

Chapter 2

A Panel VAR Approach for Internal Migration Modelling and Regional Labor Market Dynamics in Germany

2.1 Introduction

Given the rather low mobility rates for EU member states compared to the US and Australia, the extent to which regional disparities in real wages, income, and unemployment can be balanced through labor migration is a subject of obvious interest for economic policy (see, e.g., Bonin et al. 2008). According to mainstream neo-classical theory the link between migration and regional labor market variables is assumed to work as follows: Regions with relatively high unemployment and low wage levels should experience net out-migration into regions with better employment opportunities. A rising number of available jobs in the target region as well as a decline in job opportunities in the home region then ensure that the regional labor market disparities will disappear over time. In the long-run cross-regional labor market equilibrium unemployment differences can then only be explained by differences in regional wage levels as compensation for the higher unemployment risks, while otherwise factor prices are assumed to equalize across regions.¹

Taking up this research question, we aim at analyzing whether and by what magnitude regional differences in wage levels, unemployment among other economic (push and pull) factors significantly influence the internal migratory behavior within

¹See Siebert (1994) for a similar line of argumentation for regional labor market dynamics in Germany. A critical view of this concept of compensating differentials is given by Blanchflower and Oswald (1994, 2005), who introduce a wage-curve linking low wage levels and high unemployment rates for a particular region. Recent empirical studies by Wagner (1994), Baltagi and Blien (1998) and Baltagi et al. (2007) indeed give evidence for a wage-curve relationship in Germany.

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Germany. We put a particular emphasis on the analysis of the West and East German labor market integration since re-unification and investigate the likely two-way interdependences among migration and labor market variables. For empirical estimation we use internal migration flows between the German federal states (NUTS1 level) between 1991 and 2006 and apply dynamic panel data methods in a VAR context.

The remainder of the chapter is organized as follows. In the next section, we present a short literature review. Section 2.3 sketches the underlying theoretical model that will serve as a starting point in specifying testable empirical specifications for estimation. Section 2.4 gives a short overview of the data used for the empirical analysis including a discussion of the time series properties. Section 2.5 describes the Panel VAR (PVAR) approach; Sect. 2.6 reports the estimation results. In Sect. 2.7, we test the explanatory power of the PVAR for predicting interregional East–West migration flows since re-unification and take a look at the East German “empirical puzzle”. Section 2.8 finally concludes the chapter.

2.2 Literature Review

This literature review mainly serves two purposes. First, from a partial equilibrium perspective we look at recent empirical contributions in specifying a stable long-run (neoclassical) migration equation. Second, using this long-run migration equation as an important building block for a more profound labor market analysis, we then augment the scope of the literature review to multiple equation approaches, which account more carefully for dynamic feedback effects among migration and labor market variables.

Given the huge body of literature on the neoclassical migration model, it is not surprising that the empirical results for the long-run migration equation are somewhat mixed and country specific. Focusing on empirical evidence for Germany, Decressin (1994) examines gross flows for West German states between 1977 and 1988. His results show that a wage increase in one region relative to others causes a disproportional rise in the gross migration flows in the first region, while a rise in the unemployment rate for a region relative to others disproportionally lowers the gross flows. However, the author does not find a significant link between bilateral gross migration and regional differences in wage level or unemployment when purely cross-sectional estimates are considered. Difficulties in proving a significant influence of regional wage decreases on the migratory behavior within Germany are also found in earlier empirical studies based on micro-data to motivate individual migratory behavior in Germany. Among these are Hatzius (1994) for West Germany, as well as Schwarze and Wagner (1992), Wagner (1992), Burda (1993) and Büchel and Schwarze (1994) for the East German states. Subsequent micro studies mainly focused on qualifying the theoretically unsatisfactory result with respect to wage rates. Schwarze (1996) for example shows that by using the expected rather than actual wage rate the results turn significant. The latter is also confirmed in Brücker and Trübswetter (2004) focusing on the role of self-selection in East–West migration.

Opposed to this earlier evidence, recent macroeconomic studies assign a more prominent role to regional wage rate differentials in predicting German internal migration flows. Parikh and Van Leuvensteijn (2003) use the core neoclassical migration model with regional wage and unemployment differentials as driving forces for interregional migration augmented by additional indicators such as regional housing costs, geographical distance and inequality measures. For the short sample period 1993–1995, the authors find a significant non-linear relationship between disaggregated regional wage rate differences and East–West migration, while unemployment differences are found to be insignificant. Hunt (2000) and Burda and Hunt (2001) analogously identify wage rate differentials and particularly the closing gap in regional differences driven by a fast East–West convergence as a powerful indicator in explaining observed state-to-state migration patterns. Using data up to the late 1990s, Burda and Hunt (2001) find that the decline in East–West migration starting from 1992 onwards can almost exclusively be explained by wage differentials and the fast East–West wage convergence, while unemployment differences do not seem to play an important part in explaining actual migration trends.²

So far, we have looked at single equation (partial equilibrium) approaches to estimate a stable long-run neoclassical migration equation. Building on this literature there is also a bulk of studies extending the scope of the analysis to a multiple equation setting in order to account more carefully for the likely feedback effects of migratory movements on labor market variables and their joint responses to shocks. Aiming to control for two-way effects has resulted in a variety of empirical specifications, either from a structural (see e.g. Okun 1968; Muth 1971; Salvatore 1980; Bilger et al. 1991, and the large literature following Carlino and Mills 1987) or time-series perspective (see Blanchard and Katz 1992; Decressin and Fatas 1995; Möller 1995; Lu 2001; Mäki-Arvela 2003, or Partridge and Rickman 2006). The latter approach typically applies Vector Autoregression (VAR) models, which provide a valuable tool for analyzing the dynamics of economic processes. In particular the VAR approach is well suited to analyze regional adjustment processes in reaction to exogenous (macroeconomic) shocks. A general discussion of labor market analysis with VAR models is for instance given in Summers (2000).

To our knowledge, the only empirical application of a system approach of migration and labor market dynamics for German regions is given by Möller (1995). Using a VAR model for seven West German regions between 1960 and 1993 the author mainly finds the theoretically expected negative response of net in-migration to a one standard deviation shock in unemployment with a time-lag of about two to three years. The analysis of the impulse–response functions also shows that the unemployment shock on migration is likely to have a negative long-run impact on

²When interpreting these findings, one however has to bear in mind that the above cited studies exclusively use data until the mid/late-1990s, which in fact may bias the results with respect to the wage component, given the fast (politically driven) East–West wage convergence as one overriding trend in the overall pattern of East German macroeconomic development. In the second half of the 1990s, wage convergence substantially lost pace, so that the estimated link may become less stable when extending the sample period beyond the mid-1990s.

regional population levels, which in turn bring back the unemployment rate to its old steady state level. Contrary to the predictions of the neoclassical migration model, Möller (1995) finds that migration is negatively affected by a regional wage rate increase. The author explains this latter result in terms of a reduced factor demand for labor given the change in the relative price for capital and labor input, which then overcompensates the positive initial signal of a wage rate increase to the internal and external labor market forces.

The feedback effects of labor market variables to migration shocks largely show a negative mid- to long-run impact for wages, labor productivity and labor participation. Möller (1995) takes the VAR findings that shocks are on average only gradually absorbed with full adjustment being achieved in decades rather than years in support for the existence of regional hysteresis effects. Finding appropriate answers on the latter point has already inspired empirical research since the seminal contribution of Blanchard and Katz (1992). In a similar VAR setup for Finnish regions, Mäki-Arvela (2003), for instance, gets empirical results closely related to those obtained in Möller (1995).

2.3 Modelling Migration in a System of Regional Labor Market Dynamics and Economic Development

In this section we briefly describe the neoclassical migration model and integrate the specification into a stylized framework of labor market dynamics and regional evolutions in the spirit of the Blanchard and Katz (1992) approach. One important distinction from the latter is that we explicitly include a long-run migration equation in our model rather than capturing it residually.³ Mainstream economic literature offers different theories trying to explain the reasons for people moving from one region to another, which can broadly be classified as either being micro or macro oriented (see Stillwell 2005, and Etzo 2008, for recent surveys). Within the latter category, the neoclassical framework—modelling an individual's lifetime expected income (utility) maximization approach—clearly takes an outstanding role (see e.g. Maza and Villaverde 2004).

Harris and Todaro (1970) set up a neoclassical model that centers around the concept of expected income, which—for staying in the region of residence (E_{ii})—is defined as a function of the real wage rate in region i (W_i) and the probability of being employed ($PROB_i$). The latter in turn is a function of unemployment rate in region i (UR_i) and a set of potential variables related both to economic and non-economic factors (S_i). The same set of variables, with different subscripts for region

³Blanchard and Katz (1992) set up a three-equation model including employment minus unemployment changes, the employment to labor force ratio as well as the labor force to population ratio as endogenous variables. From the behavior of these variables over time, the authors are able to compute the effect on the unemployment and the participation rate as well as the implied effect on net out-migration, e.g., as response to a reduction in employment.

j accordingly, is also used to model the expected income from moving to the alternative (destination) region. Taking also a set of economic (house prices, transfer payments, etc.) and non-economic costs (such as region specific amenities), as well as costs of moving from region i to j into account (C_{ij}), the individual's decision will be made in favor of moving to region j if

$$E_{ii} \leq E_{ij} - C_{ij}, \quad (2.1)$$

with $E_{ii} = f(\text{PROB}_i[UR_i, S_i], W_i)$ and $E_{ij} = f(\text{PROB}_j[UR_j, S_j], W_j)$. This shows that at the core of the Harris–Todaro model the agent weighs the wage level in the home (origin) and target (destination) region with the individual probability of finding employment. We are then able to set up a model for the regional net migration (NM_{ij}), which is defined as regional gross in-migration flows to i from j net of outflows from i to j as

$$NM_{ij} = f(W_i, W_j, UR_i, UR_j, S_i, S_j, C_{ij}). \quad (2.2)$$

With respect to the theoretically motivated sign of the explanatory variables, we expect that an increase in the home country's real wage rate (or alternatively, income level) *ceteris paribus* leads to higher net migration inflows, while a real wage rate increase in region j results in a decrease of the net migration rate. On the contrary, an increase in the unemployment rate in region i (j) has negative (positive) effects on the bilateral net migration from i to j . Costs of moving from i to j are typically expected to be an impediment to migration and thus are negatively correlated with net migration.

For empirical modelling purposes, we operationalize the set of additional variables (S_i, S_j) that may work as pull or push factors for regional migration flows in the following way. Given that migration flows have a long-run structural rather than just business cycle perspective; one likely determinant of migration flows is real labor productivity growth. As Coulombe (2006) argues, the transmission channel from labor productivity to migration is closely linked to the convergence concept of the (new) growth literature: Under the assumption of absolute convergence migration flows are assumed to react to different initial levels of labor productivity in two regions i and j . Gradually, the gap between the two regions will be eliminated in the catching-up process and structural migration between i and j will decrease smoothly in a time horizon that however goes well beyond the business-cycle horizon. Conditional convergence is necessarily associated with other structural differences captured in S_i and S_j so that the initial gap in labor productivities may not be fully closed, however the basic correlation between changes in labor productivity and net in-migration should hold as well until the regions have not fully converged to their respective long run steady state levels.⁴

⁴However, as McCann (2001) argues, regional economic growth is a complex process and may, for instance, be strongly influenced by the location decision of firms, which in turn gives rise to potential regional scale effects e.g. via agglomeration forces. Such forces then may act as a pull factor for migration so that also a positive correlation between productivity growth and net in-migration could be in order rather than the expected negative one from the standard growth model.

