remain agnostic as to what the most appropriate definition of a 'local labour market' is and let the data tell us whether such definitional variations matter.

A secondary goal of this paper is that it attempts to set the different estimates in the literature in context as our econometric estimation model is more general than previously used. In this respect, we introduce each of our contributions in a stepwise fashion demonstrating that we can replicate similar results to earlier papers – but that when we add important considerations like spatial dependence, regional aggregate demand shocks, lagged dependent variable regressors and other endogenous regressors, then we find clearer–less contradictory results. Hence, we examine the robustness of our results with regard to the specification issues associated with dynamic specification to incorporate the lagged effects of previous employment on current employment, and time and interaction effects. Much of the previous literature is presented 'as if' the results are in stark contrast to each other. Often, different papers estimate fundamentally different parameters and this explains a large degree of the differences in results.

To summarize, this work contributes to the literature in the following ways. Firstly we separately identify the employment effect of having a MW from the possible effects of uprating the MW. Secondly, unlike the literature, we treat the geographical units of statistical analysis as being spatially related (rather than independent). Thirdly, we explicitly take account of the current recession by direct consideration of the role of shocks to aggregate demand and, finally, we directly tackle the issue of the dynamic nature of employment process by considering the autoregressive structure of employment using Arellano–Bond type IV estimation in a system GMM context. We suggest that these advances can provide a new insight into the effect of the MW on employment.

The paper is organised as follows. Section 4.2 describes the datasets used and the characteristics of the data and highlights its spatial nature. Section 4.3 outlines the econometric methodology and identification for the analysis and section 4.4 presents the main results of the analysis. Section 4.5 concludes.

4.2 Data

In our data, we can examine the spatial association of the "bite" of the minimum wage with the geographic variation in employment. Geographical variation in wages in the UK is exploited in order to evaluate the impact of the NMW on employment at the local level. The data used in this study are drawn primarily from three sources. Data on earnings, and a restricted number of covariates all disaggregated by geography is provided by the New Earnings Survey (NES) from 1997 to 2003 and by the Annual Survey of Hours and Earnings (ASHE), which replaced the NES in 2004. In both surveys, conducted in April of each year, employers are asked to provide information on hours and earnings of the selected employees. The geographic information collected for the full sample period used in the paper is based on workplace rather than residence.

In what follows we describe the data[6]. In this paper we consider all workers, not just young people separately. This is in contrast to much of the literature. We do this because we are interested in the validly measured potential aggregate real effects of the MW on the whole labour market and not only the section of it which is most affected by the MW. In other words, we are interested in the overall effect of the MW on employment – i.e. the extensive margin of the MW effect – not its intensive margin.[7]

The geographic variation in wages will reflect the demographic and industrial composition of each local labour market. The changing industrial composition of an area and the extent to which industries are low and high paying will affect the changing incidence of the minimum wage working in a locality. Likewise the skill, age, gender and sector composition of the local workforce will be important factors. To a certain extent we can control for variation in these influences with a set of time varying local labour market control variables, drawn from either ASHE or matched in from complementary Labour Force Survey (LFS) data. However, the choice of what constitutes a local labour market is open to discussion, therefore the analysis is conducted at two different levels of aggregation. We perform our estimation separately, on the level of 140 Unitary Authorities and Counties (WAREA) and on the level of 138 travel-to-work areas (TTWA). Since our analysis is performed at both units of geography it is relevant to highlight the main differences between the different levels of analysis'. Specifically the 140 level is borne of local government administrative areas and consists of

6 More details of our data and its limitations and the technical properties of our key variables are described in appendix 4.A.1. In this appendix, we also discuss the alternative geographical units of analysis.

7 In addition it is not possible to perform the estimation for young people alone because there is no data for the policy off period of 1997 and 1998.

counties and separate conurbations. These boundaries were created largely by historical accident. The 138 TTWAs are defined by a threshold of the fraction (two thirds) who live and work in the same area. We perform our analysis for each of the two levels of geography as an important robustness test as the nature of the cross section units are fundamentally different in the case of our TTWA or WAREA areas. Since the economic geography literature is largely silent on what is the correct choice of the level of geographical analysis then we repeat our analysis for both levels. Obviously, the basis for our analysis is different if we are comparing administrative units rather than TTWA geographies. As we shall see later, we are largely reassured by the fact that our estimation results are qualitatively similar across the two different geographies.

4.2.1 The employment variable

We then match local area employment data from the LFS with the minimum wage covariates generated from ASHE. There is an important feature of the timing of data collection which we exploit in order to try and make sure that our employment variable is measured after the up-rating of the NMW. The ASHE and NES estimates for hourly earnings and therefore the minimum wage variables used in this paper are recorded in April of each year. Since the minimum wage was first introduced in April 1999 but then up-rated in October of each following year, the NMW variables are therefore generally recorded six months after each NMW up-rating.[8]

Data on employment at these levels of aggregation derived from the LFS are available via NOMIS for yearly data for 1997 and 1998. For the period 1999 to 2005 we use employment rates calculated from the quarterly LFS local area data. For the years 2006 to 2010 we use the quarterly LFS Special License data to calculate the employment rate.

4.2.2 Measuring the National Minimum Wage

The most widely used variable to measure the level of the NMW in the literature is the Kaitz index, defined as the ratio of the minimum wage relative to some measure of the average wage. We use the median wage in our study. The closer the Kaitz index is to unity the "tougher" the bite of minimum wage legislation in any area. However the denominator can be influenced by factors other than the level of the NMW and so the median wage is arguably more endogenous

8 There are, however, two exceptions that are described more in detail in appendix 4.A.1 (Definition of key variables).

in an employment regression. For example, a positive correlation between the employment rate and the median wage might be generated by an exogenous labour demand shift. This will create a negative correlation between the Kaitz index and the employment rate. When we use alternative measures of the MW both in previous work[9] and here we did not find that this alternative definitions of the MW variable made any qualitative difference to our conclusions.

4.2.3 Modelling conditional and compositional covariates

The geographical heterogeneity of areas and localities in the UK is well known. Our analysis attempts to condition out for this spatial variability by using a vector of observed (derived) covariates. Explicitly we control for: the demographic age structure of each population (using average age, age squared and age cubed); the level of human capital in each area using the fraction of those qualified to degree standard (NVQ level 4 or above in each geography); the fraction of each population of working age which is female; and the compositional industrial structure (Duranton and Overman, 2005) – specifically the fraction of who work in the public sector. The final variable requires a brief elaboration.

There is some considerable debate in the UK as to the extent to which the size of public sector 'crowds out' the private sector (Faggio and Overman, 2014). There is also a considerable debate on regional inequality and the so-called 'North-South' divide (Smith, 1994). The thinking of free market economists is that a vibrant growing economy needs an expanding private sector and that a large public sector gets in the way of such potential growth (Bacon and Eltis, 1976). This view predominated in the Thatcher era (1979–1987) and now has common currency in the coalition government (2010–2015) – but this was not the dominant view in the era leading up the NMW (1987–2010). Conversely, multiplier effects could result from a large local public sector. It was with this aim that many of the core government departments were moved out of London to the regions in the 1980s and 1990s[10]. These are the forces which have shaped the development of the regional economies of the UK over the last 20 years. We try to take account of these changes by controlling for the fraction of each local labour force working in the public sector. This is important since the public sector is not influenced by the MW as virtually all public sector workers are paid above the MW. Thus, it is important to consider (exogenous) decisions on widening and reduction of the public sector across spatial geographies.

9 See Dolton et al. (2012) where the fraction of people at or below the NMW and the spike are used.

10 Specifically, the Department of Health moved to Leeds, the Department of Work and Pensions to Sheffield, the Department of Social Security to Newcastle and the Driver and Vehicle Licensing Authority (DVLA) to Swansea.

4.2.4 Modelling the spatial nature of labour markets

One of the innovations in this paper is our attempt to capture the interconnectedness of local labour markets to estimate unbiased coefficients for the employment effects of the Minimum Wage.

The importance of the spatial nature of labour markets is now becoming more widely recognized and exploited in the work of Patacchini and Zenou (2007), Moretti (2011), and others. More specifically the suggestion that commuting patterns in UK are a way of representing this spatial interconnectedness are being used by others (e.g., Manning and Petrongolo, 2011). Where a given 'local labour market' begins and ends and the extent of interconnectedness of spatially located areas will depend on a multitude of factors, including: distances, physical geographical features like rivers (Hoxby, 2000), lakes and mountains, rail networks (Gibbons and Machin, 2006), bus links, the availability of major arterial roads, house prices (Gibbons and Machin, 2003), commuting patterns (Rouwendal, 1998; Holly et al., 2010), school quality, council tax levels, crime rates (Gibbons and Machin, 2008) and the provision of amenities, to name but a few. In some sense it is impossible to observe all these factors in determining how interconnected each labour market is to every other labour market. To a degree all these influences on the spatial nature of the location decision of where one lives and works are determined by a large number of unobservables[11]. Our approach to this problem is to assume the observed pattern of commuting behaviour is the empirical 'reduced form' of all these influences which we cannot possibly observe. In some sense, if the degree of interconnectedness of labour markets is, *de facto* the actual propensity for an individual to live in one region, and work in another, aggregated up over all regions and all workers. To the extent that true then this is what we should use in our calculations.

One concern that may be important is that using the commuting matrix as a weights matrix may be potentially endogenous in the sense that its degree of interconnectedness for any specific location may be related directly to its level of economic activity[12]. To allay this concern we also use an alternative weights matrix based on geographic contiguity. This is a logical alternative used in the literature to model the spatial dependence (Möller and Aldashev, 2007). This measure is specifically 1 if a specific location borders another location, and 0 otherwise. We use this alternative weighting system as a robustness check on the grounds that such geographical divisions are administrative and historical

11 There is a growing body of literature about commuting behavior. This includes mapping it (Titheridge and Hall, 2006; Nielsen and Hovgesen, 2008), accounting for it in labour market search models (Rouwendal, 1998) and econometrically modeling its determination (LeSage and Pace, 2008).

12 The whole issue of how a weighting matrix is conceived is discussed in Harris et al. (2011).

and therefore exogenous to current economic forces. The use of this alternative weight matrix is the other possible extreme of interconnectedness assumption – being based on simple close proximity and not any other factors which may be endogenous. This logic suggests that it is appropriate to implement the spatial dependence structure in the residual term based on the assumption that the spatial dependence structure is known but not what its explicit form is . This is the logic behind modelling spatial dependence of the error term in a so-called 'spatial error model for panel' data (SEMP).

However, there are some criticisms of spatial models which use spatial weight matrices. The main concern relates to the correct specification of the matrix and a lack of formal theory which determines its structure (e.g. Gibbons and Overman, 2012). There could be some more problems in case of the SEMP model because the (Maximum Likelihood) estimation procedure is based on strong assumptions about the underlying data generating process.

With our data, it is not possible to explore the exact spatial dependence structure and it is not our main concern. Instead our approach is to frame our analysis by: using the weakest form of spatial dependence, contiguity, and a potentially stronger form, commuting behaviour, and then let these two structures bound the analysis as a robustness check. Accordingly, we will be interested in the relative (size and) inference of the unbiased estimated effect and their standard errors. To operationalise this we used the alternative approach by Conley (1999, 2008) to draw inference on the variance-covariance matrix of the effect coefficients considering a dependence structure between areas that are situated within a certain regional distance assuming this as a proxy for "economic distance". To utilize this estimator we computed geographic coordinates of the (polygon) centroids of each of our area. Since this approach is a variance-covariance matrix estimator it is possible to estimate the effects by using the baseline regression we theoretically derive in the next section and complement the point estimators with standard errors considering a spatial dependence structure. Conley (1999) shows that his estimator remains consistent when economic distances cannot be precisely measured. Notwithstanding this robustness test, it is still the case that the estimator is based on one or other (either contiguity or commuting) assumption about the spatial dependence structure. That's why we generally tested for (remaining) strong spatial dependence in the residuals by means of Pesaran's CD statistic (Pesaran, 2004).[13] This test provides us with more insight as to whether, despite our econometric modelling, we still have strong spatial dependence in our estimation.

13 Details can be found in appendix 4.A.2.

4.2.5 Measuring the recession

The second innovation of this paper is to attempt to net out of our estimation any underlying movements in aggregate demand and more importantly the large potential effects of the current recession. This has rarely been attempted – indeed to our knowledge the only research on this topic has been our own previous attempts to tackle this issue (see Dolton et al., 2011; Dolton and Rosazza-Bondibene, 2012; Dickens and Dolton, 2010). This analysis was fairly simple in that it relied on dummy indicators for the presence of a recession or not. The problems associated with this when the formal definition of a recession is two quarters of negative GDP growth are rehearsed in Dolton et al. (2011). Here we adopt a more ambitious approach as we attempt to control for negative regional GDP growth shocks with a direct proxy for regional growth. Therefore we seek an (exogenous) variable which captures the depth of a recession on a regional basis but which is not endogenous to the determination of employment directly. The requirement that this variable is available on regional basis proved exacting. Arguably, the exogeneity requirement rules out, employment measures for other groups, unemployment or measures related to the claimant count[14]. We explored measures such as house prices as such data is collected at a local level. The problem with this data is that such series only mirror recessions with a significant and differential lag (of up to 5 years) which is dependent on geography. Another suggestion was to use VAT registrations of the birth and death of companies – but this data series ends on a regional basis in 2007. The variable which we use is the lagged level of Gross Valued Added on a regional basis which is available in Regional Trends. The definition of this variable is that it aggregates all firm revenues, profits and all wages on a regional basis to compute literally the gross value of goods and services in the regional economy. Hence, to all intents and purposes, this variable is a measure of GDP growth (per head) on a regional basis. This, in our view, is the closest one can get to a variable which measures in a continuous way the level of regional GDP growth changes over time and hence it is a variable which captures when negative aggregate demand shocks hit; when a recession occurs and how severe it is in different regions in different years. The obvious criticism of this variable is that it is potentially endogenous to employment levels in the sense that the wages of employed people are included in its calculation. But since the variable includes much more than this in terms of the values of goods and services produced, we suggest that this rate of change of GVA variable can act as

14 Dube et al. (2010) use private sector employment, Neumark and Wascher (1992) and many other authors use unemployment for adults. These measures are arguably endogenous.

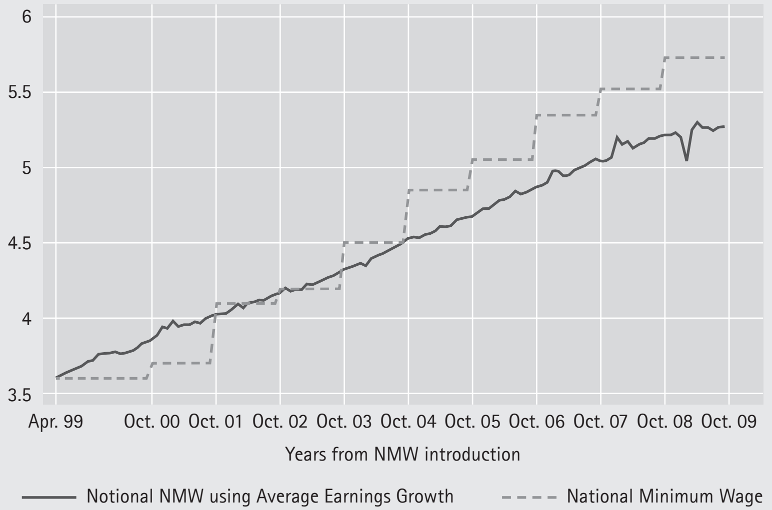
a proxy for the onset, timing, severity and duration of regional GDP growth and hence of recessions. A second response to this is that it is an advantage to have regional data on this demand shock variable as the demand level at any specific local subgeography will not be an important constituent of this variable at the regional level. An alternative criticism of this variable is that it is not measured at the precise geography of our unit of analysis. It is not possible to overcome this as movements in GDP or GVA are not measured at any finer level of geography. In addition using this level of geographical unit has the advantage that *de facto* one is using a spatial IV of the average shock at the wider geographical level.

4.2.6 The logic of identification from the data

The logic of our identification strategy is evident in the descriptive statistics we present in figure 4.1 that highlights the temporal variation in the NMW, comparing the nominal hourly wage level change of the adult NMW over time with the average earnings growth. The figure shows how the NMW grew smaller than the rise in average earnings in 2000 and then rose more steeply than this series; this trend came to an end in October 2007. Most marked is the rise in this level in both real and nominal terms since 2003 (compare this finding also with Metcalf, 2004). The largest rises in the NMW were in 2001, 2003, 2004 and 2006. This is mirrored in the rising level of the Kaitz Index over the same years, as shown in figure 4.2. The principle here is that we wish to use the height of the steps due to the up rating of the MW considered over all the different locations in our sample. Figure 4.3 is more instructive of our data as it shows the level of the NMW (right-hand scale) plotted on the same graph as the employment rate (left-hand scale) in our sample. It plots this for the 138 TTWAs at the mean of the sample with the 95% standard errors in dotted lines. Here, we can see the period of 2002–2006, the boom years prior to the recession, which began in 2008/2009. The nature of this trend in employment needs to be picked up in the data and this is why we seek to model the underlying 'steadystate of employment' by seeking to identify the autoregressive nature of this process. Figure 4.4 adds to our understanding of what was happening to employment in relation to the movements in the Kaitz index (again at the average for the sample with 95% confidence intervals plotted). Here we see that – to a large extent – the upward movements of the Kaitz are mirrored by a downward shift to the employment level.

