A Appendix Tables and Figures

Table A1: Summary statistics of state and MSA-level data.

	N	Years	Mean	SD	p5	p50	p95
Unemployment rate	1938	1976-2013	6.1	2.1	3.2	5.8	10
Employment growth	1785	1977-2013	1.3	2.0	-2.0	1.3	4.5
Participation rate	1938	1976-2013	66.3	4.1	59.5	66.5	72.6
Population growth 1/	1887	1977-2013	1.3	1.2	-0.03	1.0	3.4
Predicted employment growth ($imix$)	1887	1976-2013	1.8	1.8	-0.8	2.2	4.9
Predicted employment growth ($imix$) at MSA-level	574	2003-2013	0.9	1.7	-3.1	1.8	2.3
Employment share in oil&gas industries	1812	1976-2011	0.8	1.5	0.0	0.1	4.1
Net migration rate	1173	1991-2013	0.1	1.0	-1.2	0.1	1.6
Net migration rate (ACS)	355	2007-2013	0.0	1.1	-1.0	0.1	1.1
Net migration rate (MSA-level)	457	2005-2014	0.1	2.3	-1.5	0.0	2.5
Relative oil price growth 2/	38	1976-2013	2.5	22	-45	3.9	42
Relative house price growth 3/	1887	1977-2013	-0.1	4.4	-6.4	-0.2	7.3

1/ civilian non-institutional population 16 years and older
2/ Ratio of crude oil (petroleum) price index over US producer price index of finished goods, Source: IMF International Financial Statistics database.
3/ Ratio of state-level repeated sales house price index relative to national repeated sales price index, series based on all transactions, Source: FHFA, Quarterly All-Transactions Indexes (annualized).
Notes: The mean, standard deviation (SD) and the 5th (p5), median (p50), and 95th (p95) percentiles are shown for each variable, over all years and all states. State-level labor market variables are taken from the Local Area Unemployment Statistics (LAUS) of the BLS. State-level predicted employment growth and employment share in each industry is constructed using the BEA's Regional Economic Information System (REIS) dataset (Table S25). Net migration rate starting in 1991 is for all ages and taken from the Bureau of the Census Population Estimate Program (Census PEP). Net migration rate (ACS) is for 16-65 years old and from the American Community Survey (ACS) database. MSA-level predicted employment growth is computed by combining industry-level aggregate employment growth from BEA REIS with industry-MSA-level employment shares from Section III, Table 32 of the *Geographic Profile of Employment and Unemployment* data tabulated by the BLS. MSA-level net migration data is taken from the Census PEP, Metropolitan and Micropolitan Statistical Population Datasets.

Table A2: Employment shares by industry across US states in 2012.

2012 NAICS industry:	2012				
	Mean	SD	Min	Median	Max
Accommodation and food services	8.9%	2.3%	6.7%	8.3%	21.9%
			Connecticut	*Texas*	*Nevada*
Administrative and waste mgt. serv.	6.8%	1.3%	4.2%	6.8%	9.2%
			North Dakota	*Kansas*	*Arizona*
Arts, entertainment, & recreation	2.6%	0.5%	1.5%	2.5%	3.8%
			Arkansas	*Pennsylvania*	*Montana*
Construction	6.2%	1.2%	2.8%	6.2%	9.6%
			District of Columbia	*Tennessee*	*Wyoming*
Durable goods manufacturing	5.1%	2.4%	0.1%	5.1%	11.3%
			District of Columbia	*Missouri*	*Indiana*
Educational services	2.7%	1.4%	1.0%	2.3%	9.2%
			Nevada	*South Dakota*	*District of Columbia*
Finance and insurance	6.2%	1.6%	3.8%	5.9%	11.8%
			Alaska	*Ohio*	*Delaware*
Forestry, fishing, & related activities	0.7%	0.6%	0.0%	0.5%	3.1%
			District of Columbia	*Oklahoma*	*Alaska*
Health care and social assistance	13.2%	1.9%	8.5%	13.2%	16.9%
			Nevada	*New Hampshire*	*West Virginia*
Information	2.0%	0.5%	1.3%	1.8%	3.7%
			Mississippi	*Illinois*	*Washington*
Mgt. of companies & enterprises	1.3%	0.5%	0.4%	1.2%	2.5%
			Wyoming	*New Hampshire*	*Minnesota*
Mining	1.3%	2.2%	0.1%	0.4%	10.8%
			Massachusetts	*Virginia*	*Wyoming*
Nondurable goods manufacturing	3.2%	1.3%	0.2%	3.2%	6.2%
			District of Columbia	*New Jersey*	*Arkansas*
Other services, except public admin.	6.8%	1.1%	5.3%	6.6%	13.2%
			Nevada	*Nebraska*	*District of Columbia*
Professional, scientific & technical serv.	7.5%	2.8%	4.4%	7.1%	21.9%
			South Dakota	*Alaska*	*District of Columbia*
Real estate and rental and leasing	5.1%	1.2%	3.3%	4.9%	8.1%
			Iowa	*Alabama*	*Arizona*
Retail trade	12.3%	1.6%	3.9%	12.4%	15.2%
			District of Columbia	*Washington*	*New Hampshire*
Transportation and warehousing	3.8%	1.0%	1.2%	3.6%	6.8%
			District of Columbia	*Idaho*	*Alaska*
Utilities	0.4%	0.2%	0.1%	0.4%	0.8%
			Tennessee	*Iowa*	*Wyoming*
Wholesale trade	3.9%	0.8%	1.0%	3.9%	6.0%
			District of Columbia	*Pennsylvania*	*North Dakota*

The table gives a snapshot of the cross-sectional distribution for each industry across US states in 2012. States in the minimum, median, and maximum of the employment share distribution for each industry are given in italics. Source: Regional Economic Information System from the BEA.

Table A3: Job-search related interstate migration rate of the labor force (in percent).

Employment status in reference year:	1999-2012 average	2006-2007 benchmark	2007-2008 *(2006-2007=100)*	2008-2009 *(2006-2007=100)*	2009-2010 *(2006-2007=100)*
All	0.13	0.10	0.10	0.15	0.14
		100	*106*	*154*	*147*
Unemployed:					
partly unemployed	0.62	0.65	0.50	0.61	0.39
		100	*76*	*93*	*60*
all year unemployed	0.77	0.29	0.60	0.73	0.80
		100	*206*	*252*	*276*
Labor market entrant:					
partly NILF 1/	0.18	0.11	0.12	0.18	0.30
		100	*111*	*167*	*280*
all year NILF 2/	0.24	0.27	0.12	0.52	0.10
		100	*46*	*192*	*36*
Employed:					
all year employed	0.05	0.03	0.05	0.05	0.05
		100	*169*	*168*	*159*
Counterfactual		0.10	0.10	0.11	0.13

1/ Individuals who were never unemployed in the previous year, nor employed all year.
2/ Individuals who did not work at all in the reference year because they were not in the labor force (NILF) and are in the labor force at the time of survey.

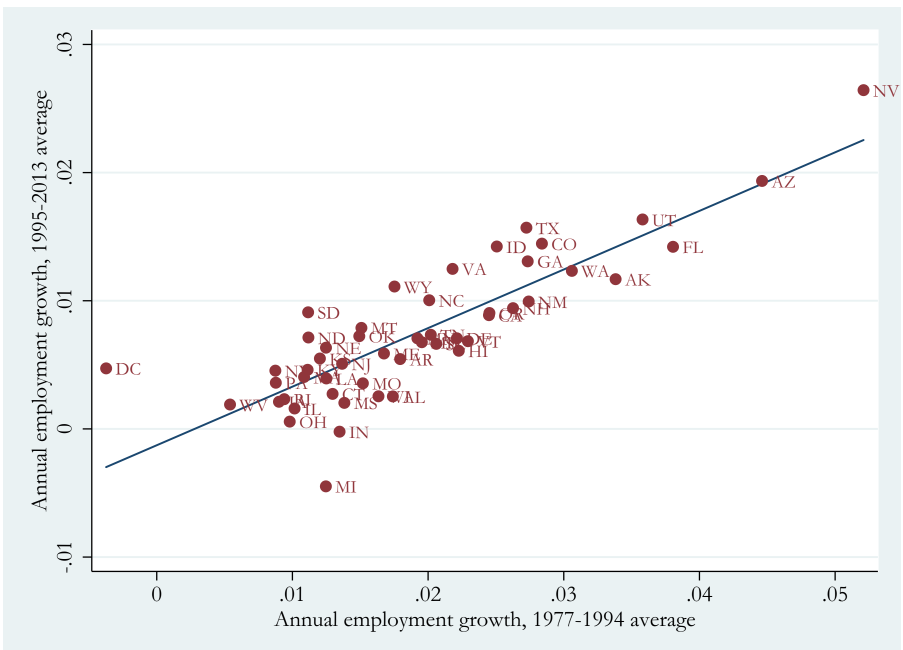
Notes: Entries are weighted percentages of respondents in the labor force between 16 and 65 years old who lived in a different state one year ago and moved "to find work or lost job", broken down by their employment status in the reference year of the move. Numbers in italics are standardized at 100 to the benchmark level in 2006-2007. Respondents with imputed migration data are excluded. Last row reports the counterfactual migration rate holding the within-group migration rates fixed at the benchmark (2006-2007) level, with only the employment status composition of the labor force changing as observed. Source: Authors' calculations from the CPS March supplements, various years.

Table A4: Shift share analysis of job-search mobility rate of the long-term unemployed and labor market entrants by demographic characteristics.

Demographic group	1999-2012 avg.	base: 2006-2007	2007-2008	2008-2009	*2008-2009 cf.*
All	0.23	0.15	0.14	0.29	*0.15*
By gender					
Male	0.31	0.20	0.21	0.44	
Female	0.17	0.11	0.09	0.17	*0.15*
By Age					
16-19	0.11	0.10	0.08	0.16	
20-24	0.31	0.21	0.16	0.31	
25-34	0.33	0.18	0.24	0.44	
35-44	0.23	0.08	0.04	0.24	
45-54	0.17	0.23	0.21	0.23	
55-64	0.22	0.07	0.05	0.34	*0.15*
By Education					
no high-school	0.26	0.12	0.26	0.29	
high-school	0.25	0.13	0.09	0.34	
some college	0.23	0.14	0.16	0.29	
college or more	0.19	0.18	0.08	0.23	*0.15*
By Occupation					
Services	0.20	0.15	0.12	0.23	
Clerical & sales	0.20	0.19	0.06	0.29	
Operators, Assemblers & Laborors	0.48	0.22	0.85	0.63	
Transport, Construction	0.30	0.12	0.22	0.51	
Production & Craft excl. Mining	0.40	0.28	0.07	0.61	
Managers, Professionals	0.18	0.11	0.08	0.13	*0.15*
By race					
white	0.23	0.18	0.15	0.28	
black	0.21	0.02	0.12	0.41	
other	0.27	0.00	0.09	0.24	*0.15*
By marital status					
Married	0.19	0.05	0.14	0.18	
Separated/Divorced	0.36	0.37	0.13	0.65	
Widowed	0.08			0.70	
Single	0.25	0.20	0.15	0.30	*0.15*

Notes: Entries are weighted percentages of respondents in the labor force between 16 and 64 years old who lived in a different state one year ago, were full-year unemployed or entered the labor force during the previous year, and moved "to find work or lost job" (job-search migration rate), broken down by their demographic characteristics. Last column shows the counterfactual job-search migration rate that would prevail were the within-group migrate rate fixed, with only the population shares of individual demographic groups in the long-term and labor force entrants pool changed as observed. Counterfactual value in the first row is obtained by letting population shares along all demographic dimensions vary jointly as observed. Empty cells indicate not sufficient observation in the respective year and group. Source: CPS March supplements, 1999-2013.

Figure A1: Persistence of Employment Growth Rates across US States, 1977-2013.



Note: Authors' calculations based on data from the BLS Local Area Unemployment Statistics (LAUS) data. Data points are represent the average employment growth rate for each state over 1977-1994 (horizontal axis, and 1995-2012 (vertical axis). The linear fit has an R-squared statistics of 0.7.

Figure A2: Cumulative employment growth, U.S. states relative to national average, 1947-2013.

