Labor Reallocation over the Business Cycle: New Evidence from Internal Migration

Raven E. Saks
Federal Reserve Board of Governors
raven.e.saks@frb.gov

Abigail Wozniak
Department of Economics and Econometrics
University of Notre Dame and IZA
a_wozniak@nd.edu

Abstract

This paper establishes the cyclical properties of a novel measure of worker reallocation: long-distance migration rates within the US. Combining evidence from a number of datasets spanning the entire postwar era, we find that internal migration within the US is procyclical. This result cannot be explained by cyclical variation in relative local economic conditions, suggesting that the net benefit of moving rises during booms. Migration is most procyclical for younger labor-force participants. Therefore, cyclical fluctuations in the net benefit of moving appear to be related to conditions in the labor market and the spatial reallocation of labor.

The views in this paper do not reflect those of the Board of Governors of the Federal Reserve System or its staff. We thank Chris Foote and Jed Frees for providing the IRS data on state-to-state migration flows. The authors also thank seminar participants at the University of Notre Dame, McGill University, Western Michigan University, the Upjohn Institute, Michigan State University, Georgetown University, and the US Bureau of Labor Statistics for helpful comments. Corresponding author: Abigail Wozniak, 441 Flanner Hall, University of Notre Dame, Notre Dame IN 46556. Email: a_wozniak@nd.edu. Updated versions of this paper can be downloaded from www.nd.edu/~awaggone/research.htm.

I. Introduction

Summarizing the literature on labor market frictions and employment fluctuations, Robert Hall noted that "[t]he labor market occupies center stage in modern theories of fluctuations." (Hall, 1999, p.1138) In spite of a vast body of research, many questions remain about how and even whether labor market adjustment contributes to national business cycles. We shed new light on this topic by examining long-distance migration patterns – defined as relocation across state, metropolitan area, or county boundaries – and establishing that this internal migration is strongly procyclical. Long-distance migration constitutes a measure of worker reallocation because it is frequently accompanied by a change of local labor markets, a new employer-employee match, or a change in labor force status.[1] Therefore, studying the cyclical properties of geographic reallocation of the labor force help characterize labor market adjustment over the business cycle.

Although prior research has examined the cyclical properties of a number of labor market measures in detail, geographic flows have so far received little attention.[2] In a list of 71 correlates with the business cycle in the Handbook of Macroeconomics, internal migration is not included. This omission is surprising because evidence based on migration patterns has several advantages over previously-explored measures of reallocation in the labor market.[3] First, migration theory offers a simple and well developed framework for isolating the effect of national conditions on the spatial reallocation of the labor force.[4] Migration theory tells us that workers move between local markets for one of three reasons: to arbitrage spatial differences in economic opportunity, for personal reasons related to the lifecycle or preferences for local

[1] Among household heads in the PSID who move across state lines from 1968 to 1993, 28 percent changed employment status and 34 percent changed employers, compared with 15 percent and 12 percent, respectively, for heads that did not change states.
[2] For examples see Rogerson et al. 2005; Shimer 2005a; Davis et al. 2006; Hall 2003 and 2005. An exception that analyzes migration over the cycle is Foote and Kahn, 2000.
[3] For an up to date overview of this literature with a focus on unemployment flow cyclicality, see Elsby, Michaels and Solon (2007).
[4] This is in contrast to the case of wages, where differences in local and aggregate cyclicality have been well documented (Ziliak et al. 1999) but are less well understood theoretically.

amenities, or because net benefits to moving have increased (for example, through lower moving costs or better long-distance matches between workers and firms). These net benefits are our primary covariate of interest because they have the potential to shed light on the forces driving aggregate fluctuations in the economy. We isolate changes in these net benefits by controlling directly for annual changes in the distribution of local economic opportunities. Assuming that migration for personal reasons is unrelated to the business cycle, any residual correlation of internal migration with national business cycle measures is driven by changes in the net benefits to moving.

A second advantage of studying worker reallocation through the lens of migration is that migration rates are available over a long period of time spanning many business cycles. Our longest series encompasses ten recessions over six decades, providing more variation to identify cyclical effects than other data sources.[5] With this long series we can also examine whether the cycles of reallocation documented in more recent data are similar to earlier periods. Moreover, migration data do not suffer from the same degree of composition bias that challenges researchers studying wage cyclicality (Solon, Barsky, and Parker, 1994).

We use several nationally-representative datasets to assess the cyclical behavior of migration. We find that migration is strongly procyclical, even after accounting for relative variation in local economic conditions over the cycle. These results suggest that the net benefit to moving rises during booms. To investigate the nature of these net benefits, we examine the characteristics of individuals for whom migration is most procyclical. Younger workers have markedly more procyclical migration patterns than older workers. We also find that the procyclicality of migration is limited to individuals in the labor force and that homeownership plays no role. We conclude that cyclical fluctuations in household relocation decisions are

[5] See Davis, Faberman and Haltiwanger (2006) for a survey of data sets.

related to churning in the labor market rather than to changes in national housing market conditions.

Not only does our work have implications for models of aggregate business cycle fluctuations, but it also has implications for other studies of migration. For example, migration is often considered a means for local economies to adjust to shocks, although estimates of its importance vary (Blanchard and Katz 1992; Bartik 1993). However, national economic conditions may offset this spatial arbitrage, making adjustment to local shocks incomplete even in the face of substantial migration flows (Lkhagvasuren 2005). Our work also raises the possibility that the size of the migration response to local government programs may depend on national conditions. For example, Meyer (2000) reports higher levels of interstate welfare migration in the late-70s compared with the late-80s. However, the larger amount of migration in the earlier period may be due in part to the greater improvement in national economic conditions during that time.

