nccr trade regulation
swiss national centre of competence in research

Working Paper No 2011/53| May 2011

# The Wage Response to Shocks: The Role of Inter-Occupational Labor Adjustment

**Jeanne Tschopp**[†]

How does a region's average wage adjust to a shock, say trade-induced or technology-induced, on labor demand? Beaudry, Green and Sand (2010) recently demonstrated the inaccuracy of the traditionally-used shift-share analysis - a partial equilibrium exercise - in addressing this question. While they focus on shifts in the industrial composition of employment, I argue that the interplay between inter-sectoral and inter-occupational labor adjustments is fundamental in assessing the spillover effects they emphasize. I extend their search-and-bargaining model to incorporate occupations and illustrate why omitting inter-occupational labor adjustments could lead to underestimation. Using German individual-level data for 1977-2001, I estimate that omitting this dimension creates a substantial and statistically significant negative bias representing two-thirds of the total effect.

[†]HEC Lausanne. Email: jeanne.tschopp@unil.ch

FNSNF
Fonds national suisse
Schweizerischer Nationalfonds
Fondo nazionale svizzero
Swiss National Science Foundation

Die Nationalen Forschungsschwerpunkte (NFS) sind ein Förderinstrument des Schweizerischen Nationalfonds.
Les Pôles de recherche nationaux (PRN) sont un instrument d'encouragement du Fonds national suisse.
The National Centres of Competence in Research (NCCR) are a research instrument of the Swiss National Science Fondation.

# The Wage Response to Shocks: The Role of Inter-Occupational Labor Adjustment *

Jeanne Tschopp[†]

May 2011

**Abstract**

How does a region's average wage adjust to a shock, say trade-induced or technology-induced, on labor demand? Beaudry, Green and Sand (2010) recently demonstrated the inaccuracy of the traditionally-used shift-share analysis – a partial equilibrium exercise – in addressing this question. While they focus on shifts in the industrial composition of employment, I argue that the interplay between inter-sectoral and inter-occupational labor adjustments is fundamental in assessing the spillover effects they emphasize. I extend their search-and-bargaining model to incorporate occupations and illustrate why omitting inter-occupational labor adjustments could lead to underestimation. Using German individual-level data for 1977-2001, I estimate that omitting this dimension creates a substantial and statistically significant negative bias representing two-thirds of the total effect.

JEL classification numbers: J30

Keywords: wages, worker mobility, inter-industry labor adjustment, inter-occupational labor adjustment.

*Without implicating them, I would like to thank Gabriel Ahlfeldt, Paul Beaudry, Kenza Benhima, Ekkehard Ernst, David Green, Jean Imbs, Florian Pelgrin, Benjamin Sand, Pascal St-Amour, Mathias Thoenig and participants at the Doctoral Research Days 2010 in Lausanne, the ProDoc Workshop 2010 in Geneva, the SSES Annual Meeting 2010 in Fribourg, the Macro Workshop 2010 at UBC in Vancouver for helpful comments and discussions. Special thanks to my supervisors Marius Brülhart and Olivier Cadot for their constant support, guidance and assistance.

[†]HEC Lausanne. Email: jeanne.tschopp@unil.ch.

# 1 Introduction

How does a region's average wage react to a shock (say, trade-induced or technology-induced) to the inter-sectoral *and* inter-occupational structure of labor demand? In spite of a voluminous literature examining the effects of trade liberalization and technological change on wages, we know relatively little on (i) how shocks to the sectoral and occupational composition of employment *spill over* to a region's entire labor market, and (ii) how inter-sectoral and inter-occupational labor adjustments *interact* with each other.

Beaudry, Green and Sand (2010, henceforth BGS) recently argued that measuring a region's average wage response to a shock on the sectoral composition of employment by just its composition effect – a partial-equilibrium or 'shift-share' approach – would lead to underestimation.[1] To see why, consider a seach-and-bargaing framework and think of a city with two industries: a high-paying steel plant and a low-paying textile industry. Assume imperfect worker mobility (i.e. the existence of switching costs) and persistent sectoral wage premia (i.e. wage differences across sectors unexplained by worker characteristics), here in favor of the steel industry.[2] Because workers can credibly move across sectors, the outcome of wage bargaining in the textile industry will reflect the outside opportunity, i.e. the wage offered in the high-paying steel industry, given the probability to be hired there. If now the steel plant closes down, this outside option disappears for workers in the textile industry, driving down their threat point in the Nash bargaining game and inciting firms in the textile industry to bid down the wage offered. Wages in the textile industry may then fall even in the absence of actual labor movements between the two sectors. Thus, the path of wages *within* industries will be affected by shifts in the sectoral composition of labor demand, and this spillover effect on average wages will reinforce the composition effect. BGS show that

[1] A shift-share approach is a partial equilibrium exercise which consists in multiplying each industry average wage in a base year by the corresponding change in industrial employment shares and then summing up across industries. See Loveridge and Selting (1992) for a summary of the literature on shift-share analysis, and López and Mayor (2008) for extensions of the classical deterministic approach to spatial stochastic analysis.

[2] If workers were immobile, moving across sectors would not be a credible threat. If they were perfectly mobile, wages would equalize and there would be no incentive for workers to move across sectors.

the spillover effect is substantial—over twice the magnitude of the composition effect.

I take this idea one step further. Consider a shock to the inter-sectoral *and* inter-occupational composition of labor demand and suppose that workers are (imperfectly) mobile not only across sectors, but also across occupations. Then inter-sectoral and inter-occupational labor adjustments to the shock may either reinforce or offset each other. They will strengthen each other if employement shifts toward high-paying industries and occupations, or the reverse. In all other cases they will cancel each other (i.e. if employment shifts toward high-paying industries and low-paying occupations, or the reverse). In the latter case, even BGS's procedure will underestimate the total effect on a region's average wage.

Do we have a reason to believe that sectoral and occupational labor adjustments to shocks would offset each other? To fix ideas, think of a trade shock—a reduction in trade costs in a two-by-two economy (skilled vs. unskilled labor, skill-intensive vs. unskilled-intensive industries). The Stolper-Samuelson theorem predicts that if Home is skill-abundant, the skill-intensive sector will expand (a sectoral labor adjustment), but every industry will become less skill-intensive (an occupational labor adjustment). Thus, in the case of a trade shock, the negative relationship between sectoral and occupational shifts in labor demand is precisely what is to be expected, because the second is endogenous to the first.[3] In that case, the effect of the inter-sectoral shift in labor demand on the local economy's average wages will certainly be understimated by shift-share analysis, but it will *also* be underestimated by BGS's procedure, because it will be confounded with the opposite effect of the occupational shift.

So far, the trade-and-wages literature (surveyed by Slaughter 1998) has largely disregarded this issue. Several papers focused primarily on the impact of trade shocks on wage inequality. Some of the papers considered the correlation between industry product-price changes and relative factor-employment levels (Lawrence and Slaughter 1993, Sachs and

[3]This negative correlation between occupational (within-industry) and sectoral (between industries) shifts in labor demand in the case of a trade shock was used by Berman, Bound and Griliches (1994) to discriminate between trade-induced and technology-induced explanations for the rise in the skill premium observed in OECD countries. They rejected trade as the *dominant* explanation for this rise, but that does not preclude the *occurrence* of trade shocks.

Shatz 1994) or industry factor cost shares (Leamer 1996, Baldwin and Cain 1997, Kruger 1997). Other studies focused on the factor content of trade volumes (Krugman 1995, Borjas, Freeman and Katz 1991, 1997). Overall, little of the rising wage inequality observed in OECD countries was found to be explained by trade. Other papers looked more directly into the effect of trade on average wages, but typically at the industry level. That is, they regressed changes in sectoral wages on changes in import prices (Revenga 1992) or trade policy (Attanasio, Goldberg and Pavcnik 2004). They typically found that the effect of trade on wages was relatively small. Most recently, Brülhart, Carrère and Trionfetti 2010 used a natural experiment (the fall of the Iron Curtain) to evaluate the impact of improved market access on employment and wages in Austria's Eastern municipalities, and found that the wage effect preceded but was eventually superseded by the employment effect. To our knowledge, none of these studies simultaneously considered forces working through both inter-industry and inter-occupational labor adjustment—nor were they designed to do so.

A distinct literature looked at frictions and adjustment costs on labor markets (see the contributions in Porto and Hoekman 2010). Lee and Wolpin (2006) and Artuc, Chaudhuri and McLaren (2010) focused on inter-sectoral reallocation. Others, such as Lee (2005), Keane and Wolpin (1997) focused on inter-occupational labor adjustments. Kennan and Walker (2003) studied the movement of workers across regions. Again, none of these studies provided estimates of *both* industrial and occupational worker mobility costs.

I motivate my analysis using patterns of labor mobility observed in Western Germany over 1977-2001 using a rich data set containing, *inter alia*, occupational as well as sectoral employment information. The extent of inter-occupation and inter-industry mobility appears to be comparable in the data. This suggests that, in a wage-bargaining model, shifts in the occupational composition of labor demand and in its sectoral composition are similarly likely to affect the bargaining position of workers, and therefore wages. Moreover—and most interestingly—German employment tends to shift toward high-paying sectors and low-paying occupations. Following our earlier argument, this may lead to underestimation of the effect of a shock on a region's average wages if occupational shifts are not properly taken into account.

I follow BGS in combining structural modeling (a search-and-bargaining model taken from the labor economics literature) with instrumental-variables estimation, using individual-level data for German cities over 1977-2001. My results strongly suggest that considering the occupational dimension matters when assessing the response of average wages to exogeneous shocks. Indeed, in the case of Germany, a BGS-type analysis omitting the occupational dimension of shocks would conclude to the insignificance of spillovers and thus suggest that shift-share analysis is adequate. By contrast, taking into account the sectoral and occupational dimensions of shocks shows that both dimensions generate large and significant spillovers, but that they happened to offset each other. The estimated negative bias is substantial and statistically significant and represents two-thirds of the total effect. In addition, my approach generates estimates of the relative costs of inter-sectoral vs. inter-occupational mobility (from the probabilities of moving). Perhaps surprisingly, revealed inter-industry mobility costs are 1.4 times larger than revealed inter-occupational mobility costs.

The remainder of this paper is organized as follows. Section 2 presents some relevant stylized facts. Section 3 extends BGS's search-and-bargaining model to occupations. The resulting wage equation sheds light on the importance of considering both inter-industry and inter-occupational labor adjustments simultaneously. Section 4 discusses my strategies for identification and estimation. Section 5 describes the empirical setting. Section 6 presents baseline results and sensitivity analyses. Section 7 concludes.

# 2 Motivating Observations

Patterns of the labor market observed in Western Germany over 1977-2001 are constructed using individual-level IAB data which are provided by the German Institute of Employment Research. The IAB database is described in the empirical setting section. The classification of industries and occupations is specific to Germany, with no evident correspondence with international tables. In the IAB original file, industries and occupations are classified at the 1-digit and 2-digit level, respectively. The anonymized sample, available to the research community, provides 16 industries and 130 occupations. In this study, I group occupations into 33 broader categories, according to the 1975 German classification of occupations. The industrial and occupational classifications into 16 and 33 categories are shown in Tables 1 and 2, respectively. Industries and occupations are reported by firms and are therefore accurately classified. I define cities as commuting areas, according to the Federal Office for Building and Regional Planing. This yields 38 local labor markets, whose urban centers are listed in Table 3.

**Worker mobility** Figure 1 and Table 4 present evidence of inter-industry and inter-occupational worker mobility for Western Germany over 1977-2001. Evidence is constructed on the basis of employed individuals who can be traced over two consecutive years. Inter-industry mobility is defined as the fraction of currently employed individuals who report a current industry different from their previous report of an industry. Inter-occupational mobility is defined equivalently. Note that job switches across firms within a particular occupation-industry cell are not observed.

Figure 1 shows the evolution of worker mobility across industries within a particular occupation, across occupations within a particular industry and across *both* industries and occupations, as a share of employed workers. Table 4 presents the associated summary statistics. On average, 8% of workers move across industries and/or occupations from one year to the other. 2.85% of workers move across industries within a particular occupation, 2.51% move across occupations within a particular industry and 2.67% move across both industries and occupations. Inter-industry and inter-occupational worker mobility are on average 5.52% and 5.18%, respectively.[4]

In the United States, evidence suggests that, on average, inter-industry and inter-occupational mobility is 10% at the two-digit level and 15% at the one-digit level, respectively (Kambourov and Manovskii 2008). Observed mobility in the United States largerly exceeds observed mo-

[4] A transition matrix for average cross-occupational mobility in Western Germany over the period 1977-2001 is shown in Tables 12-15.

bility in Germany. This might be because evidence in the United States relies on a finer classification of industries and occupations. Alternatively, this might be because worker moving costs are higher in Germany or because the United States faced larger shocks forcing the labor force to reallocate more frequently. Nevertheless, it is interesting to note that in both countries inter-occupational mobility is at least as important as inter-industry worker mobility. Thus, shifts in the composition of employment across occupations should affect average wages, just like shifts in the industrial composition of employment.

**Correlation between industry and occupational composition** Let me construct, like BGS did, an index capturing the industrial employment composition of a city and its occupational counterpart. For clarity, the time subscript is omitted where possible. Let $c$ denote a city, $j$ an industry and $q$ an occupation. Let $\eta_{jc}$ and $\eta_{qc}$ denote industry-$j$ and occupation-$q$ employment as a share of city-$c$ employment, respectively. $\nu_j$ and $\nu_r$ are industry-$j$ and occupation-$q$ national wage premia, respectively, which are constructed using the same approach as BGS. Industrial wage premia are estimated from a yearly regression at the national level of log individual real wages on a vector individual characteristics (i.e. the age, the square of age, a gender dummy, a nationality dummy, a categorical variable for eduction and a full set of education-gender, education-nationality and education-age interactions) and a full set of industry dummy variables. The industrial wage premia are given by the coefficients on the industry dummy variables. Occupational wage premia are estimated equivalently, replacing industry by occupation dummy variables in the regression. BGS's industrial composition index, denoted $\tilde{R}_c^{IND}$, and its occupational counterpart, denoted $\tilde{R}_c^{OCC}$, are respectively defined as follows:

$$\tilde{R}_c^{IND} = \sum_j \eta_{jc}\nu_j \quad \text{and} \quad \tilde{R}_c^{OCC} = \sum_q \eta_{qc}\nu_q.$$

Everything else equal, industrial and occupational composition indices increase when employment shifts toward high-wage industries and occupations, respectively.

Controlling for city fixed effects, Figure 2 suggests a negative correlation between industrial and occupational composition indices over the period 1980-2001. Figure 3 shows the evolution of industrial and occupational composition indices, averaged across cities of Western Germany, over the period 1980-2001. Everything else equal, from 1985 on, it indicates that the negative correlation observed in Figure 2 masks a tendency for labor to shift toward high-wage industries but low-wage occupations, at least at the national level, as captured by the increase and the decrease in the average industrial and occupational composition indices, respectively. This trend seems to hold across cities, as suggested by Figure 4 which shows a positive correlation between industrial and occupational composition indices across cities of Western Germany, controlling for time fixed effects. Overall, this suggests that the effects of industrial employment shifts on a region's average wage may be underestimated when the occupational dimension of labor adjustment to a shock is omitted from the analysis.

## 3 Model

This section presents an extension of the search-and-bargaining model developed by BGS to incorporate occupations. This extension implies remodeling the technology and worker matching to firms. Adding occupations to BGS model requires introducing some complementarity across occupations in the production function (i.e. maintaining a constant marginal productivity of labor as in BGS would imply full specialization of firms in a particular occupation). Besides, adding occupations extends labor mobility to a three-dimensional mobility (across industries, across occupations and across *both* industries and occupations), therefore enlarging the set of matching possibilities. I derive a structural equation that relates industrial and occupational composition of employment to occupation-industry-city-level average wages. When the workforce is imperfectly mobile across *both* industries and occupations, occupation-industry-city-level average wages act as strategic complements. This implies that both industrial- and occupational-composition shifts create spillover effects on average wages.

## 3.1 Setup

Consider an economy, made up of $C$ local labor markets, which will be called "cities", denoted by $c$. The economy is composed of $I$ industries producing intermediate goods, all of them present in each city (we shall also refer to these as "industrial" goods). Let $i$ and $j$ be industry subscripts. All industries $i$, $j$ in city $c$ consist of homogeneous firms, the number of which is determined endogeneously in equilibrium.[5] For simplicity, I omit capital and concentrate on labor market adjustments.[6] An occupation is defined by a task that has to be executed for production. Production involves $Q$ distinct tasks, which enter as complements in the production function. Let $q$ and $r$ be occupation subscripts. $N_{qic}$ denotes the amount of type-$q$ labor employed at the firm level within industry $i$ and city $c$. Let $\theta_{qic}$ be an exogeneous technology parameter and let $A_{ic}$ be an exogeneous industry-city-specific productivity shifter. Define $y_{ic} = \prod_q (N_{qic})^{\theta_{qic}}$. Each firm within industry $i$ and city $c$ produces a quantity $Y_{ic}$ according to the following Cobb-Douglas production function:

$$\begin{aligned} Y_{ic} &= A_{ic} \prod_q (N_{qic})^{\theta_{qic}} \\ &= A_{ic} y_{ic}, \end{aligned}$$

where $\theta_{qic} \in (0,1)$ to reflect decreasing marginal returns to labor. Due to the across-industry variability of the technology parameter $\theta_{qic}$, the within-industry allocation of labor differs across industries in a particular city. Because the parameter $\theta_{qic}$ varies across cities, the distribution of labor within a particular industry differs across cities. The distribution of labor across industries differs across cities, due to the industry-city-specific productivity shifter $A_{ic}$. Let $Y_i$ be the economy-wide output of the intermediate good $i$. It is given by

[5] If one allows for heterogeneous firms, the wage equation differs at the firm level but has qualitatively similar implications when averaged at the occupation-industry-city level.

[6] Inclusion of capital alters steady state city-level employment in a particular occupation-industry cell but leaves the wage equation derived below unaffected (since capital does not intervene in the wage bargaining process).

the sum of city-level outputs, $Y_{ic}$, across cities. The final good, denoted $Z$, is given by:

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

where $\chi < 1$ and $a_i$ is a parameter reflecting aggregate demand for intermediate good $i$ (i.e. an increase in $a_i$ reflects a rise in aggregate demand for intermediate good $i$). The price of the final good is normalized to one. The price of the intermediate good $i$ is $p_i$. Thus, we assume costless trade among cities.

The labor market considered is characterized by search and matching frictions. I focus on decentralized wage bargaining and in particular on individual wage contracts. The timing of the model goes as follows. First, firms set the scale of production and decide on the number of jobs they want to create. Then, workers are matched to firms at a rate given by a matching technology, and layoffs occur at an exogeneous rate, denoted $\delta$. Quits are assumed away. On-the-job search is excluded.[7] There are $L_c$ atomistic and homogeneous workers in city $c$ (i.e. every worker has the ability to execute any task in any industry).[8] For simplicity, workers are assumed to be immobile across cities. The implications of relaxing this assumption are discussed at the end of this section. This implies that the labor force, $L_c$, is exogeneous. The probability that a worker is matched to *a particular* job depends on his mobility across industries and occupations. The matching technology and worker mobility are described below. Once matches are made, workers and firms bargain over the wage rate, which is set according to Nash bargaining in a complete information context. The model is couched in continuous time. Workers and firms live forever, discount the future at an exogeneous rate $\rho$ and are risk neutral. Workers seek to maximize the expected discounted sum of future utility flows and firms are profit maximizers.

In equilibrium, firms create jobs until the value of a vacancy is zero, the number of matches equals the number of jobs that are destroyed, and wages are set according to Nash

[7]Implications with one-the-job search are left for future research.

[8]Implications are qualitatively similar if workers are heterogeneous in terms of their ability to execute tasks.

bargaining. Let $ER_c$ denote the employment rate in city $c$ and $w_{qic}$ be the occupation-industry-city-specific wage. Then, the steady state is characterized by values of $ER_c$, $w_{qic}$ and $N_{qic}$. At the aggregate level, prices adjust such that markets for industrial goods clear. Prices react to shifts in demand for industrial goods, as captured by $a_i$. Local outcomes respond to changes in industry price $p_i$ (i.e. to a trade shock), changes in the exogeneous technology parameter $\theta_{qic}$ (i.e. to a technology shock), and changes in the exogeneous industry-city-specific term $A_{ic}$ (i.e. to a technology shock).

