Job Mobility Networks and Endogenous Labor Markets*

Jan Sebastian Nimczik
Humboldt University Berlin and IZA†

March 29, 2018

[Latest version]

Abstract

Which factors determine the size and shape of labor markets? Large parts of the current literature in labor economics rely on a geographically determined definition of local labor markets. In this paper, I introduce a novel method to identify endogenous labor markets which are revealed by job mobility flows rather than pre-defined administrative boundaries. In particular, I decompose a large job mobility network that is generated by the universe of job-to-job transitions in the economy into separate markets. The estimation is based on the stochastic block model (SBM) from the literature on network analysis and micro-founded by a simple firm choice model. Firms are in the same labor market if they have similar links to other firms and not because they are located in the same region. In an extensive descriptive analysis, I compare endogenous markets to geographically separated markets. Based on the novel concept, I analyze employment spillovers following a large local labor demand shock as well as mobility responses to import competition from China and Eastern Europe. My results show that endogenous labor markets are better suited to explain and predict adjustments to both local and global shocks than local areas.

*I am grateful to Andrea Weber and Antonio Ciccone for their support and guidance. I thank Albrecht Bohne, David Card, Andreas Dzemski, Sebastian Findeisen, Bryan Graham, Jasper Haller, Stephen Kastoryano, Pat Kline, and the audiences at Berkeley, Mannheim, Stanford, UCL, EALE '16, Warwick PhD Conference '16, EEA Annual Conference '15, EALE/SOLE World Conference '15, ESPE Annual Conference '15, and SFB-TR15 YRW Bonn for valuable comments and discussions.

†Humboldt University Berlin, School of Business and Economics, Unter den Linden 6, 10099 Berlin, Germany, jan.nimczik@hu-berlin.de

1 Introduction

Large parts of the current literature in labor economics rely on the concept of separate and largely self-contained local labor markets. Recent examples include studies that use variation between local labor markets to identify the impact of global trade shocks (Autor, Dorn, and Hanson, 2013) or immigration (Dustmann, Schönberg, and Stuhler, 2016) on wages and employment. Boundaries of local markets are also important to determine treatment and control groups in the evaluation of local policies and shocks (e.g., Lalive, Landais, and Zweimüller, 2015) and in the analysis of spillover effects (Crepon, Duflo, Gurgand, Rathelot, and Zamora, 2013; Ferracci, Jolivet, and van den Berg, 2014; Gathmann, Helm, and Schönberg, 2016). Furthermore, the definition of local markets is crucial for the explanation of disparities in regional economic activity within countries, agglomeration economies, and the estimation of spatial equilibrium models (for an overview see Moretti, 2011).

From an empirical perspective, however, it is unclear how to determine the boundaries of local markets. More generally, it is unclear whether geographical borders of labor markets can be identified at all. The predominant approach in the literature uses predefined, geographically separated regional entities such as states, metropolitan statistical areas, or counties to approximate labor markets. In a more elaborate concept, commuting zones pool smaller areas that are connected through high commuter flows. These concepts however are subject to a number of important drawbacks. First, empirical researchers have little guidance on which specific geographical unit to consider.[1] Second, secular trends in the geographical mobility of workers cannot be captured by the fixed boundaries of local areas. This is connected to decreasing search costs triggered by the availability of modern technologies. Online job search potentially enlarges labor markets as workers can search for distant jobs at very low cost. Finally, geographical areas are identical for any type of worker while the local availability of jobs and preferences towards job mobility can be

[1]For instance, Moretti (2011) provides a discussion of human capital spillovers on wages within local labor markets. He argues that differences in the evidence for spillovers on the state level (Acemoglu and Angrist, 2000) and the Metropolitan Statistical Area level (Moretti, 2004) could be partly explained by the rate of spatial decline in the importance of proximity to college for spillovers.

very heterogeneous across subgroups of the working force.

In this paper, I propose a new and flexible approach to endogenously determine the size and shape of labor markets. Rather than depending on predefined geographical boundaries, endogenous labor markets are revealed by common patterns in the observed worker flows between firms. The approach is based on a network view of the labor market, where firms are linked to each other through worker transitions. Building on the universe of job-to-job transitions in the economy, I construct a job mobility network that reflects actual market interactions between firms. In particular, the firms in the economy constitute the nodes in the network and are connected by job-to-job transitions which generate directed and weighted links.[2] I partition this job mobility network into separate markets adapting a model from the literature on statistical network analysis. The basic idea in this novel approach is that two firms are in the same labor market if they have similar probabilities to link to the rest of the network and not because they are located in the same geographical area. This captures the possibility that – in addition to observed characteristics such as region and industry – labor markets are determined by unobserved factors. Consider, for instance, a market that contains firms which are employing computer scientists with expertise in a specific programming language, a market for jobs in an elite political class that can only be accessed by graduates of certain schools, or even a market that is characterized by a common dress code.[3]

The separation into endogenous labor markets is based on the stochastic block model (SBM) (Holland, Laskey, and Leinhardt, 1983; Karrer and Newman, 2011) which is the work-horse model for the detection of communities in the literature on network analysis. In my adaption of the SBM, firms are characterized by two sources of unobserved heterogeneity. First, they have an individual propensity to attract and release workers that captures firm-level differences in productivity and turnover. Second, they operate on

[2] In this definition, links connect employers who draw on the same kind of skills. Moreover, the links entail information flows and spillover effects. The importance of job mobility for firm productivity and agglomeration economics is emphasized by a growing body of empirical research (Balsvik, 2011; Dasgupta, 2012; Poole, 2013; Stoyanov and Zubanov, 2012, 2014; Serafinelli, 2014).

[3] Indeed, the British Social Mobility Commission has recently identified obstacles to enter jobs in British investment banks that preclude market entrance of individuals who do not know the common code of conduct or dress code in some institutions.

separate, unobserved labor markets. Firms in the same labor market are characterized by common unobserved latent factors that determine their probability to link to each other. Worker transitions between firms are governed by the interplay of firm-level and market-level characteristics.

The SBM is related to a gravity-type equation where interactions between two agents are determined by individual characteristics and a measure of distance. In the spirit of Eaton and Kortum (2002) and Cortes and Gallipoli (forthcoming), the SBM can therefore be micro-founded by a simple model of firm choice where job transitions are determined by the costs of switching. The main goal of the empirical analysis is then to identify sets of firms that have a similar structure of switching costs. In contrast to the existing literature, switching costs do not only comprise moving costs but can also include skill transferability, preferences for jobs, and other unobserved components.

My empirical analysis is based on administrative records from the Austrian Social Security Database (ASSD) which provides detailed matched employer-employee data for all private sector employees in Austria. Building on the universe of job-to-job transitions from 1975 to 2005, I compute a large and detailed job mobility network and analyze the resulting network structure. The job mobility network consists of about 930,000 job-to-job transitions and more than 95,000 firms. Given this observed job mobility network, I estimate the SBM by maximum likelihood via Markov Chain Monte Carlo methods in order to assign firms to endogenous labor markets conditional on their individual propensity to attract workers.

In an extensive descriptive analysis, I examine the characteristics of my endogenous labor markets. Compared to local labor markets, endogenous labor markets are more self-contained. I find higher shares of job transitions within endogenous labor markets than within geographical entities of the same size. The estimated markets nevertheless reveal a "local" structure of job transitions as firms within the same endogenous market are spatially clustered. The resulting geographical structure of endogenous labor markets however deviates from administrative borders in three important ways. First, there are several largely unconnected endogenous markets located within the same geographical region. The separation of these markets can be partly rationalized by differences in the industry composition and wage distribution. Second, some endogenous labor markets are scattered across several regions and contain very distant firms. Geographically dispersed endogenous markets tend to be relatively more specialized in particular industries than geographically concentrated markets. In general, however, endogenous labor markets are not particularly concentrated within specific industries. Workers regularly switch industries and firms hire from a variety of different occupations.[4] Third, the geographical structure of endogenous labor markets varies over time. In particular, the average spatial distance between firms in the same market has increased by about 30% between the early 1980s and 2000s. In contrast, the industry dispersion within endogenous labor markets has slightly decreased over time.

The flexibility of the SBM further allows to examine heterogeneity in the scope of endogenous labor markets for various subgroups of the working force. I separately analyze job transitions by gender, age group, nationality, and skill-level. Most importantly, endogenous labor markets differ substantially between high- and low-skilled individuals. On average, the spatial distance between firms within endogenous labor markets for high-skilled individuals is about 1.3 times bigger than for low-skilled individuals. In contrast, markets for high-skilled workers are more concentrated within particular industries than markets for low-skilled workers. While endogenous labor markets of female workers were more specialized in particular industries in the 1980s, these differences vanished in the late 1990s.

My novel approach for the estimation of endogenous labor markets can provide new answers to a range of important economic questions. In the present paper, I utilize the model to analyze the impact of local labor demand shocks and global trade shocks on employment and worker mobility. In particular, I demonstrate that endogenous labor markets estimated in the period prior to the shock can explain and predict worker flows in response to the break-down of the Austrian steel industry at the end of the 1980s

[4]This is consistent with evidence from other countries. For instance, Bjelland, Fallick, Haltiwanger, and McEntarfer (2011) show that more than 60% of job-to-job transitions in the US are reallocations across the 11 NAICS super-sectors.

and to the increasing exposure of manufacturing industries to trade with China and Eastern Europe. In the first application, I examine employment spillovers following a series of unexpected mass layoffs in the Austrian steel industry in 1986. The breakdown of the steel industry caused adverse effects on employment in firms from the same endogenous labor market, both in the region of the shock as well as in distant regions. At the same time, employment in firms from the same region but different endogenous labor markets remained unaffected. My results show that a traditional definition of regional labor markets leads to an underestimation of spillover effects by about 50% of the actual effect. Transition probabilities between endogenous labor markets were also affected by the shock. In particular, there were less transitions into the affected market and more transitions out of this market. Importantly, the change in worker transitions was proportional to the predicted pre-shock transition probability. In the second application, I exploit the astonishing rise in trade with China and Eastern Europe in the past decades and quantify the relative importance of different margins of mobility adjustments. The negative impact of import competition from eastern countries on wages and employment of manufacturing workers can be partly offset by job mobility. In an analysis that follows the identification strategies of Autor, Dorn, Hanson, and Song (2014) and Dauth, Findeisen, and Suedekum (2016), I show that the endogenous labor markets estimated in the period prior to the shock can accurately predict job mobility responses to trade shocks. In contrast, markets based on geographical areas fail to explain important parts of the worker movements.

The remainder of the paper is organized as follows. I discuss the related literature in Section 2. Section 3 describes the data, the definition of the job mobility network, and aggregate network characteristics. In Section 4, I explain the stochastic block model and the estimation strategy in detail. I provide a descriptive analysis of the endogenous labor markets and evidence for worker heterogeneity in section 5. Section 6 examines spillover effects and mobility responses to local demand shocks and global trade shocks. Section 7 concludes.

2 Related Literature

My proposed new model contributes to a relatively new literature on alternative definitions of local labor markets. In a recent contribution to this literature, Manning and Petrongolo (forthcoming) endogenously determine the size of a spatial but flexible concept of local labor markets by optimal job search strategies of unemployed individuals. They find relatively narrow local markets as workers' search effort is sharply declining with distance to a vacancy. Lalive et al. (2015) use particular information on the characteristics of vacancies to predict whether two unemployed individuals would apply for the same job and hence be in the same market. Lechner, Wunsch, and Scioch (2013) exploit information on firm and worker location to determine hiring regions of workers. Commonly, however, the definition of labor markets in these papers is based exclusively on observable characteristics. My approach contributes to this literature by explicitly incorporating unobserved determinants of labor markets. I provide evidence for the importance of these unobserved determinants in the analysis of spillover effects and mobility responses to economic shocks.

My approach is also related to Schmutte (2014) who employs computer-based community detection algorithms to determine the boundaries of job mobility using data from the Panel Study of Income Dynamics (PSID). He finds four large segments of the labor market that do not coincide with industry, occupation, or education categories.

The method proposed in this paper adds to a rapidly growing literature that studies worker flows across firms in order to gain insight into the quality and preferences of workers and firms. Card, Heining, and Kline (2013) and subsequent papers revived the interest in the estimation of wage decompositions in the tradition of Abowd, Kramarz, and Margolis (1999). Similar to the job mobility network in my paper, the identification of worker and firm fixed effects in these studies is based on the set of firms that are connected by worker mobility. In a recent contribution, Sorkin (2015) exploits worker flows across firms to reveal preferences for non-wage characteristics of firms and compensating differentials. My paper complements these approaches in detecting common unobserved market-level characteristics of firms that are revealed by common patterns in worker flows.[5]

As shown in the application of my model to large economic shocks, estimating endogenous labor markets based on the SBM generates new insights into mobility adjustments to local shocks. The paper therefore contributes to an important literature that analyzes and estimates the incidence of shocks to local labor demand and supply (see, e.g., Blanchard and Katz., 1992; Bound and Holzer, 2000; Notowidigdo, 2013). While existing papers take the size of the local labor markets as given using predefined regions, endogenizing labor markets allows for various sources of heterogeneity in these effects. This also holds true for related studies that examine spillover effects of positive or negative shocks to local economies (Greenstone, Hornbeck, and Moretti, 2010; Busso, Gregory, and Kline, 2013; Gathmann et al., 2016). In two recent papers, Cestone, Fumagalli, Kramarz, and Pica (2016) and Giroud and Mueller (2017) show that local economic shocks are absorbed through worker flows within internal labor markets that consist of firms affiliated to the larger groups. The empirical evidence in this paper confirms the view that economic ties are more relevant for the transmission of economic shocks than geographical proximity.

Finally, my paper adds to a very recent literature that tries to incorporate methods and insights from machine-learning into economics. To the best of my knowledge, it is the first application of the well-established stochastic block model from the statistics literature to an economic question. The SBM (Holland et al., 1983; Karrer and Newman, 2011) is the workhorse model in the literature on statistical networks to partition networks into groups based on the observed linkages. This task has also been coined community detection. In the original stochastic block model of Holland et al. (1983), all nodes in the same community behave stochastically equivalent and have the same probability distribution of links. The modified version of Karrer and Newman (2011) allows for heterogeneity within communities by preserving the observed distribution of connections. This is achieved by including node-specific fixed degree parameters and relates the approach to a recent literature of network formation with unobserved individual

[5]The goal of endogenously grouping firms is also pursued in recent contributions by Bonhomme and Manresa (2015) and Bonhomme, Lamadon, and Manresa (2016). In contrast to my paper, the assignment of firms to groups is based on similarities in outcomes such as the distribution of wages in these papers.

heterogeneity (Graham, forthcoming; Dzemski, 2014). Community detection has a long tradition in physics and computer sciences and has given rise to a variety of methods and algorithms (for an overview see Fortunato, 2010). The methods can be roughly classified into greedy ad-hoc algorithms such as hierarchical clustering (e.g. Clauset, Newman, and Moore, 2004), algorithms that optimize global criteria over all possible network partitions (e.g. the modularity score of Newman and Girvan, 2004), and model-based methods. In this paper, I consider a model-based approach, which makes the underlying assumptions and structure explicit.[6] This novel approach of unsupervised machine learning is broadly applicable to other economic contexts as for instance the analysis of supplier relationships among firms, trade networks, and others.

3 Data

The empirical analysis is based on administrative records for the universe of private sector employment in Austria. The matched employer-employee data from the Austrian Social Security Database (ASSD, see Zweimüller, Winter-Ebmer, Lalive, Kuhn, Wuellrich, Ruf, and Büchi, 2009) provides detailed daily information on employment and unemployment spells as well as on other social security related states such as sickness, retirement, or maternity leave since 1972. Each individual employment spell is linked to an employer identifier and some firm-level information.[7] Moreover, annual earnings are provided for each worker-firm combination.

To define the job mobility network, I extract all job-to-job transitions from the ASSD that occurred between 1975 and 2005 and satisfy the following criteria: First, a change of employer is classified as a job-to-job transition if there are at most 30 days of non-employment in between two consecutive employment spells. Second, the sample is restricted to transitions where workers had a minimum tenure of one year in both their old

[6] For an application of modularity score maximization in the context of job mobility see Schmutte (2014).

[7] I use the terms employer identifier and firm interchangeably. Fink, Kalkbrenner, Weber, and Zulehner (2010) compare the distribution of employers in the ASSD with official firm registers from Statistics Austria and find only negligible differences. Hence, they conclude that multi-establishment firms are not an important component in the Austrian market.

and new job. This allows me to examine only relatively stable relationships that are not prone to seasonal fluctuations.[8] Third, the sample is restricted to transitions between firms with five or more employees. Fourth, I exclude transitions of apprentices, marginal, and contract workers. Finally, spurious transitions due to firm renaming, spin-offs, and takeovers are excluded using the worker flow approach detailed in Fink et al. (2010).

Table 1 shows summary statistics of these job-to-job transitions in Austria. The first column refers to all job-to-job transitions that occurred in the entire observation period between 1975 and 2005, in the other columns I split the sample into job-to-job transitions from shorter periods in order to track developments over time. In total, there are more than 930,000 job-to-job transitions. Over time, the number of transition exhibits an upward trend.

The share of job-to-job transitions by female workers amounts to 41% and increases over time. About 96% of all transitions are experienced by Austrians with a slight decrease from 97% to 95%. The average age at the beginning of the new spell fluctuates between 31 and 35 years.

When switching their job, workers on average engage in more stable relationships. The average spell duration at the old firm amounts to 1550 days, while the new job last for 2350 days on average. The average time in between two spells decreased from 4.4 days in the late 1970s to 3.5 days in the early 2000s.

Regional mobility is relatively low as about 75-80% of the job switchers transit to a firm in the same state and 65% remain in their NUTS-3 region.[9] In contrast, mobility across industries is much higher as about two thirds of the job-to-job transitions occur between firms that are affiliated to different NACE 2-digit industries. This finding is consistent with recent evidence from the US (Bjelland et al., 2011) where about 60% of job switches are reallocations across the 11 broad NAICS super-sectors. Over time, however, there are opposite trends in mobility across regions and industries. While regional persis-

[8] A substantial part of the Austrian economy is characterized by seasonal sectors such as construction and tourism. An alternative version of the model that includes jobs with minimum spell duration above one month does not change the results substantially but generates additional noise.

[9] Austria consists of 9 very heterogeneous states. The "Nomenclature of territorial units for statistics" classification of Eurostat counts 35 NUTS-3 regions in Austria, see also the maps in figure 5. NUTS-3 regions in Austria are aggregations of several municipalities.

tence has slightly decreased in the beginning of the 2000s, there is a clear upward trend in the share of workers that remain in their industry starting from the early 1990s. The vast majority of workers remain in their broad occupation (white- or blue-collar workers) with a slight increase in later periods.

In general, most workers move up the job ladder when switching their employer. For more than 60% of the workers the transition is associated with a wage raise. Moreover, 74% of transitions lead workers to a firm with a higher firm fixed effect as measured by a wage decomposition as in Abowd et al. (1999).[10] Interestingly, however, this share deteriorates sharply over time from 90% in the late 70s to only 62% in the early 2000s.

The main idea behind defining the job mobility network is that job-to-job transitions establish links between the two firms involved in the transition. Figure 1 depicts the concept of link formation. When workers flow between firms i and j (Figure 1a), directed and weighted links are established between those firms (Figure 1b). In particular, the link from i to j is stronger the more transitions occur in this direction during the sample period.

Applying this procedure to the universe of job-to-job transitions in Austria results in a large and very detailed job mobility network. Formally, the job mobility network $G = \{V, E\}$ consists of a set of N nodes $V = \{1, 2, \ldots, N\}$, i.e., the firms in the economy, and a set of links E, i.e., the job-to-job transitions.[11] An $N \times N$ adjacency matrix A indicates which firms are linked and how strong the ties are. Particularly, A_{ij} denotes the number of job-to-job transitions from firm i to firm j within the sample period.[12]

[10] Firm fixed effects and worker fixed effects are obtained from estimating the following equation for log earnings

$$y_{wt} = \alpha_w + \Psi_{J(w,t)} + x'_{wt}\beta + \varepsilon_{wt},$$

where y_{wt} are log earnings of worker w at time t, α_w is a worker fixed effect, $\Psi_{J(w,t)}$ is the firm fixed effect at firm j where worker w is employed at time t, x contains a set of covariates such as age and education, and ε is an error term. This decomposition is known as the AKM decomposition (after Abowd et al., 1999) and will be used at several points in the paper.

[11] More precisely, V contains only the non-isolate firms in the economy, that is, firms, which are involved in at least one job-to-job transition during the sample period (see also appendix A).

[12] A formal definition of the adjacency matrix is provided in Appendix A. The job mobility network defined in this paper differs from the approach proposed in Schmutte (2014) in a number of important ways. First, it corresponds to the one-mode employer projection graph of his realized mobility network but additionally allows for *directed* links that capture actual flows. Second, it distinguishes *direct* and *indirect* connections between firms while this is not possible in his approach where all firms a worker has worked for at any time are directly connected.

There are two important economic aspects of link formation in the job mobility network. First, links connect firms that employ the same worker within a short period of time. This ensures homogeneity of closely connected firms as they are drawing on the same worker type and skill set. Second, links are potential channels for information flows and knowledge spillovers between firms. Recent theoretical and empirical work has pointed out the importance of job mobility for knowledge transfers and spillovers (see Balsvik, 2011; Dasgupta, 2012; Poole, 2013; Stoyanov and Zubanov, 2012, 2014; Serafinelli, 2014). These papers show that it matters to which firms a firm is connected as incoming workers from highly productive firms often generate positive productivity spillovers. Cestone et al. (2016) and Giroud and Mueller (2017) show that job mobility between tightly linked firms can also serve as an insurance mechanism within internal labor markets of larger corporate companies.

Table 2 provides an overview of the number of links and nodes in the job mobility network. Again, column 1 refers to the full network obtained from transitions between 1975 and 2005 while the other columns show dynamic developments between shorter periods. In total, there are more than 95,000 firms (nodes) in the network and about 930,000 transitions (links). Over time, these figures tend to rise, reflecting the increase in job mobility and the number of firms involved. The third row of Table 2 shows the number of connected components in the network. A connected component is a subgraph of the job mobility network within which all firms are connected by some path, but not connected to the other subgraphs. In the full network, there are 755 components. The vast majority of these components, however, contains only 2 firms while the largest connected component (the *giant component*) contains about 98% of the firms and almost all links (rows 4 and 5). The analysis in the remainder of the paper is therefore restricted to the giant component.[13]

The last row of Table 2 displays the average degree in the network which denotes the average number of transitions per firm. On average, a firm is connected to 19.84

[13]This restriction is identical to limitations in the literature on AKM-type wage decompositions where worker and firm fixed effects are only separately identified within connected sets of firms that are linked by worker mobility (Abowd, Creecy, and Kramarz, 2002).

other firms in the full network. The average degree is naturally lower when considering shorter time periods and tends to slightly rise over time. The average degree however hides substantial heterogeneity within the network. Many firms in the job mobility network are involved only in a low number of job-to-job transitions while others have many connections and serve as "hubs" in the economy. In appendix A, I provide a detailed discussion on various network characteristics and document the heterogeneity in the number of connections. In my model for the estimation of endogenous labor markets in the following section, I specifically address firm-level heterogeneity by including popularity parameters that guide the individual attractiveness of firms to workers.

4 Model

In this section, I present a novel method that allows to endogenously determine labor markets based on common patterns of worker flows observed in the job mobility network. First, I set up a model of job mobility that generates job-to-job transitions which are restricted by transition costs and search frictions. The model is based on a model of occupational flows in Cortes and Gallipoli (forthcoming) which in turn draws on the literature in international trade, particularly on Eaton and Kortum (2002). The key equation of the job mobility model is a gravity equation that relates flows between firms to (market-level) transition costs. In a second step, I use the Stochastic Block Model from the literature on network analysis in order to estimate the most likely assignment of firms to markets using this equation.

The model economy is populated by a finite set of firms indexed by $i \in \{1, \ldots, N\}$ and a continuum of workers of measure one indexed by ℓ. Workers differ in observable characteristics and their initial firm. A worker's firm at the beginning of the period is predetermined and given by i.

The potential payoff from switching to firm j for worker ℓ who is currently employed at firm i is denoted by

$$\phi_j(\ell|i) = p_j \, f\left[X_\ell\right] \left(\frac{x_j(\ell)}{d_{ij}}\right) \tag{1}$$

where p_j is a single index subsuming firm-level factors that affect all workers at firm j (i.e., the general attractiveness of j), X_ℓ is a vector of individual characteristics that change returns for worker ℓ in all firms (as for instance general human capital of worker ℓ), $x_j(\ell)$ is a worker specific match-quality shock that measures how well worker ℓ is matched with firm j in terms of productivity and preferences, and d_{ij} represents the costs of switching from firm i to j.

I assume that the costs of transitioning between firms are not firm-pair specific but are determined on the market level. Specifically, each firm operates on one of k different markets in the economy. An $N \times 1$ vector z denotes the assignment of firms to markets with $z_i \in \{1, \ldots, k\}$. Formally, $d_{ij} = d_{z_i z_j}$ and two firms i and j are in the same market, i.e., $z_i = z_j$ if the utility costs of moving to other firms in the economy are identical. I normalize costs such that moves within the same market have a cost of one, $d_{uu} = 1$, while switches across markets are associated with positive costs, $d_{uv} > 0 \, \forall v \neq u$. These utility costs could represent pure moving costs that depend on spatial distance.[14] However, these costs could also represent time and efficiency costs associated with adapting to the new firm, skill transferability between industries and occupations, or other – unobserved – components. The main idea of the approach is to determine the assignments of firms to markets endogenously, that is use observed transitions to identify firms that compete for the same worker by a revealed preference argument.

Match-quality is drawn from a Fréchet distribution

$$x_j \sim F_j(x) = \exp(-T_j x^{-\theta}) \tag{2}$$

where $T-j$ is a firm-specific location parameter and θ governs the dispersion of the shock. At the beginning of the period, workers receive the opportunity to examine outside options with arrival rate λ. If they get this opportunity, they sample match-qualities, drawing a value for each firm. They then compare potential payoffs based on the realized draws and decide whether to switch and where to go.

[14] If markets are purely determined by geographical regions, this is consistent with the common assumption that moves within regions are costless while workers have to pay utility costs to move across regions.