The paper proceeds in six sections. In Section II we discuss additional related literature and incorporate national conditions into the traditional migration choice framework. In Section III we present evidence on the cyclicality of migration using aggregate migration rates from published reports of the CPS. In Section IV we distinguish between the net cost of moving and dispersion in local conditions in explaining cyclical migration patterns. In Section V we examine differences in procyclicality across groups of individuals using microdata, and we make concluding remarks in Section VI.

II. Background on the Relationship between Internal Migration and the Business Cycle

A. Related Research

Labor markets in the United States are well-known for having a high degree of geographic mobility. Population flows between states far surpass net changes in state populations, suggesting a large degree of churning in geographic relocation patterns (Census Bureau 2003). Many factors influence migration rates including the age distribution of the population, heterogeneous preferences for local amenities, and changes in local housing markets. Spatial differences in local labor demand also contribute to worker relocation, although evidence suggests that labor markets explain only a small portion of total migration flows (Davies, Greenwood and Li 2001, Wozniak 2008, Bound and Holzer 2000, Gabriel, Shack-Marquez and Wascher 1993).[6]

This paper asks whether internal migration is correlated with fluctuations in the *national* business cycle, as opposed to regional differences in local business cycles. Although this question has yet to be answered satisfactorily, a related literature has found that churning in the US labor market along other dimensions is procyclical (Shimer 2005a, Darby et al (1986), and Fujita and Ramey (2006)). For example, Caballero and Hammour (2005) show that job restructuring, defined as the sum of job creation and job destruction, falls during national recessions. Fallick and Fleischman (2004) document that the number of workers who change employers is also procyclical.

Although the existing evidence on the cyclical properties of migration is far from conclusive, a number of researchers have observed that these flows are positively correlated with the national business cycle (Greenwood 1997). However, these studies are based on data from relatively short time periods that span few business cycles. For example, Pissarides and Wadsworth (1989) document that migration between regions in Great Britain was lower in a year when aggregate unemployment was high compared with another year when unemployment was low. Similarly, Makower, Marschak and Robinson (1938, 1939) found that migration between regions in Great Britain in the early 1930s was lower than in the 5 preceding and subsequent years. Milne (1993) shows that a procyclical pattern holds for internal migration in Canada,

[6] In particular, Wozniak (2008) finds that arbitrage migration makes up only a small fraction of total migration among 24-30 year olds, the most mobile age group.

although again the result is based on data from a more limited number of years and pertains to a country with historically lower migration rates than the US. Also using Canadian data, Vanderkamp (1971) finds that the correlation of migration with income in the destination region was stronger in booms from 1947 to 1966, but he does not examine the aggregate cyclicality of migration rates independent of local conditions.

Stronger evidence is presented by Greenwood, Hunt and McDowell (1986), who use annual data on migration between metropolitan areas in the United States from 1958 to 1975 to examine net local population responses to MSA-level employment growth. They find that the local population is more responsive to employment growth during national upswings; however, this result is confounded by a shift from positive economic conditions in the early part of their sample to a severe recession in later years. Their study leaves open the question of whether the result would pertain to other time periods after accounting for the downward secular trend in migration.

Indeed, what is striking about the literature is that the cyclicality in migration patterns has escaped a thorough examination for so long. In a 1968 paper, Milton Friedman pointed to the costs of migration as one of the factors that determine the natural rate of unemployment. However, compared to other items in his list, mobility costs and migration patterns have received little attention from business cycle researchers.[7]

B. Theoretical Framework

In the standard human capital model of migration, workers move from local labor markets where the return on their individual skills is relatively low to markets where this return is relatively high. Thus, geographic differences in the relative return to skills, and therefore in

[7] He wrote, "[It] is the level that would be ground out by the Walrasian system of general equilibrium equations, provided there is imbedded in them the actual structural characteristics of the labor and commodity markets, including market imperfections, stochastic variability in demands and supplies, the cost of gathering information about job vacancies and other availabilities, *the costs of mobility*, and so on. [Emphasis added.]"

local labor market conditions, generate migration flows.[8] In this paper, we are primarily concerned with the role of *aggregate* conditions in generating migration—that is, the component of the business cycle that is common to all locations. To see how aggregate conditions might influence migration choices, we use the framework developed by Kennan and Walker (2009; hereafter KW), who are the first to model migration as a sequential problem. Their micro-founded approach brings a needed dynamic dimension to a literature that had focused on static or one-shot migration choices. Although the KW model does not explicitly include a role for aggregate factors in individual migration decisions, it is straightforward to consider how aggregate factors would function in the model. A complete solution of an extended version of the model is beyond the scope of this paper. Instead we summarize the existing model and show how aggregate conditions could be incorporated.

B.1. Summary of the Kennan-Walker Structural Dynamic Migration Model

KW model an individual's sequence of migration choices at each age as a dynamic programming problem. In each period, an individual must choose whether to continue in her current location or to move to a new location.[9] Locations and labor markets are equivalent in the model, and individuals seek to maximize their lifetime expected incomes.

