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## Regional Labor Market Adjustments in the United States and Europe

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**IMF Working Paper**

Research Department

**Regional Labor Market Adjustments in the United States and Europe**

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**Abstract**

We examine patterns of regional adjustments to shocks in the US during the past 40 years. Using state-level data, we estimate the dynamic response of regional employment, unemployment, participation rates and net migration to state-relative labor demand shocks. We find that (i) the long-run effect of a state-specific shock on the state employment level has decreased over time, suggesting less overall net migration in response to a regional shock, (ii) the role of the participation rate as absorber of regional shocks has increased, (iii) the response of net migration to regional shocks is stronger, while that of relative unemployment is weaker during aggregate downturns, and (iv) the change in the response intensity of migration is related to the declining trend in regional dispersion of labor market conditions. Finally, using regional data for a set of 21 European countries, we show that while the short-term response of participation rates to labor demand shocks is typically larger in Europe than in the US, the immediate response of net migration in Europe has increased over time

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## Contents

	Page
I Introduction . . . . .	4
II Statistical properties of regional employment . . . . .	5
III Baseline econometric approach and results . . . . .	7
IV Endogeneity of state labor demand shocks . . . . .	8
A Test of OLS identification assumption . . . . .	8
B Validation of results with migration and population data . . . . .	12
V The evolution of regional adjustment . . . . .	15
A Tracing the evolution of regional adjustment . . . . .	15
B What drives the evolution of regional adjustment? . . . . .	17
VI Regional adjustments in Europe . . . . .	19
VII Concluding remarks . . . . .	21
References . . . . .	22

### Tables

1 Endogeneity and 2SLS: Employment rate ( $le$ ) equation . . . . .	9
2 Endogeneity and 2SLS: Participation rate ( $lp$ ) equation . . . . .	10
3 Direct estimation of migration response to labor market shocks using ACS data. . . . .	15
4 The effect of spatial dispersion on regional adjustment . . . . .	18
5 Persistence of relative regional labor market variables in the EU and US. . . . .	20

### Figures

1 Persistence of Employment Growth Rates across US States, 1976-2011 . . . . .	25
2 Persistence of Unemployment Rates across US States, 1976-2011 . . . . .	25
3 Response of state-relative labor market variables: OLS. . . . .	26
4 Decomposition of adjustment: OLS . . . . .	27
5 Response of state-relative labor market variables: OLS vs. 2SLS. . . . .	28
6 Decomposition of adjustment: OLS vs. 2SLS . . . . .	29
7 Validation with migration and population data . . . . .	30
8 Evolution of migration response . . . . .	31
9 Dispersion of Employment Growth Rates across US States, 1976-2011 . . . . .	32
10 Dispersion of Unemployment Rates across US States, 1976-2011 . . . . .	32
11 State unemployment dispersion and gains from migration . . . . .	33
12 Relative labor market dynamics in the EU . . . . .	34

13	Relative labor market dynamics in the EU: select countries. . . . .	35
14	Sub-sample heterogeneity in EU migration response . . . . .	36

## I. INTRODUCTION

One of the often cited positive features of the US labor market is its high degree of labor mobility, distinguishing it from labor markets in other advanced countries such as continental Europe. The Brookings Paper by Blanchard and Katz (1992), henceforth BK, established some important stylized facts about how states in the US respond to regional shocks in terms of adjustment in unemployment, participation and interstate migration in the post-war period up to 1990. It concludes that interstate migration plays the most important role for adjustments to regional shocks, both in the short as well as long term, more so than regional relative wages or firm reallocation. This is in line with wide-held belief that geographic mobility in the United States is among the highest in the world.

In the decades that followed, facilitated particularly by the availability of new sources for migration data, a large literature has developed documenting various trends in migration in the US as well as other developed countries (see the review in Molloy et al., 2011). One salient trend in aggregate migration that has been widely documented is the steady and widespread reduction in (gross) internal migration rates in the US since the 1980s. Another stylized fact is that internal migration is procyclical in the US, implying higher net benefits to moving in good economic times and vice versa (Molloy and Wozniak, 2011).

In this paper, we first go back to the question in the BK exercise: How have regional labor market flows, including interstate migration and regional labor supply (unemployment and participation), acted as adjustment channels to regional booms and busts in recent years? We go further than just adding 20 years to the BK exercise. Given the availability of migration data starting in 1990, right after the end of the BK sample, we can also directly look at the behavior of migration in response to regional and aggregate shocks, as opposed to treating it as a residual, and thus verify the BK identification assumption. Second, can one detect any shift in adjustment patterns in the last 20 years as compared to the BK findings? We relate our macro findings with those in the micro literature on internal migration and offer some explanation for the declining trend in gross net migration based on our macro level results.

We establish several results that reveal interesting patterns and shifts in regional adjustment mechanisms: First, the long-term effect of a regional shock on the state-relative employment level has declined. Compared to the earlier sample up to 1990, this long-term effect has roughly halved in recent years, suggesting a smaller response of long-term labor reallocation to regional shocks. Second, over time, a given regional shock has triggered less interstate net migration, and a larger response of regional unemployment and participation in the short-run. That is, following the same negative shock to labor demand, affected workers have more and more tended to either drop out of the labor force or remain unemployed instead of relocate, particularly within the first two years of the shock. In addition to the long-term trend, the sensitivity of state-relative participation rates, unemployment, and migration to state-specific shocks has also displayed strong cyclical patterns. Bad times trigger more adjustment through relocation and less adjustment through participation and unemployment in response to state-specific shocks than good times.

We go further by looking at possible determinants of the observed evolution of migration and regional labor supply in response to regional shocks. We find that the spatial dispersion of labor market conditions plays an important role. Spatial dispersion spikes up during recessions and narrows in booms. That means that the net benefit in terms of increased job opportunities for relocating from the low performing regions to the better-performing regions is larger in recessions. This is consistent with our finding that migration responds stronger in recession to a given regional shock than in booms. At the same time, we also observe that the dispersion of labor market conditions has declined over the sample period, notwithstanding the cyclical spikes. This, in turn, seems to be associated with the secular decline in the migration response to regional shocks on average. The lower conditional migration response to regional labor market fluctuations may therefore be one force lowering the gross (unconditional) migration rates in the last two decades, a central question in the current migration literature.

Finally, using regional data for a set of 21 European countries, we investigate the adjustment mechanisms to shocks in Europe and compare the results to those obtained for the US. The results show that while the short-term response of participation rates to labor demand shocks is typically larger in Europe than in the US, in Europe, the immediate response of net migration has increased over time.

The paper proceeds in five sections. In the next section, we provide some key summary statistics of the persistence and dispersion of regional labor market conditions over time. In section III, we revisit the panel VAR framework proposed by BK to update the estimation results and discuss in detail the identification strategy in section IV. In section V, we document the evolution of the regional adjustment mechanism over the past three decades and discuss an underlying force for this evolution. Section VI documents the regional adjustment mechanisms in Europe and how they have evolved over time. Some concluding remarks on macroeconomic implications of our findings are given in Section VI.

## II. STATISTICAL PROPERTIES OF REGIONAL EMPLOYMENT

An important stylized fact from the BK paper is that US states have been experiencing very different growth rates in employment, and that these different growth rates have been consistently sustained over decades from 1950-1990. To see if this observation still holds, we split our sample of state-level data and plot average annual employment growth between 1976 and 1993 against the same average growth rate between 1994 and 2011 by state, as shown in Figure 1.

The first sub-sample largely overlaps with the second half of BK's sample, during which states showed strong employment growth persistence relative to the preceding decades in the postwar period. Looking at Figure 1, it is clear that the persistence of state-specific employment growth rates still holds two decades later. At the top, we have Nevada, Arizona and Utah continuing to grow faster than in the rest of the nation, while Florida and Alaska, traditionally among the top performers, appear to slow relative to the national average. Towards the lower end, we have Michigan increasingly deteriorating, while North and South

Dakota and the District of Columbia have been experiencing a relative surge in employment growth. The slope of the regression line is 0.5 and R squared is 0.7, hence the explanatory power of past for future average employment growth remains largely the same as in the BK sample, although the correlation is somewhat weaker.

A similar picture emerges when we plot the state unemployment rates over the same times period: 1976-1993 against 1994-2011, in Figure 2. As is the case with employment growth, there is a strong positive correlation between past and future average unemployment rates across states, with the slope coefficient being 0.6 and R squared 0.7. One observation to note is that over the two 18-year subsamples, the average employment growth as well as the unemployment rate have become less dispersed across states. This is visible in both Figures 1 and 2, where the vertical axis has a smaller range than the horizontal one and by looking at the sample standard deviation: it falls from 1% to 0.6 % between the two sub-samples for state employment growth, and from 1.4% to 1% for the state unemployment rate. That is, although the average labor market conditions display strong persistence over long time periods, this persistence has somewhat weakened and state fortunes have converged more toward each other. We will come back to this important fact later when interpreting our empirical results.

For the remainder of the analysis, we will look at the joint behavior of state-level labor market variables that should cover different employment statuses. Suppose that each state produces a different bundle of goods, due to different industrial structure, and hence is subject to different shocks or responds differently to aggregate shocks. If a state is hit with a negative relative labor demand shock - that is, relative to the national average - the workers affected either become unemployed, drop out of the labor force, or migrate out of state. We investigate the magnitude and composition of this response by estimating a joint dynamic system in the three state-level variables: employment, unemployment rate, and labor participation rate. For comparability of results, we follow BK in terms of variable specification and estimation method in this section.

All labor market outcome variables are taken from various local and national datasets of the Bureau of Labor Statistics (BLS). In particular, state employment and unemployment data are taken from the Local Area Unemployment Statistics (LAUS) dataset from the BLS, which is in part based on CPS survey data. The state-relative variables are defined in log deviation from their national aggregates. That is, for employment,  $e_s$  is the log employment in state  $s$  minus log employment in the US. Consistent with BK, we find that state-relative employment levels are non-stationary as the hypothesis of a unit root cannot be rejected in the majority of the states as well as using panel unit root tests. We therefore use the first difference  $\Delta e_s$  which corresponds to state-relative employment growth. Unlike the relative employment level, the relative employment/unemployment and participation rates do not exhibit the same persistence and tend to revert to long-term averages. The Im-Pesaran-Shin panel unit root test, allowing for 4 lags, a state-specific constant and a time trend can reject the hypothesis of a unit root for the relative log employment rate (the negative of the relative log unemployment rate)  $le$  and relative log participation rate  $lp$  at the 5 and 10 percent level of significance respectively.

Overall, we can summarize that the employment growth and unemployment rates across states show strong, albeit weakening, persistence. Moreover, this persistence is related to the persistence of the mean of the employment growth and unemployment rates as opposed to persistent deviations from the means, as the stochastic behavior of both variables display strong mean-reversion, a feature already documented by BK. Moreover, a new trend to note is the reduced dispersion of state-level labor market conditions over the last 20 years, an issue we will look into more in detail in section V.

