Labor mobility and Unemployment over the Business Cycle

Andrea Foschi, University of Michigan
Christopher L. House, University of Michigan and NBER
Christian Proebsting, KU Leuven
Linda L. Tesar, University of Michigan, CEPR and NBER

A significant share of business cycle risk is regional, affecting some parts of the United States more than others. In theory, one response to such risks is for workers to relocate. However, the extent to which individuals *actually* move in response to shocks remains a question of considerable debate. In one of the earliest and most well-known studies on labor market adjustment, Blanchard and Katz (1992) found a substantial amount of labor mobility. Subsequent studies, however, have found that labor market adjustment is far from frictionless, resulting in depressed employment in affected areas that persists for years. A number of studies focusing on the Great Recession, for example, find that frictions prevented workers from relocating as local conditions deteriorated (Mian and Sufi, 2014, Foote, Grosz and Stevens, 2019, and Autor, Dorn and Hanson, 2021).

In this short paper, we re-examine the magnitude of labor mobility in the United States over the last 45 years. We measure labor mobility as the elasticity of net migration to variation in unemployment rates across the United States at the business cycle frequency. We show that the estimate of the degree of labor mobility depends on the underlying source of data, the treatment of the data and the sample period. In our baseline specification, we find that an increase of 100 unemployed workers in a given area is associated with net out-migration of approximately 48 workers. We also find that the responsiveness of labor to unemployment shocks at the business cycle frequency is stable over time, inclusive of the Great Recession.

I. Net Migration and Unemployment

We estimate the elasticity of net migration to annual changes in local economic conditions, as measured by the unemployment rate. Our basic regression specification in equation (1) has labor migration as the independent variable and the local unemployment rate as the independent variable.

$$nm_{i,t} = \alpha + \beta ur_{i,t} + \varepsilon_{i,t} \tag{1}$$

Here $nm_{i,t}$ is a measure of net migration in year t, region i and $ur_{i,t}$ is the associated unemployment rate. A negative β implies that higher local unemployment rates are associated with negative net migration flows – i.e., an out-migration of workers.

To estimate (1), we need reliable measures of migration and unemployment at the regional level. Our main results are based on population data from the U.S. Census and unemployment data from the BLS. Net migration is defined as the annual percent change in a state's population.[1] Data on

[1] The change in the population includes both the change in demographic variables (births less deaths) and the net inflow of residents. We compare our results to data from the IRS, that reports the change in filing location of tax returns. We find little difference in the estimates using the alternative measure of net migration.

state unemployment rates are provided by the Bureau of Labor Statistics. Our baseline specification involves de-meaning the unemployment and migration rates in both the cross-section and the time dimension. This removes long-run average differences as well as common cyclical variations. We do this because many regions have persistently high (or low) unemployment rates and persistently high (or low) migration rates that are not related to the business cycle adjustments that are the focus of our analysis. This demeaning procedure is similar to applying state and time fixed effects though there are small differences because our panel is not balanced and because we detrend with the national unemployment rate, a population-weighted average for the time fixed effect.[2]

Figure 1A is a scatterplot of annual net migration rates (on the vertical axis) against unemployment rates (the horizontal axis) for U.S. states from 1977 to 2019. There appears to be no systematic relationship between labor migration and local economic conditions and a regression of net migration on the unemployment rate yields a coefficient close to zero. This conclusion is premature, however. Figure 1B shows the same data after removing time-series and state-specific means. There is now a clear negative relationship between the two variables, with a regression coefficient of -0.30 (see Table 1). That is, if the unemployment rate is one percent above average for a given state, that state experiences a net outflow roughly equal to one quarter of one percent of the state's population. This implies a fairly large degree of labor market adjustment through relocation at an annual frequency – if 100 workers become unemployed then this suggests that $30/LFP \approx 48$ people leave the state (using a labor force participation ratio of 62 percent).