From the viewpoint of the conditional convergence assumption of the new growth theory, one key factor driving differences in the long run steady-state labor productivity level is the regional endowment with human capital. Hence, the link between migration and regional human capital may be of great importance, e.g., in analyzing the causes and consequences for a regional ‘brain drain’ associated with a sharp decline in the regional skill composition due to net out-migration. In the microeconomic literature, the link between the formal skill level of the prospect migrant and the actual migration decision is already well-documented, where recent contributions typically establish a positive correlation between individual qualification and mobility (see, e.g., Borjas 1987 for a theoretical discussion, and Wolff 2006, as well as Bode and Zwing 2008, for an overview of empirical studies for Germany).⁵

At the empirical level, typically a log-linear form of the stylized migration equation in (2.2) is chosen, which may either include contemporaneous and/or lagged values for the explanatory and also endogenous variable. As suggested by Puhani (2001), the latter lag structure accounts for likely time delays in the transmission process of labor market signals to migration flows. The inclusion of lagged terms for the endogenous variable reflects different channels through which past flows may affect current migration such as communication links between migrants and friends and relatives left behind. The latter linkage in turn may influence prospective migrants who want to live in an area where they share cultural and social backgrounds with other residents (see Chun 1996, for a detailed discussion). Finally, we restrict the explanatory variables to enter as inter-regional differences yielding a triple-indexed model specification (ij, t) , where ij denote the difference between region i and region j and t is the time index. Allowing for a general lag structure the migration equation may be written as:

$$nm_{ij,t} = \gamma_{10} + \gamma_{11}(L)nm_{ij,t-1} + \gamma_{12}(L)\tilde{w}r_{ij,t-1} + \gamma_{13}(L)\tilde{u}r_{ij,t-1} \\ + \gamma_{14}(L)\tilde{y}lr_{ij,t-1} + \gamma_{15}(L)\tilde{q}_{ij,t-1} + \gamma_{16}(L)\tilde{h}c_{ij,t-1} + e_{ij,t}, \quad (2.3)$$

where $\tilde{x}_{ij,t}$ for any variable $x_{ij,t}$ is defined as $\tilde{x}_{ij,t} = (x_{i,t} - x_{j,t})$ and (L) is the lag operator. The error term $e_{ij,t} = \mu_{ij} + v_{ij,t}$ is assumed to have the typical one-way error component structure including time-fixed individual effects and a remainder error term. Next to the core labor market variables as real wage ($\tilde{w}r$) and unemployment rate differences ($\tilde{u}r$), we include changes in real labor productivity ($\Delta \tilde{y}lr$), the labor participation rate (\tilde{q}), and an index for human capital ($\tilde{h}c$) as control variables in S_{ij} .

Equation (2.3) is frequently used in a partial equilibrium framework in order to estimate the elasticity of migratory movements with respect to labor market and further (macro)economic variables. However, as Gallin (1999) points out, this type of analysis can be misleading because migration and labor market conditions are

⁵One pitfall at the empirical level is to find an appropriate proxy for the regional human capital endowment (see, e.g., Dreger et al. 2008, as well as Ragnitz 2007, for a special focus on East-West differences). We therefore test different proxies in form of a composite indicator based on the regional human capital potential (high school and university graduates), the skill level of employee as well as innovative activities such as regional patent intensities.

usually jointly determined. To do so, we set up a small-scale model for regional labor market and economic development, which closely follows the specification in Möller (1995). Centering around the neoclassical migration equation with regional differences in the unemployment and real wage rate as explanatory variables, the author includes a set of behavioral equations derived from an eclectic model of regional evolutions first proposed by Blanchard and Katz (1992).⁶ We use a similar equation system of the following form:

$$\begin{aligned}\tilde{w}r_{ij,t} = & \gamma_{20} + \gamma_{21}(L)nm_{ij,t-1} + \gamma_{22}(L)\tilde{w}r_{ij,t-1} + \gamma_{23}(L)\tilde{u}r_{ij,t-1} \\ & + \gamma_{24}(L)\Delta\tilde{y}lr_{ij,t-1} + \gamma_{25}(L)\tilde{q}_{ij,t-1} + \gamma_{26}(L)\tilde{h}c_{ij,t-1} + e_{ij,t},\end{aligned}\quad (2.4)$$

$$\begin{aligned}\tilde{u}r_{ij,t} = & \gamma_{30} + \gamma_{31}(L)nm_{ij,t-1} + \gamma_{32}(L)\tilde{w}r_{ij,t-1} + \gamma_{33}(L)\tilde{u}r_{ij,t-1} \\ & + \gamma_{34}(L)\Delta\tilde{y}lr_{ij,t-1} + \gamma_{35}(L)\tilde{q}_{ij,t-1} + \gamma_{36}(L)\tilde{h}c_{ij,t-1} + e_{ij,t},\end{aligned}\quad (2.5)$$

$$\begin{aligned}\Delta\tilde{y}lr_{ij,t} = & \gamma_{40} + \gamma_{41}(L)nm_{ij,t-1} + \gamma_{42}(L)\tilde{w}r_{ij,t-1} + \gamma_{43}(L)\tilde{u}r_{ij,t-1} \\ & + \gamma_{44}(L)\Delta\tilde{y}lr_{ij,t-1} + \gamma_{45}(L)\tilde{q}_{ij,t-1} + \gamma_{46}(L)\tilde{h}c_{ij,t-1} + e_{ij,t},\end{aligned}\quad (2.6)$$

$$\begin{aligned}\tilde{q}_{ij,t} = & \gamma_{50} + \gamma_{51}(L)nm_{ij,t-1} + \gamma_{52}(L)\tilde{w}r_{ij,t-1} + \gamma_{53}(L)\tilde{u}r_{ij,t-1} \\ & + \gamma_{54}(L)\Delta\tilde{y}lr_{ij,t-1} + \gamma_{55}(L)\tilde{q}_{ij,t-1} + \gamma_{56}(L)\tilde{h}c_{ij,t-1} + e_{ij,t},\end{aligned}\quad (2.7)$$

$$\begin{aligned}\tilde{h}c_{ij,t} = & \gamma_{60} + \gamma_{61}(L)nm_{ij,t-1} + \gamma_{62}(L)\tilde{w}r_{ij,t-1} + \gamma_{63}(L)\tilde{u}r_{ij,t-1} \\ & + \gamma_{64}(L)\Delta\tilde{y}lr_{ij,t-1} + \gamma_{65}(L)\tilde{q}_{ij,t-1} + \gamma_{66}(L)\tilde{h}c_{ij,t-1} + e_{ij,t},\end{aligned}\quad (2.8)$$

There are different ways to put theoretically motivated sign restrictions on the variable coefficients of the system in (2.4)–(2.8).⁷ However, our empirical strategy deliberately rests on an eclectic modelling strategy to first select theoretical motivated variables and thereafter use a flexible VAR approach for estimation. This strategy relaxes (arbitrary) theoretical restrictions put on right-hand-side variables and lets the data determine whether migration has equilibrating or disequilibrating effects on the labor market and, e.g., whether a ‘wage’ or ‘Phillips’ curve may be in order for the wage equation in the system. We will give a discussion of the specification and estimations issues of the Panel VAR (PVAR) approach in the following. However, before that we first briefly describe the data base used for estimation and discuss the time series properties of the variables in the next section. The latter in fact may have important implications for the selection of appropriate estimation techniques in the context of dynamic panel data models.

⁶The approach in Möller (1995) defines regional differences for region i relative to the rest of the country aggregate j .

⁷A discussion of theoretical motivated coefficient signs in (2.4)–(2.8) is given in an extended working paper version. See Alecke et al. (2009).

2.4 Data and Stylized Facts of Intra-German Migration

For empirical estimation we use data for the 16 German states between 1991 and 2006. We model migration based on inter-regional migration flow data (disregarding within-state flows with a total of $N \times (N - 1) \times T = 16 \times 15 \times 16 = 3840$ observations) rather than aggregating state level net migration relative to the rest of the country (that is, summed over all regions minus region i). The former strategy gives us more degrees of freedom for estimation and avoids an artificial averaging of migration flows. Though we use population rather than labor force migration, we assume that both variables are highly correlated and that the former may serve as a proxy for the latter. All economic variables are denoted in real terms. That is, we account explicitly for the evolution of regional differences in price levels. Such data is typically ignored in empirical analysis given its scarce evidence at an intra-country perspective. Here we use data compiled by Roos (2006) based on prices indices for 50 German cities in 1993 and construct a time series of regional price levels by using state level inflations rates for consumer prices between 1991 and 2006. Since differences in regional price levels may offset or even increase regional wage rate differentials, an explicit account for regional (consumer) prices in estimating migration flows seems promising. A full description of the data sources is given in Table 2.1.

Looking at selected stylized facts, in particular the evolution of East–West migration flows since re-unification deserves attention. Figure 2.1 plots state level net in-migration rates between 1991 and 2006. Additionally, Fig. 2.2 reports aggregated migration flows for the two East–West macro regions, which allows to identify distinct waves in macro regional migration over time.⁸ As Fig. 2.1 shows, West German states benefit on average from the net out-migration trend of Eastern states. The only outlier among the West German states is Lower Saxony. However, the latter trend in its internal migration flows is largely exogenously driven by German resettlers from abroad.⁹ For empirical estimation, we will explicitly control for the latter exogenously induced migration effect, which does not bear much economic interpretation. Taking a closer look at the evolution of state level net migration rates for East Germany, only Brandenburg has a positive migration balance throughout the 1990s benefiting from its geographical proximity to Berlin. The time series pattern of other East German states is persistently negative over the whole sample period. If we aggregate the inter-regional state level flows to gross and net out-migration among the two macro regions West and East (including Berlin), Fig. 2.2 allows to identify the two waves of East–West net outflows with peaks in the early 1990s and around 2001. Compared to this, West to East migratory flows have been rather stable (and much lower) over time.

⁸East Germany including Berlin.

⁹The explanation is that these resettlers are legally obliged to first move to the central base Friesland in Lower Saxony and then only subsequently can freely migrate to other states within Germany.