### III. BASELINE ECONOMETRIC APPROACH AND RESULTS

Given the time series properties above, which confirm with the original assessment by BK, we estimate a system of panel VAR equations as follows:

$$\begin{aligned}\Delta e_{st} &= \alpha_{s10} + \alpha_{11}(L)\Delta e_{s,t-1} + \alpha_{12}(L)le_{s,t-1} + \alpha_{13}(L)lp_{s,t-1} + \epsilon_{set}, \\ le_{st} &= \alpha_{s20} + \alpha_{21}(L)\Delta e_{s,t} + \alpha_{22}(L)le_{s,t-1} + \alpha_{23}(L)lp_{s,t-1} + \epsilon_{sut}, \\ lp_{st} &= \alpha_{s30} + \alpha_{31}(L)\Delta e_{s,t} + \alpha_{32}(L)le_{s,t-1} + \alpha_{33}(L)lp_{s,t-1} + \epsilon_{spt}.\end{aligned}\quad (1)$$

We pool all states while allowing for state-specific constant, thus estimate the dynamics of the average state. We include two lags for each variable, following BK, and to keep the degrees of freedom for estimation with shorter sub-samples, though extending up to four lags does not change the estimates substantially. This identification strategy assumes that current unexpected changes to state-relative employment growth within the year primarily reflect movements in regional labor demand. This assumption allows us to estimate the dynamic effects of a 1 percent shock to labor demand in a typical state on its relative unemployment rate, labor participation rate, and as a residual, the net-migration rate from other states. This is because in any period, we can decompose the change in the relative log employment level  $de$  (where  $d$  denotes the change relative to pre-shock baseline) into:

$$de = dle + dlp + m,$$

where  $m$  stands for the implied change in state-relative log working-age population  $d \ln P$ , i.e. the net migration rate following the shock.

There are several ways to estimate the system in 1. Given the identification assumption that current shocks to employment growth are driven by labor demand only,  $\Delta e_{s,t}$  is weakly exogenous to the equations for  $le$  and  $lp$  and the system can be consistently estimated by OLS equation-by-equation, which is the estimation we use. The results are identical to transforming the system to a reduced form VAR and order employment growth first. Finally, we also use panel GMM to estimate the system to control for potential inconsistency of the fixed effects in the presence of lagged dependent variable. Given the long time series, the difference in estimation results is marginal (results not shown but available). The impulse responses estimated using OLS for the whole sample to a negative 1 percent shock to relative labor demand are plotted in Figure 3, with standard errors computed using Monte Carlo simulations with 500 replications.

In the first year, a 1 percent shock to labor demand raises the state-relative unemployment rate by 0.22 percentage points and lowers the participation rate by 0.24 percentage points, with the effect peaking at 0.29 and -0.34 percentage points after 2 years respectively. The effect on the relative employment level peaks after four years at -1.73 percent, before decreasing gradually to a long-run value of around -1.2 percent. Hence over the long run, an initial shock of 1 percent leads to a permanent loss of 1.2 percent in the employment level, while employment *growth*, as well as unemployment and participation rates revert to the pre-shock average eventually. That is, interstate migration following the regional shock drives permanent changes in relative employment levels. It is perhaps more instructive to look at changes in terms of number of workers instead of the rates. Figure 4 decomposes the employment response following a 1 percent negative labor demand shock corresponding to 1 worker to the different margins of adjustments: increase in unemployment, decrease in participation and (negative) net migration (all measured in number workers). Of every 10 workers that lose employment, 2 workers become unemployed, 2 drop out of the labor force, and 6 worker migrate out of state within the first year following the shock. Compared to the BK results, the role of the participation margin increased (from 5 to 20 %), that of unemployment decreased (from 30 to 20 %) while net out-migration accounted for roughly the same 60 percent of the shock within the first year.

#### IV. ENDOGENEITY OF STATE LABOR DEMAND SHOCKS

##### A. Test of OLS identification assumption

Before moving on to analyze the evolution over time of regional adjustment, which is the main goal of this paper, we step back to test the identification assumption of BK that was used for the OLS estimation above, as well as by many other studies on labor mobility (see e.g. Decressin and Fatas, 1995; Jimeno and Bentolila, 1998). The crucial assumption is that unexpected shocks to relative employment growth  $\epsilon_{set}$  in the first equation of the system in 1 are purely state-relative labor *demand* shocks. This is equivalent to assuming that the contemporaneous employment growth  $\Delta e_{s,t}$  is (weakly) exogenous in the second and third equation of the system 1. To test this assumption, we consider two instrumental variables (IVs). The first IV is the so-called industry shift or industry mix variable, first proposed by Bartik (1991) and subsequently used extensively in the urban/regional economics literature: It measures the predicted employment growth in each state based on the state's industrial composition of employment and the nation-wide employment growth of each industry. That is, the instrument  $imix_{st}$  is defined as:

$$imix_{s,t} = \sum_{j=1}^J [(e_{sjt} + \dots + e_{sjt-4}) / (e_{st} + \dots + e_{st-4})] \Delta \ln(\bar{e}_{jt}), \quad (2)$$

where the state-specific industry share of employment is taken as a 5-year moving average to avoid endogeneity with respect to current regional labor market conditions. The state-level industry employment shares as well as the national employment growth rates ( $\Delta \ln(\bar{e}_{jt})$ ) are taken from the Bureau of Economic Analysis (BEA) Regional Economic Accounts (Table SA25). The industries  $j$  are based on 20 2-digit code SIC industries up until 2000, and 20

2-digit code NAICS industries starting in 2001, both cover the whole economy, excluding the public sector. The identification relies on the plausible assumption that an industry's national growth rate is uncorrelated with state-specific labor supply shocks. The second IV we consider picks up exogenous changes to state-level labor demand in oil and gas extraction industries triggered by changes to aggregate oil prices. That is, we have:

$$oil_{s,t} = \left[ (e_{st}^{o\&g} + \dots + e_{st-4}^{o\&g}) / (e_{st} + \dots + e_{st-4}) \right] \Delta \ln \left( \frac{\bar{P}^{oil}}{\bar{P} \bar{P} I} \right)_t, \quad (3)$$

where for each state, the aggregate relative price of oil (crude oil relative to national PPI) is interacted with the state-specific employment share in oil and gas extraction industries (computed in 5-year moving average). While the first IV measures state-level labor demand based on state-specific overall industrial composition and aggregate sectoral employment growth, the second IV picks up state-level labor demand variation driven by one particular sector (oil and gas) which plays a very important role in some states and less in others, hence the heterogeneity over time and space.<sup>1</sup>

Table 1: Endogeneity and 2SLS: Employment rate ( $le$ ) equation

	OLS	2SLS		
$\Delta \ln(e_t)$	0.241*** (0.023)	0.656*** (0.080)	0.438*** (0.114)	0.645*** (0.082)
Hausman test (p)	0.00	0.07	0.00	0.00
1st Stage				
<i>imix</i>		0.88*** (0.118)		0.776*** (0.146)
<i>oil</i>			0.405*** (0.087)	0.283*** (0.087)
F stat	-	55.76	21.38	31.29
N	1736	1683	1460	1409

*Note:* The instruments *imix* and *oil* are as defined in equations 2 and 3 in the text. Robust standard errors in parenthesis. All regressions also include the set of lagged variables as in each equation of the system in 1 as well as state and time fixed effects.

Using  $imix_{st}$  to instrument for  $\Delta \ln e_{s,t}$  in the equations for employment rate  $le$  and participation rate  $lp$ , we obtain the 2 SLS results summarized in Table 1 and Table 2 respectively. In each table, we first present the OLS results underlying the IRF in Figure 3. The second and third column in each table shows the 2SLS using each of the two IVs, while the last column shows the 2SLS result using both IVs. Let us first look at the employment rate regressions. First of all, both IVs show strong positive correlation with contemporaneous

<sup>1</sup>Variants of this IV have also been used in e.g. Molloy and Wozniak (2011) and Gallin (2004).

Table 2: Endogeneity and 2SLS: Participation rate ( $lp$ ) equation

	OLS	2SLS		
$\Delta \ln(e_t)$	0.387*** (0.025)	0.154* (0.084)	0.380*** (0.116)	0.180*** (0.077)
Hausman test (p)		0.00	0.78	0.00
1st Stage				
<i>imix</i>		0.88*** (0.118)		0.776*** (0.146)
<i>oil</i>			0.405*** (0.087)	0.283*** (0.087)
F stat		55.76	21.38	31.29
N	1736	1683	1460	1409

*Note:* The instruments *imix* and *oil* are as defined in equations 2 and 3 in the text. Robust standard errors in parenthesis. All regressions also include the set of lagged variables as in each equation of the system in 1 as well as state and time fixed effects.

employment growth, with the industry mix variable being the stronger of the two as it picks up more variation across different industries (reflected in larger 1st stage coefficient and higher F statistics). In fact, when both IVs are used, the second stage estimate is close to the one with only *imix* as the IV, due to the much stronger first stage coefficient on *imix* compared to *oil*. Second, the second stage results, no matter using which IV, reveal a much stronger response of the state-relative employment (or unemployment) rate to state-specific labor demand shocks than do OLS results: a 1 percent negative employment shock from labor demand reduces the employment rate by 0.65 (or 0.44 using the oil IV) instead of 0.24 percent. The Hausman test therefore clearly suggests a rejection of the exogeneity assumption in the OLS regression used by BK.

Results for the participation rate equation in Table 2 using the industry mix variable (either as the only IV or with together with the oil IV) also lead to rejection of the OLS identification assumption. The response of state-relative participation rate is in fact smaller using the IV compared with OLS: a 1 percent negative employment shock reduces the participation rate by 0.15 to 0.18 percent instead of 0.39 percent with OLS. The second stage estimate is close to the OLS result when the oil IV is used alone to identify state-specific labor demand shock. However, the oil IV turns out to be only a weak instrument as it reduces the first stage F statistics when added to the industry mix 2SLS regression (also the case in the employment rate equation) and hence is likely to have a larger bias towards the OLS estimate. Our application is an example of the so-called treatment effect/parameter heterogeneity discussed in Angrist and Imbens (1995). There are many reasons to expect that states with different industrial composition respond differently to sector-specific shocks. In particular, the oil price shock only picks up labor demand changes in oil-producing states, a subpopulation that

is bound to behave differently than states with no relevant oil and gas industry employment, even if hit with a labor demand shock of the same size. Hence this heterogeneity among states in response to different instruments leads to different estimates in the second stage, each specific to the subpopulation (i.e. set of states) that respond to the instrument's "treatment".<sup>2</sup> As the industry mix variable affects a larger set of states than the oil IV and is shown to be the dominant source of variation in the multiple IV regression, we choose it to be the preferred IV for the identification of state-specific labor demand shocks from now on.<sup>3</sup>

To trace the joint dynamic response of each labor market variable to a regional labor demand shock using the industry mix variable, we estimate the following VAR system with  $imix$  being an exogenous forcing variable:

$$\begin{aligned}\Delta e_{st} &= \alpha_{s10} + \alpha_{11}(L)imix_{s,t} + \beta_{11}(L)\Delta e_{s,t-1} + \beta_{12}(L)le_{s,t-1} + \beta_{13}(L)lp_{s,t-1} + \epsilon_{set}, \\ le_{st} &= \beta_{s20} + \alpha_{21}(L)imix_{s,t} + \beta_{21}(L)\Delta e_{s,t-1} + \beta_{22}(L)le_{s,t-1} + \beta_{23}(L)lp_{s,t-1} + \epsilon_{sut}, \\ lp_{st} &= \beta_{s30} + \alpha_{31}(L)imix_{s,t} + \beta_{31}(L)\Delta e_{s,t-1} + \beta_{32}(L)le_{s,t-1} + \beta_{33}(L)lp_{s,t-1} + \epsilon_{spt}.\end{aligned}\quad (4)$$

To illustrate the difference between the OLS and the IV estimates for the regional adjustment mechanism, in Figure 5, we plot the response of the each labor market variable, including net migration, to a 1 percent labor demand shock. As already implied by the parameter estimates in Table 1, the response of state-relative unemployment rate to a given 1 % labor demand shock is much stronger using the 2SLS identification in the first two years following the shock, whereas the participation rate responds less at all horizons. The net migration response is also substantially weaker than under OLS within the first year: a 1 % labor demand shock reduces the working-age population by 0.1 % instead of 0.4 % through net migration. While the migration response after 2 to 5 years is broadly similar across the two estimations, the long-term adjustment through net migration is by a third weaker, leading to a smaller total employment level change under 2SLS (around 0.8 % instead of 1.2 %). It is also instructive to look at the decomposition chart in Figure 6 corresponding to the impulse response results. The decomposition of a 1 worker negative labor demand shock to changes in the pool of unemployed, non-participating, and net migrating workers gives an overview of the proportion of adjustment margins, particularly in the short-term. The same decomposition chart as in Figure 4 using OLS is compared against that obtained under 2SLS using the preferred  $imix$  IV as well as the  $oil$  IV as described above. The main difference is that the share of workers joining the pool of unemployed is much larger under the 2SLS estimation: between 46 and 75 % compared to 19 % of the workers losing employment join the unemployment pool within the first year and between 60 and 80 % instead of 22 % within

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<sup>2</sup>This treatment effect heterogeneity also renders the usual test for over-identifying restrictions uninformative as it becomes rather a test of treatment effect homogeneity.