Demeaning the data strongly alters our view on the role of labor migration in absorbing local shocks. Another reason for the various views on labor migration in the literature could be the source of the data. Alternative sources of information on labor migration are provided by the American Community Survey (ACS), the Census and the IRS.[3] The IRS reports migration data based on the mailing addresses of tax returns and covers all U.S. tax filers. These data start in 1975. In contrast, the ACS provides more comprehensive responses to a variety of survey questions but covers a smaller set of individuals and data collection starts in 2005. Table 1 shows the regression estimates for each of the three datasets (Census, IRS and ACS). For each case, we consider the raw data and the demeaned data. Focusing first on the raw data, we see that the relationship between net migration and unemployment is weakly negative. After demeaning the coefficients increase significantly, though the ACS coefficient remains the lowest at -0.12, significant at the 5 percent level.

There are two key shortcomings of the ACS data set. First, the ACS has a smaller sample than either the Census or the IRS data, sampling about 1.5% - 2% of the population. This problem is especially acute for states with small populations, as the survey results may be based on just a handful of survey respondents that may have just recently moved.

A second problem is that there are important coding mistakes in the survey itself (see U.S. Census, 2016). For example, in 2008, a period during which a number of well-known studies find little evidence of migration, an outsized number of survey respondents were reported to have lived in

[2] The results with the more conventional time and state fixed effects are nearly identical.

[3] While the IRS data and the ACS data are independent data sources, the Census is not. The Census uses both the IRS data and the ACS (among other information) to construct its measures of state population.

Alaska the previous year. As shown in Figure 2, the ACS data indicate that approximately 10 percent of the population of Alaska moved out of the state in 2008. This error was caused by Alaska appearing as the first entry in the dropdown menu for the survey. Respondents who did not provide an answer were automatically coded as living in Alaska. Not surprisingly this caused a substantial error in the migration statistics not just for Alaska, but for any state whose responses were accidentally attributed to Alaska.

Figure 2 illustrates the problem with measurement error in the ACS. We plot IRS and ACS net migration rates for the five smallest states (including Alaska) where survey samples are likely to be the smallest. The reported ACS data have much more volatility than the IRS data and suggest unrealistically large swings in state populations. Table 1 reports the net migration elasticity based on ACS data after we remove these five states. This trimmed sample yields estimates that look closer to the Census. Given the volatility of the ACS migration figures, our preferred estimates use either IRS or Census data.

The estimated elasticity of net migration to variation in unemployment is relatively stable over time. Figure 3 repeats the estimation from our baseline specification (Census data, demeaned) separately for each year. While the estimates change from year to year, they remain relatively close to the overall average of -0.30, though the elasticity of net migration has become slightly weaker over time.

II. Migration Results: Different Specifications and Different Geographic Levels

Table 2 reports the elasticity estimates at the state, commuting zone, and county levels for different econometric specifications. The estimates for our baseline specification (Table 2.A) are statistically and economically significant at all regional levels. Perhaps somewhat surprisingly, the estimates become smaller as we move to finer levels of aggregation. This could be due to increased measurement error in unemployment rates for smaller regions (leading to an attenuation bias) or may reflect true differences in factors driving migration in smaller regions. For instance, Molloy and Smith (2019) report that short-distance moves are less likely to be related to job changes but are more often motivated by reasons related to housing.

Table 2.B reports estimates where each observation is weighted by population. Relative to the baseline, the net migration elasticity becomes slightly smaller for states and larger for commuting zones without altering the ranking of the estimates. This suggests that smaller states have a lower migration elasticity, whereas within states, smaller places have a large migration elasticity.

The regression results based on equation (1) provide evidence of an association between net migration and unemployment but not necessarily a causal relationship. A potential concern is that a change in net migration -- for example, a sudden inflow of workers -- could generate an increase in unemployment, rather than net migration *reacting* to a shift in unemployment. Similarly, region-specific changes in labor force participation could drive both unemployment and net migration. Dao *et al*. (2017) suggest using a Bartik shift-share variable $Z_{i,t}$ based on the composition of industries at the state level to capture exogenous changes in local labor demand:

$$Z_{i,t} = \sum_j s_{i,j,t} \frac{L_{j,t} - L_{j,t-1}}{L_{j,t-1}}$$

where $s_{i,j,t}$ is the share of industry *j* in state *i*'s total employment in the five years prior to *t*, and $\frac{L_{j,t}-L_{j,t-1}}{L_{j,t-1}}$ is the employment growth rate in industry *j* between *t-1* and *t* at the national level.[4]