## 3.2 Search, matching and mobility

Let $E_c$ and $N_c$ denote the number of employed workers and the number of available jobs in city $c$, respectively. The number of matches produced per unit of time, denoted by $M$, is given by the following matching technology:[9]

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

where $L_c - E_c$ is the level of unemployment in city $c$ and $N_c - E_c$ is the number of vacancies. We assume that the matching technology is increasing in both its arguments and concave, which is standard in the search an bargaining literature.[10] Let $\psi_c$ be the probability that an unemployed worker gets $a$ job and $\phi_c$ be the probability that a firm fills a vacancy. These probabilities are respectively given by:

$$\psi_c = \frac{m\left((L_c - E_c), (N_c - E_c)\right)}{L_c - E_c} \quad \text{and} \quad \phi_c = \frac{m\left((L_c - E_c), (N_c - E_c)\right)}{N_c - E_c}.$$

Conditional on belonging to the pool of unemployed individuals who meet a vacancy, a worker probability to meet *a particular* job is a function of his mobility across industries,

[9]Implications of two-sided heterogeneity and possible assortative matching are left for future research.

[10]Empirical evidence supports constant returns to scale in the German matching function. Nevertheless, I impose no restrictions on the homogeneity of the matching technology. This allows for the existence of potential search externalities. As have been largely documented in the matching literature, increasing returns to matching may lead to multiple equilibria (See Petrongolo and Pissarides [2001] for a survey on the matching function).

across occupations and across the entire occupation-industry matrix. Mobility across industries is defined by worker ability to execute the same task across industries. Mobility across occupations is defined by worker's ability to execute different tasks within the same industry. Mobility across the entire occupation-industry matrix depends on both mobility across industries and occupations. With workers assumed to be homogeneous in terms of their ability to execute tasks, mobility across industries and/or occupations is assumed to be identical across workers.

Mobility is modeled as follows. Consider an unemployed worker belonging to the pool of individuals who meet a vacancy. Let me refer to the "own occupation" and "own industry" as the occupation and industry in which an unemployed worker was working prior to becoming unemployed. With exogeneous probabilities $\varphi^{IND}$ and $1-\varphi^{IND}$, that individual gets a random draw from jobs in his "own industry" and in any industry, respectively. He gets a random draw from jobs in his "own occupation" and in any occupation with exogeneous probabilities $\varphi^{OCC}$ and $1-\varphi^{OCC}$, respectively.[11] With probability $\varphi^{IND}\varphi^{OCC}$ a worker *is constrained* to stay in the "own industry" and "own occupation". Thus, it represents worker immobility across occupation-industry cells.[12] $(1-\varphi^{IND})\varphi^{OCC}$ and $\varphi^{IND}(1-\varphi^{OCC})$ are probabilities of being tied to the "own occupation" and "own industry", respectively. They capture the importance of mobility across industries and across occupations, respectively. The importance of mobility across the entire industry-occupation matrix is captured by $(1-\varphi^{IND})(1-\varphi^{OCC})$. Moves across industries occur either within a particular occupation or across occupations. Thus, $\varphi^{OCC}$ reflects mobility across industries. Similarily, moves across occupations occur either within a particular industry or across industries such that $\varphi^{IND}$ reflects mobility across occupations. Mobility across industries exceeds mobility across occupations if $\varphi_{OCC} > \varphi_{IND}$. A worker is immobile if $\varphi^{IND} = \varphi^{OCC} = 1$, imperfectly mobile if $\varphi^{IND}$ and $\varphi^{OCC} \in (0,1)$ and perfectly mobile if $\varphi^{IND} = \varphi^{OCC} = 0$. From now on, we refer to $\varphi^{IND}$ and $\varphi^{OCC}$ as "mobility parameters". For simplicity, $\varphi^{IND}$ and $\varphi^{OCC}$ are assumed

[11] For simplicity, I assume independence of the parameters $\varphi^{IND}$ and $\varphi^{OCC}$. Relaxing this assumption would leave the model unaltered. Moreover, I impose no restrictions on the parameters in the estimation.

[12] This does not exlude mobility across firms within that particular cell.

to be constant across industries and across occupations, respectively.[13] Figure 5 provides an illustration of mobility in a two-by-two occupation-industry model.

### 3.3 Wage determination

Let $V^f_{qic}$ and $V^v_{qic}$ be the discounted value to the firm of a filled position and a vacancy, and let $U^e_{qic}$ and $U^u_{qic}$ be the discounted value to the worker of being employed and unemployed in a particular $qic$ cell, respectively. $\kappa$ is the relative bargaining power of firms and workers. In steady state, wages are set by Nash bargaining with disagreement points (outside options) $V^v_{qic}$ and $U^u_{qic}$ for firms and workers, respectively:

$$\left(V^f_{qic} - V^v_{qic}\right) = \left(U^e_{qic} - U^u_{qic}\right)\kappa. \tag{1}$$

Define $\lambda_{qic} = A_{ic}\theta_{qic}p_i\frac{y_{ic}}{N_{qic}}$, the value of the marginal product of type-q labor in industry $i$ and city $c$. If a position is filled, it generates a flow of profits of $(\lambda_{qic} - w_{qic})$. With probability $\delta$, any particular worker is laid off, his position becomes vacant and is filled in the subsequent period with probability $\phi_c$. Assume that there are no costs to maintaining a vacant position. Then, the value of a match to a firm relative to the value of a vacancy is given by:

$$V^f_{qic} - V^v_{qic} = \frac{\lambda_{qic} - w_{qic}}{\rho + \delta + \phi_c}. \tag{2}$$

[13]Implications are threefold. First, this means that worker attachment to the "own industry" and to the "own occupation" is identical across industries and across occupations, respectively. The main implications are not altered if both $\varphi^{IND}$ and $\varphi^{OCC}$ differ across industries and occupations (i.e. mobility parameters become $\varphi^{IND}_i$ and $\varphi^{OCC}_q$). In terms of the empirics, that means letting the coefficients on composition indices (the variables of interest) vary across occupations and industries. Second, this implies that worker mobility is independent of the destination industry and of the destination occupation. Hence, moving from industry $i$ to industry $j$ is as costly as moving from industry $i$ to industry $k$. Similarly, moving from occupation $q$ to occupation $r$ is as costly as moving from occupation $q$ to occupation $s$. Third, this implies that the direction of the move is of no relevance in determining worker mobility. This means that moving from industry $i$ to industry $j$ is as costly as moving from industry $j$ to industry $i$. Similarly, moving from occupation $q$ to occupation $r$ is as costly as moving from occupation $r$ to occupation $q$. The mechanism of the model is unchanged if the destination industry, the destination occupation and/or the direction of the move are relevant in determining worker mobility (i.e. mobility parameters become $\varphi^{IND}_{j,i}$ and $\varphi^{OCC}_{r,q}$, $\forall\, j, r$). However, identification is not feasible because mobility parameters (which we seek to estimate) cannot be disentangled from composition indices (the variables of interest). Hence, what I observe can be considered an average of a potentially heterogeneous effect.

An employed worker earns the wage $w_{qic}$ and becomes unemployed with the exogeneous probability $\delta$.[14] Let $\eta_{qc,i}$ be occupation-$q$ vacancies as a share of industry-$i$ vacancies in city $c$. Let $\eta_{ic,q}$ be industry-$i$ vacancies as a share of occupation-$q$ vacancies in city $c$. Let $\eta_{qic}$ be occupation-industry-$qi$ vacancies as a share of city-$c$ vacancies. These fractions are endogeneously determined in equilibrium. Then, the value of finding a job to a worker relative to being unemployed in a particular $qic$ cell is given by:

$$\begin{aligned} U^e_{qic} - U^u_{qic} &= \frac{w_{qic}}{\rho + \delta + \psi_c \varphi^{IND} \varphi^{OCC}} \\ &- \frac{\psi_c}{(\rho + \delta + \psi_c \varphi^{IND} \varphi^{OCC})(\rho + \delta + \psi_c)} \Bigg[ (1 - \varphi^{IND}) \varphi^{OCC} \sum_j \eta_{jc,q} w_{qjc} \\ &+ \varphi^{IND}(1 - \varphi^{OCC}) \sum_r \eta_{rc,i} w_{ric} + (1 - \varphi^{IND})(1 - \varphi^{OCC}) \sum_j \sum_r \eta_{rjc} w_{rjc} \Bigg] \quad (3) \end{aligned}$$

Substituting (2) and (3) into (1), occupation-industry-city-level average wages can be expressed as:

$$\begin{aligned} w_{qic} &= \gamma_{c1} \lambda_{qic} + \gamma_{c2} \Big[ (1 - \varphi^{IND}) \varphi^{OCC} \sum_j \eta_{jc,q} w_{qjc} \\ &+ \varphi^{IND}(1 - \varphi^{OCC}) \sum_r \eta_{rc,i} w_{ric} + (1 - \varphi^{IND})(1 - \varphi^{OCC}) \sum_j \sum_r \eta_{rjc} w_{rjc} \Big], \quad (4) \end{aligned}$$

where the coefficients are given by:

$$\begin{aligned} \gamma_{c1} &= \frac{(\rho + \delta + \psi_c \varphi^{IND} \varphi^{OCC})}{[(\rho + \delta + \psi_c \varphi^{IND} \varphi^{OCC}) + \kappa(\rho + \delta + \phi_c)]} \\ \gamma_{c2} &= \frac{(\rho + \delta + \phi_c)\kappa}{[(\rho + \delta + \psi_c \varphi^{IND} \varphi^{OCC}) + \kappa(\rho + \delta + \phi_c)]} \frac{\psi_c}{(\rho + \delta + \psi_c)}. \end{aligned}$$

These coefficients are functions of city's employment rate, as captured by $\phi_c$ and $\psi_c$.

Let me refer to outside employment opportunities as options outside the "own industry" and "own occupation" cell. If workers are immobile (i.e. $\varphi^{IND} = \varphi^{OCC} = 1$), outside

[14] For clarity, any relevant city-specific features such as amenities and unemployment benefits are normalized to zero. Qualitative results are not altered by this simplification.

employment opportunities are not credible options to bargain with. As a result, shifts in the distribution of employment across industries and/or occupations do not create general equilibrium wage effects. If workers are imperfectly mobile (i.e. $\varphi^{IND}$ and $\varphi^{OCC} \in (0,1)$), outside employment opportunities are credible options to bargain with. This causes occupation-industry-city-level average wages to act as strategic complements. The mechanism underlying strategic complementarity is the following. Higher outside wages raise the worker's threat point in the Nash bargaining game. Bargaining implies that a firm which wants to attract a worker must offer a higher wage. The strategic complementarity of wages results in a feedback pattern that leads shifts in the distribution of employment across industries and/or occupations to generate spillover effects on wages.

Identification of these spillover effects from equation (4) is difficult; first, because of the feedback pattern just described, and, second, because the employment rate in a city is treated as given and implicitly expressed through the $\gamma_c$s. Thus, equation (4) is a set of simultaneous equations that I now reformulate to obtain an estimable reduced form.

### 3.4 Wage equation: a reduced form

The reduced form of equation (4) is obtained using a first-order Taylor series approximation around the point where occupation-industry-city-level average wages are identical across cities.[15] This occurs when the technology parameter $\theta_{qic}$ and the productivity shifter $A_{ic}$ are city-invariant, i.e. $\theta_{qic} = \theta_{qi}$ and $A_{ic} = A_i$, which implies that the employment rate and the distribution of employment across and within industries are constant across cities. Define $\hat{\theta}_{qic} = \theta_{qic} - \theta_{qi}$, the occupation-industry-specific relative advantage component in the technology for city $c$, such that $\sum_c \hat{\theta}_{qic} = 0$. Similarly, define $\hat{A}_{ic} = A_{ic} - A_i$, the industry-specific relative advantage component in the productivity for city $c$, such that $\sum_c \hat{A}_{ic} = 0$. Thus, the distribution of employment across industries and occupations is identical across cities

[15] Linearizing equation (4) with a first-order approximation may be an empirical issue if higher-order terms are correlated with the regressors of interest. In their Web Appendix, BGS present results of a Monte Carlo simulation evaluating their first-order linear approximation. They conclude that the wage generation process is not essentially non-linear.

(i.e. $\theta_{qic} = \theta_{qi}$ and $A_{ic} = A_i$) when the relative advantage components $\hat{\theta}_{qic}$ and $\hat{A}_{ic}$ are zero. Details of the derivation are provided in the appendix. Let $\lambda_{qi}$ be $\lambda_{qic}$ evaluated at the point where occupation-industry-city level average wages are identical across cities. Let $w_{qi}$ be the national occupation-industry average wage and $\nu_{qi} = (w_{qi} - w_{11})$ be the national occupation-industry wage premium relative to the numeraire occupation and numeraire industry. The following reduced form is obtained from the first-order approximation:

$$\begin{aligned} w_{qic} &= \frac{\gamma_1\gamma_2(1-\varphi^{IND}\varphi^{OCC})}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}\lambda_{11} + \gamma_1\lambda_{qi} + f_{qi}ER_c \\ &+ \frac{\gamma_2}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}\Bigg[(1-\varphi^{IND})\varphi^{OCC}\sum_j \eta_{jc,q}\nu_{qj} + \varphi^{IND}(1-\varphi^{OCC})\sum_r \eta_{rc,i}\nu_{ri} \\ &+ (1-\varphi^{IND})(1-\varphi^{OCC})\sum_j\sum_r \eta_{rjc}\nu_{rj}\Bigg] + \xi_{qic}, \end{aligned} \tag{5}$$

where the terms $\gamma_1$ and $\gamma_2$ are $\gamma_{1c}$ and $\gamma_{2c}$ evaluated at the point where the relative advantage components $\hat{\theta}_{qic}$ and $\hat{A}_{ic}$ are zero. The term $f_{qi}$ is an occupation-industry-specific term obtained from the linear approximation. The term $\xi_{qic}$ is a function of the relative advantage components $\hat{\theta}_{qic}$ and $\hat{A}_{ic}$ and corresponds to the error term in the empirical section.[16]

Finally, to focus on labor market adjustments, equation (5) is first-differenced with re-

[16]The error term is given by:

$$\begin{aligned} \xi_{qic} &= \gamma_1\left(g_{qi}\hat{\theta}_{qic} + h_{qi}\hat{A}_{ic}\right) \\ &+ \frac{\gamma_1\gamma_2}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}\Bigg[(1-\varphi^{IND})\varphi^{OCC}\sum_j \eta_{j,q}\left(g_{qj}\hat{\theta}_{qjc} + h_{qj}\hat{A}_{jc}\right) \\ &+ \varphi^{IND}(1-\varphi^{OCC})\sum_r \eta_{r,i}\left(g_{ri}\hat{\theta}_{ric} + h_{ri}\hat{A}_{ic}\right) \\ &+ (1-\varphi^{IND})(1-\varphi^{OCC})\sum_j\sum_r \eta_{rj}\left(g_{rj}\hat{\theta}_{rjc} + h_{rj}\hat{A}_{jc}\right)\Bigg], \end{aligned}$$

where $\eta_{r,i}$, $\eta_{j,q}$ and $\eta_{rj}$ are respectively $\eta_{rc,i}$, $\eta_{jc,q}$ and $\eta_{rjc}$ evaluated at $\hat{\theta}_{qic} = 0$ and $\hat{A}_{ic} = 0$. The occupation-industry-specific terms $g_{qi}$ and $h_{qi}$ are obtained from the linear approximation and are functions of the following set of parameters: $\gamma_1$, $\gamma_2$, $\varphi^{IND}$, $\varphi^{OCC}$ and $\lambda_{qi}$.

spect to time, denoted $\tau$:

$$\Delta w_{qic\tau} = \Delta d_{qi\tau} + \beta_1 \Delta R^{IND}_{qc\tau} + \beta_2 \Delta R^{OCC}_{ic\tau} + \beta_3 \Delta R^{CITY}_{c\tau} + f_{qi} \Delta ER_{c\tau} + \Delta \xi_{qic\tau}, \tag{6}$$

where $f_{qi} > 0$ and

$$\begin{aligned}
d_{qi\tau} &= \frac{\gamma_1 \gamma_2 (1-\varphi^{IND}\varphi^{OCC})}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}\lambda_{11\tau} + \gamma_1 \lambda_{qi\tau} \\
R^{IND}_{qc\tau} &= \sum_j \eta_{jc\tau,q}\nu_{qj\tau} \\
R^{OCC}_{ic\tau} &= \sum_r \eta_{rc\tau,i}\nu_{ri\tau} \\
R^{CITY}_{c\tau} &= \sum_j \sum_r \eta_{rjc\tau}\nu_{rj\tau}
\end{aligned}$$

and

$$\begin{aligned}
\beta_1 &= \frac{\gamma_2}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}(1-\varphi^{IND})\varphi^{OCC} \geq 0 \\
\beta_2 &= \frac{\gamma_2}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}\varphi^{IND}(1-\varphi^{OCC}) \geq 0 \\
\beta_3 &= \frac{\gamma_2}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}(1-\varphi^{IND})(1-\varphi^{OCC}) \geq 0.
\end{aligned}$$

$R^{IND}_{qc\tau}$, $R^{OCC}_{ic\tau}$ and $R^{CITY}_{c\tau}$ are referred to as industrial, occupational and city composition indices, respectively. $\Delta d_{qi\tau}$ is a occupation-industry-time fixed effect. It controls, *inter alia*, for changes over time in national occupation-industry wage premia. Mobility parameters are identified from the $\beta$s:

$$\varphi_{IND} = \frac{\beta_2}{\beta_2 + \beta_3} \quad \text{and} \quad \varphi_{OCC} = \frac{\beta_1}{\beta_1 + \beta_3}. \tag{7}$$

With $\varphi_{IND}$ and $\varphi_{OCC} \in [0,1]$, the $\beta$s are nonnegative. Mobility across industries exceeds mobility across occupations if $\varphi_{OCC} > \varphi_{IND}$, which is the case if $\beta_1 > \beta_2$. The reverse holds if mobility across occupations exceeds mobility across industries.

When workers are imperfectly mobile (i.e. $\varphi^{IND}$ and $\varphi^{OCC} \in (0,1)$), extending BGS to a three-dimensional worker mobility (i.e. across industries, across occupations and across the entire industry-occupation matrix) involves three channels through which exogeneous shocks can work: an industrial, an occupational and a city composition index. The magnitude of the associated spillover effects is captured by the $\beta$s.

## 3.5 Omitting the occupational channel of labor adjustment

Let me now discuss why a BGS approach is likely to underestimate a region's average wage response to a change in the structure of labor demand induced by a shock (assumed to leave national wage premia unaffected). Formal details of the discussion are left to the appendix.