KW assume that individuals experience transitory fluctuations in earnings in any given labor market, but their permanent income in a market is fixed. Thus, the migration problem becomes a labor search problem. Individuals must find the market that provides the highest permanent income subject to the cost of moving. KW assume that individuals must relocate to a new market in order to learn their current wage in that market, but search costs within markets are assumed to be trivial. Therefore, as soon as an individual arrives in a new market, she

[8] Differences in the relative return to skills across space drive migration in both static models of the migration decision (Schultz, 1961; Dahl, 2002) and newer dynamic models (Kennan and Walker, 2009).
[9] Periods correspond to age in the KW model. Individuals live for T periods, so in period T-1 and individual is one period away from the final period (age of death).

receives a wage that reflects her permanent earning power plus a local shock. The individual's (recursive) decision problem is to choose a location that maximizes indirect utility:

$$(1)\ V(x,\zeta) = \max_{j}\left(v(x,j) + \zeta_j\right)$$

where

$$v(x,j) = u(x,j) + \beta\Theta$$

Indirect utility is equal to the flow value in location j, $v(x,j)$, plus a period-specific utility shock, ζ_j. The flow value consists of the utility flow in the current period, $u(x,j)$, plus the discounted value of re-optimizing in the next period, Θ. x is the state vector, and it keeps track of an individual's wages, preferences for amenities, current and past locations, and age.

To reduce the complexity of the problem, KW further assume that individuals have limited information about their potential earnings in most markets. Specifically, individuals only have good information regarding wages in their current market as well as in markets they visited in the recent past.

B.2. Generating Cyclical Migration in the KW Model

The KW model includes several determinants of migration that are common in the literature. Consider the following a simplified version of their utility function:

$$(2)\ u(x,j) = \alpha\omega_j + \Gamma Y_j - c(x,j) + \zeta_j$$

Utility is a function of wages in location j, ω_j, a vector of amenities in j, Y_j, moving costs incurred in getting to j (which may depend on an individual's age and previous locations through the state vector x), plus the utility shock, ζ_j. For our purposes, the utility shock can represent a wage shock, a preference shock, or a shock to moving costs.

It is now easy to see how both local and aggregate economic conditions might affect migration. When local conditions change, individuals update their estimates of their permanent wages in the markets about which they have information. Individuals will be more likely to move if the expected permanent wage in an alternative location increases relative to their current location. In addition, the aggregate business cycle can also affect migration through shocks to the utility flow ζ_j, even when the distribution of relative wages across locations is unchanged. Although preferences are unlikely to fluctuate over the business cycle, wages and moving costs could be cyclical for a number of reasons.

First, procyclical fluctuations in aggregate wages could generate procyclical migration by allowing credit-constrained individuals to finance moves to new markets. For instance, individuals may take advantage of temporarily high earnings to finance a move back to their home state or to a place with more amenities, like a large city or a warm climate.[10] Such moves could be more common in aggregate upswings because higher wages allow more individuals to buy a normal good—in this case, relocation.[11] On this note, Makower, Jarschak and Robinson (1938) speculate that individuals who have experienced a prolonged period of unemployment, as is more often the case in a national recession, have fewer resources to bear the cost of moving. Gregg, Machin, and Manning (2004) show that the unemployed in Great Britain are unlikely to move without having a job, possibly due to the difficulty of finding a place to live without a documented source of income.

A number of other channels would lead to countercyclical variation in moving costs, and therefore procyclical migration. If job search costs are non-trivial, then workers have to spend some time searching for a job once they arrive in a new market. They face some probability that they will either fail to find a match before their accumulated assets are depleted or that they will need to accept a poor match. Thick market externalities may mean that it is less costly to search

[10] Eventually, this increase in demand for high-amenity value locations will be capitalized into housing prices (Roback 1987). If this process is not instantaneous, workers may still be able to use temporarily high wages to finance a move to a new market under the "old" prices.
[11] A related form of household readjustment is divorce, which has also been shown to be procyclical (Hellerstein and Morrill 2010).

when lots of other people are searching and lots of firms are posting vacancies.[12] Thus, people would be more willing to risk moving to a new location during booms, when the probability of finding a good match is higher.

Informational asymmetries provide another channel through which the moving cost might vary over the business cycle. The KW model assumes that individuals have no information about specific markets other than their current and recently visited markets. In an expanded model, individuals could use information they receive about the aggregate business cycle to infer the average condition of other markets. This would generate procyclical migration, as individuals in underperforming markets would be more likely to depart for "the average market" in booms.

Migration costs could also be cyclical for reasons unrelated to the labor market. For example, if there are thick market externalities in the housing market, it would be easier both to buy and sell a home when many other people are doing the same. In this case, a larger number of homes on the market would expand the choice set of potential buyers, improving the house-owner match quality. Similarly, a larger number of potential buyers would improve the likelihood that a prospective seller would receive an acceptable offer.[13]

No matter the reason, cyclical fluctuations in ζ_j will cause an individual's migration propensity to rise in times of aggregate prosperity, even if the dispersion of local wages is the same. Adding up across individuals, aggregate migration rates will be procyclical. Empirically, we will distinguish between local and aggregate factors by expressing all local variables relative to their national average. In this way, we separate the role of economic conditions into two components: a *relative* component due to a location's deviation from aggregate conditions and

[12] Previous research has found that match quality is procyclical, consistent with more efficient search in aggregate upswings (Bowlus 1995, Barlevy 2002). Researchers differ in the mechanisms to which they attribute this effect.
[13] Some aspects of housing transaction costs, like realtors' fees and deed transfer taxes, are procyclical because they are proportional to the value of the house. There is no empirical evidence on changes in the total cost of moving over the business cycle. For a recent analysis of the magnitude of average moving costs, see Notowidigo (2009).

an *aggregate cyclical* component due to changes in labor market conditions that are common to all locations.

