Wage Bargaining as a Social Interaction Problem: An Application to Germany *

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Abstract

This paper examines the importance of workers' outside options in wage determination. In a model of search and bargaining, holding the marginal product constant, a worker's wage is determined by a weighted average of wages in alternate jobs, turning wage formation into a social interaction problem. I develop a search and bargaining model with heterogeneous workers and propose novel strategies to identify the importance of this network structure in the formation of wages. Specifically, I explore differences in the mobility costs of workers as an additional source of variation for identification. Using a unique administrative panel database for Germany, I find that a 1% increase in the outside options of a worker generates a 0.7% wage increase. In addition, my results suggest that differences in workers' mobility generate asymmetric wage externalities across occupations and industries and play an important role in the transmission of a labor demand shock on a worker's wage.

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Introduction

How does the decline of the car industry in Detroit affect wages of workers in the textile industry? How does the rise of Maquilladoras and the resulting offshoring of textile machine operators affect secretaries' wages in U.S. border cities? The answer to this type of questions depends on the conceptual framework underlying the determination of wages. There are two competing views on how to conceptualize the labor market: the standard neoclassical model, where the wage equals the value of marginal product; and models with frictions of various kinds where wages are divorced from the value of marginal product. This paper focuses, in particular, on search and bargaining models. In this class of models, the wage of a worker is generally below the value of marginal product and partly reflects his reservation utility. Search and bargaining implies that, holding marginal product constant, a change in a worker's outside options generates a wage externality which is absent from competitive labor markets. Returning to the Detroit example, in such a model, the decline in the auto industry (and in the high paying jobs that go with it) would imply that workers in textile manufacturing firms will have weakened outside options. As a result, textile sector wages in Detroit would fall, even in the absence of any effects on labor productivity in that sector. While the importance of workers' outside options in the determination of wages is well established from a theoretical perspective, there have been few empirical attempts to evaluate their relevance. A likely reason for this limited amount of evidence is the difficulty in identifying changes in workers' outside options that are independent of changes in their marginal product. The objective of this paper is to examine empirically the importance of workers' outside options in the determination of wages. Using a search and bargaining framework with heterogeneous workers, I propose different identification strategies. Specifically, I explore differences in workers' mobility costs across occupations and industries as an additional source of variation for identification.

In a search and bargaining model, for a given productivity, the outside option effects just discussed imply that a worker's wage in a particular job is determined by a weighted average of wages in alternate jobs, turning wage formation into a social interaction (or reflection) problem (Manski, 1993; Moffitt, 2001; Beaudry et al., 2012). Thus, wage determination takes the form of a network structure in which linkage intensity depends on the weights workers attribute to their employment alternatives. Estimating the parameter capturing these types of network effects poses two main difficulties: the first one is well recognized and is associated with the endogeneity that results from the social interaction. The second one requires dealing with the heterogeneity of workers, which is difficult because this heterogeneity causes asymmetric wage spillovers to the same shock to the labor market. In particular, in an environment populated by heterogeneous individuals, the set of matching probabilities, and therefore the network structure characterizing the determination of wages, is worker-specific and implies that the wage effects of a similar change in workers' outside options is heterogeneous too. Taking the Detroit example again, one would expect engineers, textile operators and secretaries' wages to adjust differently to the decline of the car industry. Thus, the second challenge consists in developing a model which is rich enough to capture this type of asymmetry, but, at the same time, sufficiently tractable to be brought to the data without imposing substantial theoretical restrictions. The main contribution of this paper is to explore one aspect of workers' heterogeneity as an additional source of variation to identify the importance of these network effects.

My approach adheres to the logic that combines structural modeling with instrumental variables estimation (Blundell et al., 1998; Beaudry et al., 2012). To provide structure for the identification strategy, I build on a multi-city multi-sector model of search and bargaining and introduce worker heterogeneity in the form of differences in occupational and sectoral mobility. Such an extension implies that the weight a worker attributes to an outside option becomes a transition probability. In steady state, this transition probability is given by a trajectory-specific function of the option's corresponding employment share and of the mobility cost that would be entailed to switch jobs, where, in this framework, a job is defined as an occupation-industry cell.

The form of the transition probability highlights two types of asymmetries: one that is associated with the mobility of workers, and another one that results from the structure of employment in a labor market. The first one suggests that, holding marginal product constant, asymmetric effects on workers' outside options from the same shock are fully captured by mobility costs. This prediction matches with intuition. Consider for example a secretary. If she faces a higher cost than a technician does to becoming an engineer then a positive shock on engineers would have a larger wage spillover effect on technicians. The second asymmetry is consistent with Beaudry et al. (2012)'s argument that differences in the industrial composition of employment matter for explaining wage disparities across cities. In this paper, the multi-city dimension of the model implies that the weighted average of alternate wages, i.e. the component capturing the social interaction, is *city*-job-specific. Thus, everything else being equal, within a particular job, wage disparities across cities result from differences in the local structure of employment, as captured by the employment shares in the transition probabilities.

From a practical perspective, the empirical implementation requires construction of a transition matrix for all combinations of jobs (i.e. occupation-industry cells) and to deal with workers' residential and occupational choices. To meet these requirements, it is important to be able to trace individuals over time, cities and jobs. For this reason, I rely on the employment statistics of the Institute of Employment Research (IAB) of Germany, which provide a unique administrative panel database.

I exploit job-city-specific periodical differences in wages *across* and *within* cities of Western Germany for the period 1977-2001. The variation 'within jobs across cities' purges job-city-specific periodical differences in wages from national-level movements in occupation and industry factors. In the context of this study, this variation ensures that my estimate captures decentralization mechanisms and not collective bargaining forces working through the German Confederation of Trade Union. In comparing job-city-specific periodical differences in wages to their corresponding local average, the 'within city across jobs' variation provides a way of controlling for time-varying city-specific variables that may affect wages. In particular, this type of variation isolates search and bargaining forces from alternative city-specific mechanisms associated with education (Acemoglu and Angrist, 2000; Moretti, 2004), demand or agglomeration externalities (Blanchard and Katz, 1992; Glaeser et al., 1992; Glaeser and Gottlieb, 2009) , local amenities or local housing prices.

The instrumental variable strategy flows directly from theory. Specifically, the model suggests predicting workers' outside options by combining national job wage premia with the local structure of employment that would prevail if job-city employment had grown according to the national trend. The exogenous variation stems from national-level differences in wage premia and employment growth across jobs. The identifying assumption implied by the model requires that local productivity shocks are uncorrelated with past job-city-specific comparative advantages, or in intuitive terms, that the local structure of employment in the past is uncorrelated with present changes in the general conditions in a city. While this assumption may be questioned in practice, the model provides a set of overidentifying restrictions to test its validity.

The findings of this paper are twofold. First, job-city wages in Germany conform to the predictions of search and bargaining theory, which suggests that wage determination takes the form of a social interaction problem. The network effects are strong: a 1% increase in the term capturing a worker's outside options generates a 0.7% wage increase. The estimates are robust to a large set of sensitivity checks and in particular to correcting for the selection of workers into cities Dahl (2002) and occupations (Gibbons et al., 2005; Groes et al., 2009). Moreover, the overidentifying restrictions implied by theory and tests of the validity of the model are not rejected by the data.

Second, I find that a model that accounts for asymmetries in the wage spillover effects performs better than one which assumes homogeneous workers. Thus, mobility appears to play an important role in the transmission of a labor demand shock on a worker's wage. This finding is important as it implies a policy prescription that differs from a model with homogeneous labor. To see why, consider the polarization phenomenon that has been observed in developed countries since the 1980s. As a result of routine-biased technical change, the share of high-skill, high-wage occupations (non-routine cognitive) and low-skill, low-wage occupations (non-routine manual) has increased relative to the share of occupations in the middle of the distribution (routine). At the same time, the occupational wage premia for the top and bottom sections have increased.[1] An approach which assumes homogeneous labor would predict a positive wage externality that would equally spill over to occupations in the middle of the distribution. Yet, the wage effects on the middle section would appear to be tiny if the remaining routine jobs involve occupation-industry-specific skills that are not easily transferable.

Related literature

This study contributes to the literature examining the determinants of city-specific wage changes and wage disparities across cities. To explain local labor market peformances, several explanations have been advanced, including employment diversity (Glaeser et al., 1992), education externalities (Moretti, 2004; Acemoglu and Angrist, 2000), demand and migration effects (Blanchard and Katz, 1992) and, more recently, agglomeration effects and housing price changes (Glaeser and Gottlieb, 2009; Moretti, 2010a). My paper is most closely related to Beaudry et al. (2012), who provide an

[1]The polarization phenomenon for the US is well documented in Acemoglu and Autor (2011), Autor et al. (2003), Autor et al. (2006) and Cortes (2012). Goos and Manning (2007), Dustmann et al. (2009) and Goos et al. (2009) provide studies for European countries.

exploration of a search and bargaining mechansism, by which differences in the sectoral composition of employment result in wage disparities across cities. I depart from their study by the following aspects. First and most importantly, they assume that workers are homogeneous. Second, they restrict the analysis to the sectoral level. As a by-product of the analysis, I show that, by isolating industry-level variations only, their approach neglects the wage externalities working through occupational labor adjustment and would lead to a rejection of search and bargaining theory as a useful framework for analyzing labor market dynamics. Third, the context of this study is substantially different: they focus on a fully decentralized economy, while I gauge the relevance of search and bargaining concepts in a mixed labor market.

This paper also complements the literature analyzing whether and how human capital relates to wages. Earliest contributions measure human capital with job seniority or experience. While Topel (1991) and Dustmann and Meghir (2005), associate returns to firm tenure, Neal (1995) and Parent (2000) find evidence in favor of industry-specific human capital. Recent findings by Kambourov and Manovskii (2009b) or Sullivan (2010) suggest that occupational components dominate firm and industry tenure in determining wages and shifted the center of attention towards occupational mobility. Later contributions such as Poletaev and Robinson (2008), Gathmann and Schonberg (2010), Cortes (2012) associate human capital to tasks and propose to evaluate its occupational specificity using occupational transitions. In particular, they generate measures of occupational distances based on the skill content of occupations and use observed mobility to evaluate the impact of human capital transferability (or distance switched) on wage changes – the underlying idea being, the higher the distance switched, the higher the wage loss. While these studies evaluate the direct impact of workers' mobility costs on wages, my paper points to an alternative mechanism: by diminishing the threat point in the Nash bargaining game, higher transition costs translate in lower wages, even in the absence of actual labor movement. This alternative mechanism suggests that these recent contributions may underestimate the importance of skill flexibility.

Additionally, this work provides a deeper understanding of wage formation in Germany from 1980 onwards. A large body of research has analyzed the German wage structure with a primary focus on documenting and explaining the differential trends in wage inequality in the U.S. and Germany (Abraham and Houseman, 1995; Beaudry and Green, 2003; Steiner and Wagner, 1998; Prasad, 2004; Dustmann et al., 2009; Antonczyk et al., 2010a,b). Several possible explanations for rising wage inequality have been put forward, involving for example the expansion in the relative supply of the high-skilled workers, institutional factors, trade or technology-related reasons. My work differs from these studies by using a search and bargaining perspective to examine the wage determination in Germany and to study the drivers of wage asymmetries across workers.

Finally, this paper is also related to the literature on social and economic networks. One strand of the literature on social networks studies how patterns of information transfers affect economic outcomes. Another strand of literature views social networks as system of strategic interactions between individuals. The spillover externalities emerging from this type of social interactions imply that the payoff or the behavior of an individual is determined by some aggregate of the actions of others. The presence of network effects has long been recognized in several situations, e.g. in residential choices (Benabou, 1993) or in technology adoption (Acemoglu, 1997), but less so in the context of wage formation (Beaudry et al., 2012). In most of the job search literature, social linkages work as an information platform whereby workers learn about job opportunities. This paper relates to the second strand of literature by making the presence of spillover externalities in the wage determination explicit.

This paper proceeds as follows: Section 1 presents the model, while section 2 discusses the identification strategy. Section 3 describes the empirical setting and section 4 presents the results. Supplementary sensitivity checks can be found in section 5.

1 Model

This section generalizes Beaudry et al. (2012) multi-city multi-sector model of search and bargaining and includes the heterogeneity of workers in the form of differences in occupational and sectoral mobility.

1.1 Setup

Consider an economy with one final good Y, assembled from the economy-wide output Z_i of I industries. Let I be the set of industries and let $\{i, j, k\} \in I$. The final good Y is given by

$$Y = \left(\sum_i a_i Z_i^{\chi} \right)^{\frac{1}{\chi}},$$

where $\chi < 1$ and a_i is a parameter reflecting aggregate demand for the industrial good i. The price of the final good is normalized to one. The price of the industrial good i is p_i. The economy is segmented into C local labor markets, which I will call "cities". The industrial good can be produced in any city and the economy-wide output Z_i is given by the sum of X_{ic}, the output produced in each city. Let Q denote the set of occupations and let $\{q, r, s\} \in Q$. To keep the job creation intelligible, I assume that firm-level production involves labor only and uses Q complementary occupations with unit-factor requirement given by $\frac{1}{\theta_{qic}}$. In this framework, an occupation-industry cell is associated to a specific set of skills and entirely characterizes a job and a worker's type.

The number of firms and aggregate employment in an industry and a city are endogenously determined by a free entry condition within a framework à la Fonseca et al. (2001). In this framework, an individual receives the option of creating a firm in industry i with probability Ω_{ic}. Upon learning Ω_{ic}, the individual finds out n, the amount of labor he can manage, where $n \sim F(n)$. Within an industry and a city, differences in entrepreneurial ability to manage jobs is the only source of firm heterogeneity. Finally, to enter the production market, he faces an constant start-up cost, denoted K. Free entry implies that individuals with expected payoff larger than the fixed entry cost K become an entrepreneur.