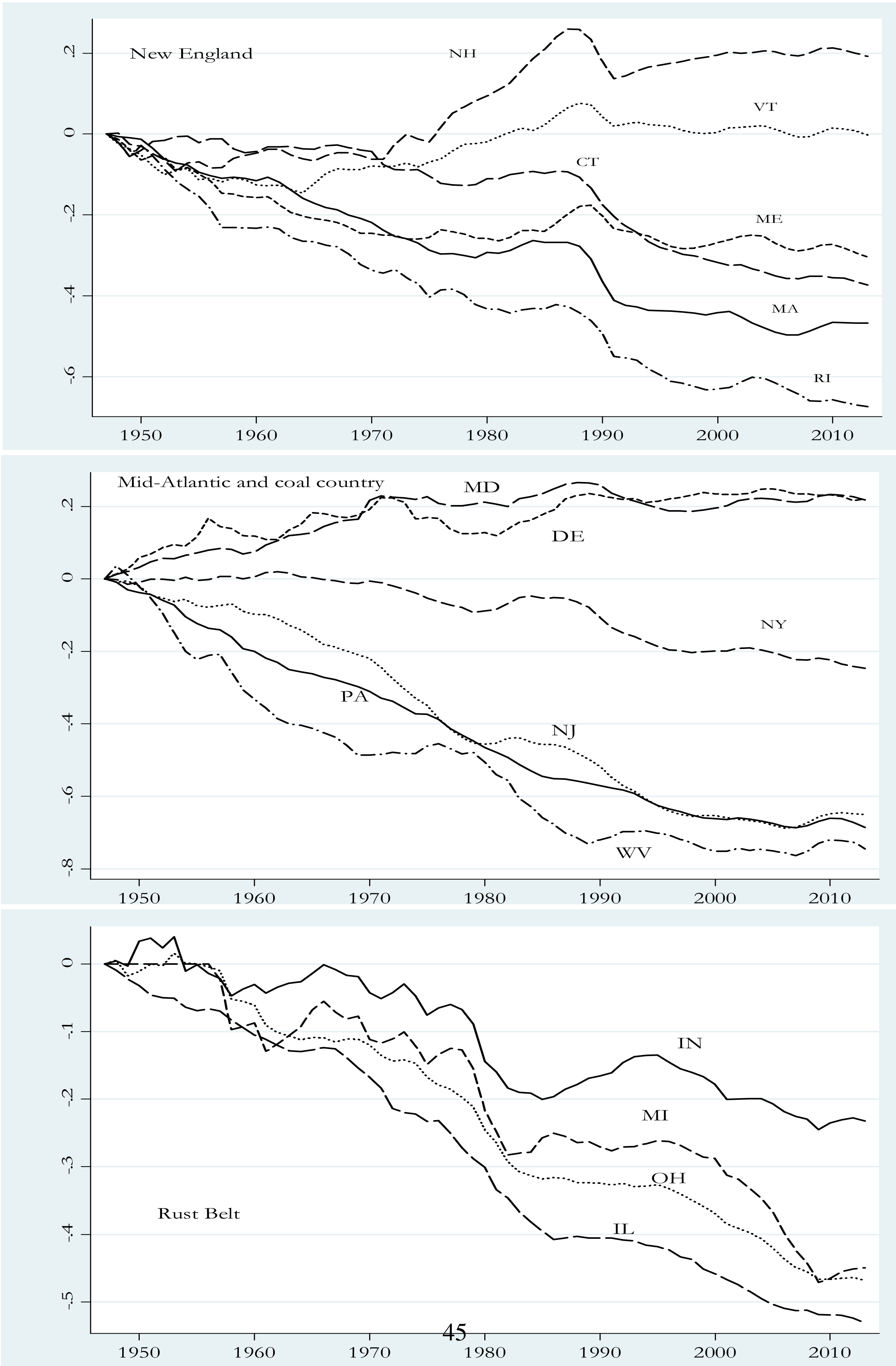


Figure A3: Cumulative employment growth, U.S. states relative to national average, 1947-2013 (cont'd).

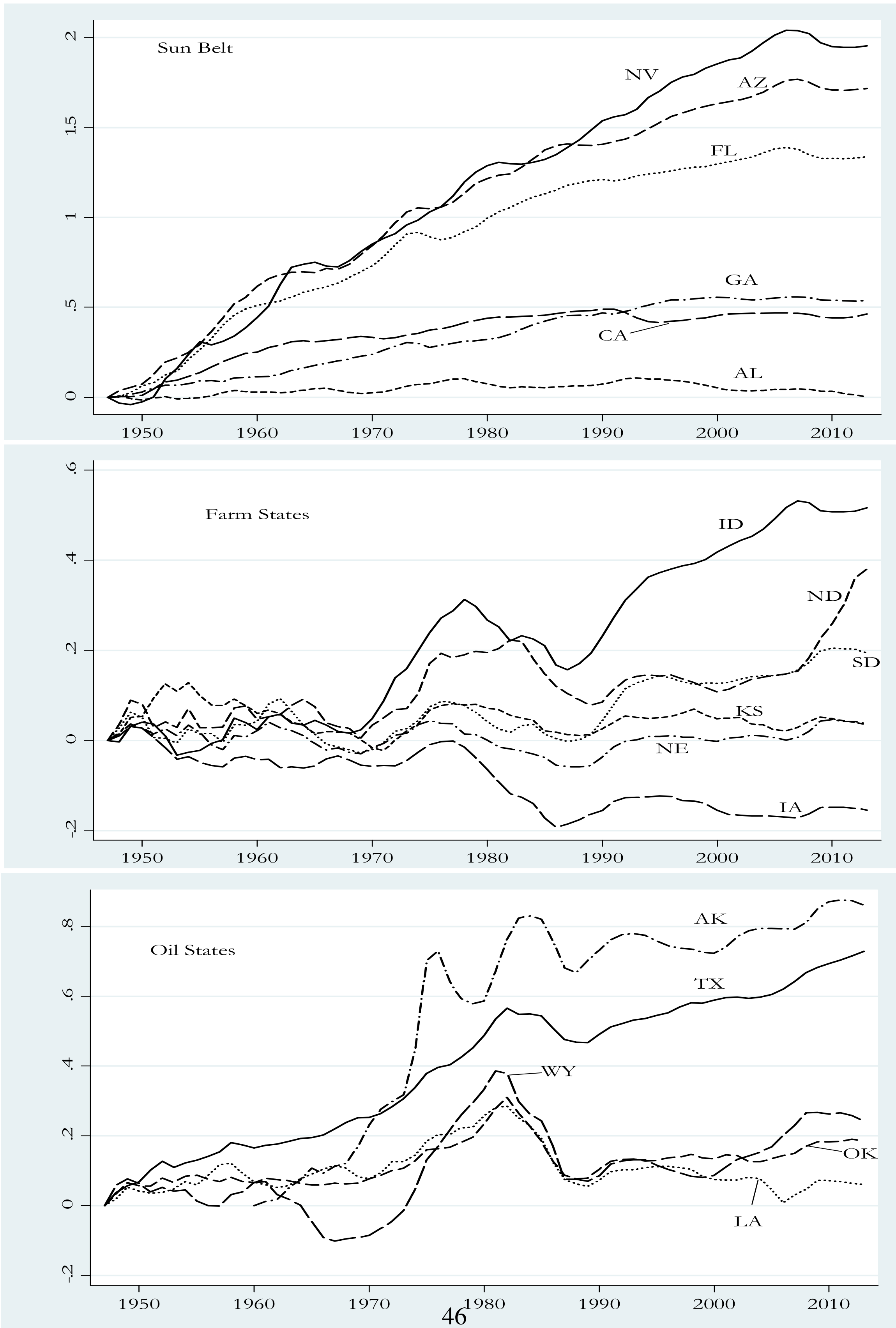
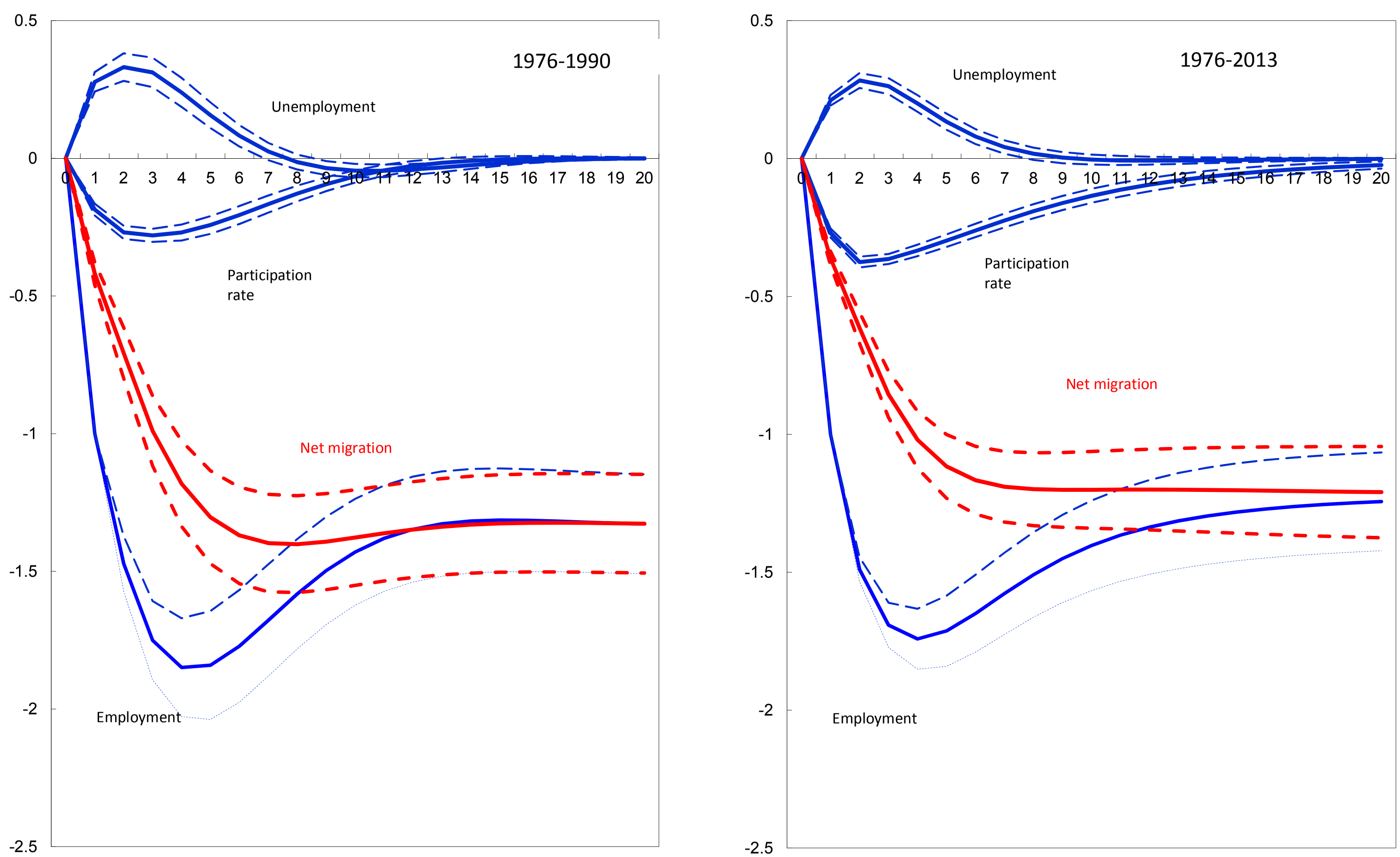
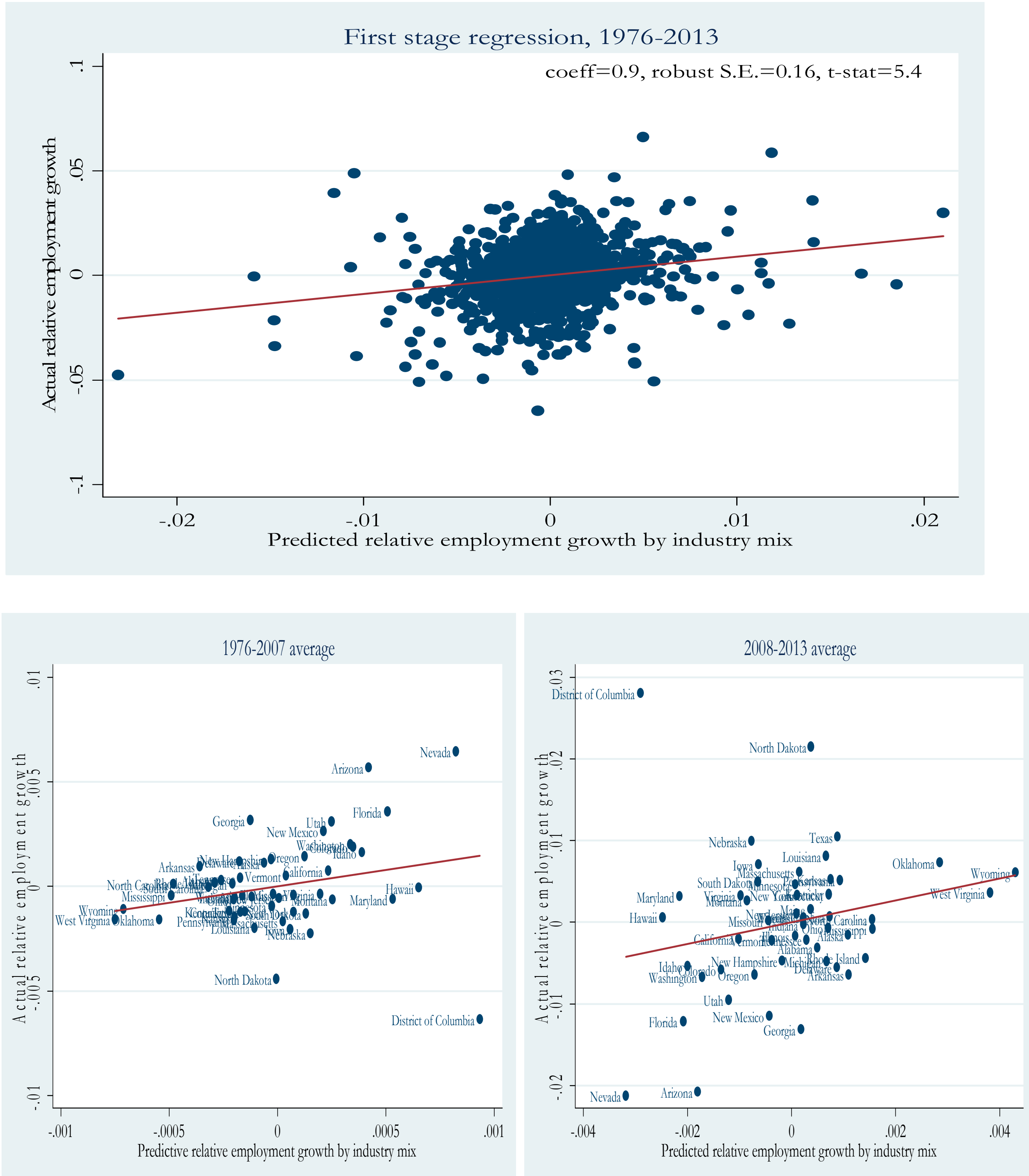


Figure A4: Response of state-relative labor market variables: replication and update of the BK baseline regression results.