To do so, let me first relate BGS industrial composition index ($\tilde{R}^{IND}_{c\tau}$) to the composition indices derived in the previous section ($R^{IND}_{qc\tau}$, $R^{OCC}_{ic\tau}$ and $R^{CITY}_{c\tau}$). Let $w_{ic\tau}$ denote industry-$i$ average wage in city $c$, i.e. $w_{ic\tau} = \sum_r \eta_{rc\tau,i} w_{ric\tau}$, and note that a region's average wage can either be written:

$$w_{c\tau} = \sum_j \eta_{jc\tau} w_{jc\tau} \qquad \text{or} \qquad w_{c\tau} = \sum_j \sum_r \eta_{rjc\tau} w_{rjc\tau}.$$

Hence, a region's average wage response to a shock on labor demand can be identified either by looking at changes in the composition of employment at the industry level, as captured by changes in $\tilde{R}^{IND}_{c\tau}$, or by looking at the occupation-industry level, as captured by changes in $R^{CITY}_{c\tau}$. Let $\tilde{\beta}_1$ be the parameter for the effect of a shift in BGS industrial composition index on industrial city-specific average wages, i.e. $\tilde{\beta}_1 = \frac{\partial w_{ic\tau}}{\partial \tilde{R}^{IND}_{c\tau}}$. Then, the change in a region's average wage is given by:

$$dw_{c\tau} = \underbrace{\frac{\partial w_{c\tau}}{\partial \tilde{R}^{IND}_{c\tau}} d\tilde{R}^{IND}_{c\tau}}_{\text{direct (composition) effect}} + \underbrace{\sum_j \frac{\partial w_{c\tau}}{\partial w_{jc\tau}} \frac{\partial w_{jc\tau}}{\partial \tilde{R}^{IND}_{c\tau}} d\tilde{R}^{IND}_{c\tau}}_{\text{indirect (spillover) effect}} = (1+\tilde{\beta}_1) d\tilde{R}^{IND}_{c\tau} \tag{8}$$

or, taking a more disaggregated route, by:

$$\begin{aligned} dw_{c\tau} &= \underbrace{\frac{\partial w_{c\tau}}{\partial \tilde{R}^{CITY}_{c\tau}} d\tilde{R}^{CITY}_{c\tau}}_{\text{direct (composition) effect}} + \underbrace{\sum_j \sum_r \frac{\partial w_{c\tau}}{\partial w_{rjc\tau}} \left[ \frac{\partial w_{rjc\tau}}{\partial R^{IND}_{rc\tau}} dR^{IND}_{rc\tau} + \frac{\partial w_{rjc\tau}}{\partial R^{OCC}_{jc\tau}} dR^{OCC}_{jc\tau} + \frac{\partial w_{rjc\tau}}{\partial R^{CITY}_{c\tau}} dR^{CITY}_{c\tau} \right]}_{\text{indirect (spillover) effect}} \\ &= (1+\beta_3) dR^{CITY}_{c\tau} + \beta_1 \sum_r \eta_{rc\tau} dR^{IND}_{rc\tau} + \beta_2 \sum_j \eta_{jc\tau} dR^{OCC}_{jc\tau}. \end{aligned} \tag{9}$$

Combining (8) and (9), and replacing $dR$ by $\Delta R$, the indices are related by the following relationship:[17]

$$(1+\tilde{\beta}_1)\Delta \tilde{R}^{IND}_{c\tau} = \beta_1 \sum_r \eta_{rc\tau} \Delta R^{IND}_{c\tau} + \beta_2 \sum_j \eta_{jc\tau} \Delta R^{OCC}_{jc\tau} + (1+\beta_3)\Delta R^{CITY}_{c\tau}. \tag{10}$$

If the true model is given by equation (6), estimating BGS model, i.e.

$$\Delta w_{ic\tau} = \Delta d_{i\tau} + \tilde{\beta}_1 \Delta \tilde{R}^{IND}_{c\tau} + f_i \Delta ER_{c\tau} + \Delta \varepsilon_{ic\tau}, \tag{11}$$

will provide a biased estimate of $\tilde{\beta}_1$. Using expression (10), it can be shown that if

$$E\left[\Delta \tilde{R}^{IND}_{c\tau} \left( \Delta R^{OCC}_{ic\tau} - \sum_j \eta_{jc\tau} \Delta R^{OCC}_{jc\tau} \right)\right] < 0, \tag{12}$$

estimating BGS model necessarily produces a downward biased estimate of $\tilde{\beta}_1$ and leads to underestimate a region's average wage response to a shock on labor demand. Note that $\left[\Delta R^{OCC}_{ic\tau} - \sum_j \eta_{jc\tau} \Delta R^{OCC}_{jc\tau}\right]$ is the differential between industry-$i$ occupational composition and the average occupational composition across industries in city $c$. A positive difference thus indicates that the employment composition in industry $i$ has become more favorable (i.e. oriented toward high-premia occupations) relative to the average occupational composition across industries in city $c$. There exists two circumstances under which such a negative correlation is observed. In one case, employment in each city moves toward high-paying

[17] Note that the direct effect in (8) is not equal to the direct effect in (9). This also holds for the indirect effects. The aggregate effects only are equivalent.

industries (i.e. industries that use high-premia occupations intensively), but toward low-premia occupations within each industry. In the other case, the composition of employment in each city shifts toward low-premia industries, but toward high-paying occupations within each industry.

In the context of international trade, the Stolper-Samuelson theorem predicts these types of labor reallocation. Assume that trade is liberalized in a Northern country. The high-skill industry expands (i.e. $\Delta \tilde{R}^{IND}_{c\tau} > 0$) bidding up the relative wage of skilled workers and inducing every industry to substitute white collars by cheaper blue collars (i.e. $\forall i$, $\Delta R^{IND}_{ic\tau} - \sum_j \Delta R^{IND}_{jc\tau} < 0$). Alternatively, consider a trade liberalization in the South. The low-skill intensive industry expands (i.e. $\Delta \tilde{R}^{IND}_{c\tau} < 0$). Due to better technology (e.g. embodied in imported capital equipment) industries experience a technological upgrading which biases labor demand toward high-skill workers (i.e. $\forall i$, $\Delta R^{IND}_{ic\tau} - \sum_j \Delta R^{IND}_{jc\tau} > 0$).

Overall, the discussion points out that identification of a region's average wage response to a shock on labor demand requires estimating $\beta_1$, $\beta_2$ and $\beta_3$ with model (6). The desired effect is then obtained from (9) or (8), where in the latter case an unbiased estimate of $\tilde{\beta}_1$ is obtained by substituting $\beta_1$, $\beta_2$ and $\beta_3$ into (10).

The decomposition of labor adjustments offered by model (6) is not only useful for identifying the effect of a shock on *average* wages, but also for assessing its effect on *relative* wages. The effect of trade liberalization on the widening skill wage premium is a case in point. Consider a trade liberalization that alters the composition of employment across and within industries. Let $q$ denote the high-skill occupation and $r$ the low-sill occupation. Then, in industry $i$ and city $c$, the change in the high-skill wage relative to the low-skill wage is given by:

$$\Delta \left( w_{qic\tau} - w_{ric\tau} \right) = \beta_1 \left( \Delta R^{IND}_{qc\tau} - \Delta R^{IND}_{rc\tau} \right),$$

which taking the average across industries and cities becomes:

$$\Delta (w_{q\tau} - w_{r\tau}) = \beta_1 \left( \Delta R^{IND}_{q\tau} - \Delta R^{IND}_{r\tau} \right),$$

where $w_{q\tau} = \frac{1}{C}\frac{1}{J}\sum_c \sum_J w_{qjc\tau}$ and $R^{IND}_{q\tau} = \frac{1}{C}\frac{1}{J}\sum_c \sum_j R^{IND}_{qc\tau}$ (and similarly for $w_{r\tau}$ and $R^{IND}_{r\tau}$).

### 3.6 Implications of worker mobility across cities

Let me discuss the implications of relaxing the assumption of worker immobility across cities. Worker mobility across cities can be modeled either as a random or a directed search across cities. Let me now extend the model to allow for a random search across cities. Essentially, this extension modifies $U^u_{qic}$, the value of being unemployed to a worker. Assume that with probability $(1-\Gamma)$ an unemployed worker gets a random draw from jobs in his city, while with probability $\Gamma$ he gets a random draw from jobs in *all* cities. Letting $U^{u'}_{qic}$ be the extended version of $U^u_{qic}$ under random search I get:

$$\begin{aligned}
\rho U^{u'}_{qic} &= (1-\Gamma)U^u_{qic} + \Gamma\Big[\varphi^{IND}\varphi^{OCC}\underbrace{\sum_c \frac{N_{qic}}{N_{qi}}U^e_{qic}}_{qi\text{-specific term}} + (1-\varphi^{IND})\varphi^{OCC}\underbrace{\sum_c\sum_j \frac{N_{qjc}}{N_j}U^e_{qjc}}_{q\text{-specific term}} \\
&+ \varphi^{IND}(1-\varphi^{OCC})\underbrace{\sum_c\sum_r \frac{N_{ric}}{N_r}U^e_{ric}}_{i\text{-specific term}} + (1-\varphi^{IND})(1-\varphi^{OCC})\underbrace{\sum_c\sum_j\sum_r \frac{N_{rjc}}{N}U^e_{rjc}}_{\text{constant term}} - U^{u'}_{qic}\Big],
\end{aligned}$$

where $N_{qi}$, $N_q$ and $N_i$ are respectively occupation-industry, occupation and industry national employments. $N$ denote the level of the national employment. Hence, three additional terms which vary across occupations, industries and across both industries and occupations are added to the wage equation given by (5). This extension would have no implications on the estimates because these terms will be captured by occupation-specific, industry-specific and occupation-industry-specific time fixed effects in my baseline specification.

More interestingly, modeling worker mobility across cities as a directed search allows to account for potential agglomeration externalities. Assume that with probability $\Lambda$, an unemployed worker is immobile across cities. With probability $(1-\Lambda)$ he is imperfectly mobile across cities and chooses to move to the city $c'$ that maximizes his value of finding a job relative to being unemployed. Let $U^{u*}_{qic}$ be the extended version of $U^u_{qic}$ under directed search. The discounted value of being being unemployed to a worker is:

$$\rho U^{u*}_{qic} = (1-\Lambda)U^{u}_{qic} + \Lambda \max_{c'} \left[ \underbrace{\sum_{j}\sum_{r} \eta_{ric'} U^{u}_{qic'}}_{c'\text{-specific term}} - U^{u*}_{qic} \right].$$

Thus, allowing for directed search across cities implies adding a constant term to (5). This would have no incidence on the estimated coefficients since this term will be captured by time fixed effects in the baseline specification. Allowing for directed search implies introducing housing prices, which adjust to equilibrate the migration flow across cities. As BGS argue

> [...] A city with a higher employment rate or a better employment mix, [...], will attract more workers. This immigration will drive up local housing prices, causing the migration to stop before wages are equalized across cities. Housing prices will adjust such that a city with a favorable composition of jobs [...] has local benefits that are captured by local landowners.[18]

Because housing costs are paid whether employed or unemployed, they do not alter the value of finding a job to a worker relative to being unemployed. Therefore, the wage equation given by (5) remains unaltered.

# 4 Baseline specification and identification strategy

The specification of interest is given by equation (6). A log specification is obtained by dividing both sides of (6) by the constant average wage $w_0$.[19] $t$ denotes an individual year and $\tau$ a five-year period. The equation of interest is estimated using five-year averages of annual data taking mutually exclusive and jointly exhaustive intervals. This reduces measurement

[18] Beaudry, Green and Sand (2010), p. 15-16.

[19] To see why a log specification is equivalent to (6), let $log\ w_{qic\tau}$ be approximated around the constant average wage $w_0$:

$$log\ w_{qic\tau} \simeq log\ w_0 + \frac{w_{qic\tau} - w_0}{w_0}, \tag{13}$$

error and purges variations due to business cycles. Thus, my baseline specification takes the form:

$$\Delta ln\ w_{qic\tau} = \beta_1 \Delta R^{IND}_{qc\tau} + \beta_2 \Delta R^{OCC}_{ic\tau} + \beta_3 \Delta R^{CITY}_{c\tau} + f_{qi} \Delta ER_{c\tau} + \Delta d_{qi\tau} + \Delta \xi_{qic\tau}, \qquad (15)$$

where $\beta_1$, $\beta_2$ and $\beta_3$ are the coefficients we are interested in. According to the model, the $\beta$s should be nonnegative. Even though the equation that comes out of theory is based on independence of the mobility parameters $\varphi^{IND}$ and $\varphi^{OCC}$, I do not impose any restrictions on the parameters in the estimation. Standard errors are clustered at the city level.

Because employment and wages are simultaneously determined, the $\beta$s are expected to be inconsistent if estimated with OLS. Instrumental variables are used to deal with endogeneity of the composition indices and of the employment rate.

Let $\hat{}$ be a predicted value and $N_{qit}$ be national occupation-industry employment. For a particular occupation and industry, city-level employment is predicted and combined in various ways to build instruments for the indices and for the employment rate. It is predicted as if it had grown at the same rate as national employment: $\hat{N}_{qict} = N_{qic(t-6)} \frac{N_{qit}}{N_{qi(t-6)}}$. Then, $\hat{N}_{qic\tau}$ is computed as the mean of $\hat{N}_{qict}$ over the corresponding five-year interval.

This means that the baseline identification strategy hinges on two assumptions. First, in a particular occupation-industry cell, past city-level employment and changes in past city-level employment should be uncorrelated to future idiosyncratic shocks on wages. Second, national employment and changes in national employment, in a particular occupation-industry cell, should be uncorrelated to present and future idiosyncratic shocks on wages.

The appendix shows that the first requirement holds if within a particular city, productivity and technology shocks *relative* to other cities, as captured by $\Delta\hat{\theta}_{qic\tau}$ and $\Delta\hat{A}_{ic\tau}$, are uncorrelated to each other over time. In terms of the model, the second requirement

such that the yearly change in the log average wage is given by:

$$\Delta log\ w_{qic\tau} \simeq \frac{w_{qic\tau} - w_{qic(\tau-1)}}{w_0}. \qquad (14)$$

Hence, dividing both sides of equation (6) by the constant average wage $w_0$ provides a log specification, where $w_0$ is captured by the constant term in the estimation.

is necessarily satisfied. Empirically, this may not be the case in a small country such as Germany. As a robustness check, I relax the second assumption and require instead that French employment and changes in French employment, in a particular occupation-industry cell, be uncorrelated to present and future idiosyncratic shocks on wages in Germany.

**Instruments for the composition indices** The occupational composition index, $\Delta R^{OCC}_{ic\tau}$, can be decomposed into two components: the between and the within components. These components capture the variations in the indices that are attributable to changes in the distribution of employment and to changes in the wage premia, respectively:

$$\Delta R^{OCC}_{ic\tau} = \underbrace{\sum_r \nu_{ri(\tau-1)} \left(\eta_{rc\tau,i} - \eta_{rc(\tau-1),i}\right)}_{Between\ component} + \underbrace{\sum_r \eta_{rc\tau,i} \left(\nu_{ri\tau} - \nu_{ri(\tau-1)}\right)}_{Within\ component} . \tag{16}$$

Replacing $\eta_{qc\tau,i}$ by its predicted value, both components are forecast and used separately as instruments:

$$\begin{aligned} IV^{OCC,BETWEEN} &= \sum_r \nu_{ri(\tau-1)} \left(\hat{\eta}_{rc\tau,i} - \hat{\eta}_{rc(\tau-1),i}\right) \\ IV^{OCC,WHITHIN} &= \sum_r \hat{\eta}_{rc\tau,i} \left(\nu_{ri\tau} - \nu_{ri(\tau-1)}\right) , \end{aligned}$$

where $\hat{\eta}_{qc\tau,i} = \frac{\hat{N}_{qic\tau}}{\sum_r \hat{N}_{ric\tau}}$. The industrial and city composition indices are instrumented equivalently, forecasting both components of the indices with the corresponding predicted employment shares.

**Instruments for the employment rate** The rate of growth of the employment rate can be partitioned into two elements, one that is associated to the growth of employment and one that relates to the growth of the workforce. The predicted values of both elements are used as instruments for the employment rate. Predicted employment growth is computed as:

$$IV^{EMPLGROWTH} = \sum_i \sum_r \hat{\eta}_{ric(\tau-1)} \frac{N_{ri\tau}}{N_{ri(\tau-1)}}. \tag{17}$$

This instrument is a weighted average of national occupation-industry employment growth rates, the weights being the start of period corresponding city-level employment shares.

The predicted workforce growth is constructed in a similar way. Let $N_{qic}^{wf}$ denote the workforce in an occupation-industry-city cell and $\eta_{qic}^{wf}$ be the corresponding workforce share. Let $N_{qi}^{wf}$ be the national workforce, in occupation-industry cell. Then:

$$IV^{WORKFORCE} = \sum_i \sum_r \hat{\eta}_{ric(\tau-1)}^{wf} \frac{N_{ri\tau}^{wf}}{N_{ri(\tau-1)}^{wf}}. \tag{18}$$

# 5 Empirical setting

## 5.1 Data source

I take this model to data for German cities. The data are taken from the official employment statistics of the Institute of 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. Information on wages captures all earnings subject to statutory social security contributions and reported at least once annually. For each notification period, a daily income is reported, such that partial as well as full-time workers can be considered. 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. I work with a 2% anonymous sample of the original IAB employment database. Over the entire period, namely 1975-2002, a 2% representative sample is drawn from four clusters, namely German nationals, foreign nationals, West-German residents and East-German residents.[20]

[20] In order to reduce a potential overweighting of foreigners, Mincer equations described in the next subsection include a nationality dummy.

Our focus is on West-German residents and the period 1977-2001. With data on Eastern Germany available only from 1991 onwards, I concentrate on the former Federal Republic of Germany.

In the IAB original 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 16 industries and 130 occupations. In this study, occupations are grouped into 33 broader categories, according to the 1975 German classification of occupations. The industrial and occupational classifications into 16 and 33 categories are shown in Tables 1 and 2, respectively. Industries and occupations are reported by firms. Hence, they should be accurately classified. Cities are defined as commuting areas, according to the Federal Office for Building and Regional Planing. This yields 38 local labor markets, whose urban centers are listed in Table 3.

## 5.2 Wage premia

Let $k$ denote an individual worker. The dependent variable is estimated from Mincer equations: for each industry and year, log individual wages are regressed on a vector of individual characteristics and a complete set of occupation-city interactions. In performing $i \times t$ regressions, returns to skill are allowed to vary over time and across industries. Let $d_q$ be occupation dummies, $d_c$ city dummies, $d_{qc}$ be occupation-city interactions and $W_k$ be the individual wage. The latter is expressed in euros and converted into real wages using the consumer price index, base 2005, provided by the German federal statistical office. $Z$ is a vector of individual characteristics consisting of 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. For each $i$ and $t$, I estimate

$$ln\ W_{kqc} = \varrho_0 + Z\varrho + d_{qc} + \zeta_{kqc}, \qquad (19)$$

where $\zeta_{kqc}$ is an error term. Equation (19) is estimated with OLS. Standard errors are robust. F-tests of the joint significance (joint nullity and joint equality) of $d_{qc}$ are rejected.[21]

For each industry and year, the dependent variable of my equation of interest, $w_{qic\tau}$, is computed as the mean of $d_{qc}$ over five-years intervals and the national wage premia, $\nu_{qi\tau}$, are computed as the mean of $\sum_c \frac{N_{qict}}{\sum_c N_{qict}} d_{qc}$ over five-years intervals.[22]

# 6 Results

**Baseline results** Column (1) of Table 6 shows IV estimates for the baseline specification.[23] First-stage F-statistics are above the conventional level of ten. With a p-value on the Hansen test of 0.22, the hypothesis of overidentification is rejected.[24] As predicted by the theory, the estimated coefficients are positive. The size of the coefficients on the industrial, occupational and city composition indices is 1.072, 2.75 and 0.647, respectively. Only the coefficients on the industrial and occupational composition indices are statistically significant. This is in line with evidence of worker mobility across industries and occupations. The implied $\varphi^{IND}$ and $\varphi^{OCC}$ are 0.832 and 0.576, respectively, indicating that moving costs to workers are rather high. Inter-industry mobility costs are thus estimated to be 1.5 times larger than inter-occupational mobility costs.

Column (2) of table 6 presents results obtained with the BGS specification, omitting occupations. As for column (1), first-stage F-statistics and the Hansen test are well-behaved. The coefficient on the industrial composition index is negative, $-0.189$, and statistically

[21] These tests as well as the estimated wage premia are available upon request.

[22] The German wage bargaining system combines elements of both industry-wide collective agreements and decentralized individual agreements between employer and employee. Today, Germany tends toward a more decentralized wage bargainaing system. The mechanism described in this paper is the result of decentralized wage bargaining. The effect of industry-wide unions, which establish minimum wages, is captured by the constant. This ensures that the estimated wage premia do not reflect unionization but instead decentralized wage bargaining.

[23] The model suggests that the coefficient on the employment rate should vary across occupations and industries. For computational reasons, it is imposed to be constant in a city. In the estimation based on a major occupation classification of occupations and industries, one can show that letting the employment rate vary in the occupation-industry dimension or imposing it to be constant leads to quantitatively similar results.

[24] First-stage regressions are available upon request.

insignificant. As discussed previously, an unbiased estimate of $\tilde{\beta}_1$, the coefficient on BGS industrial composition index, can be computed out of equation (24). Column (3) presents this estimate, obtained by substituting the baseline estimates of $\beta_1$, $\beta_2$ and $\beta_3$ and the statistics of Table 5 into equation (24). The unbiased coefficient is large, 2.313, and statistically significant at a 5% level, implying that the negative bias on $\tilde{\beta}_1$ produced by a BGS procedure amounts to 2.32 (i.e. 2.313 + 0.189) in the case of Germany. Thus, combining this result with equation (8), a region's average wage response to a shock on labor demand would be underestimated by $(2.32 * \Delta\tilde{R}^{IND}_{c\tau})$ when ignoring inter-occupational labor adjustments. I interpret this as being the result of shocks that induce inter-industry and inter-occupational adjustment forces to work in opposite directions (as suggested by the stylized facts presented at the beginning of this paper), therefore causing a negative correlation between the industrial and occupational indices.

**Sensitivity analysis: selection 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 according to unobserved earnings-related reasons. If worker selection is correlated to the unobserved components of wages (e.g. individual abilities), the conditional mean error term won't be zero. The estimates of the coefficients on the composition indices will be inconsistent if the structure of employment within cities is correlated with worker selection decision into cities. As BGS did, I use Dahl (2002) non-parametric approach to correct for sample selection bias.