<sup>3</sup>We have also tried adding a third instrument: the relative oil price change interacted with the intensity of oil usage in state-specific production, measured by petroleum use in barrels per chained 2005 Dollar of real GDP (data from the Energy Information Administration: [www.eia.gov/states/seds/](http://www.eia.gov/states/seds/)). The first stage is as expected negative but conditional on the industry mix IV, this third IV does not add any additional variation/information to the estimation and results are almost identical to those using  $imix$  alone, most probably because  $imix$  already incorporates variation in industries' sensitivity to oil price changes.

2 years of the shock. Consequently, the share of workers leaving the state upon a negative employment shock is much smaller under 2SLS: only 13% or 30%, depending on the IV, instead of 61% of job losers leave the state within the first year. It is these short-term adjustments that should be of higher relevance to the empirical analysis; the long-term adjustment of the regional labor markets are not much affected by the estimation strategy as by definition, the unemployment and participation rate go back to pre-shock levels and all adjustment is accounted for by net migration.

Overall, the IV identification reveals a lower degree of inter-state worker mobility in response to state-relative labor demand shocks and in turn, a larger response of state-relative unemployment rates in the short run, reflected in smaller share of net-migration and larger share of unemployment flows conditional on a given size of labor demand shock. In the long-run, the *total magnitude* of inter-state migration which pins down the change in state-relative employment level is lower than previously identified through OLS estimations.

## B. Validation of results with migration and population data

So far, the measured inter-state migration was backed out from the response of the employment and participation rates (as they jointly pin down the change in working-age population). It would be interesting to compare this derived response with one that is estimated using migration data directly. This is what we do in the following, using three different sets of inter-state migration and population data.

The first migration dataset we use is the annual *State Population Estimates and Demographic Components of Change* data from the US Census Bureau's Population Estimates Program. The annual population estimates start with the decennial census data as benchmarks and add annual population component of change data, that is births, deaths, internal migration, immigration, emigration, and Federal (armed forces and civilian) movements, which derive from various governmental administrative records (national and local) and census distributions.<sup>4</sup> In particular, state-level net domestic migration, our variable of interest, is derived by computing the net migration rate implied by the share of tax filers and dependents (equal exemptions) who changed addresses between any two tax filings based on IRS supplied Federal tax returns for the population 64 years and younger, and the implied net migration rate from the Medicare enrollment data for the population 65 years and older. This methodology to account for domestic migration (and separately, for international migration), was only introduced for the post-1990 population estimates, with the previous years' estimates only accounting for births and deaths and other components of change lumped into one residual. The available sample of state-level domestic net migration data therefore starts in 1991 and currently goes up until 2011.

We estimate the following equation using the interstate migration data:

$$m_{st} = \alpha_s + \gamma_t + \beta(L)m_{s,t-1} + \gamma(L)imix_{s,t} + \epsilon_{st}, \quad (5)$$

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<sup>4</sup>See detailed description in the U.S. Census Bureau, Statistical Abstract of the United States: 2000.

where  $m_{st}$  is the state migration rate, i.e. total domestic net migration as a share of initial state population, detrended by a state-specific linear trend. The labor demand shock is identified by the same method using the contemporaneous change in employment predicted by a state's industrial composition  $imix$ . Furthermore, two lags of the dependent variable and the exogenous variable are allowed to be consistent with the VAR specification. The estimating equation is left parsimonious to infer the unrestricted response of migration to the labor demand shock. However, results are little changed if other lagged dependent variables of the VAR system 4 are also included as right hand side variables in (5). To compare the backed-out migration response using the VAR with those using migration data directly, we simulate the cumulative response of net migration implied by the estimated equation (5), with the cumulative response of the working-age population from 4 following a shock to  $imix$  of the same size (in this case, 1.13 percent, which leads to 1 percent increase in contemporaneous relative employment growth). To make the same comparison for the OLS identification, we estimate equation (5) with labor demand identified by unexpected relative employment growth  $\Delta e_{st}$  instead of  $imix$ , and compare the simulated response with the one backed out from the OLS system in (1). That is, we estimate:

$$m_{st} = \alpha_s + \gamma_t + \beta(L)m_{s,t-1} + \gamma(L)\Delta e_{s,t} + \delta_1(L)le_{s,t-1} + \delta_2(L)lp_{s,t-1} + \epsilon_{s,t}, \quad (6)$$

In this case, we also include the other lagged endogenous variables on the left hand side of the VAR system 1, so that a contemporaneous change to  $\Delta e_{st}$  is the same unexpected innovation as the one captured in the VAR. Also, the paths of  $\Delta e_{st}$ ,  $le_{st}$  and  $lp_{st}$  are calibrated to exactly match the VAR-implied IRF paths. Note that for this validation exercise, we re-estimate the VAR systems 1 and 4 using the same sample period as that available for equation 5 and 6, namely 1991-2011.

The second dataset we use is the state-level civilian noninstitutional population (16 years and older), also taken from the LAUS dataset of the BLS, which exists from 1976. We estimate the same equations 5 and 6 using population growth instead of net migration rates and cumulate the changes to get the total response of working-age population to a labor demand shock. Figure 7 plots the implied response of state-level population to a 1 percent labor demand shock from the VAR and direct estimation using net migration (upper panel) and population data (lower panel). All changes are expressed in percentage of initial working-age population.

Comparing the left two charts to the right ones, we can clearly see that the identification of state-relative labor demand shocks using  $imix$  leads to a much closer result between the VAR model and the data directly, particularly in the short and medium run. In the case using migration data, the response is somewhat larger than the model-implied one in the longer run. This is not surprising as the Census bureau's migration data covers net migration of all ages instead of just 16 years and older as used in the definition of employment and participation rates. Therefore, subject to the same shock, if over time, children and teenagers also respond to labor demand shocks (by following their families), this of course would lead to a larger overall population change. In the case using LAUS working-age population data, the data and model-implied responses are very close to each other using the IV identification. The

right hand side charts using the OLS identification show instead a large discrepancy between the VAR-implied responses to the same labor demand shock and those estimated from migration and population data directly. The consistency of results derived from the VAR using the IV identification with those obtained by direct estimates with migration and population data therefore strongly supports the estimation approach using *imix* as measure of shocks to regional labor demand.

We do one last check of the VAR implied and directly estimated migration response by using the American Community Survey (ACS) data, which is a nation-wide survey by the US Census Bureau that started in 2005 to collect similar information as the decennial census, but at an annual frequency.<sup>5</sup> The advantage of this data is that we can construct annual net migration rates by age groups (as it is based on annual individual and household surveys instead of estimated as in the intercensal *Population Estimates*), and hence explicitly look at working-age migration rates. The big disadvantage is that net migration rates are only available starting 2007 until 2011, hence not allowing us to estimate dynamic paths of adjustment as we did using longer time series of migration and population data above. We therefore only look at the short-term response of migration to labor market shocks, i.e. maximum 2 years after the shock.

To validate the identification strategy using *imix*, we first estimate a similar equation as (5) using the ACS (working-age) migration rates by state, but without lagged dependent variable as the 5 year sample is too short to alleviate concerns about fixed effect bias. To account for the dynamics of the dependent variable, we also estimate the equation by GLS by allowing for first order autocorrelation in the residual in addition to OLS. Due to the short sample, we only include the current value of *imix* and its first lag; extending up to 2 lags would not change the results but reduces efficiency. Similarly, to validate the OLS identification, we also estimate a similar equation as 5, but with current and lagged employment growth instead of *imix*, as well as lagged employment and participation rates. The results are summarized in Table 3.

Although both identifications give a positive statistically significant response of working-age population migration to a state-relative labor demand shock within 2 years, only the estimation using *imix* for labor demand leads to a cumulative change that is not statistically different from the one obtained under the VAR (which is 0.494 percent after 2 years), with most of the response occurring with a 1 year lag. Using the OLS identification, the response is much smaller, occurring mostly in the current year, and the equality with the VAR implied response of 0.651 can be strongly rejected.<sup>6</sup>

To conclude, the validation exercise using three different datasets provides supporting evidence for the identification strategy adopted in the VAR system with the *imix* variable in

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<sup>5</sup>Information from the survey generates data that help determine how federal and state funds are distributed each year.

<sup>6</sup>These VAR implied responses are computed based on estimates over 1990-2011, hence a longer sample than the ACS data coverage. The consistency between ACS estimated and VAR implied migration responses rely on the stability of migration response over the 1990-2011 period, an issue we will take up in the following section.

Table 3: Direct estimation of migration response to labor market shocks using ACS data.

<i>Dependent variable:</i>	ACS migration rate			
	OLS (1)	GLS (2)	OLS (3)	GLS (4)
$imix_{s,t}$	-0.186 (0.178)	-0.199 (0.156)	-	-
$imix_{s,t-1}$	0.338** (0.142)	0.402** (0.166)	-	-
$\Delta e_{s,t}$	-	-	0.092** (0.034)	0.182*** (0.049)
$\Delta e_{s,t-1}$	-	-	-0.025 (0.028)	-0.366 (0.043)
$H_0 : cum.\Delta \ln Pop = VAR$ (p-val)	0.18	0.40	0.00	0.00
$N$	255	204	255	204
$R^2$	0.07	0.09	0.06	0.09

*Note:* ACS migration rates (measured as working-age net migrants/initial working-age population by state) are detrended using state-specific linear trends. Robust standard errors in parenthesis. All regressions also include a set of state and time fixed effects. Column (3) and (4) also include  $le_{s,t-1}$  and  $lp_{s,t-1}$ . The p-values derive from a Wald test that the cumulative effect of 1 percent labor demand shock on population change is equal to the one obtained under the corresponding VAR model.

Equation 4. By the same token, it also confirms that at least in the short-run, state-level shocks are absorbed to a larger extent by state-level unemployment instead of interstate migration, in contrast to the original result in BK.