The idea underlying the instrument is that national fluctuations in a particular industry will be more correlated with changes in labor demand in states that are specialized in that industry. For example, if there is a sharp increase in national automobile production, one would expect that labor demand for auto workers would increase in states like Michigan, that have a larger share of auto production. This helps separate labor demand shifts from potential labor supply shifts and will isolate the response of net migration to labor demand shocks. Results for this instrumental variable approach are in Table 2.C According to the IV estimates, the elasticity is -0.57 – nearly twice the baseline result. The estimates are also greater for the commuting zone data and county level data.[5]

Unfortunately, the exclusion restriction for this instrument likely fails (see Borusyak, Dix-Carneiro and Kovak, 2021). The instrument affects state *i*'s net migration not only through changes in unemployment in region *i,* but also through unemployment changes in neighboring regions. Even if workers are responsive to differences in labor demand conditions, there will be little incentive to migrate if workers' current and potential alternative locations face the same labor demand shocks. This problem is worse for regions with similar industrial composition and with large migration flows. For instance, consider Ohio and Michigan: two states that both specialize in car manufacturing and that have large cross-state migration flows. A drop in demand for cars will increase unemployment in both states but there will be little incentive to migrate between the two states.

To address this concern, we include in the regression a measure of unemployment in migration partners; that is, regions that are likely migration destinations and origins. The unemployment rate for the migration partner is the weighted average across likely destinations and origins for movers. We instrument regional unemployment rates with the Bartik instrument described earlier. The instrument for unemployment for the migration partner is the weighted average across likely destinations and origins for movers.[6] With this specification, the response of migration to its own unemployment rate becomes consequently larger (Table 2.D). The response of migration to the migration *partner's* unemployment rate is positive and, for counties and commuting zones, roughly of the same size.

[4] We rely on the County Business Patterns data collected by the U.S. Census Bureau with adjustments for missing values as detailed in Eckert *et al*. (2020) and aggregate the data to commuting zones and states as needed. National employment growth rates are taken from the Quarterly Census of Employment and Wages. We use the most detailed industry level whenever possible (6-digit NAICS) but rely on more aggregate figures whenever industry shares or national employment growth rates are not available.

[5] The Table reports F-statistics for the first stage regressions. For reference, the critical value for first stage F-statistics used for IV regressions at the 10 percent level is 23.11 (see Pfluger and Olea 2013).

[6] The correlation between a region's own labor demand shock and the shock in its migration partner is 0.55 at the state level, 0.69 at the commuting zone level and 0.65 at the county level.

III. Labor Migration During the Great Recession

We next turn to the question of labor mobility during the Great Recession. As seen in Figure 3, *prior* to the Great Recession, our baseline estimate of the net migration elasticity seems unusually low but for the critical years following the recession it is at the mean of -0.30. A regression based on the raw data (without fixed effects and without demeaning) would yield an estimated elasticity of roughly -0.09 at the state level. This would suggest a very weak migration response to the severe contraction that occurred in some regions of the United States. The estimated elasticity during 2008-09 for the baseline specification at the state level is -0.23. This underscores the need to take trend migration rates and trend unemployment rates into account. Consider, for example, the impact of the Great Recession on Michigan and California. States in the Sun Belt like California have experienced substantial migration inflows over the last 40 years, often from colder states like Michigan. At the same time, states in the Sun Belt were the most negatively affected by the housing crisis during the Great Recession. The rise in unemployment coincided with reduced inflows of workers and therefore pushed migration rates down to those observed in other states, flattening out the relationship between unemployment and net migration.

To further assess the role of labor mobility during the Great Recession, we run a series of cross-sectional local projections at the commuting zone level:

$$\sum_{s=1}^{h} nm_{i,2006+s} = \alpha_h - \beta_h \sum_j s_{i,j} \frac{L_{j,2009} - L_{j,2006}}{L_{j,2006}} + \varepsilon_{i,h}$$

where $\sum_{s=1}^{h} nm_{i,2006+s}$ is the migration-induced change in population in commuting zone i between 2006 and 2006+h and $\sum_j s_{i,j} \frac{L_{j,2009}-L_{j,2006}}{L_{j,2006}}$ is the predicted percent change in employment between 2006 and 2009 based on the Bartik industry mix instrument, which we take as our Great Recession shock.