From the distributional assumption of match-quality it follows that the probability of a switch from firm i to firm j is

$$\pi_{ij}(\ell) = \underbrace{\lambda}_{\text{switching opportunity}} \times \underbrace{\frac{T_j d_{z_i z_j}^{-\theta} p_j^{\theta}}{\sum_{s=1}^{N} T_s d_{z_i z_s}^{-\theta} p_s^{\theta}}}_{j \text{ offers the highest payoff of all firms for a worker who starts in } i}. \tag{3}$$

This result is borrowed from the literature on international trade (Eaton and Kortum, 2002) and derived in more detail in Appendix B. Notably, the switching probability does not dependent on individual worker level characteristics.

Normalizing by the probability that origin firm i offers the highest payoff, we get an expression that relates worker flows to a set of firm-level characteristics and the transition costs.

$$a_{ij} = \lambda \times \frac{T_j d_{z_i z_j}^{-\theta} p_j^{\theta}}{T_i p_i^{\theta}} \tag{4}$$

According to the assumption of Poisson arrivals, the number of job-to-job transitions between any two firms i and j within a certain time period is an independent draw from the Poisson distribution

$$A_{ij} \overset{ind.}{\sim} Pois(\gamma_i^- \gamma_j^+ M_{z_i z_j}), \tag{5}$$

where γ_i^- summarizes firm-level characteristics of the firm of origin (i.e., T_i and p_i) and γ_j^+ summarizes destination firm characteristics (T_j and p_j). The $k \times k$ matrix M captures (the inverse of) the common cost component of transition probabilities within and between markets where the typical element M_{uv} indicates how likely a firm in market u experiences a job-to-job transition of one of its workers to a firm in market v.

This implies that the expected number of transitions from i to j, $E[A_{ij}] = \gamma_i^- \gamma_j^+ M_{z_i z_j}$, is increasing in the propensity of i to loose workers, the propensity of j to attract workers, and on the inverse of the transition costs between the markets of i and j.

In the data, the labor market assignments of firms are unobserved. Hence, the primary goal is to estimate these assignments given the observed job mobility network G described in section 3. For a given number of markets, k, the expression in equation (5) corresponds to the key equation of the Stochastic Block Model (SBM) from the literature on stochastic network formation.[15] Here we interpret the number of transitions between i and j as a weighted link between the two firms. The SBM can be summarized in the following likelihood function:

$$\begin{aligned}\mathcal{L}(G|M,z,\gamma) &= \prod_{i,j} Pr(i \to j|M,z,\gamma) \\ &= \prod_{i\neq j} \text{Poisson}(\gamma_i^- \gamma_j^+ M_{z_i z_j}) \\ &= \prod_{i\neq j} \frac{(\gamma_i^- \gamma_j^+ M_{z_i z_j})^{A_{ij}}}{A_{ij}!} \exp(-\gamma_i^- \gamma_j^+ M_{z_i z_j}).\end{aligned} \tag{6}$$

The product is taken over all combinations of i and j while self-loops (job-to-job transition of a firm to itself) are not allowed in the model. In order to identify the popularity parameters, I normalize the sum of all incoming and outgoing links in a market to one, $\sum_i \gamma_i^+ \mathbb{1}\{z_i = u\} = 1$ and $\sum_i \gamma_i^- \mathbb{1}\{z_i = u\} = 1$ for each market u. Imposing these constraints, the likelihood can be simplified to

$$\mathcal{L}(G|M,z,\gamma) = \Big(\prod_{i\neq j} A_{ij}!\Big)^{-1} \prod_i (\gamma_i^-)^{d_i^-} (\gamma_i^+)^{d_i^+} \prod_{u,v} M_{uv}^{E_{uv}} \exp\big(-M_{uv}\big) \tag{7}$$

where $d_i^- = \sum_j A_{ij}$ and $d_i^+ = \sum_j A_{ji}$ denote out- and indegree of firm i, and $E_{uv} = \sum_{ij} A_{ij} \mathbb{1}\{z_i = u\}\mathbb{1}\{z_j = v\}$ is the total number of links between firms in markets u and v.

Given the observed job mobility network network G, the model parameters can be estimated in a two-step procedure. In the first step, maximum likelihood estimators for

[15] The original stochastic block model (SBM) of Holland et al. (1983) and Wang and Wong (1987) defines a probability distribution over networks G, $Pr(G|z, M)$ that is guided only by the parameters z and M. The underlying assumption is that nodes within a group are stochastically equivalent, that is, all nodes from group u have the same independent probability of linking to a node from group v. Hence, the SBM does not allow for degree heterogeneity within groups. As there is typically ample variation in the connectedness of nodes in empirical networks (compare also figure E.10 for the present case), it is important to account for this kind of heterogeneity. Furthermore, in the original SBM the link variables are independent Bernoulli random variables. Simulation evidence in Zhao, Levina, and Zhu (2012) however shows that the difference between Bernoulli and Poisson is negligible especially with many nodes and small interaction probabilities.

M, γ^+, and γ^- conditional on a partition z are derived from the logarithm of equation (7). In particular, taking derivatives of the log-likelihood under the identification constraint yields

$$\hat{\gamma}_i{}^+ = \frac{d_i^+}{\delta_{z_i}^+}, \quad \hat{\gamma}_i{}^- = \frac{d_i^-}{\delta_{z_i}^-}, \qquad \text{and} \qquad \hat{M}_{uv} = E_{uv}, \tag{8}$$

where $\delta_u = \sum_{i:z_i=u} d_i$ denotes the sum of degrees in group u. These maximum likelihood estimators are very intuitive as relative popularity is measured by the relative number of connections and transition probabilities are measured by the number of observed transitions. Substituting the estimators in equation (8) into the (log-)likelihood and neglecting terms that do not depend on the model parameters considerably simplifies the expression to

$$\ln \mathcal{L}(G|z) = \sum_{u,v} E_{uv} \ln \frac{E_{uv}}{\delta_u^+ \delta_v^-}, \tag{9}$$

which depends only on the counts induced by the choice of the partition z.

In the second step, the log-likelihood is maximized by choosing the partition of firms into markets z which maximizes (9). Since it is not feasible to evaluate all possible combinations of firms and markets, the empirical analysis relies on computational approximations via a Markov-chain Monte-Carlo (MCMC) algorithm. In particular, the market assignments of the firms are modified in a random fashion and each move is accepted or rejected depending on the change in the likelihood (for details of the algorithm see Peixoto, 2014a). The estimation is repeated for different starting partitions in order to avoid lock-in at local maxima.

A generalized consistency framework for community detection using the SBM is provided by Bickel and Chen (2009) and (including the popularity parameters) by Zhao et al. (2012).

The remaining issue pertains to the choice of the number of markets k which has been treated as fixed so far. This parameter guides the "size" of the model as a larger k implies more parameters in the transition matrix M. It can also be used to "zoom" into or out of the economy in order to analyze different levels of market aggregation. However, a tradeoff between more flexible models and the threat of over-fitting arises. In the empirical analysis, I estimate the SBM for various choices of k and evaluate the different fits using the modularity score of Newman and Girvan (2004).[16] The modularity score measures how well a network decomposes into self-contained communities. A high score indicates dense connections between firms within markets but only sparse connections between firms from different markets.[17] Figure 2 displays the modularity score for varying k in the job mobility network for the years 1975-2005. There is a clear peak at $k = 9$ groups, indicating that a SBM with nine markets is best suited to describe the structure of labor markets in Austria.

5 Descriptive Analysis of Endogenous Labor Markets

In this section, I present and discuss the endogenous labor markets that arise from partitioning the job mobility network among Austrian firms via the stochastic block model (SBM). I start by comparing endogenous labor markets to geographical characterizations of labor markets in section 5.1. In section 5.2, the analysis continues with a comparison of endogenous labor markets for several subgroups of the working force.

5.1 Endogenous versus Local Labor Markets

This section provides an extensive descriptive analysis of endogenous labor markets in Austria. Particularly, I compare the estimates from the SBM to local labor markets that are based on predefined geographical characteristics.

[16] In principle, regularization methods such as information criteria (BIC, AIC, etc.), minimum description length, or likelihood ratio tests, could guide the choice of k. Due to the complex asymptotic behavior of network models, however, traditional criteria are biased in many ways and finding corrections for model selection is an active strand of the statistical networks literature (see Yan, Shalizi, Jensen, Krzakala, Moore, Zdeborova, Zhang, and Zhu, 2014).

[17] In particular, the modularity score is defined as $Q = \frac{1}{2|E|} \sum_{ij} \left(A_{ij} - \frac{d_i d_j}{2|E|} \right) 1\{z_i = z_j\}$ where $|E|$ is the total number of transitions in the network. It compares the share of links within a market to the expected share in a model where all firms have the same number of links but links are generated uniformly at random (ignoring the market structure). This implies that the score is 0 if the markets have no explanatory power while a positive score indicates that there are more links within communities than expected under random link formation (cf. Jackson, 2008).

5.1.1 Self-Containedness

Figure 3 gives an overview of endogenous labor markets estimated based on the job mobility network for the time period from 1975 to 2005. Each circle represents one of the $k = 9$ sets of firms that has been assigned to the same market by the SBM.[18]

The transition probabilities across and within markets are represented by the gray edges, which are thicker the more likely a transition is. Job-to-job transitions within markets are much more probable than transitions between different markets. This clear segmentation can also be seen in Figure 4 which displays the estimated transition probabilities (normalized to sum up to one).[19] In total, 80% of all job-to-job transitions occur within endogenous labor markets.[20] Transitions between markets are much less likely. The closest connection is between markets 1 and 3 where 1.7% (from market 1 to market 3) and 1.9% (from 3 to 1) of all transitions occur.

A natural metric to evaluate how self-contained different definitions of labor markets are is the modularity score of Newman and Girvan (2004). It computes the share of transitions between firms *within* the same market among all transitions and normalizes it by the share of within market transitions that would be expected if links were generated uniformly at random (ignoring the market structure).[21] The modularity score therefore measures the explanatory power of the inherent market structure in excess of random link formation and a positive value indicates that there are more links within markets than expected. Table 3 displays the modularity score for endogenous labor markets with $k = 9$ and $k = 35$ as well as for markets defined by the 9 states, the 35 NUTS-3 regions, 2-digit industries, and state times 2-digit industry cells in Austria.

For the entire period from 1975 to 2005 and for each of the shorter sample periods, the SBM outperforms markets based on predefined geographical or industry characteristics. Endogenous labor markets with $k = 9$ have higher modularity scores than the 9 Austrian

[18]The numbering of the markets bears no particular meaning and only serves to label markets. The size of each circle is proportional to the number of firms in the respective market. The coloring of the circles represents the average firm size in the market. Evidently, firms in markets with many firms tend to be smaller on average than firms in markets with fewer firms.

[19]The actual estimates are reported in Panel A of Table A1 in the appendix.

[20]Recall that 77.5% of all transitions occurred within Federal states, 64.3% within Nuts-3 regions, and 22.4% within 2-digit industries.

[21]See also footnote 17.

states and scores for endogenous markets with $k = 35$ exceed the scores for the 35 NUTS-3 regions in Austria. Not surprisingly, 2-digit industries and state by industry cells have much lower scores. Most importantly, the development over time indicates that the advantage of my novel method to determine endogenous labor markets grows with increasing mobility in the society.[22]

5.1.2 The Geography of Endogenous Labor Markets

The regional structure of the endogenous labor markets is illustrated in Figure 5. For each of the 9 markets, the figure presents a map with boundaries according to the NUTS-3 classification (Nomenclature of territorial units for statistics) of Eurostat. In each map, the 35 Austrian NUTS-3 regions are colored according to the share of firms from the relevant market within the respective region. There is clearly a *local* structure of labor markets in Austria as firms in the same endogenous market are geographically clustered. For each endogenous labor market, the vast majority of firms is concentrated within one Austrian state. The endogenous market structure however deviates from a classification that is solely based on geographical boundaries in two important aspects. First, firms in the same geographical area can be part of different endogenous labor markets. Second, sometimes distant firms from separate local labor markets are part of the same endogenous market.

Separate Endogenous Markets in the Same Area The maps in Figure 5 indicate several mostly separated endogenous labor markets within the same region. In particular, markets 3, 8, and 9 are all primarily located within Vienna. The estimated probability to switch between any of these markets is however less than 1.5%. Even within Vienna, the distribution of firms across different postal code areas is remarkably similar among these three markets (see the histograms in Figure 6).[23] Hence, firms in the same local labor

[22] A second test of the performance of the SBM is provided in appendix C. I conduct a Monte-Carlo simulation study with varying degrees of correlation between regions and true labor markets. The results demonstrate that even slight deviations from perfect correlation lead to the SBM outperforming regional characteristics.

[23] Note that Figure 6 (and Figure 7) only lists postal code areas (2-digit industries) where at least one of the markets has more than 2.5% of firms.

market are located in different endogenous labor markets. It is therefore interesting to ask what distinguishes these endogenous markets from each other.

The histograms in Figure 7 illustrate the 2-digit industry composition of the three Viennese markets and reveal interesting differences between them. Despite the fact that substantial shares of firms in all three markets are affiliated to generic 2-digit industries such as Wholesale, Retail, and Construction, there are clear patterns of specialization. Many firms in market 3 are affiliated to manufacturing industries such as Food and Tobacco, Metal Products, Paper and Print, or the sale, maintenance, and repair of Motor Vehicles. Firms in market 8 are predominantly affiliated to Business Activities, Financial Services and Computer-related industries. Finally, firms from market 9 are specialized in Health, Public Administration, Lobbying, and Education.

Further important differences between the three Viennese markets can be found in terms of the wage structure. Figure 8 indicates that the distribution of firm fixed effects from an AKM wage decomposition is shifted to the right and more compressed in market 8 compared to markets 3 and 9. Not surprisingly, the market with a larger share of high-paying firms is the one specialized in Business and Financial Services.

Distant Firms in the Same Endogenous Market Some endogenous labor markets are spread across a variety of regions and contain firms from a various states. While the industry affiliation of firms is in general not a good predictor of their assignment to endogenous labor markets, it becomes more important for markets that are spread out across the country.

For each of the 9 markets, Figure 9 provides a histogram of the broad sectoral composition. All markets consist of firms from a broad variety of industries. Evidently, sectors with a high degree of fluctuation such as construction, wholesale and retail, and hotels and restaurants are strongly represented in the sample of job-to-job transitions. There are however some markets with a stronger focus on particular sectors such as the dominance of professional services in market 8, or the health sector in market 9.

In Figure 10, I show an inverse relation between geographical and industry concentration. Concentration is measured using the popular Ellison-Glaeser concentration index

(Ellison and Glaeser, 1997) which facilitates the comparison of regional and industry concentration between different markets.[24] In general, values for regional concentration are much higher than values for industry concentration. Moreover, high values of geographic concentration coincide with low values of industry concentration while markets that are more scattered around the country tend to be more specialized in specific industries.

5.1.3 Time Trends in the Geography of Endogenous Labor Markets over 1975-2005

In this section, I track developments in the structure of endogenous labor markets over time by estimating the SBM based on job mobility networks from the shorter sampling periods 1975-1980 until 2000-2005. This flexibility further distinguishes endogenous labor markets from the fixed nature of predefined local markets.

Figures E.1 to E.6 in the appendix display maps of the regional structure for job mobility networks for the (overlapping) six-year periods from 1975-1980 to 2000-2005. In general, they show a striking persistence in regional characteristics of the endogenous labor markets. Moreover, with exception of the early period from 1975-1980, there is a clear trend of increasing geographical mobility as labor markets are more and more scattered across several regions.

This is also supported by an increase in the average distance between firms within labor markets. Table 4 shows aggregate statistics for the distribution of distances between all pairs of firms in the same labor market.[25] The average distance between firms within labor markets is 90.4 km in the late 1970s and 103.2 km in the early 2000s. After an initial decrease, it increased by 30% from the 1980s to the 2000s. The median distance

[24]For a given market u, the Ellison-Glaeser index of concentration within R regions (or industries) is

$$EG_u = \frac{\sum_{r=1}^{R}(s_r - x_r)^2 - \left(1 - \sum_{r=1}^{R} x_r^2\right)H_u}{\left(1 - \sum_{r=1}^{R} x_r^2\right)(1 - H_u)},$$

where s_r denotes the share of market u employment in region (or industry) r, x_r denotes the share of total employment in region (industry) r and H_u is the Herfindahl index of the market firm size distribution, i.e., $H_u = \sum_{i:z_i=u} \left(\frac{\text{employment in } i}{\text{employment in } u}\right)^2$.

[25]Distances are computed by a relatively rough calculation where I assign to each firm the geographical coordinates of the centroid of the political district it is residing in. There are 95 political districts in Austria. The distance between firms in the same political district is underestimated as it is set to zero. The distance between firms in different political districts can be both under- or overestimated depending on the relative location to the centroid.

increased by 31% from 56.3 km to 73.7 km over time. The largest increase can be found in the lower part of the distribution as the distance at the 1st quartile increased by 119%.

While geographical concentration is decreasing over time, the concentration of industries within endogenous labor markets increases slightly. The development of industry composition within endogenous markets over time is depicted in Figures E.7 to E.8 in the appendix. Moreover, Figure 11 compares the average Ellison-Glaeser index for geographical and industry concentration over all markets for each of the shorter sampling periods. After an initial increase between 1975-80 and 1980-85, geographical concentration steadily decreases over time while industry concentration exhibits an inverse pattern. Additionally, the error bars in Figure 11 indicate that the difference between both ways of concentration is statistically significant in earlier periods but becomes insignificant later on. These developments lend support to the hypothesis that over time individuals become more mobile (consistent with the larger size of labor markets in Table 4) and more specialized in specific industries.

Summarizing the evidence so far, geographical factors seem to be the most important determinant for the emergence of distinct labor markets. Additionally, largely separated markets in the same region differ by their industry or wage structure. Importantly, however, there is still substantial overlap in the distribution of observed characteristics such as regions, industries, and wages between markets. The endogenous labor market measure proposed in this paper allows to capture these unobserved determinants that drive frequent worker transitions between observationally different firms.

5.2 Worker Heterogeneity

In this section, I compare the scope of endogenous labor markets for various subgroups of the working force. The size and shape of labor markets can differ between worker types as the local availability of specific jobs varies and preferences towards mobility across regions and industries are heterogeneous. In the empirical analysis, I compare the outcome of the SBM estimated from job-to-job transitions separately by gender, nationality, age groups, and several skill measures.[26]

The most striking differences occur in the comparison of high-skilled and low-skilled workers. Figure 12 illustrates the development over time of endogenous labor markets defined by various measures of skill level. The graphs on the left refer to geographical concentration on the NUTS-3 level while the graphs on the right refer to 2-digit industry concentration, both measured by the average Ellison-Glaeser index over all markets. Remarkably, the different measures all point to the same conclusion: labor markets for higher skilled individuals are more dispersed in terms of geography but more specialized in specific industries than labor markets for low-skilled individuals. Panel 12a shows this difference for individuals without (blue dots) and with a highschool degree (red triangles), Panel 12b confirms that the same is true when considering individuals below (blue dots) and above the median (red triangles) in the distribution of individual fixed effects from an AKM wage decomposition, and Panel 12c shows the same pattern for blue collar (blue dots) versus white collar workers (red triangles). Difference between skill groups in the geographical scope of endogenous labor markets are also expressed in the geographical distances between firms in the same labor markets. Table 5 displays aggregate statistics of the distribution of distances (in km) between firms. On average, endogenous markets for white collar workers are about 25% bigger than endogenous markets for blue collar workers. The difference is even stronger between different schooling degrees. The average distance between firms in the same endogenous market is 69 km for individuals without highschool degree, 115 km for individuals with highschool degree, and 135 km for individuals with a university degree.

Finally, there is a similar difference for workers whose transition is associated with a wage increase compared to those who incur a loss (Panel 12d). In particular, wage increases are associated with low regional concentration but higher industry concentration. The pattern is reversed for workers who incur wage cuts through the transition. Here regional concentration is higher than industry concentration. A potential interpre-

[26]Note that the modularity maximizing number of markets could be estimated differently in the subgroups making a comparison of the market structure more difficult. I therefore fix k to 9, the number that maximizes modularity in the full job mobility network.

tation pertains to job specialization which might be rewarded with high premiums while regionally less flexible workers incur wage cuts.

In figure 13, I display the development over time of endogenous labor markets defined by gender, nationality, and age. Again, the graphs on the left refer to geographical concentration on the NUTS-3 level while the graphs on the right refer to 2-digit industry concentration, both measured by the average Ellison-Glaeser index over all markets. Consistent with the aggregate trends described in section 5.1.3, there is a clear decrease in geographical concentration for all subgroups while industry concentration exhibits no strong direction.

Panel 13a indicates that there are no clear gender differences in the geographical concentration of labor markets. In terms of industry affiliation, however, labor markets of women (blue dots) are more specialized into specific industries than markets of men (red triangles) in the early periods until they converge in the late 1990s and 2000s. The situation is similar for Austrian (red triangles) versus Non-Austrian (blue dots) workers. Panel 13b shows no significant difference between geographical concentration in both subgroups. In early years, labor markets defined by Austrians were more concentrated within specific industries with convergence in later years.

Panel 13c compares endogenous labor markets for three age groups: young workers below 30 years of age (blue dots), middle-aged workers from 30 to 50 (red triangles), and elder workers above 50 (green squares). From the late 1980s on, middle aged workers are the most geographically mobile age group with least concentrated markets. Geographical concentration is higher for both younger and older workers. In terms of industry concentration, young workers have the most specialized markets for most of the time. Markets of middle-aged and older workers have low levels of industry concentration with a slight increase for middle-aged workers in later periods.

6 Mobility Responses to Economic Shocks

Based on my novel method to endogenously determine labor markets, I analyze mobility responses to large economic shocks. In particular, I use the SBM to predict the reactions to both, local and global shocks that hit specific parts of the economy.

The analysis proceeds in two parts. In the first application, I examine spillover effects of a large local labor demand shock, the breakdown of the Austrian steel industry in the late 1980s. I document negative spillover effects on employment in other firms from the same endogenous labor market both within and outside of the geographical location of the shock. In contrast, employment in firms from other endogenous markets within the affected region is largely unaffected by the shock. My results show that a traditional definition of regional labor markets underestimates spillover effects by about 50% of the actual effect size.

In the second application, I use endogenous labor markets to predict mobility responses to global trade shocks, particularly the rising import competition from China and Eastern Europe. Previous research has identified the importance of job mobility to mitigate the negative consequences of global trade shocks (Autor et al., 2014; Dauth et al., 2016). An important and policy-relevant question however is *where* workers go when they are hit by trade shocks. The analysis shows that endogenous labor markets, estimated in the period *prior* to the shock, can accurately predict mobility responses while markets based on geographical areas fail to explain substantial parts of these movements.

In both applications, I take advantage of the flexibility of the SBM and vary the resolution of the analysis by modifying the number of markets, k. This allows me to quantify the effects at different levels of aggregation.

6.1 Local Labor Demand Shocks

The breakdown of the Austrian steel industry at the end of the 1980s was a particularly large shock that hit the Austrian economy unexpectedly. After World War II, Austria had nationalized its iron, steel, and oil industry in a protectionist act fearing expropriation by the Russian Army. The steel sector was mainly organized in one large company, the VÖEST. Mismanagement led to serious financial problems already starting in the mid-1970s. For several years, however, the Austrian government covered these losses. In November 1985, a big oil speculation scandal as well as the failure of a gigantic US plant project lead to an immediate turnaround in the company's strategy. The government installed a new management and enacted a strict restructuring plan with big mass layoffs and plant closures.[27]

6.1.1 Employment Spillovers

Mass layoffs that affect large companies can lead to substantial spillover effects on the surrounding economy (Gathmann et al., 2016). The existence and scope of these spillover effects is highly policy relevant. On the one hand, policy makers rationalize discretionary interventions to rescue failing firms by potential negative spillovers on the local economy. On the other hand, the effectiveness of interventions targeted towards disadvantaged areas depends crucially on the scope of labor markets. Researchers and policy makers alike need a solid understanding of who is affected by a local shock (i.e., what determines the treatment group) and who can be used as a couterfactual (i.e., what determined the control group). This question was particularly relevant in the Austria, when the government enacted the Regional Extended Benefit Program in 1988 aimed to targeted individuals affected by the steel shock. As discussed in Lalive et al. (2015), however, the selection of the treatment group was determined in a crude political process rather than by economic arguments. The concept of endogenous labor markets provides a novel mean to examine and predict the scope of affected workers and firms due to its foundation on economic connections.

To determine the scope of spillover effects of the Austrian steel shock, I extend the research design in Gathmann et al. (2016) by using the flexible definition of endogenous

[27] Three years later, the trouble in the steel industry lead to an endogenous policy reaction, the massive extension of unemployment benefits in the Regional Extended Benefits Program from 1988. A series of paper is concerned with various effects of this policy change (Lalive and Zweimüller, 2004; Lalive, 2008; Lalive et al., 2015). Rather than looking at the effects of the policy response, the present application deals with the direct labor market effects of the breakdown.

labor markets. I examine spillovers of the steel shock on employment (and wages) in firms excluding both, the event firm and other firms from the (broadly defined) steel sector. Hence, the treatment group in this analysis are firms that are in the same market as the steel company but operate in any sector outside the steel industry. I compare outcomes in this treatment group to a control group that consists of firms in a market with similar industry structure as the treatment group. Finding a suitable control group ensures that spillover effects are not driven by common industry-wide shocks that hit particular sectors but are result of actual spillovers of the steel company's break-down. The control group is obtained by nearest-neighbor matching or by the synthetic control method.[28]

I run the analysis separately for both, the traditional concept of local labor markets and the flexible approach of endogeneous labor markets and show that a focus on regional markets underestimates the total impact of spillover effects vastly. In order to account for potential simultaneity in the determination of endogenous markets and responses to the shock, I estimate the SBM based on job mobility in the 5 years prior to the shock, 1980-1985.[29]

Figure 14 gives clear indication of spillover effects on employment in non-steel sector firms in both market concepts. Panel 14a compares the treated market to a matched control market where matching is based on similarity in the four years prior to the shock with respect to the industry structure (14 broad industries), average worker age, and the skill composition (blue- and white-collar workers). Panel 14b compares the treatment group to a synthetic control group that is determined based on similarity in pre-treatment outcomes and industry structure. In each panel, the left graph shows employment growth for (non-steel sector) firms in the NUTS-3 region of the steel company and the control

[28]Difference-in-differences estimation combined with matching is the preferred identification strategy in Gathmann et al. (2016) who analyze spillovers of several mass layoff events in Germany. The Austrian steel shock, however, is a comparative case study with a single treated unit. The synthetic control method suits such a setting particularly well and provides a framework for exact inference via permutation tests where the actual treatment effect is compared to the distribution of placebo effects permuting the group of (pseudo-)treatment. Details on the exact specification of both methods are provided in Appendix D.