## V. THE EVOLUTION OF REGIONAL ADJUSTMENT

### A. Tracing the evolution of regional adjustment

One major purpose of the paper is to document whether patterns and channels of regional adjustments have changed over time. Having outlined an estimation framework that is supported by different datasets, we now embark on measuring dynamic evolution of the estimates over time. Given the same size regional shock, how has the propensity to migrate, become unemployed, or drop out of the labor force changed over the last 35 years? Do changes follow a cyclical or long-term pattern? To answer this question, we choose the following estimation strategy. We implement two sets of expanding window regressions: First, we estimate the VAR system in 4 from 1976 to 1990. We then expand the sample by adding one year at a time and re-estimate the VAR. The difference in estimates between any consecutive expanding windows reflects solely the contribution of the last year of observation. This allows us to construct annual changes between 1990 and 2011 to any

statistics of interest as opposed to using rolling window regressions.<sup>7</sup> To obtain annual changes to the model's estimates in the older sub-period 1976-1990, we apply a backward expanding window regression: We first estimate the VAR system over 1991-2011, and then add one past year to the beginning of the sample at a time, starting with 1990 and going back until 1976.

For each sub-sample window, we estimate the VAR as in 4 calculate the implied propensity to migrate, become unemployed or drop out of the labor force given a negative labor demand shock of 1 worker, that is, the relative length of each bar in Figure 6. We calculate the change of each adjustment margin in each year by comparing the consecutive expanding window regressions and plot the level series, standardized at 100 for 1976. The evolution of the migration, unemployment and participation response is given in Figure 8.

Looking at the evolution of migration response, two features stand out: First, migration adjustment to a given state labor demand shock increases during downturns. Second: since the mid 1980's, there has been a declining trend in migration adjustment during normal times (i.e. apart from the spikes during recessions). In fact, starting in 1985 until just before the Great Recession, the propensity to migrate in response to a given labor demand shock has decreased by more than half. Of course, fluctuations in migration response have to be compensated by other margins of adjustment. Corresponding to the cyclical and secular pattern of migration response, we observe a decrease in unemployment response during downturns and an increasing trend since the mid 1980's in participation response (which roughly tripled between 1985 and 2006). To sum up, ever since the mid 1980's, in response to a given state labor demand shock, affected workers tended less to migrate out of state and instead were more inclined to drop out of the labor force in the first year following the shock. Notwithstanding this long-term trend, the propensity to migrate following a shock increased greatly around each recession, reducing the response of state unemployment in return. The response of state-relative participation does not appear to exhibit cyclical swings but is dominated by a secularly increasing trend since 1985 instead. Most of these patterns also hold for the relative magnitudes of adjustment within 2 years of the shock, while longer-term adjustments are more stable over the years.

The finding that the propensity to migrate conditional on a given demand shock has been steadily declining since the 1980's connects to the growing literature that documents and attempts to explain a secular decline in the gross migration rate in the US starting around the same time, see e.g. Molloy et al. (2011). The potential explanation that we raise is that this overall decline is at least partially driven by a declining trend in the *conditional* response of net migration to regional labor market shocks. That is, for the same difference in labor demand between two states, there is now less outflow from the worse performing state and less inflow into the better performing state, leading to a decrease in gross migration rates in these states. Our second finding, that the propensity to migrate in response to relative labor demand shocks is counter-cyclical, may seem at odds with the finding in the literature that internal migration rates in the US are pro-cyclical, as in Molloy and Wozniak (2011).

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<sup>7</sup>These methods have been widely used in the finance literature, in particular for forecasting purposes. See e.g. Pesaran and Timmerman (2002).

However, the counter-cyclicality we document applies to the *conditional* migration response to shocks, or the importance of migration as a channel of adjustment relative to state-specific employment rate adjustment, while the pro-cyclicality is found after accounting for relative local economic conditions. This pro-cyclical migration is likely caused by other factors, particularly as it is driven by migration of younger workers and those more marginally attached to the labor force (Molloy and Wozniak, 2011).

## B. What drives the evolution of regional adjustment?

Having established the cyclical pattern as well as the evolution of regional adjustment over the last 36 years, we now turn to the possible drivers of these changes. Exploring the reason behind the change in migration response, for example, has important implications for the efficiency of the aggregate labor market and policy. Is the reduced migration response to labor market shocks over time a result of increased frictions that impede labor mobility or an efficient reaction of economic agents to shifts in fundamentals?

We approach this question by first looking at the some statistics describing the dispersion of regional labor market conditions over time. Figures 9 and 10 show the spatial dispersion measured as standard deviation of state-level employment growth rates and unemployment rates at each year over the sample period. We note a striking parallel to the evolution of the migration response in Figure 8: the dispersion of labor market conditions spikes up during recessions, while on average has been decreasing during normal times. That is, recessions were times when the dispersion among states increased at the same time as the propensity to migrate for given labor demand differential was higher. On the other hand, states' labor market conditions have been increasingly less dispersed/ more similar during normal times, at the same time as the propensity to migrate for a given labor demand differential has been decreasing. We confirm the magnitude and statistical significance of this correlation between dispersion and migration propensity by running some simple regressions summarized in Table 4.

Confirming the visual inspection, the regressions show that the response of migration to a given regional labor market shock has weakened over time (negative time trend), while that of participation has increased (since the mid 1980s). That is, given the same, say negative, relative labor market shock, affected workers have tended more to drop out of the labor market than to migrate out of state. Accounting for the dynamics of spatial dispersion of state unemployment explains virtually all of the secular decline in migration response (column 2). That is, the declining dispersion of labor market conditions drives the decreased migration response to a *given* shock to a state's labor market. Why is that? Suppose state relative unemployment follows a symmetric distribution around zero (deviation from national mean) as in Figure 11, brown line. The secular decline in dispersion then corresponds to a mean-preserving spread of this distribution's density function (blue line). Now consider a given negative shock to state unemployment from say the mean to  $x_0 > 0$  under both distributions. A worker that experiences the bad shock may migrate out of state to a state with lower unemployment  $u_s < x_0$ . The conditional mean unemployment rate he can expect under the brown distribution is larger than under the less dispersed blue distribution as more

Table 4: The effect of spatial dispersion on regional adjustment

	(1) M-shr	(2) M-shr	(3) U-shr	(4) P-shr	(5) P-shr <i>from 1984</i>	(6) P-shr <i>from 1984</i>
trend	-0.013** (0.006)	-0.003 (0.004)	-	-	0.033*** (0.009)	0.019*** (0.004)
$I_t^{rec}$	-0.015 (0.094)	0.070 (0.092)	-0.058* (0.032)	0.341 (0.319)	-0.004 (0.130)	-0.121 (0.076)
$I_{t-1}^{rec}$	0.299*** (0.094)	0.072 (0.074)	-0.020 (0.030)	0.258 (0.263)	-0.130 (0.189)	0.115 (0.111)
$\sigma(UR)_t$		0.470*** (0.079)	-0.061** (0.029)	-0.479** (0.189)	-	-0.633*** (0.083)
N	34	34	34	34	28	28
r2	0.334	0.623	0.317	0.181	0.465	0.839

*Note:* The dependent variables are the log share of adjustment through each of the 3 margins (M-shr: migration, U-shr: unemployment and P-shr: participation) as calculated in Figure 8. Robust standard errors in parenthesis.  $I_t^{rec}$  is a dummy variable for NBER recession years and  $\sigma(UR)_t$  is the standard deviation of unemployment rates across states for each year.

mass is placed on the left end of the support. Therefore if migration costs are constant under both distributions, then given the higher expected gains with more dispersed state unemployment rates, the propensity to migrate is also higher, even if the shock under both distributions is the same. The same argument holds for a positive shock and the decision for inward migration. The dynamics of spatial dispersion at the business cycle frequency also explain the cyclical pattern of migration response (columns 1, 2): recessions are episodes with increased dispersion and thus stronger migration response to regional shocks. Indeed, including the dispersion variable in the regression in column 2 explains most of the spikes in recessions captured in column 1.

If migration is less likely to act as a channel for adjustment to regional shocks when dispersions become smaller, the role for state-relative unemployment rate and/or participation rates in the adjustment process must increase. Indeed the dispersion variable is statistically significant in the unemployment and participation regressions (columns 3-5) and has the opposite sign as in the migration equation. The dispersion variable explains any cyclical variation in participation response (column 5), while some cyclical pattern of unemployment response appears to be driven by other factors beyond dispersion (column 3).<sup>8</sup> Regarding the long-term trend, declining dispersion explains some, but not all of the positive trend in participation response since the mid 1980s.

<sup>8</sup>One such factor could be the dynamics of relative real wage rigidity. The lack of state specific CPI series makes it difficult to test this.

The secular decline in spatial dispersion has been discussed elsewhere for the US labor market, for example by Kaplan and Schulhofer-Wohl (2013), who show that the mix of jobs and the income for a worker in a particular occupation/industry has become more and more similar across states in the past 20 years. Importantly, they also argue that this decline in geographic dispersion explains a large share of the decline in gross inter-state migration rates using micro data. While the decline in gross migration rates may be a result of smaller state-specific shocks due to more similar labor markets, we show that even in response to equally large shocks, less dispersion implies less net-migration.

Geography also has an important role for the propagation of business cycle shocks. Indeed, the cyclicity of spatial dispersion of unemployment has been documented for the US for example by Fogli et al. (2012) and holds also at the much more disaggregate county level. Geographic specialization obviously plays a role: as some industries (e.g. auto industry around Detroit, construction industry in Las Vegas) are more cyclical, that is, sensitive to aggregate shocks than others, a recession hits regions specializing in these cyclical industries harder, increasing the dispersion of unemployment across regions. But even absent geographic specialization, if prior to a recession, most regions have relatively low unemployment, and at the onset of the recession unemployment increases in some states but not in others, dispersion will increase (whether these states are spatially concentrated or not). Our contribution is to link this cyclical pattern of spatial dispersion with the cyclicity of conditional net-migration.

## VI. REGIONAL ADJUSTMENTS IN EUROPE

This section replicates the baseline BK analysis of labor adjustments done for the US for a sample of 21 European economies. The labor market outcome variables are taken from the OECD Regional Statistics database (last update 2011) which provides data for 173 macro regions corresponding to the Eurostat NUTS 1 classification- for 21 European (OECD) countries over the period 1998-2009.

Before turning to the analysis of how shocks to regional labor demand in Europe are absorbed, it is useful to look at the persistence of employment, unemployment and participation. To do so, we estimate the following simple univariate processes for each of the three labor market variables:

$$x_{it} = \alpha_{it} + \alpha(L)x_{it} + \nu_{it}, \quad (7)$$

where  $x$  stands for the employment growth, unemployment rate and participation rate of the region relative to the EU average. These regressions pool the entire sample and allow for region-specific fixed effects. Table 5 shows the estimates for each of the labor outcome variables we considered. The corresponding estimates for the US are given for comparison (based on the same sample period).

Table 5: Persistence of relative regional labor market variables in the EU and US.

	EU		US	
	1st lag	2nd lag	1st lag	2nd lag
Employment growth	0.009 (0.045)	-0.096* (0.053)	0.302*** (0.050)	-0.233*** (0.052)
Unemployment rate	1.074*** (0.178)	-0.212 (0.155)	1.154*** (0.078)	-0.360*** (0.090)
Participation rate	0.960*** (0.111)	-0.033 (0.144)	0.952*** (0.049)	-0.197*** (0.045)

*Note:* Variables are defined in annual deviation from EU average and US national average respectively. Robust standard errors, clustered at the regional level, are reported in parenthesis. Period covered: 1998-2009.