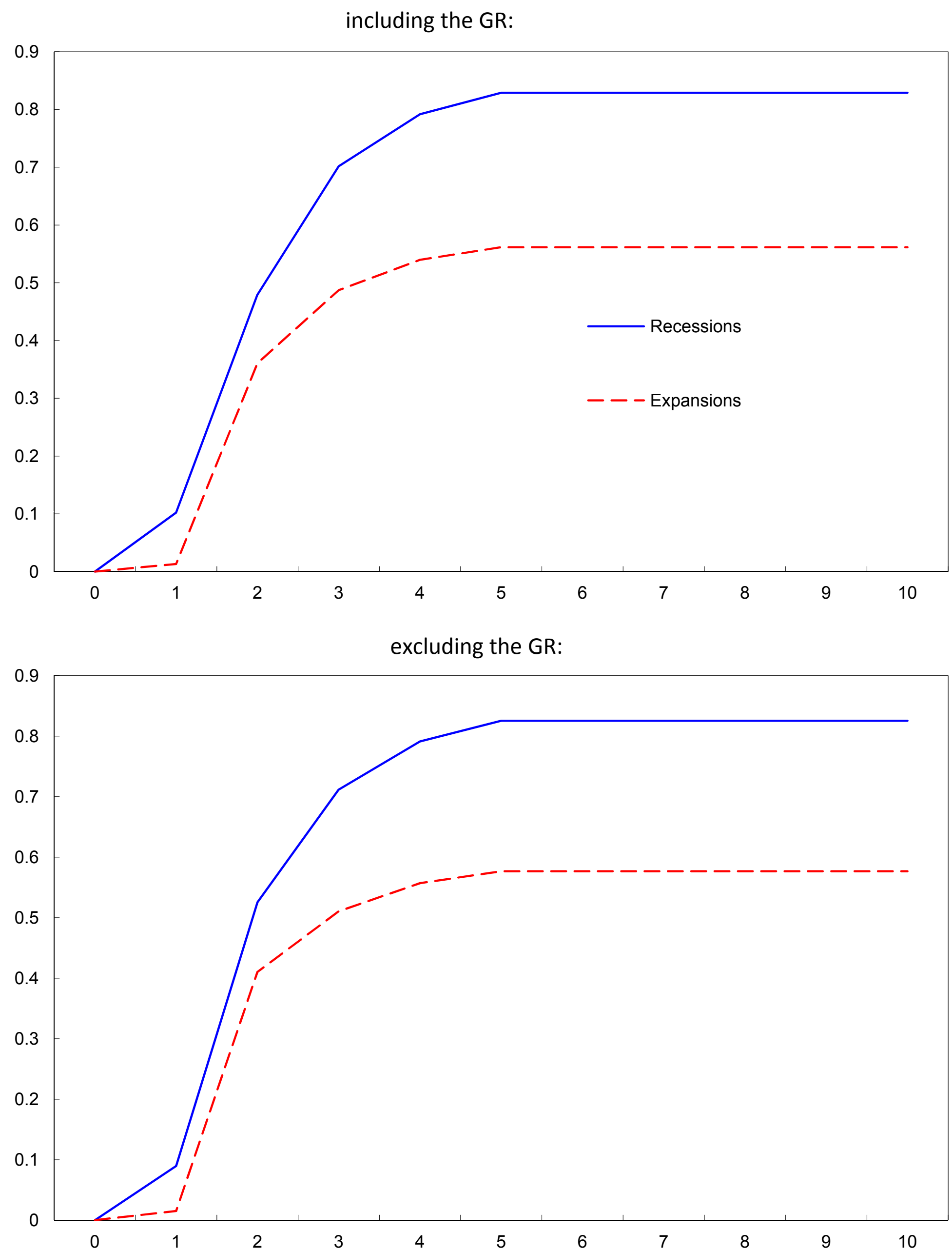
Note: the lines represent estimated response of the relative unemployment rate, participation rate (in percentage points), relative employment (in percent) and cumulative net migration (in percent of population) to 1 percent relative negative labor demand shock using the BK approach on the original and extended sample. Bands of one standard error (obtained through bootstrap) are shown around each line.

Figure A5: 2SLS first stage correlation, full sample and sub-samples.



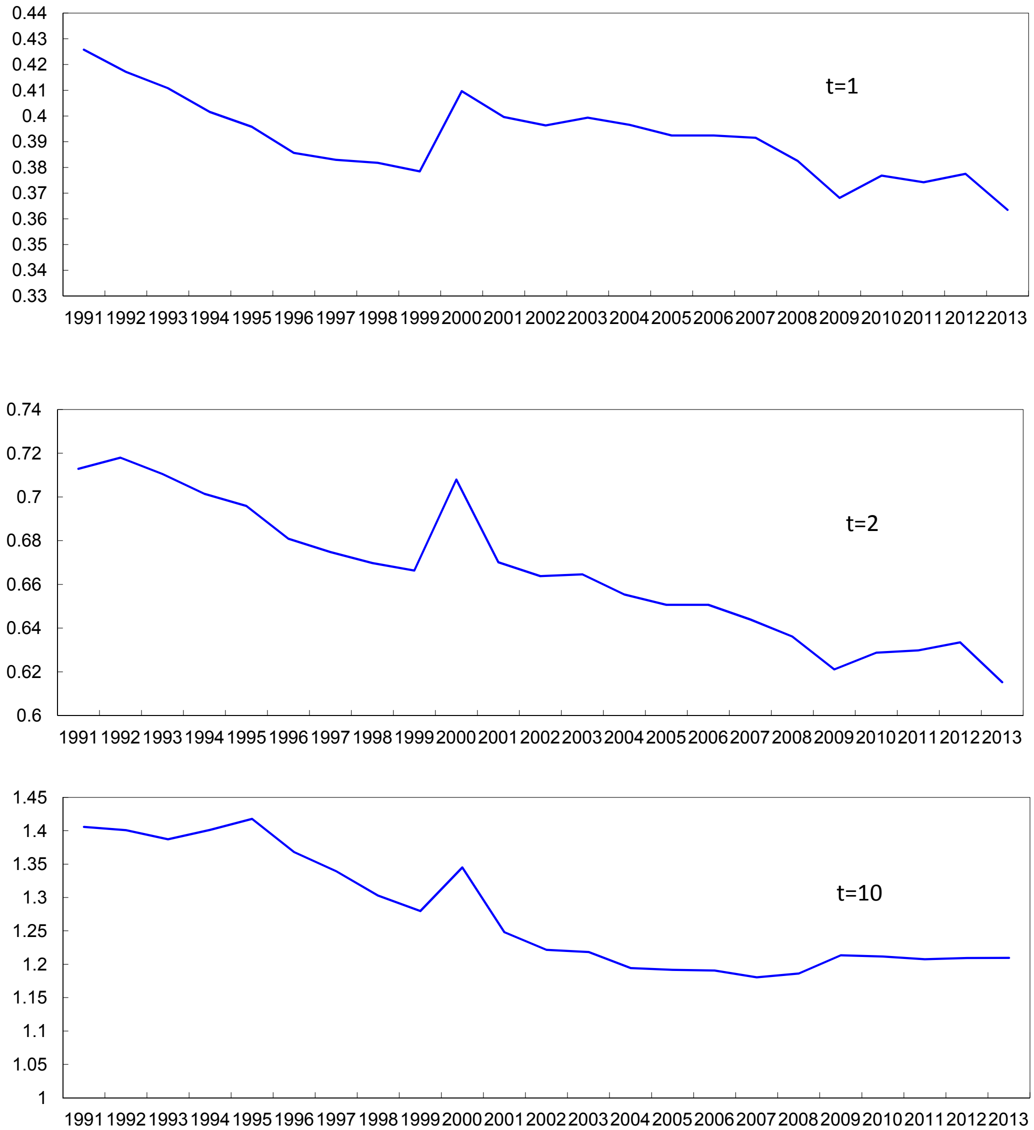
Note: First stage correlation between actual relative employment growth (Δe) and the IV ($rimix$) for the whole sample, and split before vs. after the Great Recession.

Figure A6: Response of cumulative net migration to a 1 percent relative labor demand shock: business cycle interaction.



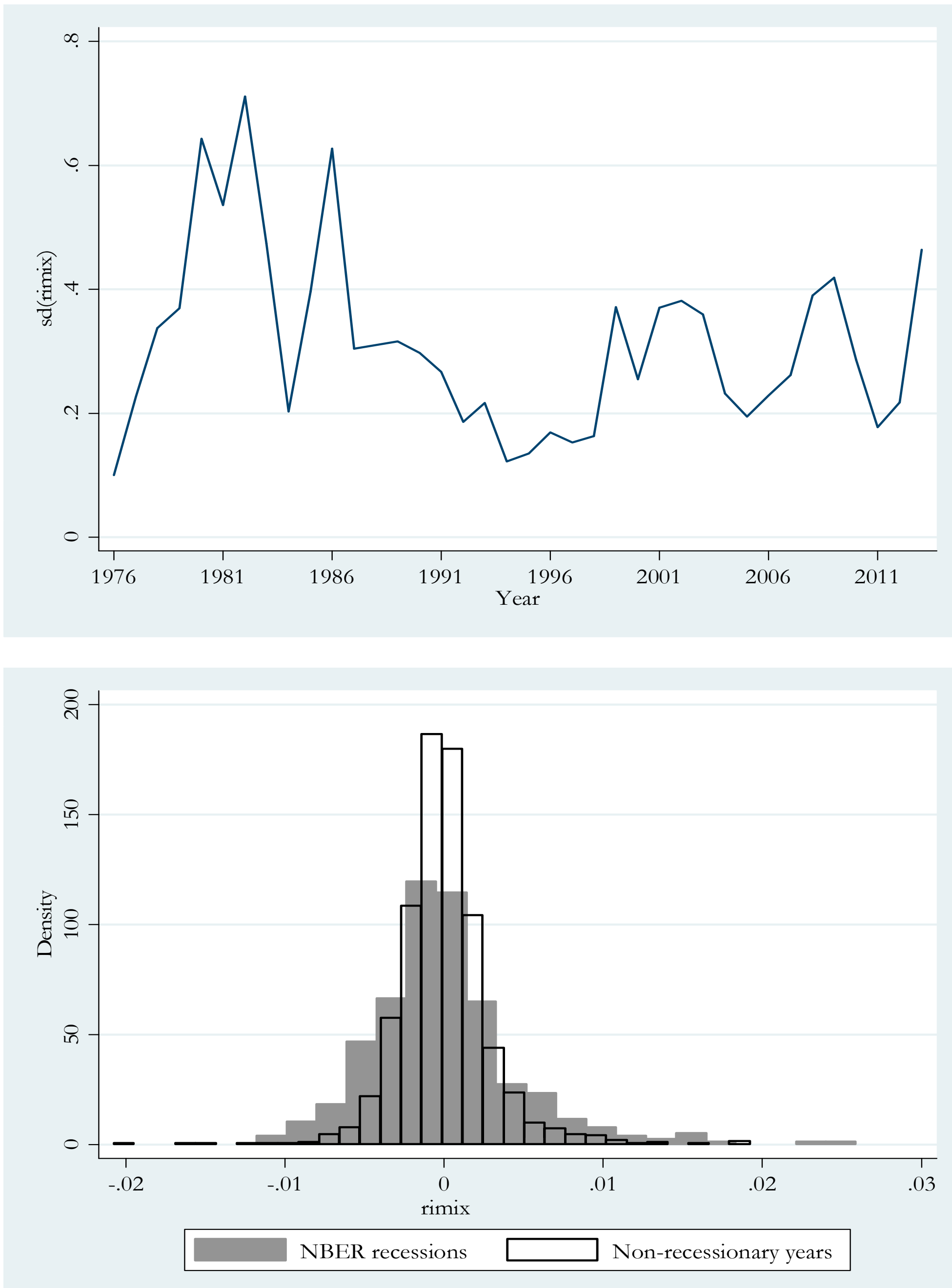
Note: Response of net migration to a 1 percent relative labor demand shock ($\Delta rimix = -0.01$) is derived from the estimating equation (13) using state-level population growth data from LAUS-BLS, differentiating between recessions and expansion. Upper panel uses the full sample (1976-2013), lower panel leaves out the Great Recession (1976-2006). Units on vertical axis in percent of pre-shock civilian population.