Table 2.1 Data description and source

Variable	Description	Source
$outm_{ijt}$	Total number of out-migration from region i to j	Destatis (2008a)
inm_{ijt}	Total number of in-migration from region i to j	Destatis (2008a)
$y_{i(j)t}$	Gross domestic product in region i and j respectively	VGRdL (2008)
$py_{i(j)t}$	GDP deflator in region i and j respectively	VGRdL (2008)
$ylr_{i(j)t}$	Real labor productivity defined as $(yl_{j,t} - py_{j,t})$	VGRdL (2008)
$pop_{i(j)t}$	Population in region i and j respectively	VGRdL (2008)
$emp_{i(j)t}$	Total employment in region i and j respectively	VGRdL (2008)
$unemp_{i(j)t}$	Total unemployment in region i and j respectively	VGRdL (2008)
$uri_{i(j)t}$	Unemployment rate in region i and j respectively defined as $(unemp_{i,t} - emp_{i,t})$	VGRdL (2008)
$pcpi_{i(j)t}$	Consumer price index in region i and j respectively based on Roos (2006) and regional CPI inflation rates	Roos (2006), RWI (2009)
$wri_{i(j)t}$	Real wage rate in region i and j respectively defined as wage compensation per employee deflated by $pcpi_{i(j)t}$	VGRdL (2008)
$qi_{i(j)t}$	Labor market participation rate in region i and j respectively defined as $(emp_{i,t} - pop_{i,t})$	VGRdL (2008)
$hci_{i(j)t}$	Human capital index as weighted average of: 1) high school graduates with university qualification per total population between 18–20 years ($hcschool$), 2) number of university degrees per total population between 25–30 years ($hcuni$), 3) share of employed persons with a university degree relative to total employment ($hcsvh$), 4) number of patents per pop. ($hcpat$)	Destatis (2008b, 2008c), Federal Employment Agency (2009), DPMA (2008)

Note: All variables in logs. For Bremen, Hamburg and Schleswig-Holstein no consumer price inflation rates are available. We took the West German aggregate for these states, this also accounts for Rhineland-Palatine and Saarland until 1995

Since we are dealing with macroeconomic time series, the (non)-stationarity of the data and thus spurious regression may be an issue. We therefore perform the Im–Pesaran–Shin (2003) panel unit root tests for the variables in the system of equation. Optimal lag length is chosen according to the Akaike information criterion (AIC). The results are shown in Table 2.2. In all cases the IPS test rejects the null hypothesis of non-stationarity. These results are broadly in line with our theoretical expectations concerning the order of integration of the variables: Migration and labor market variables (unemployment rate, labor participation rate etc.) are typically assumed to be stationary processes and the same accounts for labor productivity (growth). Human capital endowment is likewise expected to change only gradually over time. These results give us a high level of flexibility in terms of employing different dynamic panel data (DPD) estimators both in levels and first differences as typically proposed in the recent literature.

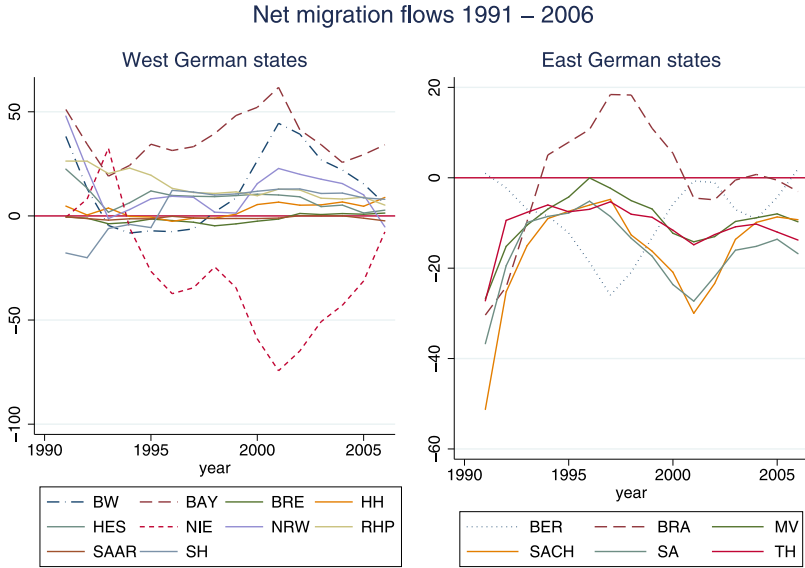
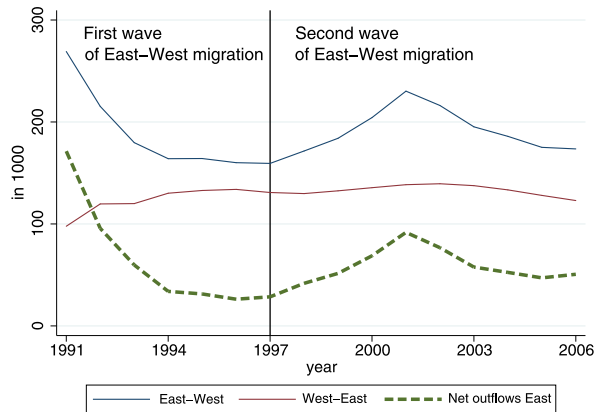


Fig. 2.1 Time series plots for German state level net migration between 1991 and 2006. *Note:* BW = Baden-Württemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia. *Source:* Data from Destatis (2008a)

Fig. 2.2 Gross and net migration flows between East and West Germany 1991–2006. *Source:* Data from Destatis (2008a)



2.5 Dynamic Panel Data Estimators in a VAR Framework

The Panel VAR (PVAR) technique combines the traditional VAR approach treating all variables of the system as endogenous with estimation techniques for panel data and was first employed by Holtz-Eakin et al. (1988). While the use of VAR models in time series analysis is a common standard, the use in a panel data context is less

Table 2.2 Im–Pesaran–Shin (2003) panel unit root test for variables

Specification	IPS test for $N \times (N - 1)$, $T = (240, 16)$		
	H_0 : All panels contain unit roots		
	W[t-bar]	p -value	Lags
$nm_{ij,t}$	−16.75	(0.00)	0.36
$\tilde{u}r_{ij,t}$	−17.69	(0.00)	0.64
$\tilde{w}r_{ij,t}$	−96.09	(0.00)	0.55
$\Delta y \tilde{l}r_{ij,t}$	−67.42	(0.00)	0.34
$\tilde{q}_{ij,t}$	−15.59	(0.00)	0.59
$\tilde{h}c_{ij,t}$	−21.56	(0.00)	0.33

Note: Including a constant term; optimal (average) lag length selection according to the AIC

common. However, a recent comparison of different PVAR estimators together with a Monte Carlo simulation experiments for standard small T , large N data settings is given by Binder et al. (2005). As Mäki-Arvela (2003) argues, the unrestricted VAR methodology is ideally suited for an examination of interrelated time series variables and their dynamics in a labor market setting, where a particular focus is to explore the strengths of different adjustment mechanisms in response to economic shocks. Throughout the analysis we restrict our estimation approach to a first-order PVAR(1) written in matrix form as:¹⁰

$$z_{i,t} = \Gamma_0 + \Gamma_1 z_{i,t-1} + e_{i,t} \quad (2.9)$$

where $z_{i,t}$ is an $m \times 1$ vector. In our case, $z_{i,t} = [nm_{ij,t}, \tilde{w}r_{ij,t}, \tilde{u}r_{ij,t}, \Delta y \tilde{l}r_{ij,t}, \tilde{q}_{ij,t}, \tilde{h}c_{ij,t}]$, Γ_1 is an $m \times m$ matrix of slope coefficients, $e_{i,t}$ is an $m \times 1$ vector of the composed error term as discussed above, including unobserved individual effects and a remainder component. The PVAR(1) model is thus a straightforward generalization of a univariate dynamic panel data model.

There are numerous contributions in the recent literature for a dynamic single equation model of the above type, which especially deal with the problem introduced by the inclusion of the lagged dependent variable on the right hand side of the estimation equation and its built-in correlation with the combined error term. Arellano and Bond (1991), for instance, propose an GMM estimator in first differences, which employs valid instruments for the lagged endogenous variable of the form:

$$E(y_{i,t-\rho} \Delta u_{i,t}) = 0 \quad \text{for all } \rho = 2, \dots, t-1. \quad (2.10)$$

Equation (2.10) is also called the ‘standard moment condition’ and is widely used in empirical estimation. The resulting instrument matrix for past values of the endogenous variable can then be written as:

¹⁰As Binder et al. (2005) note, higher-order models can be treated in conceptually the same manner as the first-order representation. For ease of presentation, we denote the cross section dimension by i rather than ij .

$$Z_i^{\Delta,(y)} = \begin{pmatrix} y_{i0} & 0 & \cdots & \cdots & 0 & \cdots & 0 \\ 0 & y_{i0} & y_{i1} & 0 & 0 & \cdots & 0 \\ 0 & \cdots & \cdots & \vdots & \vdots & \cdots & 0 \\ 0 & \cdots & 0 & 0 & y_{i0} & \cdots & y_{iT-2} \end{pmatrix} \quad (2.11)$$

and analogously for the set of strictly exogenous explanatory variables (X_{it-1}):

$$Z_i^{\Delta,(x)} = \begin{pmatrix} x'_{i0} & \cdots & x'_{iT-1} & 0 & \cdots & \cdots & 0 & \cdots & 0 \\ 0 & \cdots & 0 & x'_{i0} & \cdots & x'_{iT} & 0 & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & 0 & \cdots & \cdots & \cdots & 0 \\ 0 & \cdots & \cdots & \cdots & 0 & x'_{i0} & \cdots & x'_{iT-1} \end{pmatrix} \quad (2.12)$$

and the full instrumental variable set for the first-difference (FD) transformed model (Z_i^{Δ}) is given by

$$Z_i^{\Delta} = (Z_i^{\Delta,(y)}, Z_i^{\Delta,(x)}). \quad (2.13)$$

One general drawback of dynamic model estimators in first differences is their rather weak empirical performance. As Bond et al. (2001) argue, IV and Generalized Method of Moments (GMM) estimators in first differences can behave poorly, since lagged levels of the time series provide only ‘weak instruments’ for subsequent first-differences. In response to this critique, a second generation DPD models has been developed, which also makes use of appropriate orthogonality conditions for the equation in levels (see, e.g., Blundell and Bond 1998) as:

$$E(\Delta y_{i,t-1} u_{i,t}) = 0 \quad \text{for } t = 3, \dots, T. \quad (2.14)$$

Rather than using lagged levels of variables for equations in first difference as in the case of FD-estimators, we get an orthogonality condition for the model in level that uses instruments in first differences.

Equation (2.14) is also called the ‘stationarity moment condition’. Blundell and Bond (1998) propose a GMM estimator that uses jointly both the standard and stationarity moment conditions. This latter approach is typically known as ‘system’ GMM (SYS-GMM) combining ‘level’ and ‘difference’ GMM. Though labeled system GMM, this estimator treats the data system as a single-equation problem since the same linear functional relationship is believed to apply in both the transformed and untransformed variables as

$$\begin{pmatrix} \Delta y \\ y \end{pmatrix} = \alpha \begin{pmatrix} \Delta y_{-1} \\ y_{-1} \end{pmatrix} + \beta \begin{pmatrix} \Delta X_{-1} \\ X_{-1} \end{pmatrix} + \begin{pmatrix} \Delta u \\ u \end{pmatrix} \quad (2.15)$$

and the overall instrument set in the case of system GMM is $Z_i = (Z_i^{\Delta}, Z_i^L)$, where the latter is the instrument set for the equation in levels based on valid orthogonality conditions for $y_{i,t-1}$ and $X_{i,t-1}$.