[29]Note that this implicitly assumes that assignments to endogenous labor markets are fixed in the short run. Moreover, new firms that are founded after 1985 are therefore excluded from the analysis.For comparison with the NUTS-3 regional classification, the SBM is estimated with $k = 35$ endogenous markets. The results also hold for other choices of k.

region. The right graph shows the same outcome for (non-steel sector) firms in the endogenous labor market of the steel firm (as estimated in the pre-treatment period from 1980-1985) and its control market. The onset of the shock is indicated by the vertical line in November 1985. All figures indicate nice parallel trends in the period before the breakdown of the steel industry. Details on the balance between treatment and control with respect to matched and un-matched observable characteristics can be found in Tables 6. After the steel shock, however, employment growth differs substantially between treatment and control markets as the shock caused strong negative spillovers on the connected economy. Most interestingly, the decline in employment growth but also the difference between treatment and control group is much larger when labor markets are defined by endogenous labor markets rather than geographical regions. Table 7 illustrates regression results for this analysis. The overall effect of the steel shock on non-steel firms in the treated region (Columns 1-3) or market (Columns 4-6) is provided in Panel A. Spillover effects of the steel shock lead to a reduction in employment in non-steel firms in the treatment region by 1.2%. At the same time, employment in the endogenous labor market of the steel company was reduced more severely by 1.8 to 2.4%. Panel B reports detailed results for the timing of the spillovers by reporting results for each quarter relative to the first period of treatment (last quarter of 1985). The estimates indicate that the effect started with delay, further supporting the hypothesis that these are spillover effects of the steel shock which need time to materialize. Four years after the shock, the employment reduction in the treated region amounted to 2.7% while it was 4.9% in the treated market. Permutation tests allow to conduct exact inference in the case of synthetic control groups despite the small sample size that invalidates conventional large sample inference. Figure 15 compares the employment gap between treatment and synthetic control group (black line) to the distribution of placebo gaps (grey lines) where each unit serves as a placebo treatment group once. For regional (left panel) as well as market spillovers (right panel) the actual treatment effect is clearly exceptional compared to the distribution of placebo effects. Columns 3 and 6 of Table 7 indicate p-values as the fraction of placebo effects that are lower than the actual treatment effect for each period.

Compared to the evidence in Gathmann et al. (2016), regional spillovers of the steel shock are slightly larger (which is no surprise given the enormous importance of the VOEST for the Austrian economy). The market spillovers however, are much larger than regional spillovers indicating that connections detected and predicted by the SBM are capturing the boundaries that are relevant for the transmission of economic shocks.

The larger decline in employment can be rationalized by a more homogenous worker composition in endogenous labor markets compared to local markets as endogenous markets are defined by transitions of workers with similar skill sets. The stronger difference between treatment and control shows that the focus on regional labor markets masks important heterogeneity in spillover impacts of economic shocks. This marks the central finding of my analysis: Spillover effects of mass layoffs are not necessarily bounded within local areas. Neither are spillover effects distributed evenly on firms within the local area. Instead, the concept of endogenous labor markets makes clear that firms and workers affected by spillovers of mass layoffs are those that have close economic ties to the event firm through common labor pools. Figure 16 illustrates this point. Within the treatment region (Panel 16a) employment growth in firms from the endogenous labor market of the event firm (blue line) experienced a strong decline shortly after the shock while employment growth in firms from other endogenous markets in the treatment region (red line) remains largely unaffected. At the same time, employment in other regions (Panel 16b) remains unaffected except for firms from the same endogenous market as the steel company.[30]

Consistent with the descriptive evidence in Section 5, there are several independent labor markets within the same region. Economic shocks that hit one of these markets do not necessarily impact other markets. At the same time, labor markets comprise firms from various – even distant – areas. Local shocks can therefore cause consequences for workers and firms in very distant regions. The evidence strongly indicates that spillovers

[30] As a robustness check, I also compute employment effects in (non-steel sector) firms from the same endogenous labor market that are located outside the REBP area defined in Lalive et al. (2015) which excludes other areas that focus on steel-related industries (besides the main center in Linz, parts of the Austrian steel industry were located in various parts of Styria). The pattern of rapid decline after the onset of the shock is unchanged. The evidence therefore suggests that the SBM can also detect and predict relevant economic ties to other firms outside the steel sector and the original location.

to other firms operate on the level of economic ties, and in particular common labor markets, rather than through local multipliers. This is in line with recent evidence in Gathmann et al. (2016), Cestone et al. (2016), and Giroud and Mueller (2017) who emphasize the importance of economic ties through common industry affiliations, firm clusters, or agglomerations.[31] Endogenous labor markets estimated by the SBM seem to be better suited to detect such economic connections than fixed geographical boundaries.

6.1.2 Mobility Responses

In this section, I briefly examine the effect of the local demand shock on the transition probabilities between the endogenous labor markets. On the worker level, the negative impact on employment in the endogenous labor market that contained the steel company can be partly offset by job mobility to other markets.

After the shock, I find an increase in the share of job-to-job transitions out of the endogenous labor market containing the steel company and a decrease in the share of job-to-job transitions into this market. The share of transitions away from the affected market to other endogenous markets among all transitions in the economy increases from 1.5 to 1.9 percent. At the same time, transitions into the affected market decrease from 1.5 to 1.2 percent of all job-to-job transitions.

Most importantly, the impact on transition probabilities to other markets is larger the higher the initial transition probability was in the period before the shock. Figure 17 shows a scatter plot of transition probabilities in the period prior to the shock (1980-1985 on the vertical axes) plotted against transition probabilities after the shock (1986-1990 on the horizontal axes). Comparison to the dashed 45 degree line indicates that there is a change in the composition of transitions between these periods. In the upper panel, I illustrate the probability of transitions from the affected endogenous market into the other 34 markets. Workers who leave the affected market increasingly target those markets that had a stronger connection before the shock. The opposite pattern can be found for transitions into the affected endogenous market in panel (b). Transitions into this

[31] Similarly to these papers, I do not find significant impacts of the labor demand shock on wages. This could potentially be explained by downward wage rigidity.

market become less likely, especially those from markets with a high pre-shock transition probability. The evidence suggests that an adverse shock to local labor demand leads to changes in job mobility that are roughly proportional to the transition probabilities predicted by the SBM.

In summary, endogenous labor markets estimated by the SBM help to identify the relevant parts of the economy that are affected by spillover effects of adverse economic shocks. Moreover, they help to predict job mobility flows in response to such shocks. In the following section, I further analyze the policy-relevant question of worker reallocation by examining a different type of shock, the increase in import competition from eastern countries.

6.2 Global Trade Shocks

The unprecedented rise in the importance of China and Eastern Europe for global trade over the past decades has caused strong disruptions in the job biographies of workers in industrialized countries (Autor et al., 2013, 2014; Dauth, Findeisen, and Suedekum, 2014; Dauth et al., 2016). Import competition through largely exogenous shifts in the productivity of eastern countries triggered a rapid decline in wages and employment for workers in affected manufacturing industries, both in the US and Germany.[32][33]

Workers who suffer from wage or employment losses through strong exposure to import competition can mitigate the negative impact by switching their employer, industry, sector, or region. In the present application, I am particularly interested in the relative importance of different margins of mobility. Specifically, I examine whether the SBM introduced in section 4 is able to predict the mobility responses following global trade shocks more accurately than ad-hoc definitions of local markets such as regional entities.

[32] The fall of the iron curtain and the ensuing transition of eastern European countries into market economies can be considered a largely unexpected event. Similarly, the rapid improvements in China's competitiveness, also boosted by its entry into the WTO in 2001, are mainly driven by internal factors. Furthermore, I follow the common strategy in the literature and instrument Austria's exposure to trade with Eastern countries using trade exposure of other high-income countries in order to account for possible correlation between imports and domestic demand or productivity shocks. Detailed discussions of the identification strategy are provided by Autor et al. (2014) and Dauth et al. (2016).

[33] Export opportunities due to market liberalization in eastern countries, in contrast, increased wages and employment in specific industries in Germany while there seems to be no such offsetting effect for US manufacturing workers.

To this aim, I augment the studies of Autor et al. (2014) and Dauth et al. (2016) by introducing endogenous labor markets estimated by the SBM. The analysis proceeds in two steps. First, following Autor et al. (2014) I decompose the causal impact of trade shocks on medium-run accumulated earnings into additive components that accrue within the original firm, region, industry, and endogenous labor market and through mobility between these units. Second, following Dauth et al. (2016) I estimate the contemporaneous impact of trade shocks on earnings using high-dimensional fixed effects to separate direct responses and mobility responses.

Both strategies show that endogenous labor markets estimated in the period *prior* to the shock are much better predictors of mobility adjustments after the shock than traditional concepts based on predefined characteristics. Workers with strong exposure to the shock mitigate the negative impact by switching to firms within the original labor market but in different industries and regions.

6.2.1 Data

Data on trade exposure I acquire data on trade exposure from the United Nations Commodity Trade Statistics Database (Comtrade) which provides annual import and export statistics of over 170 reporter countries detailed by commodities and trade partner countries. I obtain Austrian trade data on the SITC3 5-digit commodity level and merge it to the NACE95 3-digit industries in the ASSD using correspondence tables provided by the World Bank.[34]

Figure 18 demonstrates the growing importance of imports from the East compared to total imports.[35] Trade volumes are normalized to 1 in 1990 and shown on a log-scale. The solid red line indicates a tenfold increase in imports from the East between 1990 and 2010 for the median industry. In contrast, total imports from all countries have only doubled for the median industry as shown by the solid black line. The dashed lines illustrate the

[34] As in Dauth et al. (2016), ambivalent cases are partitioned according to Austrian employment shares in 1978. Moreover, I convert all trade values into 2010-Euros using historical exchange rates provided by the Austrian National Bank and the Austrian CPI.

[35] The countries subsumed in the East comprise Bulgaria, China, the Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, Russia, Belarus, Estonia, Hongkong, Latvia, Lithuania, Macau, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

increase in imports for industries at the 25th and 75th percentile respectively and show that there is also more variation between industries in import exposure to the East.[36]

Exposure to imports from the East varies on the 3-digit industry level. For each worker i in industry $j(i)$, import exposure in year t is measured by

$$ImE_{j(i),t} = 100 \times \frac{IM_{j(i),t}^{EAST \rightarrow AUT}}{\sum_{\ell:j(\ell)=j(i)} w_{\ell,t-1}}, \tag{10}$$

where, $IM_{j,t}^{EAST \rightarrow AUT}$ denotes aggregate Austrian imports from the East in industry j and year t. Imports are normalized by the initial size of industry j in the Austrian economy, measured by the total wage bill in the previous year, $\sum_{\ell:j(\ell)=j(i)} w_{\ell,t-1}$.

Panel of Manufacturing workers I merge the information on trade exposure to individual level data on workers from the ASSD in the time period from 1990 - 2010. Following Dauth et al. (2016), I split the data into two balanced ten-year panels with base years 1990 and 2000. Each panel consists of all individuals who are between 22 and 54 years old and have their main job (i.e., the job spell with the longest duration) in the manufacturing sector in the base year.[37] For each worker, I track the job biography over the 10 year period and compute the sum of annual earnings for each year (which could be zero due to non-employment in some years).[38] In case of multiple job spells within a year, regional, industry, and labor market information refers to the main job. In case of non-employment, these characteristics are taken from the last employment spell, assuming some short term attachment to regions, industries and markets. Most importantly, the assignment of firms to endogenous labor markets is estimated based on worker flows in the 5-year period prior to the shock (1985-1990 for the base year 1990 and 1995-2000 for the base year 2000) in order to account for potential simultaneity in the formation of the network and the

[36]Figure E.9 in the appendix shows a similar picture for exports. The rise in Austrian exports to the East is much less pronounced than for imports. In the empirical analysis, I therefore focus on the exposure of the Austrian economy to imports from the East. Tables A3 and A4 in the appendix report the industries with the largest increase in im- and exports respectively.

[37]Individuals who die within 10-year period are dropped.

[38]Since wage information in the ASSD is censored at the social security contribution limit, I merge the data to uncensored tax records from the Austrian Ministry of Finance. Uncensored information, however, is only available since 1995. For earlier periods, I therefore impute the upper tail of the wage distribution using a strategy similar to the one used in Card et al. (2013).

mobility responses to trade shocks.

Table 8 presents summary statistics for earnings and trade exposure of workers separately for both periods. The first row in each panel characterizes the distribution of base year earnings in the sample. The second row shows accumulated earnings for the ten-year period relative to the base year earnings level. The median worker received exactly 10 times his base-year earnings for the period from 1990 to 2000 while there is a substantial degree of (right-skewed) variation around the median. Values for the 2000s are slightly higher and more compressed. The third row characterizes the distribution of yearly earnings relative to the base-year level. The median amounts to 100% of base year earnings, again with substantial variation. In particular, the first quartile of yearly relative earnings is only 69% (89% in the second period) of the base level while the third quartile of yearly earnings amounts to 117% (115%) of base-year earnings. There is also substantial variation in the individual exposure to imports from the East. The median change in the eleven-year difference of equation (10) is 0.143 (0.186) while the difference in exposure is 0.031 (0.078) for workers at the first quartile and 0.329 (0.295) for workers at the third quartile. Similarly, the yearly change in the exposure measure in row 5 shows substantial variation across workers.

6.2.2 Medium-run Analysis

In the first estimation strategy, I follow Autor et al. (2014) and estimate the impact of the eleven-year difference of trade exposure in the base year industry on accumulated earnings over the entire period (relative to base year earnings). I pool both panels and estimate the following model:

$$Y_{i\tau} = \beta_0 + \beta_1 \Delta ImE_{j(i),\tau} + \mathbf{x}'_{i\tau}\boldsymbol{\alpha} + \phi_{J(i),\tau} + \phi_{R(i),\tau} + \phi_{M(i),\tau} + \phi_\tau + \varepsilon_{i\tau}, \qquad (11)$$

where $Y_{i\tau} = \sum_{t=\tau+1}^{t=\tau+10} \frac{Y_{it}}{Y_{i\tau}}$ denotes accumulated earnings relative to base year earnings for $\tau \in \{1990, 2000\}$ and $\Delta ImE_{j(i),\tau} = ImE_{j(i),\tau+10} - ImE_{j(i),\tau}$ denotes the change in import exposure in the industry where i was employed in base year τ. Additional controls subsumed in $\mathbf{x}_i$, are indicators for female gender and foreign born status, for 7 different age categories, 3 different occupation categories, 3 different tenure groups, and for 5 different groups of firm size in the base year.

Identification of causal effects in this model is extensively discussed in Autor et al. (2014). I follow their strategy and instrument import and export exposure using trade flows between other countries and the East in order to purge the effect of domestic shocks within Austria that simultaneously affect trade and labor market outcomes.[39] Moreover, the model includes dummies for broad manufacturing industries, $\phi_{J(i),\tau}$, states, $\phi_{R(i),\tau}$, and endogenous labor markets, $\phi_{M(i),\tau}$, in order to control for potentially different industry-, state-, or market-level trends. Finally, the dummy ϕ_τ separates the two ten-year panels.

The main estimate for the model in equation (11) is shown in the first column of Table 9. There is a strong and (weakly) significant negative impact of the eleven-year change in import exposure on accumulated earnings.

The main purpose of the analysis is to decompose this total effect of trade exposure on accumulated earnings into additive parts that capture the direct effect of the shock (excluding mobility responses) as well as the different mobility margins. Column 2 of Table 9 shows estimates for the effect of trade exposure on all earnings that accrued in the initial firm which employed the worker in the base year. This effect is even more negative than the total effect, indicating that workers incur huge earnings and job losses in firms that are negatively affected by import exposure over the eleven-year period. They can however partly make up for these losses by switching to different firms, industries, regions, or labor markets. Columns (3) to (6) display different types of mobility responses within and between 3-digit industries, NUTS-3 regions, and endogenous labor markets with k = 35. The estimates referring to industry and market mobility in the first row indicate

[39] In particular, import exposure is instrumented by trade flows of other (non-neighboring) developed countries which are not in the Euro zone,

$$ImE_{j(i),t}^{INSTR} = \frac{IM_{j(i),t}^{EAST \rightarrow INSTR}}{\sum_{\ell : j(\ell)=j(i)} w_{\ell,t-3}}$$

where $INSTR$ comprises Australia, New Zealand, Japan, Singapore, Canada, Denmark, Sweden, Norway, and the UK. Note that the normalization now contains the wage bill in $t-3$ in order to account for sorting across industries in anticipation of future trade flows with China.

that workers with larger shocks generate significantly less earnings from firms in the same 3-digit industry (columns 3 and 5). They have however significantly higher earnings from firms in the same endogenous market but different industries (column 4). The impact on earnings from outside the original labor market and industry is small and insignificant. The estimates referring to regional and market mobility in the second row are very noisy. The direction of the effects however suggests that individuals with a stronger exposure to the shock generate more earnings from other firms in the same endogenous labor market (columns 3 and 4) but less earnings from firms in the same region but in a different labor market (column 5). Panel B of Table 9 displays the results for a related analysis where I replace the outcome variable with job switch indicators and estimate linear probability models. Column (3) indicates that workers with stronger import exposure have a lower probability to stay in their original 3-digit industry and endogenous labor market. There is however a positive and significant effect on the probability to switch the industry but to remain in the original endogenous labor market (column 4). Conversely, the probability to switch the labor market but to remain in the original industry is slightly negatively affected by the shock. The probability to switch both, endogenous market and industry, is also increased for highly exposed workers. The picture looks very similar for job switch probabilities between NUTS-3 regions and endogenous labor markets. In summary, mobility *between* regions and industries but *within* endogenous labor markets appears to be a main mechanism to mitigate the negative impacts of exposure to import competition from eastern countries.

6.2.3 Short-run Analysis

In the second empirical strategy, I address the caveat that in the medium-run model in equation (11) all outcomes are related to the trade shock in the initial industry. As mobility responses are an important aspect of adjustments to trade shocks, it is important to examine the impact of the actual contemporaneous exposure to trade in the current industry on earnings. To this aim, I follow Dauth et al. (2016) in estimating an annual panel model,[40]

$$Y_{it} = \beta_0 + \beta_1 \cdot ImE_{j(i),t} + \mathbf{x}'_{it}\boldsymbol{\alpha} + \phi_{t,J(j)} + \phi_{t,R(i)} + \phi_{t,M(i)} + \gamma_i + \varepsilon_{it}. \tag{12}$$

The most important difference to the medium-term model in equation (11) is the inclusion of individual level fixed effects, γ_i. Hence, the effect of trade exposure on earnings is identified on variation *within* individuals rather than *between* individuals with common observable characteristics. Estimation results for the baseline version of equation (12) are displayed in column 1 of Table 10. The total effect of contemporaneous import exposure on annual earnings is significantly negative confirming the medium-run evidence in the previous analysis. It is identified by within variation in earnings due to wage changes and non-employment as well as by variation due to job mobility.

In order to assess the relative importance of various margins of mobility responses to the contemporaneous trade shock, I replace the individual fixed effects by different sets of higher-dimensional fixed effects in equation (12). Particularly, including individual times firm-level fixed effects captures the *direct* effect of import exposure on earnings by exploiting only variation within spells in the same firm. The estimates in column (2) of Table 10 indicate that the negative impact is much stronger in this specification (consistent with the evidence from the medium-term analysis). The difference between the two estimates in columns (1) and (2) derives from mobility responses as the direct effect excludes variation that derives from firm switches. To examine which type of mobility responses helps to mitigate the adverse direct impact, I include fixed effects on the individual times industry level (column 3), individual times state level (column 4), individual times NUTS3-region level (column 5), and the individual times endogenous labor market level (column 6 with $k = 9$ labor markets and column 7 with $k = 35$ labor markets). Absorbing variation between industries into the individual times (3-digit) industry fixed effect (column 3) leads to a strongly negative effect that is similar to the direct effect in column 2. Movements between 3-digit industries are therefore very important to mitigate negative trade impacts. Columns 4 and 5 show that the estimates

[40] Again, import exposure is instrumented with the relevant exposure from other countries.

absorbing movements across states and NUTS3 regions are in between the direct and the aggregate effect. Mobility adjustments between NUTS3 regions are still an important part of wage responses while absorbing variation between states has almost no impact on the trade effect.

Similarly to the evidence from the medium-run analysis, it is variation on the endogenous labor market level that returns an the estimate closest to the aggregate effect. The estimates using only variation within the endogenous labor markets with $k = 9$ and $k = 35$ are very close to the aggregate effect. Moreover, Figure 19 shows that this is the case even for a finer disaggregations of endogenous labor markets. This confirms the striking ability of the SBM to predict labor market flows that mitigate the negative impact of global trade shocks. Even for a detailed view on the economy with 1000 labor markets (about 95 firms on average per market) the SBM accurately predicts those sets of firms that offer better employment and earnings possibilities to workers.

7 Conclusion

The Stochastic Block Model is an interesting novel device to enrich the toolbox of economists who work with network data. In the present context, it allows recovering endogenous labor markets in Austria from observed worker flows. These endogenous labor markets are geographically clustered but differ substantially from labor markets based on administrative borders. Furthermore, reflecting differences in mobility patterns, markets become more geographically dispersed over time and vary substantially across worker types.

The empirical analysis of job mobility responses to labor demand and trade shocks highlighted how endogenously determined labor markets can be used to better predict and understand worker flows in the economy. The increasing availability of administrative matched employer-employee data covering full populations should allow to apply my method to other countries and contexts. Interesting extensions such as migration induced labor supply shocks could therefore be addressed in future research. An important question for the future of the European Union regards the degree of between-country job mobility to balance inequalities. Endogenous international labor markets could provide answers to important policy questions in this context.

The SBM can be used to identify endogenous markets based on different kinds of networks. In the trade literature, for instance, researchers have analyzed the role of production networks (based on supplier relationships between firms) for aggregate outcomes (e.g., Carvalho, 2014; Chaney, 2014). Understanding the market structure in these networks might help to examine spillover effects between firms or countries that are not directly linked but exposed to similar market-level shocks.

Finally, several model extensions of the SBM have been introduced in the recent network literature. Airoldi, Blei, Fienberg, and Xing (2009) and Aicher, Jacobs, and Clauset (2015) consider mixed-membership models where nodes can belong to different communities depending on the kind of interaction. Peixoto (2014b) describes a hierarchical SBM where communities are nested in multiple levels. Finding consistent estimation methods and applying these models to economic networks is an interesting avenue for future research.

Bibliography

Alberto Abadie and Javier Gardeazabal. The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review*, 93(1):113–132, March 2003.

Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, 105(490):493–505, 2010.

Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Comparative Politics and the Synthetic Control Method. *American Journal of Political Science*, 59(2):495–510, 2015.

John M. Abowd, Francis Kramarz, and David N. Margolis. High Wage Workers and High Wage Firms. *Econometrica*, 67(2):251–333, 1999.

John M. Abowd, Robert Creecy, and Francis Kramarz. Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data. Unpublished working paper, Cornell University Department of Economics, March 2002.

Daron Acemoglu and Joshua Angrist. How Large are Human-capital Externalities? Evidence from Compulsory-schooling Laws. In *NBER Macroeconomics Annual 2000, Volume 15*, pages 9–74. MIT Press, 2000.

Christopher Aicher, Abigail Z. Jacobs, and Aaron Clauset. Learning Latent Block Structure in Weighted Networks. *Journal of Complex Networks*, 3(2):221–248, 2015.

Edoardo M Airoldi, David M Blei, Stephen E Fienberg, and Eric P Xing. Mixed Membership Stochastic Blockmodels. In *Advances in Neural Information Processing Systems*, pages 33–40, 2009.

David H. Autor, David Dorn, and Gordon H. Hanson. The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–2168, 2013.

David H. Autor, David Dorn, Gordon H. Hanson, and Jae Song. Trade Adjustment: Worker Level Evidence. *Quarterly Journal of Economics*, 129(4), 2014.

Ragnhild Balsvik. Is Labor Mobility a Channel for Spillovers from Multinationals? Evidence from Norwegian Manufacturing. *The Review of Economics and Statistics*, 93(1): 285–297, 2011.

Peter J Bickel and Aiyou Chen. A Nonparametric View of Network Models and Newman–Girvan and other Modularities. *Proceedings of the National Academy of Sciences*, 106 (50):21068–21073, 2009.

Melissa Bjelland, Bruce Fallick, John Haltiwanger, and Erika McEntarfer. Employer-to-Employer Flows in the United States: Estimates Using Linked Employer-Employee Data. *Journal of Business & Economic Statistics*, 29(4):493–505, 2011.

Olivier Blanchard and Larry Katz. Regional Evolutions. *Brookings Papers on Economic Activity*, 1:1–75, 1992.

Stéphane Bonhomme and Elena Manresa. Grouped Patterns of Heterogeneity in Panel Data. *Econometrica*, 83(3):1147–1184, 2015.

Stéphane Bonhomme, Thibaut Lamadon, and Elena Manresa. A Distributional Framework for Matched Employer Employee Data. Unpublished manuscript, University of Chicago, 2016.

John Bound and Harry Holzer. Demand Shifts, Population Adjustments and Labor Market Outcomes during the 1980s. *Journal of Labor Economics*, 18:20–54, 2000.

Matias Busso, Jesse Gregory, and Patrick Kline. Assessing the Incidence and Efficiency of a Prominent Place Based Policy. *American Economic Review*, 103(2):897–947, 2013.

David Card, Jörg Heining, and Patrick Kline. Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics*, 128, August 2013.

Vasco M. Carvalho. From Micro to Macro via Production Networks. *Journal of Economic Perspectives*, 28(4):23–48, 2014.

Giacinta Cestone, Chiara Fumagalli, Francis Kramarz, and Giovanni Pica. Insurance Between Firms: The Role of Internal Labor Markets. Technical Report DP11336, CEPR, June 2016.

Thomas Chaney. The Network Structure of International Trade. *American Economic Review*, 104:3600–3634, 2014.