The labor market considered is characterized by search and matching frictions. For clarity, I assume that workers can move within but not across cities. In subsection 1.5, I will discuss the implications of workers' mobility across cities and demonstrate that the results are robust to an extension allowing for this type of mobility. To switch job, a worker incurs a cost reflecting the skill differential implied by the move. This paper focuses on random search and ignores quits as well as on-the-job search.[2] The search and matching process will be described in more details in subsection 1.2. Once matches are made, workers and firms bargain over the wage rate, through Nash bargaining in a complete information context. Layoffs occur at an exogenous rate, denoted δ.

The model is couched in continuous time. Workers and firms live forever, discount the future at an exogenous rate ρ and are risk neutral. Workers seek to maximize the expected discounted sum of future utility flows, and firms are profit maximizers. Finally, let ER_c denote the employment rate in city c, w_{qic} be the job-city-specific wage and η_{qic} denote job's employment as a share of city-c employment. The steady state is characterized by values of ER_c, w_{qic} and η_{qic}. At the aggregate

[2] Implications of directed search and on-the-job search are beyond the scope of this study and left for future research.

level, prices adjust such that markets for industrial goods clear. Prices react to shifts in demand for industrial goods, as captured by a_i.

1.2 Search and matching

In each city, there is a pool U_c of unemployed workers drawing job offers from the entire local labor market. Barriers to mobility prevent workers from being matched to the desired position and their assignment to a particular job is a function of labor market frictions (as captured by a matching function), job vacancies and of their ability to transfer human capital across the occupation-industry space.

The rate at which unemployed workers are matched to firms is governed by a city-specific matching technology given by

$$M_c = M\left(\left(L_c - E_c\right), \left(N_c - E_c\right)\right),$$

where E_c denote the number of employed workers in city c, $(L_c - E_c)$ the number of unemployed workers in city c and $(N_c - E_c)$ is the number of vacant jobs available in city c. The matching function exhibits constant returns to scale and is increasing in both arguments, as is standard in the search and bargaining literature. Assuming a Cobb-Douglas matching function, the proportion of filled jobs equals the proportion of vacant jobs in steady state.

The probability that an unemployed individual previously employed in qic (i.e. a qic-type unemployed worker) encounters a vacancy in rjc is given by

$$\tilde{\psi}_{rjc|qic} = \frac{M_{rjc|qic}}{\lambda_{qic}(L_c - E_c)}, \tag{1}$$

where λ_{qic} represents the fraction of qic-type unemployed individuals and $M_{rjc|qic}$ denotes the number of qic-type unemployed workers who are matched to rjc. $M_{rjc|qic}$ is given by

$$M_{rjc|qic} = \psi_{rjc|qic} \sum_{r,j} M_{rjc|qic}, \tag{2}$$

where $\sum_{r,j} M_{rjc|qic}$ is the total number of matches created with workers originating from qic and $\psi_{rjc|qic}$ is the transition probability from state qic to rjc. I assume that $\psi_{rjc|qic}$ is a function of two terms: $\varphi_{rj|qi} \in [0,1]$, a mobility mesure relecting the ease of transiting from qi to rj, and η_{rjc}, the relative size of the destination cell rjc. Specifically,

$$\psi_{rjc|qic} = \frac{\varphi_{rj|qi}}{\sum_{r,j} \varphi_{rj|qi}\eta_{rjc}}\eta_{rjc}, \tag{3}$$

where $\frac{\varphi_{rj|qi}}{\sum_{r,j} \varphi_{rj|qi}\eta_{rjc}}$ captures the cost a qic-type worker faces to move to rjc relative to moving anywhere else. The transition probability is zero if the cost of moving between two cells is prohibitive (i.e. $\varphi_{rj|qi} = 0$). If instead, individuals are perfectly mobile (i.e. $\varphi_{rj|qi} = 1$) or identically mobile across occupations and industries (i.e. $\varphi_{rj|qi} = \varphi$), the transition probability $\psi_{rjc|qic}$ equals the relative size of the destination cell η_{rjc} and does not depend upon the origin of workers qic. In steady state, the number of jobs that are destroyed equals the number of matches, i.e. $\delta E_c = M_c$, $\delta E_{rjc} = \sum_{q,i} M_{rjc|qic}$ and λ_{rjc} satisfies $\delta E_{qic} = \sum_{r,j} M_{rjc|qic}$. Using this steady state condition together with (2) and (3), equation (1) becomes[3]

$$\tilde{\psi}_{rjc|qic} = \chi_{rjc|qi}\eta_{rjc}\psi_c, \tag{4}$$

where I define $\chi_{rjc|qi} = \frac{\varphi_{rj|qi}}{\sum_{r,j} \varphi_{rj|qi}\eta_{rjc}}$ and $\psi_c = \frac{M_c}{L_c - E_c}$. Figure (1) provides an illustration of workers' mobility in a two-by-two occupation-industry model.

< Figure (1) here >

[3]

$$\begin{aligned}
\tilde{\psi}_{rjc|qic} &= \frac{M_{rjc|qic}}{\lambda_{qic}(L_c - E_c)} \\
&= \frac{\psi_{rjc|qic}\sum_{r,j} M_{rjc|qic}}{\lambda_{qic}U_c} \\
&= \frac{\psi_{rjc|qic}\delta E_{qic}}{\lambda_{qic}U_c} \\
&= \frac{\psi_{rjc|qic}M_{qic}}{\lambda_{qic}U_c} \\
&= \frac{\psi_{rjc|qic}\lambda_{qic}M_c}{\lambda_{qic}U_c} \\
&= \chi_{rjc|qi}\eta_{rjc}\psi_c.
\end{aligned}$$

1.3 The objective function of firms and workers

Let V^f_{qic} and V^v_{qic} be the discounted values to firms of a filled position and a vacancy, respectively. If a position is filled, it generates a flow of profits of $\theta_{qic}p_i - w_{qic}$. With probability δ a worker is laid off in the subsequent period and the position becomes vacant. Thus,

$$\rho V^f_{qic} = (\theta_{qic}p_i - w_{qic}) - \delta\left(V^f_{qic} - V^v_{qic}\right). \tag{5}$$

For clarity, I assume that if a firm does not fill a job, there is no cost to maintain the position. With probability ϕ_c the vacancy is filled in the following period. Hence,

$$\rho V^v_{qic} = \phi_c\left(V^f_{qic} - V^v_{qic}\right), \tag{6}$$

where ϕ_c denotes the probability that a firm fills a posted vacancy. Combining equations (5) and (6) together, the value of a match to a firm relative to the value of a vacancy is given by

$$V^f_{qic} - V^v_{qic} = \frac{\theta_{qic}p_i - w_{qic}}{\rho + \delta + \phi_c}. \tag{7}$$

Let U^e_{qic} and U^u_{qic} be the discounted values to workers of being employed and unemployed in a particular qic cell, respectively. For clarity, any relevant city-specific features such as amenities and unemployment benefits are normalized to zero.[4] An employed worker receives the wage w_{qic} and is laid off with probability δ in the next period. Therefore,

$$\rho U^e_{qic} = w_{qic} - \delta\left(U^e_{qic} - U^u_{qic}\right). \tag{8}$$

With probability $\tilde{\psi}_{rjc|qic}$, a qic-type unemployed worker is matched to rjc. With probability $(1-\psi_c)$ he remains unemployed in the coming period. Using (4), I obtain

$$\rho U^u_{qic} = \psi_c \sum_{r,j} \chi_{rjc|qi}\eta_{rjc}U^e_{rjc} - \psi_c U^u_{qic}. \tag{9}$$

A worker's utility of being unemployed is a fraction of the weighted average of the employment

[4] Local amenities and unemployment benefits will be captured by an entire set of city time-varying dummies in the empirical section.

utilities in all alternate jobs. Because of the trajectory-specificity of the term in the summation, solving for U^u_{qic} without the help of an additional restriction on the behavior of the mobility term $\varphi_{rj|qi}$ would require a matrix resolution. However, the main objective of the model is to develop an identification strategy allowing a direct confrontation of the wage equation with the data. The matrix resolution renders this task impossible as it would involve estimating the coefficient of interest combining estimated structural parameters with the data. Therefore, in order to keep the model tractable, I assume that $\varphi_{rj|qi}$ is path independent, i.e. $\varphi_{sk|qi} = \varphi_{sk|rj} \cdot \varphi_{rj|qi}$. This assumption implies that to upgrade to an occupation-industry cell with higher skill content, a worker has to acquire the entire skill differential between the cells across which he is moving. Once a worker reaches a particular cell, he takes on the identity of the individuals at the destination and faces the same mobility costs. Consider for example a secretary, a legal assistant and a lawyer, each of them ranked according to their skill content. This assumption implies that, because skills are added on top of each other, it is identically costly for the secretary to acquire skills to first become a legal assistant and second a lawyer or to immediately develop the skills to become a lawyer.

Combining (8) and (9) together with the path-independent property of $\varphi_{rj|qi}$, the value of finding a job to a worker relative to being unemployed simplifies to

$$(U^e_{qic} - U^u_{qic}) = \frac{1}{(\rho+\delta)} w_{qic} - \frac{\psi_c}{(\rho+\delta)\,(\rho+\delta+\psi_c)} \sum_{r,j} \eta_{rjc} \chi_{rjc|qi} w_{rjc}. \tag{10}$$

1.4 Wage determination

In steady state, wages are set by Nash bargaining with disagreement points V^v_{qic} and U^u_{qic} for firms and workers, respectively

$$\left(V^f_{qic} - V^v_{qic}\right) = \left(U^e_{qic} - U^u_{qic}\right) \kappa, \tag{11}$$

where $\kappa \in [0,1]$ is the relative bargaining power of firms and workers. Combining (7) and (10) together with (11), the wage in qic can be expressed as

$$w_{qic} = \gamma_{1c} \theta_{qic} p_i + \gamma_{2c} \sum_{r,j} \chi_{rjc|qi} \eta_{rjc} w_{rjc}, \tag{12}$$

where the γ's are functions of the employment rate, as capured by ϕ_c and ψ_c.[5]

When workers are, to some extent, mobile (i.e. $\chi_{rjc|qi} \neq 0$), wages are determined by the value of the marginal product and by the weighted average of the wages in alternate jobs. Thus, equation (12) has the form of a social interaction problem (Manski, 1993; Moffitt, 2001; Beaudry et al., 2012) whereby linkage intensity depends on workers' transition probabilities and in which network effects are captured by γ_{2c}. When workers are homogeneous (i.e. $\chi_{rjc|qi} = 1$), the probability to encounter a particular vacancy is orthogonal to a worker's origin and only depends on the relative size of the destination cell. In such a case, the aggregate of workers' outside options is given by the average wage in the city and, with a labor market, the externalities emerging from the social interaction problem are symmetric across jobs. When workers face differences in occupational and sectoral mobility, attainable employment opportunities are the only options with which to convincingly bargain and the transition probabilities become the relevant weights on outside wages. This type of heterogeneity implies that the network structure characterizing the determination of wages is city-job-specific and generates asymmetric wage spillover effects across occupations and industries. Therefore, search and bargaining mechansims imply that, holding the marginal product constant, wage disparities across jobs are fully captured by differences in workers' mobility. In addition, the structure of the wage equation is consistent with Beaudry et al. (2012) finding that, for a particular job, wage disparities across cities result from differences in the local distribution of employment.

1.5 Implications of workers' mobility across cities

Allowing workers to search across cities modifies the value of being unemployed by expanding the set of a worker's outside options. Whether modeled as random or directed search, this extension can be captured by a set of occupation-industry time-varying dummies in the empirical section.

Consider first random search: with probability $(1 - \Gamma)$, an unemployed worker gets a random draw in his city; with probability Γ he gets a draw in *any* city. In this case, the value of being

[5] In particular,

$$\gamma_{1c} = \frac{\kappa(\rho+\delta)}{(\rho+\delta)+\kappa(\rho+\delta+\phi_c)} \in (0,1) \qquad \text{and} \qquad \gamma_{2c} = \frac{\kappa(\rho+\delta+\phi_c)}{(\rho+\delta)+\kappa(\rho+\delta+\phi_c)} \frac{\psi_c}{(\rho+\delta+\psi_c)} > 0.$$

unemployed can be expressed as

$$\rho U^u_{qic} \quad = \quad (1-\Gamma)\psi_c \sum_{r,j} \chi_{rjc|qi}\eta_{rjc}U^e_{rjc} + \Gamma \underbrace{\sum_{c'} \psi_{c'} \sum_{r,j} \chi_{rjc'|qi}\eta_{rjc'}U^e_{rjc'}}_{\text{qi-specific term}} - \psi_c U^u_{qic}, \tag{13}$$

where $\Gamma \sum_{c'} \psi_{c'} \sum_{r,j} \chi_{rjc'|qi}\eta_{rjc'}U^e_{rjc'}$ captures the option to search across cities. Since mobility costs $\varphi_{rj|qi}$ are measured nationally, the transition probability only depends on the city of destination, which implies that workers' mobility across cities is entirely captured by an job-specific term.

Consider now directed search. With probability Λ, an unemployed worker can change geographic location and chooses to move to the city which maximizes his value of being employed. Then,

$$\rho U^u_{qic} = (1-\Lambda)\psi_c \sum_{r,j} \chi_{rjc|qi}\eta_{rjc}U^e_{rjc} + \Lambda \underbrace{\max_{c'} \left[\psi_{c'} \sum_{r,j} \chi_{rjc'|qi}\eta_{rjc'}U^e_{rjc'} \right]}_{\text{qi-specific term}} - \psi_c U^u_{qic}, \tag{14}$$

where $\max_{c'} \left[\psi_{c'} \sum_{r,j} \chi_{rjc'|qi}\eta_{rjc'}U^e_{rjc'} \right]$ results from directed search across cities. As for a given job there is only one location which maximizes the value of being unemployed, workers' mobility across cities can be captured by an occupation-industry-specific term.