III. The Cyclical Behavior of Internal Migration: Time Series Evidence from Aggregate Current Population Survey Data

Our main goal is to establish the correlation between internal migration rates and national economic conditions. In order to observe migration over the largest possible number of business cycles, we construct a time series on aggregate migration in the United States based on the Current Population Survey (CPS). To our knowledge, this survey provides the longest nationally-representative time series on annual migration rates in the US.

Figure 1 presents simple visual evidence on the cyclicality of migration rates. We calculate these rates as the number of individuals age 14 and up who moved between states or counties during the previous 12 months relative to the total population of the same age group. From 1948 to 1976, the data are taken from historical CPS reports published by the Bureau of Labor Statistics. For 1980 onwards, we tabulate the fraction of migrants from CPS microdata.[14] The years 1972-75, 1977-79, 1990 and 1995 are missing because in those years the CPS did not ask respondents where they were living in the previous year. All data are from the March CPS, so the migration rates reflect geographic reallocation from April of the preceding year to March of the current year.

Ideally, we would like to observe migration between local labor markets. Inter-state moves will understate the degree of geographic churning that may occur in large states with multiple labor markets. On the other hand, some inter-county movers (and even some inter-state movers) remain in the same local labor and housing market, which means that inter-county

[14] Because the CPS microdata are a subsample of the entire CPS, our count of the number of migrants does not match the published totals exactly. However, for the years we can compare, the difference between the published totals and our tabulations are very small. We exclude imputed values from the microdata when possible (from 1995 to 2009) because the Census Bureau's methodology for imputing migration artificially boosted migration rates from 1999 to 2005 (Kaplan and Schulhofer-Wohl 2010).

migration will overstate inter-labor market migration.[15] In this paper we examine migration between states, metropolitan areas and counties, depending on data availability.[16]

The shaded regions of the Figure 1 show recession periods as defined by the NBER. The figure suggests that migration declines during a recession, no matter whether it is measured as inter-county moves or state-to-state relocation. With the exception of the recessions in 1957 and 1960, inter-state migration is lower at the end of the recession than it was prior to when the recession began.[17] Although it is difficult to assess the timing more precisely without monthly migration data, it appears that migration is lowest near the end of a recession or during the year after a trough has been reached.

The most recent few years are an interesting period because migration dropped sharply from March 2006 to March 2007 and had not yet recovered through March 2009. Because this drop began well ahead of the business cycle peak—which the NBER dates at December 2007—the business cycle is unlikely to explain this entire episode. Rather, the large decrease might be related to the housing market contraction, which began around 2006 and may have prevented homeowners with underwater mortgages from moving (Ferreira, Gyourko and Tracy 2010). It also might represent an acceleration of the longer-run downward trend, which might be related to demographics/the aging of the population. The current business cycle is too recent for us to observe the level of migration after the cycle, so it remains to be seen whether the usual procyclicality of migration operated during this episode.

[15] For more recent periods, we can assess the potential bias from these approximations by computing the share of inter-county and inter-state migrants who actually moved between MSAs. According to the Bureau of Labor Statistics, approximately ½ of inter-county migrants moved across metropolitan areas from 1990 to 1995. About 87 percent of inter-MSA movers also crossed state lines. CPS microdata from 1980 and 1985 reveal that roughly 75 percent of people who changed counties within a state also changed SMSAs.

[16] Our results using state-level data are unchanged if we exclude the states in the New York, Washington DC and Kansas City metropolitan areas. Therefore, the state-level migration data do not appear to be overly influenced by flows within the same labor market area.

[17] In the case of the 1960 recession, migration fell noticeably in the year following the trough. Because the CPS measures migration from April of the preceding year to March of the current year, it is possible that much of this decline occurred during the recession.

The NBER's designation is the most widely used measure of recessions, but it does not reflect the amplitude of fluctuations in national economic activity. Therefore, we calculate three different measures of the business cycle. Each of these measures has advantages and drawbacks, so we present results using all three throughout our empirical analysis. The first is the "employment gap," which we define as the logarithm of aggregate employment relative to its trend, where this trend is estimated from a Hodrick-Prescott filter.[18] To be consistent with the timing of the migration data, we define the annual employment gap as the average monthly gap from April of the previous year to March of the current year. Advantages of this measure are that it can be computed for the entire post-war period and that its monthly frequency can be converted to the same April-March frequency as the CPS data. The second variable we consider is the national unemployment rate, which has been widely used to measure business cycles in other studies such as Barsky et al (1989) and Solon et al (1994), but is only available at the state level since the mid-1970s. Again to be consistent with the timing of the CPS, we calculate the unemployment rate for each year as the average from April in the previous year to March in the current year. The third variable is the number of unemployment insurance claimants relative to total covered employment, which we call the "UI claims rate."[19] Not only is this measure available for our entire sample period, but it offers an additional advantage in that it is based on the location of the employer, so the local UI claims rate is not influenced by inflows or outflows of migrants. The UI data are only available as annual averages prior to 1971, so we associate the number of migrants in March of year t with the average claims rate in year $t-1$. Appendix Figure 1 shows that the three business cycle measures are strongly correlated with one another.

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[18] The Hodrick-Prescott filter is a commonly-used method to remove both low frequency and high frequency fluctuations in a variable that are not at a business-cycle frequency (Stock and Watson 1999).