Figure A7: Short and long-run response of cumulative migration response to relative labor demand shock: OLS (BK) identification.



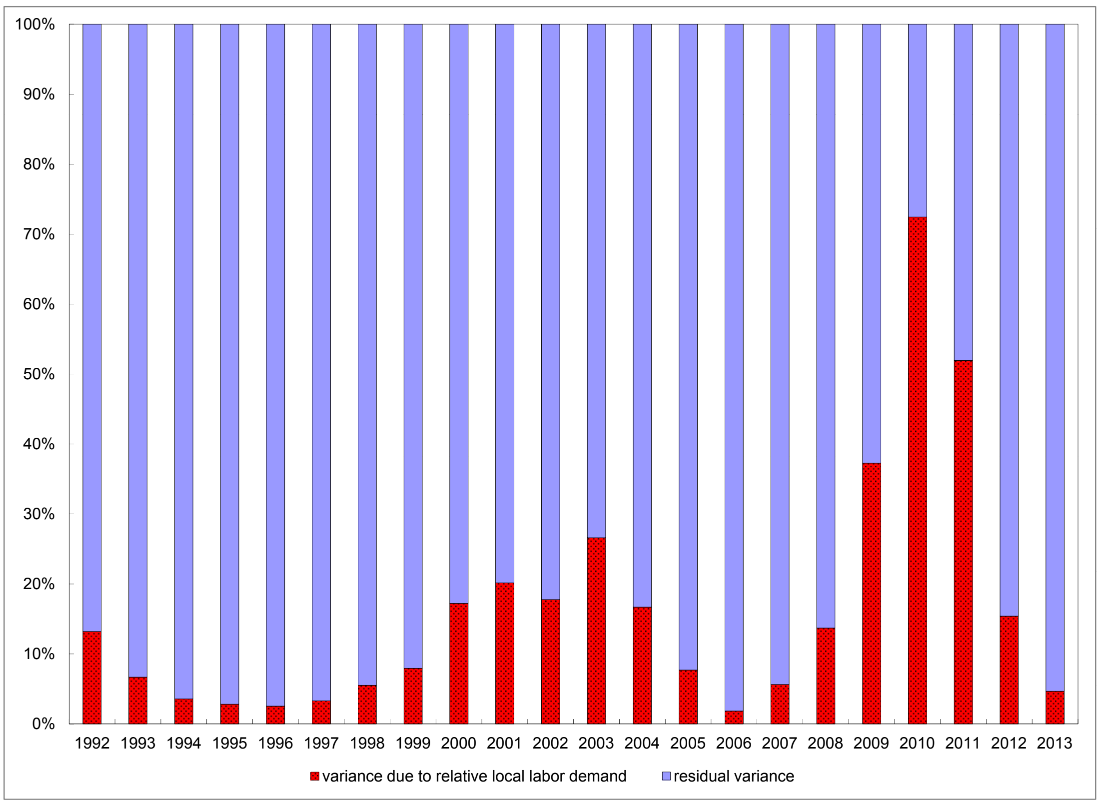
Note: Response of net migration to a 1 percent relative labor demand shock is derived from the original OLS system of equations (1) as used in BK. Impact response as well as cumulative response after 1, 2 and 10 years are shown in percent of civilian population.

Figure A8: Dispersion of relative labor demand over time and across business cycles.



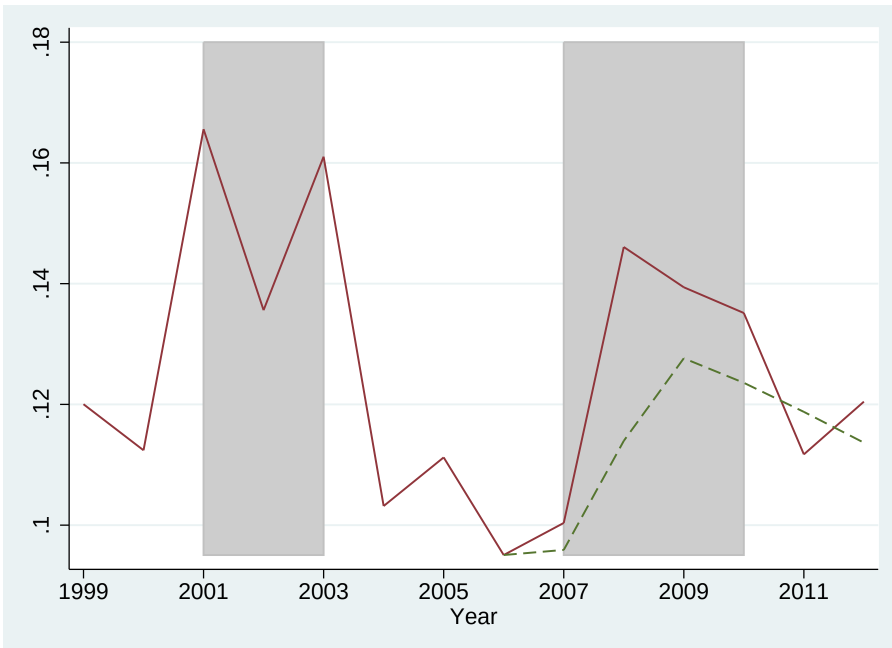
Note: Upper panel shows the evolution of the standard deviation of relative labor demand across states ($rimix_{s,t}$) in each year (in percentage points). Lower panel shows the histogram of relative labor demand in years with NBER recessions versus non-recessionary years.

Figure A9: Cross-sectional variance decomposition of interstate net migration rate.



Note: Variance decomposition is derived in Appendix B. Cross-sectional variance of net migration rate is decomposed into contribution of relative labor demand variation across states ($rimix_{s,t}$) and other factors that are orthogonal to relative labor demand (residual factors). Net migration series is from the Census PEP.

Figure A10: Interstate migration rate for job-search: percent of labor force.



Source: Authors' calculation based on CPS March supplement micro data, 1999-2013. Respondents with imputed migration status were excluded from the computation starting 1996 to avoid the upward bias documented in Kaplan and Schulhofer-Wohl (2012). Dashed green line is the counterfactual migration rate resulting from the shift share analysis in Table A3. Shaded areas encompass years between trough and peak of the unemployment rate around each recession.

B Test of BK identification with alternative instrumental variable

The second IV we consider (in addition to the industry-mix variable) picks up exogenous changes to state-level labor demand in oil and gas extraction industries triggered by changes to the aggregate oil price. That is, we have:

$$oil_{s,t} = \bar{\theta}_{st}^{o\&g} \Delta \ln(\frac{\bar{P^{oil}}}{\bar{PPI}})_t, \tag{11}$$

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 $\bar{\theta}_{st}^{o\&g}$ (computed as 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.[30] Because we are interested in states' relative labor market outcomes (relative unemployment, relative participation), and net-migration responds to relative, not absolute labor market conditions (see BK and other models of spatial equilibrium such as Roback, 1982), we take deviations of $oil_{s,t}$ from their national averages to obtain measures of relative labor demand changes:

$$roil_{s,t} = oil_{s,t} - \bar{oil}_t$$

Using $roil_{st}$ to instrument for $\Delta \ln e_{s,t}$ in the equations for relative employment rate le and participation rate lp from the system of equations (1), we obtain the 2SLS results summarized in column 3 of Table B5. Moreover, OLS results and 2SLS with the baseline industry-mix variable is reproduced in column 1-2, while 2SLS results using both IV's jointly are given in column 4.

C Validation of baseline results using LAUS population and ACS interstate migration data

The second dataset we use to validate the results is the state-level civilian non-institutional population (16 years and older) series, taken from the LAUS-BLS, and runs from 1976. Relative to the Census PEP internal net-migration data, which explicitly measures population change due to interstate movers derived from IRS tax filings, population growth from the LAUS is the net result of interstate migration, but also differences in adult mortality, immigration from abroad and incarceration. However, we expect the change in this measure of population that is due to state-level labor demand shock to be mainly driven by net migration. Therefore, we estimate the same equations (5) and (6) using de-trended 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. The two lower quadrants in Figure C11 plot the implied response of cumulative population change to a 1 percent labor demand shock from the OLS (C quadrant) and IV (D quadrant), each compared against direct estimation using state-level population growth data. This validation exercise relies

[30] Variants of this IV have also been used in e.g. Saks and Wozniak (2011) and Gallin (2004).

Table B5: Endogeneity of contemporaneous employment growth: Employment rate (le) and Participation rate (lp) equation.

	OLS	2SLS		
le : $\Delta e_{s,t}$	0.225***	0.792***	0.948***	0.848***
	(0.021)	(0.149)	(0.233)	(0.144)
Hausman endog. test (p)	-	0.00	0.00	0.00
Hansen overid. test (p)	-	-	-	0.483
lp : $\Delta e_{s,t}$	0.411***	0.095	0.284*	0.114
	(0.025)	(0.134)	(0.160)	(0.126)
Hausman endog. test (p)	-	0.00	0.453	0.01
Hansen overid. test (p)	-	-	-	0.277
1st Stage				
$rimix$		0.580***		0.478***
		(0.133)		(0.139)
$roil$			0.286***	0.188***
			(0.098)	(0.098)
F stat	-	19.09	8.51	11.63
N	1785	1734	1773	1722

Note: The entries in the first and fourth row show the second stage estimates of le and lp on $\Delta e_{s,t}$ using OLS and 2SLS. The first stage panel shows the estimates of the endogenous variable $\Delta e_{s,t}$ on the IV's separately and jointly. The instruments $rimix$ and $roil$ are as defined in equations 3 and 11 in the text. Robust standard errors clustered on states are given in parenthesis. All regressions also include the set of lagged endogenous variables as in each equation of the system in (1) as well as state fixed effects.

on a longer time series than the Census migration data, but leads to the same conclusion. While the OLS identification leads to large and widening discrepancies between system-implied and directly estimated population responses, the IV identification implies population adjustment that closely tracks that derived directly from population data.

We use the LAUS-BLS civilian non-institutional population growth data as a direct measure for $m_{s,t}$ in the stacked systems 8 in the main text. The resulting Chi-squared test statistics and the p-value under the null hypothesis for the first 3 years after a given shock to relative labor demand are summarized in Table C6. The test results confirm the visual conclusion from Figure 3. While the OLS identification can be rejected at confidence levels of 97 percent or higher at all three time horizons, using either dataset, the IV identification yields estimates for implied migration responses that are statistically indistinguishable from directly estimated ones.

Table C6: Test statistics (p-value) for rejecting the null hypothesis of over-identification using LAUS-BLS population growth data.

	OLS-VAR	IV-VAR
LAUS population data for m		
t=1	5.33 (0.02)	0.19 (0.66)
t=2	4.63 (0.03)	0.14 (0.71)
t=3	819.2 (0.00)	0.03 (0.87)

Note: The entries present the Chi-squared test statistics (with 1 degree freedom) and, in parenthesis, the p-values for the cross-equation restrictions that correspond to the null hypothesis that the VAR-implied migration response are equal the directly estimated migration response at each of the 3 years after the relative labor demand shock. The first column tests the over-identification in the stacked OLS-VAR model (7) and the second column in the stacked RFIV-VAR model (8) in the text.

Finally, we do one last cross-check of the VAR-implied against directly estimated migration response by using the American Community Survey (ACS) data, which is a nation-wide survey started in 2005 to collect similar information as the decennial census, but at an annual frequency. The advantage of this data relative to the Census PEP 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. Relative to the LAUS data, the ACS migration rate only captures individuals within each age group that moved across state lines only and hence is not confounded by differences in mortality, international immigration or incarceration (also because the ACS sample includes group quarter population starting in 2006). The big disadvantage is that net migration rates are only available starting in 2007, 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. up to 2 years after the shock.

To validate the identification strategy using $rimix$, we first estimate a similar equation as (6) using the ACS (working-age) migration rates by state, but without lagged dependent variable as the 7 year sample is too short to alleviate concerns about fixed effect bias in dynamic panels. Due to the short sample, we only include the current value of $rimix$ and its first lag; extending up to 2 lags would not change the results but reduces efficiency. We cluster standard errors at the state level to allow for auto-correlation of variables across years. The results are summarized in the first

2 columns of Table C7. Similar to preceding results using Census and LAUS migration data (and those obtained from the RFIV-VAR system above), we again find that a predicted relative employment shock of 1 percent has no contemporaneous effect on net-migration, but triggers around 0.4 percent change in population after 2 years. The estimate for the lagged response is unchanged if we leave out the contemporaneous value of $rimix$ (column (2)). To explicitly test for consistency between model-implied and direct estimates, we repeat the stacked regression in the augmented system (8), allowing for only 1 lag of all independent variables and excluding lagged dependent variable in each equation due to the short time-series, which we now limit to correspond to the ACS net migration data availability: 2007-2013. As the test results in the lower panel of Table C7 reveal, the point estimates for the population response in the first and second year after the shock are very similar for the system-implied and directly estimated results, with the Wald test failing to reject equality.