2 Identification

2.1 Estimable wage equation

In practice, the fraction of unemployed workers who are matched to their previous occupation and industry is important. To avoid estimating a tautological regression, let me rewrite equation (12) as follows

$$w_{qic} = \frac{\gamma_{1c}}{1-\gamma_{2c}\mu_{qic}}\theta_{qi}p_i + \frac{\gamma_{2c}(1-\mu_{qic})}{1-\gamma_{2c}\mu_{qic}} \sum_{r,j\neq q,i} \tilde{\chi}_{rjc|qi}\eta_{rjc}w_{rjc} + \frac{\gamma_{1c}}{1-\gamma_{2c}\mu_{qic}}\varepsilon_{qic}p_i, \tag{15}$$

where $\mu_{qic} = \eta_{qic}\chi_{qic|qi}$ and $\chi_{rjc|qi} = (1-\mu_{qic})\tilde{\chi}_{rjc|qi} \quad \forall r, j \neq q, i$. In writing equation (15), I have decomposed the marginal productivity of labor θ_{qic} into an occupation-industry absolute advantage component θ_{qi} and a city-specific occupation-industry relative advantage component ε_{qic} such that

$\theta_{qic} = \theta_{qi} + \varepsilon_{qic}$ and $\sum_c \varepsilon_{qic} = 0$.

In order to explicate the relationship between job-city wages and a city's employment rate, I first-order linear approximate equation (15) around the point where cities have identical employment rates ($ER_c = ER$) and where employment is uniformly distributed across jobs ($\eta_{rjc} = \frac{1}{QI}$). This occurs when the relative advantage component is zero, i.e. when $\varepsilon_{qic} = 0$, and when both the value of the marginal productivity of labor and mobility costs are constant across industries and occupations, i.e. when $\theta_{qi} p_i = \theta p$ and $\varphi_{rj|qi} = \varphi$. Defining $R_{qic} = \sum_{r,j \neq q,i} \tilde{\chi}_{rjc|qi} \eta_{rjc} w_{rjc}$, I obtain

$$w_{qic} = d_{qi} + \tilde{\gamma}_2 R_{qic} + \tilde{\gamma}_3 ER_c + \tilde{\gamma}_1 \varepsilon_{qic} p, \tag{16}$$

where d_{qi} is an occupation-industry-specific term that includes $\theta_{qi} p_i$ and where the $\tilde{\gamma}$'s are constant terms obtained from the linear approximation.[6] For simplicity, I have assumed that the probability of re-employment is constant jobs, i.e. $\mu_{qic} = \mu$.[7] R_{qic} is the variable of interest and I shall refer to it as 'transition index' from now on.

2.2 Sources of variation

The specification of interest is a log specification of equation (16), expressed as the first difference between two steady state equilibria, i.e.

$$\Delta \ln w_{qic\tau} = \Delta d_{qi\tau} + \tilde{\gamma}_2 \Delta R_{qic\tau} + \tilde{\gamma}_3 \Delta ER_{c\tau} + \Delta \xi_{qic\tau}, \tag{17}$$

[6] In particular,

$$\tilde{\gamma}_1 = \frac{\gamma_1}{1 - \gamma_2 \mu} \quad \text{and} \quad \tilde{\gamma}_2 = \frac{\gamma_2 (1 - \mu)}{1 - \gamma_2 \mu}.$$

[7] As shown in Appendix A of the Supplementary Material, assuming $\mu_{qic} = \mu$ implies that higher comparative advantages in a particular job must be compensated by a higher mobility cost of re-employment. For instance, if rj has a comparative advantage relative to qi, i.e. $\varepsilon_{rjc} > \varepsilon_{qic}$, than it must be that the mobility cost of re-employment in rj is higher, i.e. $\varphi_{rj|rj} < \varphi_{qi|qi}$. If this were not the case, than the probability of re-employment in rj would be higher, i.e. $\mu_{rjc} > \mu_{qic}$. While this may appear somewhat restrictive, it is important to note that letting μ_{qic} vary across jobs modifies the error term in equation (16) in a way that would not affect the identification strategy. Alternatively, one could note that μ_{qic} is a non-linear function of the employment shares and expand the linear approximation to include η_{qic} to equation (16). As will be shown in Table (1), Appendix I of the Supplementary material, adding η_{qic} has no impact on the estimate of interest.

where $\Delta\xi_{qic} = \tilde{\gamma}_1 \Delta\varepsilon_{qic} p$ represents the error term, τ is the time subscript and $\Delta d_{qi\tau}$ denotes a set of occupation-industry time-varying dummies.[8] The inclusion of $\Delta d_{qi\tau}$ purges job-city-specific differences in wages from national-level movements in occupation and industry factors (e.g. from the effect of the German Confederation of Trade Unions).

By focusing on a 'within job across city' comparison of periodical differences in wages only, equation (17) does not exploit 'within city across jobs' wage variations that emerge from workers' heterogeneity. To take advantage of this source of variation, I estimate the wage equation in triple differences: including a full set of city-time dummies $\Delta d_{c\tau}$, equation (17) becomes

$$\Delta \ln w_{qic\tau} = \Delta d_{qi\tau} + \Delta d_{c\tau} + \tilde{\gamma}_2 \Delta R_{qic\tau} + \Delta\xi_{qic\tau}. \tag{18}$$

The inclusion of $\Delta d_{c\tau}$ provides a direct way of controlling for city-specific variables that may affects wages. Specifically, it allows to isolate search and bargaining forces from alternative city-specific factors related to education, demand or agglomeration externalities, local amenities or local housing prices. Therefore, estimating equation (18) implies that the identification of $\tilde{\gamma}_2$ relies on a comparison of job-city-specific differences in wages $\Delta w_{qic\tau}$ to changes in average job-specific ($\Delta w_{qi\tau}$) and city-specific ($\Delta w_{c\tau}$) wages.[9]

[8] A log specification is obtained by dividing both sides of the wage equation by a constant average wage, denoted w_0. To see why, note that $log\ w_{qic\tau}$ approximated around the constant average wage w_0 satisfies

$$log\ w_{qic\tau} \simeq log\ w_0 + \frac{w_{qic\tau} - w_0}{w_0}.$$

It follows that the yearly change in the log average wage premium is given by

$$\Delta log\ w_{qic\tau} \simeq \frac{w_{qic\tau} - w_{qic(\tau-1)}}{w_0}.$$

Hence, dividing both sides of the wage equation by the constant average wage w_0 provides a log specification, where w_0 is captured by the constant term in the estimation.

[9] To see why, note that specification (17) implies the following transformation on the dependent variable:

$$\Delta \ln w_{qic\tau} - \underbrace{\sum_c \Delta \ln w_{qic\tau}}_{\Delta \ln w_{qi\tau}}.$$

Adding city-time dummies and estimating (18) implies the following transformation:

$$\Delta \ln w_{qic\tau} - \underbrace{\sum_c \Delta \ln w_{qic\tau}}_{\Delta \ln w_{qi\tau}} - \underbrace{\sum_{r,j} \Delta \ln w_{rjc\tau}}_{\Delta \ln w_{c\tau}},$$

where the last term uses the within-city variation in wages.

I estimate equation (18) with five-year averages of annual data, taking mutually exclusive and jointly exhaustive intervals. Thus, $w_{qic\tau}$ is a five-year average of annual wages, and both $ER_{c\tau}$ and η_{rjc} in $R_{qic\tau}$ are constructed using averages of annual employment data. In doing so, I reduce measurement errors and purge variations due to business cycles. Details regarding data are left to the empirical section. For clarity, I will omit the time subscript where possible henceforth.

2.3 The social interaction problem and the endogeneity of the transition index

An important element of the identification consists in dealing with the social interaction problem and with the endogeneity related to employment measures. The instrumental variable strategy derives from the reduced-form counterpart of the transition index, which I obtain from the reduced form of the wage equation (15). Mathematical details linking the Nash bargaining solution to the reduced-form equation are left to Appendix B of the Supplementary Material. The reduced-form counterpart of the transition index, denoted I_{qic}, takes the following form,

$$I_{qic} = \sum_{r,j \neq q,i} \tilde{\chi}_{rjc|qi} \eta_{rjc} \nu_{rj}, \tag{19}$$

where ν_{rj} is the national wage premium relative to the numeraire occupation-industry-11 cell.

If the transition probabilities are uncorrelated with the error term, the index I_{qic} itself is a valid instrument for coping with the social interaction problem. Let me first examine the conditions under which this is the case. In order to do so, it is useful to discuss the employment determination and rewrite the transition probabilities as the sum of two components: one which is associated to the employment share η_{rjc} and another one reflecting the mobility cost $\varphi_{rj|qi}$.

2.3.1 Employment determination and the exogeneity of the transition probabilities

Employment is determined by a free entry condition whereby individuals with expected payoff larger than the fixed entry cost K become an entrepreneur. Thus,

$$N_{qic} = \frac{1}{\theta_{qic}} L_c \Omega_{ic} \int_{\frac{K}{V_{ic}^{v}}}^{\infty} n f(n) dn, \tag{20}$$

where $V^v_{ic} = \sum_r \frac{1}{\theta_{ric}} V^r_{ric}$. Substituting (20) in the transition probability, one obtains

$$\tilde{\chi}_{rjc|qi}\eta_{rjc} = \frac{\varphi_{rj|qi}\frac{1}{\theta_{rjc}}\Omega_{jc}\int_{\frac{K}{V^v_{jc}}}^{\infty} nf(n)dn}{\sum_{sk\neq qi}\varphi_{sk|qi}\frac{1}{\theta_{skc}}\Omega_{kc}\int_{\frac{K}{V^v_{kc}}}^{\infty} nf(n)dn} \quad \forall r,j \neq q,i. \tag{21}$$

Taking a linear approximation around the point where cities have identical employment rates and a similar employment structure, equation (21) can be rewritten as

$$\begin{aligned}\tilde{\chi}_{rjc|qi}\eta_{rjc} \quad &\approx \quad \frac{1}{QI-1} + \tilde{\pi}_1\left[\Omega_{jc} - \frac{1}{QI-1}\sum_{s,k\neq q,i}\Omega_{kc}\right] + \tilde{\pi}_2\left[\varepsilon_{rjc} - \frac{1}{QI-1}\sum_{s,k\neq q,i}\varepsilon_{skc}\right] \\ &+ \quad \tilde{\pi}_3\left[\varphi_{rj|qi} - \frac{1}{QI-1}\sum_{s,k\neq q,i}\varphi_{sk|qi}\right] \quad \forall r,j\neq q,i, \end{aligned} \tag{22}$$

where the $\tilde{\pi}$s are positive terms obtained from the linear approximation.

To understand the restrictions underlying consistency, it is useful to express ε_{qic} as the sum of two elements: an absolute advantage common to all jobs of the same city, ε_c, and a relative advantage, $\upsilon^{\varepsilon}_{qic}$, where by definition $\sum_{r,j}\upsilon^{\varepsilon}_{rjc} = 0$. By the same token, define $\Omega_{ic} = \Omega_c + \upsilon^{\Omega}_{ic}$, where

$\sum_j \upsilon_{jc}^{\Omega} = 0$. With some algebra, equation (22) can be rewritten as[10]

$$\tilde{\chi}_{rjc|qi}\eta_{rjc} \approx \pi_0 + \frac{QI}{QI-1}\left[\underbrace{\frac{1}{QI} + \pi_1\upsilon_{jc}^{\Omega} + \pi_2\upsilon_{rjc}^{\varepsilon}}_{\text{linear approximation of } \eta_{rjc}} + \overbrace{\pi_3\varphi_{rj|qi}}^{\text{mobility component}}\right] \quad \forall r, j \neq q, i, \tag{23}$$

The first three terms in the bracket are associated with employment shares η_{rjc}. The last component reflects the mobility term $\varphi_{rj|qi}$.

Since $\varphi_{rj|qi}$ is an aggregate measure, the transition probabilities (and thus I_{qic}) are exogenous if the employment shares η_{rjc} are uncorrelated to the error term $\gamma_1 \Delta\varepsilon_{qic} p_i$. This is the case if ε_c follows a random walk and is independent of present values and of changes of $\upsilon_{qic}^{\varepsilon}$ and υ_{ic}^{Ω}. A detailed discussion of why this is the case can be found in Appendix C-1 of the Supplementary Material. Intuitively, this requires that shifts in the local composition of employment arising from changes in job-city specific comparative advantages $\Delta\upsilon_{qic}^{\varepsilon}$ and $\Delta\upsilon_{ic}^{\Omega}$ are uncorrelated to city-specific productivity shocks $\Delta\varepsilon_c$. If this were not the case, the estimate of interest would partially capture the effect of local productivity shocks rather than the effects induced by changes in the outside options of workers.

[10]

$$\begin{aligned}\tilde{\chi}_{rjc|qi}\eta_{rjc} \quad &\approx \quad \frac{QI}{QI-1}\left[\underbrace{\frac{1}{QI} + \pi_1\upsilon_{jc}^{\Omega} + \pi_2\upsilon_{rjc}^{\varepsilon}}_{\text{linear approximation of } \eta_{rjc}} + \overbrace{\pi_3\varphi_{rj|qi}}^{\text{mobility component}}\right] \\ &- \quad \underbrace{\frac{QI}{(QI-1)^2}\left[\pi_1\left(1-\upsilon_{ic}^{\Omega}\right) + \pi_2\left(1-\upsilon_{qic}^{\varepsilon}\right) + \pi_3\left(1-\varphi_{qi|qi}\right)\right]}_{\text{adjustment for the probability of re-employment}} \quad \forall r, j \neq q, i,\end{aligned}$$

where $\pi_1 = \frac{QI-1}{QI}\tilde{\pi}_1$, $\pi_2 = \frac{QI-1}{QI}\tilde{\pi}_2$ and $\pi_3 = \frac{QI-1}{QI}\tilde{\pi}_3$ and where $\sum_{r,j\neq q,i}\tilde{\chi}_{rjc|qi}\eta_{rjc} = 1$. With $\mu_{qic} = \mu$, one finally obtains

$$\tilde{\chi}_{rjc|qi}\eta_{rjc} \approx \pi_0 + \frac{QI}{QI-1}\left[\underbrace{\frac{1}{QI} + \pi_1\upsilon_{jc}^{\Omega} + \pi_2\upsilon_{rjc}^{\varepsilon}}_{\text{linear approximation of } \eta_{rjc}} + \overbrace{\pi_3\varphi_{rj|qi}}^{\text{mobility component}}\right] \quad \forall r, j \neq q, i,$$

where $-\frac{QI}{(QI-1)^2}\left[\pi_1\left(1-\upsilon_{ic}^{\Omega}\right) + \pi_2\left(1-\upsilon_{qic}^{\varepsilon}\right) + \pi_3\left(1-\varphi_{qi|qi}\right)\right] = \pi_0 \ \forall \ q, i$.