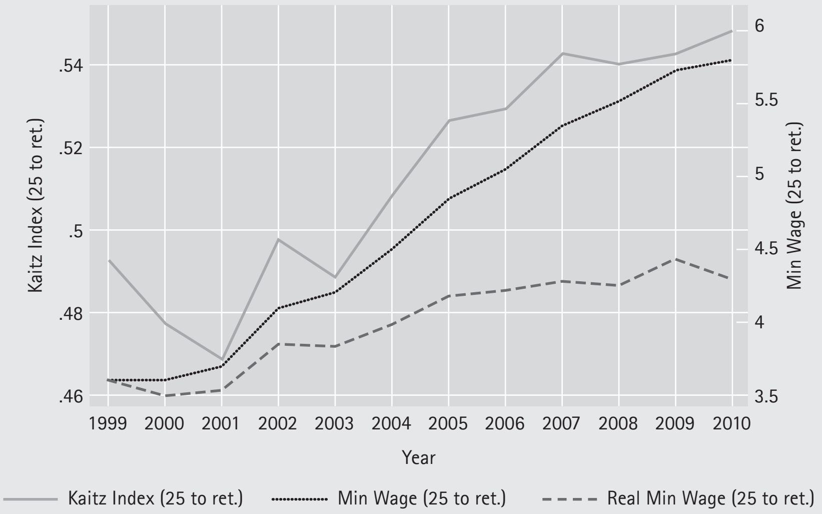
Hence we would expect to see an overall negative relationship between these two key variables. Reassuringly – this is what we find – although what we set out to do is condition out the problems which beset this kind of data–namely, endogeneity, demand shocks, and the nature of the underlying employment process.

Figure 4.1: Change in nominal hourly wage level of the NMW and average earnings



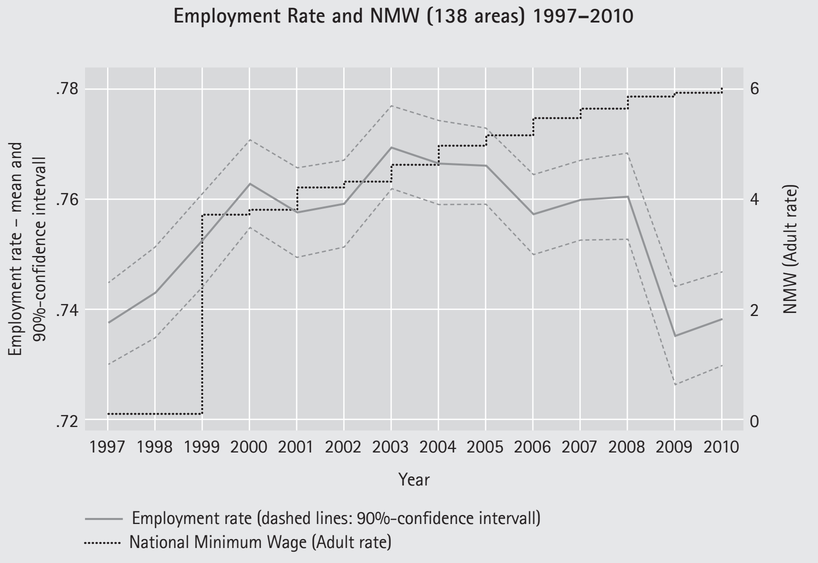
Source: NMW: UK Low Pay Commission, www.lowpay.gov.uk; Average Earnings Growth: http://data.gov.uk/dataset/average_earnings_index.

Figure 4.2: Change in the estimated NMW and Kaitz index over time



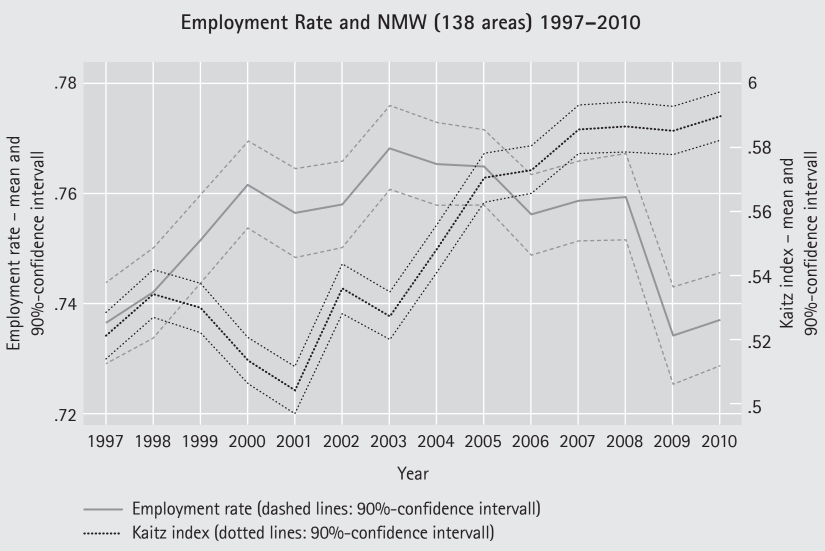
Source: NMW: UK Low Pay Commission, www.lowpay.gov.uk; Kaitz Index: ASHE, own calculation; Real NMW: deflated by RPI, http://www.ons.gov.uk/ons/publications/re-reference-tables.html?edition=tcm%3A77-260874

Figure 4.3: National Minimum Wage (Adult Rate) and employment rate in the UK 1997–2010



Source: NMW: UK Low Pay Commision, www.lowpay.gov.uk; unweighted yearly averages of the Employment Rate, own calculation.

Figure 4.4: Kaitz index (Adult Rate) and employment rate in the UK 1997–2010



Note: Unweighted yearly averages of the Employment Rate and the Kaitz index (MW/Median), own calculation.

4.3 Methodology and identification

4.3.1 Invoking and change of the National Minimum Wage[15]

To understand any of the estimation results relating to the impact of the NMW one must be clear about the simplest econometric specification and which parameters we seek to identify in the model. As a baseline reference we begin with the most basic model and develop it. Neumark and Wascher (1992) were among the first to utilize panel data to address the question of the impact of the MW.[16] They estimated the model:

$$E_{jt} = \mathrm{a} + \gamma T_t + J_j + \beta Mw_{jt} + \pi D_{jt} + \delta X_{jt} + \varepsilon_{jt} \tag{4.1}$$

Where E_{jt} is employment at time t in local area j, MW_{jt} is the level of the MW (adjusted for coverage) at time t in local area j, D_{jt} is a measure of aggregate labour demand (or the recession) in region j in year t, X_{jt} is a set of controlling regressors at time t in local areas j, T_t is a set of year effects, and J_j is a set of spatial fixed effects. Fixed effect estimation identifies potential causal inferences based on changes in the regressor and regressand given the assumption that the unobserved heterogeneity across areas remains constant over time. Later Neumark and Wascher (2004) use nearly the same specification to estimate the impact of the NMW laws across countries with the slight modification that now the term is similar to the Kaitz index using the ratio of the NMW in country j at time t divided by the average wage in that year[17]. Neumark and Wascher in their various papers, whether at the US State level or at the level of countries, find a negative employment effect of the NMW.

The logical critique of this panel model is that it still suffers from potentially all the same sources of potential heterogeneity bias as the simple time series model. Indeed it could even be argued that using US States as the unit of observation could potentially have even more problems – if for example – one state legislature's decision to implement or change a MW is heavily influenced by the current level of unemployment or a neighbouring state's policy decision. This concern is less of a problem in the UK context as there is a national NMW rather than a state MW–in which case the actual level (and change) in the NMW is not under the control of the authorities in any particular location.

15 For the derivation of the baseline equation (4.5) in this subsection, we follow Dolton et al. (2012).

16 More precisely, they used US states data from 1973 to 1989.

17 Usually, the Kaitz index is also weighted by some measure of 'coverage' of the NMW in the sense of the fraction of the labour force that the NMW applies to.

A related methodological departure focused on identification is suggested by Card (1992) and Stewart (2002) who propose a 'structural' econometric model consisting of two equations. The first is a form of labour demand equation which suggests that any change in the employment rate in area j is a movement along the labour demand curve which results from a change in the wage level in area j conditioning out for any shocks in aggregate labour demand, D.

$$\Delta E_j = \gamma_0 + \eta \Delta W_{jt} + \pi D_j + \varepsilon_{1j} \tag{4.2}$$

The second equation is a form of identity suggesting that the wage increase in area j is a function of the proportion in the area who are 'low paid', P_j.

$$\Delta W_j = \alpha_1 + \omega P_j + \varepsilon_{2j} \tag{4.3}$$

Substituting equation (4.3) into equation (4.2) we get:

$$\Delta E_j = \gamma_0 + \beta P_j + \pi D_j + \varepsilon_{1j} \tag{4.4}$$

Where $\beta = \eta\omega$, with ω assumed to be positive, implying that β has the same sign as η which basic economic theory would suggest is negative if the demand for labour falls as wages rise. According to Stewart (2002) the precondition for identification is that the proportion in the area that are 'low paid', is a predetermined instrument for the endogenous wage change. In this paper, we use the Kaitz index to act as a proxy for the wage effect of the NMW.[18]. The central idea of our paper is also to see whether geographic variation in the "bite" of the minimum wage is associated with geographic variation in employment. However, we also allow the effect of any treatment to vary over time, given the differential pattern of upratings that we observe in the data. This can be done by pooling over the fourteen year period and letting the treatment be the measures of the "bite" of the NMW in each area at time t, P_{jt}, so that the baseline equation for the estimated model is:

$$E_{jt} = \gamma_0 + J_j + \gamma_t \sum_{k=1999}^{t} Y_{k(t)} + \theta_0 P_{jt} + \theta_t^{IDiD} \sum_{k=1999}^{t} Y_{k(t)} P_{jt} + \pi D_{jt} + \delta X_{jt} + \epsilon_{jt} \tag{4.5}$$

18 In a previous paper we explore two other measures of the MW and the substantive conclusions do not differ (Dolton et al., 2011). We also re-estimated a model using the share measure of the MW as the wage regressor. None of our substantive conclusions change and, therefore, our results are not sensitive to the nature of which wage regressor is used. The authors provide estimation results for the fraction at or below the NMW upon request. In our later section we nevertheless examine the possibility that the Katiz index is itself endogenous. Here, we use a novel IV strategy.

Where E_{jt} is a measure of area labour market performance in area *j* at time t and J_j are area effects. $Y_{k(t)}$ is a set of dummy year effects for the years 1999 to the observation period t that amount to 1 if t equals k and otherwise 0. The index k starts from 1999 as the year in which the NMW was introduced and is subsequently up-rated. Our pre-period are the years 1997 and 1998 were we use a notional measure of the Kaitz index in these years by taking the NMW in 1999 and deflating it by the level of wage inflation to provide estimates of what this ratio might have been in these years (in the absence of a NMW). This is the most appropriate logical assumption to make with our data regarding the unobserved counterfactual (of what the NMW would have been set at, if it had been introduced in 1997).[19] Namely that, in this period, adjustments would have been largely conditioned on what was happening to wage inflation. Area fixed effects are included to control for omitted variables that vary across local areas but not over time such as unmeasured economic conditions of local areas economies that give rise to persistently tight labour markets and high wages in particular areas independently of national labour market conditions. Time fixed effects control for omitted variables that are constant across local areas but evolve over time.

The Incremental Difference-in-Difference coefficients θ_t^{IDiD} on the interaction of the year dummies and the measure of the bite, capture the average effect of the up-rating of the NMW in each year, starting from the introduction of the policy in 1999, all relative to the 'off period' of 1997 and 1998, provided of course that the proportion in the area who are 'low paid', is a valid instrument for the endogenous wage change. The advantage of using the IDiD estimation procedure is that it facilitates the estimation of year-on-year incremental effects of each year's up-rating. So, even if the average overall effect of introducing a NMW, θ_0, is insignificantly different from zero, this does not necessarily mean that the effect of any individual year's change in the NMW is also zero. Note that one cannot deduce the longer run effect of all the changes in the NMW by simply summing all the year-on-year IDiD coefficients.[20] The long run effect can only be measured in aggregate by using one DiD coefficient for the whole period. We therefore present both short run IDiD and medium run DiD estimates in what follows.

Though we have 3 more years with observations compared to previous work in Dolton et al. (2012) our time series remains quite short. Therefore there is no

19 We also compared our assumption to the existing Agricultural MW changes over the 1997 and 1998 period and these changes did not depart much from what was happening to wage inflation. In a previous paper, (Dolton and Rosazza-Bondibene, 2012, p. 95, table A5) also explored alternative specifications of base years and found that the results were not sensitive to this assumption.

20 This is because some additional (untestable) assumptions relating to the independence of effects over time would be necessary. In addition, since we use a dummy variable interaction term rather than a normalised metric on how large each increment was, then this also makes aggregation of the individual interaction term estimates difficult.

statistical method that could test for autocorrelation of a higher order in our panel data set. An additional concern, we also already mentioned in Dolton et al. (2012), is that spatially dependent areas lead to heteroskedastic errors. In what follows, we explicitly model these spatial relations.

4.3.2 Basic identification issues

An issue which must be addressed from the outset is the extent to which the process of choosing the initial rate of the MW in 1999 was endogenous. More specifically, was the rate set initially very low in 1999 deliberately to prevent employment effects with attendant expectation that later (possibly above inflation) rises in the MW rate would be appropriate and justifiable. We have researched this carefully. In choosing the initial rate the Low Pay Commission's (LPC) stated aim was: '… to balance the aim to address low pay and the need to ensure that the level is manageable for business and the economy'[21] No mention was made in the lengthy chapter in Low Pay Commission (1998) on 'choosing the rate' of attempting to minimise the employment consequences or intentionally to have a rate which was low to begin with and subsequently uprated by more that inflation. Metcalf (1999, p. F61) has also said in reflecting on the process of choosing the rate that '… It is impossible to forecast now whether the NMW will have any favourable or adverse direct employment consequences.'[22] Another important consideration is the simple dynamics of our investigation. Specifically, how long will it take the introduction (or changes) in the NMW to have their full effects on employment and other economic indicators (especially since some of the variables in the data are already measured with a lag). This raises the econometric issue about including a lagged effect of the minimum wage variable in the regression. The literature to date is divided on this issue. On the one hand, employers might react relatively quickly to increases in minimum wages. Employers might even adapt before the implementation of the minimum wage. Brown et al. (1982, pp. 496), regarding employment, argue that: "One important consideration is the fact that plausible adjustment in employment of minimum wage workers can be accomplished simply by reducing the rate at which replacements for normal turnover are hired". The authors also suggest that minimum wage increases are announced months before they are implemented – typically six months in the UK – therefore, firms may have begun to adapt before the increase of the minimum wage come effectively into

21 See chapter 6 in Low Pay Commission (1998, p. 89).

22 We have also had further correspondence with Sir David Metcalf (a member of the original LPC) to clarify this issue and he has reaffirmed to the authors in correspondence that the process of setting the NMW initially was not endogenous.

force. On the other hand, it might take time for employers to adjust factor inputs to changes in factor prices. Hamermesh (1995) points out that in the short run, costly capital inputs are not easily adjusted. If firms adjust capital slowly following an increase of the minimum wage, the adjustments of labour input might be slowed as well. The use of a lagged minimum wage measure as well as the inclusion of fixed (area) effects in the regression also helps to overcome the possible endogeneity of the minimum wage variable which occurs as a result of correlation of either the proportion paid at the minimum or, in case of the Kaitz index, the minimum wage and the median wage with labour market conditions or productivity.

An issue of identification arises from the 'common trends assumption' which, in our context, is the assumption that the effect of market conditions will be the same across all geographic units before the introduction of the NMW – resulting in any differences in the employment across geographical units being constant, prior to the introduction of the NMW. One way of examining this is to consider whether the employment rate has the same underlying trend across all our geographical units before the introduction of the NMW. In our case we cannot do this because the small geography LFS data which we use to construct the employment rate does not go back before 1997. However, it is possible to have a longer off-period starting from 1994 and using 95 areas, which correspond to the coding used on the NES (the National Earnings Survey which preceded the ASHE) up to 1996.[23] The results of the test give us some confidence about the internal validity of the model, being unable to reject the null of a common trend at 10% level.[24] Whilst this is no proof of the presence of common trends in our data, this gives us some confidence about the internal validity of our model for the full set of more detailed geographies.

4.3.3 Modelling spatial dependencies

In recent years, the econometrics literature has exhibited a growing interest in specifying spatial dependencies, or more generally, cross sectional dependencies because estimation results could be spurious if there is spatial dependency that is not considered in the model (LeSage and Pace, 2009).

The idea is that an economic aggregate like employment in a certain region does not only depend on economic forces in the same region but also in other regions.

23 The areas comprise all existent counties, the counties abolished with the 1996 local government reform and the London boroughs. The "City of London" was deleted from the dataset due to small sample size and the Scottish Islands were excluded from the analysis because they are not present in the data across all years.

24 For all workers (16 years to retirement) we cannot reject the null of a common trend at the 10% level ($F(91, 276)=1.45$) if we omit three areas, all with small sample sizes (Scottish Borders, Gwynedd and Shropshire). However, omitting these areas from our IDiD regressions does not change our main results.