Looking at the results for employment growth it is possible to see that employment growth in European regions is not very persistent and much less so than in the US. Given this low degree of persistence in employment growth, shocks to regional employment are likely to have weak long-run effect on population change and hence the employment level. In contrast, deviations in regional unemployment tend to be highly persistent, more so than for the US (where mean reversion is stronger). Finally, looking at the response of labor participation to shocks, it seems that also regional deviations in participation rates tend to be more persistent than in the US.

The evidence that deviations of regional unemployment rates and participation are persistent in Europe may suggest that regional employment shocks tend to be largely absorbed by changes in regional unemployment rates and labor force, rather than by interregional migration flows, as in the US. In order to provide further support for this evidence, we make use of the BK framework to formally analyze the joint behavior of regional relative employment, relative unemployment rate and relative participation in response to labor demand shocks and compare the results to those presented in the previous section for the US.

Figure 12 top panel shows the impulse response of employment, the employment rate, and labor force participation to a 1 percent shock in relative labor demand. In the first year, a 1 percent (negative) shock to labor demand reduces the region-relative employment rate by 0.16 percentage points and the participation rate by 0.6 percentage points. Over the long run, an initial shock of 1 percent leads to a decrease of about 0.4 percent in the employment level, while employment growth, as well as unemployment and participation rates revert to the pre-shock average eventually. That is, interstate migration following the regional shock drives permanent changes in relative employment levels.

By looking at changes in terms of number of workers instead of the rates, Figure 12 bottom panel decomposes the employment response following a 1 percent negative labor demand shock corresponding to 1 worker to the different margins of adjustments: increase in unemployment, decrease in participation and (negative) net migration (all measured in

number workers). Of every 10 workers that lose employment, about 1 worker becomes unemployed, about 6 drop out of the labor force, and about 3 workers migrate out of state within the first year following the shock.

Comparing the results for Europe to those from the US, the main difference arises from the roles played by labor force participation and migration. In particular, compared to the OLS results for the US, the role of the participation margin is significantly larger in Europe than in the US (60% of shock absorbed in Europe compared to 20% in the US), while the role of net out-migration as shock absorber is significantly smaller (30% of shock absorbed in Europe compared to 60% in the US).

We check whether the relative weak response of regional migration to labor demand shocks in Europe is the result of the reluctance of people to migrate across countries or the reluctance to migrate even within countries. To this purpose, we have analyzed the response of regional labor demand shock within countries and separately re-estimated the BK framework for each of the country in the sample. The results vary considerably across countries. While migration acts as the main shock absorber for some countries (such as Germany, Figure 13 third panel), participation and unemployment rates are the most responsive variables in other countries (such as Italy and the United Kingdom, Figure 13 first and second panel). Overall, the results seem to suggest that while the relative weak response of regional migration to labor demand shocks in Europe is partly attributable to the reluctance of people to migrate even within some countries, it is mostly the result of the reluctance of people to migrate across countries.

We have also checked whether the response of migration in Europe is different between E21 and E15 countries. The results presented in Figure 14 suggest that this is the case, and show that the role of migration as shock absorber is considerably larger in the case of EU21 than when we restrict the sample to the EU15. This also suggests that the response of migration to regional labor demand shocks in Central and Eastern European countries has been on average larger than in Western European countries.

Finally, we have checked whether the adjustment mechanisms through which regional labor demand shocks are absorbed have changed over time. To do so, given the limited time sample, we have replicated the analysis splitting the sample only in two periods: 1998-2003 and 2004-2009. The results of this exercise are presented in Figure 14b. The figure shows the response of net migration to 1 percent negative labor demand shock. Looking at the figure, it is possible to observe that the response of migration, particularly after the second year, has considerably increased during the most recent period. In contrast, the role of participation rate has decreased. Overall, the evidence for Europe seems to contrast with the one for the US. While the role of migration (participation) as shock absorber has increased (decreased) over time in Europe, it has decreased (increased) in the US.

## VII. CONCLUDING REMARKS

The findings of our paper address some of the important questions on the efficiency of the US labor market. First, the widely documented decrease in gross inter-state migration poses the

question whether this reduced migration has led to a less a flexible labor market overall (see Molloy et al., 2011). We show that not only the unconditional gross migration rate, but also the response of net-migration conditional on given regional labor market shocks has declined over the last three decades. However, this decline is not necessarily a sign of decreased efficiency: it is largely driven by a change in the underlying dispersion of labor market conditions across regions and hence might represent an optimal response of workers to changing fundamentals. Our results also speaks to the literature on mismatch in the US labor market and its implication for the recovery from the Great Recession. We show that, notwithstanding the negative secular trend, the response of inter-state migration actually increases in recessions in response to regional asymmetries in employment opportunities. Therefore, geographic mismatch, due for example to so-called "house locks", is not likely to play a role in the weak labor market recovery. This is consistent with findings in Sahin et al. (2011) who also conclude, using micro data, that geographic mismatch plays no role for the rise in the unemployment rate during the crisis and its aftermath.

Having focused on the dynamics of labor market dispersion as a determinant for regional adjustment, our paper leaves open the deeper question of why dispersions have narrowed across regions in the US. The answer arguably lies in a confluence of factors. From the (job) supply side, Dumais et al. (2002) show that the geographic concentration of industries has been declining since the early 1980s, driven by new firm startups being distant from industry centers, possibly due to increased externalities between diverse industries. Increased capital mobility brought about by interstate banking integration, which became permitted in most US states by the late 1980s, has also been shown to make state business cycles more alike in Morgan et al. (2004). An increase in workers' industry and occupational mobility documented in Kambourov and Manovskii (2008) may have substituted partially for inter-regional mobility in response to industry-specific demand shocks. Exploring how these and other factors have been interacting with the evolution of labor mobility remains an important object for research.

In the context of the literature on optimal currency area, the results for Europe have important implications for the single currency area. The experience of the US shows that in response to an adverse shock in demand, adjustment factors do not prevent increases in unemployment or reduction in the participation rates. In the European Monetary Union (EMU), given lower labor mobility - even though increasing- the adjustment to labor demand shocks is likely to be even more painful. In addition, because risk-sharing mechanisms in EMU are significantly less effective than in the US (Furceri and Zdzienicka, 2013) the adjustment to shocks in EMU may be a costly and protracted process. More generally, studying spatial patterns of labor market adjustments offers an alternative lens to understanding the workings of the aggregate labor market and its macroeconomic implications.

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Figure 1: Persistence of Employment Growth Rates across US States, 1976-2011

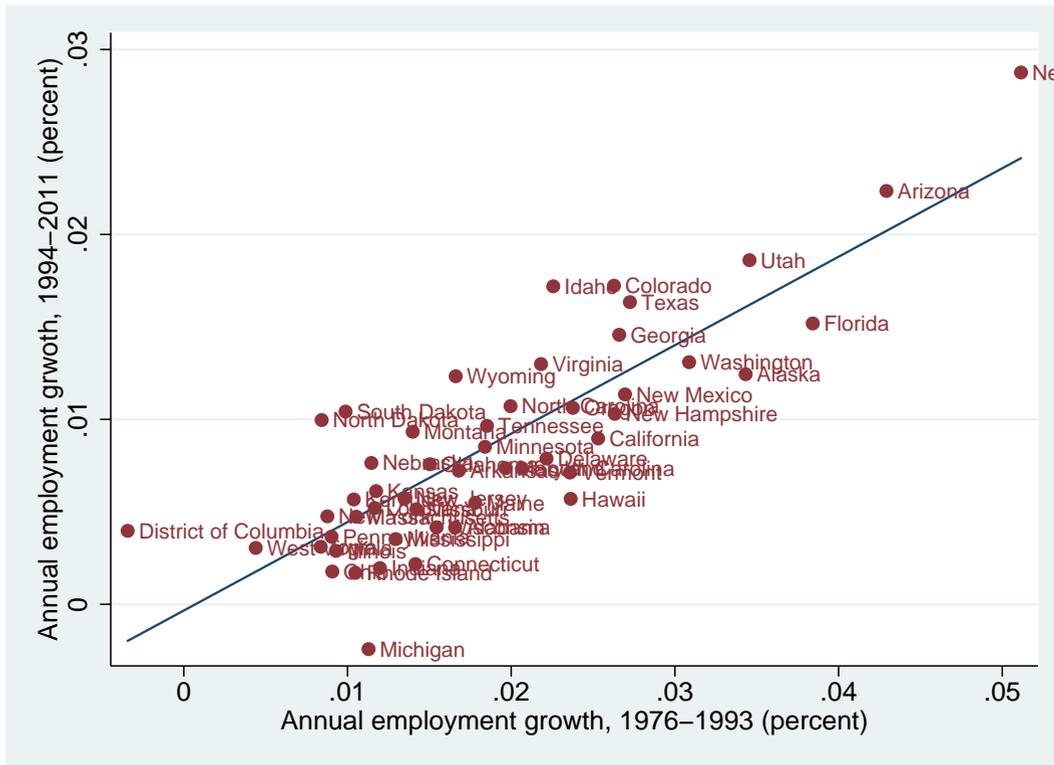
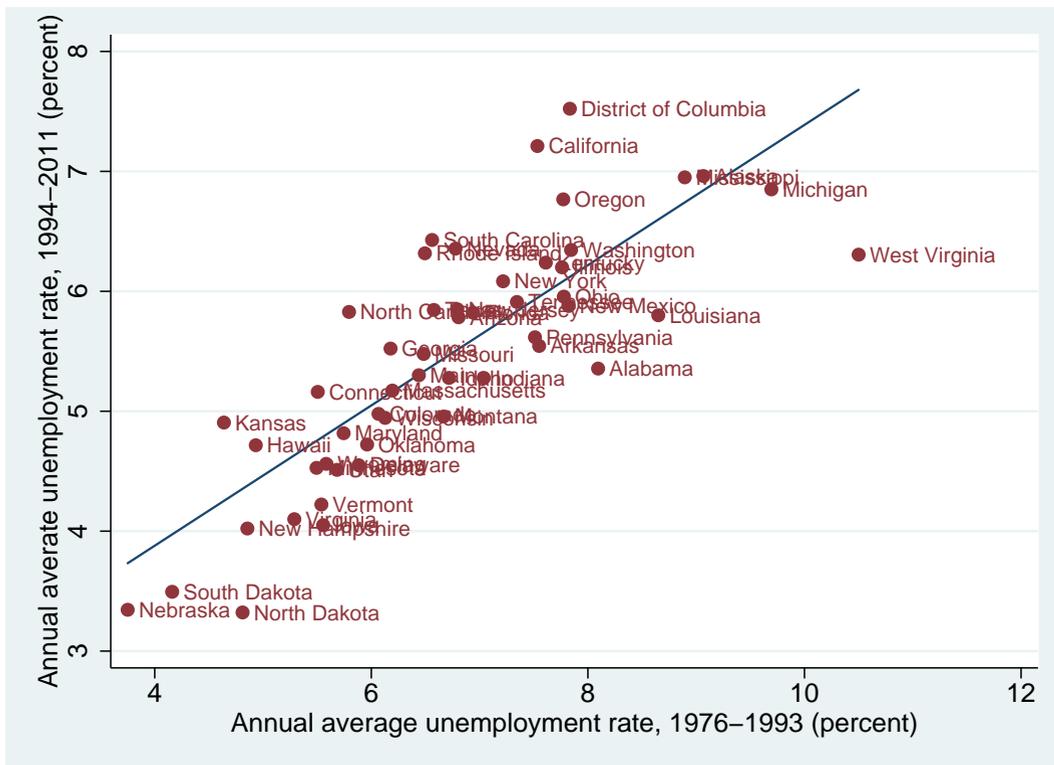
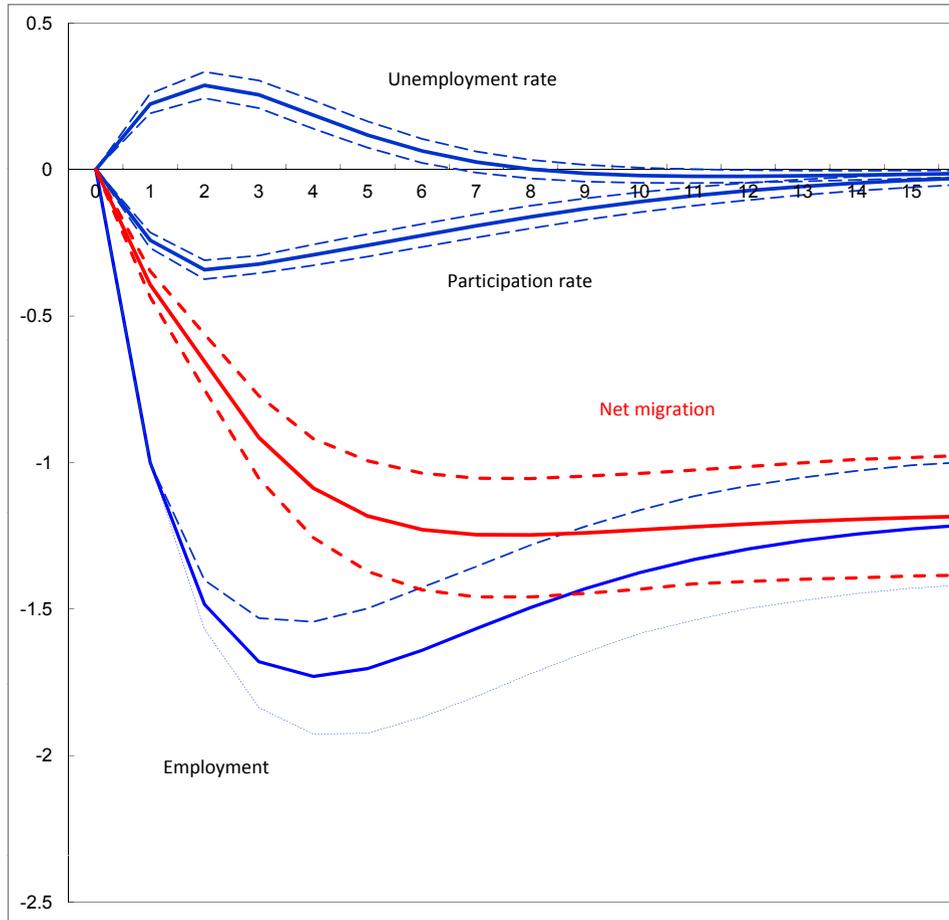