2.3.2 Predicted employment

While employment shares may be exogenous, it is preferable to construct instruments based on the looser assumption that local productivity shocks $\Delta\varepsilon_c$ are uncorrelated to *past* occupation-industry-city-specific comparative advantages $\upsilon^{\varepsilon}_{rjc}$ and υ^{Ω}_{jc} only. Fundamentally, this assumption requires that the local structure of employment in the past is uncorrelated to present city-specific productivity shocks and therefore suggests to predict present occupation-industry-city employment, bringing together national components with start-of-period local employment.

Let $\hat{}$ denote a prediction. Specifically, employment is predicted as if it had grown at the same rate as national employment:

$$\hat{N}_{rjc\tau} = N_{rjc(\tau-1)} \frac{N_{rj\tau}}{N_{rj(\tau-1)}}, \tag{24}$$

where $N_{rj\tau}$ denote national occupation-industry employment and $(\tau - 1)$ is the start of period. The choice of the base year from which the growth rate is computed trades off exogeneity against its potential to provide a good predictor of the transition index. Let t denote a year. The baseline specification uses

$$N_{rjc(\tau-1)} = \frac{1}{5}\sum_{t}^{t+4} N_{rjct}, \quad t \in (\tau - 1) \tag{25}$$

as start-of-period employment to predict $N_{rjc\tau}$, which is akin to using the fifth lag to predict actual local employment.

2.3.3 Instruments

The proposed instrumental variables strategy is based on a within versus between decomposition of the index I_{qic} and replaces employment shares in the transition probabilities by their predicted counterparts $\hat{\eta}_{rjc\tau}$, where $\hat{\eta}_{rjc\tau} = \frac{\hat{N}_{rjc\tau}}{\hat{N}_{c\tau}}$ and $\hat{N}_{c\tau} = \sum_{r,j} \hat{N}_{rjc\tau}$.

The first instrument isolates a within variation based on changes in the wage premia

$$IV_1 = \sum_{r,j \neq q,i} \hat{\eta}_{rjc\tau} \hat{\hat{\chi}}_{rjc\tau|qi} \Delta\nu_{rj\tau}, \tag{26}$$

where $\hat{\hat{\chi}}_{rjc\tau} = \frac{\varphi_{rj|qi}}{\sum_{r,j\neq q,i}\varphi_{rj|qi}\hat{\eta}_{rjc\tau}}$. The second instrument identifies a between variation that captures changes in the transition probabilities

$$IV_2 = \sum_{r,j\neq q,i} \nu_{rj(\tau-1)}\Delta\left[\hat{\eta}_{rjc\tau}\hat{\hat{\chi}}_{rjc\tau|qi}\right]. \tag{27}$$

In addition, IV_2 can be decomposed into two further elements:

$$IV_3 \;\; = \;\; \sum_{r,j} \nu_{rj(\tau-1)}\hat{\hat{\chi}}_{rjc(\tau-1)|qi}\Delta\hat{\eta}_{rjc\tau}, \tag{28}$$

which is associated to changes in the distribution of employment and

$$IV_4 \;\; = \;\; \sum_{r,j} \hat{\eta}_{rjc\tau}\nu_{rj(\tau-1)}\Delta\hat{\hat{\chi}}_{rjc\tau|qi}, \tag{29}$$

which is based on changes in the relative mobility measure.

The inclusion of heterogeneous mobility costs provides additional overidentifying restrictions, $IV2$ and IV_4, which, to the best of my knowledge, have not been recognized previously. If the variation stemming from differences in sectoral and occupational mobility matters for the wage determination, the first stage estimates on $IV2$ and $IV4$ should enter in a positive, similar and statistically significant manner. Moreover, since each instrument explores a different type of data variation, any deviation from the identifying assumption is expected to produce different estimates. Therefore, if local productivity shocks are uncorrelated to past job-city-specific comparative advantages, each set of instruments should generate similar estimates.

Proofs regarding the validity of the instruments $IV1$ and $IV2$ can be found in Appendix C-2 of the Supplementary Material. As for $IV3$ and $IV4$, the proofs are entirely symmetric to $IV2$. Details associated with the construction of the wage premia $\nu_{rj\tau}$ and with the mobility parameters $\varphi_{rj|qi}$ are provided in the empirical setting.

2.4 Endogeneity of the employment rate

Estimating equation (17) consistently requires dealing with the endogeneity of the employment rate. Noting that the emloyment rate can be linear approximated as $\Delta ER_c \approx \pi_5\Delta\Omega_c + \pi_6\Delta\varepsilon_c$, it is straightforward to see that

$$\lim_{Q,I,C\to\infty}\sum_{q,i,c}\Delta ER_c \Delta\xi_{qic} \neq 0. \tag{30}$$

The instruments for the employment rate are built in a way analogous to those for the transition index, using $\hat{N}_{rjc\tau}$ as a prediction for $N_{rjc\tau}$. Therefore, their validity relies on the same assumption that local productivity shocks $\Delta\varepsilon_c$ are uncorrelated to *past* occupation-industry-city-specific comparative advantages $\upsilon^{\varepsilon}_{rjc}$ and υ^{Ω}_{jc}.

The traditional approach to dealing with the endogeneity of the employment rate is to construct the so-called Bartik instrument, used in various studies (Blanchard and Katz, 1992; Beaudry et al., 2012, 2011). Exploiting the disaggregation at the occupational level, the Bartik instrument is given by

$$IV^{BK}_1 = \sum_{r,j}\eta_{rjc(\tau-1)}\frac{N_{rj\tau}-N_{rj(\tau-1)}}{N_{rj(\tau-1)}}, \tag{31}$$

and can be rewritten as

$$IV^{BK}_1 = \frac{\hat{N}_{c\tau}}{N_{c(\tau-1)}} - 1. \tag{32}$$

By predicting local employment growth solely, the Bartik instrument focuses on the numerator of the employment rate and neglects changes driven by shifts in the labor force. Since Western Germany experienced important variations in the population (especially following the immigration wave that occured after the fall of the iron curtain), the Bartik instrument may perform poorly if used on its own to predict the employment rate. Presumably, limited information on unemployed workers prevented US studies from creating the labor force counterpart of the Bartik instrument. German data, however, allow to trace individuals over time and therefore to affiliate unemployed workers to a particular occupation and industry. I take advantage of this source of information to create a second instrument which I denote IV^{BK}_2. Letting L stand for the labor force and l be its corresponding labor force share, I construct

$$IV^{BK}_2 = \sum_{r,j} l_{rjc(\tau-1)}\frac{L_{rj\tau}-L_{rj(\tau-1)}}{L_{rj(\tau-1)}}, \tag{33}$$

which is equivalent to

$$IV_2^{BK} = \frac{\hat{L}_{c\tau}}{L_{c(\tau-1)}} - 1. \tag{34}$$

Since (34) concentrates on variations associated with the growth of the labor force, its effect on the employment rate is expected to be negative and of a magnitude similar to that of the Bartik instrument. This additional instrument allows to test for overidentifying restrictions.[11]

3 Empirical setting

3.1 Data source

This paper uses the factually anonymous IAB Employment Sample (IABS) for the years 1975-2001. Data access is provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB). IAB employment statistics cover all employees registered by the German social insurance system and subject to social insurance contributions. In 1995, the data cover 79.4 % of all employed persons in Western Germany. The self-employed are not covered. I only observe whether an individual works full- or part-time; information on the hours worked is not available. Therefore, I focus on full-time workers. Information on wages captures all earnings subject to statutory social security contributions and reported at least once annually. The wage measure corresponds to daily wages. The reporting of income is truncated from above and from below. The upper limit is the contribution assessment ceiling for social insurance, which is adapted annually to the growth of nominal wages, and the lower limit is the minimum wage. The baseline estimates are based on the entire wage distribution.[12] The Scientific Use File provides a 2% anonymous sample of the original IAB employment database. Over the entire sample period, a 2% representative sample is drawn from four clusters, namely German nationals, foreign nationals, West-German residents and East-German residents. With data on Eastern Germany available only from 1991 onwards, I

[11] As a robustness test, I will use other decompositions of the employment rate, based the same assumption and exploiting the same type of data variation.

[12] As a sensitivity check, I will present results on the uncensored part only and show that the qualitative aspect of the results remain unaltered.

concentrate on West-German residents, aged 16 to 62, over the period 1977-2001.[13]

3.2 Defining occupation-industry-city cells

An important step of the data work consists in choosing an aggregation level of occupations, industries and cities which fits the needs of the analysis. To ensure the precision of the measures reflecting wage premia, employment shares and employment transitions, I require that each occupation-industry-city cell contains at least 20 employed individuals every year. Cities are constructed according to Kropp and Schwengler (2011) definition of labor markets.[14] According to their definition, Western Germany comprises 38 labor markets and 9 regions. The constraint of 20 individuals per cell requires merging Kropp and Schwengler (2011) labor markets into 19 geographical areas corresponding to what I call "cities". Aggregation details of Kropp and Schwengler (2011) labor markets into cities are provided in Appendix D of the Supplementary Material. In the original IAB file, industries are classified according to the 1973 3-digit German classification of economic activities, which has no evident correspondence with NACE or ISIC. Occupations are classified according to the 1975 German classification of occupations. The anonymous sample provides only 16 industries and 130 occupations. I group occupations into 32 broader categories, according to the 1975 German classification of occupations. This allows me to work with an aggregation level closer to that of industries and to obtain a reasonable number of observations per occupation-industry-city cells. The industrial and occupational classifications into 16 and 33 categories are shown Appendix E and F of the Supplementary Material, respectively.[15]

Occupation-industry cells are retained according to the following criteria. First, an occupation-industry cell has to be present over the years 1977 to 2001. Second, a cell must be observed in at least 5 cities, to ensure that national-level variables differ from the city level. Given the constraint of 20 employed individuals per occupation-industry-city cell, each occupation-industry cell contains at least 100 employed workers. 135 occupation-industry cells meet these criteria. Appendix G of the Supplementary Material provides a Table of the occupation-industry mix represented in this study. The Table also informs on the representation of occupations within industries and across

[13]In the Appendix of the Supplementary Material, I show that results remain qualitatively similar when the sample is restricted to workers aged 21-60 and excludes individuals in apprenticeship.

[14]Kropp and Schwengler (2011) correspondence table between districts, labor markets and regions can be downloaded at http://www.iab.de/389/section.aspx/Publikation/k110222301

[15]Industries and occupations are reported by firms, and not by workers. Hence, they should be accurately classified.

cities.

3.3 Wages adjusted for workers' characteristics

This paper focuses on differences in wages across occupations, industries and cities over time. To control for individual observable characteristics, I adopt a common two-stage procedure. The second stage estimates the relationship of interest. The first stage consists in purging individual wages from components which are associated with age, gender, nationality or education, using a series of Mincer-type regressions.

For each year, log individual wages are regressed on a vector of individual characteristics and a complete set of occupation-industry-city interaction terms. Individual wages are expressed in euros and converted into real wages using the consumer price index, base 2005, provided by the German federal statistical office. The vector of individual characteristics includes the age, the square of age, a gender dummy, a nationality dummy, a categorical variable for education and a full set of education-gender, education-nationality and education-age interactions.[16] In performing yearly regressions, returns to skill are allowed to vary over time. The dependent variable $w_{qic\tau}$ is constructed using five-year averages of the coefficients on the occupation-industry-city dummies, which as mentioned before, represent at least 20 individuals. As for the wage premia, the same approach is used: log individual wages are regressed on the same vector of individual characteristics and a complete set of occupation-industry dummies. The coefficients on the dummies are used to compute $\nu_{qi\tau}$, the occupation-industry wage premia. I use the square root of the number of observations in each occupation-industry-city cell to create weights for the second stage estimation. The main results are based on this approach. I will discuss the selection of workers into cities and occupations later on and show that estimates remain unaltered to a specification that addresses this issue.

3.4 Mobility measures

The mobility measures $\varphi_{rj|qi}$ are constructed using the observed yearly transitions of workers across occupation-industry cells. In order to obtain a representative number of individuals moving across

[16]The educational variable includes six categories: without vocational training, apprenticeship, highschool with *Abitur*, highschool without *Abitur*, polytechnic, university.

cells, the data are pooled over the entire period (1977-2001). Specifically, $\varphi_{rj|qi}$ is given by

$$\varphi_{rj|qi} = \frac{N_{rj|qi}}{\sum_{r,j} N_{rj|qi}}, \tag{35}$$

where $N_{rj|qi} = \sum_t N_{rjt|qi(t-1)}$, and where $N_{rjt|qi(t-1)}$ denote the number of workers transiting from qi at $(t-1)$ to rj at t. To be consistent with the constraint of 20 individuals per cell, given the 25-years horizon and given that a minimum of 4% of the labor force moves across occupations and industries every year, I restrict the analysis to switches representing at least 100 individuals (100*0.04*25). Appendix K of the Supplementary Material provides Tables indicating where individuals are observed moving depending on their origin. As a sensitivity analysis, I will consider two alternatives which introduce some time and spatial flexibility in computing the mobility measures $\varphi_{rj|qi}$.

If a particular move, say from qi to rj, is not observed in the data, then the mobility measure $\varphi_{rj|qi}$ is zero and the factor weighting the outside wage w_{rjc} will be zero $\forall$ c. This implies that w_{rjc} will only affect w_{qic} indirectly through its potential effect on other occupation-industry local wages. Figure (2) provides a simple illustration of an environment where individuals can work either in A, B or C. Assume that workers can move from A to B but that direct moves from A to C are not observed. However, workers in A can reach C indirectly by first moving to B. In such a case, workers in A will attribute a zero weight on option C and the wage offered in C will enter the wage determination of A only indirectly through option B.

