Labor Mobility and Unemployment over the Business Cycle

By Andrea Foschi, Christopher L. House, Christian Proebsting, and Linda L. Tesar

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 is still debated. 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 persistent low employment. Studies focusing on the Great Recession 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).

We reexamine 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. Our estimate of labor mobility depends on the data source, detrending, and the sample period. Our baseline estimate suggests that an increase of 100 unemployed workers in a given area is associated with net out-migration of approximately 47 workers. 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 is

\[ nm_{i,t} = \alpha + \beta u_{i,t} + \varepsilon_{i,t}, \]

where \( nm_{i,t} \) is net migration in year \( t \), region \( i \) and \( u_{i,t} \) is the unemployment rate. A negative \( \beta \) implies that higher local unemployment rates are associated with negative net migration flows—that is, an out-migration of workers.

Our main results are based on population data from the US census and unemployment data from the Bureau of Labor Statistics. Net migration is defined as the annual percent change in a state’s population. Importantly, we de-mean 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 persistent in- (or out-) migration. Our focus is on cyclical adjustments, separate from long-run trends.

Figure 1, panel A is a scatterplot of annual net migration rates against unemployment rates for US states from 1976 to 2018. For the raw data, a regression of net migration on unemployment yields a coefficient close to zero. De-meaning the data strongly alters our view on the role of labor migration in absorbing local shocks. Figure 1, panel B shows the same data after de-meaning.

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1 Net migration in year \( t \) refers to migration between July 1 of year \( t \) and July 1 of year \( t+1 \).

2 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 Internal Revenue Service (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.

3 This de-meaning 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. Results with time and state fixed effects are nearly identical.
There is now a clear negative relationship between the two variables, with a regression coefficient of $-0.29$ (see Table 1). That is, if the unemployment rate is 1 percent above the average for a given state, that state has a net outflow of roughly one-quarter of 1 percent of the state’s population. This implies a fairly large amount of labor market adjustment through relocation—if 100 workers become unemployed, then $29/LFP \approx 47$ people leave the state (using a labor force participation ratio of 62 percent).

Another reason for different estimates of labor migration is the source of the data. We consider three commonly used data sources: the American Community Survey (ACS), the census, and the IRS. The IRS data are based on mailing addresses of tax returns and cover all US tax filers starting 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 de-meaned data. The relationship between net migration and unemployment in the raw data is weakly negative. After de-meaning, the coefficients increase significantly, though the ACS coefficient remains the lowest at $-0.08$, significant at the 5 percent level.

There are two key shortcomings of the ACS dataset. First, the ACS has a smaller sample than either the census or the IRS data, sampling about 1.5–2 percent of the population. This problem is especially acute for states with small populations.

Second, there are important coding mistakes in the survey itself (see US Census 2016). For example, in 2008, a period in which several studies find little evidence of migration, an outsized number of survey respondents were reported to have moved from Alaska. As shown below, the ACS data indicate that roughly 10 percent of the population of Alaska moved out of the state in 2008. This error may have been due to Alaska appearing as the first entry in the drop-down menu for the survey. Respondents who did not provide an answer were automatically coded as living in Alaska.

Figure 2 plots IRS and ACS net migration rates for the five smallest states (including Alaska). The ACS data are much more volatile 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. Given the volatility of the ACS migration figures, our preferred estimates use either IRS or census data.

Finally, the estimated migration elasticity is relatively stable over time. Figure 3 repeats the estimation from (1) separately for each year.

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 population data.
While the estimates change from year to year, they are close to the overall average of $-0.29$.

II. Alternative Specifications

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, panel A) are statistically and economically significant at all regional levels. Surprisingly, the estimates become smaller as we move to finer levels of aggregation. This could be due to measurement error in unemployment rates for smaller regions (leading to 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, panel B reports estimates where each observation is weighted by population. Relative to the baseline, the net migration elasticity becomes slightly smaller for states and commuting zones and larger for counties without altering the ranking of the estimates. This suggests that smaller states have higher migration elasticities, whereas smaller counties have lower migration elasticities.

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, Fureri, and Loungani (2017) suggest using a Bartik shift-share variable $Z_{ij}$ 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 national employment growth in industry \( j \) between \( t-1 \) and \( t \).

The idea is that national fluctuations in an industry will cause changes in labor demand in states specializing in that industry—an increase in national automobile production causes a disproportionate increase in labor demand in states like Michigan that have a larger share of auto production. This helps separate labor demand shifts from potential labor supply shifts and isolates the response of net migration to labor demand shocks. Using this IV approach (see Table 2, panel C), the elasticity is \(-0.72\)—more than twice the baseline result. The estimates are also greater for the commuting zone– and county-level data.