Similarly, to assess validity of the OLS identification, we also estimate a similar equation as (5), where relative labor demand shocks are identified with contemporaneous change in relative employment growth conditional on past employment and participation rates. Estimates from the single equation using ACS migration rates are given in column (3) of Table C7, with the system-implied results using OLS identification (over the same time period) and over-identification test results based on stacked regression given in the lower panel. Relative to direct ACS estimates, and similar to over-identification results using the previous datasets, the OLS system overestimates both the impact and lagged effect of relative labor demand shocks. As a consequence, the Wald test strongly rejects the null hypothesis of equality within the first and second year of the shock.

D Expanding window regression

In this section, we implement a sequence of expanding window regressions for the symmetric model to derive the overall evolution of population adjustment (that is, to an average of positive and negative shocks): First, we estimate the RFIV-VAR system in (4) from 1976 to 1990 (the BK sample). We then expand the sample by adding one year at a time and re-estimate the RFIV-VAR. The difference in estimates between any consecutive expanding windows reflects how the last year of observation changes the estimated average dynamics. This allows us to construct annual changes between 1990 and 2013 to any statistics of interest.[31] After estimating a VAR system for each sub-sample, we calculate the response of net migration to a 1 percentage point change in relative predicted employment growth ($\Delta rimix = 0.01$) at different time horizons. To enhance representativeness and avoid that the estimation be overly influenced by small states with big shocks in the marginal year, we weight the observations by state-level population (averaged over the sample period). The implied evolution of migration sensitivity in the same year ($t = 1$) and 1 to 10 years after the shock ($t = 2$ to $t = 11$) are plotted in Figure D12.[32]

Looking at the evolution of migration response, one observation immediately stands out: The period 2007-2010 saw a stronger adjustment of net migration to relative labor demand across states at all time horizons.[33] For example, while the population adjustment within the first year of the

[31]These methods have been widely used in the finance literature, in particular for forecasting purposes. See e.g. Pesaran and Timmerman (2002).

[32]The un-weighted series delivers largely the same result, but is somewhat more volatile.

[33]In fact, migration response already picks up somewhat in 2006 before the Great Recession. This increase is most

Table C7: Direct estimation of migration response to relative labor demand shocks using ACS data.

	Dependent variable: ACS net migration rate		
	(1)	(2)	(3)
$rimix_t$	-0.117	-	-
	(0.079)		
$rimix_{t-1}$	0.36***	0.392***	-
	(0.132)	(0.117)	
Δe_t	-	-	0.079***
			(0.021)
Δe_{t-1}	-	-	-0.015
			(0.025)
N	355	355	355
R^2	0.08	0.07	0.05
System over-ident. test:			
system-implied response in t	0.001	-	0.273
$\chi^2(1)$, (p-value)	0.19 (0.67)		28.03 (0.00)
system-implied response in $t+1$	0.311	0.311	0.552
$\chi^2(1)$, (p-value)	0.02 (0.88)	0.06 (0.80)	53.91 (0.00)

Note: ACS migration rates are measured as net inflow of 16-64 year old adults as percent of beginning of year working age population. Robust standard errors clustered on states in parenthesis. All regressions include a set of state and year fixed effects. Column (1) and (2) apply the reduced form IV identification according to equation system (5) and column (3) the OLS identification according to the system (1) for relative labor demand shocks. Column (3) OLS regression also includes $le_{s,t-1}$ and $lp_{s,t-1}$ as additional covariates. Lower panel shows over-identification test results based on cross-equation restrictions of the stacked regression model analogous to (7) and (8) (with 1 lag and no lagged dependent variables). Number for the system-implied response is derived as residual response from the first 3 equations of the model. The χ^2 statistic and p-value in each case are derived for a Wald test of the impact and cumulative effect of 1 percent relative labor demand shock on population change being statistically equal between the direct estimates with ACS data and system-implied results.

shock is, as we have shown before, close to zero on average, this average increases more than five fold between the sub-sample until 2006 and that until 2010, when the Great Recession years are included. As these are differences between expanding-sample averages (that is, sample excluding vs. the one including the Great Recession), they reflect an even bigger underlying increase in the average response during the Great Recession alone. The increased contemporaneous responsiveness of migration during this period also raises the cumulative adjustment in the medium and long run (i.e. in $t = 2$ to $t = 10$). The average response after 1 year increases by about a third, while that after 10 years increases by a quarter between the same sub-samples.[34] We also register a spike in migration response around the 1990-1991 recession, but none around the short 2001 recession. This is possibly because the 2001 was a short and shallow recession compared with other downturns in US history, and one from which the economy recovered quickly. Given that the response of migration typically materializes 1-2 years after the shock, the brevity of the 2001 recession is therefore consistent with the lack of surge in migration response relative to other recessions in the sample.

Apart from the contemporaneous and long-term response, where the most pronounced changes are the cyclical peaks, migration responsiveness at intermediate time horizons display a gradual decline from the early 1990s. Between the sample until the early 1990s and that up to 2004, subject to the same 1 percent shock to relative labor demand, cumulative population adjustment declines from 0.7 percent to 0.4 percent after 1 year, and from 1.5 percent to 0.5 percent after 4 years.

likely driven by the aftermath of Hurricane Katrina, which triggered one of largest diaspora within the United States in modern times.

[34]The change in responsiveness triggered by an additional year in the sample decreases with the time horizon as the weight of current shock decreases and past shocks increases for longer-term responses.

Was the increased responsiveness if population adjustment during the Great Recession accompanied by a corresponding decrease in relative unemployment and participation rates adjustment, so that the relative employment response remained unchanged, or did the other two margins of adjustment increase as well, boosting the equilibrium employment adjustment? In Figure D13 we plot the response of state-relative unemployment and participation rate on impact and after 1 and 4 years following a 1 percent relative labor demand shock using the same expanding window regression of the RFIV-VAR system above. Unlike net migration, relative unemployment and participation rates are not immediately more sensitive to relative demand shocks during the Great Recession (that is, in $t = 1$). Rather, the contemporaneous adjustment of these labor market variables have been dominated by a gradual downward trend since the early 1990s, implying that a given ex-ante labor demand shock resulted in smaller ex-post employment adjustment across states. The 1-4 year lagged adjustment of the relative unemployment rate, however, has been stronger during the Great Recession, though, unlike net migration, such an increase in not registered for the 1990-1991 recession.[35] As for the participation rate, no clear cyclical pattern can be identified during the last 3 recessions, with the over-riding pattern being the gradually declining sensitivity to relative shocks. This declining trend in participation adjustment since the early 1990s is consistent with a declining overall aggregate labor force participation rate in the US due to aging demographics and hence less mobility into and out of the labor force as older workers' participation rate is less cyclical (see Balakrishnan et al., 2014). It may also be related to the declining share of marginally attached persons in the non-participation pool and thus less cyclical transition from non-participation as documented by Barnichon and Figura (2013).

Overall, the expanding window regression exercise allowed us establish more clearly an increased responsiveness of net migration to relative labor demand shocks across states during aggregate downturns and particularly during the Great Recession, confirming the preceding stylized facts. Such counter-cyclical sensitivity is not as consistently observed for the other margins of labor market adjustment (employment and participation rates). At the same time, adjustment of all three margins to a given ex-ante relative shock has been weakening since the early 1990s, implying smaller ex-post variation in employment growth across states subject to similar variation in ex-ante relative demand shocks. Both results are consistent with the earlier observation (from Figure 1) that variation in employment growth has been declining on average, but spiking up during aggregate downturns. Moreover, the declining trend does not appear to be reflected to the same extent in a gradually declining variation of underlying ex-ante shocks to state-relative demand: The cross-sectional dispersion of the exogenous underlying shock $rimix$ - while on average higher in recessions - does not exhibit a declining trend since the early 1990's (see Appendix Figure A8). Less responsiveness to similarly dispersed shocks thus appears to drive the declining cross-section dispersion of employment growth over time, while stronger migration response to more dispersed shocks drive the higher dispersion of employment growth in recessions.

There is also a compositional effect underlying the counter-cyclical responsiveness of population adjustment. As a relative positive shock triggers stronger in-migration on average, a larger share of variation in relative shocks coming from the group of positive states in a sample would increase the estimated average response in that sample and vice versa, even if the within-group

[35] If anything, there seems to be an opposite change of lower sensitivity in unemployment to relative shocks in 1990-1991, though the length of the expanding window sample does not allow an examination of the period before 1990.

responses are unchanged (see Appendix C for derivation). Figure D14 decomposes the change in estimated short-run responsiveness during the 2007-2013 period to contributions coming from the within-group changes (positive versus negative groups) and from the compositional change. This exercise shows that almost all of the increase in 2007 and more than 75 percent of the increase in 2008 and 2009 (relative to the baseline in 2006) was driven by increased responsiveness to relative positive shocks. Starting in 2010, responsiveness to negative shocks starts increasing too, contributing to half of the increased responsiveness in 2010 relative to 2006.[36]

[36]The compositional effect contributes less than one-tenth of the increase in estimated migration response during the Great Recession.

E Regression with smooth business cycle interaction

The evidence presented in Figures 4 to D12 consistently show that the responsiveness of net interstate migration to relative shocks increased during the Great Recession. Though the expanding window regressions allowed us track annual changes after 1990, in particular during the Great Recession, we could not rely on this exercise (which requires sufficiently long samples) to verify whether this counter-cyclical sensitivity holds generally across preceding aggregate downturns as well. To explicitly differentiate regional adjustment dynamics across different states of the aggregate business cycle, and following Auerbach and Gorodnichenko (2012), we modify the system of equations (4) as follows:

$$\begin{aligned} x_{st} &= \alpha_{s10} + \alpha^{r}_{11} F(z_t)(L) rimix_{s,t} + \beta^{r}_{11} F(z_t)(L)\Delta e_{s,t-1} + \beta^{r}_{12} F(z_t)(L) le_{s,t-1} + \beta^{r}_{13} F(z_t)(L) lp_{s,t-1} \\ &+ \alpha^{e}_{11}(1-F(z_t))(L) rimix_{s,t} + \beta^{e}_{11}(1-F(z_t))(L)\Delta e_{s,t-1} \\ &+ \beta^{e}_{12}(1-F(z_t))(L) le_{s,t-1} + \beta^{e}_{13}(1-F(z_t))(L) lp_{s,t-1} \\ &+ \epsilon_{sxt}, \\ & F(z_t) = \frac{exp(-\gamma z_t)}{1+exp(-\gamma z_t)},\ Var(z_t)=1,\ E(z_t)=0 \end{aligned} \tag{12}$$

where x stands for each of the three variables Δe, le, and lp as in the RFIV-VAR system 4 and $F(.)$ is a transition function of the state of the economy z (normalized so that γ is scale invariant). A positive z indicates an expansion, while a negative z indicates a recession. We set z equal to the three-years moving average of US output growth rate and we calibrate $\gamma = 1.5$ so that economy spends about 20 percent of time in a recession regime (that is, $Pr(F(z_t) > 0.8) = 0.2$) where we define an economy to be in recession if $F(z_t) > 0.8$. The calibration is consistent with the duration of U.S. recessions according to NBER business cycle dates (Auerbach and Gorodnichenko, 2012). This modified system of three equations is essentially an augmented version of equation system (4) where each coefficient is interacted with a measure of the state of the aggregate economy and hence allowed to vary continuously along the business cycle.

This approach is equivalent to the smooth transition autoregressive (STAR) model developed by Granger and Teravistra (1993). The advantage of this approach is twofold. First, compared to a model where each dependent variable is interacted with the level of unemployment rate or business cycle measures, it allows us to directly test whether the response of migration varies across different regimes such as recessions (e.g. output growth below a given threshold) and expansions. Second, compared to estimating SVARs for each regime it allows the response of migration to change smoothly between recessions and expansions by considering a continuum of states to compute the impulse response functions, making thus the response more stable and precise.[37] Figure E15 presents the response of cumulative net migration to a 1 percent relative labor demand shock ($\Delta rimix = 0.01$) during recessions $F(z_t) = 1$, and expansions $F(z_t) = 0$, as implied by the system in (12). Consistent with the expanding window regressions results, we see a stronger reaction of net migration to the same relative shock during aggregate downturns than during expansions. As most of the adjustment occurs 1 and 2 years after the shock, we apply the delta method to formally

[37] This approach has been applied to model non-lienarities in number of different economic issues such as exchange rates dynamics (Sarno and Taylor, 2002); sectoral performance during the business cycle (Fok et al., 2005); money demand (Chen and Wu, 2005) fiscal multipliers (Auerbach and Gorodnichenko, 2012).

test for the difference in response at these time horizons. The Chi-square test statistics suggests rejection of the null hypothesis of no difference at 3 and 1 percent significance level respectively.