< Figure (2) here >

4 Results

4.1 Main results

The baseline results are presented in Table (1). Each of the specifications includes a full set of time-varying occupation-industry dummies to control for changes in industry and occupation aggregates, including changes in national occupation-industry wage premia and industry-wide bargaining. Standard errors are clustered at the level of the city, thus allowing the error terms to be heteroscedastic and correlated within city.

< Table (1) here >

Columns (1)-(3) present the results corresponding to specification (17), which relies on a comparison of periodical differences in wages within occupation-industry cells across cities. The estimate obtained with OLS is large at 0.363 and statistically significant at the 1% level. Column (2) uses IV_1 (the 'within' component) and IV_2 (the 'between' component) as instruments for the transition index. Column (3) is based on the further decomposition of the 'between' instrument into IV_3 and IV_4, which, as stated before, isolates movements in the local composition of employment and changes in the relative mobility costs (as captured by $\tilde{\chi}_{rjc|qi}$). Whichever IV specification one looks at, the estimates obtained are similar, 0.644 in column (2) and at 0.603 in column (3), and statistically significant at the 1% level. These results suggest that the network effects emerging from the social interaction are strong: a 1% increase in a worker's outside options generate a more than 6% wage increase.

The two sets of instruments (here IV_1 and IV_2 versus IV_1, IV_3 and IV_4) offer a test of overidentifying restrictions. Since each instrument explores a distinct type of data variation, any deviation from the identifying assumption would be weighted differently and therefore, produce different estimates. For this reason, the similarity of the results obtained in columns (2) and (3) can be interpreted as an evidence that local productivity shocks are uncorrelated to past job-city-specific comparative advantages. The Hansen test at the bottom of the Table gives support to this argument. The second section of the Table shows the first stage (but only the relevant estimates, i.e. IV_1-IV_4 on $R_{qic\tau}$ and IV_1^{BK}-IV_2^{BK} on ER_c). Each of the IV's estimates is statistically significant at the 1% level and as expected, affect the index in a similar fashion. Importantly, the fact that the estimates on $IV2$ and $IV4$ are statistically significant provides support to the mechanism put forward in this paper that workers' mobility costs across occupations and industries also enter the wage bargaining process of individuals. The IV's corresponding F-statistics of the excluded instruments is above 10, suggesting that the relevance condition is satisfied. For each endogenous regressor, the Angrist-Pischke p-value is zero, indicating the absence of a weak instrumental variables problem.[17] As for the employment rate, the Bartik instruments enter the first stage in a

[17]The Angrist-Pischke p-value is indicated in the notes at the bottom of each Table.

statistically significant manner. Not surprisingly, the labor force counterpart of the original Bartik measure is negative.

Columns (4)-(6) present the estimates associated to specification (18), which, by including city time-varying dummies is akin to a triple-difference estimation. This specification controls for all competing explanations for differences in wages (or growth performances) across cities such as education externalities (Acemoglu and Angrist, 2000; Moretti, 2004), employment diversity or agglomeration forces (Blanchard and Katz, 1992; Glaeser et al., 1992; Glaeser and Gottlieb, 2009). On top of that, the inclusion of city-time dummies allows to purge the estimate from the indirect effect working through local housing prices and to focus on the impact of changes in outside employment opportunities on wages, holding constant the local cost of living.[18] As in the previous specification, diagnostic tests are satisfactory at any conventional level. The robustness of the IV results to the inclusion of $d_{c\tau}$ is remarkable: in each case, the estimate is statistically significant at the 1% level, and of a magnitude of 0.713 when estimated with the first set of instruments and of 0.655 when estimated with the second one.

Finally, columns (7) and (9) investigate whether local demand effects interfere with $\tilde{\gamma}_2$, the estimate capturing search and bargaining mechanisms. Consider a shock shifting labor demand across occupations and industries at the national level. Presumably, a local labor market response to such a shock depends on the cost workers would suffer to reallocate within city. For this reason, local demand changes may be correlated with the transition index and create an omitted variable bias. I examine this possibility in the following way. I construct a measure reflecting the ease with which workers in a particular occupation-industry cell reallocate across occupations and industries within city following national-level changes in labor demand. Specifically, I create $D_{qic\tau} = \sum_{r,j \neq q,i} \chi_{rjc\tau|qi} \eta_{rjc\tau} \frac{N_{rj\tau} - N_{rj(\tau-1)}}{N_{rj(t-1)}}$, where the growth rate of employment, $\frac{N_{rj\tau} - N_{rj(\tau-1)}}{N_{rj(t-1)}}$, captures national-level labor demand changes across occupations and industries, and where the transition probability, $\chi_{rjc\tau|qi} \eta_{rjc\tau}$, reflects the ease with which workers move within city. A high value for this index indicates that qi-workers are the one facing the lowest mobility cost to adjust to labor demand changes. Because it is built using local employment shares, $D_{qic\tau}$ is likely to be endogenous. As with the transition index, $D_{qic\tau}$ is instrumented with its predicted counterpart, i.e. using $\sum_{r,j \neq q,i} \hat{\chi}_{rjc\tau|qi} \hat{\eta}_{rjc\tau} \frac{N_{rj\tau} - N_{rj(\tau-1)}}{N_{rj(t-1)}}$ as an instrument. The estimates obtained on the local

[18] Housing costs decrease the value of being employed (and therefore the value of a match). It follows that firms located in cities where the local cost of living is high have to offer higher wages.

demand variable is statistically highly insignificant and more importantly the coefficients on the transition index remain unaltered, suggesting that these types of local demand effects do not drive my estimates.

This paper tests a mechanism through which, with employment (or marginal productivity) held constant, changes in outside options – as captured by the transition index – affect occupation-industry-city wages. At this stage, it is important to make sure that the impact of a change in the employment composition on wages reflects the effect of a change in outside employment opportunities and not the effect resulting from supply and demand changes, as it would be the case in a neo-classical framework. To do so, Table (2) introduces the log change in employment (at the industry-, occupation- and occupation-industry-city levels) to the baseline specification. Employment is instrumented using its predicted counterpart. Once instrumented, the employment variable enters in statistically insignificant manner and does not alter the estimate of interest, indicating that shifts in the transition index affect wages through changes in outside options and not through moves along the marginal product curve.[19]

< Table (2) here >

4.2 A quantitative assessment

Overall, the estimates obtained in the previous section suggest that the wage determination process in Germany responds to search and bargaining mechanisms. Ultimately, the question in which we are interested is: What are the implications of these findings in terms of the wage effects of a labor demand shock? While my model does not provide a general answer, it can be used without difficulty to assess the impact of a shift in the structure of employment on occupation-industry-specific local wages.

In order to do so, one first has to overcome the feedback dynamics of the reflection equation (12). In what follows, let me solve (12) for wages. Let W, $\tilde{\theta}$ and $\tilde{\varepsilon}$ be $QICX1$-dimensional vectors of occupation-industry-city wages, of the values of the marginal productivity of labor $\theta_{qic}p_i$ and of

[19] Appendix I, Table (2), of the Supplementary Material excludes the transition index from the wage equation and investigates the impact of $IV1 - IV4$ on the employment variables. Focusing on the first stage, the estimates on the instruments are statistically insignificant, with a F-statistics of 2.5 and partial R-squared of 0.002 at most. These results suggest that the variation used to identify $\tilde{\gamma}_2$ is uncorrelated with employment and again, suggest that shifts in the transition index do not reflect supply-demand effects.

the terms $\varepsilon_{qic}p_i$. Likewise, let T be a $QICXQIC$-dimensional matrix of transition probabilities $\chi_{rjc|qi}\eta_{rjc}$ and M be a $QICXQIC$-identity matrix. For clarity, let me omit the time dimension. Equation (12) can be rewritten as follows [20]

$$W = \tilde{\gamma}_{1c}\tilde{\theta} + \tilde{\gamma}_{2c}T \times W + \tilde{\gamma}_{1c}\tilde{\varepsilon}, \tag{36}$$

or, solving for the vector of wages and substituting back into (36),

$$W = \tilde{\gamma}_{1c}\theta + \tilde{\gamma}_{1c}\tilde{\gamma}_{2c}T \times [M - \tilde{\gamma}_{2c}T]^{-1} \times \tilde{\theta} + \tilde{\gamma}_{1c}\tilde{\gamma}_{2c}T \times [M - \tilde{\gamma}_{2c}T]^{-1}\tilde{\varepsilon} + \tilde{\gamma}_{1c}\tilde{\varepsilon}. \tag{37}$$

Finally, let me take a linear approximation around the point where cities have identical employment rates and where employment is uniformly distributed across occupations and industries. I obtain the following system of equations

$$\Delta W = D + \tilde{\gamma}_2\Delta\Big[T \times [M - \tilde{\gamma}_2 T]^{-1} \times V\Big] + \Delta\tilde{\xi}, \tag{38}$$

where D, V and $\tilde{\xi}$ are $QIX1$-dimensional vectors of occupation-industry dummies, national occupation-industry wage premia and of the error components. The term $T \times [M - \tilde{\gamma}_2 T]^{-1} \times V$ is a vector combining the estimated parameter $\tilde{\gamma}_2$, the mobility measures $\chi_{rjc|qi}$, employment shares η_{rjc} and national wage premia ν_{qi}.

Everything else being equal, a quantitative assessment of the wage effects across occupations, industries and cities of changes in the local conditions of employment is directly obtained by introducing the relevant employment shares, mobility measures and wage premia into the vector

$$\tilde{\gamma}_2\Delta\Big[T \times [M - \tilde{\gamma}_2 T]^{-1} \times V\Big].$$

Let me provide you with a stylized example. In doing so, I will also illustrate how differences in workers' mobility costs may induce heterogenous wage responses across jobs to a shock on the

[20]

$$\begin{bmatrix} w_{11c} \\ \cdots \\ w_{qic} \\ \cdots \\ w_{QIC} \end{bmatrix} = \tilde{\gamma}_{1c}\begin{bmatrix} \theta_{11}p_1 \\ \cdots \\ \theta_{qi}p_i \\ \cdots \\ \theta_{QI}p_I \end{bmatrix} + \tilde{\gamma}_{2c}\begin{bmatrix} \chi_{11c|11}\eta_{11c} & \cdots & \chi_{QIc|11}\eta_{QIc} \\ \cdots & \cdots & \cdots \\ \chi_{11c|qi}\eta_{11c} & \cdots & \chi_{QIc|qi}\eta_{QIc} \\ \cdots & \cdots & \cdots \\ \chi_{11c|QI}\eta_{11c} & \cdots & \chi_{QIC|QI}\eta_{QIC} \end{bmatrix}\begin{bmatrix} w_{11c} \\ \cdots \\ w_{qic} \\ \cdots \\ w_{QIC} \end{bmatrix} + \tilde{\gamma}_{1c}\begin{bmatrix} \varepsilon_{11c}p_1 \\ \cdots \\ \varepsilon_{qic}p_i \\ \cdots \\ \varepsilon_{QIC}p_I \end{bmatrix}$$

structure of employment. Consider an environment with two types of jobs, A and B. Let A and B denote high-skill high-paying and low-skill low-paying jobs, respectively. Assume that relative to B, high-skill jobs pay a wage premium of 20%. In addition, assume that, initially, the fraction of workers employed in A and B is identical.

Consider first a scenario where a shock on labor demand shifts the composition of employment towards high-skill high-paying jobs. In particular, assume that the fraction of A jobs increases to 60%. If one takes the baseline estimate of 0.65 as a reference point, the total impact on wages in A and B can be computed from $\tilde{\gamma}_2\Delta\Big[T \times [M - \tilde{\gamma}_2 T]^{-1} \times V\Big]$. In order to see how differences in workers' mobility costs generate differential wage outcomes to a shift in the composition of employment, consider two extreme cases. In the first one, let workers be identically mobile across jobs. In the second one instead, assume that B-type workers cannot move to A jobs (but that workers in A are still identically mobile across jobs).

In the first case, a 10 percentage point shift of employment towards high-skill high-paying jobs increases wages by 3.7% in both A and B. Overall, this implies a 5.7% increase in the average city wage, that is to say, an increase which is 2.9 times the one that would be predicted by a standard decomposition approach.[21] In the second case however, the model implies an increase in wages of 3.1% for workers in A but no wage effects for B-types jobs, inducing a 4.2% increase in the average city wage. Since workers in B are immobile, A-type jobs do not constitute options with which to convincingly bargain and for this reason, a shock affecting A jobs will have no wage effect on low-skill low-paying jobs.

Consider now the reverse scenario where the fraction of low-skill low-paying jobs increases to 60%. When workers face similar mobility costs, the model predicts a symmetric decrease of 3.7% in wages across jobs, i.e. a decrease of 5.7% in the average local wage. In the second case where B-type workers are immobile, the shift of employment towards low-skill low-paying jobs only reduce wages in the high-skill jobs. Specifically, A-type wages are predicted to decrease by 2.6%. This implies a city average wage decline of 3.6%. Since workers in B are confined to the same type of jobs, their probability to be matched to B is one, regardless of the local employment structure. As for A-workers, the shift towards low-skill low-paying jobs generates a deterioration of their employment

[21] A standard decomposition approach consists in multiplying each occupation-industry wage in a base year by the corresponding change in employment shares and then summing up across occupations and industries. In this example, the effect predicted by such an approach is 0.02, i.e. $w_A\Delta\eta_A + w_B\Delta\eta_B = 0.2 * 0.1 + 0 * 0.1$.

opportunities, therefore inducing a reduction of their wages.

This stylized exercice exemplifies how the positive wage externality generated form a shift of employment towards high-paying jobs may be mitigated for workers facing high-mobility costs. In addition, it suggests that, to the extent that high-skill workers are sufficiently mobile, an increase in the proportion of low-skill low-paying jobs may affect high-skill wages negatively and importantly, disproportionately more.