Aaron Clauset, Mark EJ Newman, and Cristopher Moore. Finding Community Structure in Very Large Networks. *Physical review E*, 70(6):066111, 2004.

Guido Matias Cortes and Giovanni Gallipoli. The Costs of Occupational Mobility: An Aggregate Analysis. *Journal of the European Economic Association*, forthcoming.

Bruno Crepon, Esther Duflo, Marc Gurgand, Roland Rathelot, and Philippe Zamora. Do Labor Market Policies have Displacement Effects? Evidence from a Clustered Randomized Experiment. *Quarterly Journal of Economics*, 128(2):531–580, 2013.

Leon Danon, Albert Diaz-Guilera, Jordi Duch, and Alex Arenas. Comparing Community Structure Identification. *Journal of Statistical Mechanics: Theory and Experiment*, 2005(09):P09008, 2005.

Kunal Dasgupta. Learning and Knowledge Diffusion in a Global Economy. *Journal of International Economics*, 87(2):323–336, 2012.

Wolfgang Dauth, Sebastian Findeisen, and Jens Suedekum. The Rise of the East and the Far East: German Labor Markets and Trade Integration. *Journal of the European Economic Association*, 12(6):1643–1675, 2014.

Wolfgang Dauth, Sebastian Findeisen, and Jens Suedekum. Adjusting to Globalization - Evidence from Worker-Establishment Matches in Germany. Technical report, University of Mannheim, 2016.

Christian Dustmann, Uta Schönberg, and Jan Stuhler. Labor Supply Shocks and the Dynamics of Local Wages and Employment. *Quarterly Journal of Economics*, forthcoming, 2016.

Andreas Dzemski. An Empirical Model of Dyadic Link Formation in a Network with Unobserved Heterogeneity. Technical report, University of Mannheim, 2014.

Jonathan Eaton and Samuel Kortum. Technology, Geography, and Trade. *Econometrica*, 70(5):1741–1779, 2002.

Glenn Ellison and Edward L. Glaeser. Geographic Concentration in US Manufacturing Industries: A Dartboard Approach. *Journal of Political Economy*, 105:889–927, 1997.

Marc Ferracci, Grégory Jolivet, and Gerard J. van den Berg. Evidence of Treatment Spillovers Within Markets. *Review of Economics and Statistics*, 96(5):812–823, 2014.

Martina Fink, Esther Kalkbrenner, Andrea Weber, and Christine Zulehner. Extracting Firm Information from Administrative Records: The ASSD Firm Panel. Technical report, NRN Working Paper: The Austrian Center for Labor Economics and the Analysis of the Welfare State, 2010.

Santo Fortunato. Community Detection in Graphs. *Physics Reports*, 486(3):75–174, 2010.

Christina Gathmann, Ines Helm, and Uta Schönberg. Spillover Effects in Local Labor Markets: Evidence from Mass Layoffs. Technical report, UCL, 2016.

Xavier Giroud and Holger M. Mueller. Firms' Internal Networks and Local Economic Shocks. Technical report, MIT, 2017.

Bryan S. Graham. An Empirical Model of Link Formation with Degree Heterogeneity. *Econometrica*, forthcoming.

Michael Greenstone, Richard Hornbeck, and Enrico Moretti. Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings. *Journal of Political Economy*, 118(3):536–598, 2010.

Paul W. Holland, Kathryn Blackmond Laskey, and Samuel Leinhardt. Stochastic Blockmodels: First Steps. *Social networks*, 5(2):109–137, 1983.

Lawrence Hubert and Phipps Arabie. Comparing Partitions. *Journal of Classification*, 2 (1):193–218, 1985.

Matthew O. Jackson. *Social and Economic Networks*. Princeton University Press, 2008.

Matthew O. Jackson and Brian W. Rogers. The Economics of Small Worlds. *Journal of the European Economic Association*, 3(2-3):617–627, 2005.

Brian Karrer and Mark E.J. Newman. Stochastic Blockmodels and Community Structure in Networks. *Physical Review E*, 83(1):016107, 2011.

Rafael Lalive. How do Extended Benefits Affect Unemployment Duration? A Regression Discontinuity Approach. *Journal of Econometrics*, 142(2):785 – 806, 2008.

Rafael Lalive and Josef Zweimüller. Benefit Entitlement and Unemployment Duration: The Role of Policy Endogeneity. *Journal of Public Economics*, 88(12):2587 – 2616, 2004.

Rafael Lalive, Camille Landais, and Josef Zweimüller. Market Externalities of Large Unemployment Extension Programs. *American Economic Review*, 105(12):3564–96, 2015.

Michael Lechner, Conny Wunsch, and Patrycja Scioch. Do Firms Benefit from Active Labour Market Policies? Economics Working Paper Series 1318, University of St. Gallen, 2013.

Alan Manning and Barbara Petrongolo. How Local are Labor Markets? Evidence from a Spatial Job Search Model. *American Economic Review*, forthcoming.

Enrico Moretti. Workers' Education, Spillovers, and Productivity: Evidence from Plant-level Production Functions. *American Economic Review*, 94(3):656–690, 2004.

Enrico Moretti. Local Labor Markets. In *Handbook of Labor Economics*, volume 4, pages 1237–1313. Elsevier, 2011.

Mark E.J. Newman and Michelle Girvan. Finding and Evaluating Community Structure in Networks. *Physical review E*, 69(2):026113, 2004.

Matthew J. Notowidigdo. The Incidence of Local Labor Demand Shocks. Technical report, National Bureau of Economic Research, 2013.

Tiago P Peixoto. Efficient Monte Carlo and Greedy Heuristic for the Inference of Stochastic Block Models. *Physical Review E*, 89(1):012804, 2014a.

Tiago P. Peixoto. Hierarchical Block Structures and High-resolution Model Selection in Large Networks. *Physical Review X*, 4(1):011047, 2014b.

Jennifer P. Poole. Knowledge Transfers from Multinational to Domestic Firms: Evidence from Worker Mobility. *Review of Economics and Statistics*, 95(2):393–406, 2013.

Ian M. Schmutte. Free to Move? A Network Analytic Approach for Learning the Limits to Job Mobility. *Labour Economics*, 29:49–61, 2014.

Michel Serafinelli. Good Firms, Worker Flows and Local Productivity. Technical report, University of Toronto, 2014.

Isaak Sorkin. Ranking Firms Using Revealed Preference. Technical report, Unpublished Manuscript, 2015.

Andrey Stoyanov and Nikolay Zubanov. Productivity Spillovers across Firms through Worker Mobility. *American Economic Journal: Applied Economics*, 4(2):168–198, 2012.

Andrey Stoyanov and Nikolay Zubanov. The Distribution of the Gains from Spillovers through Worker Mobility between Workers and Firms. *European Economic Review*, 70:17–35, 2014.

Yuchung J. Wang and George Y. Wong. Stochastic Blockmodels for Directed Graphs. *Journal of the American Statistical Association*, 82(397):8–19, 1987.

Xiaoran Yan, Cosma Shalizi, Jacob E. Jensen, Florent Krzakala, Cristopher Moore, Lenka Zdeborova, Pan Zhang, and Yaojia Zhu. Model Selection for Degree-corrected Block Models. *Journal of Statistical Mechanics: Theory and Experiment*, 2014(5):P05007, 2014.

Yunpeng Zhao, Elizaveta Levina, and Ji Zhu. Consistency of Community Detection in Networks under Degree-corrected Stochastic Block Models. *The Annals of Statistics*, 40(4):2266–2292, 2012.

Josef Zweimüller, Rudolf Winter-Ebmer, Rafael Lalive, Andreas Kuhn, Jean-Philippe Wuellrich, Oliver Ruf, and Simon Büchi. Austrian Social Security Database. *NRN: The Austrian Center for Labor Economics and the Analysis of the Welfare State*, 2009.

Table 1: Summary Statistics of Job-to-Job Transitions

	1975-2005	1975-1980	1980-1985	1985-1990	1990-1995	1995-2000	2000-2005
Demographics							
share of females	0.41	0.37	0.37	0.41	0.42	0.41	0.42
	(0.492)	(0.482)	(0.489)	(0.491)	(0.495)	(0.492)	(0.494)
share of Austrians	0.96	0.97	0.97	0.97	0.94	0.94	0.95
	(0.201)	(0.180)	(0.173)	(0.174)	(0.233)	(0.234)	(0.222)
avg. age	33.0	33.3	31.9	31.0	32.0	33.4	34.7
	(9.75)	(10.69)	(10.16)	(9.50)	(9.34)	(9.12)	(9.28)
Avg. duration (in days) of							
spell at old firm	1545.9	1158.0	1429.5	1491.4	1509.6	1583.5	1625.4
	(1445.52)	(659.41)	(1075.05)	(1317.09)	(1462.83)	(1567.81)	(1657.43)
spell at new firm	2354.0	2650.2	2613.0	2389.4	2237.3	1997.0	1596.4
	(2153.34)	(2687.41)	(2565.27)	(2234.63)	(1890.99)	(1443.00)	(907.22)
intermission between spells	4.0	4.4	4.2	4.0	4.1	3.7	3.5
	(5.98)	(6.33)	(6.22)	(5.92)	(6.06)	(5.70)	(5.56)
Share of workers staying in the same							
state	0.78	0.79	0.78	0.78	0.79	0.78	0.74
	(0.417)	(0.409)	(0.414)	(0.411)	(0.407)	(0.417)	(0.440)
NUTS-3 region	0.64	0.66	0.65	0.66	0.66	0.66	0.63
	(0.479)	(0.473)	(0.476)	(0.474)	(0.472)	(0.475)	(0.484)
2-digit industry	0.22	0.21	0.21	0.20	0.23	0.26	0.28
	(0.417)	(0.410)	(0.404)	(0.400)	(0.422)	(0.441)	(0.447)
occupation (white- and blue-collar)	0.86	0.87	0.85	0.85	0.86	0.87	0.88
	(0.346)	(0.341)	(0.355)	(0.361)	(0.351)	(0.332)	(0.320)
Share of workers with							
wage increase	0.61	0.65	0.63	0.64	0.63	0.60	0.60
	(0.487)	(0.476)	(0.484)	(0.481)	(0.483)	(0.492)	(0.490)
increase in firm fixed effect	0.74	0.89	0.86	0.83	0.78	0.72	0.62
	(0.441)	(0.31)	(0.35)	(0.379)	(0.415)	(0.451)	(0.485)
Number of transitions	930,027	258,837	204,832	234,580	273,099	263,006	281,880

Note: Standard deviations in parenthesis. This table reports summary statistics for job-to-job transitions in the specified period. A change of employer is classified as a job-to-job transition if there are at most 30 days of intermission in between two consecutive employment spells and tenure at both employers exceeds one year. Transitions between small firms with less than 5 employees and transitions of apprentices and marginal workers are excluded.

Table 2: Links and Nodes in the Job Mobility Networks

	1975-2005	1975-1980	1980-1985	1985-1990	1990-1995	1995-2000	2000-2005
# of nodes	95,237	54,080	51,406	54,615	59,215	59,444	61,068
# of links	930,027	258,837	204,832	234,580	273,099	263,006	281,880
# of components	755	1232	1549	1407	1265	1725	1889
in giant component							
% of nodes	0.98	0.95	0.93	0.94	0.95	0.94	0.93
% of links	1.00	0.99	0.99	0.99	0.99	0.99	0.99
average degree	19.84	9.98	8.42	9.00	9.59	9.31	9.75

Note: All measures correspond to the job mobility network sampled during the years indicated. The number of components counts all subgraphs of the network within which all firms are connected by some path, but not connected to the other subgraphs. Avg. degree measures the average number of incoming and outgoing connections per firm.

Table 3: Modularity Scores for the SBM vs. Predefined Markets

	SBM with 9 markets	SBM with 35 markets	Federal States	NUTS-3 Regions	2-digit Industries	States × Industries
1975–2005	0.683	0.536	0.610	0.519	0.130	0.102
1975–1980	0.679	0.563	0.607	0.535	0.121	0.106
1980–1985	0.671	0.558	0.613	0.529	0.122	0.099
1985–1990	0.675	0.548	0.616	0.529	0.125	0.099
1990–1995	0.681	0.566	0.619	0.530	0.142	0.111
1995–2000	0.681	0.549	0.598	0.508	0.158	0.121
2000–2005	0.679	0.580	0.567	0.478	0.159	0.118

Note: This table reports modularity scores for labor markets estimated by the SBM (with $k = 9$ and $k = 35$) and defined by several observable characteristics. The modularity score compares the observed share of links within markets to the expected share in a model with the same degree distribution but random link formation. Higher values indicate more self-contained markets.

Table 4: Firm Distances within Labor Markets in km

	mean	sd.	1st quartile	median	3rd quartile
1975-1980	90.38	98.49	13.91	56.35	137.58
1980-1985	79.26	91.50	14.25	54.73	113.14
1985-1990	81.24	92.38	14.25	54.73	117.66
1990-1995	90.80	103.31	24.99	55.08	124.47
1995-2000	94.08	94.92	27.16	66.34	144.34
2000-2005	103.14	97.83	30.42	73.72	153.34

Note: Distance between firms is calculated according to the geographical distance between the centroid of the respective political districts.

Table 5: Firm Distances within Labor Markets in km (1975-2005)

	mean	sd.	1st quartile	median	3rd quartile
Occupation					
blue collar workers	77.26	93.97	14.25	48.84	101.10
white collar workers	96.77	100.77	26.80	67.23	144.34
Education					
no highschool degree	68.90	81.08	0	45.56	96.58
highschool degree	115.12	111.25	16.69	100.95	178.13
university degree	135.21	121.77	16.69	141.60	201.98
Worker fixed effect					
below median	72.41	80.41	16.69	53.25	98.91
above median	94.86	101.43	26.30	62.46	140.97

Note: Distance between firms is calculated according to the geographical distance between the centroid of the respective political districts.

Table 6: Covariate Balance of Matching Procedure and Synthetic Control Method

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Regions				Markets			
	Treated	Average	Matched	Synthetic	Treated	Average	Matched	Synthetic
Panel A. Non-matched characteristics								
Employment	176,690	49,304.64	76,132	71,815.51	116,823	50,713.34	103,980	66,392.05
Employment Growth	.03	.01	.03	.03	.00	.01	.00	.01
Avg. Wage	1801.45	1715.49	1752.29	1741.30	1737.72	1800.69	1686.99	1757.76
Wage growth	.13	.13	.15	.15	.14	.13	.14	.14
Share of Females	.436	.371	.417	.411	.400	.423	.356	.363
Share of Austrians	.977	.969	.984	.985	.977	.961	.989	.976
Panel B. Matched characteristics								
Avg. Age	31.53	31.27	31.51	31.35	31.02	32.62	31.12	31.25
Industry Share								
Agriculture	.006	.018	.013	.014	.011	.014	.010	.013
Mining	.001	.008	.003	.004	.005	.004	.004	.006
Manufacturing	.195	.227	.191	.195	.240	.198	.184	.220
Electricity, Gas, Water	.088	.125	.086	.089	.105	.119	.100	.109
Construction	.002	.006	.002	.003	.003	.004	.007	.005
Wholesale and Retail	.235	.217	.249	.247	.227	.218	.237	.225
Hotels and Restaurants	.035	.048	.048	.047	.045	.049	.036	.040
Transportation	.033	.046	.033	.033	.037	.041	.039	.041
Finance and Real Estate	.038	.038	.050	.049	.019	.035	.021	.029
Professional Services	.068	.040	.065	.062	.056	.064	.047	.050
Public Administration	.026	.046	.038	.037	.037	.049	.031	.040
Education	.012	.009	.011	.012	.012	.018	.009	.011
Health	.019	.018	.020	.019	.013	.048	.014	.020
Other	.242	.153	.189	.189	.191	.140	.262	.190
Share of								
White-collar Workers	.510	.361	.548	.525	.430	.476	.390	.424
Blue-collar Workers	.437	.564	.394	.415	.503	.474	.534	.510

Note: Comparison of baseline characteristics of event region, Average over all regions, matched control region, and synthetic control region. Panel A indicates covariate balance for variables that were not included in the matching (synthetic control) procedure while Panel B indicates balance in matched variables.

Table 7: Estimation Results - Difference in Differences Model

	Regional Spillovers			Market Spillovers		
	(1)	(2)	(3)	(4)	(5)	(6)
	Matched Control	Synthetic Control		Matched Control	Synthetic Control	
Panel A. Overall Effect						
Steel Shock	-0.012***	-0.012***		-0.018***	-0.024***	
	(0.0040)	(0.0038)		(0.0051)	(0.0064)	
Quarter Fixed Effects	Yes	Yes		Yes	Yes	
Panel B. Timing						
Pre-Treatment						
t - 16	0.0065	0.0069*	[0.057]	-0.012	0.0067	[0.429]
t - 15	-0.0012	-0.00077**	[0.029]	-0.016	0.00028	[0.543]
t - 14	-0.00020	0.00058**	[0.029]	-0.0051	0.012	[0.200]
t - 13	-0.0016	-0.00079**	[0.029]	-0.0047	0.011	[0.743]
t - 12	0.0055	0.0060**	[0.029]	-0.0072	0.011	[0.914]
t - 11	-0.0011	-0.00047***	[0.000]	-0.0090	0.0064	[0.171]
t - 10	0.0049	0.0055***	[0.000]	0.0032	0.016	[0.371]
t - 9	0.0039	0.0047***	[0.000]	-0.0021	0.0086	[1.000]
t - 8	0.0088	0.0093***	[0.000]	0.0017	0.0076	[0.829]
t - 7	-0.00097	-0.00034***	[0.000]	0.00069	0.0031	[0.514]
t - 6	-0.0053	-0.0047***	[0.000]	-0.0045	0.00086	[0.457]
t - 5	-0.0086	-0.0081***	[0.000]	-0.0011	-0.00035	[0.657]
t - 4	0.00053	0.00097**	[0.029]	0.0053	0.0015	[0.543]
t - 3	-0.0022	-0.0019	[0.114]	0	0	[0.886]
t - 2	0.00014	0.00035*	[0.086]	-0.00086	-0.0034	[0.914]
t - 1	0.0020	0.0019***	[0.000]	-0.00098**	-0.0015	[0.029]
Post-Treatment						
$t + 1$	0.0011	0.00096	[0.943]	-0.00067	-0.0035*	[0.088]
$t + 2$	0.0025	0.0023	[0.914]	-0.0068	-0.0050*	[0.088]
$t + 3$	0.0061	0.0058	[0.486]	-0.0043	-0.00058	[0.176]
$t + 4$	-0.0036	-0.0037	[0.400]	-0.0066	0.0012	[0.206]
$t + 5$	-0.0013	-0.0015*	[0.086]	-0.0071	0.0055	[0.118]
$t + 6$	0.0014	0.0013	[0.171]	-0.0087	0.0049	[0.118]
$t + 7$	-0.0046	-0.0045	[0.429]	-0.0094	0.0039	[0.118]
$t + 8$	0	0	[0.114]	-0.018	-0.0040*	[0.059]
$t + 9$	-0.012	-0.012**	[0.029]	-0.031	-0.015***	[0.000]
$t + 10$	-0.0080	-0.0078**	[0.029]	-0.025	-0.015***	[0.000]
$t + 11$	-0.024	-0.024**	[0.029]	-0.049	-0.049***	[0.000]
$t + 12$	-0.028	-0.027**	[0.029]	-0.045	-0.048***	[0.000]
$t + 13$	-0.037	-0.036**	[0.029]	-0.047	-0.052***	[0.000]
$t + 14$	-0.036	-0.034**	[0.029]	-0.047	-0.054***	[0.000]
$t + 15$	-0.028	-0.027**	[0.029]	-0.043	-0.049***	[0.000]
Observations	62	62		62	62	

Note: Regression results for various specifications of a difference in differences model. The outcome variable is (log) employment growth. In Panel A. this is regressed on an indicator for the treatment market (region in columns 1-3, endogenous labor market in columns 4-6, an indicator for quarters after the shock, and the interaction (steel shock effect). Additionally, the model includes quarter fixed effects. Columns 1 and 4 use a matched control group while Columns 2,3,5, and 6 a synthetic control group. Details on the methods are given in Appendix D. Panel B. extends the previous model by including interactions for each quarter with a treatment indicator (the first quarter after treatment is the left-out category). P-values from randomization inference for the synthetic control method are given in brackets in Columns 3 and 6.

Table 8: Descriptive Statistics

	mean	sd.	1st quartile	median	3rd quartile
Panel A. 1990-2000					
Earnings					
base year	29798.14	18324.82	19351.46	27489.76	36986.72
accumulated / base year	1182.09	4826.94	611.66	1003.99	1188.88
yearly / base year	116.55	501.75	68.76	100.81	117.84
Δ Import Exposure					
in base year industry	.257	.474	.031	.143	.329
yearly	.012	.193	-.003	.003	.028
Observations	499,706				
Panel B. 2000-2010					
Earnings					
base year	34823.11	19969.02	23452.34	31808.98	42130.67
accumulated / base year	1196.39	5307.30	811.53	1026.18	1167.24
yearly / base year	117.85	540.70	89.54	101.15	115.33
Δ Import Exposure					
in base year industry	.325	.835	.078	.186	.295
yearly	.008	.346	-.009	.004	.049
Observations	436,735				

Note: The change in import exposure is measured on the 3-digit industry level and computed by the change in imports from the East normalized by the (lagged) wage bill. Results are derived from 5,496,766 yearly observations of 499,706 workers in Panel a. and 4,804,085 observations from 436,735 workers in Panel B. workers. Base year earnings are expressed in 2010 Euros. Accumulated Earnings are added over the entire period and normalized by base year earnings. The change in import exposure is computed for the base year industry over the entire period and on a yearly base for the current industry.

Table 9: Estimation Results - Accumulated Earnings and Job Switch Probabilities

	(1)	(2)	(3)	(4)	(5)	(6)
	all employers	initial firm	endogenous labor market			
			same		other	
Panel A. Accumulated Wages						
same 3-digit industry			yes	no	yes	no
ΔImE	-48.11**	-59.90***	-31.29	48.07***	-8.820***	3.835
	(23.04)	(21.73)	(19.55)	(18.06)	(2.333)	(16.91)
same NUTS-3 region			yes	no	yes	no
ΔImE			5.707	11.06	-5.984	0.998
			(20.61)	(10.11)	(14.52)	(7.521)
Panel B. Job Switch Indicator						
same 3-digit industry			yes	no	yes	no
ΔImE			-0.045***	0.027***	-0.006***	0.024***
			(0.013)	(0.009)	(0.002)	(0.009)
same NUTS-3 region			yes	no	yes	no
ΔImE			-0.035***	0.018**	0.008	0.010**
			(0.011)	(0.008)	(0.005)	(0.005)
1st stage F	12.166					
N	936,392					

Note: Clustered standard errors on the industry times base year level in parentheses. Results are reported for 2SLS estimates of equation (11) where the change in import exposure is instrumented with the corresponding change of exposure in other high-income countries. The decomposition of the total effect is additive such that the difference between the aggregate effect in column (1) and the effect in the initial firm in column (2)results from the sum of the effects in columns (3) to (6). Endogenous labor markets are estimated in the 5 years before the base year with $k = 35$ markets.