As an alternative approach to test whether the response of net migration varies with the state of the economy using the RFIV-VAR, we look at relative growth working-age population data (from LAUS-BLS) directly. In particular, we modify equation (6) as follows:[38]

$$\begin{aligned} m_{st} = \alpha_s + \gamma_t \quad &+ \quad \beta^r F(z_t)(L)m_{s,t-1} + \gamma^r F(z_t)(L)rimix_{s,t} \\ &+ \quad \beta^e(1 - F(z_t))(L)m_{s,t-1} + \gamma^e(1 - F(z_t))(L)rimix_{s,t} + \epsilon_{st}, \end{aligned} \tag{13}$$

The results from estimating equation (13) are close to the system-derived one, confirming that net migration adjustment to relative shocks is larger in recessions than in expansions, both in the short and long run. Moreover, excluding the years of the Great Recession (in the lower panel) do not change the result qualitatively, confirming that the counter-cyclical responsiveness of population adjustment is a general pattern holding consistently across recessions and expansions (see Appendix Figure A6).

F Decomposing the cross-sectional variance of net migration over time

Recall equation (6) in the text which gives an auto-regressive distributed lag representation of state-level net migration and state-level labor demand shocks. Taking deviation from state-level means and substituting estimated parameter values, we obtain the empirical version of equation (6) as follows:

$$\tilde{m}_{s,t} = \hat{\delta}_t + \hat{\beta}(L)\tilde{m}_{s,t-1} + \hat{\gamma}(L)ri\tilde{mi}x_{s,t} + e_{st}, \tag{14}$$

where e is the vector of estimated residuals and variables with ˜ denote deviations from state means.

Inverting equation (14) to obtain the moving average representation gives:

$$\begin{aligned} \tilde{m}_{s,t} &= \hat{\alpha}(L)\hat{\delta}_t + (1 - \hat{\beta}_{s,t}(L)L)^{-1}\hat{\gamma}(L)ri\tilde{mi}x_{s,t} + (1 - \hat{\beta}_{s,t}(L)L)^{-1}e_{st} \\ &= (1 - \hat{\beta}_{s,t}(L)L)^{-1}\hat{\delta}_t + \hat{\phi}(L)ri\tilde{mi}x_{s,t} + \hat{\eta}(L)e_{st}, \end{aligned} \tag{15}$$

where coefficients of the lag polynomial

$$\hat{\phi}(L) = 1 + \hat{\phi}_1 L + \hat{\phi}_2 L^2 + \hat{\phi}_3 L^3 + ... \tag{16}$$

represent the impulse response function of net migration to a unit shock to $rimix_s$ at each time horizon $i = 0, 1, ...\infty$, and coefficients from the polynomial $\hat{\eta}(L)$ represent the corresponding impulse responses of net migration to other factors orthogonal to $rimix$ and its lags.

[38] We use working-age population here instead of net migration to maximize the number of years to have sufficient expansions and recessions.

Taking the cross-sectional variance V_s on both sides of equation (15), we get for each period t:

$$\begin{aligned} V_s(\tilde{m}_{s,t}) &= \sum_{i=0}^{\infty} \hat{\phi}_i^2 V_s(ri\tilde{m}ix_{s,t-i}) + 2\sum_{i=0}^{\infty}\sum_{\substack{j=0\\ i\neq j}}^{\infty} \hat{\phi}_i\hat{\phi}_j Cov(ri\tilde{m}ix_{s,t-i}, ri\tilde{m}ix_{s,t-j}) \\ &\quad + \sum_{i=0}^{\infty} \hat{\eta}_i^2 V_s(e_{s,t-i}) + 2\sum_{i=0}^{\infty}\sum_{\substack{j=0\\ i\neq j}}^{\infty} \hat{\phi}_i\hat{\phi}_j Cov(e_{s,t-i}, e_{s,t-j}) \end{aligned} \tag{17}$$

where we used the property that OLS residuals are orthogonal to the covariates

$$\begin{pmatrix} rimix'_{s,t} \\ rimix'_{s,t-1} \\ rimix'_{s,t-2} \end{pmatrix} e_{s,t} = 0$$

and the fact that $V_s(\delta_t) = 0$.

We can then decompose the cross-sectional variance at each period t into the proportion attributable to current and past relative labor demand shocks $\omega_{s,t}(rimix)$:[39]

$$\omega_{s,t}(rimix) = \frac{\sum_{i=0}^{\infty} \hat{\phi}_i^2 V_s(ri\tilde{m}ix_{s,t-i}) + 2\sum_{i=0}^{\infty}\sum_{\substack{j=0\\ i\neq j}}^{\infty} \hat{\phi}_i\hat{\phi}_j Cov(ri\tilde{m}ix_{s,t-i})}{V_s(\tilde{m}_{s,t})} \tag{18}$$

Consequently, the share of variance accounted for by other factors orthogonal to relative labor demand is given each period by $1 - \omega_{s,t}(rimix)$.

In practice, due to stationarity of the time-series process for net migration, contributions of lagged $rimix$ terms far in the past have very negligible impact on the current variance of migration. In fact, while going from $i = 1$ to $i = 2$ increases the explained proportion of variance by 5 percentage points (pp) on average, adding lags 3 years back increases $\omega_{s,t}(rimix)$ by 1.4 pp, and beyond 3 years back add less than 0.2 pp. We can therefore approximate

$$\omega_{s,t}(rimix) \approx \frac{\sum_{i=0}^{4} \hat{\phi}_i^2 V_s(ri\tilde{m}ix_{s,t-i}) + 2\sum_{i=0}^{4}\sum_{\substack{j=0\\ i\neq j}}^{5} \hat{\phi}_i\hat{\phi}_j Cov(ri\tilde{m}ix_{s,t-i})}{V_s(\tilde{m}_{s,t})} \tag{19}$$

As data for the labor demand variable $rimix$ is not available for 1987 due to the break in SIC industry classification, using up to 4 lags means we can only start applying the formula above in 1992. We compute the share of variance accounted for relative labor demand shocks versus other factors using this formula for each year $t >= 1992$ by substituting the time-varying estimates of the parameters ϕ's resulting from the expanding window regression of equation system (4) and the empirical variance and covariance estimates in each year. The result is plotted in Figure A9.

[39]This also corresponds to the unconditional or long-term forecast variance.

G Decomposing the change in migration responsiveness

In the following, we show how the change in short-run migration responsiveness (that is, after 1 year of the relative labor demand shift) can be decomposed into contributions from changed responsiveness to relative positive and relative negative shocks, as well as from their composition.

We start with equation (6) for interstate net migration m_t in the text. Recognizing that the contemporaneous migration response to $rimix$ is statistically insignificant (as illustrated in Figures 2-4), and focusing in this exercise on the 1-year lagged response only, we use the following parsimonious version:

$$m_{st} = \alpha_s + \delta_t + \beta m_{s,t-1} + \gamma rimix_{s,t-1} + \epsilon_{st}, \tag{20}$$

Estimating this equation with OLS, we recover coefficient estimates that can be used to transform the original migration variable to:

$$\tilde{m}_{s,t} = m_{s,t} - \hat{\alpha_s} - \hat{\delta_t} - \hat{\beta} m_{s,t-1} \tag{21}$$

and focus on the estimated bivariate relationship:

$$\tilde{m}_{s,t} = \hat{\gamma} rimix_{s,t-1} + e_{st}, \tag{22}$$

The OLS estimate of the lagged migration response is given by:

$$\hat{\gamma} = \frac{\sigma_{rimix1,\tilde{m}}}{\sigma^2_{rimix1}},$$

where σ^2_{rimix1} is the variance of the lagged state-relative labor demand and $\sigma_{rimix1,\tilde{m}}$ the covariance of this variable with the transformed migration rate $\tilde{m}$. Defining relative positive and negative labor demand changes as in equation (9), we have:

$$\begin{aligned} rimix_{s,t} &= rimix^+_{s,t} + rimix^-_{s,t} \\ (rimix^+_{s,t})'(rimix^-_{s,t}) &= 0 \end{aligned}$$

for all s and t. The migration response parameter estimate can therefore be re-written as:

$$\begin{aligned} \hat{\gamma} &= \frac{\sigma_{rimix1^+,\tilde{m}} + \sigma_{rimix1^-,\tilde{m}}}{\sigma^2_{rimix1^+} + \sigma^2_{rimix1^-}} \\ &= \hat{\gamma_1^+} \times \frac{\sigma^2_{rimix1^+}}{\sigma^2_{rimix1^+} + \sigma^2_{rimix1^-}} + \hat{\gamma_1^-} \times \frac{\sigma^2_{rimix1^-}}{\sigma^2_{rimix1^+} + \sigma^2_{rimix1^-}} \end{aligned}$$

where $\hat{\gamma_1^+}$ and $\hat{\gamma_1^-}$ are OLS estimates of the unrestricted version of model (22):

$$\tilde{m}_{s,t} = \hat{\gamma_1^+} rimix^+_{s,t-1} + \hat{\gamma_1^-} rimix^-_{s,t-1} + e'_{st},$$

Using the definition of the transformed variable (21), the estimated parameter $\hat{\gamma}_1$ corresponds to the estimated cumulative impact of a unit change in $rimix$ on migration after 1 year, that is $\hat{\phi}_1 = \hat{\gamma}$ and similarly for the estimated effect of a positive and negative relative shock: $\hat{\phi_1}^+ = \hat{\gamma}^+$, $\hat{\phi_1}^- = \hat{\gamma}^-$.

Let $\alpha = \frac{\sigma^2_{rimix1+}}{\sigma^2_{rimix1+} + \sigma^2_{rimix1-}}$, we obtain:

$$\hat{\phi}_1 = \alpha \hat{\phi}_1^{\,+} + (1-\alpha)\hat{\phi}_1^{\,-}$$

The estimated migration response is thus a weighted average of the estimated response to relative positive and that to relative negative shocks, with the weights corresponding to the share of overall variance in relative labor demand explained by each type of shock. The values for $\hat{\phi}_1^{\,+}, \hat{\phi}_1^{\,-}$ can be estimated from the asymmetric model (9), while $\hat{\phi}_1$ is obtained by estimating the baseline system (4), allowing us to back out α. Finally, denoting the change in estimates from one expanding window sample to the next be $\Delta\hat{\phi}_1$, we have, up to first order approximation:

$$\Delta\hat{\phi}_1 = \alpha\Delta\hat{\phi}_1^{\,+} + (1-\alpha)\Delta\hat{\phi}_1^{\,-} + \Delta\alpha(\hat{\phi}_1^{\,+} - \hat{\phi}_1^{\,-})$$

That is, the change in estimated responsiveness over time can be decomposed to the contribution from changing response to positive shocks (first term on the right hand side), changing response to relative negative shocks (second term), and contribution from the changing variance composition of shocks (third term). More variation in cross-sectional labor demand being accounted for by relative positive shocks will raise the estimated response for any given level of response within each group of shocks and vice versa. This approximate decomposition of change in 1-year lagged migration responsiveness is plotted in Figure D14.

H The evolution of relative wage response

We have also carefully looked at the behavior of state-relative wages as an additional outcome variable as suggested. Following BK, we used the log hourly manufacturing wage in each state relative to the national average as the outcome variable $w_{s,t}$.[40] We replicate the baseline regression in BK for wages, but using our measure of state-level labor demand to be consistent with the baseline approach and the overwhelming supporting evidence for this identification in section 4. That is, we estimate jointly the bi-variate system with 2 lags:

$$\begin{aligned} \Delta e_{st} &= \alpha_{s10} + \alpha_{11}(L)rimix_{s,t} + \beta_{11}(L)\Delta e_{s,t-1} + \beta_{12}(L)w_{s,t-1} + \epsilon_{set}, \\ w_{st} &= \alpha_{s10} + \alpha_{11}(L)rimix_{s,t} + \beta_{11}(L)\Delta e_{s,t-1} + \beta_{12}(L)w_{s,t-1} + \epsilon_{swt}, \end{aligned} \tag{23}$$

Doing so, we find that the response of relative wages to relative demand shocks has become statistically insignificant in the second half of the sample. In fact, plotting the response of relative wages to a 1 percent shock to relative state-level labor demand in the first half of the sample (which partly includes the BK sample) versus the second half of the sample, we obtain results illustrated in Figure H16 below. In the first half of the sample, a one percent shift in relative labor demand changes relative wages by 1.2 percent after 2 years, with very high statistical significance. Over the same sample, the change in unemployment rate is 1.1 percent after 1 year, hence implying an