[19] The number of unemployment insurance claimants is the number of people receiving a UI check for the first time *in that calendar year*. Someone who received three months of UI checks for June through August of 1980 would be counted as one claimant in 1980. Someone who received checks for December through February, overlapping 1980 and 1981, would be counted as one claimant in both 1980 and 1981.

The top panel of Figure 2 plots the employment gap against the share of individuals age 14 and up who moved between counties in the previous year, where the migration rate has been detrended using an HP filter.[20] The slope of the regression line (reported in the first column of Table 1) implies that when national employment falls by one standard deviation, migration declines by about 0.1 percentage points. Compared with an average migration rate of 6.15 percent over our sample period and a standard deviation of 0.75 percent, this change in migration is small but not inconsequential.[21] The bottom two panels show similar relationships for the other measures of the business cycle, although the magnitudes are a bit smaller and the correlations are not significantly different from zero. When we break the postwar period into pre- and post-1980, we find relationships in both subsamples that are similar to the regression lines shown in Figure 2. Thus, the factors shaping the cyclical component of geographic reallocation in recent years appear to have been similar throughout the entire post-World War II era.

IV. The Roles of Aggregate and Local Shocks in Cyclical Migration Patterns

A. Aggregate Time-Series Evidence from the CPS

As we discussed in section II, aggregate fluctuations in migration can be caused by aggregate shocks to the cost of moving or by changes in the dispersion of relative local conditions. If the latter is procyclical—that is, if the dispersion of relative local economic conditions increases in national booms—then migration would also be procyclical.

[20] After detrending the migration data, the last few years of the sample do not stand out as having unusually low migration. In other words, the HP filter attributes most of the decline in migration since 2005 to trend rather than cycle. These results are similar when we use a locally weighted regression (LOESS), which is less influenced by end points than the Hodrick-Prescott filter.

[21] The magnitudes of our estimates can also be interpreted in light of recent work on excess migration by Lkhagvasuren (2005) and others showing that the level of internal migration in the US far exceeds that required to equalize regional wage and employment differentials. In that case, even modest increases in migration levels may be important for economic adjustment even though they are small compared to the usual level of migration.

However, a simple look at the dispersion of economic conditions across states suggests that relative local differences are not likely to be the primary explanation for procyclical migration patterns. In the top panel of Figure 3, we show a kernel density estimate of the distribution of state employment gaps for all the years in which the national employment gap was in the top quartile of its 1948-2009 range, compared to a kernel density estimate in years when the national employment gap was in its bottom quartile.[22] The dispersion of state employment gaps appears to be invariant to the national cycle. Similar distributions of the unemployment rate and UI claims rate are shown in the bottom two panels of Figure 3.[23] The dispersion of state-level unemployment increases when national conditions are *worse*, suggesting that dispersion in local economic conditions should exert a countercyclical effect on internal migration.

To investigate further, we regress the aggregate CPS migration rates on each of the three measures of the national business cycle and control for the standard deviation of state analogs of these measures (see column 2 of Table 1). Dispersion in local conditions is not significantly related to migration, and controlling for dispersion does not qualitatively alter the correlation of migration with the national business cycle. We obtain similar results when we end the sample in 2005 to mitigate the difficulty of detrending migration in the last few years of the sample (columns 3 and 4 of Table 2).[24] We also obtain similar results when we measure dispersion across locations as the 90-10 differential of state cycles, the 75-25 differential of state cycles, or the dispersion in employment, income, or house prices across metropolitan areas. Thus, we find no evidence that the procyclical migration patterns documented in the previous section are driven by changes in the dispersion of economic conditions across locations.

B. State-level Evidence from the IRS

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[22] The state-level employment gaps are defined as the log of state employment relative to its HP trend.

[23] State-level estimates of the unemployment rate are only available beginning in 1976, so the middle panel of Figure 3 uses the top and bottom quartile of national unemployment rates over the period 1975 to 2004.

[24] In these regressions, the trend in migration is also only estimated through 2005. All of the results presented below are also robust to excluding post-2005 data.

Although national time series provide the longest possible time span to study migration in the postwar United States, national data obscure many aspects of local labor market conditions that may be important for explaining cyclical fluctuations in migration. Because simple measures of geographic dispersion are inadequate to capture the myriad of ways that local conditions may impact migration, we turn to data on migration flows between pairs of states to flexibly control for relative economic conditions in a migrant's origin and destination locations.

Our first data source comes from the IRS, which tabulates information on migration between every pair of states in each year from 1975 to 2008.[25] Specifically, they report the total number of tax exemptions that moved out of each of the 48 continental United States and moved into each of the other 47 states.[26] Similar to the timing of the CPS, the IRS reports the number of migrants from the first quarter of one year to the first quarter of the following year. Therefore we maintain the same timing of our business cycle measures that was described earlier: the employment gap and unemployment rate are averages from April in the previous year to March in the current year, and the UI claims rate is the rate in the previous calendar year. We estimate the following regression of migration on national and local economic conditions:

(4)

$$flow_{jkt} = \alpha_0 + \alpha_1 t_t + \beta_1 C_t + \beta_2 c_{jt} + \beta_3 c_{kt} + \beta_4 i_{jt-1} + \beta_5 i_{kt-1} + \beta_6 p_{jt-1} + \beta_7 p_{kt-1} + \theta_j^{FE} + \delta_k^{FE} + \theta_j^T t_t + \delta_k^T t_t + \varepsilon_{jkt}$$

We define migration, $flow_{jkt}$, between each pair of states as the total number of tax exemptions that moved from state j to state k in year t relative to the initial number of exemptions in state j (defined as the number of non-moving exemptions plus the total number of exemptions that moved out of state j in that year). C_t represents national business cycle conditions, which we measure using each of the three business cycle variables discussed

[25] This dataset is an updated version of the data used in Frees (1992).