The right panel of Figure 4 displays the estimated coefficients $\hat{\beta}_h$ for the response of population, whereas the left panel displays the estimated coefficients for a similar regression that replaces the population response, $\sum_{s=1}^{h} nm_{i,2006+s}$, by the response of unemployment, $ur_{i,2006+h} - ur_{i,2006}$. The blue, continuous line displays the coefficients when using the raw data for net migration and unemployment. The red, dashed line displays the results when using the double-demeaned data.

Commuting zones more exposed to contracting industries during the recession saw a larger increase in their unemployment rate: A predicted 1% fall in employment raises the unemployment rate by about 0.5 percentage by the peak of the recession. But the effect is temporary and unemployment rates return to their 2006 levels by 2015. Over the same horizon, the population declines by almost 1 percent. Strikingly, a failure to take long-run trends into account would lead to the conclusion that population did not respond to the weaker labor markets in more exposed commuting zones and might have even increased after 2015. The importance of accounting of these pre-trends in the context of the Great Recession has also been acknowledged by Yagan (2016) and Bhattarai, Schwartzman and Yang (2021).

IV. Conclusion

We estimate the responsiveness of net migration to changes in local unemployment. The available data reveal a substantial amount of labor mobility in response to local shocks at the business cycle frequency. Our approach highlights the need to control for underlying trends in the data. Instrumental variables that isolate exogenous shifts in labor demand and controlling for labor market conditions in alternative migration destinations strengthen our estimates of the elasticity. Labor mobility played a significant role in regional adjustments during the Great Recession. Taken together these results suggest that worker relocation remains an important mechanism for accommodating regional business cycles. As a caveat, our data can speak only to total regional labor flows. We leave the question of precisely who moves and who stays to future work.

References

Autor, David, H., David Dorn, and Gordon H. Hanson. 2013. "The China syndrome: Local labor market effects of import competition in the United States." *American Economic Review* 103, no. 6: 2121-68.

Autor, David, David Dorn, and Gordon Hanson. Fall 2021. "On the Persistence of the China Shock." *Brookings Papers on Economic Activity* no. 2.

Bhattarai, Saroj, Felipe Schwartzman, and Choongryul Yang. 2021. "Local scars of the US housing crisis." *Journal of Monetary Economics* 119: 40-57.

Blanchard, O. J., and L. F. Katz. 1992. "Regional Evolutions", in *Brookings Papers on Economic Activity* no. 1: 1-75.

Borusyak, Kirill, Rafael Dix-Carneiro, and Brian Kovak. 2022. "Understanding Migration Responses to Local Shocks," working paper.

Dao, Mai, Davide Furceri, and Prakash Loungani. 2017. "Regional labor market adjustment in the United States: trend and cycle." *Review of Economics and Statistics* 99, no. 2: 243-257.

Eckert, Fabian, Teresa C. Fort, Peter K. Schott, and Natalie J. Yang. 2020. *Imputing Missing Values in the US Census Bureau's County Business Patterns*. No. w26632. National Bureau of Economic Research.

Foote, Andrew, Michel Grosz, and Ann Stevens. 2019. "Locate your nearest exit: Mass layoffs and local labor market response." *ILR Review* 72, no. 1: 101-126.

Mian, Atif, and Amir Sufi. 2014. "What explains the 2007–2009 drop in employment?" *Econometrica* 82, no. 6: 2197-2223.

Molloy, Raven, and Christopher Smith. 2019. "US internal migration: Recent patterns and outstanding puzzles." In *Federal Reserve Bank of Boston's 63rd Economic Conference.“A House Divided: Geographical Disparities in Twenty-First Century America*.

Olea, Jose Luis Montiel and Pflueger, Carolin. 2013 “A Robust Test for Weak Instruments,” *Journal of Business and Economic Statistics*, 31(3): 358-369.

U.S. Census. 2016. “Overestimate of Domestic Outmigration for Alaska in the American Community Survey Prior to 2015,” United States Census Bureau, errata 109.

Yagan, Danny. 2016. "The enduring employment impact of your great recession location," working paper.