For the empirical estimation of our PVAR model, we employ multiple-equation GMM (as, e.g., outlined in Hayashi 2000), which basically involves stacking our migration and labor market model in the typical system way (3SLS or SUR) and apply IV estimation using the SYS-GMM estimation strategy. The resulting IV set Z_i^S for a system of m equations (with $m = 1, \dots, M$) is a combination of the individual

equations' IV sets, where we allow the instruments to differ among the equations of the system as

$$Z_i^S = \begin{bmatrix} Z_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & Z_{iM} \end{bmatrix}. \quad (2.16)$$

Stacking the equations for multiple-equation GMM estimation may lead to further efficiency gains if the residuals of the M equations are correlated. We therefore apply a two-step approach which explicitly accounts for cross-equation residual correlation. The weighting matrix V^S in two-step efficient GMM estimation is defined as

$$V^S = N^{-1} \sum_{i=1}^N Z_i^{S'} \hat{e}_i \hat{e}_i' Z_i^S \quad (2.17)$$

and the vector of first step error terms $\hat{e}_i = (\hat{e}_{i1}, \dots, \hat{e}_{iM})'$ is derived from a consistent (equation by equation) 2SLS estimation. The system GMM estimator in the context of the PVAR(1) can then be written as:

$$\hat{\Phi}_{GMM} = \left(S_{ZX}' (V^S)^{-1} S_{ZX} \right)^{-1} S_{ZX}' (V^S)^{-1} S_{Zy}, \quad (2.18)$$

with

$$S_{ZX} = \begin{bmatrix} \frac{1}{N} \sum_{i=1}^N z'_{i1} x_{i1} & & \\ & \ddots & \\ & & \frac{1}{N} \sum_{i=1}^N z'_{iM} x_{iM} \end{bmatrix} \quad \text{and} \quad (2.19)$$

$$S_{Zy} = \begin{bmatrix} \frac{1}{N} \sum_{i=1}^N Z'_{i1} y_{i1} \\ \vdots \\ \frac{1}{N} \sum_{i=1}^N Z'_{iM} y_{iM} \end{bmatrix}.$$

2.6 Empirical Results

In this section we present the empirical results of the PVAR(1) model.¹¹ We first look at the estimation output and post estimation tests and then analyze the dynamic adjustment processes in terms of impulse response functions. One major concern in our modelling approach is to carefully check for the consistency and efficiency of the chosen estimation approach. Since the system GMM approach relies on IV estimation, we basically guide instrument selection based on the Sargan (1958)/Hansen (1982) overidentification test. Especially in a multiple equation context, appropriate IV selection is of vital importance since the full IV candidate set may become

¹¹ At this point, we focus on the PVAR(1) case since longer time lags are hardly applicable given the rather short overall sample period.

large. One has to note that the power of the Hansen J -statistic shrinks with increasing instrument number (see, e.g., Bowsher 2002, and Roodman 2009). The standard Sargan statistic is however robust to this problem. We thus use a procedure to reduce the number of orthogonality conditions employed for estimation, both by using ‘collapsed’ IV sets as well as by sorting out correlated variables with the help of the C -statistic (or ‘Diff-in-Sargan/Hansen’s J ’) as numerical difference of two overidentification tests isolating IVs under suspicion (see Eichenbaum et al. 1988, for details). Additionally, we check the likely efficiency gains of the system SYS-GMM estimation approach in terms of testing for cross-equation correlations for the first step residuals.

The estimation results for the PVAR(1) model based on the efficient two-step system SYS-GMM approach are reported in Table 2.3.¹² The estimation results for the migration equation show that the core labor market variables (both real wage and unemployment differentials as well as labor productivity growth) are statistically significant and of expected signs. Only the participation rate is statistically

Table 2.3 Estimation results—Panel VAR with lag(1) for $[nm_{ij,t}, \tilde{w}r_{ij,t}, \tilde{u}r_{ij,t}, \Delta \tilde{y}lr_{ij,t}, \tilde{q}_{ij,t}, \tilde{h}c_{ij,t}]$

Dep. var.	r.h.s. var.	Coef.	Corr. S.E.	t -stat.	p -value
$nm_{ij,t}$	$nm_{ij,t-1}$	0.43***	0.051	8.41	(0.00)
$nm_{ij,t}$	$\tilde{w}r_{ij,t-1}$	0.49***	0.144	3.41	(0.00)
$nm_{ij,t}$	$\tilde{u}r_{ij,t-1}$	-0.12**	0.050	-2.46	(0.01)
$nm_{ij,t}$	$\Delta \tilde{y}lr_{ij,t-1}$	0.66***	0.073	9.06	(0.00)
$nm_{ij,t}$	$\tilde{q}_{ij,t-1}$	0.02	0.277	0.07	(0.94)
$nm_{ij,t}$	$\tilde{h}c_{ij,t-1}$	-0.02*	0.012	-1.78	(0.07)
$\tilde{w}r_{ij,t}$	$nm_{ij,t-1}$	-0.02***	0.003	-4.89	(0.00)
$\tilde{w}r_{ij,t}$	$\tilde{w}r_{ij,t-1}$	0.46***	0.028	16.32	(0.00)
$\tilde{w}r_{ij,t}$	$\tilde{u}r_{ij,t-1}$	-0.10***	0.030	-3.35	(0.00)
$\tilde{w}r_{ij,t}$	$\Delta \tilde{y}lr_{ij,t-1}$	0.12***	0.015	7.70	(0.00)
$\tilde{w}r_{ij,t}$	$\tilde{q}_{ij,t-1}$	0.71***	0.105	6.77	(0.00)
$\tilde{w}r_{ij,t}$	$\tilde{h}c_{ij,t-1}$	-0.001	0.001	-1.37	(0.17)
$\tilde{u}r_{ij,t}$	$nm_{ij,t-1}$	0.06	0.038	1.54	(0.12)
$\tilde{u}r_{ij,t}$	$\tilde{w}r_{ij,t-1}$	-0.29***	0.063	-4.68	(0.00)
$\tilde{u}r_{ij,t}$	$\tilde{u}r_{ij,t-1}$	0.067***	0.055	12.07	(0.00)
$\tilde{u}r_{ij,t}$	$\Delta \tilde{y}lr_{ij,t-1}$	-0.39***	0.042	-9.42	(0.00)
$\tilde{u}r_{ij,t}$	$\tilde{q}_{ij,t-1}$	-0.99***	0.244	4.06	(0.00)
$\tilde{u}r_{ij,t}$	$\tilde{h}c_{ij,t-1}$	0.02***	0.005	4.10	(0.00)

(continued on the next page)

¹²Details about the IV downward testing approach with an example for the migration equation are given in Appendix A.

Table 2.3 (Continued)

Dep. var.	r.h.s. var.	Coef.	Corr. S.E.	<i>t</i> -stat.	<i>p</i> -value
$\Delta \widetilde{y}lr_{ij,t}$	$nm_{ij,t-1}$	-0.03	0.017	-1.52	(0.13)
$\Delta \widetilde{y}lr_{ij,t}$	$\widetilde{w}r_{ij,t-1}$	-0.23***	0.051	-4.51	(0.00)
$\Delta \widetilde{y}lr_{ij,t}$	$\widetilde{u}r_{ij,t-1}$	0.09***	0.023	3.90	(0.00)
$\Delta \widetilde{y}lr_{ij,t}$	$\Delta \widetilde{y}lr_{ij,t-1}$	0.55***	0.024	22.61	(0.00)
$\Delta \widetilde{y}lr_{ij,t}$	$\widetilde{q}_{ij,t-1}$	0.46***	0.124	3.71	(0.00)
$\Delta \widetilde{y}lr_{ij,t}$	$\widetilde{h}c_{ij,t-1}$	0.17***	0.026	6.41	(0.00)
$\widetilde{q}_{ij,t}$	$nm_{ij,t-1}$	0.01***	0.001	4.03	(0.00)
$\widetilde{q}_{ij,t}$	$\widetilde{w}r_{ij,t-1}$	0.08***	0.006	12.70	(0.00)
$\widetilde{q}_{ij,t}$	$\widetilde{u}r_{ij,t-1}$	-0.01**	0.003	-2.52	(0.01)
$\widetilde{q}_{ij,t}$	$\Delta \widetilde{y}lr_{ij,t-1}$	0.09***	0.004	24.70	(0.00)
$\widetilde{q}_{ij,t}$	$\widetilde{q}_{ij,t-1}$	0.81***	0.014	54.67	(0.00)
$\widetilde{q}_{ij,t}$	$\widetilde{h}c_{ij,t-1}$	-0.01***	(0.001)	-4.56	(0.00)
$\widetilde{h}c_{ij,t}$	$nm_{ij,t-1}$	0.07**	0.031	2.18	(0.02)
$\widetilde{h}c_{ij,t}$	$\widetilde{w}r_{ij,t-1}$	0.31***	0.140	2.23	(0.03)
$\widetilde{h}c_{ij,t}$	$\widetilde{u}r_{ij,t-1}$	-0.15***	0.033	-4.36	(0.00)
$\widetilde{h}c_{ij,t}$	$\Delta \widetilde{y}lr_{ij,t-1}$	0.24***	0.071	3.43	(0.00)
$\widetilde{h}c_{ij,t}$	$\widetilde{q}_{ij,t-1}$	-0.07	0.306	-0.24	(0.81)
$\widetilde{h}c_{ij,t}$	$\widetilde{h}c_{ij,t-1}$	0.55***	0.057	9.70	(0.00)
No. of obs. per eq.			3120		
No. of system obs.			18720		
No. of instruments			222		
<i>F</i> -test (joint significance)			608.6		
			(0.00)		
Sargan statistic			179.1		
			(0.61)		
Hausman $ m $ -stat.			2.45		
			(0.99)		
$\chi^2_{CE}(15)$			33.47		
			(0.00)		

Note: Standard errors are computed based on Windmeijer's (2005) finite-sample correction. χ^2_{CE} : Test for cross-equation correlation of the system's 1.step residuals as outlined in Dufour and Khalaf (2002)

* Denote statistical significance at the 10% level ** Denote statistical significance at the 5% level

*** Denote statistical significance at the 1% level

insignificant. The negative coefficient for human capital may be explained by the equilibrating effect of regional differences in human capital endowment on migration flows after controlling for the other explanatory labor market factors. However, this latter partial equilibrium view may not reflect the full direct and indirect effect of regional human capital differences on migratory movements, which has to be analyzed through impulse–response functions (e.g., in order to capture the likely link between human capital and productivity growth, which in turn may translate into a positive migration response due to a shock in regional human capital differences). Finally, we include a dummy variable for Lower Saxony (D_{NIE}), which turns out to be negative and statistically highly significant.

If we turn to the postestimation tests, Table 2.3 reports the robust Sargan statistic for our 222 chosen instruments (out of a maximum of 2382 in the full ‘uncollapsed’ IV case). Our proposed IV set passes the test statistic for reasonable confidence levels. Moreover, we compute a Breusch–Pagan LM test for the significance of cross-effects in the first step residuals (χ^2_{CE}) as suggested in Dufour and Khalaf (2002) in order to check for the likely efficiency gains in applying a full information approach. The Breusch–Pagan type test clearly rejects the null hypothesis of independence among the residuals of our 6-equation system. Finally, in order to compare the appropriateness of our chosen efficient two-step approach relative to a limited information 2SLS benchmark, we employ the Hausman (1978) m -statistics.¹³ The results do not reject the null of consistency and efficiency of our two-step approach compared to the one-step specification.

If we take a look at the estimated coefficients in the remaining equations in the PVAR(1) model, Table 2.3 shows that lagged migration has a significantly negative direct effect on the wage rate, while the impact on the participation rate and the human capital index is positive. These results already hint at the important role of instantaneous causality among the variables and support our theoretical expectations that migration has an equilibrating effect on regional labor markets in line with the neoclassical model. That is, an increased level of net in-migration in region i lowers the regional wage rate differential (the wage in region i decreases relative to j) and thus works towards a cross-regional wage equalization as outlined above. Our empirical results also indicate the existence of a wage curve à la Blanchflower and Oswald (1994, 2005) since, in the wage equation, the unemployment rate has a negative coefficient sign.