Figure 2: Persistence of Unemployment Rates across US States, 1976-2011



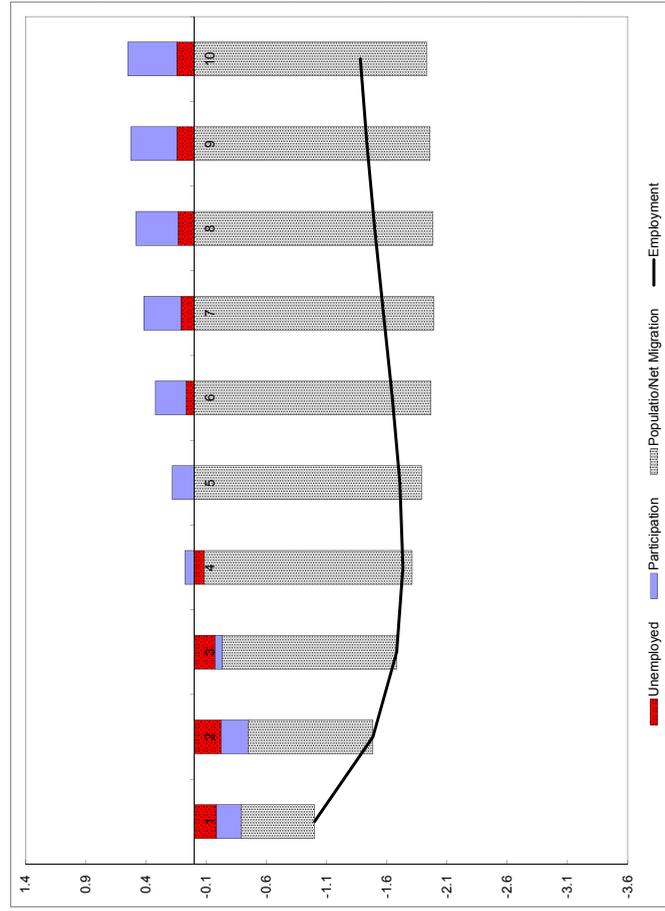
Source: Authors' calculations based on data from the BLS.

Figure 3: Response of state-relative labor market variables: OLS.



Source: Authors' calculations based on data from the BLS, estimates of system of panel VAR in (2). Confidence bands of 95 percent are bootstrapped with 500 replications. Units are percent deviation from pre-shock steady state.

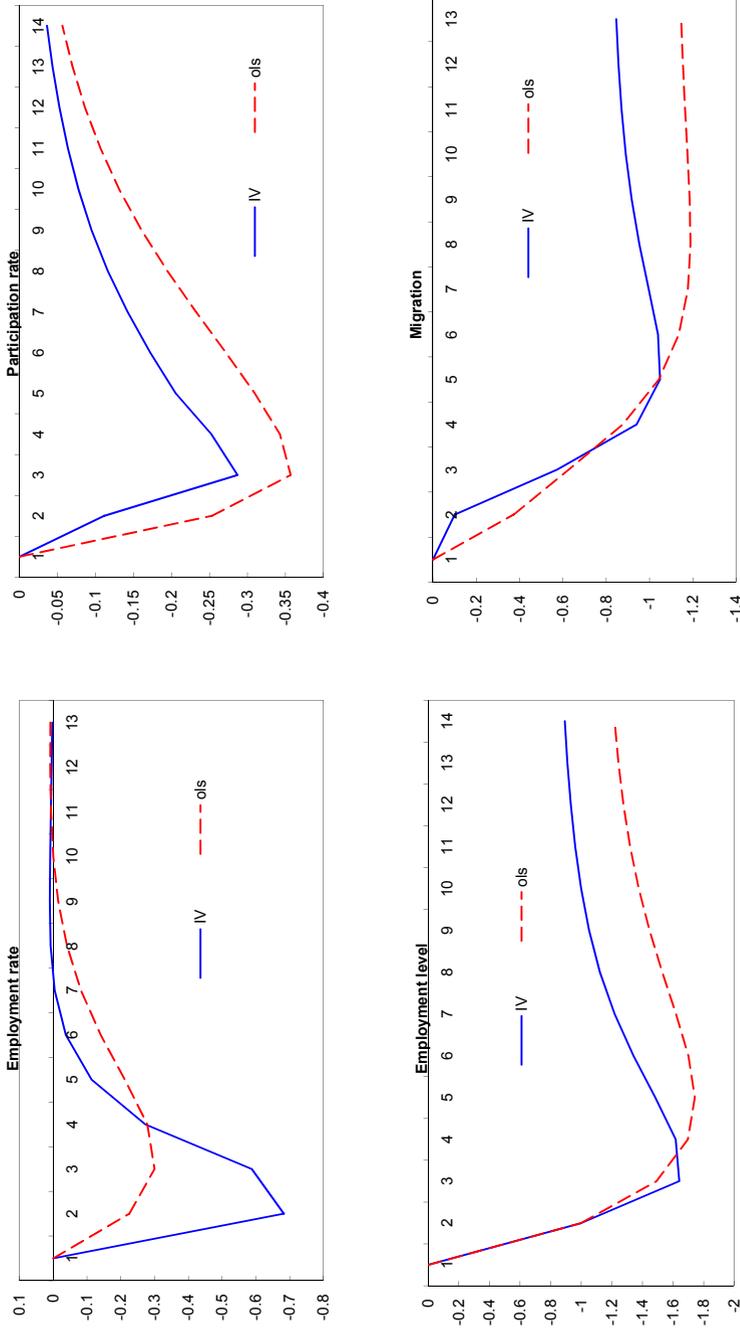
Figure 4: Decomposition of a 1 worker regional labor demand shock to 3 adjustment margins: OLS.



Computation based on the IRF results obtained in Figure 3. Unit: workers.

Figure 5: Response of state-relative labor market variables: OLS vs. 2SLS.

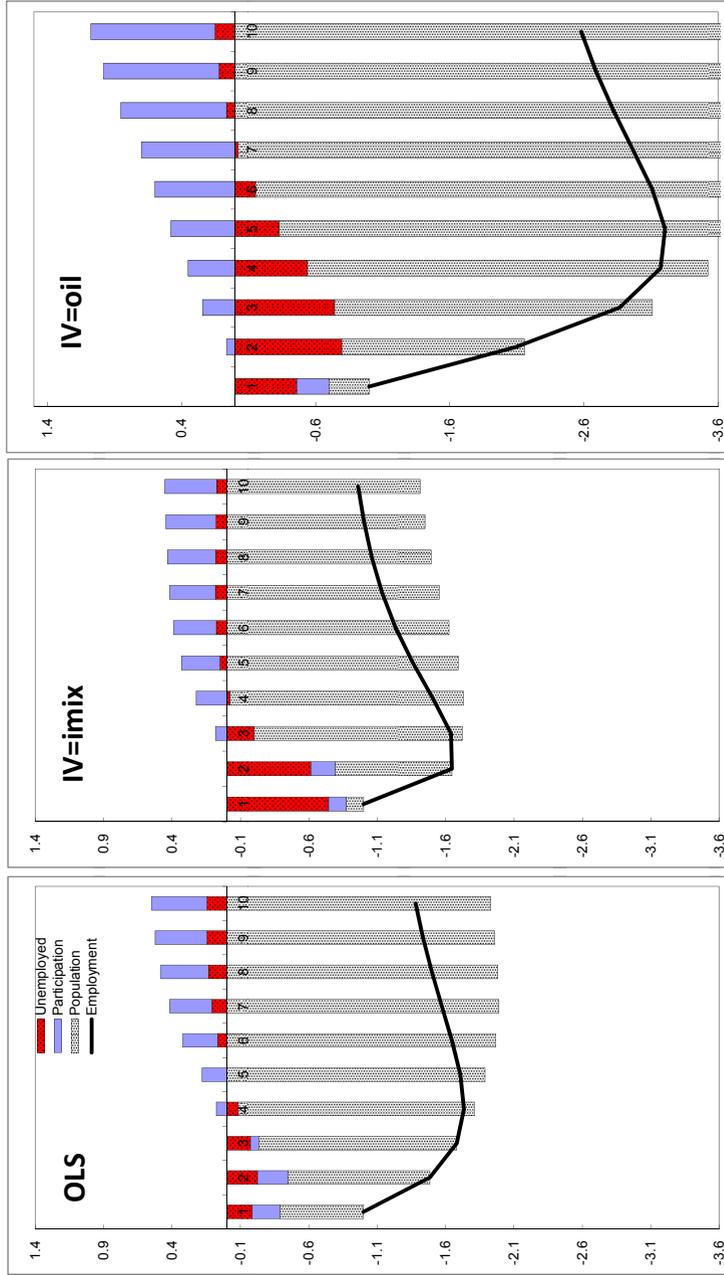
IRF with OLS and IV (imix variable)



Note: Impulse response to 1 percent negative labor demand shock under OLS and 2SLS using *imix* as IV. Units are percent deviation from pre-shock steady state.