Table 10: Estimation Results – Short-run Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ImE	-0.548***	-1.140***	-1.071***	-0.567***	-0.682***	-0.544***	-0.560***
	(0.111)	(0.205)	(0.196)	(0.112)	(0.124)	(0.107)	(0.118)
FE	i	$i \times firm$	$i \times ind.$	$i \times state$	$i \times NUTS3$	$i \times market$ ($k = 9$)	$i \times market$ ($k = 35$)
R^2	0.782	0.910	0.887	0.796	0.841	0.800	0.857
Groups	936,441	1,532,792	1,346,855	1,029,934	1,161,066	984,332	1,101,996
KP	656.1	40.57	39.24	554.9	472.7	580.8	438.5

Note: 10,300,851 observations of 936,441 workers. The main regressor is import exposure, ImE. Further controls include age polynomials, 1-digit-industry × year, state × year, and endogenous market × year dummies. Standard errors, clustered by industry × year in parentheses. KP denotes the Kleinberg-Papp statistic of the first stage. $^{***}p < 0.1$ $^{**}p < 0.05$, $^{*}p < 0.01$

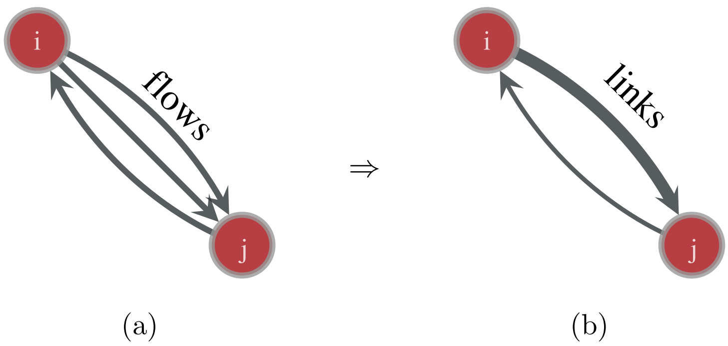


Figure 1: Link Definition Based on Job-to-job Transition

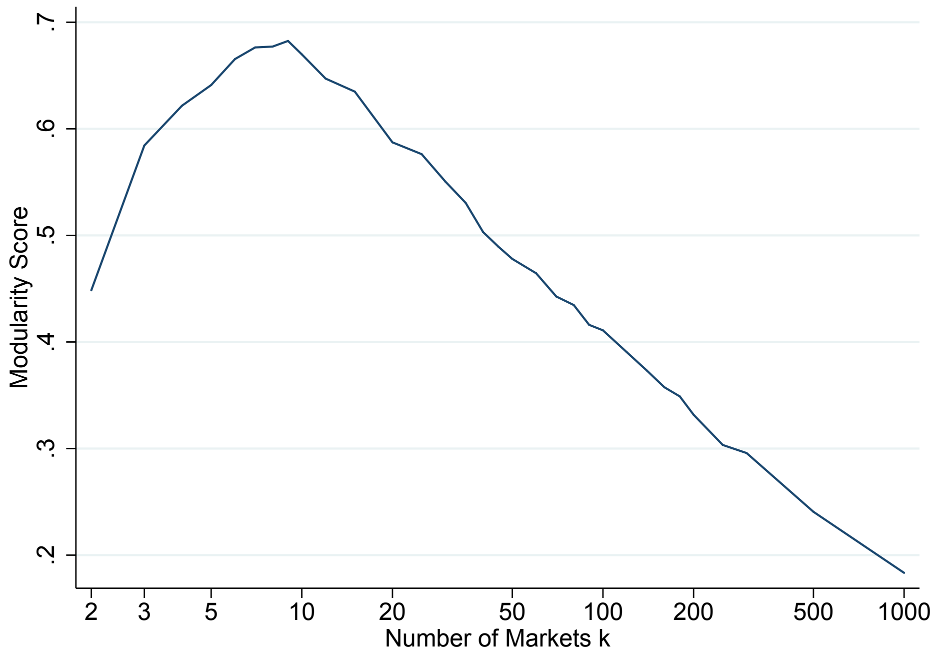


Figure 2: Modularity Score for Varying Number of Groups k in the Job Mobility Network (1975-2005)

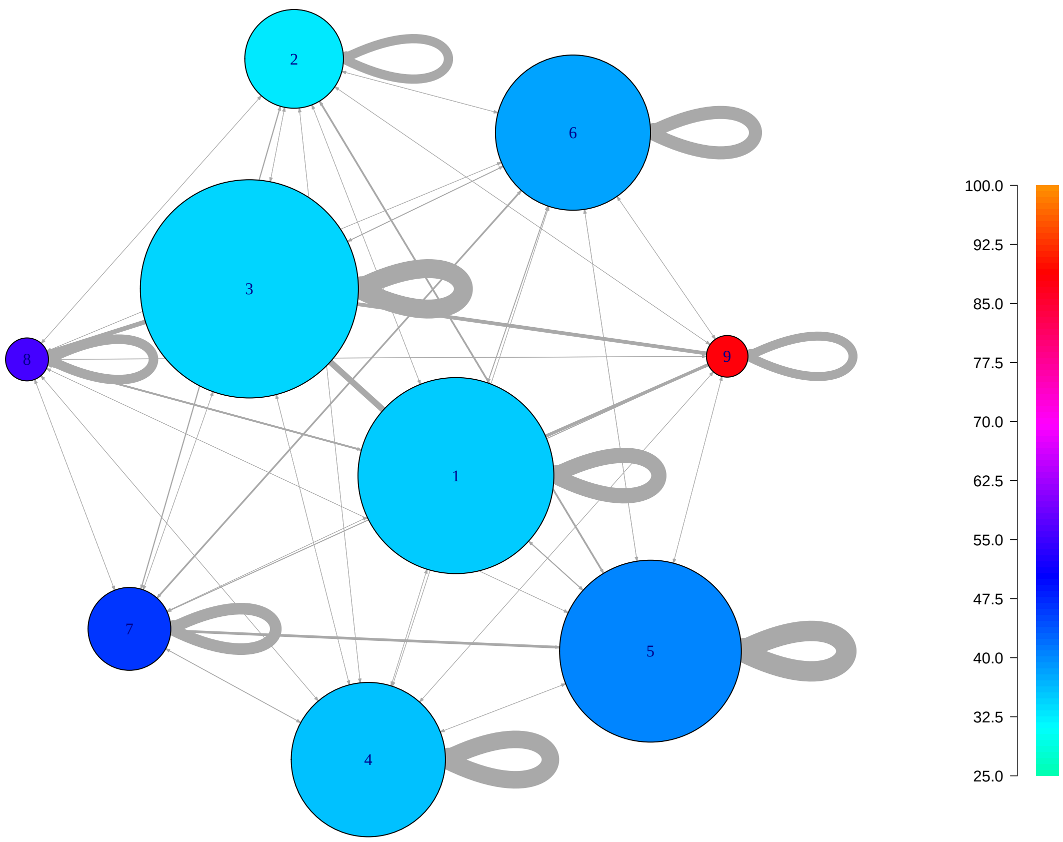


Figure 3: Estimated Block Network (node size ∝ market size, link width ∝ transition probability, colours ∝ avg. firm size)

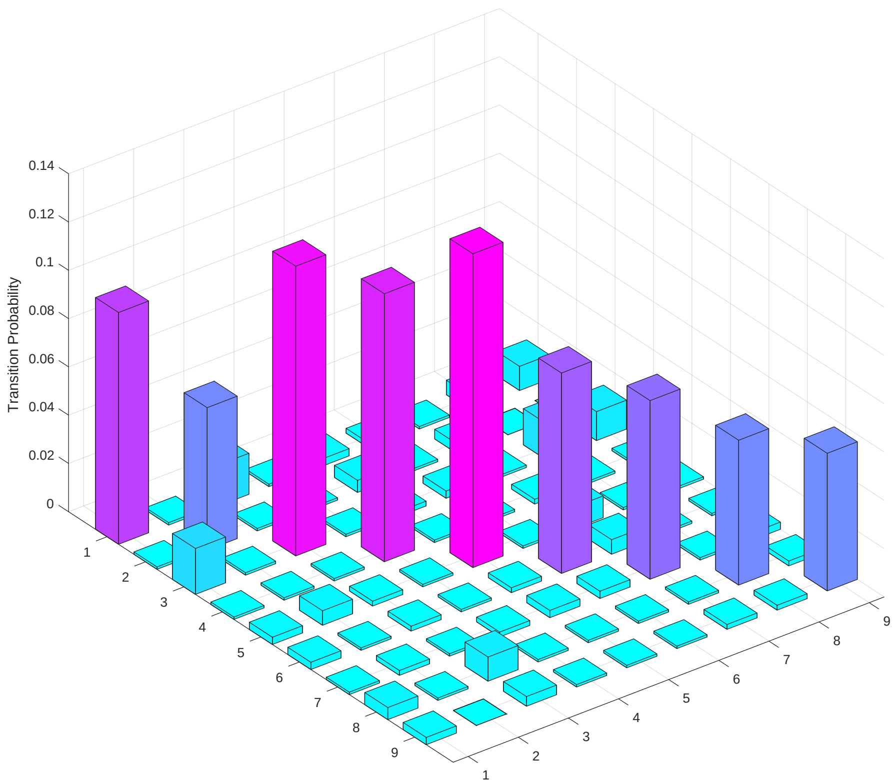


Figure 4: Estimated Transition Probabilities between Markets

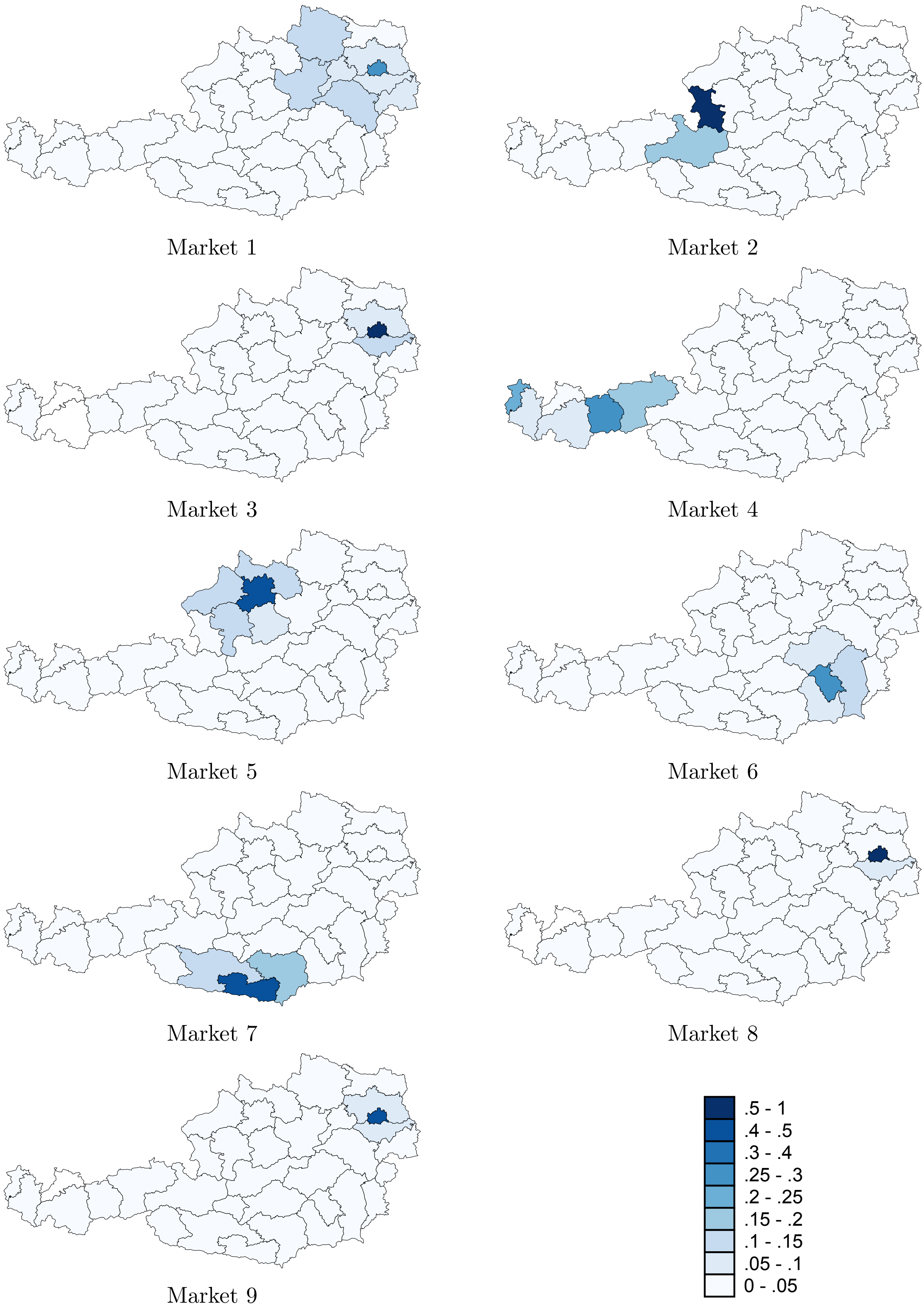


Figure 5: Share of Firms in NUTS-3 Regions for each Market (1975-2005)

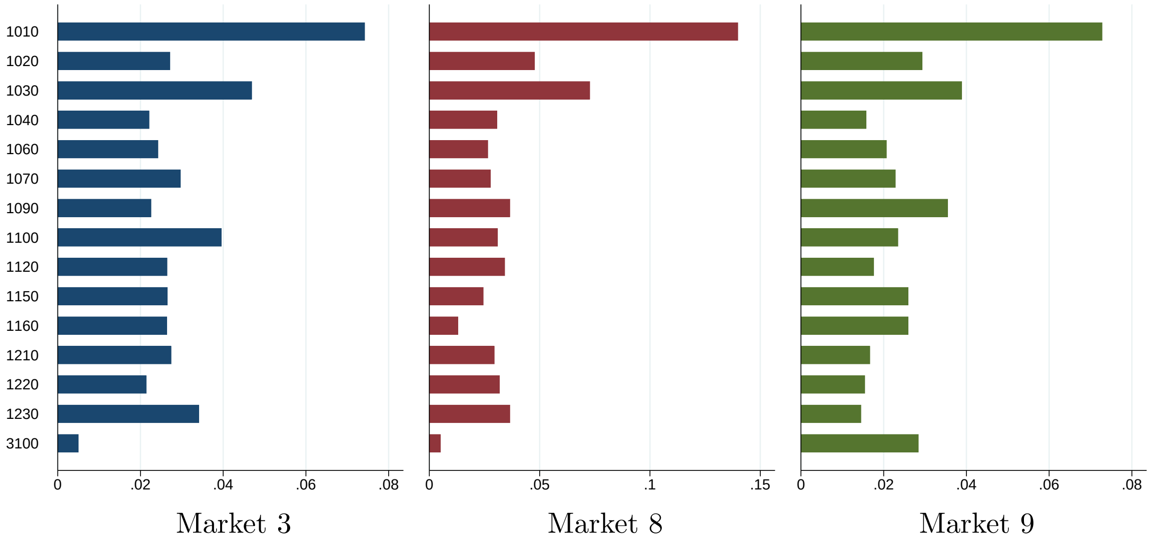


Figure 6: Histogram of Postal Code Areas for Markets in Vienna (1975-2005)

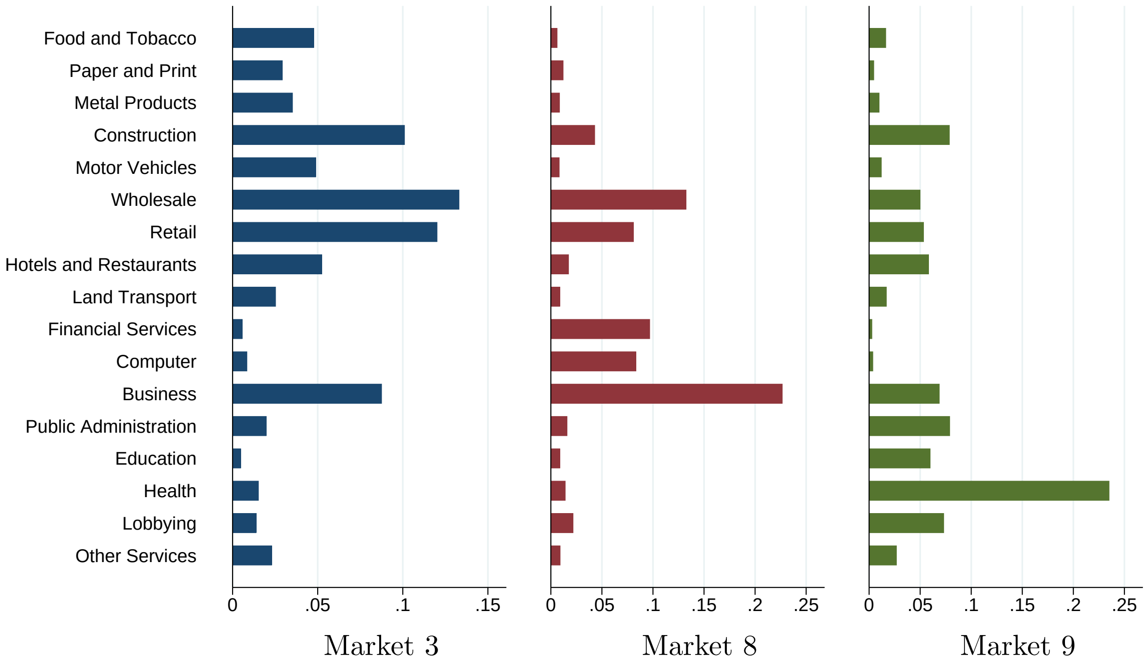


Figure 7: Histogram of 2-digit Industries for Markets in Vienna (1975-2005)

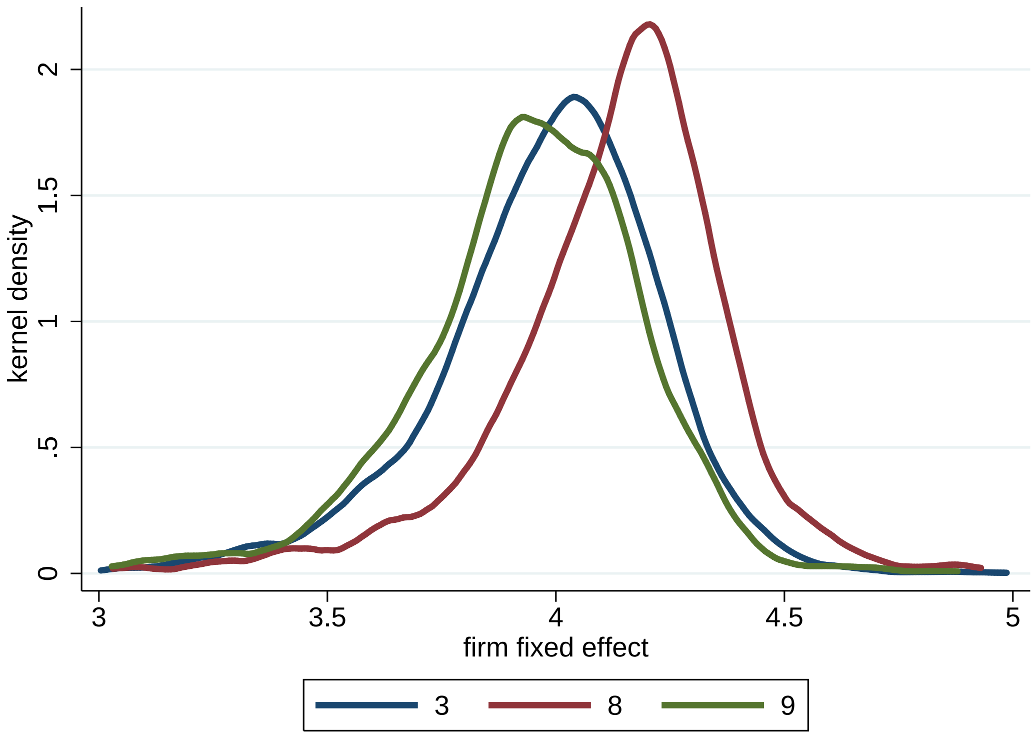


Figure 8: Kernel Density Estimates for the Distribution of Firm Fixed Effects for Markets in Vienna (1975-2005)

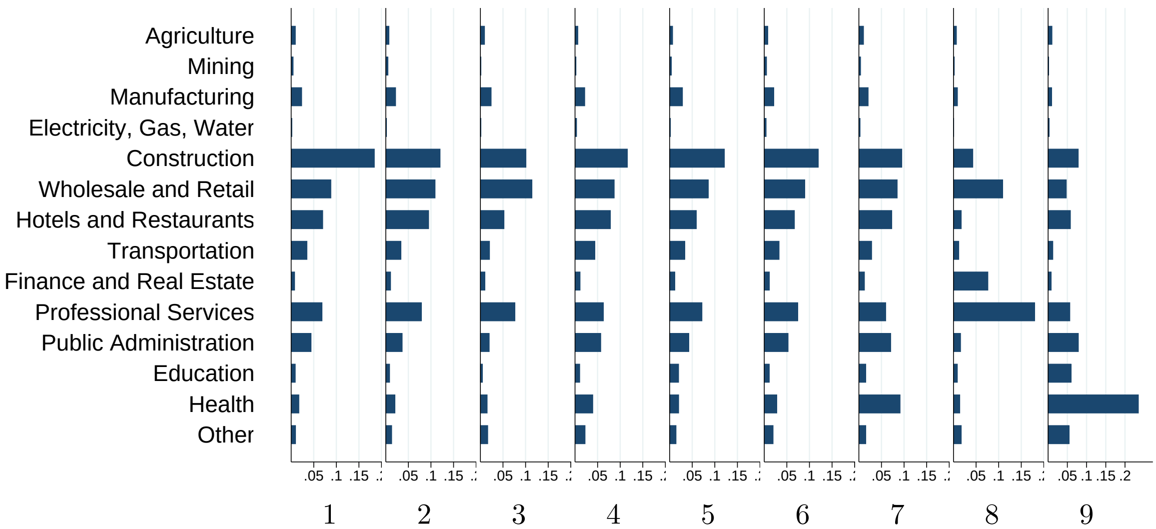


Figure 9: Histogram of Industry Composition by Market (1975-2005)

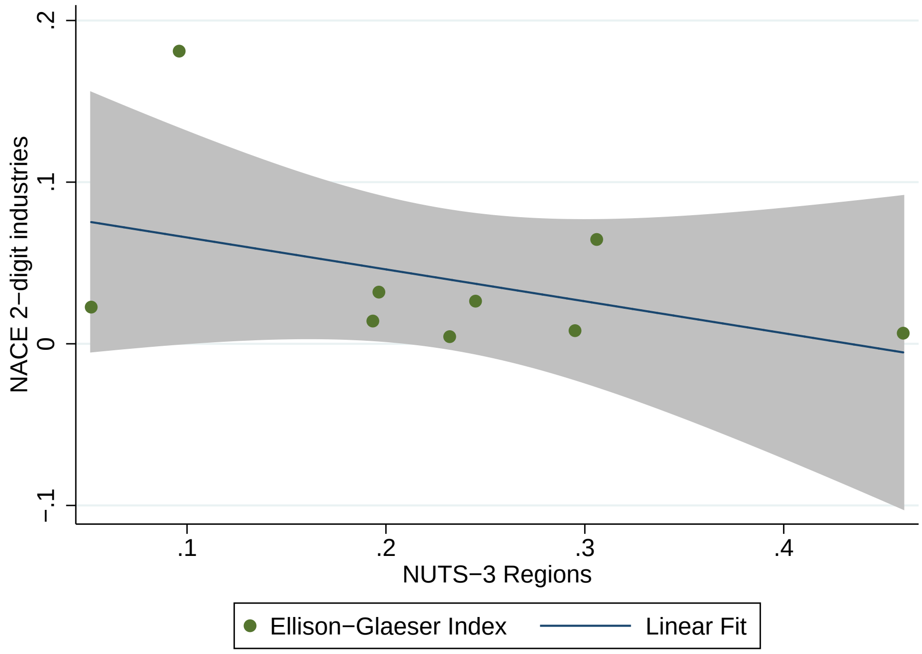


Figure 10: Ellison-Glaser-Index Regional and Industry Concentration (1975-2005)

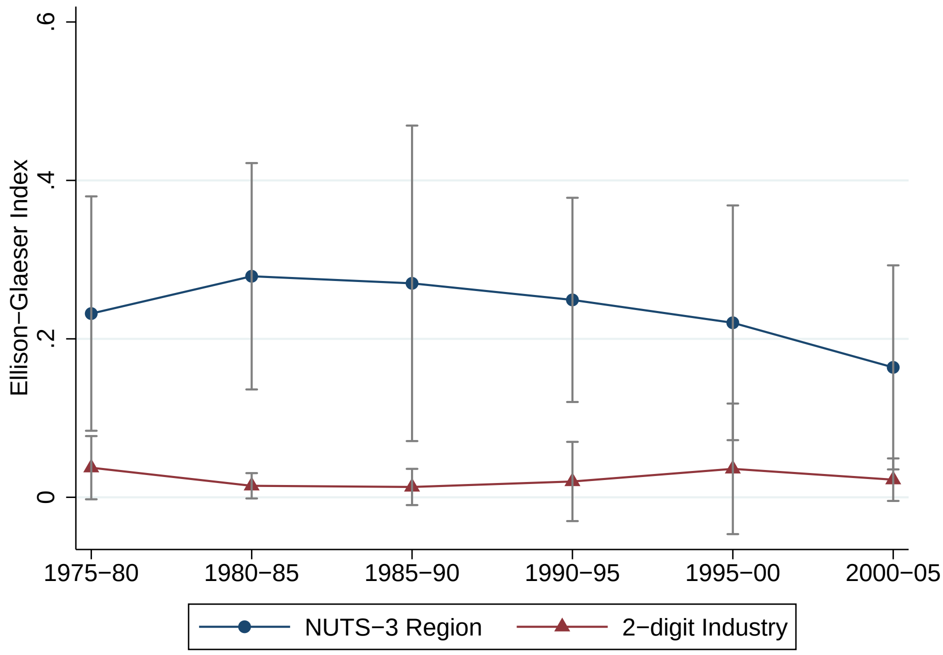
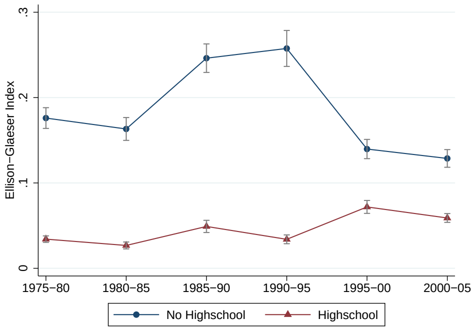


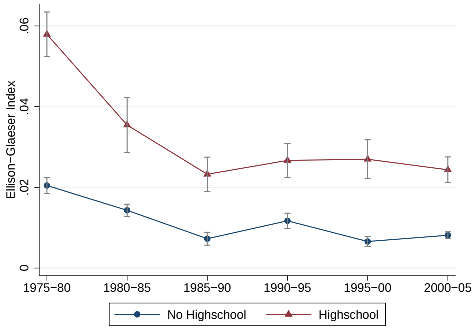
Figure 11: Ellison-Glaser-Index of NUTS-3 Region and Industry Concentration over Time

Figure 12: Concentration Indices for Markets based on Job-to-job Transitions of Sub-groups