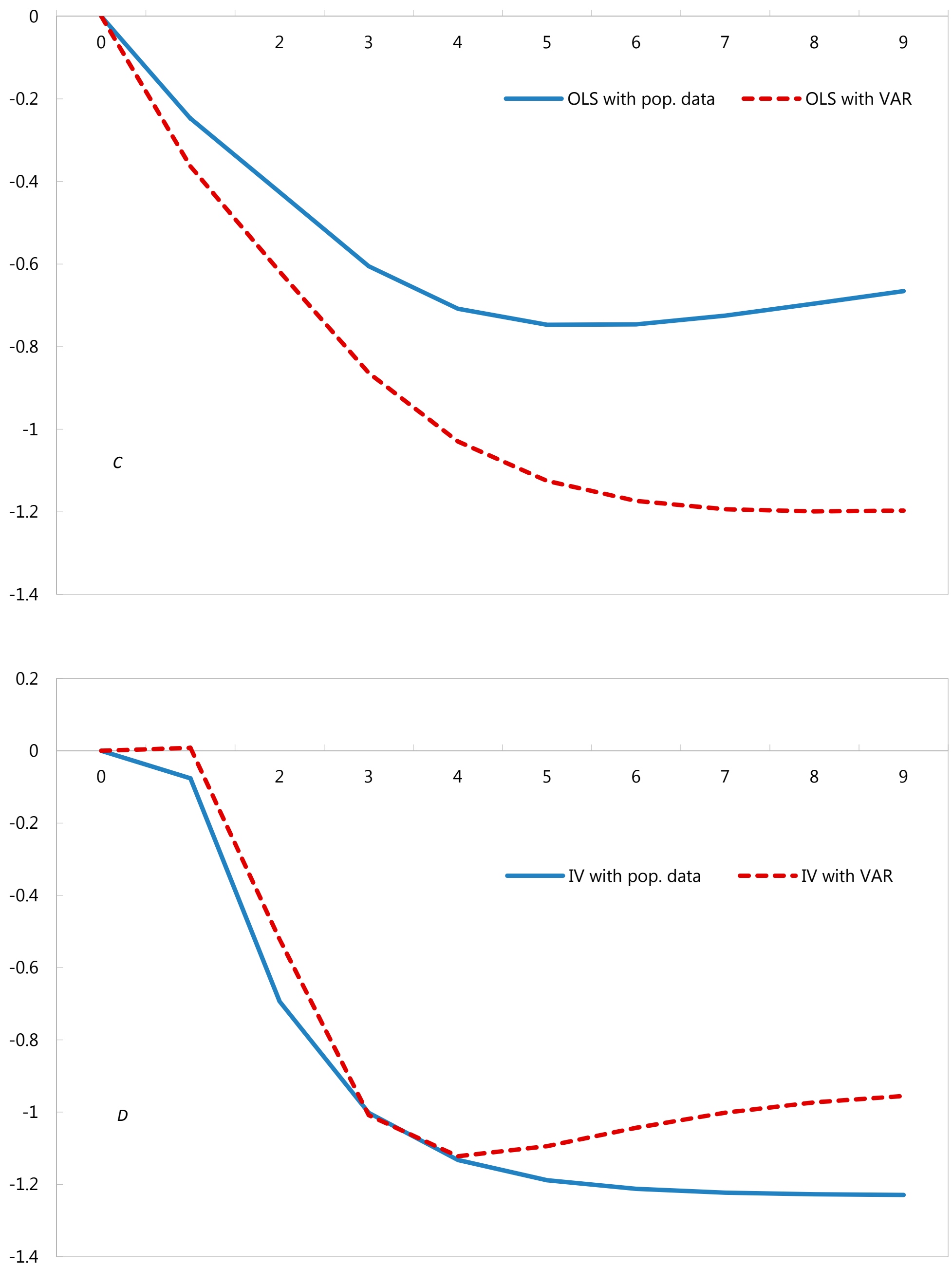
[40] BK chose the manufacturing hourly wage because it is available for the longest period. Although BK worked with data going back to 1950, data prior to 1970 is no longer available from the BLS. We use data from 1976-2013 to match the sample of our labor demand variable. Focusing on wage in one particular sector also abstracts from sector composition effects following a demand shift

elasticity of relative wages to relative unemployment of approximately unity, same as in BK. However, the response of relative wages to the same shock is negative and not statistically significantly different from zero in the second half of the sample. Tracing out the change from year to year as we do in the paper for migration response, we find that the decline in wage response has been proceeding gradually since the early 1990s, stabilizing around 2005 (Figure H17). We get qualitatively the same result if the outcome variable is a measure of relative consumption wage, that is relative hourly manufacturing wage deflated by relative non-tradable prices across states (assuming a share of housing service in CPI of 40 percent and that relative prices of other non-tradable services and tradable goods do not change, following BK). Results are also robust to extending the number of lags on the right hand side or focusing only on production workers in manufacturing.

There are several possible reasons why the estimated wage response has weakened:

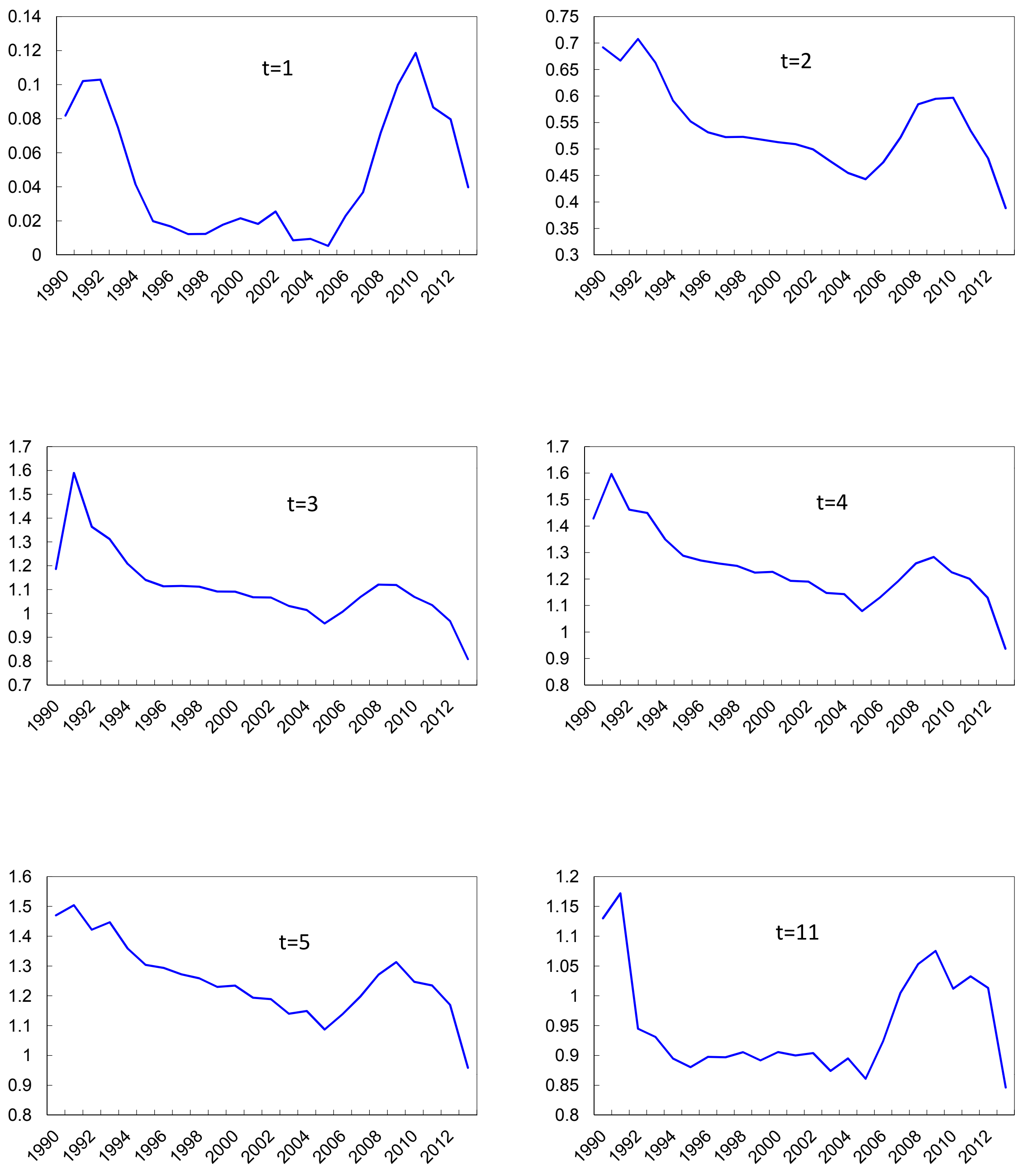
- Unlike estimates for other labor market variables, there appears to be more heterogeneity in wage response across states (as also noted by BK, see their p. 42). This heterogeneity may have increased over time, rendering a panel regression that aims to capture an average response become increasingly imprecise.
- The manufacturing wage may not capture changes in overall wages in a state. However, this is probably true for any sector-level wage series, and wages in other sectors are not available for long periods of time. It is also not necessary for the relative shock to be a manufacturing demand shock, as a lower labor demand in any sector should increase labor supply in other sectors of a state, including in manufacturing, and hence have a negative effect on wages (see also Autor et al, 2013). State-level personal income could be an alternative outcome, but such average income variables also cover non-wage income, transfers and will be confounded by compositional effects.
- We think compositional effects beyond sectoral composition may be at work. Import competition from overseas such as China have intensified over the years in our second subsample, thus playing an increasing role in driving labor demand disparities across states in the US with different exposure to import-competing manufacturing industries. At the same time, a number of papers such as Autor et al. (2013), Edwards and Lawrence (2010) document that there have been no significant negative wage effects in these sectors over a similar time period that we look at (since 1990). Although the reason for such lack of response are not entirely clear, it is often believed that either downward wage rigidities are at work (and have become more binding with increased import competition), or the composition of workers in manufacturing shifted toward more productive ones, hence raising the average wage (see Autor et al, 2013).

Figure C11: Response of cumulative net migration, using migration and population data directly vs. backed-out from VAR.



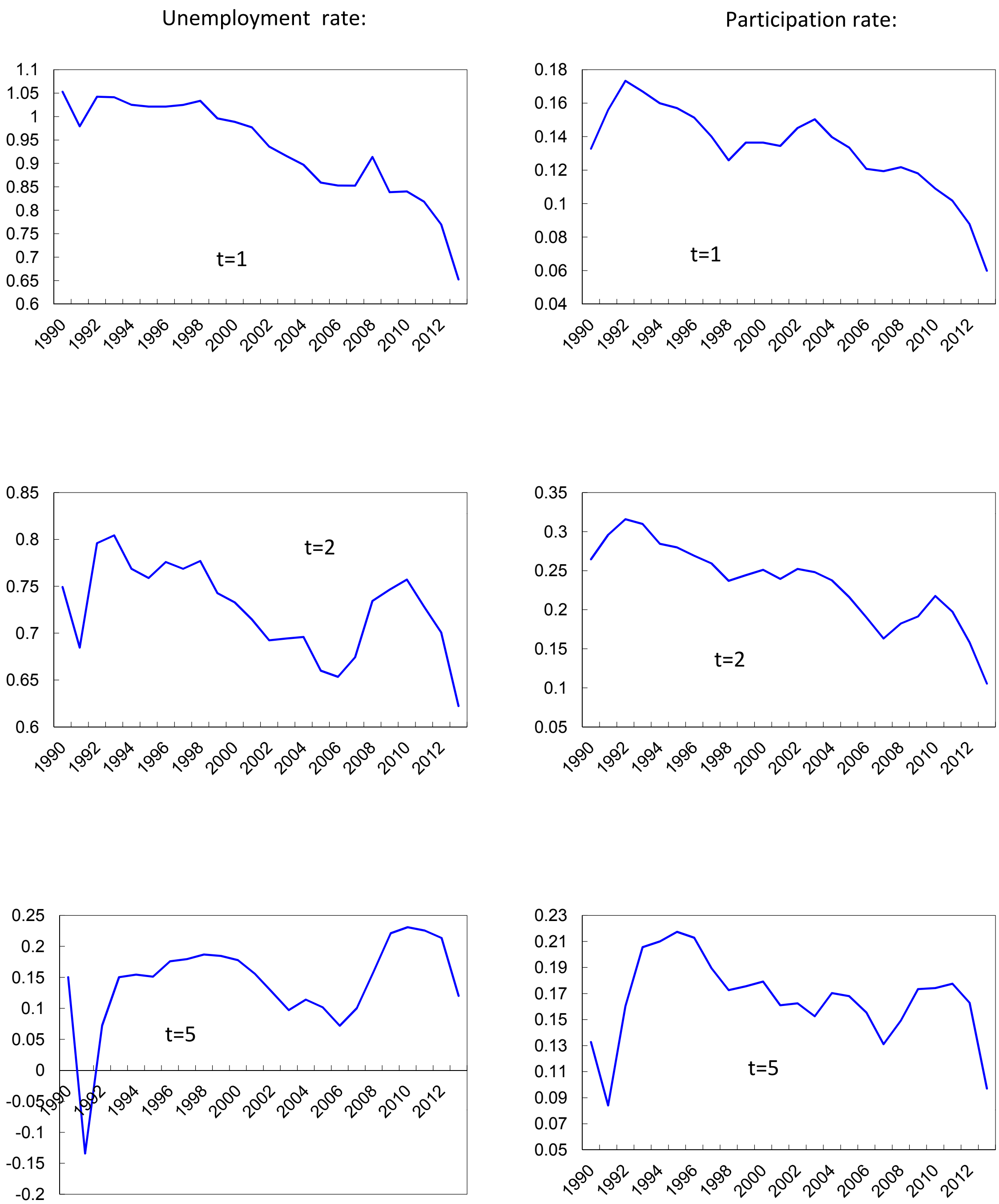
Notes: Sample period is 1991-2013 for migration data comparison against estimates from OLS-VAR model (1) in the text (A) and RFIV-VAR model (5) in the text (B panel). Horizontal axis denotes years after shock. Unit on vertical axis: percent of working-age population.