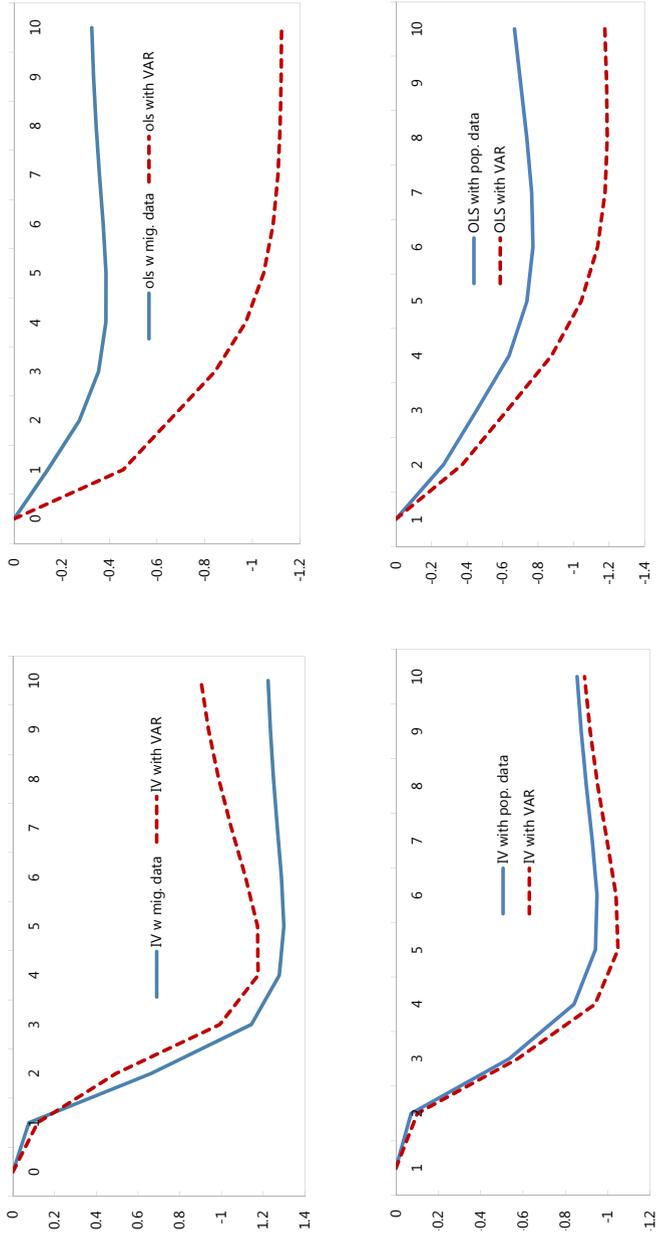
Figure 6: Decomposition of a 1 worker regional labor demand shock to 3 adjustment margins: OLS vs 2SLS.

Decomposition of adjustment margins: OLS vs. IV



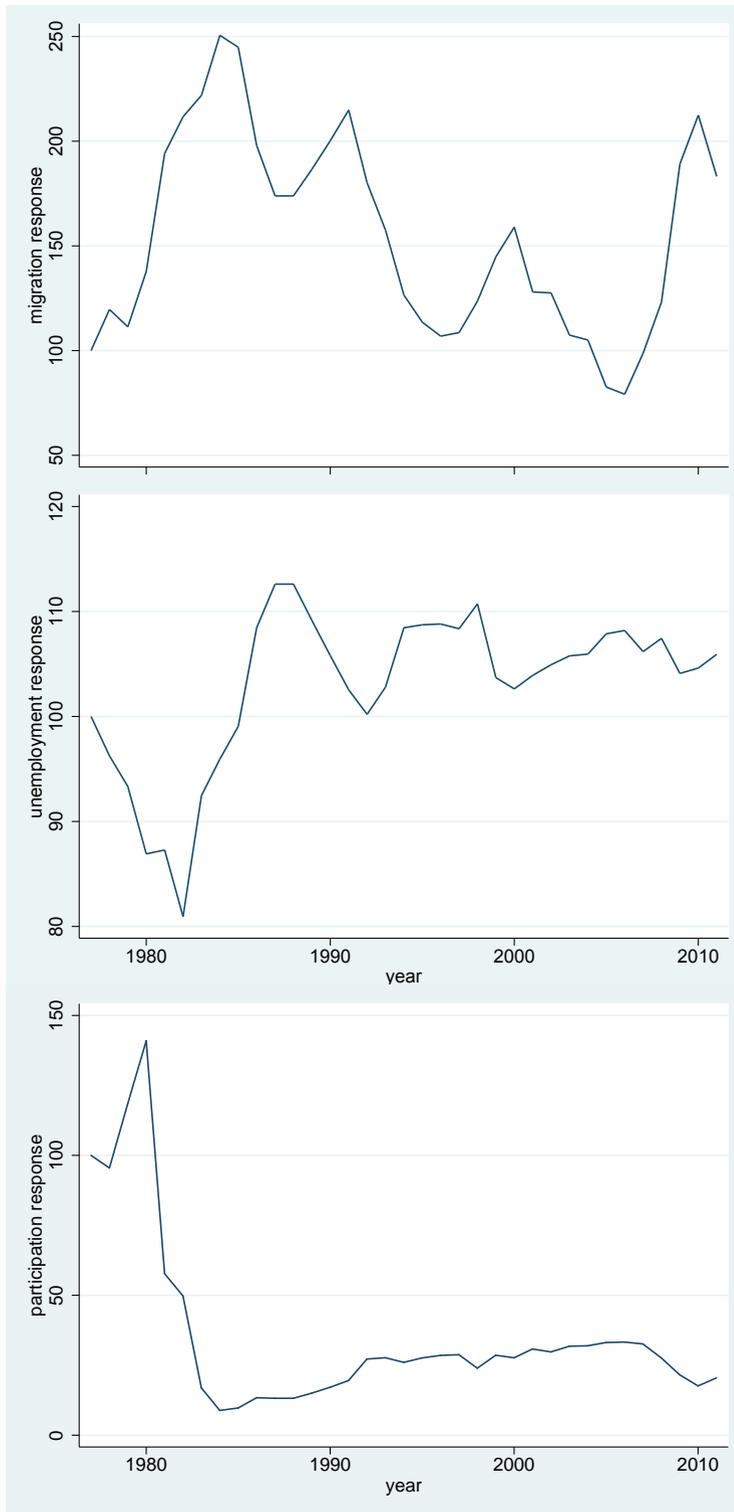
Unit: workers. OLS decomposition is the same as in Figure 4

Figure 7: Response of cumulative net migration, using migration and population data direct estimates vs. VAR identifications.



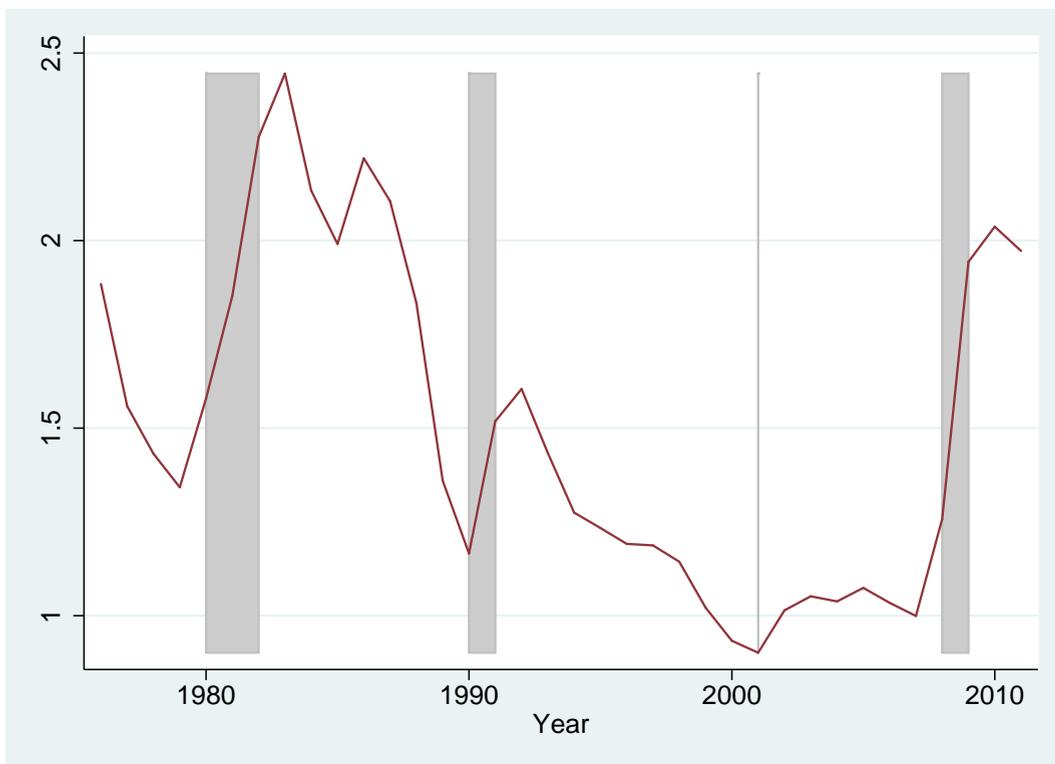
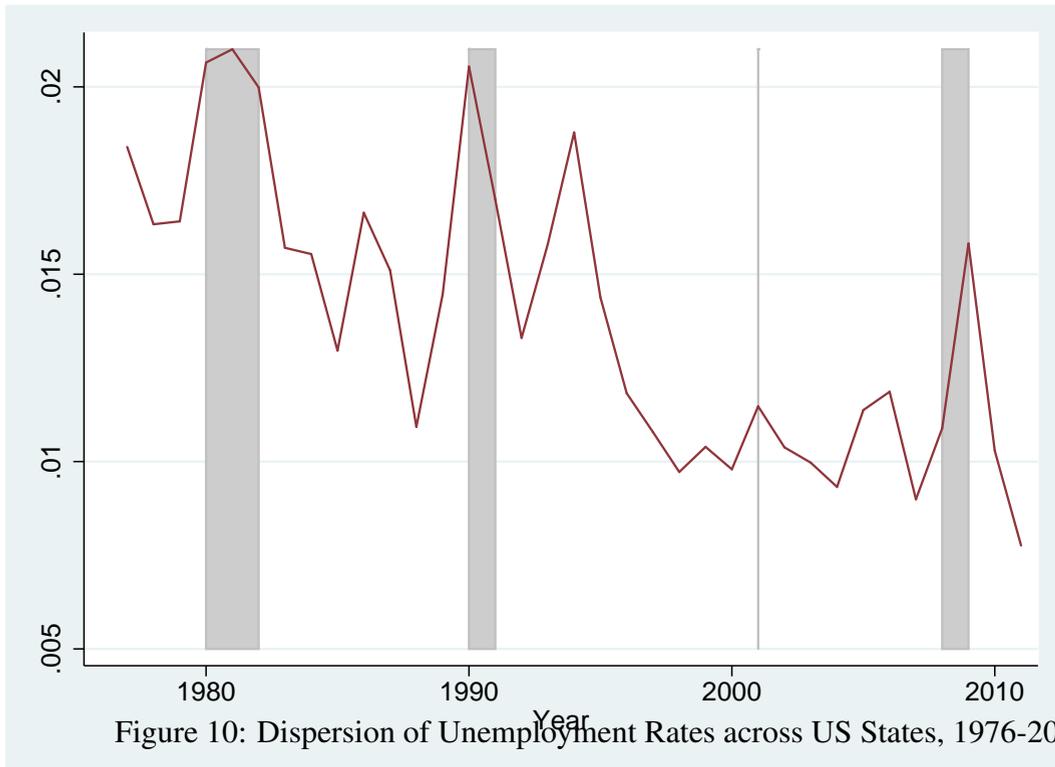
Note: Sample period is 1991-2011 for migration data comparison (upper panel) and 1976-2011 for population data comparison. Unit: percentage of civilian population. Shock is a positive 1 pct labor demand shock.