(a) Education

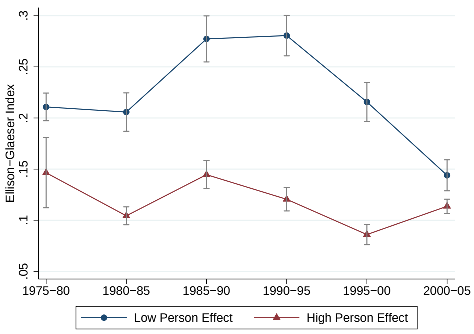


NUTS-3

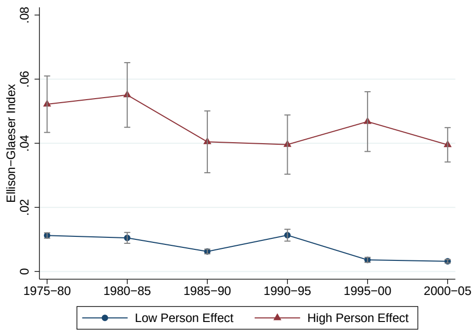


2-digit Industry

(b) Individual Fixed Effect

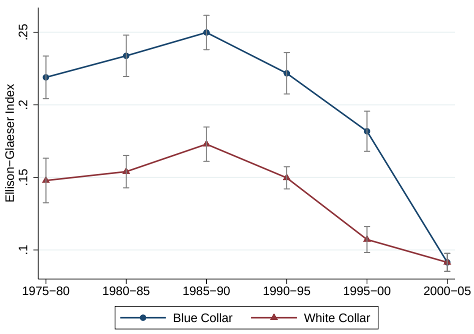


NUTS-3

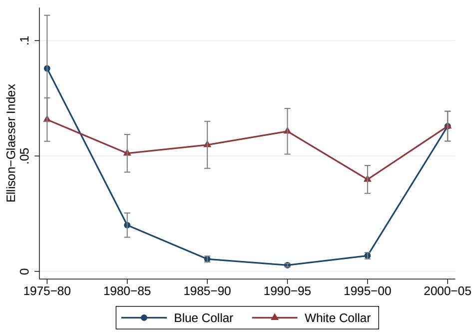


2-digit Industry

(c) Occupation

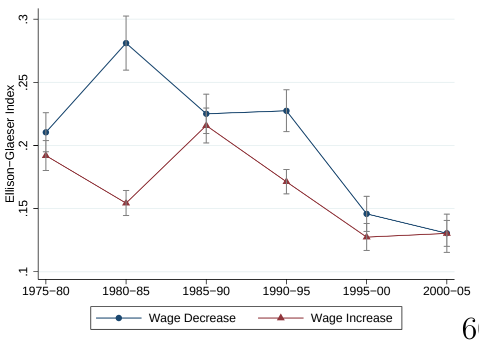


NUTS-3



2-digit Industry

(d) Wage Change

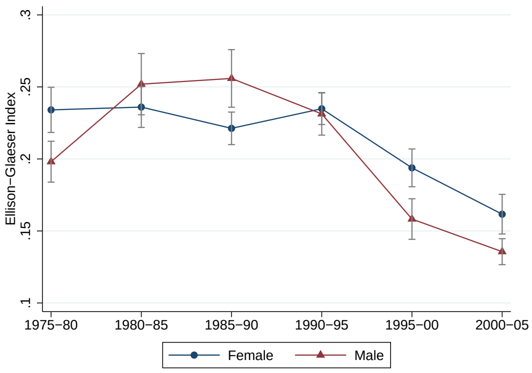


NUTS-3

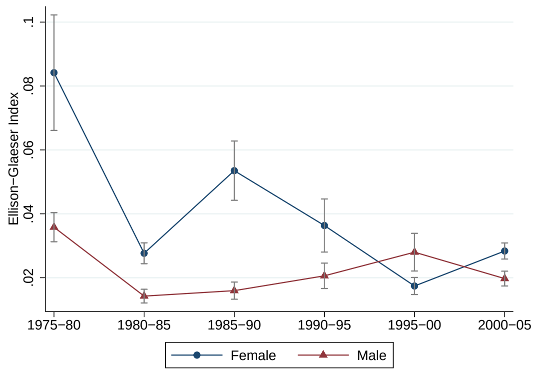
2-digit Industry

Figure 13: Concentration Indices for Markets based on Job-to-job Transitions of Subgroups

(a) Gender

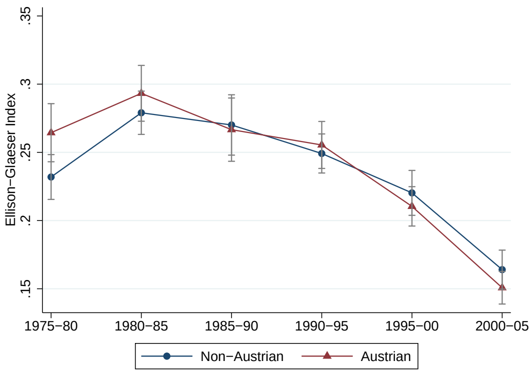


NUTS-3

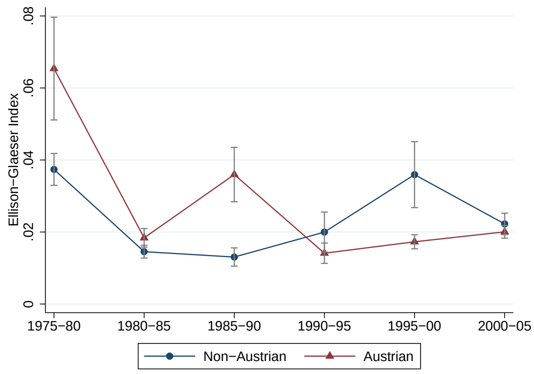


2-digit Industry

(b) Nationality

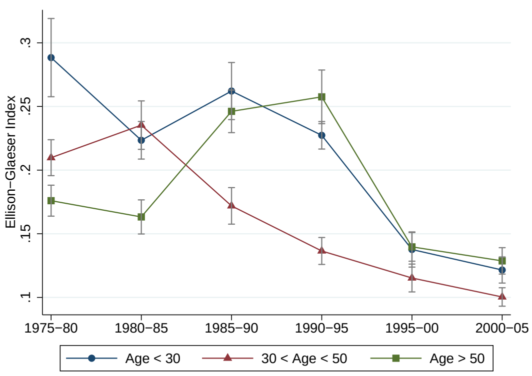


NUTS-3



2-digit Industry

(c) Age Groups

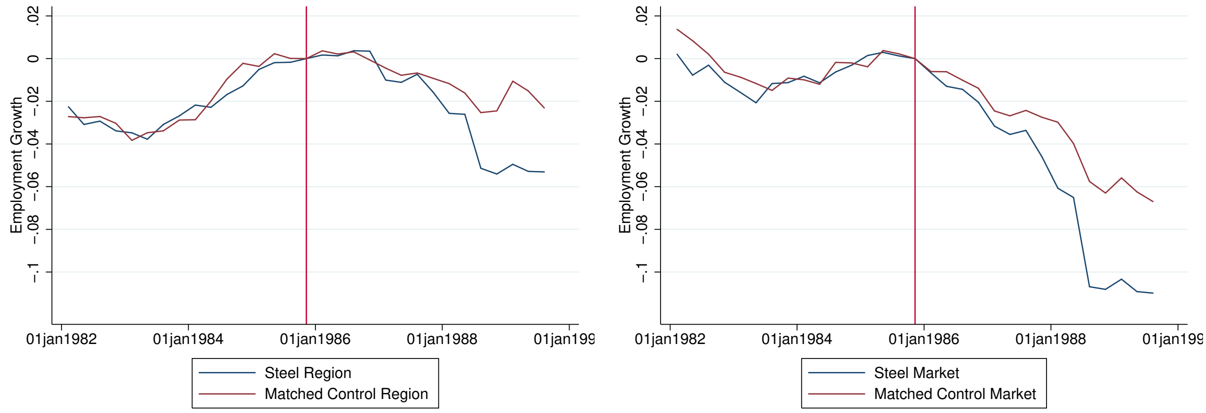


NUTS-3

2-digit Industry

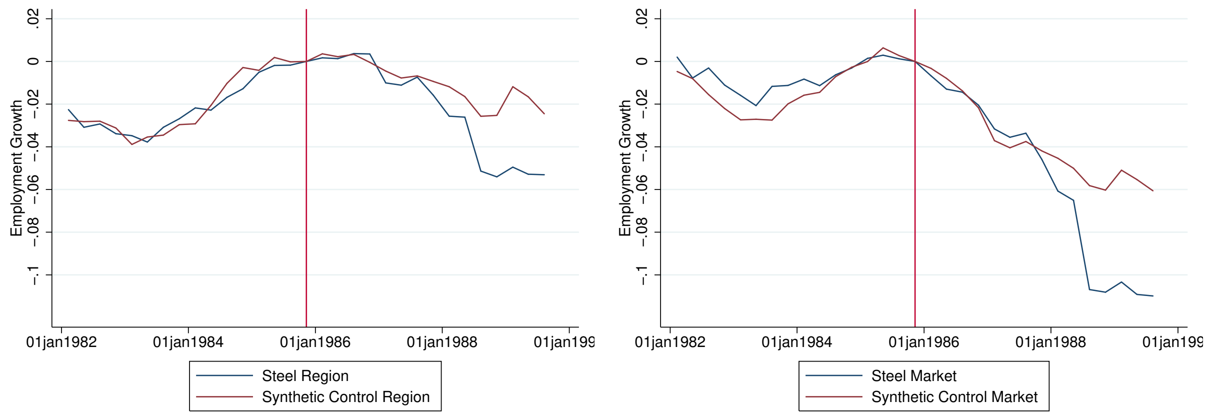
Figure 14: Employment Growth in Non-steel Firms

(a) Matched Control Group

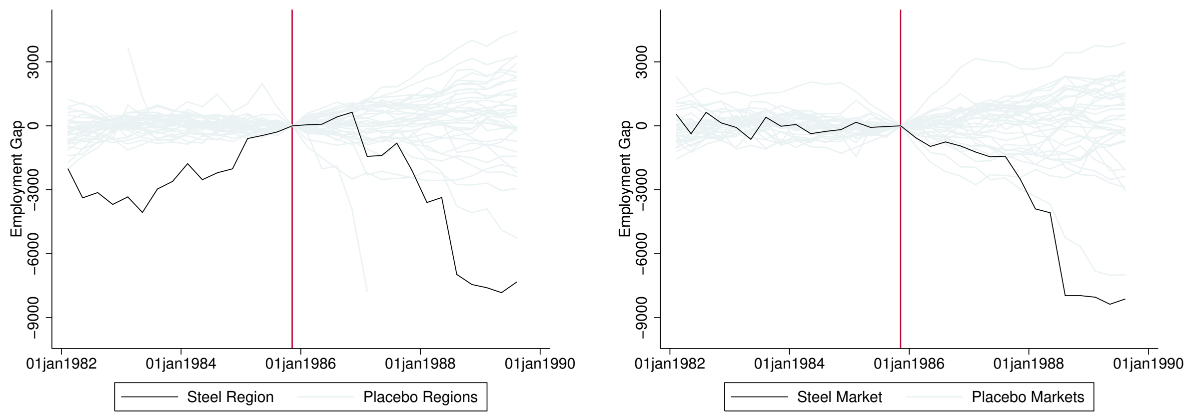


Regional Spillovers | Market Spillovers

(b) Synthetic Control Group

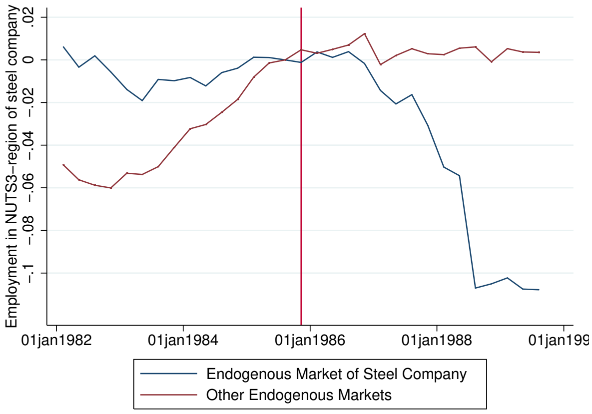


Regional Spillovers | Market Spillovers

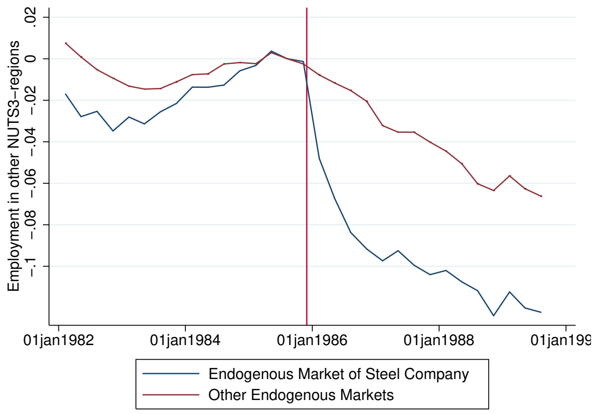


(a) Regional Spillovers | (b) Market Spillovers

Figure 15: Employment Gap between Treated and Synthetic Control with Placebo Treatments

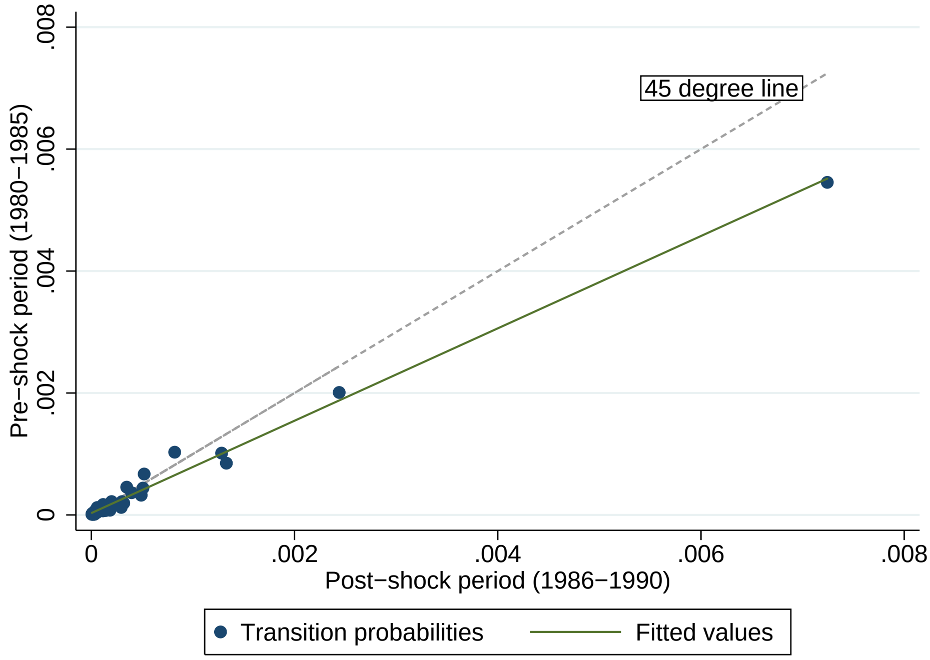


(a) Steel Region (Linz-Wels)

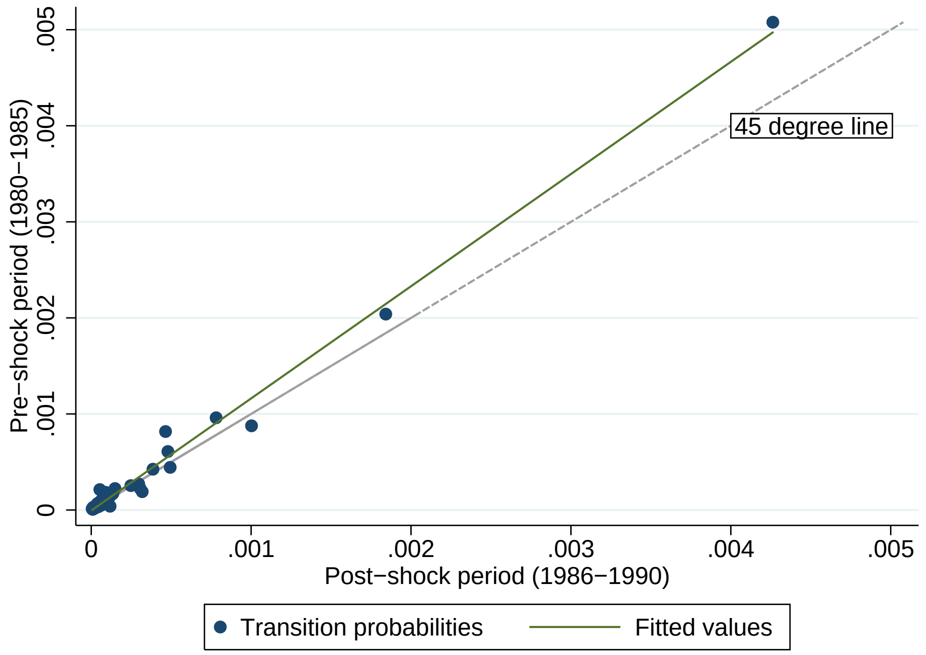


(b) All Other Regions

Figure 16: Employment Growth in Non-steel Firms by Endogenous Labor Market



(a) Transitions out of Shocked Market



(b) Transitions into Shocked Market

Figure 17: Transition Probabilities Before and After the Labor Demand Shock in the Endogenous Market of the Steel Company

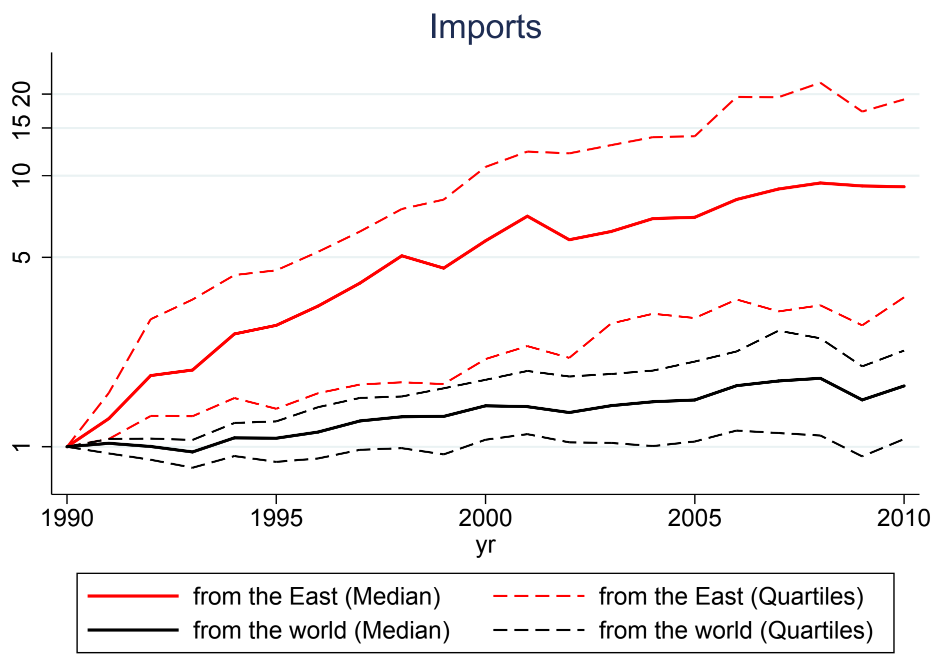


Figure 18: Rising Import Volumes in Austrian Trade

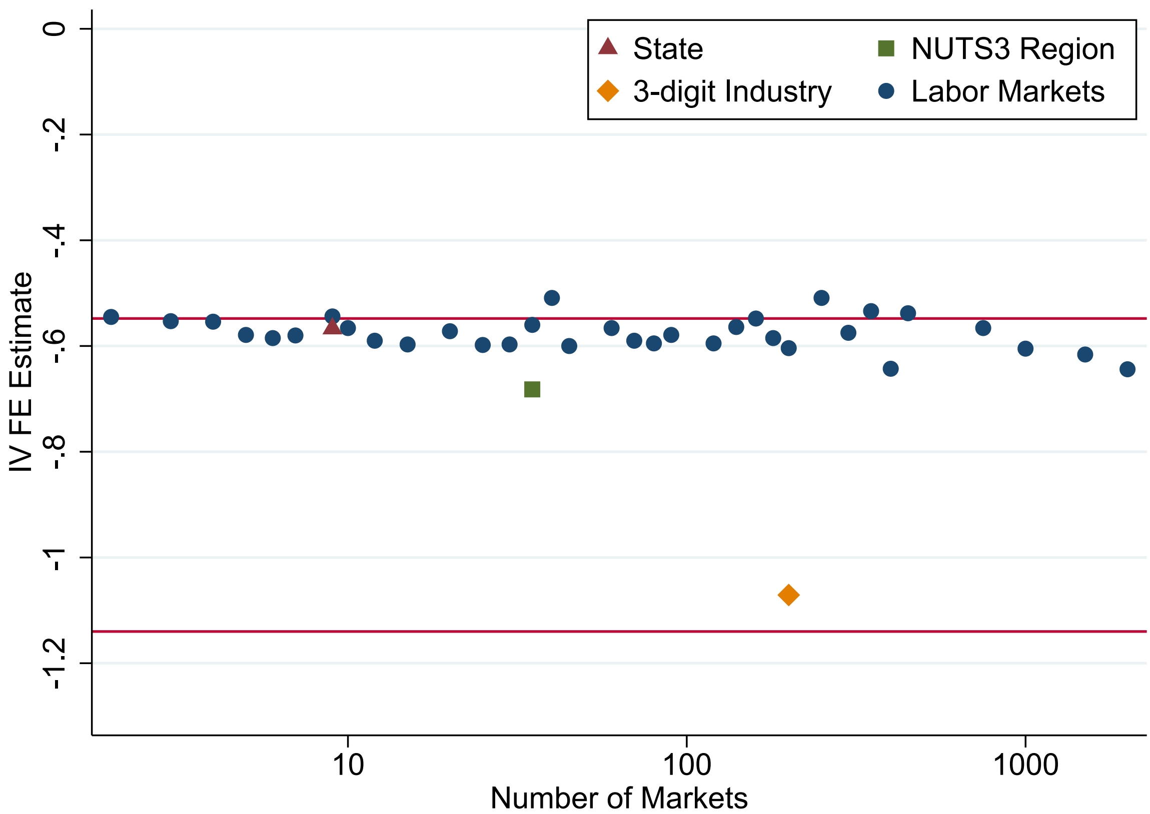


Figure 19: Impact of Trade Shock on Annual Earnings - Various Models

Supplemental Online Appendix

A Network Definition and Characteristics

A.1 A formal definition of the job mobility network

Let M be the set of firms in the economy and W be the set of workers in the economy. Further, let $t \in \{1, \ldots, T\}$ denote the time in days during the sample period. I define a function $m = m(w,t) \in M$ that returns the firm that employs worker w at time t. Then we have the following definition of the entries in the adjacency matrix of a directed and weighted network:

$$
\begin{aligned}
A_{ij} = |\omega| \quad \text{where} \quad \omega = \{w \mid \exists\, t \in T,\ 1 \leq x \leq 30 \text{ s.th.} \\
& m(w, t-365) = \cdots = m(w,t) = i \\
& m(w, t+x) = m(w, t+x+1) = \cdots = m(w, t+x+365) = j \\
& m(w, t+1), \ldots, m(w, t+x-1) \notin M\}.
\end{aligned}
$$

While the set of firms M contains all firms that exist in the economy during the sample period, the set of nodes in the network, N, contains only non isolates:

$$N = M \setminus \{i \in M \mid A_{ij} = 0\ \forall j \ \wedge\ A_{ji} = 0\ \forall j\}. \tag{13}$$

A.2 Empirical Network Characteristics

In this section, I provide additional information on the empirical characteristics of the job mobility network described in section 3. Table A5 provides various characteristics of the job mobility network. Again, column 1 refers to the full network obtained from transitions between 1975 and 2005 while the other columns show dynamic developments between shorter periods.

Panel A of Table A5 displays the most important network characteristics that describe the general structure of the job mobility network. The *average degree* in the network denotes the average number of transitions per firm. On average, a firm is connected to 19.84 other firms in the full network. The average degree is naturally lower when considering shorter time periods and tends to slightly rise over time. The ease of information flows in a network can be measured by the notion of distance between nodes. In the job mobility network, the shortest path between the two most distant firms (called *diameter* of the network) requires 17 steps (row 2). The average number of steps along the shortest paths between all possible pairs of firms in the network amounts to 4.87 steps (*average path length* in row 3). The density of the job mobility network is very sparse as only a tiny fraction of all possible links materializes (*graph density* in row 4). Finally, the *clustering coefficient* (row 5) measures the transitivity of a network, i.e., the probability that two firms with common links to a third firm are linked among themselves. Transitivity in the job mobility network is relatively low compared to other social networks as only 2-4% of all potential triangles materialize.[41] This finding suggests that, on the very local level of three firms, job-to-job mobility is not particularly clustered. In the descriptive analysis in section 5, I specifically show that job-to-job transitions are clustered on a broader labor market level rather than on subsets of a few firms.

Aggregated network characteristics such as the average degree potentially hide substantial heterogeneity within the network. In the present case, many firms in the job mobility network are involved only in a low number of job-to-job transitions while others have many connections and serve as "hubs" in the economy. This is documented by the (complementary) CDF of the degree distribution in Figure E.10. The black circles represent the empirical CDF of the degree distribution on a log-log scale. Like in many social networks, the degree distribution of the job mobility network exhibits heavy tails, as there are more nodes with very small and very large degrees than expected in a model where links are formed uniformly at random (Jackson, 2008).

In an influential paper, Jackson and Rogers (2005) analyze the interdependence between the process of link formation in social networks and the degree distribution. In a nutshell, a model where new nodes form links to existing ones *uniformly at random* is consistent with an exponential degree distribution. In contrast, a model of *preferential*

[41] The clustering coefficient in the job mobility network is higher than it would be if links were formed purely random (19.84/95237 = 0.0002). However, Jackson (2008) reports much higher coefficients obtained from various other social networks.

attachment, where the probability to receive links for existing firms is proportional to their current degree, is consistent with a degree distribution that follows a power law.

The colored lines in Figure E.10 therefore show maximum likelihood fits from both, the exponential distribution (in blue) and the power law distribution (in red). The parameter estimates of the fitted distributions are given in the first two rows of panel B in Table A5. Neither of these distributions is a good fit for the degree distribution of the job mobility network.

Most empirical networks are somewhere in between the extreme cases of random link formation and preferential attachment. Jackson and Rogers (2005) therefore develop a hybrid model where a fraction r of links is formed uniformly at random while the remainder is generated based on preferential attachment. The green line in Figure E.10 displays the fit of this hybrid model which is much closer to the observed degree distribution. The estimate in the third row of panel B in Table 2 indicates that 39% of links in the job mobility network are formed uniformly at random while the majority of 61% are formed through network-based link generation.[42]

Summing up, there is strong evidence for preferential attachment in the link formation process. In particular, workers tend to join firms that received an influx of many other workers and leave firms that are left by many others. Although not taking a dynamic perspective on link formation, I specifically address this form of firm-level heterogeneity in the model for the estimation of endogenous labor markets in section 4 by including popularity parameters that guide the individual attractiveness of firms to workers.

B Additional Derivations

If match-quality draws are distributed according to the Frechét distribution, the probability that worker ℓ starting in firm i has a payoff higher than some threshold ϕ in firm

[42]Figure E.11 illustrates the degree distribution and parametric fits for the shorter time periods. Although the share of random and network based link formation varies to some extend, the general picture is very stable over time.

j is

$$Pr[\phi_j(\ell|i) > \phi] = 1 - F_j\left(\frac{\phi d_{z_i z_j}}{p_j f[X_\ell]}\right) = 1 - e^{-T_j d_{z_i z_j}^{-\theta}(p_j f[X_\ell])^\theta \phi^{-\theta}} \tag{14}$$

and the probability that the payoff is lower than ϕ in all other firms $s \neq j$ is

$$Pr[\phi_s(\ell|i) \leq \phi, \forall s \neq j] = \prod_{s \neq j} F_s\left(\frac{\phi d_{z_i z_s}}{p_s f[X_\ell]}\right) = \prod_{s \neq j} e^{-T_s d_{z_i z_s}^{-\theta}(p_s f[X_\ell])^\theta \phi^{-\theta}} \tag{15}$$

As a result, the probability that j offers the highest payoff of all firms for a worker ℓ who starts in i is

$$\begin{aligned}
\pi_{ij}(\ell) &= Pr[\phi_j(\ell|i) \geq \max_s\{\phi_s(\ell|i)\}] \\
&= \int_0^\infty Pr[\phi_s(\ell|i) \leq \phi, \forall s \neq j] dPr[\phi_j(\ell|i) \leq \phi] \\
&= \frac{T_j d_{z_i z_j}^{-\theta} p_j^\theta}{\sum_{s=1}^N T_s d_{z_i z_s}^{-\theta} p_s^\theta}
\end{aligned}$$

C Simulation

In order to evaluate the performance of estimating the degree-corrected stochastic block model, I conduct a Monte-Carlo simulation exercise that compares the SBM to using predefined regions in a stylised economy.