Unfortunately, the exclusion restriction for this instrument likely fails (see Borusyak, Dix-Carneiro, and Kovak 2021). The instrument affects region \( i \)'s net migration through changes in unemployment in not only region \( i \) but also neighboring regions. Even if workers are responsive to unemployment, there will be little incentive to migrate if workers’ current and potential alternative locations face the same labor market conditions. 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 have large cross-state migration. 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 for “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 partner unemployment rates with the Bartik instrument described earlier.\(^6\) With this specification, the migration response to its own unemployment rate is consequently larger (Table 2, panel D). The response of migration to the partner’s unemployment rate is positive and, for counties and commuting zones, roughly the same size.

III. 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 of the recession (2008–2010), it is at the mean of \(-0.29\). A regression based on the raw data (without de-meaning)
would produce an estimate of roughly $-0.10$ for those years. This underscores the importance of detrending. For example, states in the Sun Belt like California have experienced substantial migration inflows over the last 40 years, often from colder states like Michigan. However, 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:

$$
\sum_{s=1}^{h} n_{i,2006+s} = \alpha_h - \beta_h Z_{j}^{GR} + \varepsilon_{i,h},
$$

where $\sum_{s=1}^{h} n_{i,2006+s}$ is the change in population in commuting zone $i$ from 2006 to 2006+$h$, and $Z_{j}^{GR} = \sum_{j} \beta_{ij} \frac{L_{j,2009} - L_{j,2006}}{L_{j,2006}}$ is a Bartik instrument for the Great Recession shock.

The bottom panel of Figure 4 displays the estimated coefficients $\beta_h$ for the response of population, whereas the top panel displays the estimated coefficients for a similar regression that replaces the population response by the change in unemployment $ur_{i,2006+h} - ur_{i,2006}$. The solid line plots the coefficients using raw data, while the dashed line plots the coefficients for the de-meaned data.

Commuting zones more exposed to contracting industries during the recession saw a larger increase in their unemployment rate: a predicted 1 percent 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 pretrends in the context of the Great Recession has also been acknowledged by Yagan (2016) and Bhattarai, Schwartzman, and Yang (2021).

### Table 2—Different Specifications and Different Geographic Levels

<table>
<thead>
<tr>
<th>Region</th>
<th>States</th>
<th>Commuting zones</th>
<th>Counties</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Baseline specification</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Migration elasticity</td>
<td>$-0.29$</td>
<td>$-0.23$</td>
<td>$-0.16$</td>
</tr>
<tr>
<td>Number of observations</td>
<td>$2,064$</td>
<td>$31,018$</td>
<td>$131,293$</td>
</tr>
<tr>
<td><strong>Panel B. Population weighted</strong></td>
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<td></td>
<td></td>
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<tr>
<td>Migration elasticity</td>
<td>$-0.24$</td>
<td>$-0.20$</td>
<td>$-0.18$</td>
</tr>
<tr>
<td>Number of observations</td>
<td>$2,064$</td>
<td>$31,018$</td>
<td>$131,293$</td>
</tr>
<tr>
<td><strong>Panel C. Bartik</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Migration elasticity</td>
<td>$-0.72$</td>
<td>$-0.60$</td>
<td>$-0.53$</td>
</tr>
<tr>
<td>First-stage $F$-statistic</td>
<td>$52.95$</td>
<td>$61.13$</td>
<td>$58.69$</td>
</tr>
<tr>
<td>Number of observations</td>
<td>$1,968$</td>
<td>$29,574$</td>
<td>$125,112$</td>
</tr>
<tr>
<td><strong>Panel D. Bartik, migration partner</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own unemployment</td>
<td>$-0.84$</td>
<td>$-0.71$</td>
<td>$-0.71$</td>
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<tr>
<td>Partner unemployment</td>
<td>$1.55$</td>
<td>$0.36$</td>
<td>$0.52$</td>
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<tr>
<td>First-stage $F$-statistic</td>
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<td>$53.57$</td>
<td>$39.11$</td>
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<tr>
<td>Number of observations</td>
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<td>$29,574$</td>
<td>$125,112$</td>
</tr>
</tbody>
</table>

**Notes:** Results are based on de-meaned census data. Driscoll-Kraay standard errors are in parentheses. First-stage $F$-statistics are based on Kleibergen and Paap (2006). The 5 percent critical value is 3.84.
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