To consider these dependencies a class of econometric models were developed that consider spatially autoregressive processes, e.g. in the dependent variables or in the error term. The first model is often called the Spatial Lag or Spatial Autoregressive Panel Model (SARP) and the second is called the Spatial Error Panel Model (SEMP, Elhorst, 2010c). The question is – which model specification should be preferred – models without spatial dependencies or with spatial lags? This is crucial because misspecification would lead to biased estimates of the coefficients of interest. We therefore conduct Lagrange Multiplier Tests, derived by Debarsy and Ertur (2010), which show us that spatial dependence is present and should not be neglected and there are indications that the SEMP approach should be preferred in the vast majority of specifications (all details can be found in appendix 4.A.3. Aside from this, one should also consider that a shortcoming of the utilized LM tests by Debarsy and Ertur (2010) is that they are only able to test the SEMP and SARP, their combination as well as a somewhat spatial specification against no spatial lag. Gibbons and Overman (2012) discussed the formal representation of the SEMP and SARP models with the spatial Durbin model that contains spatial lags of the dependent variable and the exogenous regressors. They show that the reduced forms of SARP and SEMP model that contain spatial lags of independent variables with order 1 to infinity only differ in their coefficient terms. On this basis, they argue that reduced forms of the SEMP and SARP cannot, in practice, be empirically distinguished from other specifications. The reason for this result is that some assumption has to be made regarding the form of the weights matrix $\mathbf{W}_T$ and the spatial lags of different orders on the explaining variables are almost always expected to be highly correlated. Apart from this statistical consideration, there is another motivation for utilizing the SEMP model that considers spatial dependence structure in unobservable (explaining) variables. This is in contrast to the SARP model that is based on the notion that the dependent variables, the employment rates, influences each other in the same observation period. This is possible, for example, in a rationale expectations model that assumes the existence of economic actors who directly or indirectly, through the independent variables, fix the employment rates in each region during each observation period. This may be possible in the case of dependent policy variables like tax rates, but it is more difficult to motivate in the case of economic aggregates like employment rates. Taking all these considerations into account we favour using the SEMP model.

Thus, we extend our model in equation (4.5) with spatial lags of the error term:

$$E_{jt} = \gamma_0 + J_j + \gamma_t \sum_{k=1999}^{t} Y_{k(t)} + \theta_0 P_{jt} + \theta_t^{IDiD} \sum_{k=1999}^{t} Y_{k(t)} P_{jt} + \pi D_{jt} + \delta X_{jt} + u_{jt} \quad (4.6)$$

$$u_{jt} = \lambda \sum_{i=1}^{n} w_{ij} u_{it} + \epsilon_{jt} \tag{4.7}$$

where λ is the coefficient for the spatial lag term $\sum_{i=1}^{n} w_{ij} u_{it}$, a linear combination of the error terms for regions i that are assumed to influence the error term in region j (LeSage and Pace, 2009). The weights w_{ij} contain zeros if there are no spatial lags and the main diagonal of the weight matrix contains zeros because it is assumed that a region cannot have an influence on itself. Furthermore, the weight matrix used for the estimation is standardized with rows summing to unity, irrespective of information used to model regional dependencies. The weights used reflect the assumption about the relative strength of the spatial lag. In every case it is intended to identify the spatial dimension of economic or regional activity and to implement that in the model.

A simple assumption is that neighbouring or nearby regions have a greater influence on other than those that do not share a border or vertex (LeSage and Pace, 2010). The contiguity weights matrix before row-standardization contains ones in case of contiguity and zeros otherwise. Like weight matrices based on distances between regions, this matrix is symmetric. This implies that, e.g., region A influences region B to the same extent as region B influences region A. It is important to acknowledge that this could be a restrictive assumption for the UK, where there are clearly asymmetric economic relations between economically strong regions like London and surrounding economically weaker provinces. It is this logic which induced us to use commuting patterns. These are good indicators of the intensity of regional labour market interdependencies since they summarize spatially related economic decisions and behaviour. Furthermore, commuting flows have direction – the number of people that go from their (home) region A to work in region B differs to that number of other people that go from region B to region A. Therefore, we decided to use commuting flows and to compare our results with specifications that are based on contiguity as a robustness check (see appendix 4.A.4 for some more details). Hence, we use the flow of commuters from their home region i to region j where they work.[25] To form a spatial lag or a linear combination of values from the "nearby" regions, for each region j, weights w_{1j} to w_{nj} are normalized to the (row) sum of unity.

Equations (4.6) and (4.7) in matrix notation are:

$$\mathbf{E} = \gamma_0 \iota_{nT} + \mathbf{Y}_N \gamma_t + \theta_0 \mathbf{P} + (\theta_N^{IDiD\prime} \mathbf{Y}_N)' \mathbf{P} + \mathbf{X}\delta + \mathbf{u} \tag{4.8}$$

25 We are sensitive to the possibility that weighting matrix $\mathbf{W}$ may be endogenous. In the empirical estimation, we also run all our analysis with an alternative 'contiguity' weighting matrix which is simply constructed as a matrix of 1's and 0's for each geographical location depending on whether the location abuts a neighbouring location (1) or not (0).

with a spatially autoregressive process in the error term **u**,

$$\mathbf{u} = \lambda \mathbf{W}_T \mathbf{u} + \varepsilon \tag{4.9}$$

Hence, $\mathbf{E}(\mathbf{P}/\mathbf{Y}_N/\mathbf{u}/\varepsilon)$ is the $nT \times 1$ vector containing the employment rates E_{jt} (the measures for the Kaitz index P_{jt}/ the year effects variables Y_t with $Y_t = 0$ for $t = 1997$, 1998/the spatially correlated residuals u_{jt}/ the error term ε_{jt}), $\mathbf{W}_T$ is a $nT \times nT$ matrix containing all weights w_{ij} that are equal for all years. ι_{nT} is a unity vector with dimension $nT \times 1$. The $nT \times 1$ vector γ_t contains the parameters for the year effects and the $nT \times 1$ vector θ_N^{IDiD} contains the (stacked) Incremental Difference-in-Difference coefficients θ_t^{IDiD}. The $nT \times k$ matrix $\mathbf{X}$ contains the k control variables including the aggregate demand shocks measure D, and the $k \times 1$ vector δ the k coefficients of the control variables.

Finally solving equation (4.9) for **u** and implementing that in (4.8) leads to the estimable SEMP model

$$\mathbf{E} = \gamma_0 \iota_{nT} + \mathbf{Y}_N \gamma_t + \theta_0 \mathbf{P} + (\theta_N^{IDiD\prime} \mathbf{Y}_N)' \mathbf{P} + \mathbf{X}\delta + (\mathbf{I} - \lambda \mathbf{W}_T)^{-1} \varepsilon \tag{4.10}$$

Since the regression equation in (4.10) is non-linear in its parameters, maximumlikelihood estimation is used to estimate the parameters. We use the estimation procedure suggested by Elhorst (2010b), which includes a bias correction for both time and spatial fixed effects (for details see Lee and Yu, 2010).

Being mindful of the problems discussed above in specifying the weight matrices in spatial specifications like the SEMP models which we present, we focus our attention on the inference in the effect estimators and their variance-covariance-matrices. To this end we additionally utilized an approach by Conley (1999, 2008) to estimate a variance-covariance matrix considering interrelatedness of local areas within a certain distance and assuming that the interrelatedness decreases with distance. According to Conley (2008) the usual point estimators for the regression coefficients of, e.g., equation (5) remain consistent in the case of weak spatial dependence. However, this does not hold for the variance-covariance matrix. Conley (1999) proposes a nonparametric estimation of the covariance matrix. The idea behind this procedure is to use time series heteroskedasticity and autocovariance (HAC) consistent covariance matrix estimation. With the use of residuals $\hat{\varepsilon}_{jt}$ as computation of ε_{jt}, the variance-covariance matrix can be estimated as a weighted sum of cross products with the regressor vectors $\mathbf{x}_{jt}$, whereas j denotes local area $j = 1, \ldots, N$ ($N = [138,140]$) and t denotes observation period $t = 1, \ldots,$ T ($T = 13$):

$$\hat{\Sigma}_N = \frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N} K_N(i,j)\mathbf{x}_{jt}\,\hat{\varepsilon}_{jt}\,\mathbf{x}'_{it}\,\hat{\varepsilon}_{it} \tag{4.11}$$

K_N denotes a kernel utilized to weight pairs of observations. Here the spatial kernel $K_N(i, j)$ is specified to be a Bartlett or a triangular window function. Thus, this kernel decays linearly with distance in all directions[26].

4.3.4 Dynamics

A standard assumption of the OLS and Fixed effects models as well as their spatial counterparts is that they require that the explanatory variables to be uncorrelated with the residuals. In practical applications like ours, this requirement is rarely completely satisfied. Potential reasons for this could be the dynamic properties of the used variables, e.g. hysteresis of the employment variable, measurement errors in the variables or further omitted variables that are not observable. To overcome these problems the most commonly used approach is to use dynamic panel instrumental variable methods (see Arellano and Bond, 1991; Greene, 2012, pp. 256).[27]

We adopt the system generalized method of moments estimator (SGMM) developed by Holtz-Eakin et al. (1988); Arellano and Bover (1995); Blundell and Bond (1998). Generally, the SGMM estimator can be applied for panel data sets with a short observation period in terms of small T and many cross section units, and thus large N (Roodman, 2009b). Furthermore, the estimator assumes that the only available instruments are "internal" in terms of lags of the instrumented variables in differences or levels. We prefer the SGMM to Difference GMM (and other alternatives) because SGMM is more efficient and precise since it reduces the finite sample bias (Baltagi, 2008). Nevertheless, a crucial initial condition for the validity of the additional instruments in SGMM is that fixed effects do not correlate with differences in the

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26 Generally, the form of the Kernel $K_N(i, j)$ should represent the idea that nearby observations receive a weight near 1 and those far apart receive weights near zero. Our estimation procedure, developed by Hsiang (2010), additionally allows a uniform kernel that equals 1 if i and j are located within a cut-off distance and zero otherwise. Conley (1999, 2008) underlines that estimations based on this Kernel are robust to location errors within in the threshold distance – the results remain stable compared to the results that would be obtained on the base of the "true" locations. Changes in weights occur only for those points whose true distance is near enough to the cut-off distance and the observed (wrong) distance between two areas and the true distance between those areas are on different sides of the cut-off distance. However, although the Bartlett window is obviously more sensitive to the "real" distances, we decided to use this kernel because the results based on the uniform kernel form do not reveal differences but, in a few cases, the computation of Conley standard errors based on this kernel was impossible due to not positive definite covariance matrices.

27 The estimation strategy behind the assumption that some or all explaining variables are correlated with the error term is that one finds a set of (instrumental) variables that are correlated with the explaining variables but not with the error terms. Due to the resulting set of relationships among instruments, explaining variables, and error terms a consistent estimator of the coefficients of interest can be derived. For this purpose a number of assumptions have to be made, Roodman (2009b).

instrumenting variables. Roodman (2009a) showed that this requirement can be satisfied in a "steady state" situation, when deviations from long-term values are not systematically related to fixed effects. A "steady state" can be assumed, if the variable of interest – here it is the employment rate – tends to converge. This can be checked empirically by unit root tests for panel models or by estimating a simple fixed effects model with only a lagged dependent variable as regressor, thus an AR(1)-model. In the latter case the coefficient of the lagged dependent variable should be smaller than the absolute value of unity. The results of these estimations confirm that our lagged dependence coefficients are significantly smaller than unity[28] for both our alternative geographical areas.

Our baseline equations are nearly equivalent to the fully specified model from equation (4.5) with and without the recession variable:

$$E_{jt} = \alpha E_{jt-1} + \gamma_0 + J_j + \gamma_t \sum_{k=1999}^{t} Y_{k(t)} + \theta_0 P_{jt} + \theta_t^{IDiD} \sum_{k=1999}^{t} Y_{k(t)} P_{jt} + \pi D_{jt} + \delta X_{jt} + \epsilon_{jt} \quad (4.12)$$

We included the lagged employment rate and complemented the model with certain levels and differences of the control variables (in X_{jt}) as instruments. There are three groups of instruments. Variables in the first group – GMM instruments – are assumed to be endogenous, hence, lags of levels and differences of those instruments are in this group. The employment rate and all or some of the control variables belong to this group. The second group – instrumented variables in levels and first differences – are handled to be strictly exogenous. We handle the recession variable, the Kaitz index, the incremental difference-in-difference variables, and remaining control variables that are not assigned to the first group as strictly exogenous. Levels and differences of those variables are utilized as instruments. The third group – instrumented variables only in levels – contains levels of all variables in the second group and, additionally, the levels of year effects.

An important consideration in our estimation strategy is to find the optimal specification in terms of the choice and number of the instruments. This is important since too many instruments could 'over-fit' the endogenous variables (of interest) and lead to invalid results (Roodman, 2009a). Regarding the choice of the instruments, we have to bear in mind that we apply a reduced form of employment equation because we cannot observe the detailed employment generating process at the micro-level, it could suggest that the employment

28 We estimated the equation $y_{it} = \alpha y_{it-1} + \mu_i + \varepsilon_{it}$ with the employment rate y_{it}, y_{it-1} in region i and time t and its value from the pre-period $t-1$, the lagged dependent coefficient α, the fixed effect μ_i, and the error term ε_{it}. The results are (1) $\alpha_{138\ areas} = 0.199^{***}$, and (2) $\alpha_{140\ areas} = 0.234^{***}$. All coefficients are significantly smaller than unity (significance level of 1 per cent).

rate[29], as well as the control variables, are also partly influenced by their previous values. The overall MW bite, as well as the yearly incremental MW bites, are considered not to be influenced by their lagged level or difference values, but in that specification they can be influenced by the (lagged) employment rate. In all our estimations, we use the two step procedure to get robust results and test statistics as well as the Windmeijer correction for small sample size to reduce the downward bias of standard errors after the two-step procedure (Windmeijer, 2005). Furthermore to handle instrument proliferation we integrated the instrument set into one column as proposed by Roodman (2009b). We utilize the Arellano-Bond test for AR(1) and AR(2) in first differences, Hansen's *J*-test of overidentifying restrictions, and the Difference-in-Hansen's *J* statistic to test the validity of the model specification[30]. Furthermore, we checked the robustness of the model specification by varying the number of lags of the instrumental variable sets Roodman (2009a). In line with Bond (2002), we checked whether the coefficient for the lagged dependent variable lies somewhere between the results obtained from adequate OLS and fixed effects estimators.[31] Throughout these specification tests, our reported results provide acceptable test values ensuring that our estimates remain robust.

4.4 Results

We present the estimates for the non-dynamic specification in table 4.1 for the 138 travel-to-work areas and in table 4.2 for the 140 areas. The first column of both tables contains the results of the DiD model in equation (4.1) using (the log of) employment as the labour market outcome of interest to summarise the NMW effect on employment over the medium term, namely, the average over 14 years since its introduction relative to the base period of 1997/1998. The coefficients of the Kaitz measure for the 138 TTWA suggest that there is an overall difference in employment growth rates between areas where the NMW bites most compared to areas where the NMW had less impact; in the case of the 140 areas this effect is notably smaller and insignificant. Columns 2 of tables 4.1 and 4.2 augment the base model with the model specification of the IDiD estimator in equation (4.5). The following column in these tables also

29 A logical question is: why did we not include a lagged term of the dependent variable in the OLS, FE, and spatial specifications. The answer is that it is known that pooled OLS specification results in an upward bias of the appropriate coefficient and FE downward biased results (Nickell, 1981, e.g.). However, we used adequate specifications to detect the validity of the SGMM. See also below in the text.

30 A further description of the mentioned tests can be found in appendix 4.A.5.

31 The results from pooled OLS and fixed effects specifications including lagged dependent variables are reported in table 4.10 in same appendix 4.A.5.

include the GVA lagged variable as a measure for the recession. As expected, the recessionary variable is positively significant suggesting the intuitively 'correct' sign of the impact of growth on employment. This is also true for all specifications in other columns. The addition of the GVA variable attenuates downwards the size of the IDiD coefficients on the NMW variables for each year. This indicates that modeling the employment effect of the MW without taking into account demand shocks and recessions is problematic and likely to overstate any measured MW effects on employment.

Columns 4 to 6 of tables 4.1 and 4.2 again present the point estimates of equation (4.5) and their standard errors computed with the variance-covariance estimations procedure by Conley (1999, 2008). based on the Bartlett kernel for three different regional distance thresholds, namely 50 km, 100 km, and 200 km. Only with a few exceptions are Conley's standard errors mainly smaller than the standard errors in column 3. We report point estimates in bold when this has implications for the significance levels. As Conley (1999); Conley and Ligon (2002) point out, the consequence of spatial dependence is generally not that the standard errors are larger, because negative spatial correlation in the residuals lead to smaller standard errors. Generally, the results suggest spatial dependence because the standard errors changed. However, the significance levels of the point estimates in column 3 change after considering that non-parametric estimation procedure only in a few cases for the 140 areas; then, the results become more precise.

Columns 7 and 8 of tables 4.1 and 4.2 contain estimates for the 'full model' using the complete Incremental Diff-in-Diff structure but includes the spatial effects using the SEMP model from equation (4.10) for the 138 and 140 samples respectively. The results for the point estimates are quite similar to the results in column 3 (to 6) where the standard errors lie mostly between those of the specifications in column 3 and Conley's standard errors (columns 4 to 6). The spatial lag coefficient λ is nearly Zero and insignificant for the 140 areas and it is weak significantly positive for the 138 areas.

The main results from our non-dynamic estimations are, first taking the common findings across nearly all specifications: we can suggest that the recession, as captured by the GVA-lagged variable, plays an important role in the determination of employment but that the consequence of this variable's inclusion is that the NMW interaction effects are always attenuated. Likewise, these estimated effects are further attenuated when we explicitly take account of the spatial effects.

Our second main finding is that after including the IDiD Kaitz interaction term the magnitude of this (negative) overall effect rises nearly in all specifications and becomes statistically significant whereas the coefficients of the Kaitz interaction term become partly significantly positive. This can be interpreted as the continuous, underlying effect of having a NMW in place rather than the effect of the size of the year on year up rating. This is an important conclusion which potentially enables us to understand much of the controversy in the research literature. Indeed it suggests that, if our specification is correct (and our logic were applicable to the US state context), then the source of much of the disagreement between the main protagonists, Card and Krueger (1994, 1995) or Neumark and Wascher (1994, 2004) may have been misplaced due to equation misspecification.