Let $d_{kct}$ be a dummy indicator taking the value of one if individual $k$ works in city $c$ at time $t$ and let $E\left[\xi_{kqict}|d_{kct}=1\right]$ be the conditional mean error term. $d_{kbct}$ is a dummy variable taking the value of one if individual $k$ born in city $b$ is working in city $c$ at time $t$. Let $Pr_{kbct}$ and $Pr_{kbbt}$ be the probabilities that individual $k$ born in city $b$ is observed in city $c$ and remains in city $b$ at time $t$, respectively. Following Dahl (2002), the conditional mean error term can be identified as a function of worker migration probabilities $Pr_{kbct}$ and $Pr_{kbbt}$.

In line with BGS, these functions are quadratic in these probabilities. For movers it is:

$$E\left[\xi_{kqict}|d_{kct}=1\right]=\sum_{b}d_{kbct}\left(Pr_{kbct}^{2}+Pr_{kbbt}^{2}\right)+\iota_{kqict},$$

while for stayers it is:

$$E\left[\xi_{kqict}|d_{kct}=1\right]=\sum_{b}d_{kbct}Pr_{kbbt}^{2}+\iota_{kqict},$$

where $\iota$ is a zero-mean residual term. The sample selection bias is corrected by introducing $\sum_b d_{kbct}\left(Pr_{kbct}^2+Pr_{kbbt}^2\right)$ and $\sum_b d_{kbct}Pr_{kbbt}^2$ in the wage premia estimations.

Let individuals be divided into cells according to their observed characteristics (i.e. age, gender, nationality, education). Within the cell which is relevant for individual $k$, the migration probabilities are computed as follows:

$$Pr_{kbct}=\frac{N_{bct}}{N_{bt}}\quad\text{and}\quad Pr_{kbbt}=\frac{N_{bbt}}{N_{bt}},$$

where $N_{bt}$ is the number of individuals born in city $b$, $N_{bbt}$ is the number of individuals born in city $b$ and still observed in city $b$ and $N_{bct}$ is the number of individuals born in city $b$ but observed in city $c$, at time $t$. Within each cell, differences in $P_{kbct}$ across movers being observed in city $c$ are due to variations in the city of birth across workers. If the city of birth is not directly correlated to individual wages, differences in probabilities across movers of the same cell reflect differences in their unobserved abilities. Taking BGS case in point,

> [...] a person born in Pennsylvania has a lower probability of being observed in Seattle than a person born in Oregon. If both are observed living in Seattle, then we are assuming that the person from Pennsylvania must have a larger Seattle specific "ability" (a stronger earnings reason for being there) and this is what is being captured by the sample correction.[25]

The IAB anonymized sample does not provide data on workers city of birth. Instead, I use

[25] Beaudry, Green and Sand (2010), p. 43.

workers city of residence at $(t-1)$ as a source of variation across workers within cells, i.e. I assume that where movers where living at $(t-1)$ does not affect their wage determination at time $t$. For stayers, Dahl (2002) decomposes each cell into a further individual characteristic, the familiy status, assumed to be independent of the wage determination process. This latter component is not available in the IAB sample. This implies that within cells, unobserved abilities – assumed to be identical across stayers – are identified with respect to movers only.

The model derived in this paper hinges on a random assignment to occupations – an assumption which is certainly not verified in practice. Hence, the issue of self-selection also applies to occupations. My approach to the question follows the self-selection into cities.

Results are shown in Table 7. Column (1) corresponds to the baseline estimates. Column (2) and (3) present results for specifications that control for the selection into cities and occupations, respectively. For both specifications, F-tests are above the conventional critical level of ten and the Hansen tests cannot be rejected. The point estimates on the industrial and occupational composition indices remain stable and statistically significant at the 1% level. The estimates on the city composition index are reduced considerably but stay positive and statistically insignificant. As regards the ratio of inter-industry to inter-occupational mobility costs, it remains similar to the baseline specification. Overall, correcting the sample selection bias gives rise to minor changes.

**Sensitivity analysis: identification issue** One of the two assumptions underlying my identification strategy requires that national employment and changes in national employment, in a particular occupation-industry cell, be uncorrelated to present and future idiosyncratic shocks on wages. In terms of the model this condition is necessarily satisfied, but it may be empirically violated, when in a relatively large country such as Germany. As an alternative, I therefore predict city-level employment in a particular occupation and industry using French employment growth. Given its proximity to Germany, France is likely to have similar production technologies and to have experienced similar shocks on labor demand, making it a good candidate to perform this exercise. If my identification strategy is valid, then using French employment growth to construct instruments should not alter the estimates.[26]

Results are presented in Table 8. Columns (1) and (2) show OLS results and IV results for the baseline specification, respectively. Column (3) shows IV results for the specification that uses French occupation-industry employment growth to create instruments. Results lend support to my identification strategy. First-stage F-tests in column (3) are above the conventional critical level of ten and the Hansen test cannot be rejected. The point estimates are very close to the baseline specification. The coefficients on composition indices increase slightly. $\beta_1$ and $\beta_2$, the coefficients on industrial and occupational composition indices, remain significant with p-value smaller than 0.01. Even though they decrease somewhat, the implied immobility parameters remain high, suggesting significant mobility costs. The ratio of inter-industry to inter-occupational mobility costs remains similar to the baseline specification.

**Sensitivity analysis: city-specific controls** To control for competing explanations for differences in wages (or growth performance) across cities, a vector of city-specific controls is added to equation (15). Results are shown in Table 9. Column (1) again presents estimates for the baseline specification. Column (2) controls for potential education externalities. These are captured by the percentage of workers with university-level qualifications, denoted $BA_{c\tau}$. The diversity of employment across industries and occupations is controlled for in column (3). It is measured using the lag of one minus the industrial Herfindahl index, $(1-HERF)^{IND}_{c\tau} = (1 - \sum_i \eta^2_{ic(\tau-1)})$, and with the lag of one minus the occupational Herfindahl index, $(1 - HERF)^{OCC}_{c\tau} = (1 - \sum_q \eta^2_{qc(\tau-1)})$. Finally, agglomeration effects and shifts in local demand are controlled for in column (5) using the log of the city labor force, denoted $lnSIZE_{c\tau}$. Following the existing literature, one would expect the effect on each of these measures to be positive. Column (5) includes all of these additional city-specific controls jointly.

All first-stage F-tests are above the conventional critical level of ten. With p-value on

[26]Data source: INSEE French employment survey, 1975-2002 period.

the Hansen test in the range of 0.107 and 0.413, I can again reject the hypothesis of instrument overidentification. The inclusion of additional regressors does not alter my results, suggesting that composition indices are not catching alternative driving forces for city-level wage changes. Whichever the specification I consider, the coefficients on my variables of interest are stable and similar to the baseline specification. The coefficients on industrial and occupational composition indices remain significant at a one percent level. Education tends to have a positive and statistically significant effect on average wages, which supports the findings of e.g. Moretti (2004) and Acemoglu and Angrist (1999).[27] The diversity of employment has a positive impact on average wages. But only industrial diversity triggers a statistically significant effect on average wages. Agglomeration effects and changes demand are positive but rather small and statistically insignificant.[28] This supports Blanchard and Katz (1992). As suggested by Glaeser, Kallal, Scheinkman and Shleifer (1992), the diversity of employment seems to be a stronger determinant of city-level growth than city size. Generally, the ratio of implied mobility parameters decreases slightly when controls are added, but the implied mobility costs remain high (i.e. $> 0.5$).

**Sensitivity analysis: industrial and occupational aggregation** The model assumes mobility parameters (or the cost of moving across industries and occupations) to be constant across industries and occupations. This means, among others, that $\varphi^{IND}$ and $\varphi^{OCC}$ are independent of industry and occupation distances. Assuming that industrial and occupational aggregation reflect distances, this implies mobility parameters and therefore the estimates of interest to be independent of industrial and occupational aggregation.

Empirically this is not the case: the cost of moving across industries and occupations is increasing in industrial and occupational distance. Thus, the coefficients of interest are expected to be decreasing in the aggregation of industries and occupations. If the aggregation

[27] Alternatively, one could proxy city-level education with city average education level. Whether one or the other measure is used, the effect of education remains similar and does not alter the coefficients on the indices.

[28] Results are unaltered if one instruments $ln\ SIZE_{c\tau}$ using its predicted counterpart (i.e. using $\hat{N}^{wf}_{c\tau} = \sum_i \sum_q \hat{N}^{wf}_{qic\tau}$, where $\hat{N}^{wf}_{qic\tau}$ is constructed as predicted in section 4).

level is too high, $\varphi^{IND} \to 1$ and $\varphi^{OCC} \to 1$ and the effect of a shift in industrial and occupational composition indices on average wages should vanish.

In Table 10, I investigate how results behave under various levels of industrial and occupational aggregation. Column (1) reproduces the baseline specification with 16 industries and 33 occupations. Columns (2), (3), (4), and (5) present results based on $16 * 16$, $10 * 10$, $6 * 16$ and $6 * 6$ classifications, respectively, where the reclassifications into broader industrial and occupational categories are choosen arbitrarily. The industrial classification into 6 and 10 categories are shown in appendix Tables 16 and 17, respectively. The occupational classification into 10 and 16 categories are shown in appendix Tables 18 and 19, respectively. As for the baseline specification, first-stage F-tests and the Hansen test are well-behaved. Results for the $16*16$ classification are close to the $33*16$ baseline classification, with a slight decrease in the coefficients of industrial and occupational composition indices. This suggests that the average distance across occupations in a $33 * 16$ and $16 * 16$ classification is similar. As expected, when switching to higher degrees of aggregation, as shown in columns (3)-(5), the effect of a shift in industrial and occupational composition, as respectively captured by the coefficients on $R^{IND}_{qc\tau}$ and $R^{OCC}_{ic\tau}$, disappear. The coefficient on the city composition index remains statistically insignificant over the specifications but becomes very noisy with aggregation degrees beyond the $10 * 10$ classification. For this reason, the implied mobility parameters are inaccurately measured in columns (3)-(5).

**Sensitivity analysis: Others** Table 11 present estimates for other sensitivity checks. Column (1) corresponds to the baseline specification. Column (2) is the weighted IV counterpart of the baseline specification, where observations are weighted by the square root of the number of individuals present in the corresponding $qic\tau$ cell. In column (3), I show that estimates are not driven by changes in own employment shares and reestimate the baseline specification, controlling for $\eta_{ic\tau,q}$, $\eta_{qc\tau,i}$ and $\eta_{qic\tau}$. Employment shares are instrumented using their predicted counterpart. Because individual wages are truncated above and below, I present in column (4) results for a specification where wage premia are estimated from a two-sided tobit. To account for the persistence of wages I estimate a dynamic version of the baseline specification, whose results are shown in column (5). Adding a lagged dependent variable leads to a dynamic panel model, which I estimate with the Arellano-Bond difference GMM estimator. The Arellano-Bond test for autocorrelation in the differenced residuals indicates a first-order correlation, suggesting the presence of first-order correlation of the residuals. Accordingly, the third to fifth lags of the dependent variable are used as instruments. As regards the indices and the employment rate, the same set of instruments described in the baseline specification is used.[29] First-stage F-tests and the Hansen test are well-behaved. Estimates remain similar to the baseline specification, except for the city composition index in column (5), which becomes negative but remains statistically insignificant. Except for the differenced GMM estimation, implied mobility parameters are in line with the baseline specification. Mobility costs are high and inter-industry mobility costs are 1.3 times larger than inter-occupational mobility costs.

# 7 Concluding remarks

BGS (2010) lately debated the adequacy of a partial equilibrium analysis in evaluating the effect of a shock on a region's average wage, highlighting spillover wage effects of shifts in industrial employment composition. In this paper I have argued that the simultaneous consideration of inter-sectoral and inter-occupational labor adjustments is essential to assess this spillover effect. I have extended BGS search-and-bargaining model to incorporate occupations and related industrial and occupational composition of employment to occupation-industry-city-level average wages. The resulting structural equation sheds light on the circumstances under which omitting the occupational dimension of labor adjustment leads to an underestimate of the effect of a shock on a region's average wage. If labor shifts toward high-paying industries but low-paying occupations (or the reverse), forces working

[29]The effect of employment diversity on the growth of wages is captured with the lag of the Herfindahl indices in level, not with the lag of their first difference. Because stata automatically transform variables in level into first differences, Herfindahl indices are not included in this dynamic specification.

through the inter-sectoral and inter-occupational dimensions will offset each other if both channels of the adjustment are not accounted for, therefore leading to underestimation. A Stolper-Samuelson-type employment reallocation following trade liberalization in a Northern country is a case in point. In the empirical section, I combine structural modeling with instrumental variable estimation – to deal with the endogeneity of employment – using individual-level data for German cities for 1977-2001. Results strongly support the argument of this paper. In the case of Germany, a region's average wage response to a shock on labor demand would be underestimated by two-thirds when ignoring inter-occupational labor adjustments. This result holds over a wide range of sensitivity checks which verify the validity of my identification strategy. To the extend that the trade-and-wages literature was not designed to simultaneously consider the interplay between inter-sectoral and inter-occupational labor adjustments, I believe that this paper offers some guidance to develop a novel approach for reexamining the impact of increased market access on wages.

# References

Acemoglu, D., and J. Angrist (1999): “How Large Are the Social Returns to Education? Evidence from Compulsory Schooling Laws,” NBER Working Papers 7444, National Bureau of Economic Research.

Artuc, E., S. Chaudhuri, and J. McLaren (2010): “Trade Shocks and labor Adjustment: A Structural Empirical Approach,” *American Economic Review*, 100(3), 1008-1045.

Attanasio, O., P. K. Goldberg, and N. Pavcnik (2004): “Trade Reforms and Wage Inequality in Colombia,” *Journal of Development Economics*, 74(2), 331-66.

Baldwin, R.E. and G.G Cain (1997): “Shifts in U.S. Relative Wages: The Role of Trade, Technology and Factor Endowments,” National Bureau of Economic Research.

Beaudry, P., D. Green, and B. Sand (2010): “Does Industrial Composition Matter for Wages: An Empirical Evaluation Based on Search and Bargaining Theory,” Working Paper, University of British Columbia.

Bender, S., A. Haas, and C. Klose (2000): “IAB Employment Subsample 1975-1995: Opportunities for Analysis Provided by the Anonymised Subsample,” IZA Discussion Paper Series.

Berman, E., J. Bound, and Z. Griliches (1994): “Changes in the Demand for Skilled labor within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufacturing,” *The Quarterly Journal of Economics*, 109(2), 367-397 .

Blanchard, O. J., and L.F. Katz (1992): “Regional Evolutions,” *Brookings Papers and Economic Activity*, (1), 1-76.

Borjas, G. J., R. B. Freeman, and L. F. Katz (1991): “On the labor Market Effects of Immigration and Trade,” Working Paper 3761, National Bureau of Economic Research.

Borjas, G. J., R. B. Freeman, L. F. Katz, J. DiNardo, and J. M. Abowd (1997): “How Much Do Immigration and Trade Affect labor Market Outcomes?” *Brookings Papers on Economic Activity*.

Brülhart, M., C. Carrère and F. Trionfetti (2010): “Decomposing Agglomeration Effects: How Wages and Employment Adjust to Improved Market Access,” Working Paper.

Dahl, G. B. (2002): “Mobility and the Return to Education: Testing a Roy Model with Multiple Markets,” *Econometrica*, 70(6), 2367-2420.

Glaser, E., H. Kallal, J. Scheinkman, and A. Shleifer (1992): "Growth in Cities," *Journal of Political Economy*, 100(6), 1126-1152.

Kambourov, G., and I. Manovskii (2008): "Rising Occupational and Industry Mobility in the United States: 1968-1997," International Economic Review, (49), 41-79.

Keane, M. P., and K. I. Wolpin (1997): "The Career Decisions of Young Men," *Journal of Political Economy*, 105(3), 473-522.

Kennan, J., and J. R. Walker (2003): "The Effect of Expected Income on Individual Migration Decisions," Working Paper 9585, National Bureau of Economic Research.

Kruger, A.B. (1997): "Labor Market Shifts and the Price Puzzle Revisited," Working Paper 5924, National Bureau of Economic Research.

Krugman, P. (1995): "Technology, Trade, and Factor Prices," Working Paper 5355, National Bureau of Economic Research.

Lawrence, R. Z., M. J. Slaughter, R. E. Hall, S. J. Davis, and R. H. Topel (1993): "International Trade and American Wages in the 1980s: Giant Sucking Sound or Small Hiccup?," *Brookings Papers on Economic Activity*, (2), 161-226.

Leamer, E. E. (1996a): "In Search of Stolper-Samuelson Effects on U.S. Wages," Working Paper 5427, National Bureau of Economic Research.

Lee, D. (2005): "An Estimable Dynamic General Equilibrium Model of Work, Schooling, and Occupational Choice," *International Economic Review*, 46(1), 1-34.

Lee, D., and K. I. Wolpin (2006): "Intersectoral labor Mobility and the Growth of the Service Sector," *Econometrica*, 74(1), 1-46.

Lopéz, A. J., and M. Mayor (2008): "Spatial Shift-Share Analysis Versus Spatial Filtering: An Application to Spanish Employment Data," *Empirical Economics*, 34(1), 123-142.

Loveridge, A. C., and S. Scott (1992): "A Summary of the Lterature on Shift-Share Analysis," Staff Papers 14086, University of Minnesota, Department of Applied Economics.

Moretti, E. (2004): "Estimating the Social Returns to Higher Education: Evidence from Longitudinal and Repeated Cross-Sectional Data," *Journal of Econometrics*, 121(1-2), 175-212.

Petrongolo, B., and C. A. Pissarides (2001): "Looking into the Black Box: A Survey of the Matching Function," *Journal of Economic Literature*, 39(2), 390-431.

Porto, G., and B. M. Hoekman (2010): "Trade Adjustment Costs in Developing Countries: Impacts, Determinants and Policy Responses," in G. Porto, and B. M. Hoekman, *Trade Adjustment Costs in Developing Countries: Impacts, Determinants and Policy Responses.*

Revenga, A. (1992): "Exporting Jobs?: The Impact of Import Competition on Employment and Wages in U.S. Manufacturing," *The Quarterly Journal of Economics*, 107(1), 255-284.

Sachs, J. D. and H. J. Shatz (1994): "Trade and Jobs in Manufacturing," Brookings Papers on Economic Activity, 25(1), 1-84.

Slaughter, M. (1998): "Trade and labor-Market Outcomes: Results, Questions and Policy Options," *The Economic Journal*, 108(450), 1452-1462.

Stolper W., and P. A. Samuelson (1941): "Protection and real wages," *Review of Economic Studies*, 9(1), 58-73.

# 8 Tables

Table 1: Industrial classification into 16 categories.

| | |
|---|---|
| **Primary sector** | *Industry 8* |
| *Industry 1* | Finishing trades |
| Agriculture, hunting, forestry and fishing | |
| Mining and quarrying | **Tertiary sector** |
| Electricity, gas and water supply | *Industry 9* |
| | Wholesale, trade and commission excl. motor vehicles |
| **Secundary sector** | |
| *Industry 2* | *Industry 10* |
| Wood and products of wood and cork | Sale of automotive fuel |
| Pulp, paper, paper products, printing and publishing | Retail trade excl. motor vehicles - repair of household goods |
| Chemical, rubber, plastics and fuel products | |
| Basic metals and fabricated metal products | *Industry 11* |
| Other non-metallic mineral products | Transport storage and communications |
| *Industry 3* | *Industry 12* |
| Machinery and equipment (nec) | Finance, insurance, real estate and business services |
| Motor vehicles, trailers and semi-trailers | |
| | *Industry 13* |
| *Industry 4* | Hotels and restaurants |
| Electrical and optical equipment | Recreational, cultural and sporting activities |
| Other transport equipment | Other service activities |
| | Private households with employed persons |
| *Industry 5* | |
| Textiles and textile products | *Industry 14* |
| Leather, leather products and footwear | Education |
| Other non-metallic mineral products | Health and social work |
| Manufacturing n.e.c. | |
| | *Industry 15* |
| *Industry 6* | Sewage and refuse disposal, sanitation and similar activities |
| Food products, beverages and tobacco | Activities of membership organizations (nec) |
| *Industry 7* | *Industry 16* |
| Construction trades | Public admin. and defense - compulsory social security |
| | Extra-territorial organizations and bodies |

Source: The IAB anonymized sample.