TABLE 1— BASELINE MIGRATION ESTIMATES, STATE LEVEL

Data Source, sample period	ACS data (2005-2019)			IRS data		Census data	
	Raw data	Trimmed	Trimmed, demeaned	Raw data	Demeaned	Raw data	Demeaned
Migration elasticity	-0.07	-0.04	-0.12	-0.06	-0.26	-0.08	-0.30
	(0.04)	(0.02)	(0.05)	(0.02)	(0.04)	(0.02)	(0.05)
N obs.	765	675	675	2064	2064	2064	2064

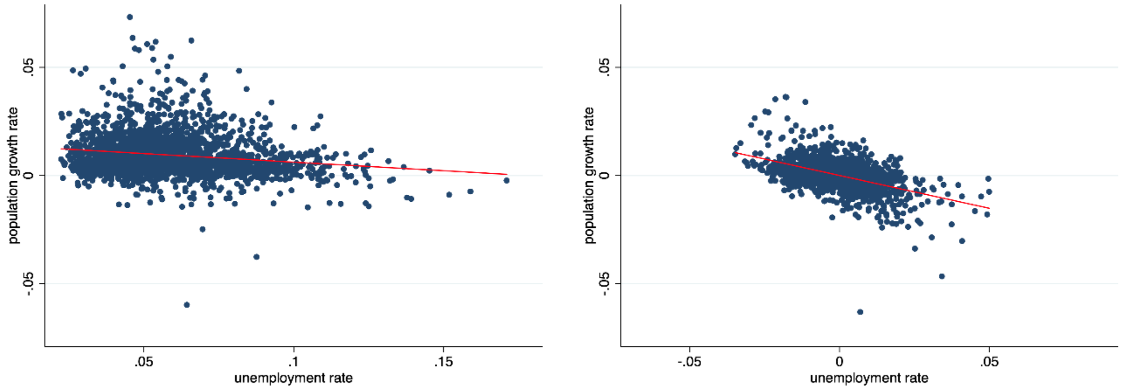
Notes: Driscoll-Kraay standard errors are in parentheses.

TABLE 2—DIFFERENT SPECIFICATIONS AND DIFFERENT GEOGRAPHIC LEVELS

Region	States	Commuting Zones	Counties
2.A Baseline Specification			
Migration elasticity	-0.30	-0.21	-0.15
	(0.03)	(0.02)	(0.02)
N obs.	2064	31046	131296
2.B Population Weighted			
Migration elasticity	-0.25	-0.20	-0.17
	(0.02)	(0.02)	(0.02)
N obs.	2064	31046	131296
2.C Bartik, Industry Share			
Migration elasticity	-0.57	-0.34	-0.33
	(0.12)	(0.07)	(0.07)
1st Stage F-statistic	14.39	344.05	798.58
N obs.	1920	28880	122062
2.C Bartik, Industry Share, Migration Partner			
Own unemployment	-0.60	-0.48	-0.51
	(0.12)	(0.08)	(0.08)
Partner unemployment	1.08	0.45	0.47
	(0.38)	(0.20)	(0.15)
N obs.	1917	28171	121884

Notes: Results are based on demeaned Census data. Driscoll-Kraay standard errors are in parentheses.

Figure 1: Net Migration versus Unemployment



1A: Raw Data

1B: Demeaned

Notes: The figure reports data on state changes in population (vertical axis) against the states unemployment rate (horizontal axis). The figure uses Census data. Each point is a year-state observation from the period 1977-2019. Panel 1B uses demeaned data that removes state average unemployment rates and the national unemployment rate.