4.3 Selection issue into cities and occupations

The baseline estimates rely on the assumption that my sample is a random draw of the population. In practice however, workers tend to self-select into cities (Dahl, 2002) and occupations (Gibbons et al., 2005; Groes et al., 2009) according to unobserved earnings-related reasons. If worker selection is correlated with unobserved determinants of wages (e.g. individual abilities), the conditional mean error term will not be zero and the estimates of the coefficient on the transition index will be inconsistent if the structure of employment within cities is correlated with worker selection decisions into cities and occupations.

In the context of BGS, the selection issue applies to cities only and can be treated using Dahl (2002) non-parametric approach.[22] In this study, the selection extends to occupations and requires a different treatment of individual wages. I exploit the traceability of workers over the years and approach this problem directly by regressing Mincer equations in first differences. The method relies on the idea that conditional on occupation fixed effects, city fixed effects and individual workers' skills, the allocation of workers across cells is random. By taking first differences, this approach has the advantage of getting rid of all the selection problem, including potential selection into industries, at once. Let L denote the set of individuals and let $\{l, m\} \in L$. For clarity, let me omit time-varying individual characteristics. I pool the years 1976 to 2001 together and estimate a first-difference version of the following equation

$$w_{lqict} = \sum_{m} \theta_m d_m + \sum_{m,r} \theta_{mr} d_{mr} + \sum_{m,d} \theta_{md} d_{md} + \sum_{r,j,d,t} \theta_{rjdt} d_{rjdt}, \tag{39}$$

where d_m is a worker fixed effect, d_{mr} is a worker-occupation fixed effect, d_{md} is a worker-city

[22] Dahl (2002) non-parametric approach addresses the selection into cities by adding a function of migration's probabilities (computed over individuals with similar characteristics) to the Mincer regressions in the first stage.

fixed effect and d_{rjdt} denote occupation-industry-city time-varying interactions. Letting $lqic$ be the cross-sectional unit and taking yearly differences, one obtains

$$\Delta w_{lqict} = \sum_{r,j,d,t} \left[\left(\theta_{rjdt} - \theta_{rjd(t-1)}\right) S_{rjdt|rjd(t-1)} + \sum_{q,i,c \neq r,j,d} \left(\theta_{rjdt} - \theta_{qic(t-1)}\right) M_{rjdt|qic(t-1)} \right], \quad (40)$$

where $S_{rjdt|rjd(t-1)}$ is a dummy variable indicating stayers and $M_{rjdt|qic(t-1)}$ is a dummy variable denoting movers. The coefficients on the stayers dummies are therefore identified with (employed) workers staying in an occupation-industry-city cell from one year to the other. The terms $\theta_{rjdt} - \theta_{rjd(t-1)}$ represent yearly differences in occupation-industry-city wages, purged from individual observable and unobservable (fixed) characteristics. They will be used to construct both the dependent variable and the national wage premia. Technicalities regarding their construction are left to Appendix H of the Supplementary Material.

< Table (3) here >

Table (3) presents the estimates obtained when correcting occupation-industry-city wages (and the corresponding national wage premia) from the selection of workers into cities and occupations. The format of this Table is identical to that of Table (1). In general, the correction produces marginally smaller estimates but nowise affects the qualitative aspect of the results. As it is the case for the baseline, OLS estimates are biased downward. The bias is even more pronounced in this case. Taking for instance columns (1)-(3) as reference, the IVs estimates are twice as big as the OLS estimates. Relative to the baseline, the similarity of the results across groups of IVs is even more striking, which again suggests that the identifying assumption is valid. Likewise, the IV estimates are exceptionally comparable across specifications. This is outstanding if one realizes that columns (4)-(9) now corresponds to a specification in quadruple difference.

4.4 Testing the validity of the model

A way of testing the validity of the model consists in comparing the baseline estimates with the one obtained with the reduced-form counterpart of the reflection equation given by (12). In order to derive this reduced form, two routes can be taken.

The first approach implies a matrix resolution and does not impose any restrictions on the behavior of the mobility measures $\varphi_{rj|qi}$. This procedure has been described in the *quantitative assessment* section and generates an alternative transition index that combines the parameter estimated in the reflection equation together with both the transition probabilities and the national occupation-industry wage premia. In particular, recall from section (4.2) that one obtains

$$\Delta W = D + \tilde{\gamma}_2 \Delta \Big[T \times [M - \tilde{\gamma}_2 T]^{-1} \times V \Big] + \Delta \tilde{\xi},$$

where each element of the vector $\Delta \Big[T \times [M - \tilde{\gamma}_2 T]^{-1} \times V \Big]$ is denoted $\Delta R^{RFM}_{qic\tau}$. If the model is sound, the estimate resulting from this methodology should be similar to that obtained with the baseline specification. Results are shown in columns (1) to (3) of Table 4.

< Table (4) here >

The vector $\Delta \Big[T \times [M - \tilde{\gamma}_2 T]^{-1} \times V \Big]$ uses 0.65 as reference parameter and is instrumented with the usual instruments IV_1-IV_4.[23] Whichever the column considered, the estimates are positive and statistically significant at the 1% level. The size of the IVs coefficients is close to that estimated in the baseline and therefore suggests that the general model proposed in this paper provides a good approximation of the wage determination process in Germany.

A second route consists in deriving the reduced form of the wage equation by assuming that the mobility parameters $\varphi_{rj|qi}$ are path independent. As shown in Appendix B of the Supplementary Material, this approach implies that the reduced-form equation takes the following form

$$w_{qic} = d_{qi} + \frac{\tilde{\gamma}_2}{1 - \tilde{\gamma}_2} I_{qic} + \tilde{\gamma}_3 ER_c + \xi_{qic},$$

where $\frac{\tilde{\gamma}_2}{1-\tilde{\gamma}_2}$ captures the spillover effect on occupation-industry local wages of a one-unit shift in I_{qic}. In practice, imposing the path-independent assumption to derive the reduced-form wage equation implies that the indirect effects associated with employment opportunities workers cannot attain immediately (but could indirectly) do not enter the determination of occupation-industry local wages. Consider again the illustration given in Figure (2). As is the case with the reflection equation, workers in A will attribute a zero weight on option C. With this approach however, the

[23] Table 10 in Appendix I of the Supplementary Material shows estimates obtained using different values of $\tilde{\gamma}_2$ in the construction of the matrix. The qualitative aspect of the results is unchanged.

indirect effect of the outside wage w_C working through B is excluded from the wage determination in A. For this reason, the estimate on the reduced-form index I_{qic} is expected to be somewhat smaller than $\frac{\tilde{\gamma}_2}{1-\tilde{\gamma}_2}$, even if the model is reasonable.

Although this exercise is not as convenient as the matrix resolution, it nevertheless provides an indication of the validity of the model. In addition, it offers a means of testing whether my approach, which, remember, consists in estimating the Nash solution directly without imposing any restrictions on the mobility parameters $\varphi_{rj|qi}$, is suitable.

Results are shown in columns (4)-(6) of the same Table. Focusing on the IV specifications, the estimates are positive (larger than 0.9) and statistically significant at the 1% level. If one takes the baseline value of 0.651 as an exact reference point, the estimates represent only half of the expected spillover effect. However, when considering a value similar to that obtained when accounting for the selection issue, say 0.55, they represent approximately 75% percent of the expected spillover effect. The estimates suggest that omitting the indirect forces described earlier on is not desirable, and therefore indicate that my approach, which does not impose restrictions on the behavior of workers' mobility in the data, is pertinent. Even though the results suffer from a downward bias, they are still at least 1.4 times larger than the estimates of $\tilde{\gamma}_2$, providing support to the model proposed in this paper.

4.5 A comparison with Beaudry et al. (2012)

This section compares my framework with Beaudry et al. (2012) model. The comparison of both frameworks implies a discussion along two dimensions, one associated with the mobility costs of workers and another one which relates to occupations. From a theoretical perspective, Beaudry et al. (2012) model can be viewed as a special case where workers face identical moving costs (i.e. $\varphi_{rj|qi} = \varphi$) and where there are no within-industry technological differences across cities (i.e. $\varepsilon_{qic} = 0$ or $\theta_{qic} = \theta_{qi}$).

Recent findings by Kambourov and Manovskii (2009b) or Sullivan (2010) have argued that the occupational specificity of human capital dominates industry components in determining wage outcomes. It is therefore natural that my framework incorporates occupational aspects to the model. Up to now, I have centered the discussion on differences in mobility costs. As we have seen, when $\varphi_{rj|qi} = \varphi$, the outside options of workers are weighted by occupation-industry employment shares and the relevant index that enters the wage equation is the city composition index $R_c = \sum_{r,j} \eta_{rjc} w_{rjc}$. To provide a complete presentation of the differences between the two frameworks for the case of Germany, let me now relate the city composition index to Beaudry et al. (2012) sectoral composition index and clarify the importance of introducing the occupational dimension.

To do so, note that the city composition index can easily be rewritten using sectoral variables, i.e.

$$\begin{aligned} R_c &= \sum_j \frac{N_{jc}}{N_c} \sum_r \frac{N_{rjc}}{N_{jc}} w_{rjc} \\ &= \sum_j \eta_{jc} w_{jc} \\ &= R_c^{BGS}, \end{aligned}$$

where R_c^{BGS} denotes Beaudry et al. (2012) industrial composition index and η_{jc} and w_{jc} denote city-specific sectoral employment shares and wages, respectively. Hence, Beaudry et al. (2012) approach should generate an OLS estimate of the Nash solution (equation 12) similar to the one obtained with a specification regressing the occupation-industry-city wage on the city composition index.

In terms of the instrumental variable strategy however, the disaggregation at the occupational level matters. When $\varepsilon_{qic} \neq 0$, the reduced-form version of the city composition index, I_c, differs from that of Beaudry et al. (2012) industrial composition index, I_c^{BGS}.[24] It follows that the instruments used in Beaudry et al. (2012) ($IV_1^{BGS} = \sum_j \hat{\eta}_{jc\tau} \Delta\nu_{j\tau}$ and $IV_2^{BGS} = \sum_j \nu_{j(\tau-1)} \Delta\hat{\eta}_{jc\tau}$) also differ from the instruments for the city composition index ($IV_1^C = \sum_{r,j} \hat{\eta}_{rjc\tau} \Delta\nu_{rj\tau}$ and $IV_2^C =$

[24] When $\varepsilon_{qic} = 0$, the within-industry occupational composition of employment is identical across cities (i.e. $\eta_{rc,j} = \eta_{r,j}$) and the city composition index becomes

$$\begin{aligned} I_c &= \sum_{r,j} \eta_{rjc} \nu_{rj} \\ &= \sum_{r,j} \frac{N_{jc}}{N_c} \frac{N_{rjc}}{N_{jc}} \nu_{rj} \\ &= \sum_j \eta_{jc} \sum_r \eta_{rc,j} \nu_{rj} \\ &= \sum_j \eta_{jc} \nu_j \\ &= I_c^{BGS} \end{aligned}$$

where $\nu_j = \sum_r \eta_{r,j} \nu_{rj}$.

$\sum_{r,j} \nu_{rj(\tau-1)} \Delta\hat{\eta}_{rjc\tau}$). By isolating industry-level variations in the index, IV_1^{BGS} and IV_2^{BGS} lead to omit the wage externalities working through the occupational dimension of search and bargaining. If these forces are important, the estimate of γ_2 is likely to be downward biased. On top of that, one would expect the between instrument (IV_2^{BGS}) to perform relatively poorly, as changes in sectoral employment shares would be incapable of truly reflecting shifts in outside options that are associated with inter-occupational labor adjustment.

< Table (5) here >

Table 5 evaluates the extent to which departures from my framework affect the estimates. Columns (1) and (2) strictly replicate Beaudry et al. (2012) approach on the reflection equation. The dependent variable corresponds to local industrial wages, adjusted for individual worker characteristics. The OLS estimate in column (1) is positive, large at 0.805, and statistically significant at the 1% level. As expected, the OLS estimate is comparable to that obtained when replacing Beaudry et al. (2012) index by the city composition index (column 4). Column (2) shows that when estimated with IV_1^{BGS} and IV_2^{BGS}, the estimate drops to 0.116 and becomes statistically insignificant.[25] At first glance, one would attribute this result to institutional rigidities merely, and conclude that decentralization mechanisms cannot be captured by the data in Germany. However, the coefficient on the between instrument IV_2^{BGS} suggests that the estimate on R_c^{BGS} omits occupational forces. The next two columns tend to confirm this statement. Column (3) shows a specification which uses IV_1^C and IV_2^C and therefore exploits variations along both the industrial and the occupational dimensions. Column (5) is more direct and regress the occupation-industry-city-specific wage on the city composition index. Although column (3) provides an imprecise estimate, the coefficients obtained in both columns are close to each other. As for the coefficient on the between instrument, it is now statistically significant at the 1% level. On the whole, the results in columns (1)-(5) indicate that within-industry differences across cities of Germany are important enough to give grounds for a disaggregation at the occupational level.

Finally, to evaluate the importance of relaxing the assumption of homogeneous moving cost, I run a specification which includes both the transition and the city composition indices. Results are shown in columns (5)-(7) and clearly indicate that a model which allows for heterogeneous moving

[25] The instruments are based on an identifying assumption identical to that underlying IV_1-IV_4.

cost is superior. In fact, the IV estimates on the city composition index become statistically highly insignificant while the estimates on the transition index remain unaltered.

5 Supplementary sensitivity checks

Appendix I of the Supplementary Material contains the Tables associated with the following sensitivity checks.

Table (1) includes periodical differences in occupation-industry-city-specific employment shares, $\Delta\eta_{qic}$, as an additional regressor in the baseline specification. Throughout the paper, I have assumed that the probability of being a stayer is constant across occupations and industries, i.e. $\mu_{qic} = \mu$. When the probability of re-employment varies across cells, μ_{qic} is a non-linear function of the employment shares. In such a case, the linear approximation of (15) would imply adding η_{qic} to the wage equation (16). I use predicted employment shares (and in particular $\hat{\eta}_{qic\tau} - \eta_{qic(\tau-1)}$) as an instrument for $\Delta\eta_{qic\tau}$. The conditions ensuring the validity of this instrument are identical to those required for IV_1-IV_4. Once instrumented, the coefficients on the employment shares become statistically insignificant. More importantly, including employment shares to the baseline specification does not alter the estimates of interest, which suggests that assuming $\mu_{qic} = \mu$ does not bias my results.