Turning to the estimations and distinguishing between the results from the different geographies is instructive. Looking first at table 4.2 relating to the 140 geography we see that there are significantly positive – at least at a 10 per cent significance level – interaction effects in the years 2000, 2003, 2004, 2006, and 2007.

For the 138 areas which are travel-to-work areas (TTWA) in table 4.1 we see that there is no evidence of interaction effects in the IDiD model with the exception of the years 2003 and 2004. This suggests that if one uses a geography which is defined on the nature of the commuting pattern – which the TTWA is – then this effectively cancels out the IDiD effect. Hence, if one believes that the analysis should be done on the basis of the TTWA geography, then there are no appreciably significant incremental year on year effects of the NMW.

Turning to the models which reflect the specification of the spatial models (columns 7 and 8) we found for the SEMP specifications a significantly positive coefficient λ for the spatial lag of the error terms in case of the TTWA geography and no significant coefficient for the WAREA geography.[32]

Overall, where our NMW incremental effects are found to be significant it should be stressed that these point estimates effects are small in magnitude, but it is clear that they are masked if the simple DiD policy-on-policy-off variable is used. If the standard assumptions of Diff-in-Diff relating to the Stable Unit Treatment are applicable (namely that no other systematic factors are varying across geography and over time) then we can interpret this as a direct impact of the year-on-year upratings to the NMW which may cancel out the overall negative impact of the presence of the

32 We found higher positive coefficients λ in all model versions without the GVA variable, though the coefficient remains insignificant for the WAREA. The explanation is that the GVA variable is measured at the Government Office Regional level which is the higher administrative geographical unit to the utilized geographies and, in effect, the spatial dimension is soaked up by the inclusion of this variable. This is reflected in the fact that the lack of significance of λ tells us that the spatial model is not necessary (when the GVA lagged term is included). The results of Lagrange Multiplier tests, presented in appendix 4.A.3, and Pesaran's CD statistic confirm this finding. The CD statistics and the estimation results for SEMP specifications without GVA variable are presented in the table in appendix 4.A.6.

NMW as captured by the Kaitz variable. On this basis, if anything, the employment rate appears to have risen more in areas where the NMW has more relevance.

Our empirical strategy is further justified by examination of the residuals for spatial autocorrelation. We found only weak spatial autocorrelation in our model specifications, even after including the demand variable. To test for spatial autocorrelation, we use Pesaran's *CD* test (Pesaran, 2004) a simple test statistic, to be found at the bottom of tables 4.1 and 4.2[33]. The statistic is reported to be robust to structural breaks and valid for panel data where the number of cross sections is larger than the number of observations periods – as it is here for our case for the two geographies. For both geographies the test statistics are below the critical value of 1.96 (equivalent to a significance level of 5 per cent). The SEMP model reduces the extent of the spatial dependence in the residuals for the geography with 138 areas and for the 140 areas based on the contiguity matrix (tables 4.1 and 4.2).

Table 4.3 contains the estimation results for the SGMM specifications. The first four columns contain results for the 138 areas and the second four columns contain results for the 140 areas. The presented model specifications differ in their number of chosen instruments (within these models that passed the specifications tests we present in table 4.4; the specifications of the instrument subsets can be found in table 4.5) and we show those to assess the robustness of the results. For the SGMM model specifications, Pesaran's *CD* statistics lie predominantly below the critical value for the 1 per cent level; and in some cases below the 5 per cent level (column 3 for the TTWA and 8 for the WAREA, see the bottom of table 4.3). We can conclude, on the equivalent significance level of 5 per cent, that there is no strong cross-sectional dependence in the residuals in the latter specifications.

A common result is the significantly positive coefficient of the lagged dependent employment variable. Compared to our previous results, our parameters of interest are notably smaller, the standard errors rise and, thus, become mostly insignificant. The rise in the standard errors can at least partly be explained by the loss of the year 1997 as an observation period because we included the lagged employment rate in our dynamic specification. But the main reason for the difference in the results from tables 4.1 and 4.2 is that the lagged employment rate soaks up the MW long-term effect and, in a few cases, also the demand variable effect. Following these results, we did not find any significant long-term effect of the Kaitz index. However, there are some – weak – significantly negative coefficients for the year-on-year adjustments, those effects are not robust and the significance level is never lower than 10 per cent; the results are different between the two geographies. All in all,

33 Details can be found in appendix 4.A.2.

Table 4.1: Within Group estimates of Minimum Wage effects on employment, 16 years to retirement age, 1997–2010, all regressions contain control variables, area and year effects. Travel-to-Work Areas (TTWA), resulting in 138 regions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Basic specifications			Spatial specifications				
	w/o Yearly Interaction MW Effects/ w/o GVA	with Yearly Interaction MW Effects		Conley Standard Errors (50 km)	Conley Standard Errors (100 km)	Conley Standard Errors (200 km)	SEMP Commuting Matrix	SEMP Contiguity Matrix
Kaitz	−0.108***	−0.145***	−0.127***	−0.127***	−0.127***	−0.127***	−0.122***	−0.123***
	(0.039)	(0.047)	(0.048)	(0.042)	(0.041)	(0.041)	(0.044)	(0.044)
GVA			0.709***	0.709***	0.709***	0.709***	0.678***	0.719***
			(0.239)	(0.181)	(0.192)	(0.209)	(0.192)	(0.190)
Share Public	−0.062	−0.059	−0.066	**−0.066***	**−0.066***	**−0.066***	−0.065**	0.066**
	(0.040)	(0.040)	(0.040)	(0.037)	(0.037)	(0.036)	(0.033)	(0.033)
Kaitz *1999		0.010	0.011	0.011	0.011	0.011	0.012	0.012
		(0.052)	(0.054)	(0.050)	(0.050)	(0.052)	(0.050)	(0.049)
Kaitz *2000		0.043	0.041	0.041	0.041	0.041	0.043	0.039
		(0.043)	(0.044)	(0.044)	(0.040)	(0.041)	(0.050)	(0.049)
Kaitz *2001		−0.010	−0.023	−0.023	−0.023	−0.023	−0.02	−0.021
		(0.037)	(0.037)	(0.035)	(0.036)	(0.037)	(0.049)	(0.048)
Kaitz *2002		0.035	0.016	0.016	0.016	0.016	0.015	0.014
		(0.032)	(0.033)	(0.035)	(0.034)	(0.032)	(0.048)	(0.048)
Kaitz *2003		0.101**	0.084**	0.084**	0.084**	0.084**	0.080	0.080
		(0.043)	(0.042)	(0.037)	(0.037)	(0.037)	(0.050)	(0.049)
Kaitz *2004		0.110**	0.091*	0.091*	0.091*	0.091*	0.090*	0.092*
		(0.048)	(0.048)	(0.048)	(0.047)	(0.048)	(0.050)	(0.049)
Kaitz *2005		0.042	0.026	0.026	0.026	0.026	0.021	0.024
		(0.050)	(0.050)	(0.048)	(0.047)	(0.049)	(0.052)	(0.051)
Kaitz *2006		0.006	−0.008	−0.008	−0.008	−0.008	−0.015	−0.015
		(0.058)	(0.057)	(0.053)	(0.046)	(0.043)	(0.053)	(0.052)
Kaitz *2007		0.053	0.040	0.040	0.040	0.040	0.037	0.034
		(0.055)	(0.055)	(0.048)	(0.051)	(0.049)	(0.052)	(0.051)
Kaitz *2008		0.074	0.060	0.060	0.060	0.060	0.06	0.061
		(0.050)	(0.050)	(0.048)	(0.049)	(0.047)	(0.051)	(0.050)
Kaitz *2009		−0.016	−0.034	−0.034	−0.034	−0.034	−0.032	−0.032
		(0.061)	(0.060)	(0.056)	(0.055)	(0.055)	(0.052)	(0.051)
Kaitz *2010		0.058	0.034	0.034	0.034	0.034	0.034	0.031
		(0.053)	(0.054)	(0.052)	(0.058)	(0.063)	(0.053)	(0.052)
Lambda							0.090**	0.061*
							(0.039)	(0.033)
Observations	1,932	1,932	1,932		1,932		1,932	1,932
R-squared	0.131	0.137	0.145		0.145			
log-likelihood							3,252.833	3,252.477
Pesaran's CD	−0.186	−0.518	−1.421		−1.421		−1.156	−1.304

*** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors in parentheses. Columns 1–3: Robust standard errors. Columns 4–6: Conley s.e. are based on spatial Bartlett kernel. Coefficients are printed in bold in case of significance level changes compared to column 3.

Table 4.2: Within Group estimates of Minimum Wage effects on employment, 16 years to retirement age, 1997–2010, all regressions contain control variables, area and year effects. Unitary Authorities and Counties (WAREA), resulting in 140 regions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Basic specifications			Spatial specifications				
	w/o Yearly Interaction MW Effects/ w/o GVA	with Yearly Interaction MW Effects		Conley Standard Errors (50 km)	Conley Standard Errors (100 km)	Conley Standard Errors (200 km)	SEMP Commuting Matrix	SEMP Contiguity Matrix
Kaitz	-0.056	-0.137***	-0.106**	-0.106**	-0.106**	-0.106**	-0.106***	-0.106***
	(0.044)	(0.050)	(0.051)	(0.043)	(0.041)	(0.041)	(0.041)	(0.041)
GVA			0.888***	0.888***	0.888***	0.888***	0.890***	0.886***
			(0.221)	(0.148)	(0.142)	(0.134)	(0.168)	(0.168)
Share Public	-0.076*	-0.072*	-0.073*	**-0.073***	**-0.073***	**-0.073***	-0.073**	-0.073**
	(0.040)	(0.040)	(0.040)	(0.036)	(0.035)	(0.034)	(0.033)	(0.033)
Kaitz *1999		0.038	0.048	0.048	0.048	0.048	0.048	0.048
		(0.036)	(0.039)	(0.039)	(0.039)	(0.043)	(0.043)	(0.043)
Kaitz *2000		0.085**	0.081*	**0.081***	0.081*	0.081*	0.080*	0.081*
		(0.040)	(0.042)	(0.039)	(0.042)	(0.042)	(0.043)	(0.044)
Kaitz *2001		0.047	0.021	0.021	0.021	0.021	0.02	0.021
		(0.045)	(0.047)	(0.044)	(0.040)	(0.034)	(0.042)	(0.042)
Kaitz *2002		0.079**	0.046	0.046	0.046	0.046	0.045	0.046
		(0.037)	(0.038)	(0.039)	(0.036)	(0.032)	(0.042)	(0.042)
Kaitz *2003		0.185***	0.150***	0.150***	0.150***	0.150***	0.15***	0.15***
		(0.053)	(0.054)	(0.041)	(0.039)	(0.039)	(0.043)	(0.044)
Kaitz *2004		0.111**	0.074	**0.074***	**0.074***	**0.074****	0.074*	0.074*
		(0.046)	(0.047)	(0.044)	(0.043)	(0.037)	(0.044)	(0.044)
Kaitz *2005		0.130***	0.099**	**0.099*****	**0.099*****	**0.099*****	0.098**	0.099
		(0.038)	(0.039)	(0.034)	(0.031)	(0.027)	(0.046)	(0.046)
Kaitz *2006		0.169***	0.121***	0.121***	0.121***	0.121***	0.122***	0.122***
		(0.039)	(0.040)	(0.034)	(0.032)	(0.029)	(0.046)	(0.047)
Kaitz *2007		0.135**	0.099*	**0.099****	**0.099****	**0.099****	0.099**	0.099**
		(0.054)	(0.054)	(0.050)	(0.045)	(0.039)	(0.046)	(0.046)
Kaitz *2008		0.105***	0.063	**0.063***	**0.063***	**0.063****	0.063	0.063
		(0.039)	(0.039)	(0.033)	(0.032)	(0.031)	(0.045)	(0.045)
Kaitz *2009		0.049	0.006	0.006	0.006	0.006	0.006	0.006
		(0.042)	(0.043)	(0.038)	(0.034)	(0.029)	(0.046)	(0.046)
Kaitz *2010		0.090*	0.030	0.030	0.030	0.030	0.03	0.03
		(0.050)	(0.050)	(0.043)	(0.044)	(0.042)	(0.048)	(0.048)
							0.048	0.048
Lambda							-0.01	-0.003
							(0.038)	(0.031)
Observations	1,960	1,960	1,960		1,960		1,960	1,960
R-squared	0.115	0.130	0.143		0.143			
log-likelihood							3,363.179	3,363.164
Pesaran's CD	0.497	0.223	-1.516		-1.516		-1.522	-1.366

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses. Columns 1–3: Robust standard errors. Columns 4–6: Conley s.e. are based on spatial Bartlett kernel. Coefficients are printed in bold in case of significance level changes compared to column 3.

Table 4.3: SGMM estimates of Minimum Wage effects on employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Travel-to-Work Areas (TTWA), 138 regions				Unitary Authorities and Counties (WAREA), 140 regions			
	SGMM	SGMM	SGMM	SGMM	SGMM	SGMM	SGMM	SGMM
Kaitz	−0.016	−0.015	−0.013	−0.030	−0.026	−0.025	−0.030	−0.073
	(0.056)	(0.056)	(0.078)	(0.071)	(0.063)	(0.062)	(0.073)	(0.093)
E_{t-1}	0.239***	0.239***	0.218***	0.241***	0.242***	0.241***	0.236***	0.250***
	(0.033)	(0.033)	(0.031)	(0.036)	(0.033)	(0.033)	(0.032)	(0.032)
GVA	0.635**	0.638**	0.646	1.045**	0.556**	0.553**	0.582**	0.485
	(0.310)	(0.310)	(0.413)	(0.410)	(0.273)	(0.272)	(0.277)	(0.343)
Share Public	−0.150***	−0.149***	−0.194*	−0.110	−0.200***	−0.201***	−0.207***	−0.269***
	(0.040)	(0.040)	(0.103)	(0.092)	(0.043)	(0.043)	(0.041)	(0.068)
Kaitz *1999	0.045	0.045	0.001	0.001	0.012	0.011	0.015	0.019
	(0.059)	(0.059)	(0.051)	(0.051)	(0.054)	(0.053)	(0.059)	(0.054)
Kaitz *2000	0.026	0.026	−0.005	−0.016	0.043	0.042	0.029	0.026
	(0.051)	(0.051)	(0.047)	(0.046)	(0.051)	(0.051)	(0.051)	(0.051)
Kaitz *2001	−0.080	−0.079	−0.102*	−0.091*	−0.073*	−0.073*	−0.091*	−0.083*
	(0.056)	(0.056)	(0.054)	(0.049)	(0.043)	(0.043)	(0.047)	(0.050)
Kaitz *2002	−0.024	−0.023	−0.042	−0.059	−0.044	−0.045	−0.065	−0.053
	(0.044)	(0.044)	(0.045)	(0.046)	(0.043)	(0.043)	(0.045)	(0.048)
Kaitz *2003	0.010	0.011	−0.010	0.007	0.096*	0.096*	0.086	0.092
	(0.057)	(0.057)	(0.058)	(0.058)	(0.057)	(0.057)	(0.068)	(0.071)
Kaitz *2004	0.054	0.055	0.012	−0.002	0.052	0.052	0.021	0.024
	(0.072)	(0.072)	(0.072)	(0.067)	(0.066)	(0.066)	(0.067)	(0.070)
Kaitz *2005	−0.011	−0.010	−0.016	−0.014	0.070	0.069	0.054	0.032
	(0.058)	(0.058)	(0.058)	(0.055)	(0.053)	(0.053)	(0.054)	(0.051)
Kaitz *2006	−0.038	−0.036	−0.054	−0.055	0.066	0.066	0.063	0.052
	(0.062)	(0.062)	(0.061)	(0.059)	(0.054)	(0.054)	(0.056)	(0.060)
Kaitz *2007	0.063	0.064	0.020	−0.010	0.004	0.004	−0.013	−0.020
	(0.079)	(0.079)	(0.074)	(0.065)	(0.067)	(0.067)	(0.068)	(0.070)
Kaitz *2008	0.033	0.033	0.010	0.030	0.033	0.033	0.028	0.017
	(0.057)	(0.057)	(0.055)	(0.053)	(0.059)	(0.059)	(0.062)	(0.060)
Kaitz *2009	−0.117*	−0.116*	−0.124*	−0.091	−0.027	−0.027	−0.039	−0.053
	(0.069)	(0.069)	(0.068)	(0.066)	(0.059)	(0.059)	(0.066)	(0.062)
Kaitz *2010	0.007	0.008	−0.033	−0.012	0.002	0.003	−0.004	0.008
	(0.077)	(0.077)	(0.074)	(0.072)	(0.071)	(0.071)	(0.075)	(0.075)
Observations	1,794	1,794	1,794	1,794	1,820	1,820	1,820	1,820
Number of instruments	70	70	82	94	70	70	82	94
Pesaran's CD	−2.088	−2.083	−1.877	−2.105	−1.983	−1.980	−2.228	−1.785

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. SGMM validity test statistics are provided in table 4.4.