[26] The IRS data represent a narrower population than the CPS in that they only reflect individuals in households who filed tax returns in two consecutive years. However, these data comprise the total universe of tax filers, and so they are less susceptible to measurement error than the CPS.

earlier.[27] These variables are standardized to have a mean of zero and standard deviation of 1 so that their coefficients can be interpreted as the effect of a 1-standard deviation change in national economic conditions.

We control for a wide variety of differences in relative economic opportunities across locations by including local business cycle, labor market and housing market conditions in both the origin and destination state. The variables c_{jt} and c_{kt} represent relative business cycle conditions in the origin and destination states, computed as the difference between the equivalent state-level business cycle measure and C_t. Because local economic conditions are affected by migration, we predict the local employment gap and local unemployment rate with two instruments. The first is a weighted-average of national industry-level employment growth rates where the weights are based on the industrial composition of employment in each location ("Bartik shock").[28] These shocks reflect the change in employment that would occur in a location if all firms hired workers at a rate equal to the national average in their industry (Bartik 1991). The second instrument is the lagged percent change in oil prices multiplied by each location's share of employment in oil and gas extraction ("oil shock"). This variable picks up locations that experience an increase in labor demand when oil prices rise (Gallin 2004).[29] We do not instrument for the UI claims rate because claimants receive benefits from the state where

[27] Ziliak et al. (1999) and Bartik (1993) provide thorough discussions of the range of model specifications used in the wage cyclicality and local labor market adjustment literatures, respectively. We prefer a levels specification with fixed effect controls where possible as it allows us to maintain consistent business cycle measures across aggregate and micro data.

[28] Specifically, the predicted shock in location *i* at time *t* is $\sum_{j=1}^{J}\left(\frac{e_{ijt-1}+...+e_{ijt-5}}{\overline{e}_{it-1}+...+\overline{e}_{it-5}}\right)\Delta\ln(\overline{e}_{jt})$ where $\overline{e}_{it}$ is total employment in location *i* and $\overline{e}_{jt}$ is aggregate employment in industry *j*. We obtain data on employment by industry, state and year from the Bureau of Economic Analysis's (BEA) Regional Economic Information System. The weights are 5-year moving averages of an industry's employment share. This 5-year window balances concerns about the endogeneity of the current industrial composition with concerns that very long lags will not be good predictors of the types of shocks currently affecting an area. Results are similar when using a moving average of employment shares lagged 6-10 years, but using such long lags reduces our sample size.

[29] We define oil prices as the PPI for crude petroleum relative to the PPI for all commodities. Like the Bartik shock, we construct the employment shares from BEA data and use 5-year moving averages. We also use the square of this oil shock as an instrument because large changes in oil prices appear to have a different effect on employment than small changes.

they were last employed as opposed to the state where they currently reside, and therefore fluctuations in the claims rate are not affected by migration.

The variables i_{jt} and i_{kt} represent relative income per capita in the origin and destination states, and p_{jt} and p_{kt} represent relative house prices in the origin and destination states. House prices are measured using repeat-sales indexes computed by LoanPerformance, a division of First American CoreLogic. These indexes are similar to the indexes published by the Federal Housing Finance Agency (FHFA), but unlike the FHFA they do not exclude prices based on purchased with a non-conforming mortgage. Both income per capita and house prices are measured in logarithms and are lagged 1 year in order to mitigate endogeneity problems associated with the effect of migrants on wages and house prices. We also include a separate fixed-effect and time trend for each origin and destination state to capture smooth, long-run changes in migration flows between states over time.[30] Due to the availability of the house price data, the sample period of each regression is from 1977 to 2008.

Table 2 reports the coefficients on the national and state economic conditions and the first-stage coefficients are reported in Appendix Table A1.[31] The F-statistics for the test that the instruments can be excluded from the first stage are 17 for the local employment gap and 73 for the unemployment rate, signaling that the shocks are good predictors of local economic conditions. The coefficients on local economic conditions in the second stage generally have the expected signs: migration is higher when relative employment opportunities and income are better in the destination state and lower when these conditions are better in the origin state. Relative house prices have the opposite sign. All three cyclical measures have statistically significant coefficients of similar magnitude: a 1 standard deviation improvement in national

[30] A specification including a separate fixed effect and time trend for each individual pair of states (48*47=2256 pairs) yielded almost identical results, but estimating such a large number of parameters increased the computation time considerably.

[31] In all of the tables, we cluster the standard errors by year to account for correlated unobservables across all locations. Results are similar (usually with smaller standard errors) when we compute Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors to account for serial correlation in migration patterns.

economic conditions is associated with .02 additional migrants for every 1000 initial residents, or a 2.5 percent increase in the migration flow.[32]

Because the local variables account for differences in local labor markets across locations, we interpret the correlation between migration and the national business cycle as evidence that the net benefits to migration are lower during economic downturns (operating through the time-varying shocks ζ_j). As discussed above, the national labor market is a one potential source for such shocks, while the national housing market is another. To distinguish between these two channels, we include national house prices or home sales along with each of our labor-market based business cycle measures.[33] In every specification, the coefficient on the labor-market cycle is unchanged and the coefficient on national house prices changes is small and insignificantly different from zero.[34] Thus, cyclical migration patterns appear to be more closely tied to labor markets than to national housing cycles.