< Table (1) of the Supplementary Material here >

Results presented in Section 4.1 suggest that shifts in the transition index affect wages through changes in outside options and not through moves along the martinal product curve. Table (2) excludes the transition index from the wage equation and investigates the impact of $IV1 - IV4$ on the employment variables. Focusing on the first stage, the estimates on the instruments are statistically insignificant, with a F-statistics of 2.5 and partial R-squared of 0.002 at most. These results suggest that the variation used to identify $\tilde{\gamma}_2$ is uncorrelated with employment and again, suggest that shifts in the transition index do not reflect supply-demand effects.

< Table (2) of the Supplementary Material here >

Table (3) shows estimates obtained using different values of $\tilde{\gamma}_2$ to construct the matrix used to test the validity of the model, as described in Section 4.4.

< Table (3) of the Supplementary Material here >

Table 4 shows the estimates obtained when addressing the reflection problem only and instrumenting the transition index with the within versus between components of the reduced-form index $I_{qic\tau}$. The presentation of the results follows the structure of Table (1). In general, the IVs estimates are statistically significant at the 1% level but of a smaller magnitude relative the baseline ones. This indicates a need for coping with the endogeneity associated to employment measures.

< Table (4) of the Supplementary Material here >

The IABS sample is top-coded at the highest level of earnings that are subject to social security contributions. Since wages would appear smaller than what they really are for some cells, this may create a biased estimate of the coefficient of interest. Since higher wages imply a higher threat point in the Nash bargaining game, one would expect the baseline estimate to be downward biased. Table 5 presents the results estimated using the uncensored sample. Relative to the baseline specification, the qualitative aspect of the results remain unaltered. The IV estimate is somewhat higher, between 0.71 and 0.75 against 0.60 and 0.71 in the baseline.

< Table (5) of the Supplementary Material here >

The top coding issue can be severe for highly educated groups (in particular, for individuals with a polytechnic or university degree). Another sensitivity analysis consists in dropping highly educated individuals from the sample when computing adjusted wages. Results from this exercise are shown in Table (6) and are similar to those found when focusing on the uncensored sample only.

< Table (6) of the Supplementary Material here >

Table 7 restricts the sample to workers aged 21 to 60 and drops individuals in apprenticeship. Results are qualitatively similar to the baseline.

< Table (7) of the Supplementary Material here >

The baseline specification uses the Bartik instrument and its labor force counterpart as instruments for the employment rate. Table 8 shows IV estimates obtained when using five alternative sets of instruments.[26] Appendix J of the Supplementary Material provides details on these alternatives. The estimates on the transition index are robust to using these various instruments. As for the coefficient on the employment rate, it generally remains statistically insignificant. Interestingly, note that since each instrument is valid under the same condition, the stability of the results across specifications is a sign in favor of the identifying assumption.

< Table (8) of the Supplementary Material here >

Table 9 introduces some flexibility in computing the mobility measures $\varphi_{rj|qi}$. In columns (1)-(3), the $\varphi_{rj|qi}$s are computed over two different intervals, 1976-1991 and 1992-2001. Columns (4)-(6) introduce spatial flexibility by separating the sample between Northwestern and Southwestern Germany. Since the constraint of 20 individuals per cell leaves little room for manoeuvre in the construction of the $\varphi_{rj|qi}$s, it is difficult to allow for even more flexibility. Whichever column one looks at, the estimates remain robust to using period-specific or region-specific measures of mobility.

< Table (9) of the Supplementary Material here >

Another sensitivity analysis consists in testing the exogeneity of the local start-of-period employment used to construct predicted employment shares. Since $N_{rjc(\tau-1)}$ is based on a five-year average of annual employment data, one might be worried about the exogeneity of the baseline prediction if $N_{rjc(t+4)}$ in $(\tau-1)$ is correlated to N_{rjct} in τ. Columns (1) and (2) in Table 10 show that the baseline results are robust to excluding the last two years of $(\tau-1)$ and thus to using $N^{-2}_{rjc(\tau-1)} = \frac{1}{3}\sum_t^{t+2} N_{rjct}, \quad t \in (\tau-1)$, as an alternative to $N_{rjc(\tau-1)}$.

< Table (10) of the Supplementary Material here >

[26] The first alternative instrument is $IV_3^{BK} = \sum_{r,j} \hat{l}_{rjc\tau} \frac{\hat{N}_{rjc\tau}}{\hat{L}_{rjc\tau}} - ER_{c(\tau-1)}$. The second one is given by $IV_4^{BK} = ER_{c(\tau-1)} \left[\frac{\hat{N}_{c\tau}}{N_{c(\tau-1)}} - \frac{\hat{L}_{c\tau}}{L_{c(\tau-1)}}\right]$. The third alternative set includes the following two instruments $IV_5^{BK} = ER_{c(\tau-1)} \frac{\hat{N}_{c\tau}}{N_{c(\tau-1)}}$ and $IV_6^{BK} = ER_{c(\tau-1)} \frac{\hat{L}_{c\tau}}{L_{c(\tau-1)}}$. The fourth alternative proposes two instruments $IV_7^{BK} = \sum_{r,j} ER_{rjc(\tau-1)} \left[\hat{l}_{rjc\tau} - l_{rjc(\tau-1)}\right]$ and $IV_8^{BK} = \sum_{r,j} \hat{l}_{rjc\tau} \left[\frac{\hat{N}_{rjc\tau}}{L_{rjc(\tau-1)}} - ER_{rjc(\tau-1)}\right]$. Finally, the last alternative uses IV_6^{BK} together with $IV_9^{BK} = \sum_{r,j} \hat{l}_{rjc\tau} ER_{rjc(\tau-1)} \left[\frac{\hat{N}_{jrc\tau}}{N_{rjc(\tau-1)}} - 1\right]$ and $IV_{10}^{BK} = \sum_{r,j} \hat{l}_{rjc\tau} ER_{rjc(\tau-1)} \left[\frac{\hat{L}_{rjc\tau}}{L_{rjc(\tau-1)}} - 1\right]$ as instruments.

Columns (4) and (6) of the same Table examine whether the effect of interest exhibits anything particular after the accession of Eastern Germany to the IAB sample in 1991 (or the Fall of the Iron curtain in 1989). The pre-1991 period experienced a relatively higher pressure from trade unions. If, as a result, wage premia were relatively smaller, one may be worried that the baseline estimate is driven by the post-1991 period only. To investigate this possibility, a dummy taking the value of one after 1991, $Post$, is interacted with the transition index. The interaction term enters the wage equation in a statistically insignificant manner and more importantly does not alter the qualitative aspect of the estimate of interest. Table (11) performs a similar exercise by splitting the sample in two intervals, the pre- and post-1991 periods. Whichever period one consider, the estimates on the transition index remain statistically significant and similar to those of the baseline specification.

$<$ Table (11) of the Supplementary Material here $>$

Table 12 investigates whether the baseline estimate differs across industries. For each industry, I run a regression over the entire sample where the transition index is interacted with a dummy for the industry under study. Each regression is based on the triple-differenced estimation. Columns (1), (3) and (5) show the main effect on the transition index. Columns (2), (4) and (6) present the estimate for the interaction term. In general, the coefficient on the interaction term is statistically insignificant, which suggests that decentralization forces are similar across industries, whichever the unionization degree they exhibit.

$<$ Table (12) of the Supplementary Material here $>$

Table 13 is the occupational counterpart of Table 12. The same conclusion holds in the case of occupations.

$<$ Table (13) of the Supplementary Material here $>$

In addition, let me construct the sectoral and occupational counterparts of the baseline transition index R_{qic}. Specifically, the sectoral transition index takes the form $R_{ic} = \sum_j \chi_{jc|i}\eta_{jc}\nu_j$ and the occupational one is given by $R_{qc} = \sum_r \chi_{rc|q}\eta_{rc}\nu_r$. The mobility measures and the instruments are constructed in a way symmetric to that used for the baseline. Results obtained with those indices are presented in Table 14. Columns (1)-(6) correspond to specifications which estimate the effect of the sectoral transition index on sectoral city-specific wages. Columns (7)-(12) focus on occupations. The industry- versus occupation-specificity of the indices allow to introduce city-time effects in addition to the set of occupation-industry time-varying dummies. Except for OLS, the estimate on the sectoral transition index is statistically insignificant (or significant at the 10% level), whether city-time interactions are included or not. As for the occupational transition index, the estimates are positive and highly significant when regressing a double-differenced estimation. However, once city-time interactions are added, the statistical significance of the effects vanishes. Once again, this shows the importance of disaggregating the analysis at the occupation-industry level. Moreover, it supports the idea that workers face heterogeneous moving costs across both, industries and occupations.

< Table (14) of the Supplementary Material here >

Table (15) of the Supplementary Material shows that clustering at the city-year level as an alternative to the city level does not alter the baseline results.

< Table (15) of the Supplementary Material here >

In the next Table, I restrict the construction of the dependent variable to workers who remain with the same employer from one year to the other and examine whether the determination of wages still takes the form of a social interaction problem. Results suggest that outside options are important determinants of wages even for workers who do not switch firm.

< Table (16) of the Supplementary Material here >

Concluding remarks

This paper examines the extent to which wage formation can be seen as taking the form of a network of outside options, whereby linkage intensity depends on worker's mobility costs. Using a multi-city multi-sector model of search and bargaining with heterogeneous workers, I have shown that differences in sectoral and occupational mobility generate an additional source of variation that can be used for identifying the importance of a worker's outside options in the wage determination. I have found that the theoretical restrictions implied by the model are well supported by the data and that a 1% increase in a worker's outside options generate a 7% wage increase. In addition, my findings suggest that a model with heterogeneous workers which captures assymetries in the wage spillover effects performs better that one which assumes symmetry of the effects. This observation has important implications, not only from a policy perspective, but also because it suggests that this type of social interaction may accentuate or attenuate wage disparities across groups of workers depending on the mobility costs they face.

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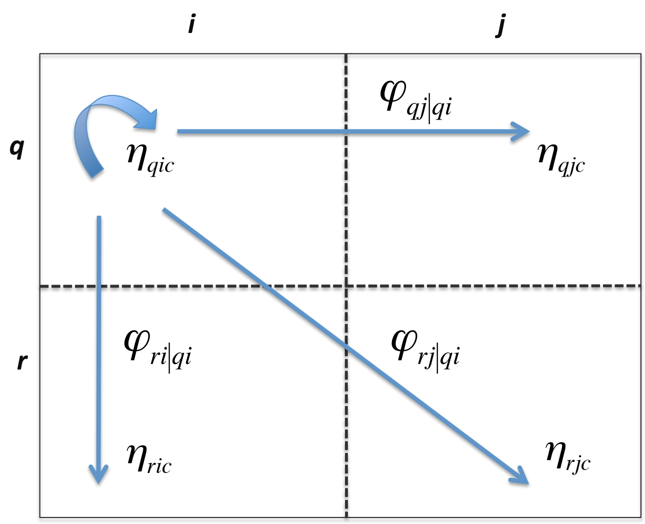
Figures

Figure 1: Mobility illustration in a two-by-two occupation-industry model.

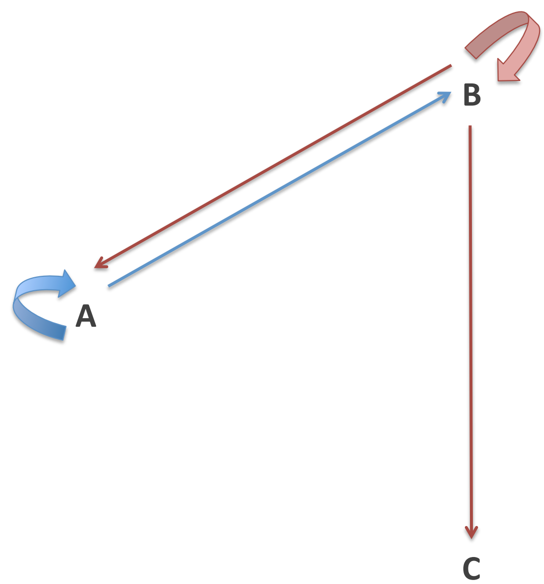


$$\psi_{rjc|qic} = \chi_{rjc|qic}\eta_{rjc} \text{ , } where \ \chi_{rjc|qic} = \frac{\varphi_{rj|qi}}{\sum_{r,j}\varphi_{rj|qi}\eta_{rjc}}$$

i and j are industry subscripts. q and r are occupation subscripts. c denotes a city. η_{rjc} is the relative size of rjc, i.e. the fraction of workers employed in rjc. $\varphi_{rj|qi}$ is a mobility measure. The arrows represent the direction of workers' mobility: the horizontal, vertical and diagonal arrows represent mobility 'within occupation across industries', 'within industry across occupations' and 'across both occupations and industries', respectively.

In this framework, a worker's transition probability, say from state qi to state rj in city c, depends not only on the relative size of the destination cell η_{rjc} but also on the mobility parameter $\varphi_{rj|qi}$. In particular, the transition probability is given by $\psi_{rjc|qic}$ and multiplies η_{rjc} by a trajectory city-specific term given by $\chi_{rjc|qic}$. This term captures the cost a worker faces to move from qi to rj relative to the cost of moving anywhere else in the labor market in which she is located.

Figure 2: Labor market with three employment options.



In this labor market, individuals can work either in A, B or C. Workers can move from A to B but direct moves from A to C are not observed. However, workers in A can reach C indirectly by first moving to B. In such a case, workers in A will attribute a zero weight on option C and the wage offered in C will enter the wage bargaining process of A only indirectly through option B.

Table 1: Baseline.