Table 4.4: SGMM estimates of Minimum Wage effects on employment, validity test statistics of estimates in table 4.3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Travel-to-Work Areas (TTWA), 138 regions				Unitary Authorities and Counties (WAREA), 140 regions			
	SGMM	SGMM	SGMM	SGMM	SGMM	SGMM	SGMM	SGMM
Number of instruments	70	70	82	94	70	70	82	94
	Arellano-Bond test for AR in first differences							
AR(1)	-6.2996	-6.3030	-6.0811	-5.8567	-6.3738	-6.3760	-6.2990	-6.3083
Prob > z	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AR(2)	-1.1015	-1.1080	-1.1223	-0.7272	1.0026	1.0027	0.8746	0.9504
Prob > z	0.2707	0.2679	0.2617	0.4671	0.3161	0.3160	0.3818	0.3419
	Hansen test of overidentified restrictions							
J	42.9479	42.9110	56.3820	69.3673	32.9967	32.9116	44.6749	54.4889
Prob > chi2	0.1980	0.1991	0.1901	0.1909	0.6122	0.6163	0.6099	0.6765
	Difference-in-Hansen tests of exogeneity of instrument subsets – GMM instruments for levels –							
C	41.7672	41.7202	52.4702	64.3460	29.5218	29.4348	40.8947	51.8766
Prob > chi2	0.1408	0.1419	0.1786	0.1820	0.6410	0.6453	0.6055	0.5947
	– Instrumented variables in levels and first differences –							
C	22.1767	22.2916	35.5849	54.4141	16.6261	16.6104	30.4035	41.6539
Prob > chi2	0.2242	0.2193	0.2612	0.1351	0.5489	0.5500	0.4965	0.5727
	– Instrumented variables only in levels –							
C	28.7026	28.7231	40.9215	53.1814	21.9747	21.5937	33.9595	39.5766
Prob > chi2	0.2315	0.2307	0.2633	0.2815	0.5808	0.6035	0.5660	0.8014

Table 4.5: SGMM estimates of Minimum Wage effects on employment, specifications of instruments subsets of regression models in table 4.3

Model no.	GMM instruments	Variable instruments for 1st differences equation	Variable instruments for level equation
	Travel-to-Work Areas (TTWA), 138 regions		
(1)	E_{t-1}, Age, Age^3	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^2, NV4qplus, female workers share	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^2, NV4qplus, female workers share, year dummies
(2)	E_{t-1}, Age, Age^2	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^3, NV4qplus, female workers share	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^3, NV4qplus, female workers share, year dummies
(3)	E_{t-1}, Age^2, Age^3, female workers share	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age, NV4qplus	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age, NV4qplus, year dummies
(4)	E_{t-1}, Age, Age^2, NV4qplus, female workers share	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^3	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^3, year dummies
	Unitary Authorities and Counties (WAREA), 140 regions		
(5)	E_{t-1}, Age, NV4qplus	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^2, Age^3, female workers share	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^2, Age^3, female workers share, year dummies
(6)	E_{t-1}, Age^2, NV4qplus	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age, Age^3, female workers share	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age, Age^3, female workers share, year dummies
(7)	E_{t-1}, Age, Age^2, NV4qplus	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^3, female workers share	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^3, female workers share, year dummies
(8)	E_{t-1}, Age, Age^2, NV4qplus, female workers share	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^3	Kaitz, Kaitz *1999–Kaitz *2010, GVA, Share Public, Age^3, year dummies

we found only rather weak evidence for year-on-year adjustment effects. The results suggest that the modelling of demand shocks and the spatial dependence pattern of employment is important for the identification of MW effects. Quite clearly these effects are severely attenuated by more rigorous econometric models and estimation methods. Reassuringly our results are robust to the fairly stern test of using two different geographical units of observation[34]. To sum up, following the results of the last model specification that takes the potential endogeneity of the Kaitz index as well as the dynamic properties of the employment equation into account we conclude that we did not find significantly negative long-term employment effects. Furthermore, our results also suggest that there are no year-on-year effects of uprating the Minimum Wage.

4.5 Conclusions

The contribution of this paper is to update the econometric evidence of the impact of the NMW on employment in the UK and focus on the particular context of the recession of 2008–2010. We use geographical variation in the impact of the NMW and the recession to identify the separate employment consequences of imposing a NMW and its up-ratings over the years. We used four sources of variation to try and identify the effect of the NMW in the UK. The first exploits a natural variation in how the NMW bites in different geographical locations. In our UK case the MW is set nationally, thus there is no decision to be made at the local level (in sharp contrast to the US States case). This implies a natural variation in the measured bite of the NMW which is different at each geographical area. Our second source of variation examined the effect of changes in the up-rating of the NMW over the years since it was introduced. This estimation is based on an Incremental Diff-in-Diff method which allows us to estimate the marginal (interaction) effect of each year's change in the NMW. The third source of variation we exploit is to allow the size, timing and duration of the recession to affect different regions differently. This provides us with the capacity to estimate the effect of the recession on local employment and to net out this factor in assessing the impact of the NMW on employment. Clearly, any

34 We also checked the robustness of our results using restricted geography samples by dropping out those regions that are economically weak. Although we use regional variation for our identification strategy, we assume that the economic behavior in terms of the employment elasticity of the bite of the minimum wage is equal over all regions. It is known that the economic power of the UK is not equally distributed over the whole country and there are some economic hot spots like – first of all – London, but also the whole area around London and there are other regions that are more or less economically dependent of those strong regions. Hence, it could be reasonable that the employment effects of the MW are somewhat different between the strong and the weaker regions. Details can be found in appendix 4.A.7. Finally, due to the concerns on the Kaitz variable, we used the fraction of people paid at or below the NMW in each local area as alternative treatment measure. The results qualitatively corroborated our main conclusion. Details can be found in appendix 4.A.8.

assessment which fails to net out this factor will bias the estimates of the impact of the NMW on employment. The final source of variation we exploit is that our spatial model allows the nature of the complex pattern of regional interconnectedness and spillover effects to be present in the estimation and thus gave us some confidence that we have netted out their impact in terms of the effect of the NMW on employment. The combination of these four different sources of variation in the data along with the rigorous use of different robustness checks means that we can be more confident about the estimated effect of the impact of the NMW. Our conclusions are all the more credible in the sense that we obtained consistent results even though we re-analysed the data using two completely different geographies. This paper makes four important contributions to the literature on evaluating the effect of the MW on employment. Our first concern is that all the existing literature on the MW is unable to distinguish between having a statutory MW in existence and the changes or up-ratings of the MW, e.g. on an annual basis. We are able to make such a distinction since we are able to observe a 'pre-period' before the MW legislation was enacted (namely, prior to 1999), when no NMW existed. It turns out that such an important distinction is vital to try and understand why the previous literature has found negative or zero employment effects of the MW.

Our second major concern focuses on previous research which has attempted to use geographical variation in the bite of the MW to identify its effects. The problem with this literature is that it has ignored the possible geographical contiguity and spatial spillovers associated with neighbouring locations. More specifically the literature to date has modelled panel data on geographical areas over time under the assumption that they are completely independent observations. We relaxed this assumption using spatial econometric methods. To do this we used the observed pattern of commuting behaviour between our geographical areas as this represents the reduced form pattern of the many observed and unobserved influences on commuting decisions and hence the interconnectedness of local labour markets. For robustness we compare our results with model specifications which utilize contiguity matrices instead and found that our results were largely unchanged.

Most of the literature on the employment impact of the MW has ignored the potential identification problem associated with netting out the effect of changes in the aggregate economy. The third contribution of this paper is to condition directly on the nature of demand shocks in our estimation of the regional employment effects of the MW. This is most pertinent since we are interested in the effect the MW in a time of the deepest recession the Western world has experienced since the Great Depression of the 1930s. We attempted to solve this problem by using geographically varying information from Gross Value Added by region which is related to the onset, severity and duration of the recession in different locations. We find that this important adaptation of the standard econometric model leads directly to a considerable attenuation of the year on year interaction effects and hence may explain why previous papers got (spuriously) positive employment effects.

Our final area of contribution relates directly to the modeling of the dynamic form of employment changes. Specifically, we use a SGMM model to circumvent potential endogeneity problems relating to the inclusion of a lagged term in the employment dependent variable. This modeling adopts an Arellano-Bond type IV estimation procedure to overcome the bias introduced by having a dynamic model of employment adjustment (Arellano and Bover, 1995). We found that when the effects of demand side shocks, a lagged dependent variable and endogenous wage effects are explicitly modeled, then the effects of the NMW on employment, which have been previously found, are largely attenuated. Specifically, we find that the incremental effects of having a NMW and invoking NMW upratings are not identified. It is quite clear that the modelling of changing demand conditions is a real contribution of this paper which suggests that: firstly, papers in the past, which have neglected to study this, may be finding spuriously significant effects when none exist; and secondly, that the overall effect of NMW depends on what stage of the cycle the economy is in. We can see that a tight labour market in a recession may induce negative employment effects – but that NMW uprating in boom times may induce little or no overall effect. This relationship points the importance of controlling adequately for demand side factors (including the steady state autoregressive path of employment) in modelling what might happen to employment in the face of a NMW (imposition or up-rating). Our further robustness checks suggest that our preferred models do not exhibit strong spatial dependence.

The conclusion from our spatial model estimations is that overall there may be incremental employment effects of up ratings to the MW in a year-on-year context. The years where the estimations for both geographies revealed a small positive coefficient are 2003, 2004, 2007 and 2010 which are historically some of the years when the NMW up rating started to exceed the RPI rise in the cost of living and hence the up rating of the NMW was relatively generous and where there is a boom in the economy and hence a potential measurement error problem in the modeling of employment. In contrast, the underlying effect of the presence of the NMW is reflected in the Kaitz index coefficient in the tables. In the spatial models this coefficient is nearly always negative and significant suggesting that the effective implementation of the NMW has an underlying negative impact on employment. It should be stressed that our measured marginal effects were consistently attenuated when we condition out for the presence and severity of the recession in the regional context. These conclusions are robust to our two different definitions of the geography, which are used to perform the estimation. Furthermore, they are robust to changing the nature of our weights matrix. Specifically, we used a simple neighbouring contiguity matrix instead of our commuting matrix and our overall conclusions did not change. Additionally they remain after utilizing a non-parametric estimation for the variance-covariance-matrix.

The central question which remains a concern for any of our spatial models is that the specific form of the spatial dependence is assumed from the outset. Our final, more general, preferred approach to this is to use System GMM estimation in which we can be more general in our approach to the dynamics of employment and the potential endogeneity of the Kaitz index wage effect term. This approach, which uses a generalized IV strategy, leads us to the conclusion that there are no effects of either having or uprating a NMW on employment (other than those which results from employment dynamics). Our SGMM results also suggest, with the use of the CD test that, with the appropriate number of instruments, the problem of strong spatial dependence can be circumvented.

Our findings are interesting as they rationalize the controversial debate in the literature as to why one might get negative impacts of the MW – i.e., due to the effect of the presence of the MW rather than its up rating. Our results are also consistent with much of the recent literature focusing on the introduction of the NMW but also because they explain why it may be possible to get both zero and positive effects. Our results thus present quite a departure from the literature which has studied the employment effects of the minimum wage but never distinguished between the effect of imposing a MW and uprating the MW on a regular basis. John Kennan's excellent review of Card and Krueger (1995) argues that when studying the effects of minimum wages on employment "we are looking for employment rate changes of about one percentage point, and such changes happen all the time, even from one month to the next. In short, we are looking for a needle in a haystack" [emphasis added] (Kennan, 1995, p. 1955). We completely agree with this conclusion and accordingly suggest the total effect of invoking and uprating a MW will nearly always be insignificantly different from zero. We have also demonstrated that the reason for some of the literature finding positive effects of the MW is that it does not distinguish between the issues of: spatial dependence, the endogeneity of the MW (in the form of the Kaitz index), recessionary demand shocks, and the steady state trend in the employment series. Our suggestion from this UK evidence is that failing to take account of these complications could lead to spuriously positive (or negative) MW effects with underestimated standard errors where strong spatial dependence is clearly present. Although our evidence is only for one country, our results suggest it may be possible to reconcile that the perennial debate between the pro- and anti-MW lobbies.

4.A Appendix to chapter 4

4.A.1 Data

Geography of 138 and 140 areas

In this paper we use two different levels of geographical aggregation. The first geography approximates travel-to-work areas (TTWAs). The second geography is borne of administrative areas (WAREA). The travel-to-work areas (TTWAs), following an ONS definition, correspond to areas in which not less than 67% of people are living and working in the same geography. Since TTWAs were not available for the entire period of analysis the only option was to attempt to replicate our results for the most reasonable definition of TTWA that we could manually reconstruct from the data available. We used ASHE data from 2002 in which we have information about 406 administrative areas for the UK where people work and the equivalent areas where they live (WLAs[35]). We then compute commuting shares (given by the proportion of people who live in an area and work in another area and the proportion of people who work in an area and live in another one). We then keep all the districts and unitary authorities where the ONS definition of travel-to-work areas holds (around 12% of areas). For the other WLAs, with the help of GIS software, we overlap the map of ONS TTWA with the map of WLAs and combine Districts and Unitary Authorities into existing TTWA boundaries. With these new geographies we compute the commuting patterns to check the consistency with ONS definition of travel-to-work areas. For the few areas (14%) where the ONS definition of travel-to-work areas still does not hold, we aggregate further. Some 90% of these are such that at least 67% of working residents work in the area and at least 67% of workers are resident in the areas. This gives us 138 (new geographical) TTWA areas for which we repeated our analysis. The median sample cell size is 581 and the smallest cell is 37.

The WAREA geography includes 34 English counties, 6 English metropolitan counties, 46 English Unitary authorities, Inner and Outer London and finally 52 Unitary authorities in Scotland and Wales. This resulted in 140 local areas[36]. Here, the median sample cell size is 581 and the smallest cell is 53.

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35 The WLA's consist of 32 London boroughs, 238 Districts, 36 metropolitan districts and the 46 Unitary Authorities in England; the 22 Unitary Authorities in Wales and 32 Unitary Councils in Scotland, resulting in 406 (WLA) local areas.

36 The Orkney Islands, Shetland Isles and Western Isles are aggregated together. The 36 English metropolitan districts are combined into 6 English Metropolitan Counties. London Boroughs are aggregated into Inner and Outer London. This allows to have match geographies in the LFS and in the ASHE/NES, using the definition of the variable "uacnty", denoting Unitary Authority/County Level, in the LFS.

Figure 4.5 helps to understand how our TTWAs actually differ from our WLAs and WAREAs. By focusing only on a small part of the country such as the south-London coast, we can see how the TTWAs are generally extending over the narrow boundaries of the Districts (figure 4.5 a), which characterize the WLAs (figure 4.5 b). They can also be smaller than the administrative counties of the WAREAs (figure 4.5 c). In addition, the administrative boundaries of the counties do not necessarily determine the boundaries of the TTWA, since people living at the borders of a county can commute and work in a neighboring town which is not necessarily part of that specific county. These figures clearly show the merits and limitations of working with different units of geography. Focus on the county for Kent (the county with the darker shading) – the most southeastern of the counties in the UK – which is at the bottom left hand corner of figures 4.5 a, b, and c. Using the WLA geography the county becomes 10 separate areas. Using the WAREA geography, we see that this whole area is basically a single geography with the sole exception of Gillingham and Chatham which adds additional further urban area in the north west of the county. Using TTWA the county becomes 4 different areas based on the feasibility of the transport connections (and by definition the observed patterns of commuting behavior). At the same time it loses a small slice of its southwestern edge to neighbouring Sussex.

Definition of key variables

Employment rate. Total number of employees, self-employed, unpaid family workers and participants in government-supported training and employment programs in working age as a proportion of people in working age in each local area. Data on employment used in this paper is taken from June to August of each year. Source: Labour Force Survey. Residence based analysis.

Kaitz Index. The ratio of the NMW to the median hourly wage in each local area:

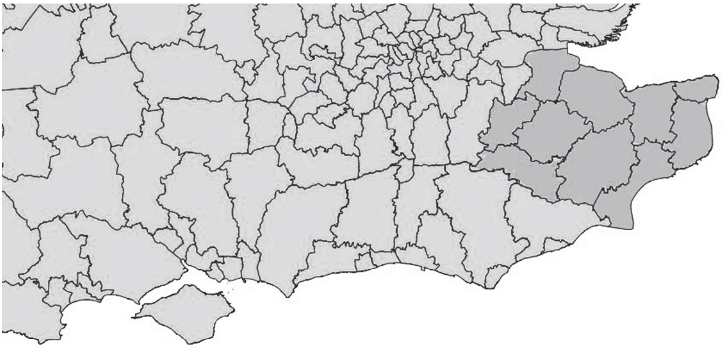
- From 1999 to 2003, we use a weighted average of the minimum wage shares of persons from 18 to 21 years and of persons from 22 to retirement age.
- From 2004 onwards, with the introduction of the new development rate for young between 16 and 17 years, we use a weighted average of the minimum wage of persons of persons of 16 and 17 years, of persons from 18 to 21 years and of persons from 22 to retirement age.

Generally, the ASHE/NES based minimum wage variables used in this paper are recorded in April of each year and the NMW variables are recorded six months after each NMW up-rating due to the fact that the minimum wage was invoked in April 1999 but then up-rated in October of each following year. There are, however, two exceptions: April 1999, which is contemporaneous to the introduction of the

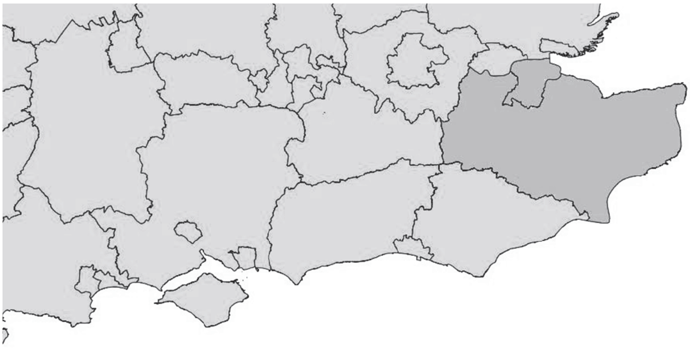
Figure 4.5: Differences between TTWA, WLA, and WAREA geographies, focusing on South-East-London coast

a) TTWA

b) WLA



c) WAREA



Note: The darker regions belong to the county of Kent.