Labor productivity growth has a positive impact on the wage rate, while in the equation for labor productivity growth, the wage rate itself has a negative effect. In the equation for the labor participation rate, the wage rate is estimated to have a positive effect, while unemployment is negatively correlated with the participation rate. The equation for human capital mainly mirrors earlier micro results finding a positive impact of wage rates and labor productivity on regional human capital

¹³By construction, if the variance of the limited information approach is larger than its full information counterpart, the test statistic will be negative. Though the original test is typically not defined for negative values, here we follow Schreiber (2007) and take the absolute value of the m -statistics as indicator.

endowments, while higher unemployment rates are negatively correlated with the regional human capital endowment. Finally, net in-migration is estimated to have a positive effect on the relative regional distribution of human capital. Whether this latter effect may hint at the possible role of regional ‘brain drain’ effects will be analyzed through the help of impulse–response functions.

In order to assess the two-way effects among migration and labor market variables, we compute impulse–response functions of the PVAR. The latter tool describes the reaction of one variable to innovations in another variable of the system, while holding all other shocks equal to zero (for details see Lütkepohl 2005). Figures 2.3 and 2.4 plot impulse–response functions together with 5 percent errors bands generated through Monte Carlo simulations with 500 repetitions.¹⁴ Additionally, Table 2.4 reports variance decompositions derived from the orthogonalized impulse–response coefficient matrices. The variance decompositions display the proportion of movements in the dependent variables that are due to their own shocks versus shocks to the other variables, which is done by determining how much of an s -step ahead MSE forecast error variance for each variable is explained by innovations to each explanatory variable (we report s until 20).

Figure 2.3 shows the responses of migration to a one standard deviation shock in the remaining variables of the PVAR (rescaled in terms of shocks of one standard deviation). As the figure shows, the shock to unemployment changes is negative with most of the migration response being absorbed after three to four years (similar results for West Germany are obtained in Möller 1995). The response to a shock in the regional wage rate differential has the expected positive dynamics. The migration responses to labor productivity and human capital shocks turn out to be positive and show a higher degree of persistence. Especially for human capital, the overall effect in the system context is thus different from the partial equilibrium view. Though the direct effect of regional human capital differences on net in-migration gave some indication for an equilibrating effect after controlling for key labor market factors, the overall effect obtained from the impulse–response functions shows that a relatively better skill composition in region i acts as a pull factor for additional net in-migration reflecting disequilibrating or agglomeration forces associated with scale effects (e.g. in the educational system). The link from human capital to enhanced in-migration is especially expected to work through the productivity growth channel of human capital, which has been tested highly significant in the PVAR(1) estimation results. The negative migration response to a positive shock in the labor participation rate may hint at the role of regional labor market tightness, which reduces net in-migration.

¹⁴A full graphical presentation of the system’s impulse–response functions is given in Appendix B. For the orthogonalized impulse–response functions we choose the following causal ordering [$\tilde{h}c_{ij,t} \rightarrow \tilde{q}_{ij,t} \rightarrow \tilde{y}lr_{ij,t} \rightarrow \tilde{w}r_{ij,t} \rightarrow \tilde{u}r_{ij,t} \rightarrow \tilde{n}m_{ij,t}$], which is based on the assumption that migration and the core labor market variables are more endogenous compared productivity growth, labor participation (due to its demographic component) and human capital endowment. Results for reversed ordering can be obtained from the authors upon request. They are much in line with our original choice of ordering.

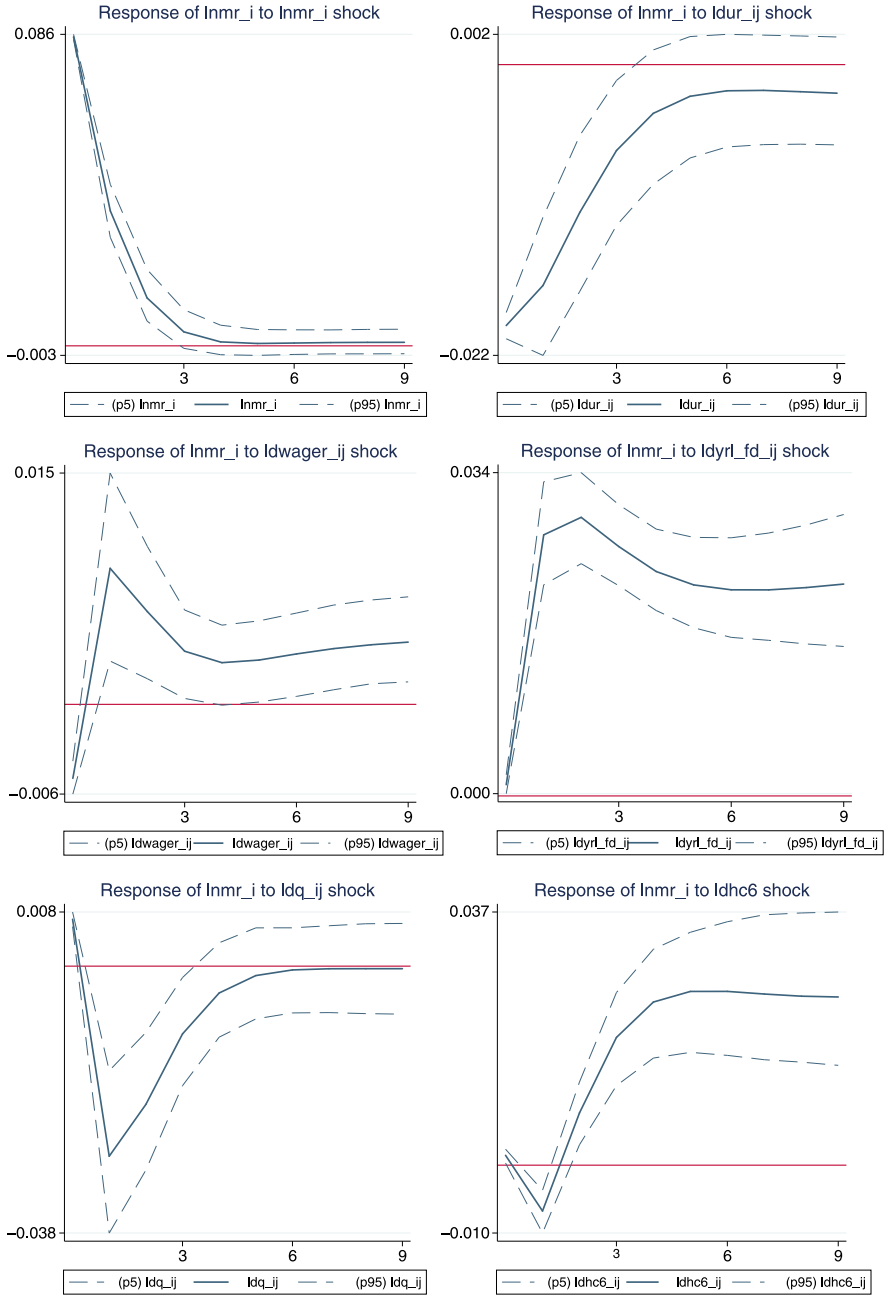


Fig. 2.3 Migration responses to shocks of one standard deviation in the variables from the PVAR(1). *Note:* Confidence intervals based on MC-simulations with 500 reps. With $nm_{ij,t} = \lnmr_i$, $\tilde{ur}_{ij,t} = \lnur_{ij}$, $\tilde{w}_{ij,t} = \lnwager_{ij}$, $\tilde{yrl}_{ij,t} = \lnyrl_fd_{ij}$, $\tilde{q}_{ij,t} = \lnq_{ij}$, $\tilde{hc}_{ij,t} = \lnhc6_{ij}$

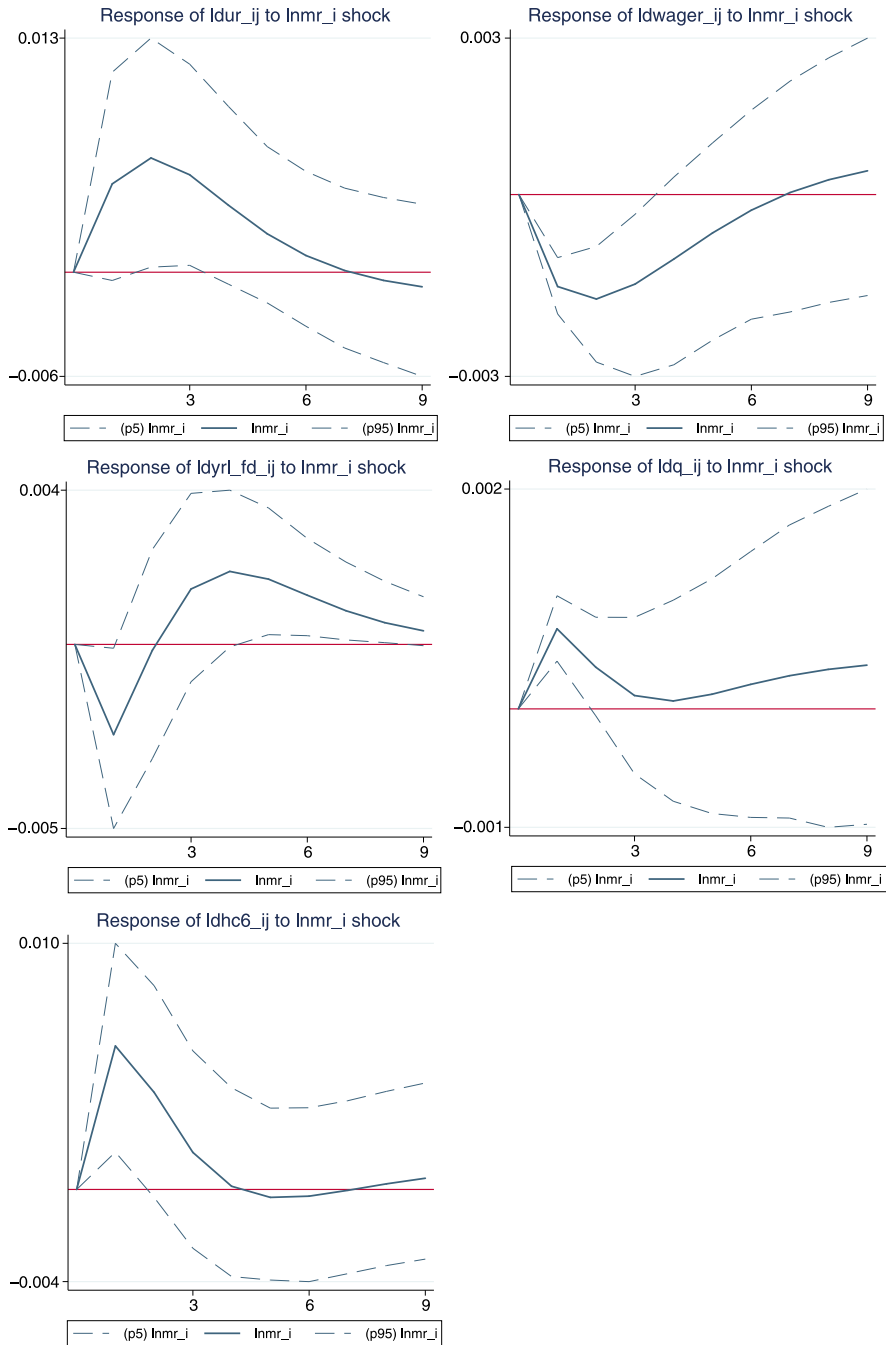


Fig. 2.4 Variable responses in the PVAR(1) to a shock of one standard deviation in the migration rate. *Note:* Confidence intervals based on MC-simulations with 500 reps. With $nm_{ij,t} = \lnmr_i$, $\tilde{u}r_{ij,t} = \text{ldur}_{ij}$, $\tilde{w}r_{ij,t} = \text{ldwager}_{ij}$, $\tilde{y}lr_{ij,t} = \text{ldyrl_fd}_{ij}$, $\tilde{q}_{ij,t} = \text{ldq}_{ij}$, $\tilde{h}c_{ij,t} = \text{ldhc6}_{ij}$