Table 2: Occupational classification into 33 categories.

| | |
|---|---|
| **Agricultural** | Painters |
| Farming, forestry, gardening, fishing | Goods sorters, packagers |
| | Assistants |
| **Mining and quarrywork** | Machine operators |
| Mining and quarrywork | |
| | **Technicians** |
| **Manufacturing** | Technicians - engineers and related |
| Stone, jewelery, brickwork | Technicians - manufacturing and science |
| Glass and ceramics | |
| Chemicals, plastics and rubber | **Services and professionals** |
| Paper and printing | Buying and selling |
| Woodwork | Banking, insurance, agents |
| Metalworkers, primary product | Arts, creative and recreational |
| Skilled metal work and related | Other services, personal and leisure services |
| Electrical | Travel and transport |
| Metal and assembly / installation | Administration and bureaucracy |
| Textiles | Public order, safety and security |
| Leather goods | Health services |
| Food, drink and tobacco | Teaching and social employment |
| Construction | |
| Building | **Other** |
| Carpenters | Other occupations |

Note: Occupations in the IAB anonymized sample are classified into 33 broader categories according to the 1975 German classification of occupations.

Table 3: Urban centers of the 38 local labor markets.

| | |
|---|---|
| Aarchen | Münster |
| Augsburg | Nürnberg-Fürth-Erlangen |
| Bielefeld | Oldenburg |
| Braunschweig-Salzgitter | Osnabrück |
| Bremen | Paderborn |
| Bremerhaven | Pforzheim |
| Freiburg im Breisgau | Regensburg |
| Göttingen | Region Hannover |
| Hamburg | Rhein-Main |
| Heilbronn | Rhein-Neckar |
| Hildesheim | Rheinschiene |
| Ingolstadt | Rhur |
| Kaiserlautern | Siegen |
| Karlsruhe | Stadtverband Saarbrücken |
| Kassel | Stuttgart-Reutlingen |
| Kiel | Trier-Saarburg and KS Trier |
| Koblenz | Ulm |
| Lübeck | Wolfsburg and Helmstadt |
| München | Wüzburg |

Note: Local labor markets are defined by commuting areas according to the Federal Office for Building and Regional Planing.

Table 4: Summary Statistics: cross-industry and cross-occupational mobility as a share of Western-German employed workers over the period 1977-2001.

| **Variable** | **Mean** | **Std. Dev.** | **Min.** | **Max.** |
|---|---|---|---|---|
| *Share of employed workers who move:* | | | | |
| Across industries within occupation | 0.029 | 0.004 | 0.022 | 0.040 |
| Across occupations within industry | 0.025 | 0.004 | 0.020 | 0.035 |
| Across both industries and occupations | 0.027 | 0.006 | 0.018 | 0.037 |
| *Mobility distribution:* | | | | |
| Across industries within occupation | 0.356 | 0.042 | 0.305 | 0.497 |
| Across occupations within industry | 0.314 | 0.038 | 0.251 | 0.383 |
| Across both industries and occupations | 0.330 | 0.032 | 0.252 | 0.380 |

Note: The statistics is constructed from the IAB anonymized sample, on the basis of employed individuals who can be traced over two consecutive years.

Table 5: Summary Statistics: indices used to compute the unbiased $\tilde{\beta}_1$.

| **Variable** | **Mean** | **Std. Dev.** | **Min.** | **Max.** |
|---|---|---|---|---|
| $\Delta\tilde{R}_c^{IND}$ | 0.0013 | 0.0097 | $-0.0216$ | 0.0246 |
| $\sum_r \eta_{rc}\Delta R_{rc\tau}^{IND}$ | 0.0009 | 0.0055 | $-0.0101$ | 0.0111 |
| $\sum_j \eta_{jc}\Delta R_{jc}^{OCC}$ | 0.0008 | 0.0056 | $-0.0097$ | 0.0122 |
| $\Delta\tilde{R}_c^{CITY}$ | 0.0012 | 0.0056 | $-0.0105$ | 0.0123 |

Table 6: Baseline specification versus omitting occupations.

| **Dependent variable** | $\Delta$ *log* $w_{qic}$ | $\Delta$ *log* $w_{ic}$ | |
|---|---|---|---|
| **Regressors** | **(1)** Baseline | **(2)** Omitting occupations | **(3)** Baseline-implied estimate |
| $\Delta\ R^{IND}_{qc}$ | 1.072*** | | |
| | (0.271) | | |
| $\Delta\ R^{OCC}_{ic}$ | 2.750*** | | |
| | (0.533) | | |
| $\Delta\ R^{CITY}_{c}$ | 0.647 | | |
| | (1.140) | | |
| $\Delta\ \tilde{R}^{IND}_{c}$ | | −0.189 | 2.131** |
| | | (1.149) | [0.048] |
| $\Delta\ ER_c$ | 0.281 | 0.415 | |
| | (0.410) | (0.580) | |
| Implied $\varphi_{IND}$ | 0.832 | | |
| Implied $\varphi_{OCC}$ | 0.576 | | |
| H0: $\beta_1 = \beta_2$ | [0.000] | | |
| Observations | 9376 | 1665 | |
| F-first stage: $\Delta\ R^{IND}_{qc}$ | 620.6 | 44.03 | |
| F-first stage: $\Delta\ R^{OCC}_{ic}$ | 201.5 | | |
| F-first stage: $\Delta\ R^{CITY}_{c}$ | 262.4 | | |
| F-first stage: $\Delta\ ER_c$ | 22.05 | 50.05 | |
| Hansen | 0.22 | 0.41 | |

Notes: Column (1) and (2) contain $d_{i\tau}$ and $d_{qi\tau}$, respectively. 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. Column (1) shows estimates for the baseline specification. Column (2) shows estimates for a specification that omits occupations. Column (3) shows the baseline-implied estimate on BGS industrial composition index.

Table 7: Selection issue.

| **Dependent variable** | $\Delta$ $log\ w_{qic}$ | | |
|---|---|---|---|
| **Regressors** | **(1)** Baseline | **(2)** City Selection | **(3)** Occupation Selection |
| $\Delta$ $R_c^{CITY}$ | 0.647 | 0.232 | 0.307 |
| | (1.140) | (1.543) | (1.194) |
| $\Delta$ $R_{qc}^{IND}$ | 1.072*** | 1.106*** | 1.303*** |
| | (0.271) | (0.211) | (0.247) |
| $\Delta$ $R_{ic}^{OCC}$ | 2.750*** | 3.172*** | 2.334*** |
| | (0.533) | (0.775) | (0.418) |
| $\Delta$ $ER_c$ | 0.281 | 0.032 | 0.198 |
| | (0.410) | (0.377) | (0.419) |
| Implied $\varphi^{IND}$ | 0.810 | 0.932 | 0.884 |
| Implied $\varphi^{OCC}$ | 0.624 | 0.826 | 0.809 |
| H0: $\beta_1 = \beta_2$ | [0.005] | [0.007] | [0.024] |
| Observations | 9376 | 9376 | 9376 |
| F-first stage: $\Delta$ $R_c^{CITY}$ | 262.4 | 221.9 | 305.2 |
| F-first stage: $\Delta$ $R_{qc}^{IND}$ | 620.6 | 1976 | 1861 |
| F-first stage: $\Delta$ $R_{ic}^{OCC}$ | 201.5 | 271.3 | 241.3 |
| F-first stage: $\Delta$ $ER_c$ | 22.05 | 22.70 | 22.77 |
| Hansen | 0.220 | 0.564 | 0.224 |

Notes: All estimations contain $d_{qi\tau}$. 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. Column (1) corresponds to the baseline estimates. Column (2) shows results for a specification that controls for the selection into cities. Column (3) shows results for a specification that controls for the selection into occupations.

Table 8: Identification issue.

| Dependent variable | $\Delta\ log\ w_{qic}$ | | |
|---|---|---|---|
| **Regressors** | **(1)** OLS | **(2)** Baseline | **(3)** French data |
| $\Delta\ R_{qc}^{IND}$ | 0.776*** | 1.072*** | 1.123*** |
| | (0.232) | (0.271) | (0.326) |
| $\Delta\ R_{ic}^{OCC}$ | 2.829*** | 2.750*** | 3.141*** |
| | (0.522) | (0.533) | (0.710) |
| $\Delta\ R_{c}^{CITY}$ | 0.572 | 0.647 | 1.007 |
| | (1.060) | (1.140) | (1.334) |
| $\Delta\ ER_c$ | 0.222 | 0.281 | 0.247 |
| | (0.247) | (0.410) | (0.438) |
| Implied $\varphi^{IND}$ | 0.832 | 0.810 | 0.757 |
| Implied $\varphi^{OCC}$ | 0.576 | 0.624 | 0.527 |
| H0: $\beta_1 = \beta_2$ | [0.000] | [0.005] | [0.008] |
| Observations | 9376 | 9376 | 8907 |
| F-first stage: $\Delta\ R_{qc}^{IND}$ | | 620.6 | 161.2 |
| F-first stage: $\Delta\ R_{ic}^{OCC}$ | | 201.5 | 56.53 |
| F-first stage: $\Delta\ R_{c}^{CITY}$ | | 262.4 | 108.2 |
| F-first stage: $\Delta\ ER_c$ | | 22.05 | 11.53 |
| Hansen | | 0.220 | 0.142 |

Notes: All estimations contain $d_{qi\tau}$. 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. Column (1) shows OLS estimates. Column (2) and (3) are the IV counterparts of column (1). Column (2) corresponds to our baseline specification. Column (3) uses French occupation-industry employment growth to create instruments.

Table 9: Additional controls.

| **Dependent variable** | $\Delta\ log\ w_{qic}$ | | | | |
|---|---|---|---|---|---|
| **Regressors** | **(1)** Baseline | **(2)** Education | **(3)** Employment diversity | **(4)** Agglomeration effects | **(5)** All controls |
| $\Delta\ R_{qc}^{IND}$ | 1.072*** | 1.045*** | 1.083*** | 1.068*** | 1.070*** |
| | (0.271) | (0.272) | (0.273) | (0.270) | (0.273) |
| $\Delta\ R_{ic}^{OCC}$ | 2.750*** | 2.785*** | 2.764*** | 2.780*** | 2.884*** |
| | (0.533) | (0.530) | (0.534) | (0.529) | (0.520) |
| $\Delta\ R_{c}^{CITY}$ | 0.647 | 0.829 | 0.722 | 0.725 | 0.722 |
| | (1.140) | (1.101) | (1.286) | (1.189) | (1.437) |
| $\Delta\ ER_c$ | 0.281 | 0.253 | 0.364 | 0.224 | 0.172 |
| | (0.410) | (0.417) | (0.399) | (0.460) | (0.481) |
| $\Delta\ BA_c$ | | 0.745* | | | 1.090** |
| | | (0.386) | | | (0.480) |
| $(1-HERF)_c^{IND}$ | | | 0.107** | | 0.142*** |
| | | | (0.045) | | (0.052) |
| $(1-HERF)_c^{OCC}$ | | | 0.191 | | 0.427 |
| | | | (0.287) | | (0.273) |
| $\Delta\ ln\ SIZE_c$ | | | | 0.067 | 0.068 |
| | | | | (0.106) | (0.114) |
| Implied $\varphi^{IND}$ | 0.810 | 0.771 | 0.793 | 0.793 | 0.780 |
| Implied $\varphi^{OCC}$ | 0.624 | 0.558 | 0.600 | 0.596 | 0.597 |
| H0: $\beta_1 = \beta_2$ | [0.005] | [0.004] | [0.006] | [0.004] | [0.002] |
| Observations | 9376 | 9376 | 9376 | 9376 | 9376 |
| F-first stage: $\Delta\ R_{qc}^{IND}$ | 620.6 | 621.4 | 647.7 | 613.5 | 629.4 |
| F-first stage: $\Delta\ R_{ic}^{OCC}$ | 201.5 | 205.0 | 202.1 | 207.0 | 213.8 |
| F-first stage: $\Delta\ R_{c}^{CITY}$ | 262.4 | 284.1 | 186.6 | 208.8 | 155.5 |
| F-first stage: $\Delta\ ER_c$ | 22.05 | 22.90 | 26.08 | 18.52 | 19.22 |
| Hansen | 0.220 | 0.413 | 0.107 | 0.214 | 0.190 |

Notes: All estimations contain $d_{qi\tau}$. 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. Column (1) is our baseline specification. Column (2) controls for education externalities, column (3) for the diversity of employment across industries and occupations, column (4) for agglomeration externalities.

Table 10: Industrial and occupational aggregation.

| **Dependent variable** | $\Delta$ *log* $w_{qic}$ | | | | |
|---|---|---|---|---|---|
| **Regressors** | **(1)** Baseline | **(2)** 16X16 | **(3)** 10X10 | **(4)** 6X16 | **(5)** 6X6 |
| $\Delta\ R_{qc}^{IND}$ | 1.072*** | 0.820** | −0.070 | −0.039 | −0.403 |
| | (0.271) | (0.388) | (0.748) | (0.654) | (0.993) |
| $\Delta\ R_{ic}^{OCC}$ | 2.750*** | 2.618*** | 2.690 | 1.614 | 0.880 |
| | (0.533) | (0.909) | (1.653) | (1.627) | (1.878) |
| $\Delta\ R_{c}^{CITY}$ | 0.647 | 1.198 | −2.984 | 1.895 | −0.035 |
| | (1.140) | (1.104) | (2.897) | (2.243) | (6.161) |
| $\Delta\ ER_c$ | 0.281 | 0.509 | 0.441 | 0.395 | 0.385 |
| | (0.410) | (0.433) | (0.283) | (0.265) | (0.398) |
| Implied $\varphi^{IND}$ | 0.810 | 0.686 | −9.150 | 0.460 | 1.041 |
| Implied $\varphi^{OCC}$ | 0.624 | 0.406 | 0.023 | −0.021 | 0.920 |
| H0: $\beta_1 = \beta_2$ | [0.005] | [0.062] | [0.155] | [0.375] | [0.548] |
| Observations | 9376 | 7439 | 4172 | 2767 | 1408 |
| F-first stage: $\Delta\ R_{qc}^{IND}$ | 620.6 | 408.3 | 433.5 | 244.5 | 152.6 |
| F-first stage: $\Delta\ R_{ic}^{OCC}$ | 201.5 | 242.7 | 232.5 | 129.1 | 95.62 |
| F-first stage: $\Delta\ R_{c}^{CITY}$ | 262.4 | 441.0 | 121.4 | 165.1 | 165.0 |
| F-first stage: $\Delta\ ER_c$ | 22.05 | 21.57 | 18.88 | 18.29 | 10.49 |
| Hansen | 0.220 | 0.193 | 0.231 | 0.432 | 0.349 |

Notes: All estimations contain $d_{qi\tau}$. Standard errors are clustered at the city level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column (1) is our baseline specification. Columns (2), (3), (4) and (5) show results for a specification based on a 16X16, 10X10, 6X16 and 6X6 classification of industries and occupations, respectively.

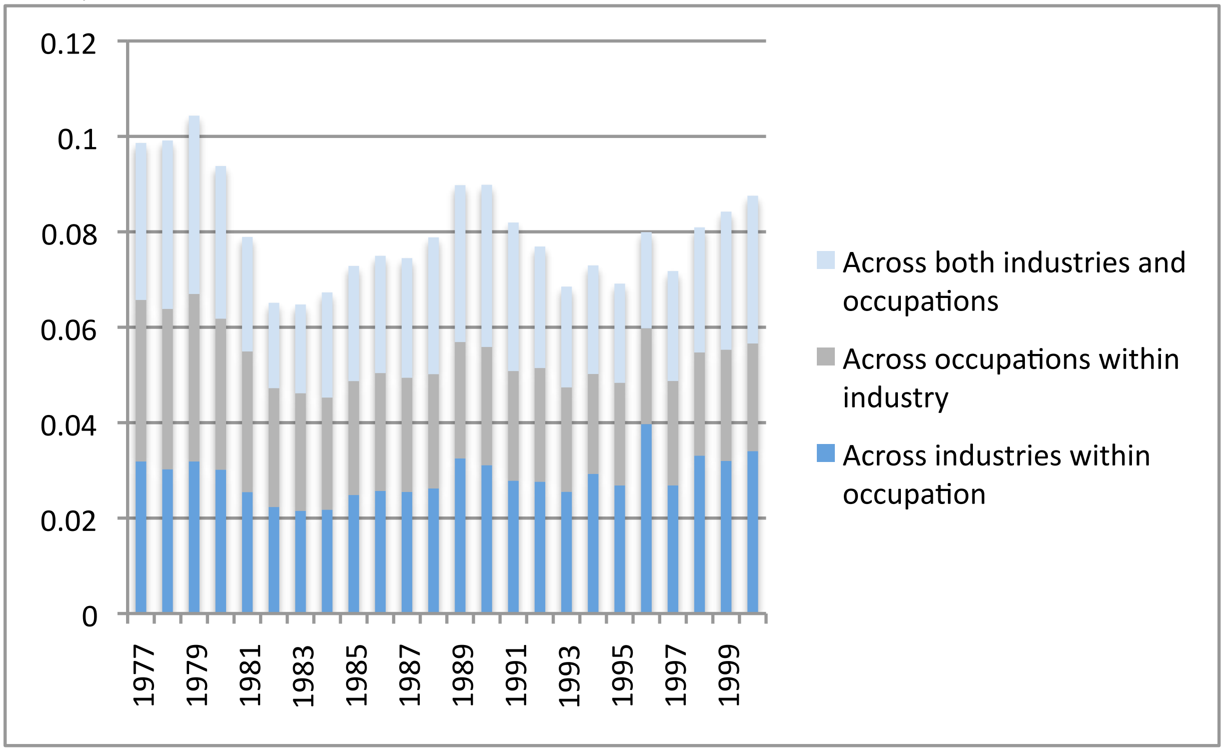
Table 11: Other robustness checks.

| **Dependent variable** | $\Delta\ log\ w_{qic}$ | | | | |
|---|---|---|---|---|---|
| **Regressors** | **(1)** Baseline | **(2)** Weights | **(3)** Controlling for own empl. shares | **(4)** Tobit | **(5)** Differenced GMM |
| $\Delta\ R_{qc}^{IND}$ | 1.072*** | 1.172*** | 1.083*** | 1.029*** | 1.423*** |
| | (0.271) | (0.228) | (0.260) | (0.265) | (0.419) |
| $\Delta\ R_{ic}^{OCC}$ | 2.750*** | 2.876*** | 2.658*** | 2.642*** | 3.284*** |
| | (0.533) | (0.443) | (0.602) | (0.578) | (0.759) |
| $\Delta\ R_{c}^{CITY}$ | 0.647 | 0.568 | 0.657 | 0.820 | −0.198 |
| | (1.140) | (1.114) | (1.182) | (1.122) | (1.116) |
| $\Delta\ ER_c$ | 0.281 | 0.224 | 0.298 | 0.334 | 0.527 |
| | (0.410) | (0.376) | (0.415) | (0.416) | (0.411) |
| L.$\Delta\ log\ w_{qic}$ | | | | | 0.738*** |
| | | | | | (0.111) |
| Implied $\varphi^{IND}$ | 0.810 | 0.835 | 0.802 | 0.763 | 1.064 |
| Implied $\varphi^{OCC}$ | 0.624 | 0.674 | 0.622 | 0.557 | 1.162 |
| H0: $\beta_1 = \beta_2$ | [0.005] | [0.000] | [0.022] | [0.013] | [0.032] |
| Observations | 9376 | 9376 | 9376 | 9376 | 8589 |
| F-first stage: $\Delta\ R_{qc}^{IND}$ | 620.6 | 820.9 | 573.8 | 619.9 | |
| F-first stage: $\Delta\ R_{ic}^{OCC}$ | 201.5 | 233.8 | 151.1 | 216.6 | |
| F-first stage: $\Delta\ R_{c}^{CITY}$ | 262.4 | 272.0 | 223.1 | 260.0 | |
| F-first stage: $\Delta\ ER_c$ | 22.05 | 27.11 | 16.06 | 21.97 | |
| Hansen | 0.220 | 0.178 | 0.203 | 0.232 | 0.503 |
| AR(2) | | | | | 0.769 |

Notes: All estimations contain $d_{qi\tau}$. Standard errors are clustered at the city level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column (1) is our baseline specification. Column (2) is a weighted IV counterpart of column (1). Column (3) controls for own employment shares. Column (4) shows results for a specification where wage premia are estimated from a two-sided tobit. Column (5) shows estimates for a dynamic differenced GMM epecification.