Figure D12: Short and long-run response of net migration to relative labor demand shock: expanding window regressions.



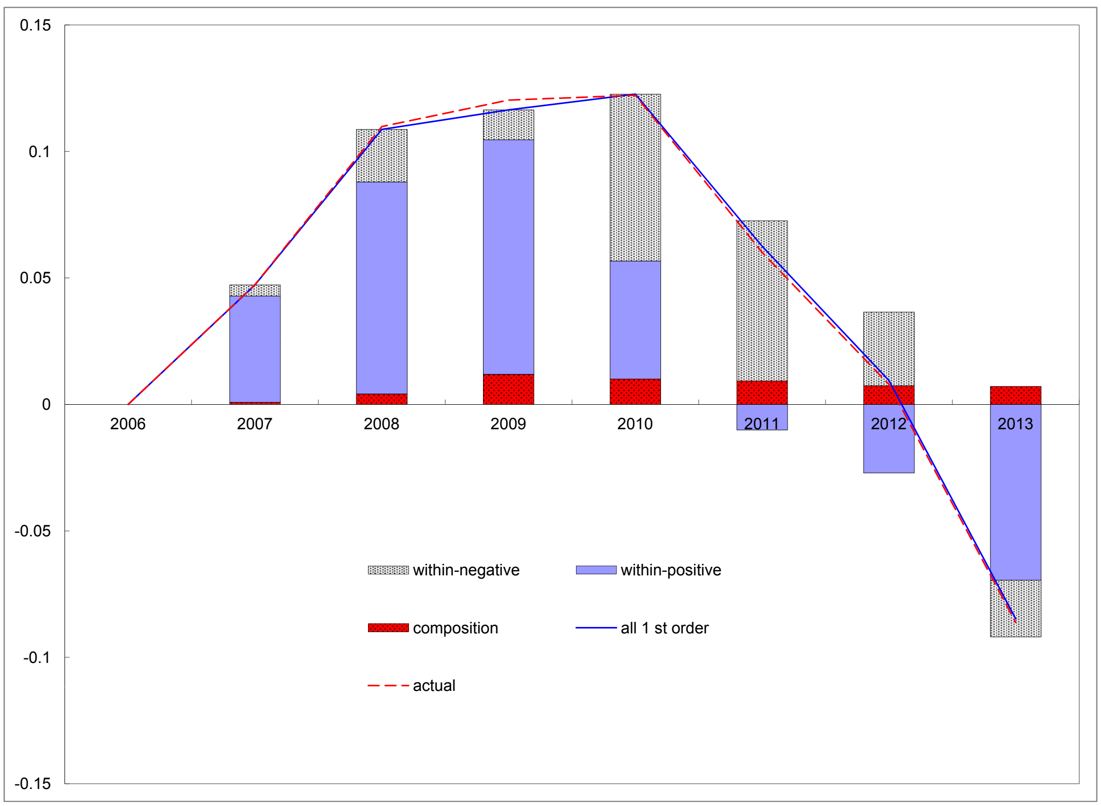
Note: Underlying shock is 1 percent change in predicted relative employment growth ($rimix$). Evolution of adjustment after 1-5 and 10 years are shown as estimated according to equation system (5) with expanding window sample. Horizontal axis denotes last year of observation in expanding window. Unit on vertical axis is percent of pre-shock working-age population.

Figure D13: Short and long-run response of relative unemployment and participation rates to relative labor demand shock: expanding window regressions.



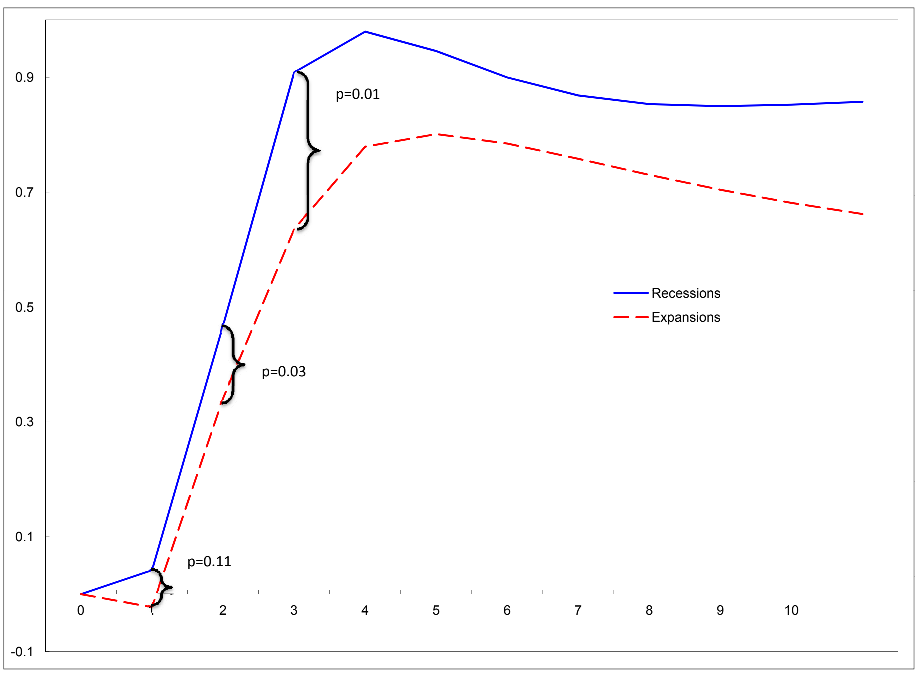
Note: Underlying shock is 1 percent change in predicted relative employment growth ($rimix$). Evolution of adjustment after 1,2 and 5 years are shown as estimated according to equation system (5) with expanding window sample. Horizontal axis denotes last year of observation in expanding window. Unit on vertical axis percentage point deviation from pre-shock levels.

Figure D14: Decomposition of change in short-run migration responsiveness during the Great Recession.



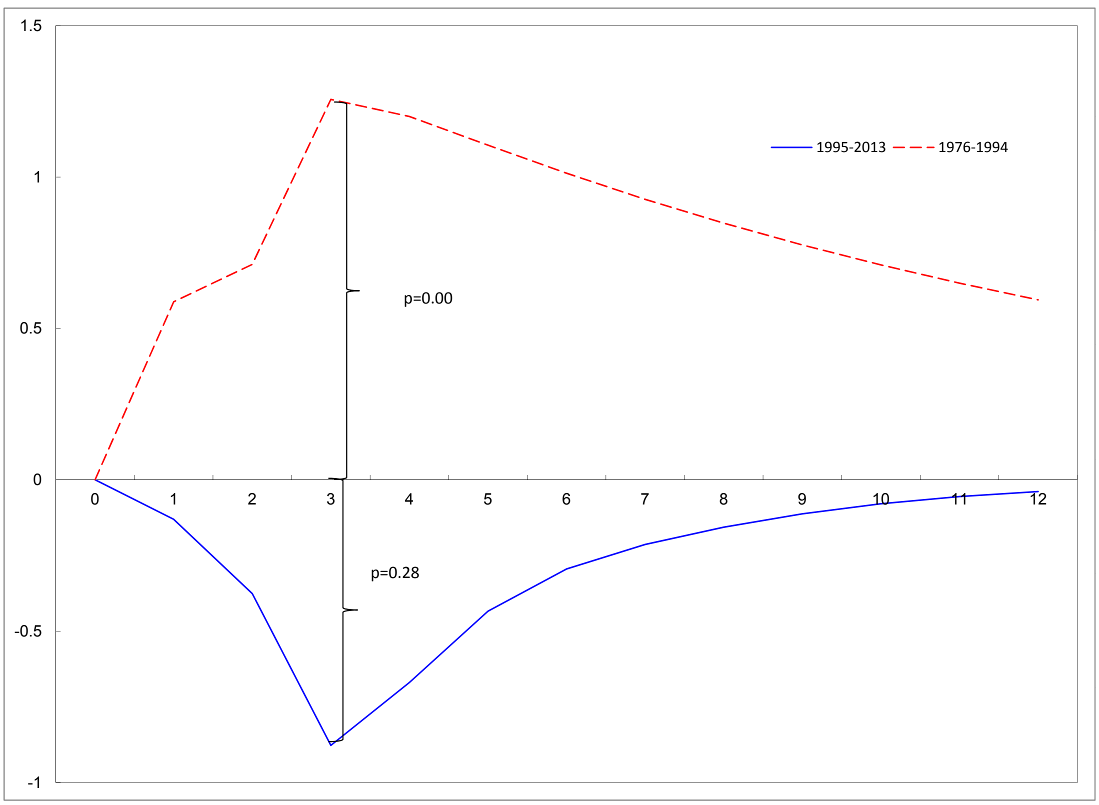
Note: Change in estimated net migration response 1 year after a 1 percent relative labor demand shock, decomposed to first order approximation into contribution from change in responsiveness within the positive group (response to $\Delta rimix^{+} = 0.01$), within the negative group (response to $\Delta rimix^{-} = -0.01$) and from the sample composition of relative dispersion across groups. All values are relative to the baseline value in 2006 (i.e. $2006 = 0$). See detailed derivation of the decomposition in Appendix C.

Figure E15: Response of cumulative net migration to a 1 percent relative labor demand shock: business cycle interaction.



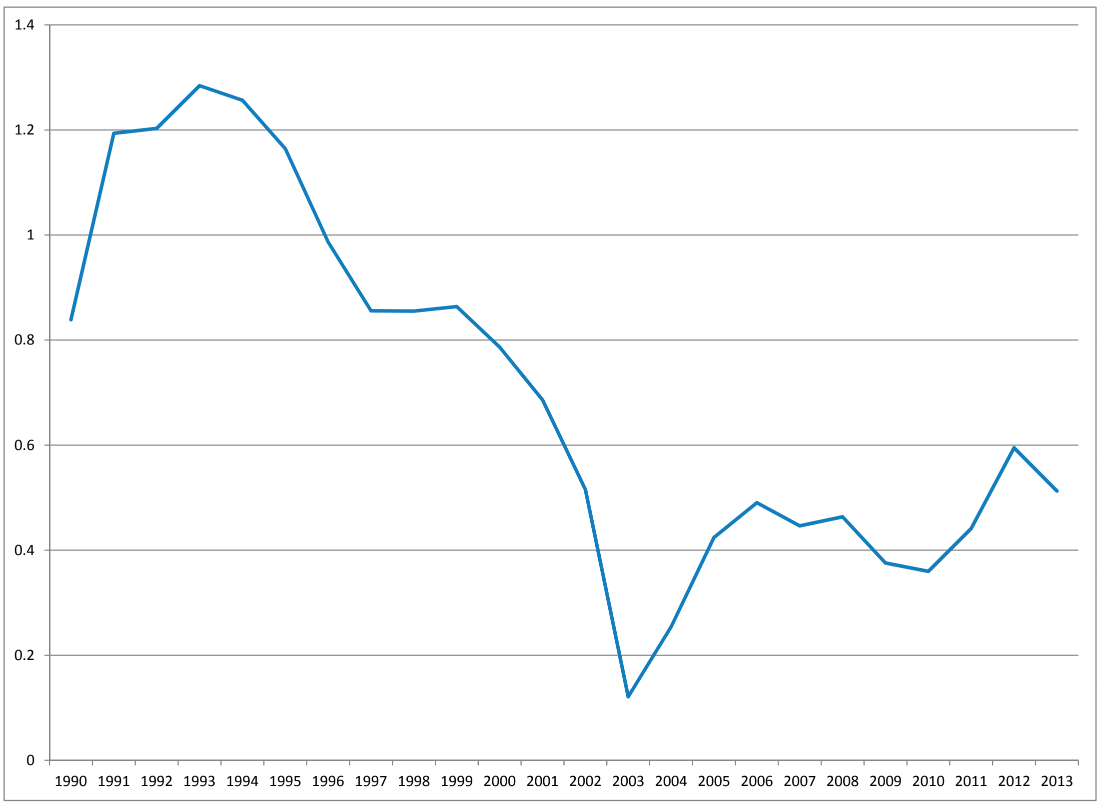
Note: Response of net migration to a 1 percent relative labor demand shock ($\Delta rimix = 0.01$) is derived from the system of equations (12), differentiating between recessions and expansion. P-values for Wald test of equality of responses between recession and expansion are derived using the delta method for $t > 1$. Unit on vertical axis is percent of pre-shock population.

Figure H16: Response of relative state-level wage to a 1 percent relative labor demand shock: 2 sub-samples.



Note: Response of relative state-level wage to a 1 percent relative labor demand shock ($\Delta rimix = 0.01$) is derived from the system of equations (23). P-values, derived with the delta method, test the null hypothesis that the peak response after 2 years is equal zero.

Figure H17: Response of relative state-level wage to a 1 percent relative labor demand shock: expanding window regressions.



Note: The figure plots the response of relative wages to 1 percent shock to relative labor demand after 2 years, ordered by last year of observation in the sequence of expanding window regressions of equation system (1), starting in 1976.