Table 2.4 Variance decomposition with percent variation in row variable explained by column variable

	s	$nm_{ij,t}$	$\tilde{u}r_{ij,t}$	$\tilde{w}r_{ij,t}$	$\Delta y\tilde{l}r_{ij,t}$	$\tilde{q}_{ij,t}$	$\tilde{h}c_{ij,t}$
$nm_{ij,t}$	5	0.590	0.056	0.010	0.188	0.084	0.069
$\tilde{u}r_{ij,t}$	5	0.008	0.548	0.009	0.191	0.201	0.041
$\tilde{w}r_{ij,t}$	5	0.004	0.057	0.324	0.228	0.334	0.051
$\Delta y\tilde{l}r_{ij,t}$	5	0.003	0.036	0.009	0.413	0.123	0.415
$\tilde{q}_{ij,t}$	5	0.002	0.008	0.045	0.508	0.311	0.126
$\tilde{h}c_{ij,t}$	5	0.002	0.021	0.004	0.047	0.039	0.886
$nm_{ij,t}$	10	0.428	0.042	0.010	0.252	0.061	0.205
$\tilde{u}r_{ij,t}$	10	0.005	0.318	0.013	0.331	0.114	0.217
$\tilde{w}r_{ij,t}$	10	0.002	0.034	0.173	0.380	0.168	0.241
$\Delta y\tilde{l}r_{ij,t}$	10	0.003	0.035	0.009	0.391	0.116	0.444
$\tilde{q}_{ij,t}$	10	0.001	0.004	0.027	0.506	0.096	0.364
$\tilde{h}c_{ij,t}$	10	0.002	0.021	0.006	0.118	0.033	0.818
$nm_{ij,t}$	20	0.256	0.027	0.012	0.332	0.036	0.334
$\tilde{u}r_{ij,t}$	20	0.002	0.131	0.014	0.408	0.046	0.396
$\tilde{w}r_{ij,t}$	20	0.001	0.015	0.072	0.431	0.061	0.418
$\Delta y\tilde{l}r_{ij,t}$	20	0.003	0.034	0.009	0.390	0.115	0.446
$\tilde{q}_{ij,t}$	20	0.001	0.004	0.019	0.472	0.029	0.473
$\tilde{h}c_{ij,t}$	20	0.001	0.015	0.009	0.232	0.022	0.718

Note: Based on the orthogonalized impulse–responses, details see text

This general picture is also supported by plotting the forecast error variance decompositions in Table 2.4. In the short run, a shock in the unemployment rate has the biggest effect on net in-migration (with a maximum after 3 periods). In the long run, most of the error variance in net in-migration is accounted for by shocks in labor productivity growth and human capital. If we look at the impulse–response functions of the remaining variables of the system subject to a one standard deviation shock in net in-migration, we get a similar picture: For the unemployment rates and real wages Fig. 2.4 shows the equilibrating effect of a positive shock in the in-migration rate: Regional differences in the unemployment rate increase in response to an inflow of migrants, while regional wage rate differentials are reduced (though smaller in magnitude). Responses of labor productivity and labor participation with respect to migration are positive but rather marginal, while the impact on human capital shows indeed some indication for regional ‘brain drain’ effects given that net out-migration negatively affects the regional skill composition (and vice versa).

The impulse responses and the computation of forecast error variance decompositions give the general impression that most adjustment processes in the PVAR

system fade out rapidly. Only migration responses to shocks in labor productivity growth and human capital endowment indicate persistent effects. Moreover, beside those effects involving migration either as source or destination of shocks, the PVAR system gives further helpful insights for a better understanding of regional labor market and macroeconomic dynamics in Germany. A full graphical description of the impulse–response functions is given in Fig. 2.8. If we look, for example, at the response of real wages and human capital endowment to a shock in regional unemployment, we see the following reaction. In both cases, the impulse–response functions show a significantly negative adjustment process, which only fades out gradually. Likewise a shock in the unemployment rate leads to a deterioration of the regional human capital endowment, which supports the view of regional ‘brain drain’ effects as a reaction to regional labor market differences operating through the above identified migration channel.

Given the overall satisfactory model reactions of our PVAR(1), we will finally apply the model to the challenging question in how far our small scale system is able to track the distinct East–West net out-migration trend since re-unification and to explain the East German “empirical puzzle”.

2.7 East–West Migration: Still an “Empirical Puzzle”?

We have already seen from the stylized facts that East–West net out-migration made up a large part of overall German internal migration flows. Moreover, we did not observe a steady stream of migratory movements but rather two distinct waves. The first one directly started after opening up the intra-German border and thereafter declined until 1997. The late 1990s then witnessed a second wave of East–West net out-migration with a distinct peak in 2001. It thus may be a challenging task to carefully check, whether the specific path of East–West migration can be explained within the above-specified neoclassical migration model embedded in the PVAR(1). We are thereby especially interested in answering the following question: Can we explain these distinct ups and downs in East–West net migration on grounds of regional disparities in labor market variables? Or are they due to other unobserved and possibly non-economic factors, which are present in the two macro regions?

The question of East–West migration is also of special interest since earlier findings in Alecke and Untiedt (2000) gave rise to such a German “empirical puzzle” in line with similar evidence found for the Italian case, where macroeconomic Harris–Todaro inspired models were only found helpful in predicting changes in migration trends, but not in their absolute levels. Both for German East–West and Italian South–North migration flows, a high degree of “immobility” was found to coexist with large regional labor market disparities.¹⁵ To find an appropriate answer to this puzzle of insufficient migration to equilibrate regional labor market disparities is of

¹⁵For a discussion of the Italian case see, e.g., Fachin (2007) or Etzo (2007).

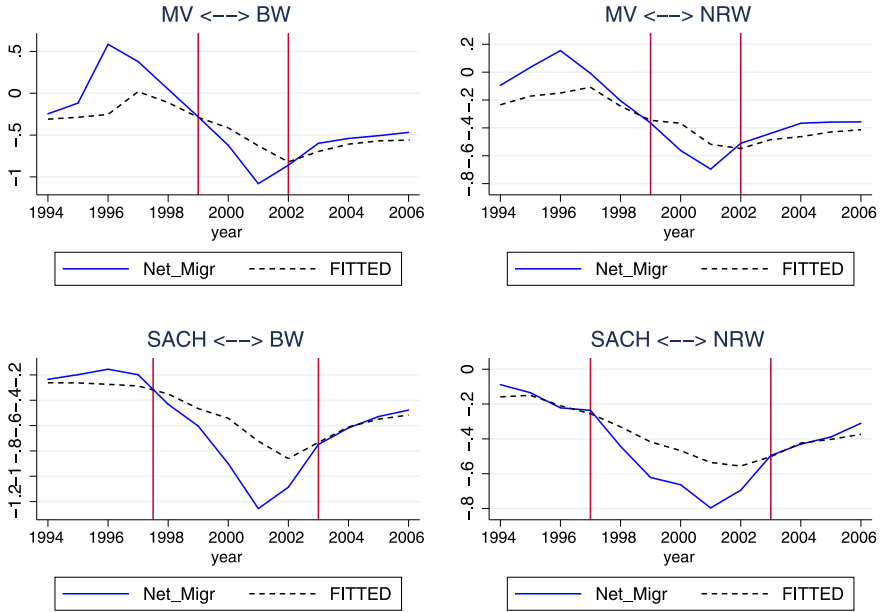


Fig. 2.5 Actual and fitted net migration for selected East–West state pairs. *Note:* BW = Baden–Württemberg, MV = Mecklenburg–Vorpommern, NRW = North Rhine–Westphalia, SACH = Saxony

special importance for determining the role of migratory movements in the process of regional economic development and income convergence. A first check for the empirical performance of our PVAR(1) model in the light of East–West migration is thus to compare the actual and (in-sample) predicted net migration flows for the involved state pairs.

In Fig. 2.5, we report the results for two selected state pairs including the East German regions Mecklenburg–Vorpommern and Saxony and their interaction with the two Western counterparts Baden–Württemberg and North Rhine–Westphalia for illustration purposes.¹⁶ As the results in Fig. 2.5 show, on average there is a rather high concordance of actual and fitted values over time for most bilateral pairs indicating that the estimated elasticities for the total German sample in conjunction with the temporal variation in the explanatory variables are able to explain the distinct trends in the East–West migration since 1994. However, though we see that the model is generally well equipped to predict changes in migratory movements for a variety of state pairs we observe a gap in the level of actual and predicted net migration flows over time, which may require a closer examination beyond the labor market signals.

¹⁶Detailed graphical plots for all East–West pairs are given in Fig. 2.9 in Appendix B.

In the exemplary case of net flows from Mecklenburg-Vorpommern and Saxony relative to Baden-Württemberg and North Rhine-Westphalia, we get the following picture. In the first part of the in-sample period until 1997, we gather from Fig. 2.5 that the structural labor market model over fits observed net migration, that is, actual net outflows out of the two East German states are much smaller than their predicted values. This result is in line with earlier evidence given in Alecke and Untiedt (2000) as well as Fachin (2007) for the Italian case. However, during the second wave of East–West migration with its peak around 2001 this relationship is reversed resulting in higher actual net outflows than predicted values based on the included structural labor market parameters. Towards the sample end actual and fitted values are again more closely in line, indicating that labor market signals now properly translate into migratory flows between East and West Germany.

In solving this implied “empirical puzzle” one prominently advocated line of argumentation in the field of regional science speaks in favor of fixed regional amenities to explain persistent labor market differences even in the long-term equilibrium. Thereby, regional amenities are typically defined as a proxy variable for (unobserved) specific climatic, ecological or social conditions in a certain region. According to the amenity approach, regional differences in labor market signals then only exhibit an effect on migration after a critical threshold has been passed. Since, in empirical terms, it is often hard to operationalize amenity relevant factors, Greenwood et al. (1991) propose to test the latter effect by the inclusion of (macro-)regional dummy variables in the empirical model. For the long run net migration equation, amenity-rich regions then should have dummy coefficients greater than zero (and vice versa), indicating that amenity-rich regions exhibit higher than average in-migration rates as we would expect after controlling for regional labor market and macroeconomic differences.