While these regressions allow for an assessment of the correlation of migration with the local conditions in the state that a migrant has chosen *ex post*, they do not explicitly account for the range of opportunities facing potential migrants *ex ante*. To proxy for the range of opportunities facing a potential migrant, we calculate a distance-weighted average of relative state-level conditions, excluding conditions in the origin state. Then we estimate the following function of migration flows either into or out of each state from all of the other 47 states:

(5) $$flow_{jt} = \alpha_0 + \alpha_1 t_t + \beta_1 C_t + \beta_2 c_{jt} + \beta_3 \overline{c}_{jt} + \beta_4 i_{jt} + \beta_5 \overline{i}_{jt} + \beta_2 p_{jt} + \beta_3 \overline{p}_{jt} + \theta_j^{FE} + \theta_j^T t_t + \varepsilon_{jt}$$

As before, C_t reflects the national business cycle and c_{jt} reflects the local business cycle conditions in each state, while i_{jt} and p_{jt} reflect income per capita and house prices. The variables $\overline{c}_{jt}$, $\overline{i}_{jt}$, and $\overline{p}_{jt}$ reflect the distance-weighted averages of each of these state economic

[32] These results, as well as the rest of the results reported in the paper, are similar when we exclude post-2005 data to mitigate concerns about the large drop in migration and the incomplete/unfinished business cycle at the end of the sample.
[33] Specifically, we have included either the level or change in the national LoanPerformance house price index and national existing home sales.
[34] Results from this analysis are available upon request.

conditions in all other states.[35] As in the previous specification, we instrument for local conditions and average conditions in all other states using the Bartik and oil shocks.

Table 3 shows the coefficient estimates from this specification. Again, migration displays a clear procyclical relationship with national economic conditions. A 1 standard deviation improvement in national conditions is correlated with about 1 additional in-migrant and 1 less out-migrant per 1000 initial residents, or equivalently a 3 percent change in the inflow and outflow.

C. MSA-level Evidence from the IRS

Although state-to-state migration patterns capture long-distance moves, they do not allow us to observe migration between labor or housing market areas within a state. Moreover, local economic conditions are arguably better reflected by conditions in the local market in which a household in located, rather than those of the entire state. Therefore, we next use data from the IRS's county-to-county migration files to calculate total migration into and out of metropolitan areas (MSAs), which are defined as a core urban area plus any adjacent county that has a high degree of social and economic integration with the urban core.[36] Because the IRS only reports migration between pairs of counties with at least a moderate population flow between the two locations, we cannot calculate migration between pairs of metropolitan areas to estimate a regression analogous to the state-pair regressions shown in Table 2. However, the files do report total migration into and out of each county, so we are able to aggregate the data into total inflows

[35] Although it is difficult to think of stories where relative conditions in unchosen markets would matter, this specification does allow us to relax the IIA assumption in the point-to-point regressions somewhat. Results are similar when using a simple average instead of a distance-weighted average.

[36] This concept is very similar to an Economic Area (EA), which is defined based on commuting patterns. EAs typically encompass one or several MSAs. We use MSAs instead of EAs because we do not have house price data for EAs. In practice, migrations patterns of EAs are very similar to MSAs. Results using EAs and MSAs are similar in some specifications, but in some specifications migration appears to be cyclical. This difference is due to our inability to control for local house prices in the EA specifications.

and total outflows for each metropolitan area.[37] The files are available for tax returns filed in 1981 and 1984-2008.[38]

We estimate the cyclical behavior of migration into and out of metropolitan areas using a specification similar to equation (2). Unemployment rates for individual counties or MSAs are not available prior to 1990, so in all equations we use the employment gap to proxy for the local business cycle. We calculate this gap from annual employment estimates by county from the BEA, which are available from 1969-2008. We do not include distance-weighted averages of conditions in other locations because we do not have data on the distance between each pair of metropolitan areas. Our state-level results suggest that this omission should not have a large impact on the results.[39] The regressions also include income per capita and the LoanPerformance house price index in the previous year. Because the distribution of migration across metropolitan areas is skewed (due to a small number of locations with high migration), we estimate the coefficients using median regressions. This strategy does not allow us to instrument for local economic conditions. However, our state-level analysis produces similar results whether or not we use the instruments.

We report coefficient estimates from this specification in Table 4. In contrast to the state-level data, in-migration appears to be somewhat more cyclical than out-migration. A 1 standard deviation improvement in national economic conditions is associated with about a 1.5 percent increase in in-migration (column 3) and a 1 percent increase in out-migration (column 4). The statistical significance of these results is somewhat weaker than the state-level estimates (only 3 of the 12 coefficient estimates are significantly different from zero at the 5 percent level), but the coefficient estimates always have the expected sign. We attribute the larger standard errors in

[37] We define metropolitan areas according to the 2005 Census definition.
[38] The data are not available in 1982 or 1983 because the IRS only produced 2-year migration flows in those years.
[39] Excluding the distance weighted average of state conditions from the Table 3 specifications does not significantly change the estimated business cycle coefficients.

these specifications to the greater variance in migration in the MSA-level data[—the variance of the logarithm of migration is 0.66 in the state-level data, but 0.90 in the MSA-level data.

It is possible that our controls for relative employment, unemployment, income and house prices introduced in this section do not adequately capture the true dispersion in local economic conditions across local markets. However, we feel this possibility is unlikely because the addition of the local controls that we do observe has little impact on our estimates of aggregate cyclicality. If our results could be explained by omitted time-varying differences in conditions across locations, then these differences would have to be uncorrelated with the observable controls that we include.