Source: http://edina.ac.uk/ukborders/, TTWA geographies are manually constructed by the authors from WLAs.

minimum wage, and April 2000, which is one year from the introduction of the minimum wage. To reduce simultaneity concerns, the wage data in April of year t is regarded as having absorbed any effect of the NMW upgrade in October of year $t-1$. This is in turn matched to employment data taken from June to August of year t. For the pre-period 1997 and 1998, data on employment rates are collected from March 1997 to February 1998 and from March 1998 to February 1999. Quarterly data is not available for these two calendar years. Since LFS Local Area data is only available in seasonal quarters, it is only possible to use the quarter June-August and not a longer period (eg. from May to September). This means that the estimated impact effect we identify is a mixture of the impact of the up-rating in year $t-1$ and any changes from the already announced anticipation of the effect of the new NMW level in year t. As a robustness check we have varied our timing assumptions and our results suggest that any anticipation effect is negligible. Swaffield (2008) shows that there is very little early upward adjustment in wages in the six months prior to October over several years of data.

Other Covariates. The other covariates in the dataset are derived from the underlying micro datasets. In the case of age, gender and sector we use the ASHE/NES to compute these variables by each of the geographies and simply computed proportions. In the case of the human capital regressor – the proportion of the workforce with a degree level qualification we used the LFS to derive this variable since the ASHE/NES does not have education information on respondents. The Gross Value Added (GVA) variable was derived from official statistics sources from table 3.3 of 'Regional Trends' from various years: Workplace-based gross value added (GVA) per head at current base prices. This GVA variable is measured at the level of the government office region and not at the level of the individual geography. It is not possible to measure the effect of aggregate demand at any finer geography than the government office region level. However, this has the advantage that we are controlling for demand shocks at a different level of geography than our basic units of observation.

Further properties of the ASHE/NES datasets to be considered

Even if ASHE is considered to give reliable wage figures though payroll records and it has a relatively large sample size, there are some limitations of this dataset which could affect this study.

- Possible measures of hourly earnings.

  The Low Pay Commission recommended construction of the hourly pay variable on the NES/ASHE data involves dividing gross pay (excluding overtime, shift and premium payments) by basic paid hours. This variable closely matches the definition of National Minimum Wage. However, the variable is available

in the panel only from 2000. It is therefore necessary to use another measure of hourly earnings in this study which covers the period 1997 to 2007.
The variable used is a "basic hourly wage rate", defined as gross weekly earnings excluding overtime, and divided by normal basic hours. As a result this variable will be slightly larger than the true hourly wage and the measurement error will tend to be larger than the higher shift and premium payments are. This might therefore result in an under-statement of the number of low paid workers.

- Discontinuities in NES/ASHE dataset across years.

Time series analysis was complicated when the ASHE replaced the NES in 2004 and also by several changes in the ASHE methodology from 2004 to 2007.

First of all, the coverage of employees for the ASHE is greater than that of the NES. The NES surveys employees from HM Revenue & Customs PAYE record, excluding the majority of those whose weekly earnings fall below the PAYE deduction threshold. Moreover, this survey does not cover employees between sample selection for a particular year and the survey reference week in April. Thus, mobile workers who have changed or started new jobs between the drawing of the sample and the reference week are excluded. In conclusion, NES understate the proportion on NMW as it does not record the earnings of many low paid workers, especially part-time and mobile workers. In 2004, the ASHE survey was introduced to improve the representation of the low paid workers: it improved the coverage of employees including mobile workers who had either changed or started new jobs between sample selection and the survey reference in April. Also, the sample was enlarged by including some of the employees outside the PAYE system.

In 2005, a new questionnaire was introduced. In particular, the definition of incentive/bonus pay changed to only include payments that were paid and earned in April. Also, a new question including "pay for other reasons" was introduced. This implies respondents might include earnings information which was not collected in the past. Even if the results for 2004 have been reworked to exclude irregular bonus/incentive payments and to allow for this missing pay, results from 1997 to 2003 remain inconsistent with the ones from 2004 onwards.

Given that the main source of information on hourly pay in this study includes shift and premium payments and from 2004 "pay for other reasons", estimations of measures of minimum wage and wage inequality might be affected by this discontinuity, with an increase of the average measurement error and the dispersion in the measurement error from 2004 onwards.

Finally, in 2007 the sample size of ASHE was reduced by 20%. ASHE results for 2007 are based on approximately 142,000 returns, down from 175,000 in

2006. The largest sample cuts occurred principally in industries where earnings are least variable, affecting the randomness of the sample.

Consistent series which takes into account of the identified changes has been produced going back from 2006 to 2004 and from 2007 to 2006. For 2004 results are also available that exclude supplementary information, to be comparable with the back series generated by imputation and weighting of the 1997 to 2003 NES data. Unfortunately, it is not possible to get consistent datasets for the entire period concerning this study (1997–2007).

4.A.2 Spatial autocorrelation in the residuals

To assess the residuals, $\hat{\varepsilon}_{jt}$, for strong spatial autocorrelation we utilize Pesaran's *CD* test, compare the last rows of tables 4.1–4.3 in the main text and tables 4.11, 4.12 and 4.13 in the appendix.
This statistic has the following form

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} \hat{\epsilon}_{it}\hat{\epsilon}_{jt}}{(\sum_{t=1}^{T} \hat{\epsilon}_{it}^2)^{1/2}(\sum_{t=1}^{T} \hat{\epsilon}_{jt}^2)^{1/2}}$$

$$CD = \sqrt{\frac{2T}{N(N-1)}}(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} \hat{\rho}_{ij})$$

According to Pesaran (2004), the *CD* statistic is $N(0,1)$ normal-distributed under the null hypothesis of i.i.d. residuals. E.g., the critical value, equivalent to the 5 per cent significance level, is 1.96.

4.A.3 Lagrange multiplier tests for spatial specification

We used the Lagrange Multiplier tests described and provided by Debarsy and Ertur (2010) for the panel models with area effects to shed more light on these questions from a statistical point of view. Therefore, at first we test for the null hypothesis of (i) no spatial lag of the dependent variables and no spatial autoregressive error term vs. there is at least one kind of spatial dependency. In this and all other tests the Null hypothesis has to be rejected if the *p* value is higher than a certain significance level. Afterwards if the null hypothesis has to be rejected we test for four specifications with the null hypothesises of

(ii) no spatial lag of the dependent variables (vs. a spatial lag),
(iii) no spatial autoregressive error terms (versus the existence of spatial autoregressive error terms),

(iv) no spatial lag of the dependent variables vs. spatial lag, given spatial autoregressive errors, and finally of
(v) no spatial autoregressive errors vs. the existence of spatial autoregressive errors, given spatial lags of dependent variables.

These (hierarchical) steps are necessary to get indices for which either model SEMP or SARP should be preferred because both models are not nested and, therefore, could not be directly compared.

The results can be found in tables 4.6 to 4.9 for the 138 TTWA and the 140 area data sets, respectively. The results for the 138 TTWA areas indicate that SEMP would be the preferred model at a significance level of ten per cent with one exception: the SARP model would be preferred for the fully specified model with GVA variable[37] (tables 4.6 and 4.7).

For the 140 area data set the joint test indicate no spatial dependencies for 2 of 4 models including the recession variable (tables 4.8 and 4.9). For the model with the full specification and those without the recession variable, spatial dependencies cannot be rejected. Further test statistics for the models without recession variables and either no interaction terms for the Kaitz index or no control variables allow us to conclude that the SEMP model should be preferred. For the full specified models (with and without recession variable) the decision between a SARP or SEMP specification is not clear, because in both models the joint tests statistics indicate spatial dependencies but the tests for no spatial lag and no spatial autoregressive term cannot be rejected. To sum up, the results of the LM tests indicate that spatial dependencies of the dependent variable and/or the error terms cannot be ruled out. This is especially true for the full specification models. Furthermore, the results lead to the conclusion that the SEMP model should be preferred in the majority of cases. For the other models other spatial specifications should be tested. In such a case LeSage and Pace (2009) recommend to test models with spatial lags of the independent variables that also include spatial lags of independent variables and error terms. However, not least because of possible identification problems, as it is notably discussed by (Gibbons and Overman, 2012), it is a task for further research to establish if these spatial specifications are indeed more adequate.

37 However, the p-value is 0.107 and therefore only 0.7 percent points higher than the chosen significance level.

Table 4.6: LM spatial specification tests, 16 years to retirement age, 138 TTWA areas, 1997–2010, commuting matrix

	Specification of the model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification of the model	Kaitz index				Y				
	Kaitz *Year effects	N	N	Y	Y	N	N	Y	Y
	Year effects				Y				
	Area effects				Y				
	Controls incl. share publ.	N	Y	N	Y	N	Y	N	Y
	GVA	N	N	N	N	Y	Y	Y	Y
Null hypotheses				Test results					
No spatial autocorrelation of the error terms and no spatial lag of the dependent variables	LM statistics	14.715	15.708	17.900	17.962	5.658	5.933	7.213	7.281
	P	0.001	0.000	0.000	0.000	0.059	0.051	0.027	0.026
No spatial lag of the dependent variable	LM statistics	12.602	8.850	10.814	7.527	5.284	4.218	4.600	3.605
	P	0.000	0.003	0.001	0.006	0.022	0.040	0.032	0.058
No spatial autocorrelation of the error terms	LM statistics	11.988	7.040	8.952	5.080	4.988	3.507	3.749	2.541
	P	0.001	0.008	0.003	0.024	0.026	0.061	0.053	0.111
No spatial lag of the dependend variable, given a spatial autocorrelation of the error terms	LM statistics	0.017	0.032	0.054	0.223	0.005	0.008	0.006	–
	P	0.895	0.858	0.816	0.637	0.944	0.928	0.936	
No spatial autocorrelation of the error terms, given a spatial lag of the dependend variable	LM statistics	499.611	240.009	314.641	170.207	184.245	107.554	135.457	–
	P	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
Preferred model (p < 0.10)		SEMP	SEMP	SEMP	SEMP	SEMP	SEMP	SEMP	SARP
	Number of observations				1,938				

Table 4.7: LM spatial specification tests, 16 years to retirement age, 138 TTWA areas, 1997–2010, contiguity matrix

	Specification of the model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification of the model	Kaitz index					Y			
	Kaitz *Year effects	N	N	Y	Y	N	N	Y	Y
	Year effects					Y			
	Area effects					Y			
	Controls incl. share publ.	N	Y	N	Y	N	Y	N	Y
	GVA	N	N	N	N	Y	Y	Y	Y
Null hypotheses					Test results				
No spatial autocorrelation of the error terms and no spatial lag of the dependent variables	LM statistics	8.123	8.691	7.082	8.119	4.278	4.001	3.526	3.365
	P	0.017	0.013	0.029	0.017	0.118	0.135	0.171	0.186
No spatial lag of the dependent variable	LM statistics	7.754	6.388	6.330	5.154	–	–	–	–
	P	0.005	0.011	0.012	0.023				
No spatial autocorrelation of the error terms	LM statistics	7.336	5.004	5.690	3.662	–	–	–	–
	P	0.007	0.025	0.017	0.056				
No spatial lag of the dependend variable, given a spatial autocorrelation of the error terms	LM statistics	0.016	0.077	0.014	0.097	–	–	–	–
	P	0.900	0.781	0.905	0.755				
No spatial autocorrelation of the error terms, given a spatial lag of the dependend variable	LM statistics	181.242	71.509	105.362	55.997	–	–	–	–
	P	0.000	0.000	0.000	0.000				
Preferred model ($p < 0.10$)		SEMP	SEMP	SEMP	SEMP	no spatial d.	no spatial d.	no spatial d.	no spatial d.
	Number of observations					1,938			

Table 4.8: LM spatial specification tests, 16 years to retirement age, 140 WAREA areas, 1997–2010, commuting matrix

	Specification of the model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification of the model	Kaitz index					Y			
	Kaitz *Year effects	N	N	Y	Y	N	N	Y	Y
	Year effects					Y			
	Area effects					Y			
	Controls incl. share publ.	N	Y	N	Y	N	Y	N	Y
	GVA	N	N	N	N	Y	Y	Y	Y
Null hypotheses		Test results							
No spatial autocorrelation of the error terms and no spatial lag of the dependent variables	LM statistics	8.984	18.525	16.841	22.246	1.492	5.489	4.142	7.761
	P	0.011	0.000	0.000	0.000	0.474	0.064	0.126	0.021
No spatial lag of the dependent variable	LM statistics	8.938	5.428	4.202	2.499	–	0.399	–	0.093
	P	0.003	0.020	0.040	0.114		0.528		0.760
No spatial autocorrelation of the error terms	LM statistics	8.967	3.767	2.289	0.654	–	0.127	–	0.025
	P	0.003	0.052	0.130	0.419		0.722		0.876
No spatial lag of the dependend variable, given a spatial autocorrelation of the error terms	LM statistics	0.011	0.029	–	–	–	–	–	–
	P	0.915	0.865						
No spatial autocorrelation of the error terms, given a spatial lag of the dependend variable	LM statistics	701.146	220.558	–	–	–	–	–	–
	P	0.000	0.000						
Preferred model ($p < 0.10$)		SEMP	SEMP	SARP	other spec.	no spatial d.	other spec.	no spatial d.	other spec.
	Number of observations					1,960			

Table 4.9: LM spatial specification tests, 16 years to retirement age, 140 WAREA areas, 1997–2010, contiguity matrix

	Specification of the model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification of the model	Kaitz index					Y			
	Kaitz *Year effects	N	N	Y	Y	N	N	Y	Y
	Year effects					Y			
	Area effects					Y			
	Controls incl. share publ.	N	Y	N	Y	N	Y	N	Y
	GVA	N	N	N	N	Y	Y	Y	Y
Null hypotheses		Test results							
No spatial autocorrelation of the error terms and no spatial lag of the dependent variables	LM statistics	6.531	17.411	14.042	20.366	1.873	5.503	2.440	6.341
	P	0.038	0.000	0.001	0.000	0.392	0.064	0.295	0.042
No spatial lag of the dependent variable	LM statistics	5.268	3.046	1.893	0.987	1.209	0.566	0.426	0.123
	P	0.022	0.081	0.169	0.320	0.272	0.452	0.514	0.726
No spatial autocorrelation of the error terms	LM statistics	4.894	1.456	0.859	0.061	1.026	0.185	0.219	0.003
	P	0.027	0.227	0.354	0.805	0.311	0.667	0.640	0.958
No spatial lag of the dependend variable, given a spatial autocorrelation of the error terms	LM statistics	0.043	–	–	–	–	–	–	–
	P	0.836							
No spatial autocorrelation of the error terms, given a spatial lag of the dependend variable	LM statistics	249.324	–	–	–	–	–	–	–
	P	0.000							
Preferred model ($p < 0.10$)		SEMP	SARP	other spec.	SEMP	no spatial d.	other spec.	no spatial d.	other spec.
	Number of observations					1,960			

4.A.4 Weight matrix in spatial specifications

We want to examine the extent to which our results are robust to the assumption that the commuting matrix is not the sole form of weights matrix which will give rise to these results. Therefore, we compare our results with model specifications containing contiguity matrices. Accordingly, we decided to handle the islands as regions without neighbours. That means that the rows and columns of the contiguity matrix for the islands (Isle of Anglesey, Isle of Wight, Orkney Islands, Shetland Islands, and Western Isles) only contains Zeros and consequently they are assumed not to interact with other regions. Compared to the results for the community matrix, we found weaker spatial interdependency coefficients. We explain that with the fact that commuting represents the spatial interdependencies of local labour markets in a more satisfactory way than by simply weighting which other areas each location shares a geographical border with. We found that the results for the NMW coefficients are robust to the variation of the weights matrix.

4.A.5 Specification tests for the SGMM model

In order to find a correct model specification with valid instruments that complies with the requirements of the SGMM estimator we conducted several statistical tests. One requirement for the validity of instruments is that the twice lagged idiosyncratic disturbance term is not autocorrelated (Arellano and Bond, 1991; Roodman, 2009b). We use the Arellano-Bond test for autoregression of first and second order in the first differences of the error term. The Null of this test is that there is no autocorrelation. While autocorrelation of first order does not violate the requirements of SGMM and hence the validity of the instruments, the Null of autocorrelation of order 2 should not be rejected. A crucial assumption of this test is that errors are not correlated across cross sectional units. We take this into account in line with Roodman (2009b) since we included time dummy variables as instruments in levels (to handle any cross-sectional dependence in terms of contemporaneous correlation). We report the test results in table 4.3 for the main analysis and in table 4.14 for the restricted geography sample. The first four rows of those table contain results of the Arellano-Bond test for autoregression of first and second order in the first differences of the error term (test statistics and p values). In all specifications for all geographies Null of no autocorellation of order 1 in first differences of the error term has to be rejected, whereas the Null of no autocorrelation of order 2 could not be rejected.

Hansen's J statistic allows to test for the Null of joint validity of all instruments considering that those should be exogenous, and thus not correlated with the error term. The test is robust against conditional heteroscedasticity and serial correlation in the error terms (Hansen, 1982). Test statistics and p values can be found in rows 6 and 7 of the mentioned tables. In all specifications for all geographies, the Null of joint validity could not be rejected.

Furthermore, we tested subsets of instruments. There are three groups of instruments: GMM instruments, instrumented variables in levels and differences and instrumented variables only in differences, compare with section 4.3. To test for the validity (exogeneity) of those subsets we use Difference-in-Hansen or *C*-statistics respectively. These are based on computations of differences of Hansen's J statistics for the "unrestricted" model without the subset and the "restricted" model including the subset, thus the increase of J statistic after the "unrestricted" model is complemented by the subset (Baum, 2006, p. 201 f.). All tests fail to reject the Null of validity of instrument subsets (compare C statistics and p values in rows 8 to 13 of table 4.4 and the final specifications of the instruments subsets in detail in table 4.5).