Dependent variable	$\Delta\ log\ w_{qic\tau}$								
	Employment rate			**City-time effects**			**Demand effects**		
Regressors	**(1)** OLS	**(2)** IV	**(3)** IV	**(4)** OLS	**(5)** IV	**(6)** IV	**(7)** OLS	**(8)** IV	**(9)** IV
$\Delta R_{qic\tau}$	0.363***	0.644***	0.603***	0.262***	0.713***	0.655***	0.261***	0.708***	0.658***
	(0.033)	(0.120)	(0.108)	(0.049)	(0.165)	(0.153)	(0.049)	(0.166)	(0.153)
$\Delta ER_{c\tau}$	0.193***	0.129	0.149*						
	(0.071)	(0.080)	(0.088)						
$D_{qic\tau}$							0.012	−0.014	−0.010
							(0.046)	(0.040)	(0.040)
$\Delta\ d_{qi\tau}$	yes	yes	yes	yes	yes	yes	yes	yes	yes
$\Delta\ d_{c\tau}$				yes	yes	yes	yes	yes	yes
Instrument Set		IV_1, IV_2 IV_1^{BK}, IV_2^{BK}	IV_1, IV_3, IV_4 IV_1^{BK}, IV_2^{BK}		IV_1, IV_2	IV_1, IV_3, IV_4		IV_1, IV_2 IV^D	IV_1, IV_3, IV_4 IV^D
First stage									
IV_1 on $\Delta R_{qic\tau}$		1.241***	1.263***		1.248***	1.278***		1.270***	1.293***
		(0.190)	(0.192)		(0.141)	(0.142)		(0.142)	(0.142)
IV_2 on $\Delta R_{qic\tau}$		1.237**			1.115**			1.067**	
		(0.452)			(0.431)			(0.423)	
IV_3 on $\Delta R_{qic\tau}$			1.077**			0.921**			0.901**
			(0.434)			(0.397)			(0.395)
IV_4 on $\Delta R_{qic\tau}$			1.814***			1.595***			1.513***
			(0.452)			(0.404)			(0.417)
IV_1^{BK} on $\Delta ER_{c\tau}$		2.382***	2.373***						
		(0.372)	(0.370)						
IV_2^{BK} on $\Delta ER_{c\tau}$		−2.290***	−2.287***						
		(0.402)	(0.401)						
F-statistics: $\Delta\ R_{qic\tau}$		16.51	13.98		41.88	35.15		29.47	29.05
F-statistics: $\Delta\ ER_{c\tau}$		15.58	12.78						
Hansen		0.356	0.396		0.287	0.152		0.280	0.151
Observations	6632	6632	6632	6632	6632	6632	6632	6632	6632

Notes: Standard errors are clustered at the city level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. p-values in brackets. F-tests are F-statistics of the excluded instruments. For each endogenous regressor, the Angrist-Pischke p-value is zero.

Table 2: Controlling for employment.

Dependent variable	$\Delta\ log\ w_{qic\tau}$								
	Industry-city			Employment: Occupation-city			Occupation-industry-city		
Regressors	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV	(7) OLS	(8) IV	(9) IV
$\Delta R_{qic\tau}$	0.224***	0.870***	0.759***	0.230***	0.860***	0.731***	0.230***	0.829***	0.709***
	(0.045)	(0.182)	(0.196)	(0.046)	(0.182)	(0.195)	(0.045)	(0.184)	(0.200)
$\Delta logE_{ic\tau}$	0.030***	−0.024	−0.018						
	(0.009)	(0.025)	(0.025)						
$\Delta logE_{qc\tau}$				0.001	−0.013	0.000			
				(0.010)	(0.039)	(0.040)			
$\Delta logE_{qc\tau}$							0.017***	0.030	0.046
							(0.007)	(0.047)	(0.049)
$\Delta\ d_{qi\tau}$	yes	yes	yes	yes	yes	yes	yes	yes	yes
$\Delta\ d_{c\tau}$	yes	yes	yes	yes	yes	yes	yes	yes	yes
Instrument Set		IV_1, IV_2 $IV^E_{ic\tau}$	IV_1, IV_3, IV_4 $IV^E_{ic\tau}$		IV_1, IV_2 $IV^E_{qc\tau}$	IV_1, IV_3, IV_4 $IV^E_{qc\tau}$		IV_1, IV_2 $IV^E_{qic\tau}$	IV_1, IV_3, IV_4 $IV^E_{qic\tau}$
First stage									
IV_1 on $\Delta R_{qic\tau}$		1.074***	1.090***		1.075***	1.091***		1.079***	1.095***
		(0.161)	(0.160)		(0.161)	(0.160)		(0.162)	(0.161)
IV_2 on $\Delta R_{qic\tau}$		1.178**			1.190**			1.187**	
		(0.466)			(0.471)			(0.472)	
IV_3 on $\Delta R_{qic\tau}$			1.021**			1.026**			1.024**
			(0.460)			(0.463)			(0.466)
IV_4 on $\Delta R_{qic\tau}$			1.493***			1.520***			1.515***
			(0.432)			(0.436)			(0.434)
F-statistics: $\Delta\ R_{qic\tau}$		17.87	18.23		15.26	15.84		14.99	15.73
Hansen		0.235	0.147		0.229	0.136		0.221	0.153
Observations	4974	4974	4974	4974	4974	4974	4974	4974	4974

Notes: Standard errors are clustered at the city level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. p-values in brackets. F-tests are F-statistics of the excluded instruments. For each endogenous regressor, the Angrist-Pischke p-value is zero.

Table 3: Addressing the selection issue into cities and occupations.

Dependent variable	$\Delta\ log\ w_{qic\tau}$								
	Employment rate			**City-time effects**			**Demand effects**		
Regressors	**(1)** OLS	**(2)** IV	**(3)** IV	**(4)** OLS	**(5)** IV	**(6)** IV	**(7)** OLS	**(8)** IV	**(9)** IV
$\Delta R_{qic\tau}$	0.279***	0.535***	0.535***	0.150***	0.545***	0.546***	0.150***	0.544***	0.545***
	(0.039)	(0.102)	(0.101)	(0.046)	(0.161)	(0.158)	(0.046)	(0.157)	(0.155)
$\Delta ER_{c\tau}$	0.305**	0.363*	0.362*						
	(0.148)	(0.216)	(0.215)						
$D_{qic\tau}$							0.027	0.024	0.024
							(0.127)	(0.103)	(0.104)
$\Delta\ d_{qi\tau}$	yes	yes	yes	yes	yes	yes	yes	yes	yes
$\Delta\ d_{c\tau}$				yes	yes	yes	yes	yes	yes
Instrument Set		IV_1, IV_2 IV_1^{BK}, IV_2^{BK}	IV_1, IV_3, IV_4 IV_1^{BK}, IV_2^{BK}		IV_1, IV_2	IV_1, IV_3, IV_4		IV_1, IV_2 IV^D	IV_1, IV_3, IV_4 IV^D
First stage									
IV_1 on $\Delta R_{qic\tau}$		0.737***	0.741***		0.883***	0.891***		0.917***	0.920***
		(0.151)	(0.149)		(0.127)	(0.124)		(0.126)	(0.124)
IV_2 on $\Delta R_{qic\tau}$		1.244***			0.971***			0.952***	
		(0.195)			(0.219)			(0.222)	
IV_3 on $\Delta R_{qic\tau}$			1.240***			0.967***			0.950***
			(0.194)			(0.220)			(0.223)
IV_4 on $\Delta R_{qic\tau}$			1.190***			0.875***			0.899***
			(0.208)			(0.225)			(0.218)
IV_1^{BK} on $\Delta ER_{c\tau}$		2.429***	2.428***						
		(0.369)	(0.369)						
IV_2^{BK} on $\Delta ER_{c\tau}$		−2.338***	−2.339***						
		(0.404)	(0.404)						
F-statistics: $\Delta\ R_{qic\tau}$		19.89	16.03		29.01	21.16		23.69	18.42
F-statistics: $\Delta\ ER_{c\tau}$		14.74	14.83						
Hansen		0.663	0.829		0.266	0.456		0.254	0.456
Observations	6190	6190	6190	6190	6190	6190	6190	6190	6190

Notes: Standard errors are clustered at the city level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. p-values in brackets. F-tests are F-statistics of the excluded instruments. For each endogenous regressor, the Angrist-Pischke p-value is zero.

Table 4: Testing the validity of the model.

Dependent variable	Δ *log* $w_{qic\tau}$					
	Matrix resolution			**Path independence**		
Regressors	**(1)** OLS	**(2)** IV	**(3)** IV	**(4)** OLS	**(5)** IV	**(6)** IV
$\Delta R^{RFM}_{qic\tau}$	0.412***	0.606***	0.606***			
	(0.078)	(0.125)	(0.125)			
$\Delta I_{qic\tau}$				0.535***	0.924***	0.925***
				(0.133)	(0.199)	(0.199)
$\Delta\ d_{qi\tau}$	yes	yes	yes	yes	yes	yes
$\Delta\ d_{c\tau}$	yes	yes	yes	yes	yes	yes
Instrument Set		IV_1, IV_2	IV_1, IV_3, IV_4		IV_1, IV_2	IV_1, IV_3, IV_4
First stage						
IV_1 on $\Delta R^{RFM}_{qic\tau}$ or $\Delta I_{qic\tau}$		1.431***	1.431***		0.947***	0.948***
		(0.054)	(0.054)		(0.025)	(0.026)
IV_2 on $\Delta R^{RFM}_{qic\tau}$ or $\Delta I_{qic\tau}$		1.710***			1.051***	
		(0.146)			(0.067)	
IV_3 on $\Delta R^{RFM}_{qic\tau}$ or $\Delta I_{qic\tau}$			1.709***			1.044***
			(0.148)			(0.071)
IV_4 on $\Delta R^{RFM}_{qic\tau}$ or $\Delta I_{qic\tau}$			1.714***			1.070***
			(0.156)			(0.066)
F-statistics: $\Delta\ R^{RFM}_{qic\tau}$		392.4	261.8			
F-statistics: $\Delta\ I_{qic\tau}$					784.8	520.8
Hansen		0.504	0.797		0.448	0.749
Observations	6632	6632	6632	6632	6632	6632

Notes: Standard errors are clustered at the city level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. p-values in brackets. F-tests are F-statistics of the excluded instruments. For each endogenous regressor, the Angrist-Pischke p-value is zero.

Table 5: BGS versus general case.

Dependent variable	$\Delta\ log\ w_{ic\tau}$			$\Delta\ log\ w_{qic\tau}$		$\Delta\ log\ w_{qic\tau}$		
	BGS			**City**		**City / Transition**		
Regressors	**(1)** OLS	**(2)** IV	**(3)** IV	**(4)** OLS	**(5)** IV	**(6)** OLS	**(7)** IV	**(8)** IV
$\Delta R_{c\tau}^{BGS}$	0.805*** (0.058)	0.116 (0.374)	0.431 (0.284)					
$\Delta R_{c\tau}$				0.728*** (0.034)	0.416*** (0.148)	0.500*** (0.065)	−0.113 (0.230)	−0.005 (0.240)
$\Delta R_{qic\tau}$						0.262*** (0.047)	0.671*** (0.158)	0.465*** (0.146)
$\Delta ER_{c\tau}$	−0.012 (0.104)	0.336 (0.304)	0.126 (0.313)	0.014 (0.056)	0.098 (0.171)	0.032 (0.050)	0.194 (0.164)	0.214 (0.179)
$\Delta\ d_{i\tau}$	yes	yes	yes					
$\Delta\ d_{qi\tau}$				yes	yes	yes	yes	yes
Instrument Set		IV_1^{BGS}, IV_2^{BGS} IV_1^{BK}, IV_2^{BK}	IV_1^{C}, IV_2^{C} IV_1^{BK}, IV_2^{BK}		IV_1^{C}, IV_2^{C} IV_1^{BK}, IV_2^{BK}		IV_1, IV_2 IV_1^{BK}, IV_2^{BK}	IV_1, IV_3, IV_4 IV_1^{BK}, IV_2^{BK}
First stage								
IV_1^{BGS} on $\Delta R_{c\tau}^{BGS}$		1.933*** (0.473)	1.867*** (0.499)					
IV_2^{BGS} or on $\Delta R_{c\tau}^{BGS}$		0.844 (2.036)	2.723*** (0.759)					
IV_1^{C} on $\Delta R_{c\tau}^{BGS}$ or on $\Delta R_{c\tau}$					1.811*** (0.440)		1.880*** (0.468)	1.890*** (0.458)
IV_2^{C} on $\Delta R_{c\tau}^{BGS}$ or on $\Delta R_{c\tau}$					2.901** (0.793)		2.981** (0.798)	2.791** (0.790)
IV_1 on $\Delta R_{qic\tau}$							1.034*** (0.199)	1.047*** (0.203)
IV_2 on $\Delta R_{qic\tau}$							0.766 (0.443)	
IV_3 on $\Delta R_{qic\tau}$								1.264*** (0.133)
IV_4 on $\Delta R_{qic\tau}$								1.141*** (0.153)
IV_1^{BK} on $\Delta ER_{c\tau}$		2.237** (0.584)			1.941*** (0.431)		1.961*** (0.426)	1.953*** (0.431)
IV_2^{BK} on $\Delta ER_{c\tau}$		−2.120** (0.616)			−1.829*** (0.431)		−1.847*** (0.428)	−1.838*** (0.432)
F-statistics: $\Delta\ R_{c\tau}^{BGS}$		8.243						
F-statistics: $\Delta\ R_{c\tau}$			9.9		11.04		8.283	24.53
F-statistics: $\Delta\ R_{qic\tau}$							13.84	31.46
F-statistics: $\Delta\ ER_{c\tau}$		19.88	12.6		13.16		10.63	9.637
Hansen		0.139	0.195		0.399		0.567	0.747
Observations	1216	1216	1216	6632	6632	6632	6632	6632

Notes: Standard errors are clustered at the city level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. p-values in brackets. F-tests are F-statistics of the excluded instruments. The Angrist-Pischke p-value for each of the indices is below 5%.