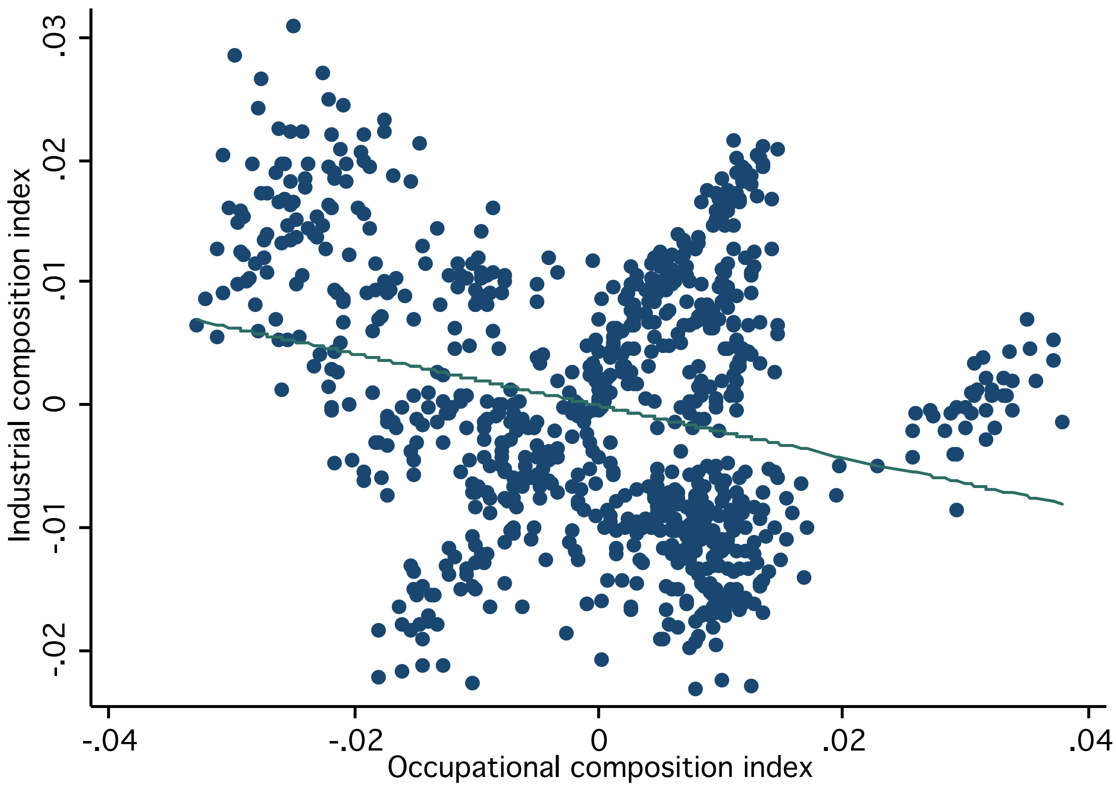
## 9 Figures

Figure 1: Evolution of worker mobility across industries within occupation, across occupations within industry and across both industries and occupations as a share of West-German employed workers over the period 1977-2001.



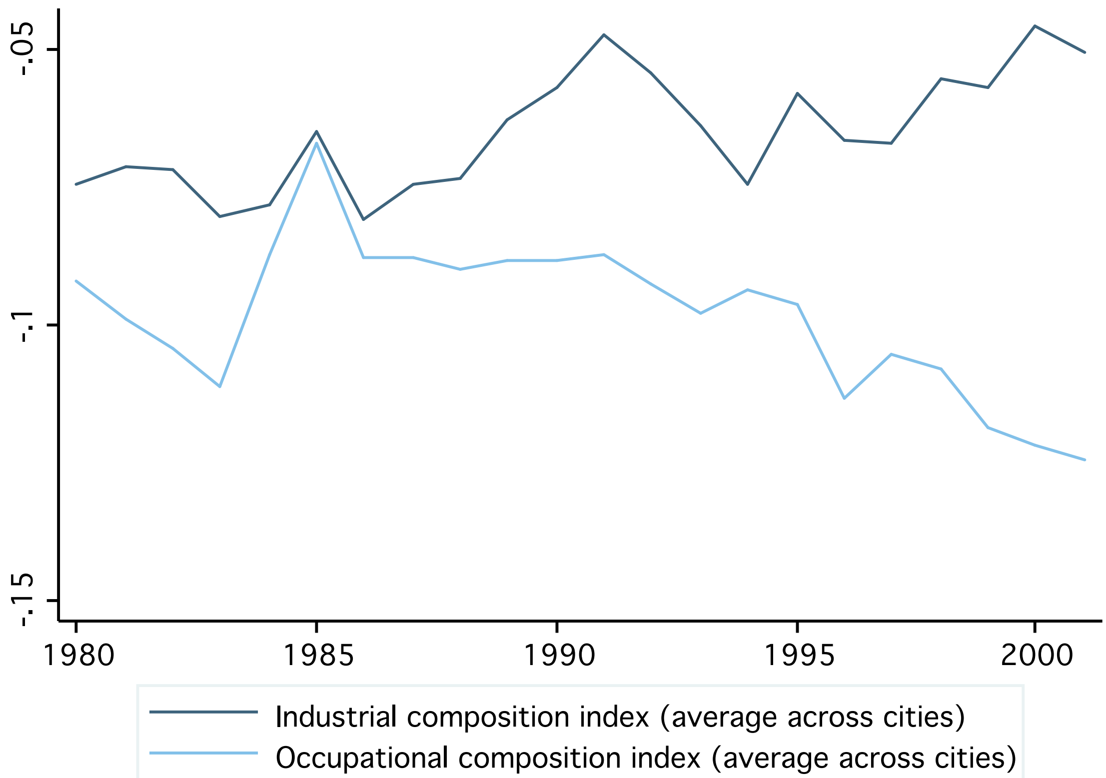

Note: The figure is constructed from the IAB anonymized sample, on the basis of employed individuals who can be traced over two consecutive years.

Figure 2: Correlation between industrial and occupational composition indices over the period 1980-2001, controlling for city fixed effects.



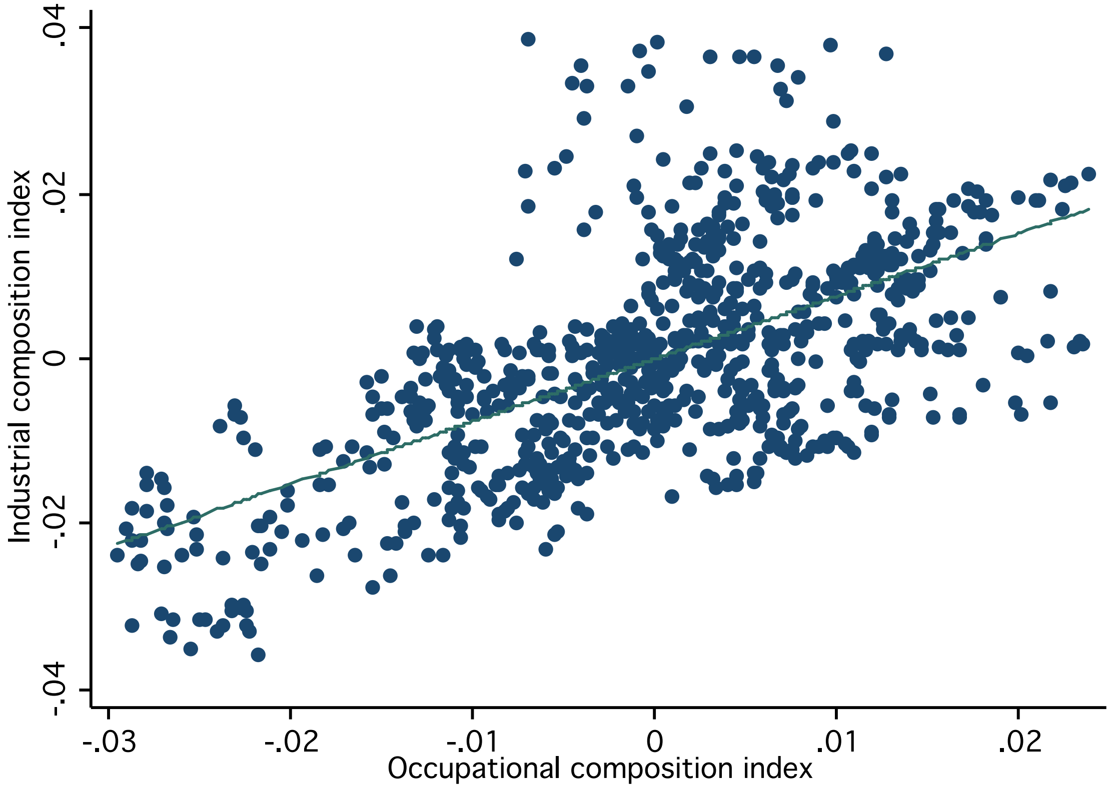

Note: The figure is constructed from the IAB anonymized sample.

Figure 3: Evolution of industrial and occupational composition indices, averaged across cities of Western Germany, over the period 1980-2001.



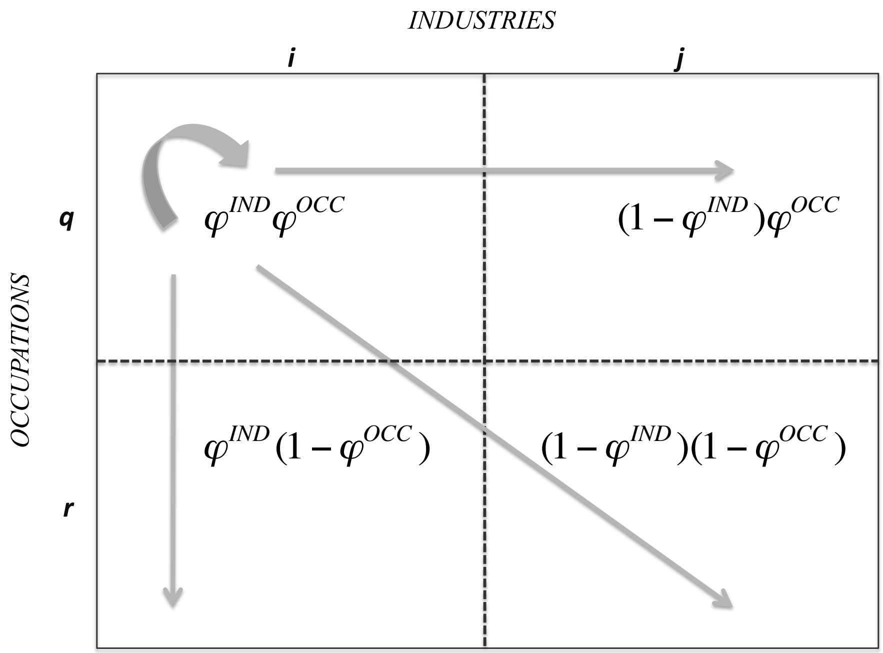

Note: The figure is constructed from the IAB anonymized sample.

Figure 4: Correlation between industrial and occupational composition indices across cities of Western Germany, controlling for year fixed effects.




Note: The figure is constructed from the IAB anonymized sample.

Figure 5: Mobility illustration in a two-by-two occupation-industry model.




$i$ and $q$ are the "own industry" and "own occupation" cells, respectively. $\varphi^{IND}\varphi^{OCC}$ captures the importance of worker immobility across occupation-industry cells. $(1-\varphi^{IND})\varphi^{OCC}$ and $\varphi^{IND}(1-\varphi^{OCC})$ capture the importance of worker mobility across industries and across occupations, respectively. The importance of mobility across the entire industry-occupation matrix is captured by $(1-\varphi^{IND})(1-\varphi^{OCC})$.

# 10 Appendix

## 10.1 Deriving a reduced form for the wage equation

Equation (4) is a set of simultaneous equations that I now reformulate to obtain an estimable reduced form. I start by solving equation (4) for $w_{qic}$ and obtain:

$$\begin{aligned} w_{qic} &= \gamma_{c1}\lambda_{qic} + \frac{\gamma_{1c}\gamma_{2c}}{1-\gamma_{2c}(1-\varphi^{IND}\varphi^{OCC})}\Bigg[(1-\varphi^{IND})\varphi^{OCC}\sum_j \eta_{jc,q}\lambda_{qjc} \\ &+ \varphi^{IND}(1-\varphi^{OCC})\sum_r \eta_{rc,i}\lambda_{ric} + (1-\varphi^{IND})(1-\varphi^{OCC})\sum_j\sum_r \eta_{rjc}\lambda_{rjc}\Bigg]. \quad (20) \end{aligned}$$

Then, I explicitly express the employment rate (as captured by $\gamma_{c1}$ and $\gamma_{c2}$) using a first-order Taylor series approximation around the point where occupation-industry-city-level average wages do not differ across cities. This occurs when the technology parameter $\theta_{qic}$ and the productivity shifter $A_{ic}$ are city-invariant, i.e. $\theta_{qic} = \theta_{qi}$ and $A_{ic} = A_i$ (which implies $\eta_{ic,q} = \eta_{i,q}$, $\eta_{qc,i} = \eta_{q,i}$, $\eta_{qic} = \eta_{qi}$ and $ER_c = ER$). Define $\hat{\theta}_{qic} = \theta_{qic} - \theta_{qi}$, the occupation-industry-specific relative advantage component in the technology for city $c$, such that $\sum_c \hat{\theta}_{qic} = 0$. Similarly, define $\hat{A}_{ic} = A_{ic} - A_i$, the industry-specific relative advantage component in the productivity for city $c$, such that $\sum_c \hat{A}_{ic} = 0$. Thus, the distribution of employment across industries and occupations is identical across cities (i.e. $\theta_{qic} = \theta_{qi}$ and $A_{ic} = A_i$) when the relative advantage components $\hat{\theta}_{qic}$ and $\hat{A}_{ic}$ are zero. Approximating equation (20) around the points where $\hat{\theta}_{qic} = 0$, $\hat{A}_{ic} = 0$, and $\eta_{ic,q} = \eta_{i,q}$, $\eta_{qc,i} = \eta_{q,i}$, $\eta_{qic} = \eta_{qi}$, $ER_c = ER$, I obtain:

$$\begin{aligned} w_{qic} &= \gamma_1 \lambda_{qi} - f_{qi} ER + f_{qi} ER_c + \frac{\gamma_1 \gamma_2}{1 - \gamma_2 (1 - \varphi^{IND} \varphi^{OCC})} \Bigg[ (1 - \varphi^{IND}) \varphi^{OCC} \sum_j \eta_{jc,q} \lambda_{qj} \\ &+ \varphi^{IND} (1 - \varphi^{OCC}) \sum_r \eta_{rc,i} \lambda_{ri} + (1 - \varphi^{IND})(1 - \varphi^{OCC}) \sum_j \sum_r \eta_{rjc} \lambda_{rj} \Bigg] + \xi_{qic}, \end{aligned}$$

where the terms $\lambda_{qi}$, $ER$, $\gamma_1$ and $\gamma_2$ are respectively $ER_c$, $\lambda_{qic}$, $\gamma_{1c}$ and $\gamma_{2c}$ evaluated at $\hat{\theta}_{qic} = 0$ and $\hat{A}_{ic} = 0$. The occupation-industry-specific term $f_{qi}$ is obtained from the linear approximation and is a function of the following set of parameters: $\gamma_1$, $\gamma_2$, $\varphi^{IND}$, $\varphi^{OCC}$ and $\lambda_{qi}$. The term $\xi_{qic}$ is also obtained from the linear approximation and corresponds to the error term in the empirical section. It essentially depends on the relative advantage components

$\hat{\theta}_{qic}$ and $\hat{A}_{ic}$:

$$
\begin{aligned}
\xi_{qic} &= \gamma_1 \left( g_{qi} \hat{\theta}_{qic} + h_{qi} \hat{A}_{ic} \right) \\
&+ \frac{\gamma_1 \gamma_2}{1 - \gamma_2 (1 - \varphi^{IND} \varphi^{OCC})} \Bigg[ (1 - \varphi^{IND}) \varphi^{OCC} \sum_j \eta_{j,q} \left( g_{qj} \hat{\theta}_{qjc} + h_{qj} \hat{A}_{jc} \right) \\
&+ \varphi^{IND} (1 - \varphi^{OCC}) \sum_r \eta_{r,i} \left( g_{ri} \hat{\theta}_{ric} + h_{ri} \hat{A}_{ic} \right) \\
&+ (1 - \varphi^{IND})(1 - \varphi^{OCC}) \sum_j \sum_r \eta_{rj} \left( g_{rj} \hat{\theta}_{rjc} + h_{rj} \hat{A}_{jc} \right) \Bigg],
\end{aligned} \tag{21}
$$

where $\eta_{r,i}$, $\eta_{j,q}$ and $\eta_{rj}$ are respectively $\eta_{rc,i}$, $\eta_{jc,q}$ and $\eta_{rjc}$ evaluated at $\hat{\theta}_{qic} = 0$ and $\hat{A}_{ic} = 0$. The occupation-industry-specific terms $g_{qi}$ and $h_{qi}$ are obtained from the linear approximation and are functions of the following set of parameters: $\gamma_1$, $\gamma_2$, $\varphi^{IND}$, $\varphi^{OCC}$ and $\lambda_{qi}$.

Let $w_{qi}$ be the national occupation-industry average wage and define $\nu_{qi} = (w_{qi} - w_{11})$, the national occupation-industry wage premium relative to the numeraire occupation and numeraire industry. Let me now relate $\lambda_{qi}$, the value of the marginal product of type-$q$ labor within industry $i$, to $\nu_{qi}$, the national occupation-industry wage premium. To do so, note that $w_{qic}$ approximated around the point where $\hat{\theta}_{qic} = 0$, $\hat{A}_{ic} = 0$, and $\eta_{ic,q} = \eta_{i,q}$, $\eta_{qc,i} = \eta_{q,i}$, $\eta_{qic} = \eta_{qi}$ satisfies:

$$
\begin{aligned}
&(w_{qic} - w_{1ic}) - (w_{q1c} - w_{11c}) \\
&= \gamma_1 \left[ (\lambda_{qi} - \lambda_{1i}) - (\lambda_{q1} - \lambda_{11}) \right] \\
&+ \gamma_1 \left[ (\xi_{qic} - \xi_{1i}) - (\xi_{q1} - \xi_{11}) \right] \\
&+ \gamma_1 \left[ \left( f_{qi} \left[ \hat{\theta}_{qic} + \hat{A}_{qic} \right] - f_{1i} \left[ \hat{\theta}_{1ic} + \hat{A}_{1ic} \right] \right) - \left( f_{q1} \left[ \hat{\theta}_{q1c} + \hat{A}_{q1c} \right] - f_{11} \left[ \hat{\theta}_{11c} + \hat{A}_{11c} \right] \right) \right],
\end{aligned}
$$

such that

$$
\sum_c (w_{qic} - w_{1ic}) - (w_{q1c} - w_{11c}) = \gamma_1 \left[ (\lambda_{qi} - \lambda_{1i}) - (\lambda_{q1} - \lambda_{11}) \right],
$$

and

$$\nu_{qi} = \gamma_1 \left( \lambda_{qi} - \lambda_{11} \right).$$

The national occupation-industry wage premium is therefore positively related to both $p_i$, the price of the intermediate good $i$, and $\lambda_{qi}$, the marginal product of type-$q$ labor within industry $i$. Substituting (22) into (21) we get:

$$\begin{aligned} w_{qic} &= \frac{\gamma_1\gamma_2(1-\varphi^{IND}\varphi^{OCC})}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}\lambda_{11} + \gamma_1\lambda_{qi} + f_{qi}ER_c \\ &+ \frac{\gamma_2}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}\Bigg[(1-\varphi^{IND})\varphi^{OCC}\sum_j \eta_{jc,q}\nu_{qj} + \varphi^{IND}(1-\varphi^{OCC})\sum_r \eta_{rc,i}\nu_{ri} \\ &+ (1-\varphi^{IND})(1-\varphi^{OCC})\sum_j\sum_r \eta_{rjc}\nu_{rj}\Bigg] + \xi_{qic}. \end{aligned} \tag{22}$$

Finally, to focus on labor market adjustments, equation (22) is first-differenced with respect to time, denoted $\tau$:

$$\Delta w_{qic\tau} = \Delta d_{qi\tau} + \beta_1 \Delta R^{IND}_{qc\tau} + \beta_2 \Delta R^{OCC}_{ic\tau} + \beta_3 \Delta R^{CITY}_{c\tau} + f_{qi}\Delta ER_{c\tau} + \Delta\xi_{qic\tau}, \tag{23}$$

where $f_{qi} > 0$ and

$$\begin{aligned} d_{qi\tau} &= \frac{\gamma_1\gamma_2(1-\varphi^{IND}\varphi^{OCC})}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}\lambda_{11\tau} + \gamma_1\lambda_{qi\tau} \\ R^{IND}_{qc\tau} &= \sum_j \eta_{jc\tau,q}\nu_{qj\tau} \\ R^{OCC}_{ic\tau} &= \sum_r \eta_{rc\tau,i}\nu_{ri\tau} \\ R^{CITY}_{c\tau} &= \sum_j\sum_r \eta_{rjc\tau}\nu_{rj\tau} \end{aligned}$$

and

$$\begin{aligned}
\beta_1 &= \frac{\gamma_2}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}(1-\varphi^{IND})\varphi^{OCC} \geq 0 \\
\beta_2 &= \frac{\gamma_2}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}\varphi^{IND}(1-\varphi^{OCC}) \geq 0 \\
\beta_3 &= \frac{\gamma_2}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}(1-\varphi^{IND})(1-\varphi^{OCC}) \geq 0.
\end{aligned}$$