Finally, we followed Bond (2002) and we checked whether the coefficient for the lagged dependent variable lies somewhere between the results obtained from adequate OLS and FE. This is true for both geographies (compare the results of the coefficients of E_{t-1} in table 4.10 with the results in table 4.3).

Table 4.10: Estimation results for specifications including a lagged dependent variable based on OLS and fixed effects estimators. 16 years to retirement age, 1997–2010, all regressions contain control variables and year effects

	(1)	(2)	(3)	(4)
	Travel-to-Work Areas (TTWA), 138 regions		Unitary Authorities and Districts (WAREA), 140 regions	
	OLS	Fixed effects	OLS	Fixed effects
Kaitz	-0.024	-0.137**	-0.001	-0.070
	(0.041)	(0.057)	(0.037)	(0.053)
E_{t-1}	0.579***	0.130***	0.645***	0.168***
	(0.026)	(0.028)	(0.024)	(0.026)
GVA	0.430**	0.501**	0.544***	0.745***
	(0.186)	(0.239)	(0.177)	(0.210)
Share public	-0.069***	-0.051	-0.106***	-0.052
	(0.022)	(0.042)	(0.022)	(0.038)
Kaitz *1999	0.046	0.033	0.030	0.038
	(0.063)	(0.057)	(0.052)	(0.042)
Kaitz *2000	0.062	0.061	0.063	0.069
	(0.056)	(0.044)	(0.047)	(0.046)
Kaitz *2001	-0.040	-0.005	-0.047	0.001
	(0.057)	(0.046)	(0.052)	(0.045)
Kaitz *2002	0.024	0.042	-0.004	0.030
	(0.054)	(0.035)	(0.049)	(0.036)
Kaitz *2003	0.085	0.106**	0.101**	0.134**
	(0.056)	(0.047)	(0.049)	(0.053)
Kaitz *2004	0.053	0.107*	-0.032	0.044
	(0.063)	(0.059)	(0.060)	(0.050)
Kaitz *2005	-0.038	0.034	0.016	0.075*
	(0.064)	(0.057)	(0.053)	(0.045)
Kaitz *2006	-0.010	0.014	0.053	0.103**
	(0.060)	(0.058)	(0.051)	(0.043)
Kaitz *2007	0.041	0.062	-0.038	0.065
	(0.072)	(0.062)	(0.054)	(0.057)
Kaitz *2008	0.031	0.082	-0.003	0.045
	(0.072)	(0.054)	(0.050)	(0.042)
Kaitz *2009	-0.057	-0.014	-0.057	-0.013
	(0.066)	(0.064)	(0.052)	(0.049)
Kaitz *2010	0.080	0.072	0.025	0.028
	(0.065)	(0.059)	(0.058)	(0.053)
Observations	1,794	1,794	1,820	1,820
R-squared OLS	0.505		0.638	
R-squared within		0.144		0.152

***p < 0.01,**p < 0.05,*p < 0.1. Robust standard errors in parentheses. OLS specification contains a constant (not reported).

4.A.6 SEMP specifications without the GVA variable

Table 4.11: Within Group estimates of Minimum Wage effects on employment, 16 years to retirement age, 1997–2010, all regressions contain control variables, area and year effects. SEMP specifications without GVA variable

	(1)	(2)	(3)	(4)
	Travel-to-Work Areas (TTWA), 138 regions		Unitary Authorities and Districts (WAREA), 140 regions	
	SEMP Commuting Matrix	SEMP Contiguity Matrix	SEMP Commuting Matrix	SEMP Contiguity Matrix
Kaitz	-0.134***	-0.139***	-0.136***	-0.137***
	(0.043)	(0.042)	(0.039)	(0.039)
GVA	–	–	–	–
Share Public	-0.060*	-0.060*	-0.072**	-0.071**
	(0.032)	(0.032)	(0.032)	(0.032)
Kaitz *1999	0.011	0.012	0.041	0.039
	(0.049)	(0.048)	(0.043)	(0.042)
Kaitz *2000	0.045	0.041	0.088**	0.086**
	(0.049)	(0.048)	(0.043)	(0.043)
Kaitz *2001	-0.009	-0.009	0.048	0.047
	(0.048)	(0.047)	(0.041)	(0.041)
Kaitz *2002	0.03	0.032	0.079*	0.079*
	(0.047)	(0.046)	(0.041)	(0.041)
Kaitz *2003	0.093	0.096**	0.184***	0.185***
	(0.049)	(0.048)	(0.043)	(0.042)
Kaitz *2004	0.105	0.110**	0.108**	0.110**
	(0.049)	(0.048)	(0.043)	(0.043)
Kaitz *2005	0.032	0.038	0.128***	0.129***
	(0.050)	(0.049)	(0.045)	(0.045)
Kaitz *2006	-0.006	-0.003	0.166***	0.168***
	(0.052)	(0.051)	(0.045)	(0.045)
Kaitz *2007	0.046	0.045	0.132***	0.134***
	(0.051)	(0.050)	(0.045)	(0.044)
Kaitz *2008	0.072	0.075	0.101**	0.104**
	(0.050)	(0.048)	(0.043)	(0.043)
Kaitz *2009	-0.018	-0.017	0.047	0.049
	(0.051)	(0.050)	(0.045)	(0.044)
Kaitz *2010	0.052	0.052	0.087*	0.089**
	(0.051)	(0.050)	(0.046)	(0.045)
Lambda	0.122***	0.068**	0.037	0.01
	(0.039)	(0.033)	(0.038)	(0.031)
Observations	1,932	1,932	1,960	1,960
log-likelihood	3,249.011	3,247.399	3,351.447	3,351.043
Pesaran's CD	-0.341	-0.515	0.265	0.500

***p < 0.01,**p < 0.05,*p < 0.1. Robust standard errors in parentheses.

4.A.7 Restricted geography sample

We tested the robustness of our results by restricting our samples: we dropped out those regions that are known to be somewhat economically weaker, such as the Western and Northern parts of England, Wales, and Scotland. Therefore we selected 82 from the 138 TTWA sample and 74 from the 140 WAREA sample. The estimation results can be found in tables 4.12 to 4.14.

The results reveal only marginal differences regarding the employment effects of the NMW. The overall effect tends to be zero or negative, whereas the incremental year-on-year effects are more likely to be zero or positive with similar patterns to the results for the full samples. This is also true for the SGMM specification (columns 9 of tables 4.12 and 4.13), where the coefficient for the lagged employment rate is – though a bit smaller – significantly positive and thus very robust. The coefficients for the spatial dependency terms become insignificant. The coefficient for the demand variable probably reveals the biggest difference: whereas we found a significantly positive influence on employment for each of the full sample data sets, the coefficient gets insignificant in all specifications.

4.A.8 Alternative variable: proportion of workers paid at or below the minimum wage

Dolton et al. (2012) used other treatment measures for the the MW: the fraction of people at or below the NMW and the "spike" in terms of the proportion of workers paid at the minimum wage in each local area. The results based on these alternative definitions of the MW variable led to the same conclusions.

In this paper we considered the proportion of workers paid at or below the minimum wage in each local area as alternative measure (Minimum wage share). The shares are generated for three age bands in each local area. Starting from 1999, the shares are a weighted average of the minimum wage shares of persons from 18 to 21 years and of persons from 22 to retirement age. From 2004, with the introduction of the new development rate for young between 16 and 17 years, the shares are a weighted average of the minimum wage shares of persons of persons of 16 and 17 years, of persons from 18 to 21 years and of persons from 22 to retirement age. The results can be found in tables 4.15, 4.16, and 4.17. Again, these results do not change our main conclusions.

Table 4.12: Robustness Check: Within Group and SGMM estimates of Minimum Wage effects on employment, 16 years to retirement age, 1997–2010, all regressions contain control variables, area and year effects. 82 selected regions (from 138 TTWA areas)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Basic specifications			Spatial specifications					SGMM
	w/o Yearly Interaction MW Effects/ w/o GVA	with Yearly Interaction MW Effects		Conley Standard Errors (50 km)	Conley Standard Errors (100 km)	Conley Standard Errors (200 km)	SEMP Commuting Matrix	SEMP Contiguity Matrix	
Kaitz	−0.021	−0.057	−0.057	−0.057	−0.057	−0.057	−0.072	−0.069	−0.112
	(0.045)	(0.049)	(0.049)	(0.059)	(0.058)	(0.057)	(0.046)	(0.048)	(0.071)
E_{t-1}									0.128***
									(0.048)
GVA			−0.242	−0.242	−0.242	−0.242	−0.311	−0.326	−0.485
			(0.334)	(0.248)	(0.261)	(0.295)	(0.336)	(0.331)	(0.499)
Share Public	−0.088	−0.088	−0.087	**−0.087***	**−0.087****	**−0.087****	−0.088*	−0.085	−0.306**
	(0.053)	(0.053)	(0.053)	(0.045)	(0.043)	(0.040)	(0.053)	(0.053)	(0.117)
Kaitz *1999		−0.034	−0.036	−0.036	−0.036	−0.036	−0.032	−0.034	0.003
		(0.055)	(0.055)	(0.053)	(0.057)	(0.061)	(0.057)	(0.055)	(0.043)
Kaitz *2000		0.041	0.039	0.039	0.039	0.039	0.041	0.039	0.074
		(0.039)	(0.040)	(0.041)	(0.042)	(0.041)	(0.041)	(0.041)	(0.055)
Kaitz *2001		−0.012	−0.009	−0.009	−0.009	−0.009	−0.008	−0.009	0.022
		(0.048)	(0.049)	(0.045)	(0.049)	(0.050)	(0.050)	(0.051)	(0.061)
Kaitz *2002		0.029	0.035	0.035	0.035	0.035	0.037	0.037	0.051
		(0.037)	(0.039)	(0.037)	(0.036)	(0.036)	(0.038)	(0.038)	(0.052)
Kaitz *2003		0.101**	0.106**	0.106**	0.106**	0.106**	0.113**	0.113**	0.122**
		(0.047)	(0.048)	(0.046)	(0.048)	(0.053)	(0.049)	(0.048)	(0.060)
Kaitz *2004		0.129***	0.134***	0.134***	0.134***	0.134***	0.142***	0.142***	0.136*
		(0.044)	(0.046)	(0.043)	(0.046)	(0.048)	(0.045)	(0.046)	(0.070)
Kaitz *2005		0.069	0.073	0.073	0.073	0.073	0.079	0.080	0.075
		(0.047)	(0.049)	(0.051)	(0.054)	(0.051)	(0.049)	(0.050)	(0.066)
Kaitz *2006		0.024	0.027	0.027	0.027	0.027	0.038	0.037	0.032
		(0.069)	(0.069)	(0.063)	(0.066)	(0.057)	(0.071)	(0.072)	(0.076)
Kaitz *2007		0.053	0.057	0.057	0.057	0.057	0.068*	0.069*	0.035
		(0.038)	(0.039)	(0.039)	(0.041)	(0.039)	(0.040)	(0.040)	(0.065)
Kaitz *2008		0.086*	0.092*	**0.092****	**0.092****	**0.092****	0.099*	0.103**	0.057
		(0.047)	(0.049)	(0.045)	(0.045)	(0.042)	(0.050)	(0.051)	(0.071)
Kaitz *2009		0.020	0.027	0.027	0.027	0.027	0.039	0.043	−0.019
		(0.059)	(0.062)	(0.053)	(0.053)	(0.056)	(0.060)	(0.061)	(0.089)
Kaitz *2010		0.105	0.116	0.116	0.116	0.116	0.133*	0.138*	0.095
		(0.071)	(0.076)	(0.071)	(0.081)	(0.094)	(0.076)	(0.077)	(0.106)
Lambda							0.031	0.067	
							(0.050)	(0.041)	
Observations	1,148	1,148	1,148		1,148		1,148	1,148	1,066
R-squared	0.180	0.191	0.192		0.192				
log-likelihood							2,058.200	2,059.391	
No. of instr.									70
Pesaran's CD	−0.707	−1.253	−0.906		−0.906		−0.837	−0.838	−2.093

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses. Columns 1–3, 9: Robust standard errors. Columns 4–6: Conley s.e. are based on spatial Bartlett kernel. Coefficients are printed in bold in case of significance level changes compared to column 3. SGMM specification: Further validity test statistics are provided in table 4.14.

Table 4.13: Robustness Check: Within Group and SGMM estimates of Minimum Wage effects on employment, 16 years to retirement age, 1997–2010, all regressions contain control variables, area and year effects. 74 selected regions (from 140 WAREA areas)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Basic specifications			Spatial specifications					SGMM
	w/o Yearly Interaction MW Effects/ w/o GVA	with Yearly Interaction MW Effects		Conley Standard Errors (50 km)	Conley Standard Errors (100 km)	Conley Standard Errors (200 km)	SEMP Commuting Matrix	SEMP Contiguity Matrix	
Kaitz	−0.090	−0.171***	−0.171***	−0.171***	−0.171***	−0.171***	−0.171***	−0.171***	−0.060
	(0.056)	(0.061)	(0.061)	(0.050)	(0.046)	(0.043)	(0.046)	(0.046)	(0.062)
E_{t-1}									0.204***
									(0.055)
GVA			0.255	0.255	0.255	0.255	0.255	0.256	0.211
			(0.255)	(0.197)	(0.196)	(0.186)	(0.213)	(0.216)	(0.346)
Share Public	−0.050	−0.046	−0.045	−0.045	−0.045	−0.045	−0.045	−0.045	−0.309***
	(0.043)	(0.043)	(0.044)	(0.043)	(0.042)	(0.037)	(0.041)	(0.041)	(0.083)
Kaitz *1999		0.003	0.006	0.006	0.006	0.006	0.006	0.006	−0.043
		(0.035)	(0.035)	(0.033)	(0.029)	(0.026)	(0.042)	(0.042)	(0.051)
Kaitz *2000		0.084**	0.086**	0.086**	**0.086*****	**0.086*****	0.085**	0.086**	0.061
		(0.034)	(0.034)	(0.035)	(0.033)	(0.028)	(0.042)	(0.043)	(0.040)
Kaitz *2001		0.071	0.068	0.068	0.068	0.068	0.067*	0.067	0.037
		(0.044)	(0.046)	(0.048)	(0.047)	(0.044)	(0.041)	(0.041)	(0.038)
Kaitz *2002		0.094**	0.087**	0.087**	**0.087*****	**0.087*****	0.087**	0.087**	0.052
		(0.036)	(0.039)	(0.036)	(0.031)	(0.024)	(0.041)	(0.042)	(0.044)
Kaitz *2003		0.159**	0.153**	**0.153*****	**0.153*****	**0.153*****	0.153***	0.152***	0.102
		(0.065)	(0.067)	(0.046)	(0.040)	(0.035)	(0.042)	(0.043)	(0.070)
Kaitz *2004		0.114**	0.108**	**0.108*****	**0.108*****	**0.108*****	0.108**	0.108**	0.074
		(0.050)	(0.052)	(0.035)	(0.031)	(0.024)	(0.042)	(0.043)	(0.060)
Kaitz *2005		0.112***	0.106***	0.106***	0.106***	0.106***	0.105**	0.106**	0.074*
		(0.035)	(0.037)	(0.035)	(0.031)	(0.024)	(0.044)	(0.044)	(0.040)
Kaitz *2006		0.152***	0.146***	0.146***	0.146***	0.146***	0.146***	0.146***	0.089
		(0.045)	(0.046)	(0.034)	(0.034)	(0.031)	(0.043)	(0.044)	(0.065)
Kaitz *2007		0.065	0.059	0.059	0.059	**0.059***	0.059	0.059	−0.016
		(0.052)	(0.052)	(0.039)	(0.036)	(0.033)	(0.043)	(0.043)	(0.063)
Kaitz *2008		0.097**	0.089*	**0.089*****	**0.089*****	**0.089*****	0.089**	0.088**	0.040
		(0.046)	(0.046)	(0.032)	(0.029)	(0.023)	(0.042)	(0.043)	(0.061)
Kaitz *2009		0.037	0.029	0.029	0.029	0.029	0.029	0.029	0.000
		(0.050)	(0.052)	(0.042)	(0.039)	(0.032)	(0.044)	(0.044)	(0.061)
Kaitz *2010		0.100*	0.088	**0.088****	**0.088****	**0.088****	0.088**	0.088*	0.064
		(0.050)	(0.054)	(0.041)	(0.041)	(0.036)	(0.045)	(0.045)	(0.077)
Lambda							−0.015	0.007	
							(0.052)	(0.041)	
Observations	1,036	1,036	1,036		1,036		1,036	1,036	962
R-squared	0.182	0.206	0.207		0.207				
log-likelihood							2,057.709	2,057.697	
No. of instr.									70
Pesaran's CD	−0.282	0.070	−0.439		−0.439		−0.454	−0.424	−2.057

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parentheses. Columns 1–3, 9: Robust standard errors. Columns 4–6: Conley s.e. are based on spatial Bartlett kernel. Coefficients are printed in bold in case of significance level changes compared to column 3. SGMM specification: Further validity test statistics are provided in table 4.14.