The economy consists of N firms $i = \{1, \ldots, N\}$ that are located in either of two regions $r_i \in \{1, 2\}$. With probability τ a firm resides in region 1 and with probability $1-\tau$ it resides in region 2. Hence, varying the parameter τ allows to examine the robustness of the model to changes in the relative size of the regions. The actual market assignments, however, are governed by an "unobserved" characteristic z which can be correlated with the region membership. The unobserved characteristic $z_i \in \{1, 2\}$ can take two distinct values and is distributed conditional on the region membership as follows: $P(z_i = r_i) = \lambda, P(z_i \neq r_i) = 1-\lambda$. Hence, varying the parameter λ from 1 (perfect positive correlation) to 0 (perfect negative correlation) determines in how far region membership guides actual market assignment. The firms in the economy are furthermore characterised by degree parameters γ_i. Degrees are drawn from a power law distribution with minimum expected degree of x_{min} and parameter α. The degree parameters γ_i are then determined fixed according to equation (8). The transition matrix between the markets is set to

$$M = \rho \begin{pmatrix} 4 & 1 \\ 1 & 4 \end{pmatrix},$$

where ρ is chosen such that it fixes the overall expected degree of the network. Finally, links between firms i and j in the economy are drawn from the Poisson distribution with mean $\gamma_i \gamma_j M_{z_i z_j}$.

The parameters in the simulation study are chosen as follows: There are $N = 1000$ firms. The group sizes are balanced in a version with $\tau = 0.5$ and unbalanced in a version with $\tau = 0.75$. The power law resembles the actual degree distribution found in the Austrian job mobility network with $x_{min} = 20$ and $\alpha = 2.5$. Similarly, ρ is chosen such that the overall average degree equals 8 as in the empirical network. To compare the solution of estimating the SBM to the true assignments and to the use of the region membership, I use the adjusted Rand index of Hubert and Arabie (1985) and the normalized mutual information criterion of Danon, Diaz-Guilera, Duch, and Arenas (2005). These indices are commonly used to measure the similarity between partitions in clustering and network analysis. Both measures are scaled such that 1 corresponds to a perfect match between two partitions while a value of 0 zero would be expected for two random partitions.

Figure **??** displays the median adjusted Rand index over 100 replications varying the correlation coefficient between regions and group assignments from 1 to 0. In panel a, the group sizes are balanced. As expected, the concordance of the predefined regions with the true group assignments decreases with a declining correlation between the two random variables. When λ equals 0.5 group assignments are independent from region membership and the Rand index approaches 0. In contrast, the degree-corrected SBM does not depend on the region membership and therefore constantly achieves high scores of the adjusted Rand index which are of similar magnitude as the simulation results for sparse networks in Zhao et al. (2012). The results in an unbalanced setting (panel b) are very similar. The estimation of the SBM, however, is a bit less precise as indicated by the standard error bars.

The results of this simulation study indicate that even for slight deviations from perfect congruence of regions and relevant labor markets, it is favorable to base the analysis on the degree-corrected SBM proposed in this paper. The fact that the SBM does not rely on observed covariates but infers the group structure solely based on observed links enables a stable detection of relationships independent of whether the relevant covariates are known or available.

D Contructing Counterfactuals

In this section, I provide details on the matching procedure and the synthetic control method used in the analysis of spillover effects in Section 6. I use quarterly firm-level employment data from the ASSD and aggregate employment on the NUTS-3 regional level and on the level of $k = 35$ endogenous labor markets, respectively. Endogenous labor markets are estimated in the period prior to the steel shock, i.e., based on job-to-job transitions between 1980 and 1985. Seasonality in employment and wage data is smoothed away by a moving average of length 5.

D.1 Matching

The matching procedure is based on nearest-neighbor Mahalanobis distance matching. The matching variables are industry composition, average worker age, share of white collar workers, and share of blue collar workers. Industry compostition is measured by the share of workers in 14 broad industries (Agriculture; Mining; Manufacturing; Electricity, Gas, and Water; Contruction; Wholesale and Retail Sale; Hotels and Restaurants; Transportation; Finance and Real Estate; Professional Services; Public Administration; Education; Health; Other). I do not match on outcomes, i.e., on employment or wages.

Distance between observations i and j is determined by the Mahalanobis distance measure

$$d_{match}(i,j) = \sqrt{(x_i - x_j)' S^{-1} (x_i - x_j)} \tag{16}$$

where $x_i = (x_{1it}, x_{2it}, \ldots, x_{nit})$ is the vector of matching variables for unit i stacked for all pre-treatment periods t and S^{-1} is the inverse of the covariance matrix of all matching variables.

Table 6 evaluates covariate balance for regional labor markets and endogenous labor markets. The steel region in Column 1 (steel market in Column 5) is substantially different from the average Austrian region in Column 2 (market in Column 6). This is true both for non-matched characteristics such as employment in the last quarter before treatment, employment growth between Oct. 1982 and Oct. 1985, mean wages, and wage growth, as well as for matched characteristics, in particular the industry composition. Matching (Columns 3 and 7), however, narrows down the differences substantially.

D.2 Synthetic Control Method

In order to deal with the fact that the treatment group in the entire analysis consists of a single unit, I perform a second counterfactual analysis using the synthetic control method (Abadie and Gardeazabal, 2003; Abadie, Diamond, and Hainmueller, 2010, 2015) which particularly suits the examination of quantitative case studies and provides a nice framework for (permutation) inference. In contrast to the matching procedure, synthetic control groups are constructed using the outcome variable to compare pre-intervention matches. Additionally, I choose the same set of variables as in the case of matching as predictor variables. Rather than selecting a single control unit that is closest to the treatment unit, the synthetic control method constructs a counterfactual that resembles the treatment unit using a weighted average of units from the pool of non-treated units. Let x_i be a a vector of pre-treatment characteristics for the treatment unit i including the outcome variable. Further, let $X_{-i} = (x_1, \ldots, x_{i-1}, x_{i+1}, x_{J+1})$ be the matrix of pre-treatment characteristics of all units except i. Then, the synthetic control method determines the distance between the treatment unit i and a synthetic control s as

$$d_{synth}(i,s) = \sqrt{(x_i - X_{-i}W)'V^{-1}(x_i - X_{-i}W)} \tag{17}$$

where W is a $J \times 1$ vector of weights that is chosen to minimize d_{synth} and V^1 is chosen among positive definite and diagonal matrices such that the mean squared prediction error of the outcome variable is minimized for the pre-intervention periods (Abadie and Gardeazabal, 2003). Table 6 shows that the synthetic control method further shrinks the difference between treatment and control group.

Inference in the synthetic control method can be obtained by permutation of the treatment group. In particular, all potential control units iteratively serve as a placebo treatment and receive a synthetic control. The gap between the actual treatment group and it's synthetic control is then compared to the distribution of all placebo gaps. Figure 15 depicts the actual treatment gap (solid black line) compared to all placebo gaps (light grey lines) and indicates that the size of the treatment gap indeed stands out. The share of placebo treatment gaps that are larger than the actual treatment gap serves as a p-value for inference in the synthetic control framework. Table 7 reports p-values in this sense for each quarter relative to the treatment quarter.

E Additional Tables and Figures

Table A1: Transition Probabilities and Market Characteristics

Market ID	1	2	3	4	5	6	7	8	9
Panel A. Transition Probabilities									
1	.096	.001	.017	.001	.003	.002	.001	.006	.010
2	.001	.059	.001	.001	.005	.001	.004	0	0
3	.019	.001	.12	.001	.002	.003	.001	.015	.012
4	.001	.001	.001	.111	.001	.001	.002	.001	.001
5	.003	.006	.002	.001	.13	.001	.009	.001	.001
6	.003	.001	.002	.001	.002	.083	.006	.001	.001
7	.001	.002	.001	.002	.003	.003	.074	.001	.003
8	.005	.001	.01	.001	.001	.001	.001	.06	.002
9	.003	0	.004	.001	.001	.001	.002	.002	.057
Panel B. Market Characteristics									
Mode state	NOE	Stm.	Wien	Tirol	OOE	Szbg	Ktn	Wien	Wien
Share in mode state	0.56	0.80	0.63	0.58	0.91	0.80	0.76	0.69	0.48
Mode Industries	Constr. Retail Business	Retail Constr. Hot.& Rest.	Wholesale Retail Constr.	Constr. Retail Wholesale	Constr. Retail Wholesale	Constr. Retail Wholesale	Retail Constr. Health	Business Wholesale Finance	Health Publ. Adm. Constr.
Share in mode industry	0.18	0.14	0.13	0.09	0.10	0.09	0.09	0.22	0.23
Avg. firm size	31.738 (108.02)	28.910 (108.98)	30.966 (100.32)	32.736 (126.03)	38.341 (262.15)	35.468 (162.31)	46.051 (327.12)	58.203 (265.10)	101.168 (910.68)
Observations	15666	7890	17439	12332	14535	12401	6618	3431	3324

Note: Standard deviations in parenthesis. Panel a. of this table presents the estimated transition probability matrix $\hat{M}$ from the SBM indicating transition probabilites within and between markets. Panel b. reports market characteristics for each market. Note that for some firms industry information is missing. The entries in the 3rd row refer to the three most common non-missing industries.

Table A2: Industries with Highest Increase in Exports to the East over 1990 to 2010

NACE 3-digit industry		Percent increase
202	Panels and boards of wood	62.57
296	Weapons and ammunition	29.56
233	Nuclear fuel	24.52
204	Wooden containers	21.83
265	Cement, lime and plaster	18.93
153	Fruits and vegetables	15.71
264	Bricks, tiles and construction products	15.01
171	Textile fibres	12.60
353	Aircraft and spacecraft	10.36
191	Tanning and dressing of leather	10.28
151	Meat products	9.70
172	Textile weaving	8.32
176	Knitted and crocheted fabrics	7.92
342	Bodies for motor vehicles, trailers	7.52
341	Motor vehicles	6.46
181	Leather clothes	6.14
354	Motorcycles and bicycles	6.02
293	Agricultural and forestry machinery	5.89
334	Optical instruments and photographic equipment	5.78
343	Parts and accessories for motor vehicles	5.40
314	Accumulators, primary cells and primary batteries	4.26
183	Dressing and dyeing of fur; articles of fur	4.11
274	Basic precious and non-ferrous metals	3.87
192	Luggage, handbags, saddlery and harness	3.64
193	Footwear	3.59

Table A3: Industry Composition of Endogenous Steel Market outside Linz-Wels

NACE 3-digit industry		Share of employment
452	Building of complete constructions	7.30
341	Manufacture of motor vehicles	6.95
361	Manufacture of furniture	5.66
751	Administration of the State	3.66
247	Manufacture of man-made fibres	3.24
524	Retail sale in specialized stores	3.24
287	Manufacture of other fabricated metal products	3.21
182	Manufacture of wearing apparel and accessories	2.59
602	Other land transportation	2.22
453	Building installation	1.96
293	Manufacture of agricultural and forestry machinery	1.91
193	Manufacture of footware	1.84
502	Maintainance and repair of motor vehicles	1.76
651	Monetary intermediation	1.73
211	Manufacture of pulp, paper amd paperboard	1.67
159	Manufacture of beverages	1.55
295	Manufacture of other special purpose machinery	1.54

Note: This table reports NACE 3-digit industry affiliations of the firms in endogenous labor market of the steel company but outside the NUTS3 region Linz-Wels for the years 1980-1990. The share for each industry is weighted by employment.

Table A4: Industries with Highest Increase in Imports from the East over 1990 to 2010

NACE 3-digit industry		Percent increase
283	Steam generators	183.96
354	Motorcycles and bicycles	160.23
233	Nuclear fuel	63.10
341	Motor vehicles	51.43
243	Paints, coatings, printing ink	48.76
322	TV, and radio transmitters, apparatus for line telephony	46.46
312	Electricity distribution and control apparatus	46.03
267	Cutting, shaping, finishing of stone	40.08
176	Knitted and crocheted fabrics	38.55
222	Printing	38.02
245	Detergents, cleaning and polishing, perfumes	30.98
273	Other first processing of iron and steel	19.79
343	Parts and accessories for motor vehicles	19.66
221	Publishing	18.45
282	Tanks, reservoirs, central heating radiators and boilers	17.82
291	Machinery for production, use of mech. power	16.99
313	Isolated wire and cable	15.46
183	Dressing and dyeing of fur; articles of fur	14.89
314	Accumulators, primary cells and primary batteries	14.78
295	Other special purpose machinery	12.10
268	Other non-metallic mineral products	12.03
342	Bodies for motor vehicles, trailers	11.85
316	Electrical equipment n. e. c.	11.82
334	Optical instruments and photographic equipment	11.75
177	Knitted and crocheted articles	11.50

Table A5: Industries with Highest Increase in Exports to the East over 1990 to 2010

NACE 3-digit industry		Percent increase
202	Panels and boards of wood	62.57
296	Weapons and ammunition	29.56
233	Nuclear fuel	24.52
204	Wooden containers	21.83
265	Cement, lime and plaster	18.93
153	Fruits and vegetables	15.71
264	Bricks, tiles and construction products	15.01
171	Textile fibres	12.60
353	Aircraft and spacecraft	10.36
191	Tanning and dressing of leather	10.28
151	Meat products	9.70
172	Textile weaving	8.32
176	Knitted and crocheted fabrics	7.92
342	Bodies for motor vehicles, trailers	7.52
341	Motor vehicles	6.46
181	Leather clothes	6.14
354	Motorcycles and bicycles	6.02
293	Agricultural and forestry machinery	5.89
334	Optical instruments and photographic equipment	5.78
343	Parts and accessories for motor vehicles	5.40
314	Accumulators, primary cells and primary batteries	4.26
183	Dressing and dyeing of fur; articles of fur	4.11
274	Basic precious and non-ferrous metals	3.87
192	Luggage, handbags, saddlery and harness	3.64
193	Footwear	3.59

Table A6: Network Characteristics of the Job Mobility Networks

	1975-2005	1975-1980	1980-1985	1985-1990	1990-1995	1995-2000	2000-2005
Panel A. Network Characteristics							
average degree	19.84	9.98	8.42	9.00	9.59	9.31	9.75
diameter	17	20	20	19	20	25	19
average path length	4.87	5.67	5.83	5.74	5.74	5.95	5.95
density ($\times 10,000$)	1.06	0.97	0.88	0.87	0.85	0.84	0.86
clustering coefficient	0.04	0.03	0.02	0.03	0.03	0.03	0.03
Panel B. Degree Distribution							
Power Law Dist. α	2.56	2.56	2.53	2.43	2.48	2.57	2.43
Exponential Dist. λ	0.34	0.43	0.47	0.45	0.44	0.46	0.45
Hybrid Model fraction r	0.37	0.74	0.57	0.59	0.62	0.7	0.5

Note: All measures correspond to the giant component of the job mobility network sampled during the years indicated. Avg. degree measures the average number of incoming and outgoing connections per firm. The diameter is the shortest path between the two most distant firms in the network. Avg. path length indicates how many steps on average it takes to get from one firm to another. Graph density is the fraction of all possible links that are actually present. The clustering coefficient measures the fraction of actually observed triangles in all potential triangles in the network. Panel B reports parameters from parametric fits to the degree distribution for three different models.

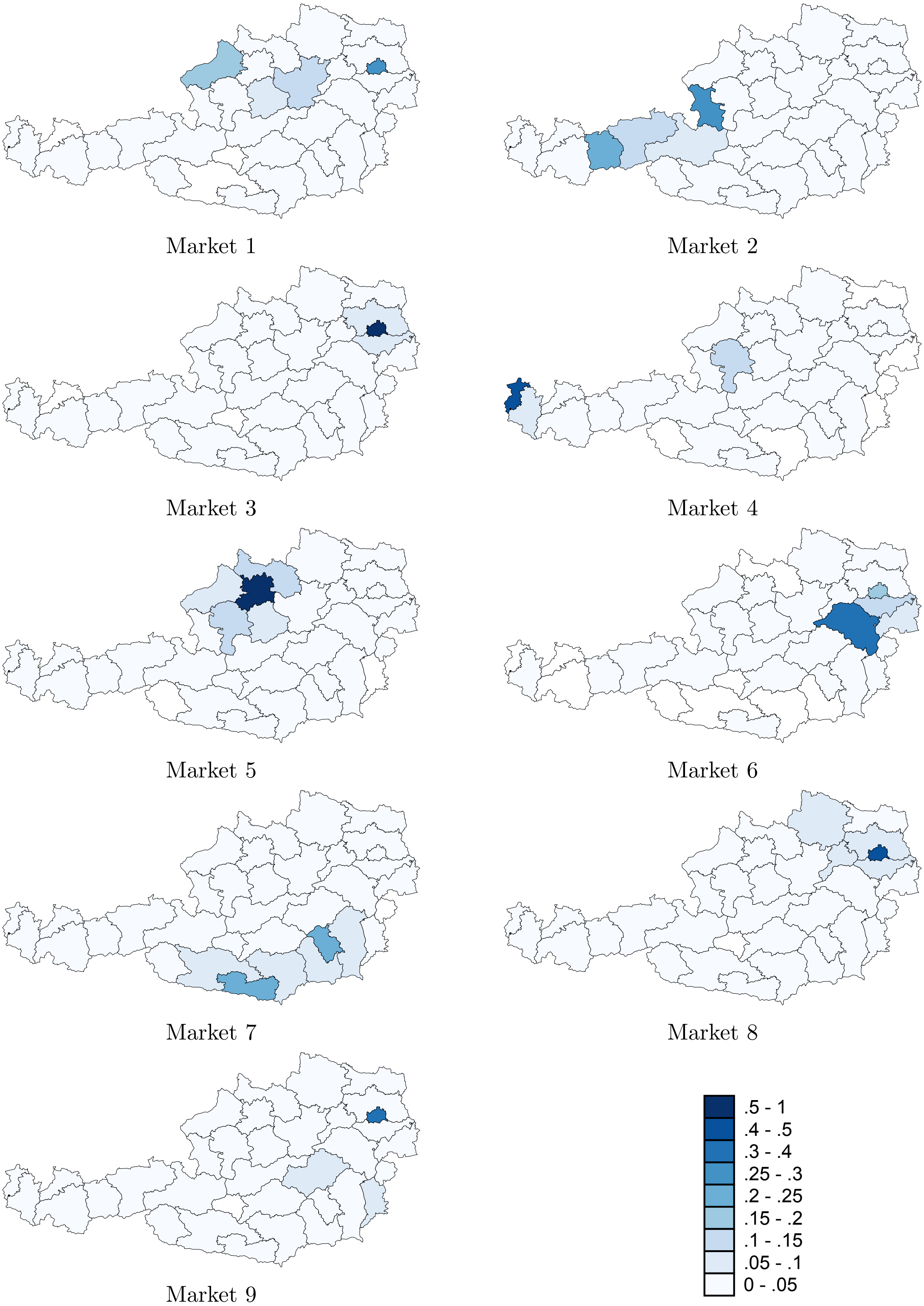


Figure E.1: Share of Firms in NUTS-3 Regions for each Market (1975-1980)

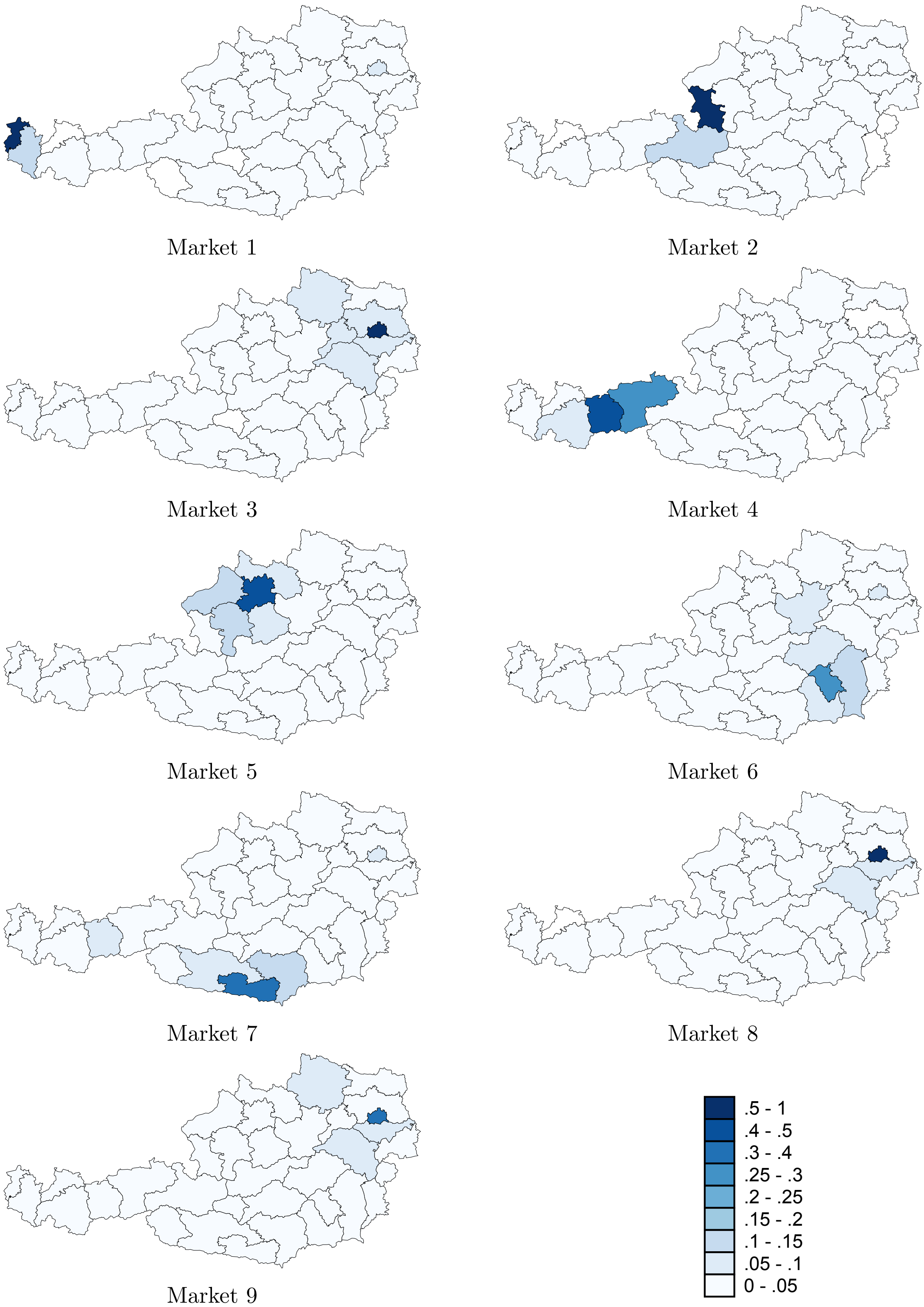


Figure E.2: Share of Firms in NUTS-3 Regions for each Market (1980-1985)

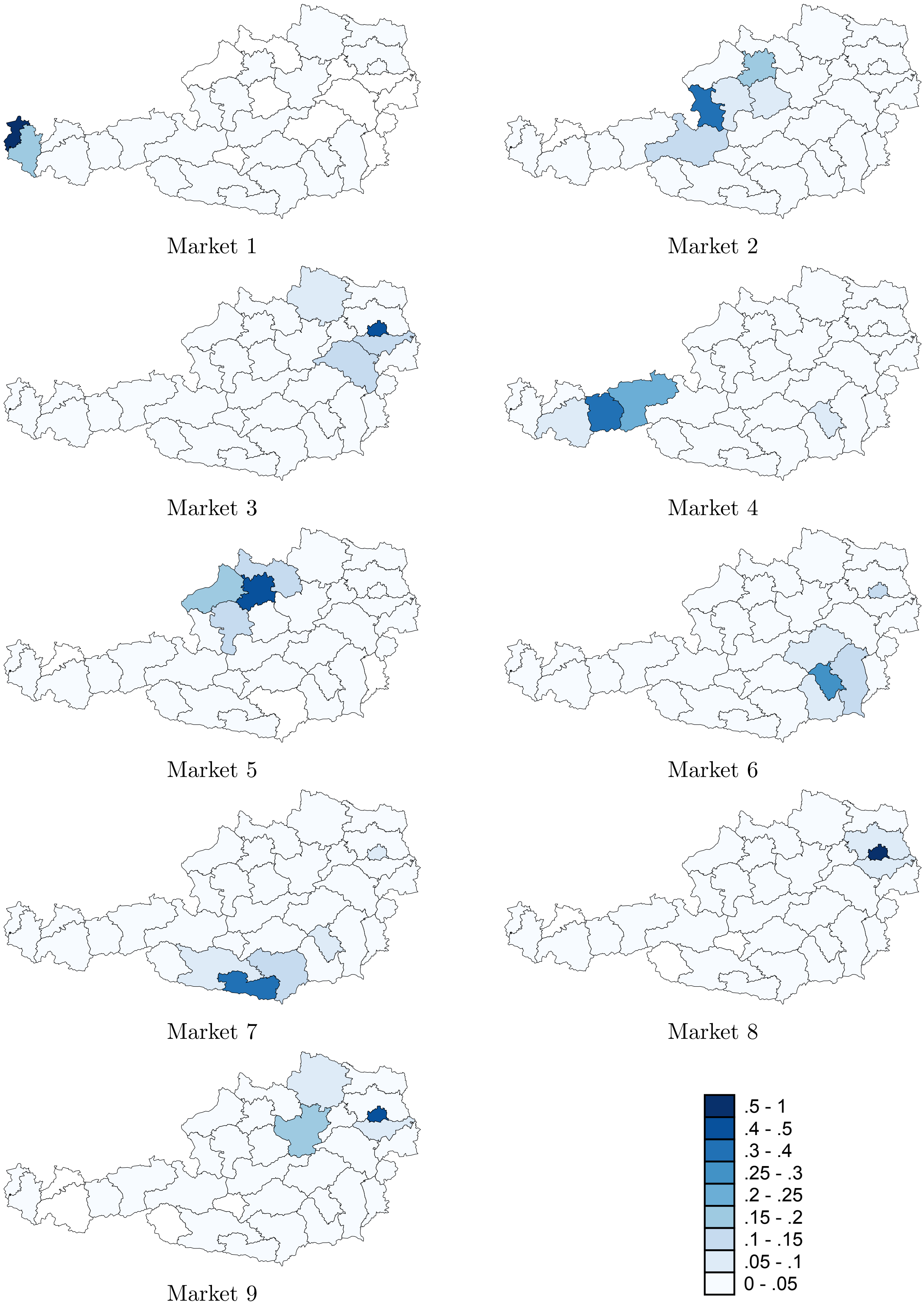


Figure E.3: Share of Firms in NUTS-3 Regions for each Market (1985-1990)