To test the above hypothesis, we thus augment the PVAR(1) by a dummy variable (for each equation) capturing inter-regional migration flows for the East German macro region. We also specify an alternative model specification with a similar dummy variable for East–West border regions. In order to analyze the time evolution of these dummies, we use a recursive estimation strategy in the following way:

$$Dummy_{[East;Border]} = \begin{cases} 1 & \text{for 1991 until } s, \text{ with } s = 1997, \dots, 2006, \\ 0 & \text{otherwise.} \end{cases} \quad (2.20)$$

The results generally show that the inclusion of the dummy variables does not affect the coefficients of the structural variables in the system. The results for the migration equation also indicate that the East dummy is insignificant for the whole sample with $s = 2006$. However, in line with Alecke and Untiedt (2000), the dummy variable for $s = 1997$ shows a positive and statistically significant coefficient sign. Similar results are found for the border dummy. For the recursive estimation experiment, we plot the time evolution of two dummy coefficients together with their respective t -values and the 10 percent critical t -value. For the East dummy in Fig. 2.6, we see that the coefficient is statistically significant and positive only up to 1997,

Fig. 2.6 Time evolution of the East German dummy in the augmented PVAR(1)

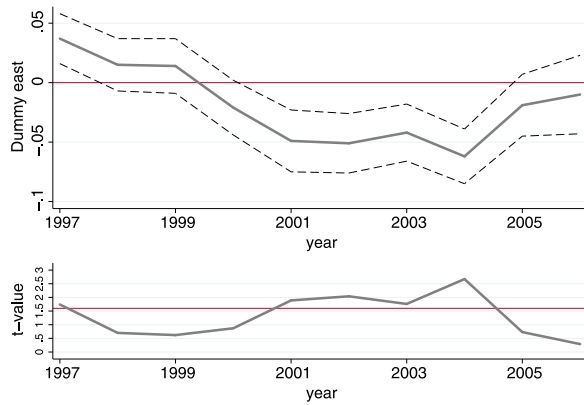
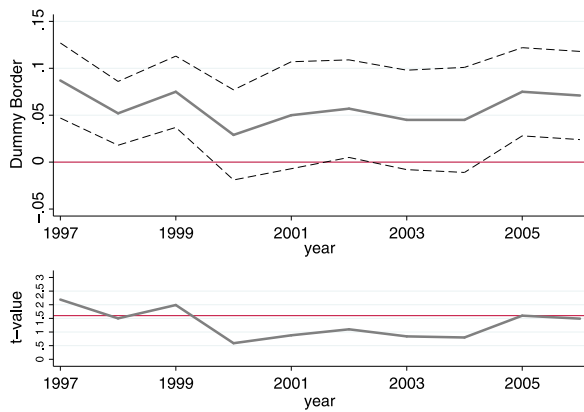


Fig. 2.7 Time evolution of the East–West border dummy in the augmented PVAR(1)



while it becomes insignificant or even turns significantly negative for subsequent periods. The latter finding coincides with the peak of the second huge wave of East–West net out-migration around 2001. The coefficient of the border dummy remains positive for the whole sample period but is found to be statistically significant only between 1997 and 1999 and again in 2005 (see Fig. 2.7).

When interpreting these results, it does not seem reasonable to take a positive dummy variable in favor of any kind of climatic or similar ecological regional fixed amenities for the East German states that keep people living there (which actually may be true for the case of Hawaii but not for Bitterfeld). A further substantial critique to the amenities interpretation of the dummy variable approach is that the latter can only be interpreted as amenities under the premise that the influence of other latent variables on regional net migration is of negligible order. However, this is more than doubtful with respect to the East German states if we, for example, consider the determinants of individual migration decisions (as worked out in the field of microeconomic migration theories) including the age structure of the work force potential, the relative wage structure, network effects, or the option value of waiting. Moreover, the analysis has only implicitly (via the labor partici-

pation rate) tackled the issue of particular high commuter flows between East and West, which may be seen as a substitute to the migration decision and give a reasonable explanation for the positive dummy variable coefficient of the Eastern border regions.

Finally and maybe most important from an aggregate East German perspective, politically induced distortions to the East German labor market and general economy may be seen as an impediment to sufficient high migration rates as balancing factor for regional labor market disparities until the mid-1990s. The latter comprises for instance a politically driven fast wage adjustment in the East (see Burda and Hunt 2001, for details on this point), as well as massive West–East financial transfers (see e.g. Bradley et al. 2006), which kept people away from leaving the Eastern states. Only recently, these transfers have been reduced in volume and now gradually fade out (e.g., the Solidarity Pact II), which in turn may explain the second wave of East German net out-migration and the estimated negative dummy variable coefficient for that period. In this interpretation the negative dummy variable hints at “repressed” migration potential in East Germany as for that period, which only cancels out in the end of the sample period along with a gradual fading out of labor market and macroeconomic distortions. A similar line of argumentation can be found for a downward sizing in expectations about the speed of convergence in East–West standards of living.

Also for the remaining equations of the PVAR(1), the inclusion of dummy variables gives some interesting results with respect to East–West labor market and macroeconomic disparities. With respect to the unemployment rate, the East dummy shows the expected negative level effect between the Eastern and Western regions even after controlling for key labor market factors and also seems to worsen over time given the strong increase in the coefficient of the dummy variable coefficient. For East German border regions, this negative effect seems to be less present. Another key fact is that growth in labor productivity does not show significant differences for the two macro-regions during the sample period 1994–2006 (after controlling for labor market differences).

This result mirrors empirical results reported in Smolny and Stiegler (2004), finding that productivity adjustment in the East German states was fast in the early years after 1991, but also that the equilibrium gap to the Western average is large (the authors calculate a gap of about 35 percent, which explains the significant reduction in the convergence speed of the East German states starting from the second half of the 1990s). Similar results were also obtained for the wage rate, for which we get insignificant dummy variable coefficients in the PVAR(1). Finally, for both border regions and East Germany as a whole, the human capital equation shows that the region has subsequently lost its initial advantage in human capital endowment. This latter trend is typically associated with the above identified ‘brain drain’ effect for East Germany (see also Schneider 2005). Summing up, these results call for further in-depths studies on the long-run structural differences in key labor market and economic indicators for the two East–West macro-regions almost twenty years after re-unification.

2.8 Conclusion

Throughout this chapter we have analyzed the linkages between regional disparities in labor market variables and interregional migration flows among German states since re-unification. Building upon recent methodological advances in the analysis of (dynamic) panel data models, we have specified a VAR model for panel data using efficient GMM estimation as proposed by Blundell and Bond (1998). One advantage of our chosen approach is that it allows us to appropriately handle the issues of endogeneity, simultaneity and multi-way feedback relationships among variables in the system. By the computation of impulse–response functions, we are able to check for the full dynamic properties of our estimated Panel VAR system and to evaluate the responses of migratory movements to different labor market shocks. Turning to the empirical results, we identify a clear role of regional disparities in the real wage and unemployment rate as major driving forces of internal migration in Germany. We also find that regional differences in labor productivity growth induce net migration flows, while a shock in the labor participation rate affects migratory movements mainly through increased labor market tightness. A positive (relative) shock in the regional human capital endowment attracts net inflows mainly through the link between human capital accumulation and productivity growth as suggested by theoretical growth theory.

Moreover, the dynamic simultaneous nature of our PVAR(1) also allows to work out the feedback effects from migratory movements to regional labor market variables. Here we mainly find that migration has an equilibrating effect on regional labor markets in line with the neoclassical view. That is, a high level of in-migration in region i increases the region's unemployment rate relative to region j , while at the same time the net in-migration lowers regional wage rate differences (the wage in region i decreases relative to j) and thus works towards a cross-regional wage equalization. Responses of labor productivity growth and the labor participation rate with respect to migration are positive but rather small in magnitude, while the revealed effect on human capital hints at the risks of regional 'brain drain' effects for German data given that increased net out-migration flows are not neutral to the regional distribution of human capital endowment but affect the relative regional skill composition. As the analysis of impulse–response functions of the PVAR(1) shows, this deterioration of the regional human capital base (via the migration channel) is largely driven by shocks in the regional unemployment rate.

We finally use the model to analyze the evolution of the two distinct waves of East–West net out-migration up to 2006. Adopting a dummy variable approach to test for structural differences for the whole East German macro region as well as the East–West border regions compared to the German average, we find that throughout the mid-1990s East–West migratory movements did not fully react to regional labor market signals as expected from the PVAR(1) results. The latter finding supports earlier empirical evidence for German and Italian regional data. Likely explanations for this "empirical puzzle" may be seen, e.g., in huge income transfers, the possibility of high East–West commuting and initially very optimistic expectations about the speed of East–West income convergence.

However, by using a recursive estimation strategy, we find that, for subsequent periods, this relationship becomes less stable or even reversed. That is, along with the peak of a second wave of East–West migratory movements around 2001, the East German dummy turns significantly negative. Since this second wave is accompanied by a gradual fading out of macroeconomic distortions such as massive East–West transfers and a downsizing of expectations about the speed of convergence, this supports the view of repressed migration flows out of East Germany for that period given the overall weak labor market and macroeconomic performance. Towards the sample end in 2006, the dummy turns insignificant, indicating that migratory movements between East and West Germany largely react to regional labor market signals. This latter result may be taken as a first hint at an advancing labor market integration between the two macro regions.

Appendix A: Testing for Instrument Validity in the Migration Equation

The inclusion of valid instrumental variables (IV) in the regression model is of vital importance for consistency of the obtained results. A statistical tool to guide IV selection is the Sargan (1958)/Hansen (1982) overidentification test (also denoted as J -statistic). As pointed out by Bowsher (2002) and Roodman (2009), one has to carefully interpret Hansen's J -statistic since it has shrinking power with increasing number of instruments. That is, numerous instruments can over fit the instrumented variables, failing to expunge their endogenous components and biasing coefficient estimates towards those from non-instrumented estimators. In a series of Monte Carlo simulations Bowsher (2002) shows that the J -statistic based on the full instrument set essentially never rejects the null when T becomes too large for a given value of N . The author proposes to reduce the number of lag length employed for estimation in order to improve the size properties of the test.

Alternatively, Roodman (2009) argues in favor of using 'collapsed' instruments, which has the potential advantage of retaining more information since no lags are dropped as instruments. This strategy is equivalent to imposing certain coefficient homogeneity assumptions on the IV set and thus makes the instrument count linear in T . The author further shows that for cases where the 'no conditional heteroscedasticity' (NCH) assumption holds, the simple Sargan (1958) statistic may be used as an appropriate indicator to check for IV consistency, which does not suffer from the above problem since it does not depend on an estimate of the optimal weighting matrix in the two-step GMM approach. Nevertheless, the problem with the Sargan statistic is that the latter performs weak for non normal errors. Our solution to these shortcomings is to combine both test statistics in an IV downward testing approach from the full instrument set to a specification that satisfies both the Sargan as well as Hansen's J -statistic.