Figure 2: State Net Migration Rates ACS versus Census Data

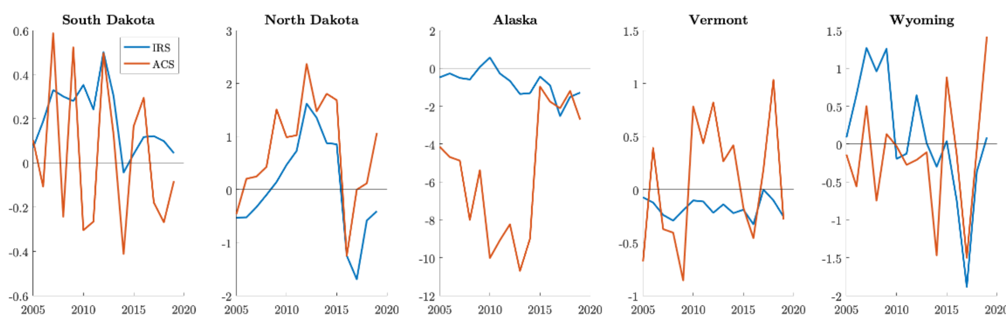
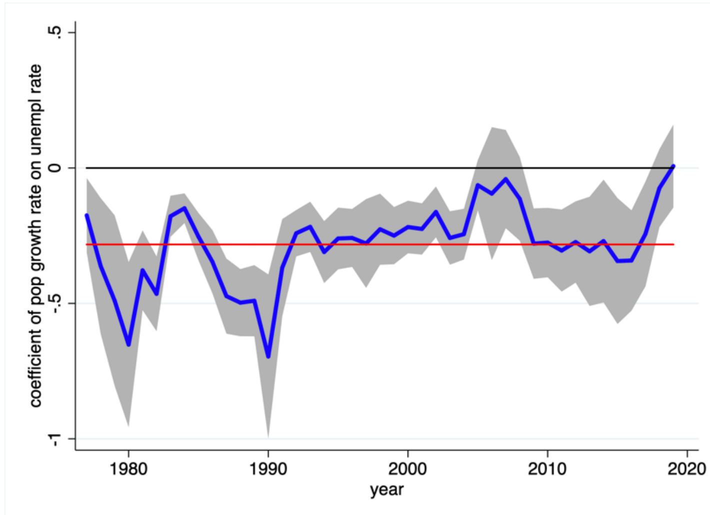
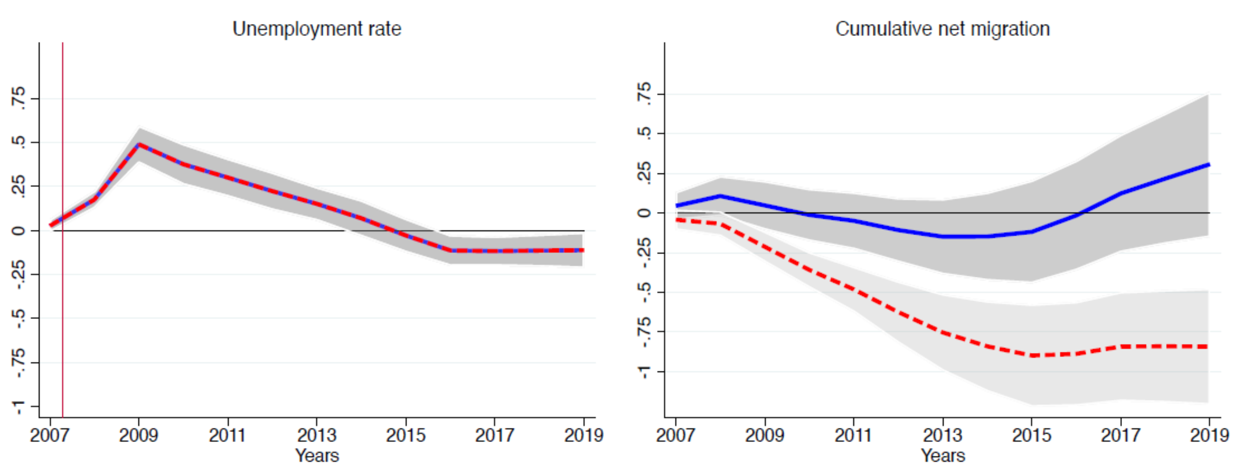


Figure 3: Repeated Cross-Sectional Regressions



Notes: The figure reports data on state changes in population (vertical axis) against the states unemployment rate (horizontal axis). The figure uses Census data. Each point is a year-state observation from the period 1977-2019. Panel 1B uses demeaned data that removes state average unemployment rates and the national unemployment rate.

Figure 4: Local Projections of Cumulative Population Change During the Great Recession



Notes: Blue: not demeaned, Red: demeaned