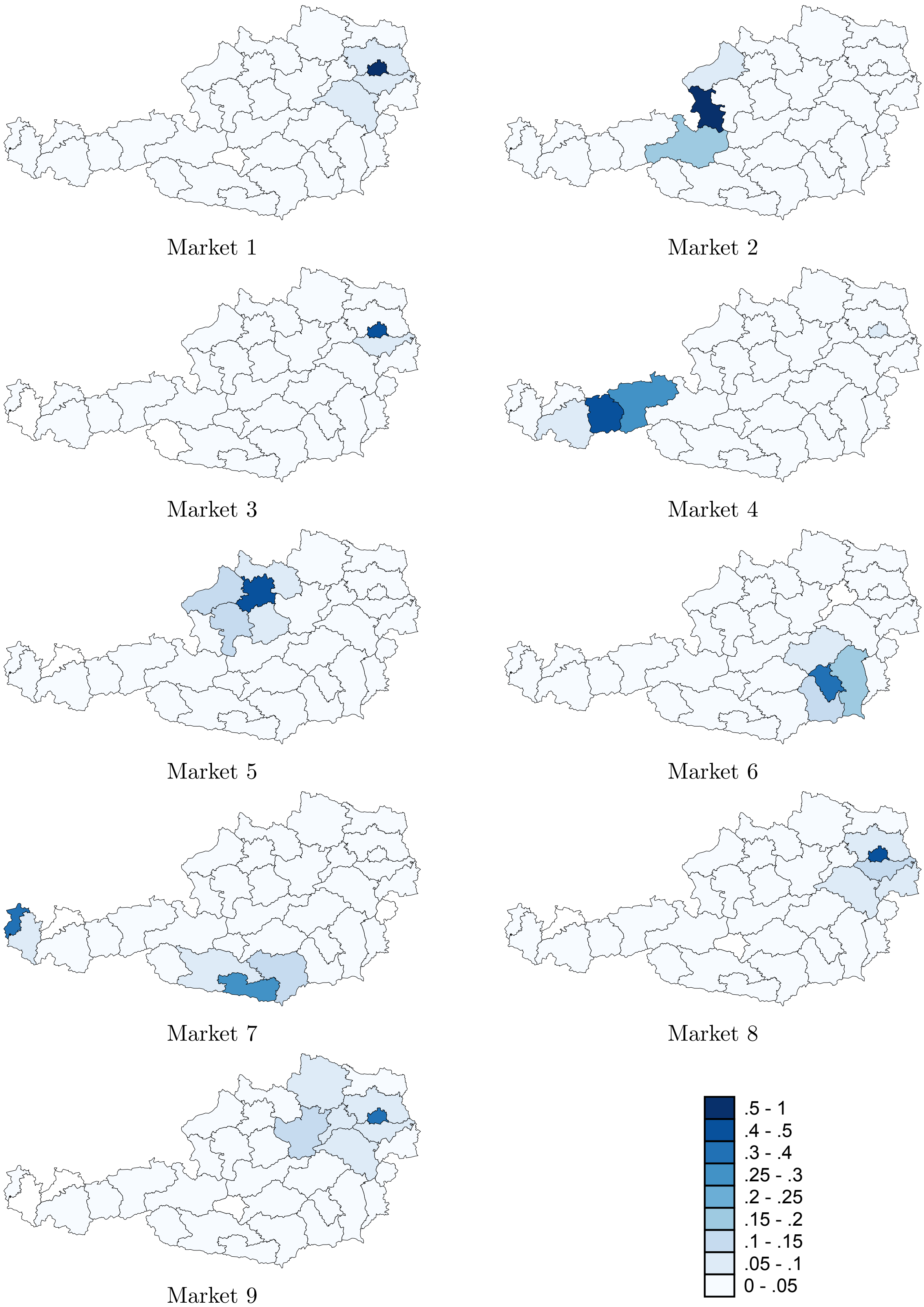


Figure E.4: Share of Firms in NUTS-3 Regions for each Market (1990-1995)

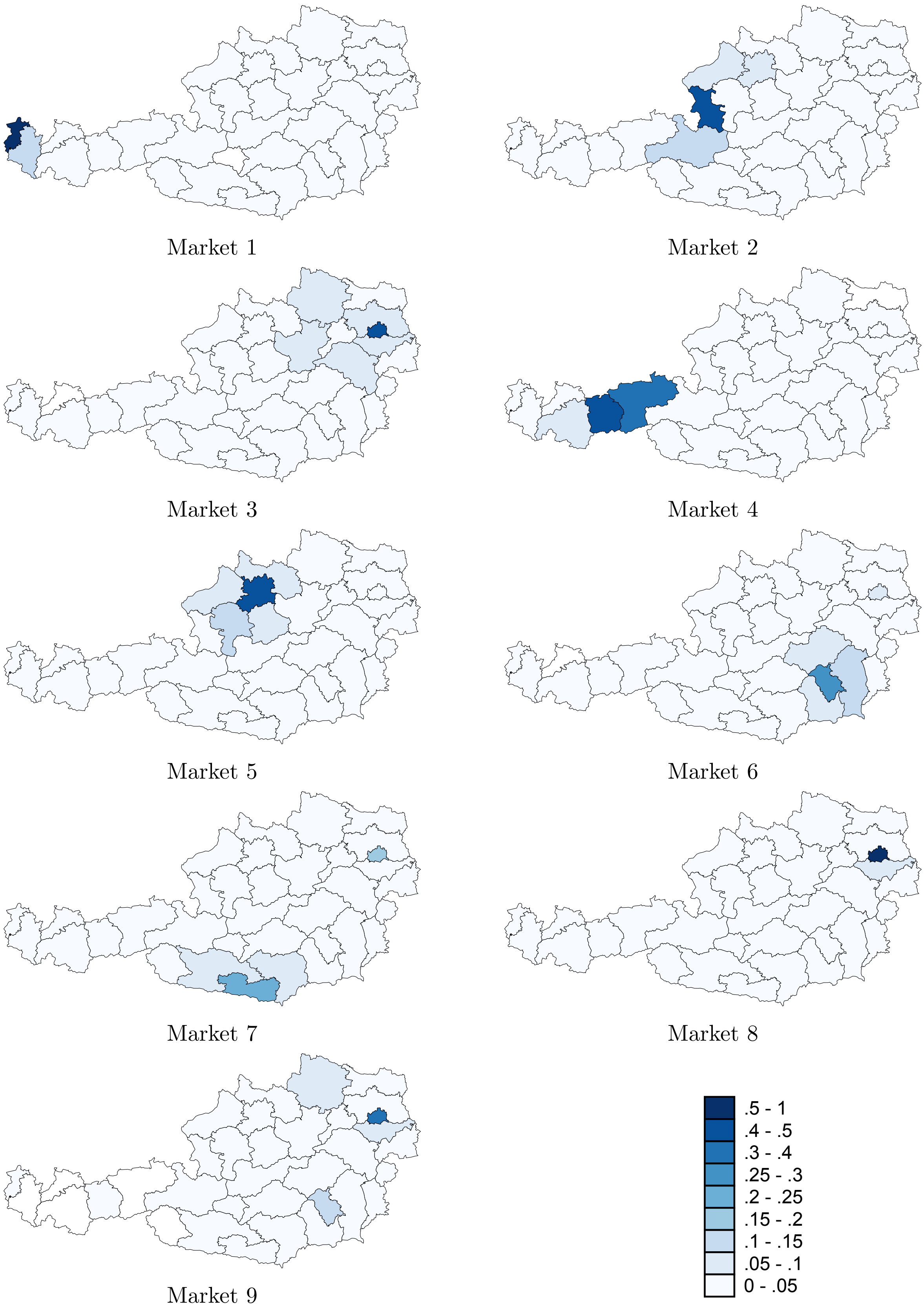


Figure E.5: Share of Firms in NUTS-3 Regions for each Market (1995-2000)

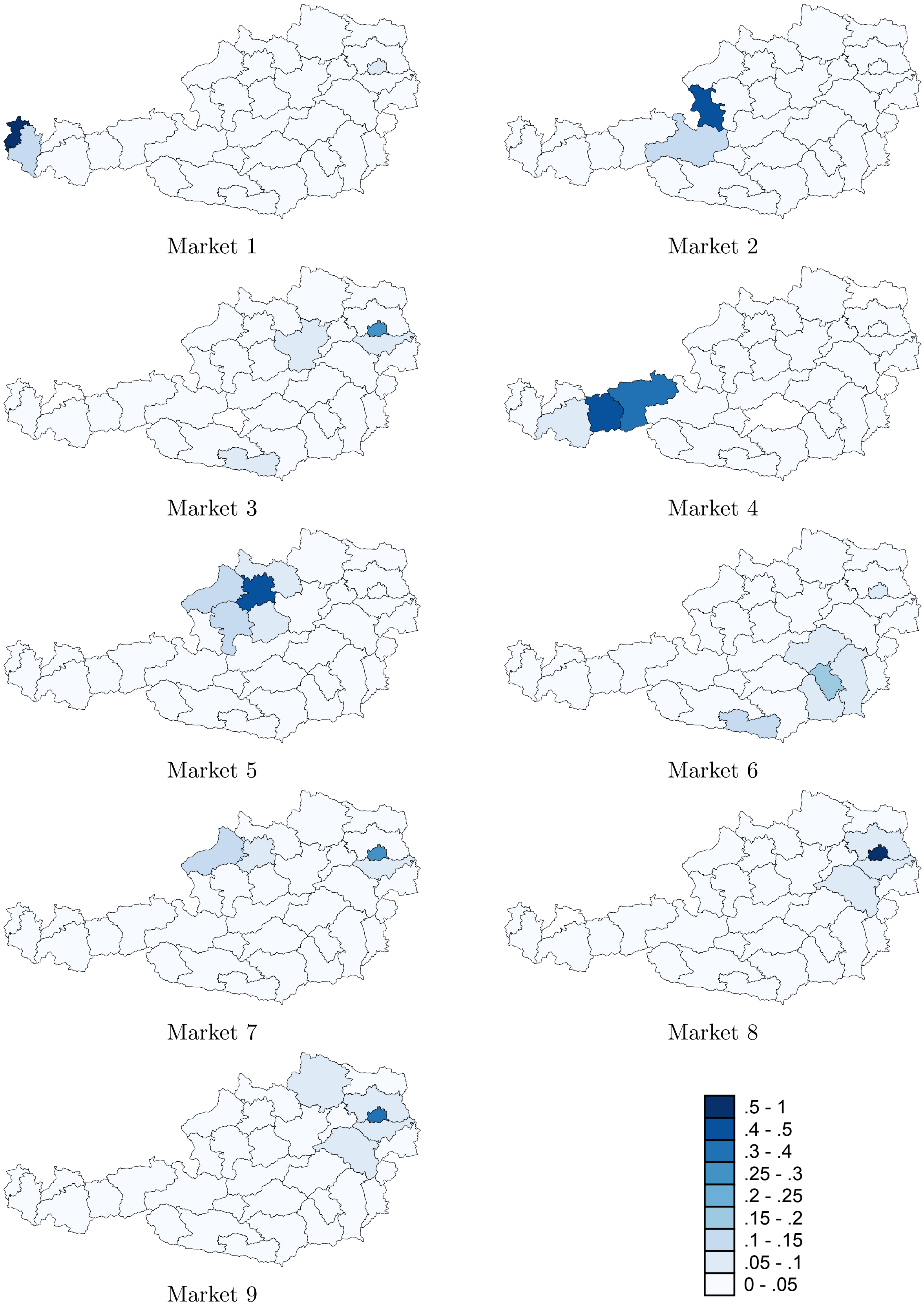


Figure E.6: Share of Firms in NUTS-3 Regions for each Market (2000-2005)

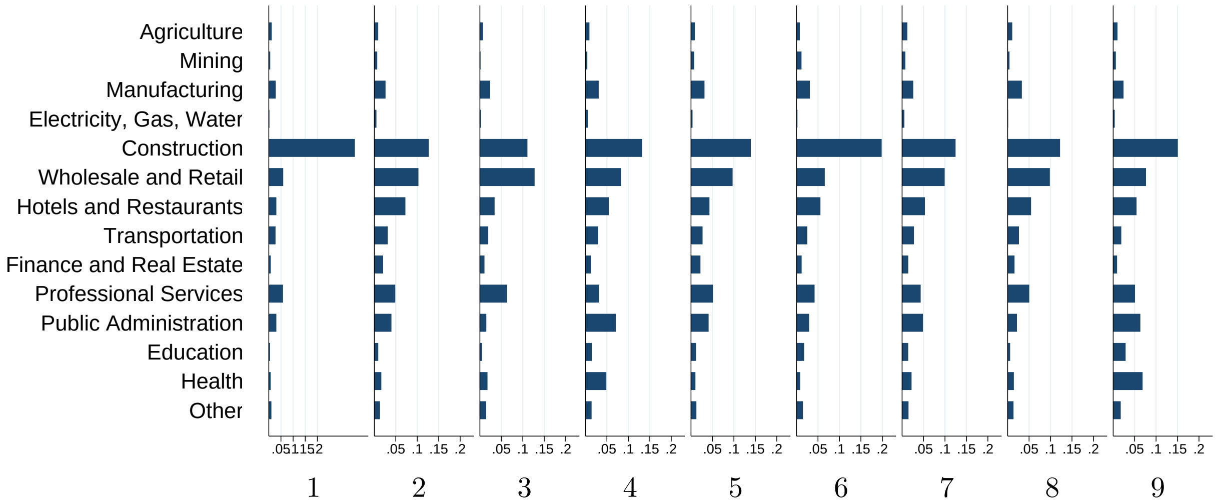


Figure E.7: Histogram of Industry Composition by Market (1975-1980)

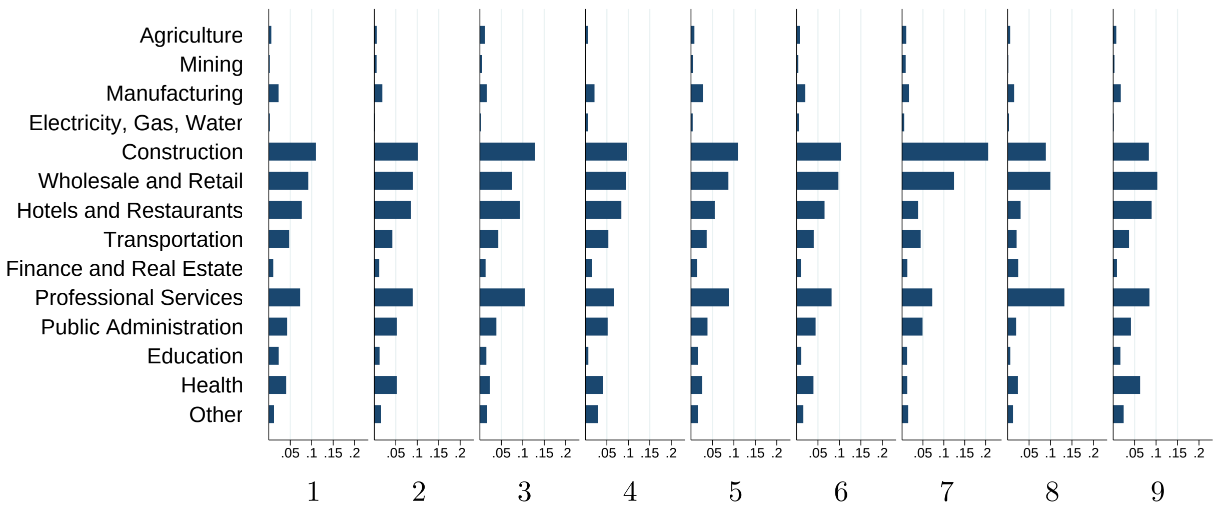


Figure E.8: Histogram of Industry Composition by Market (2000-2005)

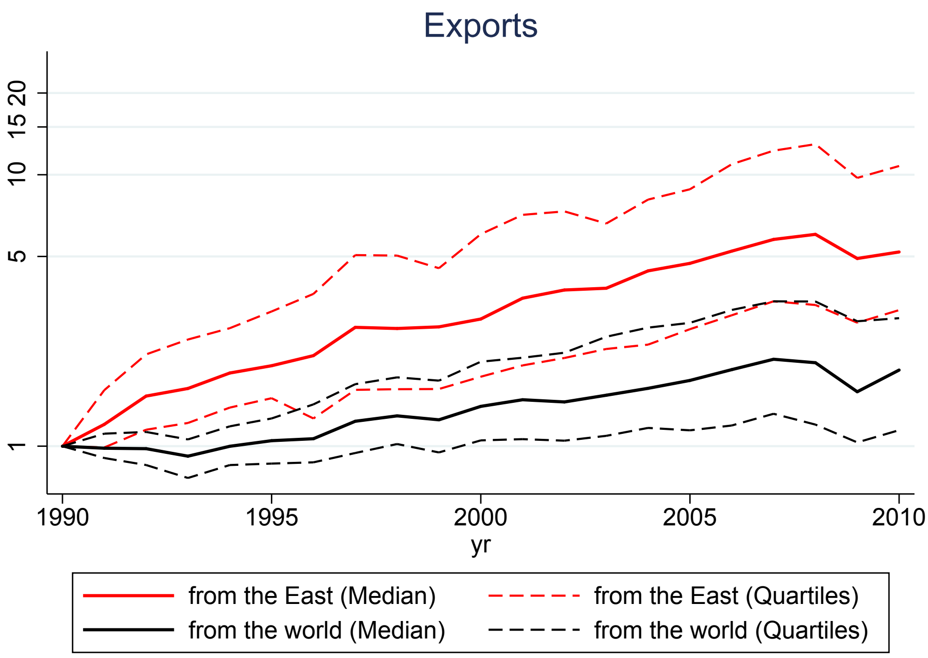


Figure E.9: Rising Export Volumes in Austrian Trade

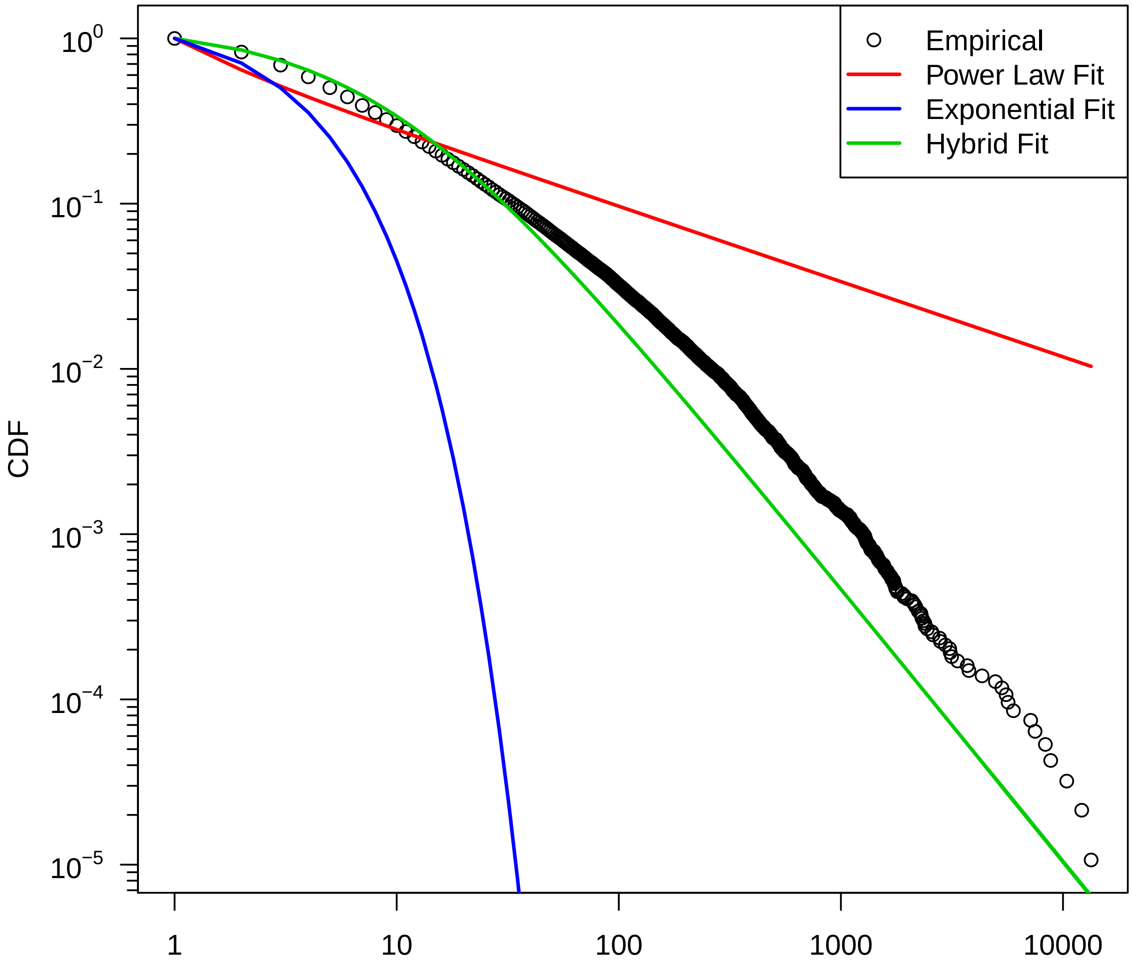


Figure E.10: Complementary CDF of the Degree Distribution in the Job Mobility Network 1975-2005

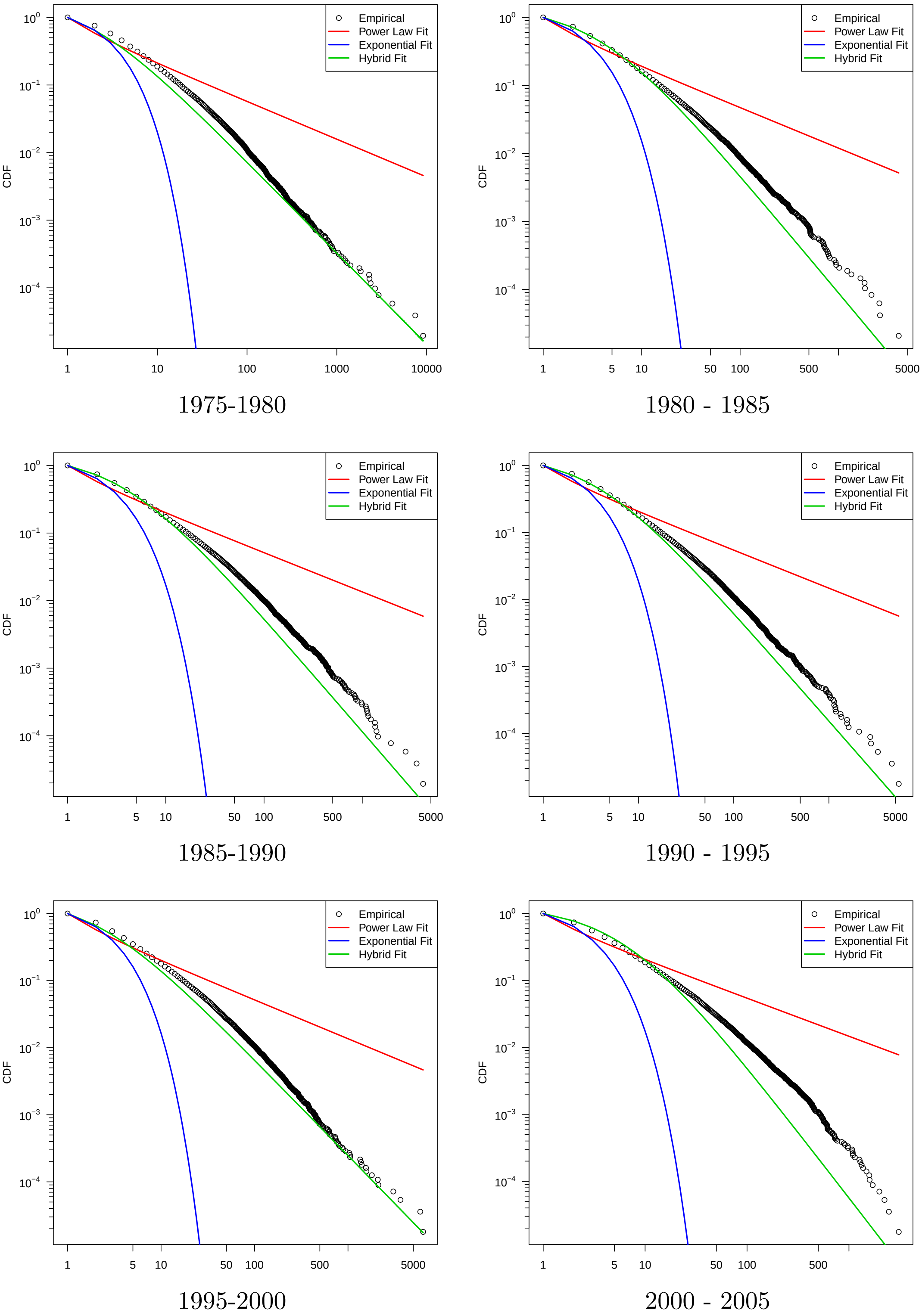


Figure E.11: Complementary CDF of the Degree Distribution in the Job Mobility Network over Time