Table 4.14: Robustness Check: SGMM estimates of Minimum Wage effects on employment, validity test statistics of estimates in columns 9 of tables 4.12 and 4.13

	82 selected regions (from 138 TTWA areas) SGMM	74 selected regions (from 140 WAREA areas) SGMM
Number of instruments	70	70
	Arellano-Bond test for AR in first differences	
AR(1)	--5.0635	-4.7720
Prob > z	0.0000	0.0000
AR(2)	-2.2441	0.1183
Prob > z	0.0248	0.9059
	Hansen test of overidentified restrictions	
J	44.4279	37.7687
Prob > chi2	0.1581	0.3884
	Difference-in-Hansen tests of exogeneity of instrument subsets – GMM instruments for levels –	
C	42.2896	35.9651
Prob > chi2	0.1290	0.3314
	– Instrumented variables in levels and first differences –	
C	23.9395	22.1308
Prob > chi2	0.1570	0.2262
	– Instrumented variables only in levels –	
C	32.8185	24.8479
Prob > chi2	0.1080	0.4141

Table 4.15: Fraction at or below the minimum wage as alternative NMW treatment variable: Within Group and SGMM estimates of Minimum Wage effects on employment, 16 years to retirement age, 1997–2010, all regressions contain control variables, area and year effects. Data set disaggregated by Travel-to-Work Areas, resulting in 138 regions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Basic specifications			Spatial specifications					SGMM
	w/o Yearly Interaction MW Effects/ w/o GVA	with Yearly Interaction MW Effects		Conley Standard Errors (50 km)	Conley Standard Errors (100 km)	Conley Standard Errors (200 km)	SEMP Commuting Matrix	SEMP Contiguity Matrix	
Share MW	0.003	−0.019***	−0.016**	−0.016**	−0.016**	−0.016**	−0.016*	−0.015*	−0.017
	(0.005)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.008)	(0.008)	(0.017)
E_{t-1}									0.231***
									(0.032)
GVA			0.686***	0.686***	0.686***	0.686***	0.651***	0.699***	0.676*
			(0.231)	(0.180)	(0.191)	(0.204)	(0.193)	(0.190)	(0.407)
Share Public	−0.042	−0.043	−0.049	−0.049	−0.049	−0.049	−0.049	−0.051	−0.185
	(0.041)	(0.040)	(0.040)	(0.036)	(0.036)	(0.035)	(0.033)	(0.033)	(0.122)
ShareMW *1999		0.007	0.008	0.008	0.008	0.008	0.008	0.009	0.019
		(0.015)	(0.015)	(0.014)	(0.016)	(0.015)	(0.013)	(0.013)	(0.017)
ShareMW *2000		0.024*	0.023*	**0.023****	0.023*	0.023*	0.024**	0.024**	0.018
		(0.014)	(0.013)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.018)
ShareMW *2001		0.015	0.012	0.012	0.012	0.012	0.012	0.012	0.001
		(0.012)	(0.012)	(0.011)	(0.011)	(0.013)	(0.012)	(0.012)	(0.018)
ShareMW *2002		0.023**	0.019*	0.019*	0.019*	0.019*	0.02	0.019	0.020
		(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.013)	(0.013)	(0.017)
ShareMW *2003		0.021*	0.018*	0.018*	0.018*	0.018*	0.017	0.017	0.019
		(0.011)	(0.011)	(0.011)	(0.010)	(0.009)	(0.013)	(0.013)	(0.021)
ShareMW *2004		0.044***	0.040***	0.040***	0.040***	0.040***	0.041***	0.041***	0.024
		(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.012)	(0.012)	(0.021)
ShareMW *2005		0.016	0.012	0.012	0.012	0.012	0.011	0.011	0.000
		(0.012)	(0.013)	(0.011)	(0.011)	(0.010)	(0.013)	(0.013)	(0.023)
ShareMW *2006		0.043***	0.039***	0.039***	0.039***	0.039***	0.038***	0.037***	0.004
		(0.013)	(0.013)	(0.011)	(0.011)	(0.009)	(0.013)	(0.013)	(0.020)
ShareMW *2007		0.013	0.009	0.009	0.009	0.009	0.007	0.007	0.009
		(0.012)	(0.012)	(0.011)	(0.010)	(0.010)	(0.012)	(0.012)	(0.017)
ShareMW *2008		0.036***	0.033***	0.033***	0.033***	0.033***	0.032***	0.032***	0.016
		(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.018)
ShareMW *2009		0.018	0.015	0.015	0.015	0.015	0.015	0.014	−0.003
		(0.014)	(0.014)	(0.014)	(0.013)	(0.012)	(0.012)	(0.012)	(0.022)
ShareMW *2010		0.021	0.017	0.017	0.017	0.017	0.017	0.016	0.011
		(0.019)	(0.018)	(0.015)	(0.014)	(0.012)	(0.013)	(0.013)	(0.022)
Lambda							0.106***	0.071**	
							(0.039)	(0.033)	
Observations	1,932	1,932	1,932		1,932		1,932	1,932	1,794
R-squared	0.127	0.138	0.145		0.145				
log-likelihood							3,254.371	3,253.656	
No. of instr.									82
Pesaran's CD	−0.619	−0.128	−0.981		−0.981		0.572	0.146	−1.631

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors in parentheses. Columns 1–3, 9: Robust standard errors. Columns 4–6: Conley s.e. are based on spatial Bartlett kernel. Coefficients are printed in bold in case of significance level changes compared to column 3. SGMM specification: Further validity test statistics are provided in table 4.17.

Table 4.16: Fraction at or below the minimum wage as alternative NMW treatment variable: Within Group and SGMM estimates of Minimum Wage effects on employment, 16 years to retirement age, 1997–2010, all regressions contain control variables, area and year effects. Data set disaggregated by Unitary Authorities and Districts (WAREA), resulting in 140 regions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Basic specifications			Spatial specifications					SGMM
	w/o Yearly Interaction MW Effects/ w/o GVA	with Yearly Interaction MW Effects		Conley Standard Errors (50 km)	Conley Standard Errors (100 km)	Conley Standard Errors (200 km)	SEMP Commuting Matrix	SEMP Contiguity Matrix	
Share MW	0.003	-0.010	-0.004	-0.004	-0.004	-0.004	-0.004	-0.003	-0.010
	(0.004)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.013)
E_{t-1}									0.241***
									(0.034)
GVA			0.898***	0.898***	0.898***	0.898***	0.898***	0.899***	0.633**
			(0.219)	(0.140)	(0.133)	(0.125)	(0.164)	(0.164)	(0.312)
Share Public	-0.064	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	-0.050	-0.198***
	(0.042)	(0.040)	(0.039)	(0.037)	(0.036)	(0.034)	(0.033)	(0.033)	(0.042)
ShareMW *1999		-0.011	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.010
		(0.011)	(0.011)	(0.012)	(0.012)	(0.010)	(0.012)	(0.012)	(0.015)
ShareMW *2000		0.005	0.003	0.003	0.003	0.003	0.003	0.003	0.004
		(0.011)	(0.011)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.014)
ShareMW *2001		0.009	0.003	0.003	0.003	0.003	0.003	0.003	-0.008
		(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.014)
ShareMW *2002		0.005	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	0.004
		(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.013)
ShareMW *2003		0.013	0.007	0.007	0.007	0.007	0.007	0.007	0.010
		(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.011)	(0.011)	(0.017)
ShareMW *2004		0.027***	0.019*	0.019*	0.019*	**0.019****	0.018*	0.018*	0.018
		(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.011)	(0.011)	(0.018)
ShareMW *2005		0.026**	0.019*	0.019*	0.019*	**0.019****	0.019*	0.019*	0.022
		(0.010)	(0.011)	(0.011)	(0.011)	(0.009)	(0.011)	(0.011)	(0.018)
ShareMW *2006		0.034***	0.023**	0.023**	0.023**	0.023***	0.023*	0.023*	0.014
		(0.010)	(0.011)	(0.010)	(0.010)	(0.009)	(0.012)	(0.012)	(0.015)
ShareMW *2007		0.029**	0.021*	0.021*	**0.021**	**0.021**	0.021**	0.021*	0.006
		(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.016)
ShareMW *2008		0.013	0.004	0.004	0.004	0.004	0.004	0.004	-0.000
		(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.011)	(0.011)	(0.016)
ShareMW *2009		0.013	0.005	0.005	0.005	0.005	0.005	0.005	-0.010
		(0.011)	(0.011)	(0.011)	(0.011)	(0.009)	(0.012)	(0.012)	(0.015)
ShareMW *2010		0.005	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.010
		(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.018)
Lambda							-0.015	0.007	
							(0.052)	(0.041)	
Observations	1,960	1,960	1,960		1,960		1,960	1,960	1,820
R-squared	0.114	0.126	0.140		0.140				
log-likelihood							3,359.811	3,359.819	
No. of instr.									70
Pesaran's CD	0.061	0.210	-1.513		-1.513		-1.514	-1.504	-2.050

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors in parentheses. Columns 1–3, 9: Robust standard errors. Columns 4–6: Conley s.e. are based on spatial Bartlett kernel. Coefficients are printed in bold in case of significance level changes compared to column 3. SGMM specification: Further validity test statistics are provided in table 4.17.

Table 4.17: Fraction at or below the minimum wage as alternative NMW treatment variable: SGMM estimates of Minimum Wage effects on employment, excluding direct effect of Minimum Wage, validity test statistics of columns 9 in tables 4.15 and 4.16

	Travel-to-Work Areas (TTWA), 138 regions SGMM	Unitary Authorities and Districts (WAREA), 140 regions SGMM
Number of instruments	82	70
	Arellano-Bond test for AR in first differences	
AR(1)	-6.1216	-6.4232
Prob > z	0.000	0.000
AR(2)	-1.2527	0.9762
Prob > z	0.2103	0.329
	Hansen test of overidentified restrictions	
J	60.6156	33.3196
Prob > chi2	0.1045	0.5967
	Difference-in-Hansen tests of exogeneity of instrument subsets – GMM instruments for levels –	
C	54.2984	30.3282
Prob > chi2	0.1374	0.6008
	– Instrumented variables in levels and first differences –	
C	39.1773	15.9183
Prob > chi2	0.1487	0.5982
	– Instrumented variables only in levels –	
C	42.5849	23.1238
Prob > chi2	0.2088	0.5125

Chapter 5

General conclusions

The following general conclusions from the previous chapters are drawn:

The central question in chapter 2 is how the empirical fact of occupational mobility can be considered in a job search and matching framework and how can a resulting matching function be empirically evaluated. In order to do this, a model is utilised that is based on the assumption that the optimal search intensity of workers or firms results from weighing up expected gains and costs of search. These costs could be higher due to the additional financial burden of, e.g., further training in the case of occupational changes. If the costs are not too high, occupational changes can occur. This has also implications for matching efficiency estimates. For the evaluation of this theoretical finding, the preferred empirical model is a pooled-mean group model including terms for cross-sectional lags of unemployed and vacancies, that is adequate to the dynamics and structure of the used panel data. It is empirically shown that there are compensation mechanisms to a long-term constant relationship between new matches and stocks of vacancies and unemployed. By using information about occupational groups, that can be considered as alternatives in recruiting or job search, the results reveal considerable dependencies between these occupational groups in the matching process. Particularly, they show the significant dependence of new matches on vacancies and unemployed in "similar" occupations. Thus, the theoretical expectations are corroborated.

Chapter 3 deals with the German labour market reforms 2003–2005 and the development of the matching productivity. It partially corroborates previous findings that the matching productivity increased during and after the reform stages and shows that this is also true for the last reform stage in 2005. Furthermore, the matching productivity increased on all occupational labour markets, though there are some differences in detail. Lastly, even when considering the local economic situation, the average matching productivity on the whole labour market as well as on some occupational labour markets was deteriorated during the financial crisis.

Finally, chapter 4 focusses on long- and short-term employment effects of the National Minimum Wage in the United Kingdom 1999–2010 facing up crucial concerns on previous studies. This analyses reveal that the total effect of invoking and uprating a minimum wage is insignificantly different from zero; thus, the results suggest no discernible employment effects of the National Minimum Wage. This is accompanied by a discussion that the reason for some other findings in the literature could be neglecting spatial dependence, the endogeneity of the minimum wage treatment in the form of the Kaitz index, recessionary demand shocks, and the steady state trend in the employment series.

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Abstract

The contributions in this book either refer to mechanisms of creating new employment or selected changes of labour market institutions and their impact.

The central question in the first contribution is how the empirical fact of occupational mobility can be considered in a job search and matching framework and how a resulting matching function can be empirically evaluated. In order to do this, a model is utilised that is based on the assumption that the optimal search intensity of workers or firms results from weighing up expected gains and costs of search. These costs could be higher due to the additional financial burden of, e.g., further training in the case of occupational changes. If the costs are not too high, occupational changes can occur. This has also implications for matching efficiency estimates. It is empirically shown that there are compensation mechanisms to a long-term constant relationship between new matches and stocks of vacancies and unemployed. By using information about occupational groups, that can be considered as alternatives in recruiting or job search, the results reveal considerable dependencies between these occupational groups in the matching process. Particularly, they show the significant dependence of new matches on vacancies and unemployed in "similar" occupations.

The second contribution deals with the German labour market reforms 2003–2005 and the development of the matching productivity. It partially corroborates previous findings that the matching productivity increased during and after the reform stages and shows that this is also true for the last reform stage in 2005. Furthermore, the matching productivity increased on all occupational labour markets, though there are some differences in detail. Lastly, even when considering the local economic situation, the average matching productivity on the whole labour market as well as on some occupational labour markets was deteriorated during the financial crisis.

The third contribution focusses on long- and short-term employment effects of the National Minimum Wage in the United Kingdom 1999–2010 facing up crucial concerns on previous studies. This analyses reveal that the total effect of invoking and uprating a minimum wage is insignificantly different from zero; thus, the results suggest no discernible employment effects of the National Minimum Wage. This is accompanied by a discussion that the reason for some other findings in the literature could be neglecting spatial dependence, the endogeneity of the minimum wage variable, recessionary demand shocks, and the steady state trend in the employment series.

Kurzfassung

Die Frage, wie der Arbeitsmarkt funktioniert und welchen Einfluss die Politik ausüben kann, ist ein Dauerbrenner in der gesellschaftlichen, politischen und wissenschaftliche Debatte. Das hierzu nötige Wissen speist sich aus der Arbeitsmarktforschung und diese bekommt häufiger die Impulse aus dem Alltagsgeschäft der Arbeitsmarktpolitik. Umgekehrt laden Fortschritte in der Methodenentwicklung und der Datenerschließung die Arbeitsmarktpolitik dazu ein, neue Fragen aufzuwerfen, die bisher nicht beantwortet werden konnten. Die Beiträge in diesem Buch greifen solche Entwicklungen auf. Dabei fokussieren sie auf drei Themenbereiche: Berufliche Mobilität und Effizienz des Arbeitsmarktausgleichs, die Entwicklung der Matchingeffizienz vor, während und nach den Jahren der deutschen Arbeitsmarktreformen 2003–2005 auf beruflichen Teilarbeitsmärkten und die Wirkung des flächendeckenden Mindestlohns in Großbritannien auf die Beschäftigung.

Der erste Beitrag befasst sich mit der Frage, wie berufliche Mobilität bei der Beurteilung der Effizienz von Arbeitsmarktausgleichsprozessen theoretisch und in Messkonzepten berücksichtigt werden sollte. Bei der Entscheidung für oder gegen eine berufliche Alternative orientieren sich Arbeitnehmer an einer ganzen Reihe von Kriterien. Das wichtigste Kriterium dabei dürfte sein, inwieweit die Erfahrungen aus der bisherigen beruflichen Tätigkeit bei der infrage stehenden beruflichen Alternative anwendbar sind. Auf Grundlage neuer Daten zu beruflichen Tätigkeitsinhalten und einem daraus konstruierten Maß für berufliche Ähnlichkeiten wurde ein zu erwartendes Muster beruflicher Mobilität abgeleitet. Auf dieser Grundlage wird eine makroökonomische Matchingfunktion geschätzt, die dieses Muster berücksichtigt. Die Ergebnisse belegen die Relevanz beruflicher Mobilität und zeigen insbesondere auch, dass in bisherigen Studien die Matchingeffizienz in einem gewissen Maß verzerrt geschätzt wurde.

Im zweiten Beitrag wird die Entwicklung der Effizienz des Arbeitsmarktausgleichs vor, während und nach den Arbeitsmarktreformen 2003–2005 beobachtet. Hierbei wurde auf einen umfangreichen und dieser Form erstmalig aufbereiteten Datensatz zurückgegriffen. Dieser erlaubt sehr genaue Effizienzmessungen auf der Grundlage etablierter Modelle und erstmalig auch für berufliche Teilarbeitsmärkte. Verbesserungen im Arbeitsmarktausgleich lassen sich im Verlauf der 2000er Jahre für nahezu alle beruflichen Teilarbeitsmärkte beobachten; Unterschiede werden während und nach der Wirtschafts- und Finanzkrise deutlich – in einigen beruflichen Teilarbeitsmärkten wird die positive Entwicklung getrübt.

Der dritte Beitrag setzt an der kontroversen Diskussion zu den Beschäftigungswirkungen von Mindestlöhnen an. Dabei kommt die Mindestlohnforschung selbst für gleiche Zeiträume und gleiche beobachtete Regionen immer noch zu widersprüch-

lichen Ergebnissen. Basierend auf regional gegliederten Datensätzen für Großbritannien wird untersucht, inwieweit die regional unterschiedliche konjunkturelle Entwicklung, inhärente Trends in der Beschäftigungsentwicklung selbst, Verflechtungen zwischen den Regionen sowie Wechselwirkungen zwischen der Beschäftigung und den Löhnen die Ergebnisse zu den Beschäftigungseffekten beeinflussen. Im Modell, das diese Aspekte aus Sicht des Autorenteams am besten berücksichtigt, können schließlich weder positive noch negative Beschäftigungseffekte nachgewiesen werden.

The functioning of the labour market and the impact of labour market policies are a long-standing issue in social and political debate. In this respect, labour market research acquires the necessary knowledge and often receives impulses from labour market policy. Conversely, progress in the development of research methods and data mining encourages labour market policymakers to ask new questions that have not been answered yet.

Michael Stops picks up such developments and focusses on the following three issues:

- Occupational mobility and the job matching efficiency
- The development of job matching efficiency on partial occupational markets before, during and after the years of the German labour market reforms 2003–2005
- The employment effect of the National Minimum Wage in the United Kingdom 1999–2012.

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