## 10.2 Deriving BGS bias

BGS industrial composition index ($\tilde{R}^{IND}_{c\tau}$) and the composition indices derived in this paper ($R^{IND}_{qc\tau}$, $R^{OCC}_{ic\tau}$ and $R^{CITY}_{c\tau}$) are related by the following relationship:

$$(1+\tilde{\beta}_1)\Delta\tilde{R}^{IND}_{c\tau} = \beta_1 \sum_r \eta_{rc\tau}\Delta R^{IND}_{c\tau} + \beta_2 \sum_j \eta_{jc\tau}\Delta R^{OCC}_{jc\tau} + (1+\beta_3)\Delta R^{CITY}_{c\tau}, \qquad (24)$$

or solving for $\sum_r \eta_{rc\tau} R^{IND}_{rc\tau}$ by:

$$\sum_r \eta_{rc\tau}\Delta R^{IND}_{rc\tau} = \frac{1+\tilde{\beta}_1}{\beta_1}\Delta\tilde{R}^{IND}_{c\tau} - \frac{\beta_2}{\beta_1}\sum_j \eta_{jc\tau}\Delta R^{OCC}_{jc\tau} - \frac{1+\beta_3}{\beta_1}\Delta R^{CITY}_{c\tau}. \qquad (25)$$

Assume that the true model is given by equation (6), which averaged at the industry level yields:

$$\Delta w_{ic\tau} = \Delta d_{i\tau} + \beta_1 \sum_r \eta_{rc\tau}\Delta R^{IND}_{rc\tau} + \beta_2 \Delta R^{OCC}_{ic\tau} + \beta_3 \Delta R^{CITY}_{c\tau} + f_i \Delta ER_{c\tau} + \Delta\xi_{ic\tau}, \qquad (26)$$

where $d_i$, $f_i$ and $\xi_{ic\tau}$ are $d_{qi}$, $f_{qi}$ and $\xi_{qic\tau}$ averaged across occupations, respectively. Substituting (25) into (26) yields:

$$\Delta w_{ic\tau} = \Delta d_{i\tau} + \tilde{\beta}_1 \Delta\tilde{R}^{IND}_{c\tau} + \beta_2 \left[\Delta R^{OCC}_{ic\tau} - \sum_j \eta_{jc\tau}\Delta R^{OCC}_{jc\tau}\right] + f_i \Delta ER_{c\tau} + \Delta\tilde{\xi}_{ic\tau}, \qquad (27)$$

where $\tilde{\xi}_{ic\tau} = \xi_{ic\tau} + \sum_j \sum_r \eta_{rjc\tau} (\nu_{j\tau} - \nu_{rj\tau})$ is the residual component. Let:

$$\Delta w_{ic\tau} = \Delta d_{i\tau} + \tilde{\beta}_1 \Delta \tilde{R}^{IND}_{c\tau} + f_i \Delta ER_{c\tau} + \Delta \varepsilon_{ic\tau} \tag{28}$$

be the version of (6) that omits the occupational dimension (i.e. BGS model). If the true model is given by equation (6) (or 27), estimating (28) provides a biased estimate of $\tilde{\beta}_1$. Using equation (27), the bias is given by:

$$E\left[\Delta \tilde{R}^{IND}_{c\tau} \Delta \varepsilon_{ic\tau}\right], \tag{29}$$

where

$$\Delta \varepsilon_{ic\tau} = \beta_2 \left[\Delta R^{OCC}_{ic\tau} - \sum_j \eta_{jct} \Delta R^{OCC}_{jct}\right] + \Delta \tilde{\xi}_{ic\tau}. \tag{30}$$

For clarity, provisionally ignore endogeneity related to employment and assume that $E\left[\Delta \tilde{R}^{IND}_{c\tau} \Delta \tilde{\xi}_{ic\tau}\right] = 0$. Then the bias is given by:

$$E\left[\Delta \tilde{R}^{IND}_{c\tau} \Delta \varepsilon_{ic\tau}\right] = \beta_2 E\left[\Delta \tilde{R}^{IND}_{c\tau} \left(\Delta R^{OCC}_{ic\tau} - \sum_j \eta_{jc\tau} \Delta R^{IND}_{jc\tau}\right)\right], \tag{31}$$

such that $\tilde{\beta}_1$ is overestimated if $E\left[\Delta \tilde{R}^{IND}_{c\tau} \left(\Delta R^{OCC}_{ic\tau} - \sum_j \eta_{jc\tau} \Delta R^{IND}_{jc\tau}\right)\right] > 0$ and underestimated if $E\left[\Delta \tilde{R}^{IND}_{c\tau} \left(\Delta R^{OCC}_{ic\tau} - \sum_j \eta_{jc\tau} \Delta R^{IND}_{jc\tau}\right)\right] < 0$.

## 10.3 Inconsistency of OLS and validity of suggested instruments

Due to the functional form of the error term $\xi_{qic}$, OLS leads to inconsistent estimates of the $\beta$s coefficients. I provide a demonstration for the coefficient on $R^{CITY}_{c\tau}$, the city composition index. Proofs for the other indices and the employment rate coefficients are similar.

Consistency of OLS requires that:

$$\lim_{I,Q,C\to\infty} \frac{1}{I}\frac{1}{Q}\frac{1}{C}\sum_i\sum_q\sum_c \Delta R_{c\tau}^{CITY}\Delta\xi_{qic\tau} = 0, \quad (32)$$

where $\xi_{qic\tau}$ is given by equation (21):

$$\begin{aligned}
\xi_{qic\tau} &= \gamma_1\left(g_{qi}\hat{\theta}_{qic\tau} + h_{qi}\hat{A}_{ic\tau}\right)\\
&+ \frac{\gamma_1\gamma_2}{1-\gamma_2(1-\varphi^{IND}\varphi^{OCC})}\Bigg[(1-\varphi^{IND})\varphi^{OCC}\sum_j \eta_{j,q}\left(g_{qj}\hat{\theta}_{qjc\tau} + h_{qj}\hat{A}_{jc\tau}\right)\\
&+ \varphi^{IND}(1-\varphi^{OCC})\sum_r \eta_{r,i}\left(g_{ri}\hat{\theta}_{ric\tau} + h_{ri}\hat{A}_{ic\tau}\right)\\
&+ (1-\varphi^{IND})(1-\varphi^{OCC})\sum_j\sum_r \eta_{rj}\left(g_{rj}\hat{\theta}_{rjc\tau} + h_{rj}\hat{A}_{jc\tau}\right)\Bigg]. \quad (33)
\end{aligned}$$

The composition index can be decomposed into two components: the between and the within components. The between and the within components isolate the variations in the index that are attributable to changes in the distribution of employment, as captured by $\Delta\eta_{rjc\tau}$, and to changes in the national occupation-industry wage premia, as captured by $\Delta\nu_{rj\tau}$, respectively:

$$\Delta R_{c\tau}^{CITY} = \underbrace{\sum_j\sum_r \nu_{rj(\tau-1)}\Delta\eta_{rjc\tau}}_{Between\ \ component} + \underbrace{\sum_j\sum_r \eta_{rjc\tau}\Delta\nu_{rj\tau}}_{Within\ \ component}. \quad (34)$$

Hence, substituting (34) into (32), consistency of OLS requires:

$$\begin{aligned}
\lim_{I,Q,C\to\infty} \frac{1}{I}\frac{1}{Q}\frac{1}{C}\Bigg[&\sum_j\sum_r \nu_{rj(\tau-1)}\sum_c \Delta\eta_{rjc\tau}\sum_i\sum_q \Delta\xi_{qic\tau}\\
&+\sum_j\sum_r \Delta\nu_{rj\tau}\sum_c \eta_{rjc\tau}\sum_i\sum_q \Delta\xi_{qic\tau}\Bigg] = 0,
\end{aligned}$$

which is equivalent to requiring that the two following conditions be satisfied:

$$\lim_{I,Q,C\to\infty} \frac{1}{I}\frac{1}{Q}\frac{1}{C}\sum_c \left[\Delta\eta_{rjc\tau}\sum_i\sum_q \Delta\xi_{qic\tau}\right] = 0$$
$$\lim_{I,Q,C\to\infty} \frac{1}{I}\frac{1}{Q}\frac{1}{C}\sum_c \left[\eta_{rjc\tau}\sum_i\sum_q \Delta\xi_{qic\tau}\right] = 0.$$

This cannot be the case because $\eta_{qic\tau}$ approximated around the point where $\hat{\theta}_{qic\tau} = 0$ and $\hat{A}_{ic\tau} = 0$ is given by:

$$\begin{aligned} \eta_{qic\tau} = \frac{1}{IQ} &+ \pi_{1qi}\left[g_{qi}\hat{\theta}_{qic\tau} + h_{qi}\hat{A}_{ic\tau}\right] \\ &+ \pi_{2qi}\sum_r \eta_{r,i}\left[g_{ri}\hat{\theta}_{ric\tau} + h_{ri}\hat{A}_{ic\tau}\right] \\ &+ \pi_{3qi}\sum_j \eta_{j,q}\left[g_{qj}\hat{\theta}_{qjc\tau} + h_{qj}\hat{A}_{ic\tau}\right] \\ &+ \pi_{4qi}\sum_j\sum_r \eta_{rj}\left[g_{rj}\hat{\theta}_{rjc\tau} + h_{rj}\hat{A}_{jc\tau}\right], \end{aligned} \tag{35}$$

where the $\pi$s are occupation-industry-specific constant obtained from the linear approximation. This justifies the use of instrumental variables. Based on the index between and within decomposition, the proposed instruments are:

$$IV^{CITY,BETWEEN} = \sum_j\sum_r \nu_{rj(\tau-1)}\Delta\hat{\eta}_{rjc\tau} \quad \text{and} \quad IV^{CITY,WHITHIN} = \sum_j\sum_r \hat{\eta}_{rjc\tau}\Delta\nu_{rj\tau},$$

where $\hat{\eta}_{rjc\tau}$ is predicted employment in a particular $rjc$ cell as a share of city $c$ predicted employment. For a particular occupation-industry cell, city-level employment is predicted using national employment growth. Let $\hat{}$ be a predicted value and $N_{qit}$ be national occupation-industry employment. Predicted shares are given by $\hat{\eta}_{rjc\tau} = \frac{\hat{N}_{rjc\tau}}{\sum_r\sum_j \hat{N}_{rjc\tau}}$, where $\hat{N}_{rjc\tau}$ is the mean of $N_{rjc(t-6)}\frac{N_{rjt}}{N_{rj(t-6)}}$ over the corresponding five-year interval. Validity of the suggested instruments requires that:

$$\lim_{I,Q,C\to\infty} \frac{1}{I}\frac{1}{Q}\frac{1}{C}\sum_c \left[\hat{\eta}_{rjc\tau}\sum_q\sum_i \Delta\xi_{qic\tau}\right] = 0$$
$$\lim_{I,Q,C\to\infty} \frac{1}{I}\frac{1}{Q}\frac{1}{C}\sum_c \left[\Delta\hat{\eta}_{rjc\tau}\sum_q\sum_i \Delta\xi_{qic\tau}\right] = 0,$$

or equivalently that:

$$E\left[\Delta\hat{\theta}_{qic\tau}\hat{\theta}_{rjc(t-6)}\right] = 0 \quad \text{and} \quad E\left[\Delta\hat{\theta}_{qic\tau}\Delta\hat{\theta}_{rjc(t-6)}\right] = 0 \quad \forall r, j$$
$$E\left[\Delta\hat{A}_{qic\tau}\hat{A}_{rjc(t-6)}\right] = 0 \quad \text{and} \quad E\left[\Delta\hat{A}_{qic\tau}\Delta\hat{A}_{rjc(t-6)}\right] = 0 \quad \forall r, j$$
$$E\left[\Delta\hat{\theta}_{qic\tau}\hat{A}_{rjc(t-6)}\right] = 0 \quad \text{and} \quad E\left[\Delta\hat{\theta}_{qic\tau}\Delta\hat{A}_{rjc(t-6)}\right] = 0 \quad \forall r, j$$
$$E\left[\Delta\hat{A}_{qic\tau}\hat{\theta}_{rjc(t-6)}\right] = 0 \quad \text{and} \quad E\left[\Delta\hat{A}_{qic\tau}\Delta\hat{\theta}_{rjc(t-6)}\right] = 0 \quad \forall r, j.$$

This requires that within cities, changes in the relative advantage components (i.e. $\Delta\hat{\theta}_{qic\tau}$ and $\Delta\hat{A}_{qic\tau}$) be uncorrelated to the entire inital set of relative advantage components (i.e. $\hat{\theta}_{rjc(t-6)}$ and $\hat{A}_{jc(t-6)}$ $\forall$ $r, j$) and to changes in the entire inital set of relative advantage components (i.e. $\Delta\hat{\theta}_{rjc(t-6)}$ and $\Delta\hat{A}_{jc(t-6)}$ $\forall$ $r, j$). In other words, the fact that within a particular city industry-$i$ productivity improves *relative* to other cities (i.e. $\hat{A}_{ic} > 0$) should be uncorrelated to past productivity improvements and past productivity in any industry, *relative* to other cities. The same logic applies to technology upgrading (i.e. $\hat{\theta}_{qic} > 0$). Thus, within a particular city, productivity and technology shocks *relative* to other cities should be uncorrelated to each other over time.

## 10.4 Additional tables

Table 12: Transition Matrix: average cross-occupational mobility in Western Germany over the period 1977-2001.

| **From occupation ↗ To occupation** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
|---|---|---|---|---|---|---|---|---|
| (1) Woodwork | 0.000 | 0.023 | 0.058 | 0.007 | 0.088 | 0.021 | 0.035 | 0.055 |
| (2) Electrical | 0.003 | 0.0000 | 0.063 | 0.001 | 0.005 | 0.008 | 0.026 | 0.022 |
| (3) Metal and assembly / installation | 0.004 | 0.053 | 0.000 | 0.003 | 0.007 | 0.015 | 0.081 | 0.051 |
| (4) Leather goods | 0.006 | 0.012 | 0.079 | 0.000 | 0.006 | 0.010 | 0.061 | 0.039 |
| (5) Carpenters | 0.049 | 0.013 | 0.032 | 0.004 | 0.000 | 0.038 | 0.024 | 0.049 |
| (6) Painters | 0.010 | 0.020 | 0.054 | 0.004 | 0.029 | 0.000 | 0.053 | 0.061 |
| (7) Goods sorters, packagers | 0.004 | 0.018 | 0.085 | 0.004 | 0.007 | 0.017 | 0.000 | 0.034 |
| (8) Assistants | 0.012 | 0.027 | 0.103 | 0.003 | 0.024 | 0.028 | 0.062 | 0.000 |
| (9) Machine operators | 0.004 | 0.032 | 0.056 | 0.001 | 0.003 | 0.007 | 0.031 | 0.022 |
| (10) Buying and selling | 0.002 | 0.009 | 0.024 | 0.003 | 0.003 | 0.003 | 0.026 | 0.010 |
| (11) Farming, forestry, gardening, fishing | 0.013 | 0.015 | 0.034 | 0.004 | 0.012 | 0.017 | 0.030 | 0.039 |
| (12) Mining and quarrywork | 0.004 | 0.062 | 0.011 | 0.000 | 0.002 | 0.002 | 0.020 | 0.062 |
| (13) Stone, jewelery, brickwork | 0.012 | 0.014 | 0.042 | 0.002 | 0.010 | 0.015 | 0.020 | 0.028 |
| (14) Glass and ceramics | 0.006 | 0.028 | 0.054 | 0.005 | 0.013 | 0.028 | 0.109 | 0.028 |
| (15) Chemicals, plastics and rubber | 0.010 | 0.019 | 0.071 | 0.006 | 0.013 | 0.016 | 0.075 | 0.032 |
| (16) Paper and printing | 0.007 | 0.015 | 0.049 | 0.003 | 0.007 | 0.012 | 0.061 | 0.026 |
| (17) Metalworkers, primary product | 0.006 | 0.026 | 0.158 | 0.002 | 0.006 | 0.016 | 0.064 | 0.039 |
| (18) Skilled metal work and related | 0.005 | 0.053 | 0.083 | 0.003 | 0.012 | 0.013 | 0.036 | 0.033 |
| (19) Textiles | 0.007 | 0.022 | 0.090 | 0.036 | 0.004 | 0.006 | 0.080 | 0.038 |
| (20) Food, drink and tobacco | 0.005 | 0.008 | 0.038 | 0.004 | 0.005 | 0.009 | 0.048 | 0.026 |
| (21) Construction | 0.012 | 0.016 | 0.037 | 0.002 | 0.028 | 0.025 | 0.023 | 0.035 |
| (22) Building | 0.006 | 0.009 | 0.040 | 0.009 | 0.031 | 0.061 | 0.019 | 0.030 |
| (23) Technicians - engineers and related | 0.001 | 0.013 | 0.003 | 0.000 | 0.006 | 0.005 | 0.010 | 0.001 |
| (24) Technicians - manufacturing and science | 0.001 | 0.082 | 0.012 | 0.001 | 0.007 | 0.002 | 0.023 | 0.005 |
| (25) Banking, insurance, agents | 0.000 | 0.003 | 0.003 | 0.000 | 0.002 | 0.001 | 0.008 | 0.002 |
| (26) Travel and transport | 0.007 | 0.031 | 0.038 | 0.003 | 0.015 | 0.012 | 0.060 | 0.031 |
| (27) Administration and bureaucracy | 0.001 | 0.007 | 0.008 | 0.001 | 0.002 | 0.002 | 0.013 | 0.006 |
| (28) Public order, safety and security | 0.001 | 0.020 | 0.018 | 0.001 | 0.013 | 0.013 | 0.024 | 0.022 |
| (29) Arts, creative and recreational | 0.000 | 0.009 | 0.013 | 0.002 | 0.006 | 0.010 | 0.010 | 0.007 |
| (30) Health services | 0.000 | 0.004 | 0.015 | 0.001 | 0.002 | 0.002 | 0.010 | 0.005 |
| (31) Teaching and social employment | 0.002 | 0.004 | 0.008 | 0.001 | 0.003 | 0.002 | 0.008 | 0.003 |
| (32) Other services, personal and leisure services | 0.003 | 0.011 | 0.047 | 0.005 | 0.004 | 0.007 | 0.041 | 0.024 |
| (33) Other occupations | 0.001 | 0.141 | 0.035 | 0.001 | 0.006 | 0.006 | 0.022 | 0.014 |

Note: The statistics is constructed from the IAB anonymized sample, on the basis of employed individuals who can be traced over two consecutive years.