Our resulting IV downward testing approach using the long-run migration equation as an example is shown in Table 2.5. In the first column of the table we apply

Table 2.5 Downward testing approach for instrument validity in PVAR model

Dep. var.	r.h.s. var.	I	II	III
$nm_{ij,t}$	$nm_{ij,t-1}$	0.37 ^{***} (0.039)	0.28 ^{***} (0.056)	0.43 ^{***} (0.052)
$nm_{ij,t}$	$\widetilde{w}r_{ij,t-1}$	0.61 ^{***} (0.095)	0.37 ^{***} (0.110)	0.49 ^{***} (0.144)
$nm_{ij,t}$	$\widetilde{u}r_{ij,t-1}$	-0.14 ^{***} (0.034)	-0.23 ^{***} (0.057)	-0.12 ^{***} (0.051)
$nm_{ij,t}$	$\Delta y \widetilde{l}r_{ij,t-1}$	0.61 ^{***} (0.052)	0.43 ^{***} (0.074)	0.66 ^{***} (0.073)
$nm_{ij,t}$	$\widetilde{q}_{ij,t-1}$	0.12 (0.110)	-0.09 (0.307)	0.02 (0.277)
$nm_{ij,t}$	$\widetilde{h}c_{ij,t-1}$	-0.02 [*] (0.011)	-0.02 [*] (0.014)	-0.02 [*] (0.013)
$nm_{ij,t}$	D_{NIE}	-0.21 ^{***} (0.053)	-0.22 ^{***} (0.090)	-0.18 ^{***} (0.055)
(...)				
F -test		219.4 (0.00)	61.18 (0.00)	109.73 (0.00)
RMSE		0.214	0.238	0.204
No. of IVs		459	90	20
Sargan		1671.9 (0.00)	343.3 (0.00)	11.2 (0.59)
Hansen J		239.9 (0.99)	191.3 (0.00)	16.7 (0.21)
C -stat. level-eq.				7.41 (0.28)
$\chi^2_{Het}(7)$				2.18 (0.94)
$\chi^2_m(7)$				10.33 (0.17)

Note: Standard errors are computed based on Windmeijer's (2005) finite-sample correction. χ^2_{Het} : Heteroscedasticity test based on the regression of squared residuals on squared fitted values. χ^2_m : Hausman $|m|$ -statistic based on the absolute values as discussed in Schreiber (2007)

*Denote statistical significance at the 10% level **Denote statistical significance at the 5% level

***Denote statistical significance at the 1% level

the full set of available instruments according to (2.10) and (2.14). Among lagged net migration ($nm_{ij,t-1}$) as right hand side regressor we include regional differences in real wages ($\tilde{w}r_{ij,t-1}$), unemployment rates ($\tilde{u}r_{ij,t-1}$), labor productivity growth ($\Delta \tilde{y}lr_{ij,t-1}$), labor participation ($\tilde{q}_{ij,t-1}$) and human capital ($\tilde{h}c_{ij,t-1}$). We also control for the distortion in the migration pattern for Lower Saxony due to German resettlers by the inclusion of a dummy variable (D_{NIE}).

We see that the Sargan (1958) and Hansen (1982) overidentification tests yield clearly contrasting testing results: While Hansen’s J -statistic does not reject the null hypothesis of the joint validity of the included IV set, the Sargan statistic casts serious doubts on the consistency of the latter. As discussed above, the reason for the divergence in the testing results is the huge number of instruments employed for estimation (a total of 459), which lowers the power of the J -statistic. The huge number of potentially available instruments in the SYS-GMM approach is due to the exponential growth of instrumental variables with increasing time horizon T according to the standard moment condition in (2.10). In order to minimize this problem, in column 2 of Table 2.5 we therefore employ the collapsed IV set, which reduces the number of instruments to 90.

For this specification the Hansen J -statistic now clearly rejects the null of joint validity of the IV set and is thus in line with the Sargan (1958) statistic. This result underlines the point raised by Bowsher (2002) and Roodman (2009) that the J -statistic has no power with increasing number of instruments, while the Sargan test still has. Finally, based on the collapsed IV set we further reduce the number of instruments using a C -statistic based algorithm, which is able to subsequently identify those IV subsets with the highest test results (see Mitze 2009, for details). This gives us a model with a total of 20 instruments, which passes both the Sargan and Hansen J -stat. criteria as reported in Table 2.5.

The regression results show that the estimated parameter coefficients are qualitatively in line with the full IV set specification in column 1. Moreover, the downward tested model also shows to have the smallest RMSE and does not show any sign of heteroscedasticity in the residuals.¹⁷ We finally apply the same estimation strategy for the whole PVAR(1) system, which reduces the number of instruments to 222 (out of a maximum of 2382 in the full ‘uncollapsed’ IV case).

Appendix B: Impulse–Response Functions and In-Sample PVAR(1) Predictions for East–West Net Migration

¹⁷For the latter, we use the approach outlined in Wooldridge (2002) and run a regression of the squared residuals on the squared fitted values.

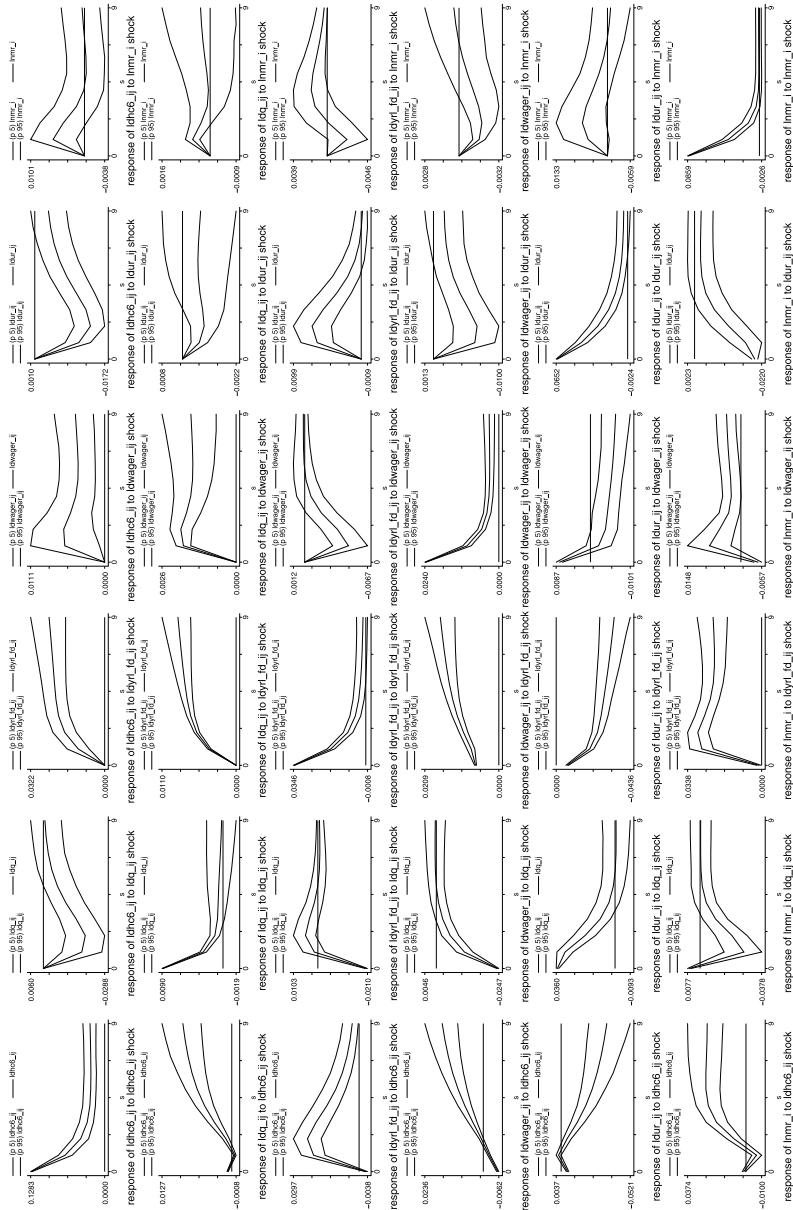


Fig. 2.8 Impulse-responses for $PVAR(1)$, $\tilde{h}c_{ij,t}$, $\tilde{q}_{ij,t}$, $\Delta \tilde{y}r_{ij,t}$, $\tilde{w}r_{ij,t}$, $\tilde{u}r_{ij,t}$, $nm_{ij,t}$. Note: With $nm_{ij,t} = lnmr_ij$, $\tilde{u}r_{ij,t} = ldur_ij$, $\tilde{w}r_{ij,t} = ldwager_ij$, $\Delta \tilde{y}r_{ij,t} = ldyr_fd_ij$, $\tilde{q}_{ij,t} = ldq_ij$, $\tilde{h}c_{ij,t} = ldhc6_ij$

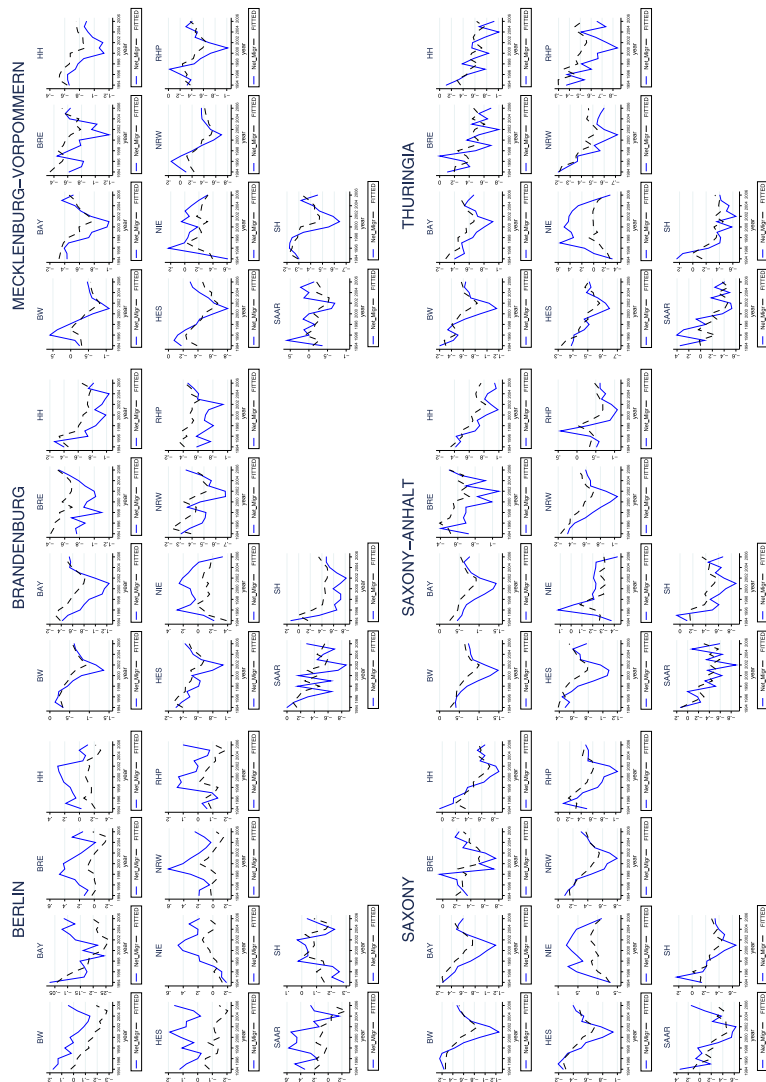


Fig. 2.9 Actual and fitted net migration between East and West German state pairs. *Note:* For details about the computation see text. BW = Baden-Württemberg, BAY = Bavaria, BRE = Bremen, HH = Hamburg, HES = Hessen, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SH = Schleswig-Holstein

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