Figure 8: Response of net migration, relative unemployment and participation to state labor demand shock within 1 year.



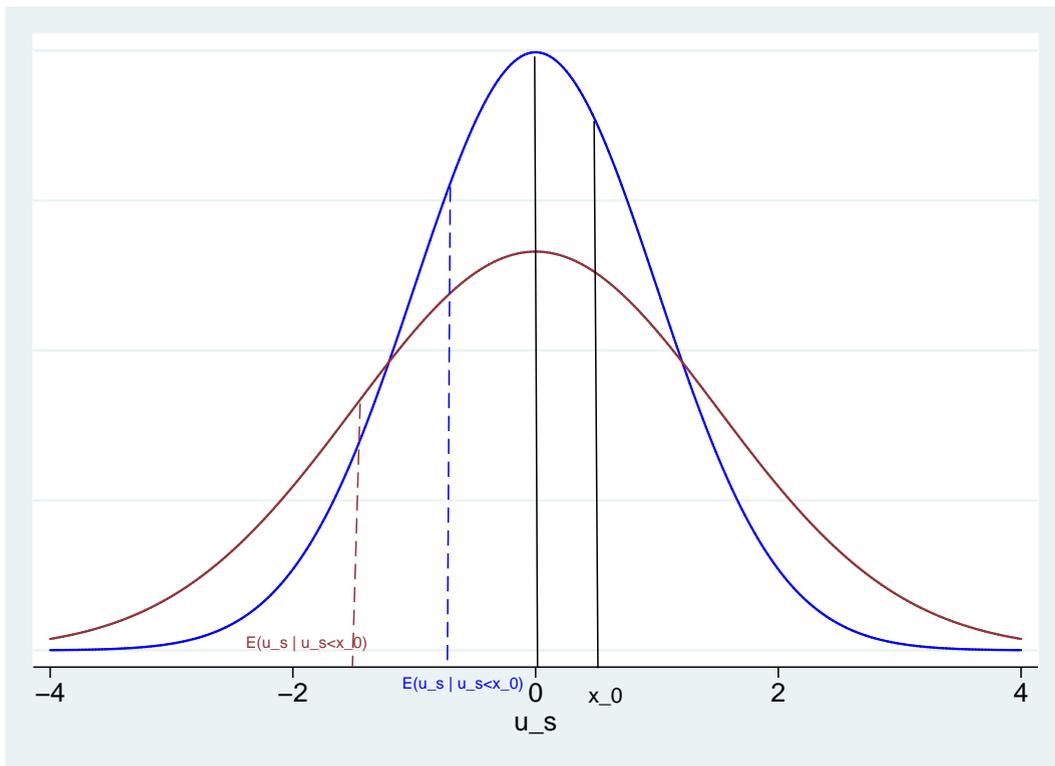
*Note:* Series constructed based on expanding window regressions from 1976 to 2011, with 1976=100.

Figure 9: Dispersion of Employment Growth Rates across US States, 1976-2011



Source: Authors' calculations based on data from the BLS, with shaded areas representing NBER recession episodes.

Figure 11: State unemployment dispersion and gains from migration



Distribution of state-relative unemployment under baseline (brown) and reduced dispersion (blue).

Figure 12: Response to 1 pct negative labor demand shock in the EU: IRF (top) and decomposition to 3 adjustment margins (bottom) using the BK approach.

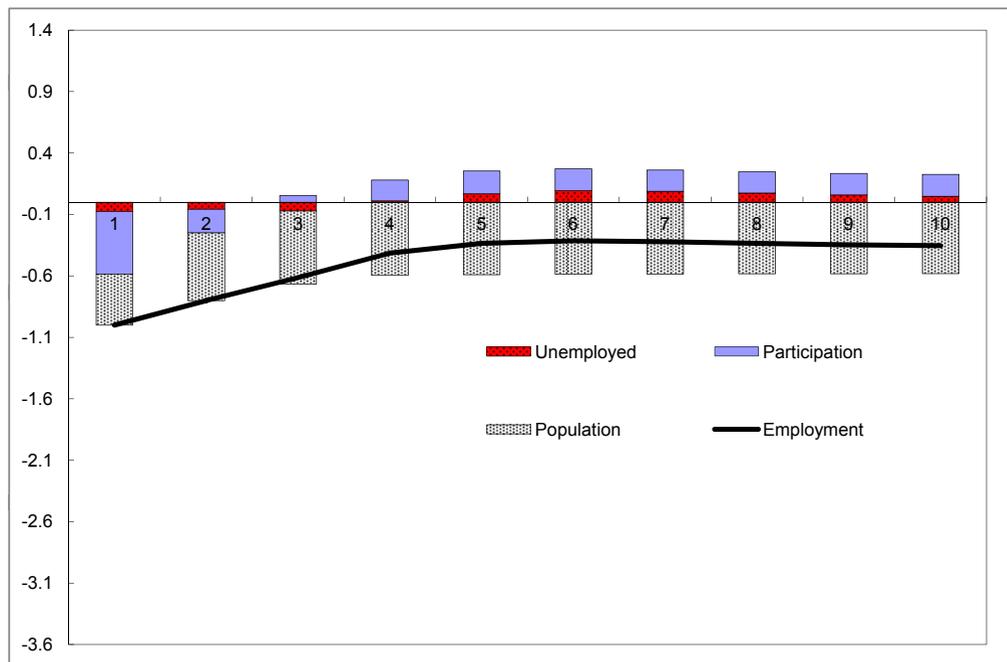
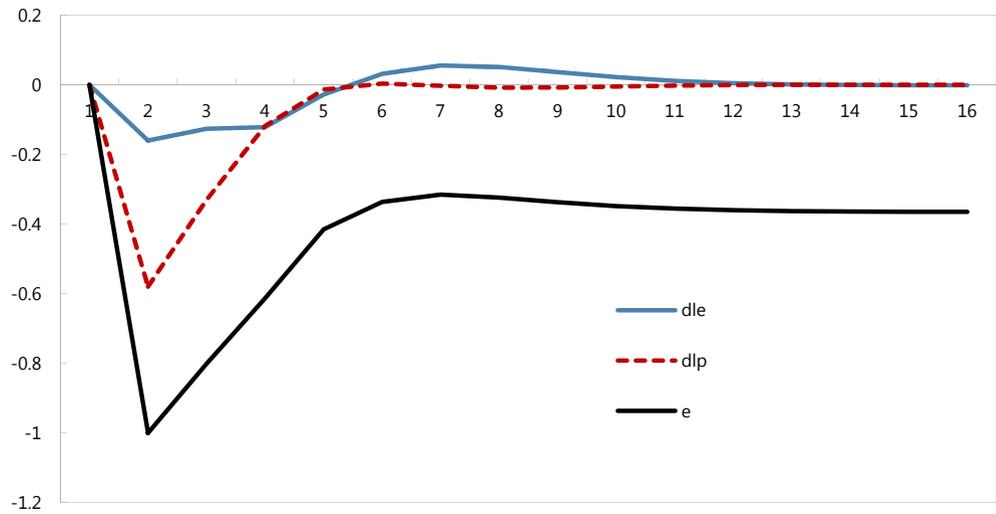


Figure 13: Relative labor market dynamics in response to 1 pct negative labor demand shock in the EU: select countries.

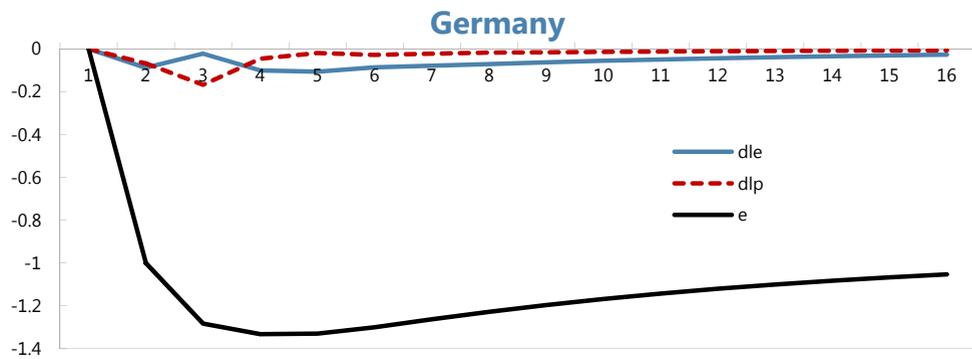
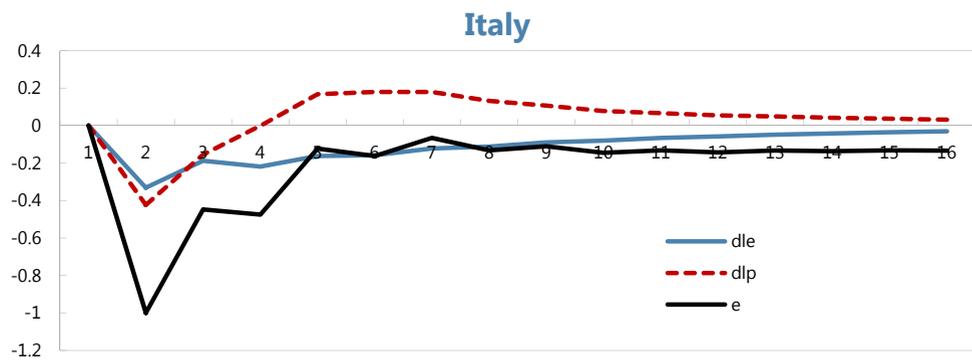
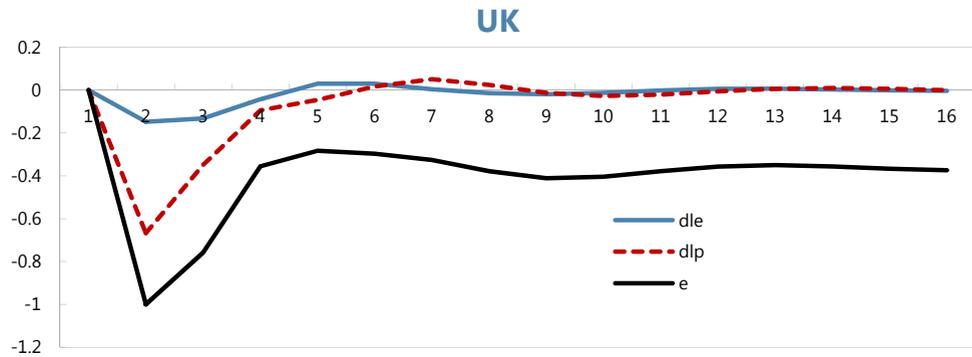


Figure 14: Sub-sample heterogeneity in cumulative migration response in the EU: among countries (top), over time (bottom). Time in years after 1 pct negative regional labor demand shock.