Table 13: Transition Matrix: average cross-occupational mobility in Western Germany over the period 1977-2001 (continued).

| **From occupation ↗ To occupation** | **(9)** | **(10)** | **(11)** | **(12)** | **(13)** | **(14)** | **(15)** | **(16)** |
|---|---|---|---|---|---|---|---|---|
| (1) Woodwork | 0.012 | 0.032 | 0.023 | 0.008 | 0.006 | 0.006 | 0.058 | 0.029 |
| (2) Electrical | 0.021 | 0.035 | 0.005 | 0.017 | 0.003 | 0.003 | 0.023 | 0.008 |
| (3) Metal and assembly / installation | 0.034 | 0.026 | 0.006 | 0.002 | 0.003 | 0.006 | 0.049 | 0.017 |
| (4) Leather goods | 0.002 | 0.063 | 0.010 | 0.001 | 0.002 | 0.005 | 0.073 | 0.020 |
| (5) Carpenters | 0.007 | 0.047 | 0.014 | 0.003 | 0.006 | 0.004 | 0.050 | 0.014 |
| (6) Painters | 0.015 | 0.030 | 0.017 | 0.004 | 0.006 | 0.012 | 0.058 | 0.016 |
| (7) Goods sorters, packagers | 0.014 | 0.067 | 0.009 | 0.003 | 0.002 | 0.012 | 0.053 | 0.026 |
| (8) Assistants | 0.015 | 0.028 | 0.018 | 0.010 | 0.004 | 0.006 | 0.045 | 0.017 |
| (9) Machine operators | 0.000 | 0.007 | 0.011 | 0.026 | 0.007 | 0.004 | 0.035 | 0.010 |
| (10) Buying and selling | 0.001 | 0.000 | 0.009 | 0.001 | 0.001 | 0.002 | 0.017 | 0.009 |
| (11) Farming, forestry, gardening, fishing | 0.015 | 0.095 | 0.000 | 0.005 | 0.008 | 0.005 | 0.028 | 0.013 |
| (12) Mining and quarrywork | 0.080 | 0.014 | 0.015 | 0.000 | 0.007 | 0.002 | 0.028 | 0.013 |
| (13) Stone, jewelery, brickwork | 0.022 | 0.013 | 0.019 | 0.013 | 0.000 | 0.022 | 0.059 | 0.014 |
| (14) Glass and ceramics | 0.010 | 0.026 | 0.012 | 0.007 | 0.019 | 0.000 | 0.060 | 0.022 |
| (15) Chemicals, plastics and rubber | 0.024 | 0.029 | 0.010 | 0.005 | 0.007 | 0.010 | 0.000 | 0.032 |
| (16) Paper and printing | 0.011 | 0.049 | 0.010 | 0.001 | 0.005 | 0.004 | 0.060 | 0.000 |
| (17) Metalworkers, primary product | 0.037 | 0.011 | 0.006 | 0.006 | 0.004 | 0.006 | 0.042 | 0.014 |
| (18) Skilled metal work and related | 0.035 | 0.032 | 0.008 | 0.018 | 0.004 | 0.005 | 0.042 | 0.014 |
| (19) Textiles | 0.004 | 0.083 | 0.004 | 0.001 | 0.005 | 0.006 | 0.058 | 0.024 |
| (20) Food, drink and tobacco | 0.004 | 0.107 | 0.015 | 0.002 | 0.004 | 0.005 | 0.036 | 0.015 |
| (21) Construction | 0.064 | 0.015 | 0.050 | 0.013 | 0.020 | 0.006 | 0.042 | 0.013 |
| (22) Building | 0.008 | 0.062 | 0.011 | 0.005 | 0.010 | 0.012 | 0.033 | 0.010 |
| (23) Technicians - engineers and related | 0.003 | 0.062 | 0.004 | 0.002 | 0.000 | 0.000 | 0.004 | 0.003 |
| (24) Technicians - manufacturing and science | 0.009 | 0.090 | 0.005 | 0.007 | 0.001 | 0.001 | 0.019 | 0.016 |
| (25) Banking, insurance, agents | 0.001 | 0.108 | 0.002 | 0.000 | 0.001 | 0.000 | 0.003 | 0.004 |
| (26) Travel and transport | 0.031 | 0.078 | 0.014 | 0.011 | 0.006 | 0.005 | 0.036 | 0.019 |
| (27) Administration and bureaucracy | 0.002 | 0.283 | 0.005 | 0.002 | 0.001 | 0.001 | 0.006 | 0.010 |
| (28) Public order, safety and security | 0.013 | 0.044 | 0.019 | 0.004 | 0.002 | 0.001 | 0.023 | 0.011 |
| (29) Arts, creative and recreational | 0.003 | 0.105 | 0.014 | 0.001 | 0.001 | 0.002 | 0.007 | 0.052 |
| (30) Health services | 0.001 | 0.092 | 0.006 | 0.000 | 0.001 | 0.001 | 0.013 | 0.005 |
| (31) Teaching and social employment | 0.001 | 0.083 | 0.008 | 0.000 | 0.001 | 0.000 | 0.005 | 0.005 |
| (32) Other services, personal and leisure services | 0.004 | 0.132 | 0.011 | 0.002 | 0.002 | 0.004 | 0.032 | 0.016 |
| (33) Other occupations | 0.010 | 0.099 | 0.005 | 0.004 | 0.000 | 0.001 | 0.010 | 0.005 |

Note: The statistics is constructed from the IAB anonymized sample, on the basis of employed individuals who can be traced over two consecutive years.

Table 14: Transition Matrix: average cross-occupational mobility in Western Germany over the period 1977-2001 (continued).

| **From occupation ↗ To occupation** | **(17)** | **(18)** | **(19)** | **(20)** | **(21)** | **(22)** | **(23)** | **(24)** |
|---|---|---|---|---|---|---|---|---|
| (1) Woodwork | 0.054 | 0.067 | 0.012 | 0.019 | 0.107 | 0.015 | 0.001 | 0.016 |
| (2) Electrical | 0.033 | 0.152 | 0.007 | 0.007 | 0.023 | 0.005 | 0.019 | 0.247 |
| (3) Metal and assembly / installation | 0.167 | 0.135 | 0.012 | 0.019 | 0.027 | 0.007 | 0.004 | 0.033 |
| (4) Leather goods | 0.036 | 0.074 | 0.093 | 0.038 | 0.022 | 0.027 | 0.000 | 0.017 |
| (5) Carpenters | 0.033 | 0.083 | 0.005 | 0.014 | 0.115 | 0.037 | 0.011 | 0.042 |
| (6) Painters | 0.059 | 0.078 | 0.003 | 0.018 | 0.085 | 0.057 | 0.011 | 0.020 |
| (7) Goods sorters, packagers | 0.062 | 0.059 | 0.019 | 0.041 | 0.019 | 0.005 | 0.009 | 0.044 |
| (8) Assistants | 0.067 | 0.095 | 0.017 | 0.029 | 0.047 | 0.018 | 0.002 | 0.016 |
| (9) Machine operators | 0.072 | 0.141 | 0.002 | 0.007 | 0.157 | 0.005 | 0.006 | 0.055 |
| (10) Buying and selling | 0.009 | 0.019 | 0.008 | 0.037 | 0.006 | 0.007 | 0.007 | 0.031 |
| (11) Farming, forestry, gardening, fishing | 0.023 | 0.043 | 0.008 | 0.039 | 0.160 | 0.008 | 0.005 | 0.016 |
| (12) Mining and quarrywork | 0.026 | 0.149 | 0.001 | 0.009 | 0.069 | 0.004 | 0.008 | 0.087 |
| (13) Stone, jewelery, brickwork | 0.059 | 0.077 | 0.006 | 0.023 | 0.195 | 0.028 | 0.005 | 0.028 |
| (14) Glass and ceramics | 0.062 | 0.093 | 0.010 | 0.015 | 0.044 | 0.035 | 0.002 | 0.030 |
| (15) Chemicals, plastics and rubber | 0.058 | 0.087 | 0.012 | 0.021 | 0.040 | 0.011 | 0.005 | 0.099 |
| (16) Paper and printing | 0.033 | 0.061 | 0.012 | 0.022 | 0.026 | 0.006 | 0.003 | 0.077 |
| (17) Metalworkers, primary product | 0.000 | 0.243 | 0.004 | 0.008 | 0.033 | 0.006 | 0.003 | 0.049 |
| (18) Skilled metal work and related | 0.140 | 0.000 | 0.004 | 0.011 | 0.044 | 0.012 | 0.009 | 0.100 |
| (19) Textiles | 0.037 | 0.028 | 0.000 | 0.038 | 0.013 | 0.026 | 0.001 | 0.044 |
| (20) Food, drink and tobacco | 0.025 | 0.028 | 0.010 | 0.000 | 0.064 | 0.008 | 0.002 | 0.012 |
| (21) Construction | 0.047 | 0.085 | 0.005 | 0.055 | 0.000 | 0.069 | 0.018 | 0.016 |
| (22) Building | 0.028 | 0.085 | 0.019 | 0.022 | 0.211 | 0.000 | 0.011 | 0.016 |
| (23) Technicians - engineers and related | 0.003 | 0.020 | 0.001 | 0.003 | 0.016 | 0.005 | 0.000 | 0.329 |
| (24) Technicians - manufacturing and science | 0.017 | 0.073 | 0.007 | 0.005 | 0.009 | 0.003 | 0.194 | 0.000 |
| (25) Banking, insurance, agents | 0.002 | 0.011 | 0.001 | 0.007 | 0.005 | 0.002 | 0.008 | 0.019 |
| (26) Travel and transport | 0.041 | 0.083 | 0.006 | 0.027 | 0.056 | 0.011 | 0.004 | 0.027 |
| (27) Administration and bureaucracy | 0.005 | 0.020 | 0.003 | 0.010 | 0.006 | 0.005 | 0.041 | 0.077 |
| (28) Public order, safety and security | 0.022 | 0.059 | 0.005 | 0.028 | 0.035 | 0.010 | 0.014 | 0.023 |
| (29) Arts, creative and recreational | 0.005 | 0.018 | 0.006 | 0.010 | 0.006 | 0.018 | 0.019 | 0.079 |
| (30) Health services | 0.005 | 0.023 | 0.006 | 0.019 | 0.002 | 0.002 | 0.003 | 0.020 |
| (31) Teaching and social employment | 0.004 | 0.012 | 0.004 | 0.015 | 0.005 | 0.002 | 0.058 | 0.026 |
| (32) Other services, personal and leisure services | 0.020 | 0.027 | 0.024 | 0.155 | 0.017 | 0.004 | 0.002 | 0.010 |
| (33) Other occupations | 0.055 | 0.108 | 0.016 | 0.006 | 0.027 | 0.005 | 0.025 | 0.059 |

Note: The statistics is constructed from the IAB anonymized sample, on the basis of employed individuals who can be traced over two consecutive years.

Table 15: Transition Matrix: average cross-occupational mobility in Western Germany over the period 1977-2001 (continued).

| **From occupation ↗ To occupation** | **(25)** | **(26)** | **(27)** | **(28)** | **(29)** | **(30)** | **(31)** | **(32)** | **(33)** |
|---|---|---|---|---|---|---|---|---|---|
| (1) Woodwork | 0.003 | 0.157 | 0.036 | 0.010 | 0.001 | 0.005 | 0.004 | 0.030 | 0.001 |
| (2) Electrical | 0.008 | 0.119 | 0.074 | 0.024 | 0.005 | 0.005 | 0.005 | 0.019 | 0.005 |
| (3) Metal and assembly / installation | 0.007 | 0.116 | 0.050 | 0.011 | 0.002 | 0.010 | 0.006 | 0.038 | 0.001 |
| (4) Leather goods | 0.005 | 0.106 | 0.067 | 0.010 | 0.004 | 0.015 | 0.013 | 0.084 | 0.000 |
| (5) Carpenters | 0.007 | 0.163 | 0.044 | 0.033 | 0.011 | 0.007 | 0.012 | 0.023 | 0.003 |
| (6) Painters | 0.008 | 0.148 | 0.032 | 0.030 | 0.009 | 0.004 | 0.005 | 0.041 | 0.001 |
| (7) Goods sorters, packagers | 0.013 | 0.190 | 0.101 | 0.015 | 0.003 | 0.009 | 0.007 | 0.050 | 0.001 |
| (8) Assistants | 0.007 | 0.163 | 0.045 | 0.017 | 0.002 | 0.006 | 0.004 | 0.060 | 0.003 |
| (9) Machine operators | 0.005 | 0.206 | 0.022 | 0.032 | 0.001 | 0.003 | 0.002 | 0.026 | 0.002 |
| (10) Buying and selling | 0.044 | 0.098 | 0.460 | 0.010 | 0.008 | 0.027 | 0.024 | 0.074 | 0.007 |
| (11) Farming, forestry, gardening, fishing | 0.007 | 0.152 | 0.058 | 0.036 | 0.009 | 0.017 | 0.018 | 0.066 | 0.004 |
| (12) Mining and quarrywork | 0.001 | 0.202 | 0.029 | 0.030 | 0.002 | 0.006 | 0.002 | 0.042 | 0.010 |
| (13) Stone, jewelery, brickwork | 0.010 | 0.165 | 0.037 | 0.014 | 0.004 | 0.005 | 0.005 | 0.03 | 0.002 |
| (14) Glass and ceramics | 0.006 | 0.136 | 0.059 | 0.014 | 0.004 | 0.011 | 0.005 | 0.043 | 0.002 |
| (15) Chemicals, plastics and rubber | 0.006 | 0.148 | 0.062 | 0.019 | 0.002 | 0.014 | 0.007 | 0.048 | 0.001 |
| (16) Paper and printing | 0.022 | 0.140 | 0.160 | 0.014 | 0.035 | 0.013 | 0.011 | 0.045 | 0.001 |
| (17) Metalworkers, primary product | 0.003 | 0.121 | 0.032 | 0.017 | 0.001 | 0.004 | 0.003 | 0.027 | 0.001 |
| (18) Skilled metal work and related | 0.010 | 0.151 | 0.056 | 0.023 | 0.002 | 0.008 | 0.006 | 0.025 | 0.003 |
| (19) Textiles | 0.006 | 0.083 | 0.066 | 0.006 | 0.005 | 0.023 | 0.013 | 0.141 | 0.003 |
| (20) Food, drink and tobacco | 0.011 | 0.131 | 0.064 | 0.017 | 0.002 | 0.020 | 0.011 | 0.259 | 0.002 |
| (21) Construction | 0.005 | 0.199 | 0.026 | 0.025 | 0.001 | 0.003 | 0.005 | 0.004 | 0.002 |
| (22) Building | 0.007 | 0.118 | 0.062 | 0.022 | 0.010 | 0.006 | 0.005 | 0.022 | 0.002 |
| (23) Technicians - engineers and related | 0.024 | 0.019 | 0.387 | 0.009 | 0.010 | 0.003 | 0.043 | 0.005 | 0.006 |
| (24) Technicians - manufacturing and science | 0.018 | 0.049 | 0.272 | 0.012 | 0.017 | 0.011 | 0.019 | 0.011 | 0.004 |
| (25) Banking, insurance, agents | 0.000 | 0.066 | 0.652 | 0.014 | 0.016 | 0.010 | 0.022 | 0.021 | 0.003 |
| (26) Travel and transport | 0.030 | 0.000 | 0.207 | 0.032 | 0.004 | 0.011 | 0.009 | 0.054 | 0.002 |
| (27) Administration and bureaucracy | 0.175 | 0.124 | 0.000 | 0.019 | 0.019 | 0.042 | 0.055 | 0.040 | 0.007 |
| (28) Public order, safety and security | 0.036 | 0.172 | 0.200 | 0.000 | 0.008 | 0.018 | 0.032 | 0.106 | 0.002 |
| (29) Arts, creative and recreational | 0.070 | 0.043 | 0.301 | 0.012 | 0.000 | 0.044 | 0.058 | 0.062 | 0.007 |
| (30) Health services | 0.021 | 0.038 | 0.341 | 0.010 | 0.013 | 0.000 | 0.261 | 0.075 | 0.004 |
| (31) Teaching and social employment | 0.027 | 0.027 | 0.288 | 0.018 | 0.023 | 0.288 | 0.000 | 0.062 | 0.006 |
| (32) Other services, personal and leisure services | 0.016 | 0.106 | 0.136 | 0.030 | 0.010 | 0.063 | 0.031 | 0.000 | 0.002 |
| (33) Other occupations | 0.019 | 0.024 | 0.214 | 0.002 | 0.021 | 0.014 | 0.027 | 0.019 | 0.000 |

Note: The statistics is constructed from the IAB anonymized sample, on the basis of employed individuals who can be traced over two consecutive years.

Table 16: Industrial classification into 6 categories.

| | |
|---|---|
| **Primary sector** | **Tertiary sector** |
| *Industry 1* | *Industry 5* |
| Agriculture, hunting, forestry and fishing | Wholesale, trade and commission excl. motor vehicles |
| Mining and quarrying | Sale of automotive fuel |
| Electricity, gas and water supply | Retail trade excl. motor vehicles - repair of household goods |
| | Transport storage and communications |
| **Secundary sector** | |
| *Industry 2* | *Industry 6* |
| Wood and products of wood and cork | Finance, insurance, real estate and business services |
| Pulp, paper, paper products, printing and publishing | Hotels and restaurants |
| Chemical, rubber, plastics and fuel products | Recreational, cultural and sporting activities |
| Basic metals and fabricated metal products | Other service activities |
| Other non-metallic mineral products | Private households with employed persons |
| Machinery and equipment (nec) | Education |
| Motor vehicles, trailers and semi-trailers | Health and social work |
| Electrical and optical equipment | Sewage and refuse disposal, sanitation and similar activities |
| Other transport equipment | Activities of membership organizations (nec) |
| | Public admin. and defense - compulsory social security |
| *Industry 3* | Extra-territorial organizations and bodies |
| Textiles and textile products | |
| Leather, leather products and footwear | |
| Other non-metallic mineral products | |
| Manufacturing n.e.c. | |
| Food products, beverages and tobacco | |
| | |
| *Industry 4* | |
| Construction trades | |
| Finishing trades | |

Table 17: Industrial classification into 10 categories.

| | |
|---|---|
| **Primary sector** | **Tertiary sector** |
| *Industry 1* | *Industry 5* |
| Agriculture, hunting, forestry and fishing | Wholesale, trade and commission excl. motor vehicles |
| Mining and quarrying | Sale of automotive fuel |
| Electricity, gas and water supply | Retail trade excl. motor vehicles - repair of household goods |
| | |
| **Secundary sector** | *Industry 6* |
| *Industry 2* | Transport storage and communications |
| Wood and products of wood and cork | |
| Pulp, paper, paper products, printing and publishing | *Industry 7* |
| Chemical, rubber, plastics and fuel products | Finance, insurance, real estate and business services |
| Basic metals and fabricated metal products | |
| Other non-metallic mineral products | *Industry 8* |
| Machinery and equipment (nec) | Hotels and restaurants |
| Motor vehicles, trailers and semi-trailers | Recreational, cultural and sporting activities |
| Electrical and optical equipment | Other service activities |
| Other transport equipment | Private households with employed persons |
| | |
| *Industry 3* | *Industry 9* |
| Textiles and textile products | Education |
| Leather, leather products and footwear | Health and social work |
| Other non-metallic mineral products | |
| Manufacturing n.e.c. | *Industry 10* |
| Food products, beverages and tobacco | Sewage and refuse disposal, sanitation and similar activities |
| | Activities of membership organizations (nec) |
| *Industry 4* | Public admin. and defense - compulsory social security |
| Construction trades | Extra-territorial organizations and bodies |
| Finishing trades | |

Table 18: Occupational classification into 10 categories.

**Agricultural**
*Occupation 1*
Farming, forestry, gardening, fishing

**Mining and quarrywork**
*Occupation 2*
Mining and quarrywork

**Manufacturing**
*Occupation 3*
Stone, jewelery, brickwork
Glass and ceramics
Chemicals, plastics and rubber
Paper and printing
Woodwork
Metalworkers, primary product
Skilled metal work and related
Electrical
Metal and assembly / installation

*Occupation 4*
Textiles
Leather goods
Food, drink and tobacco

*Occupation 5*
Construction
Building
Carpenters
Painters
Goods sorters, packagers
Assistants
Machine operators

**Technicians**
*Occupation 6*
Technicians - engineers and related
Technicians - manufacturing and science

**Services and professionals**
*Occupation 7*
Buying and selling
Banking, insurance, agents
Arts, creative and recreational
Other services, personal and leisure services

*Occupation 8*
Travel and transport
Administration and bureaucracy
Public order, safety and security

*Occupation 9*
Health services
Teaching and social employment

**Other**
*Occupation 10*
Other occupations

Table 19: Occupational classification into 16 categories.

**Agricultural**
*Occupation 1*
Farming, forestry, gardening, fishing

**Mining and quarrywork**
*Occupation 2*
Mining and quarrywork

**Manufacturing**
*Occupation 3*
Stone, jewelery, brickwork
Glass and ceramics
Chemicals, plastics and rubber

*Occupation 4*
Paper and printing
Woodwork

*Occupation 5*
Metal workers, primary product
Skilled metal work and related

*Occupation 6*
Electrical
Metal and assembly / installation

*Occupation 7*
Textiles
Leather goods

*Occupation 8*
Food, drink and tobacco

*Occupation 9*
Construction
Building
Carpenters
Painters
Goods sorters, packagers
Assistants
Machine operators

**Technicians**
*Occupation 10*
Technicians - engineers and related
Technicians - manufacturing and science

**Services and professionals**
*Occupation 11*
Buying and selling
Banking, insurance, agents
Other services, personal and leisure service

*Occupation 12*
Travel and transport

*Occupation 13*
Administration and bureaucracy
Public order, safety and security

*Occupation 14*
Arts, creative and recreational

*Occupation 15*
Health services
Teaching and social employment

**Other**
*Occupation 16*
Other occupations