V. *Migration in the Current Population Survey Microdata*

We now turn to individual-level data to determine which segments of the population are most sensitive to aggregate business cycle conditions in making their migration decisions. Because different demographic groups face different costs and benefits of migration, this analysis provides suggestive evidence on the mechanism behind procyclical migration rates. For this analysis, we use CPS microdata from the March surveys from 1964 to 2009, again excluding the years in which CPS respondents were not asked whether they resided in their current county one year ago (Ruggles et al. 2004). The CPS microdata allow us to control for major demographic characteristics, labor force status, and homeownership, which are correlated with long-distance migration propensity (Greenwood 1997).

Our sample is restricted to household heads, ages 18 to 65, since household heads are most likely to make migration decisions for a family. We exclude minors because they are unlikely to make migration decisions independently, and we exclude those over the age of 65 since migration during retirement years is likely to be qualitatively different from migration during the prime years of employment. We compute linear probability models in which the dependent variable $migrant_{ist}$ is equal to one if a respondent currently residing in state s moved across county lines in the previous year (and zero otherwise):

$$(6) \quad migrant_{ist} = \alpha + \beta_1 C_t + \beta_2 c_{st} + \mathrm{B} X_{ist} + \delta_1 t + \delta_2 t^2 + \varepsilon_{ist}$$

As in our earlier specifications, C_t represents one of our three measures of the national cycle, while c_{st} represents local economic conditions in the individual's current state of residence (i.e. a migrant's destination state).[40] We instrument for the local unemployment rate and employment gap using the Bartik and oil shocks explained earlier.[41] The model also includes controls for basic demographic characteristics, X_{ist}. These characteristics include dummy variables for six age groups, four educational attainment categories, race, ethnicity, gender, marital status, homeownership, the presence of children, and three categories of employment status (employed, unemployed, or not in the labor force). We also control for a quadratic time trend to capture smooth long-term changes in the population's propensity to migrate.

The CPS does not identify a migrant's state of origin, nor does it provide information on an individual's personal characteristics in the previous year. Therefore, we cannot control for local economic conditions in the origin state or for any more sophisticated measures of the *ex ante* array of state conditions facing a potential migrant. However, our previous analysis suggests that neither controls for local conditions nor for the dispersion in local economic conditions play a large role in explaining national cyclical fluctuations in migration, even though they may be important predictors of migration themselves. Therefore, it is unlikely that the omission of these variables will bias our estimates of the effect of the national business cycle.

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[40] In some years, states with a small population were not separately identified in the CPS, but were grouped together with other small states. In these cases, we calculate local state conditions as an average of the business cycle conditions across the component states of the group.

[41] First stage estimates for the 2SLS specifications are shown in Appendix Table 4. In the specifications using the employment gap in the younger subsample, small F-statistics give some cause for concern about weak instruments. However, our approach of clustering the standard errors by year yields very conservative estimates of the F-statistics. When we cluster the standard errors on state and year, or use HAC standard errors, all F-statistics in Appendix Table 4 are highly significant.

Table 5 presents results of estimating equation 6 separately for individuals aged 18 to 35 and individuals aged 36 to 65. The table illustrates two main points. First, the migration choices of household heads are procyclical in both samples, even after controlling for important demographic correlates of long-distance migration. This result reduces concern that the relationships identified in earlier sections were driven by omitted characteristics of workers that change over the cycle. Second, the magnitude of the procyclical relationship is much greater for the younger age group. In this sample, both inter-county and inter-state migration is significantly procyclical using all three national business cycle measures. Thus, the procyclical relationship that we find in the aggregate data appears to be driven by the responses of younger individuals.

Point estimates from the six regressions from the younger sample show that a standard deviation change in the national business cycle measures leads to changes in individual migration probabilities of 0.17 to 0.47 percentage points. These estimates are somewhat larger than those found in the aggregate data; the most comparable specification is the state-level inflow regression reported in Table 3 which suggests responses of 0.08 to 0.15 percentage points. The larger magnitudes in the CPS are due to the greater response of younger individuals.[42] Cyclical responses of older workers are considerably smaller in magnitude, ranging from zero to 0.11 percentage points for a standard deviation change in national conditions.

For the most part, the state level economic conditions also have the expected relationship with location choice, although generally they are not significant in the IV specifications. Respondents in states experiencing relatively high UI claims rates or relative low employment gaps are less likely to have moved across counties or states in the previous year. This result shows that individuals living in states experiencing relatively worse economic conditions are less likely to be in-migrants than individuals in other states, which makes sense if poor local

[42] Grouping the young and old individuals together, point estimates on the national business cycle suggest a response between 0.11 and 0.20 percentage points, only slightly larger than comparable results using the state-level in-migration data.

conditions discourage in-migration.[43] The coefficients on the individual characteristics (unreported) all have the expected relationships with the probability of moving.

To further examine whether the national business cycle impacts the migration choices of certain individuals more than others, we interact national and state level business cycle measures with demographic characteristics. As in Table 5, we produce separate estimates for older and younger individuals. Panels A through C of Table 6 show the results of interacting the business cycle measures with the major exogenous characteristics of individuals in our sample that do not change over time: gender, education, and race/ethnicity.[44] In panels D and E, we interact the business cycle measures with characteristics that may change following a long-distance move: employment status, homeownership status, and the presence of children.[45]

We consider the results for the younger subsample first. When the cycle is measured using the unemployment rate or the UI claims rate, blacks are significantly more procyclical than whites (Panel B), while female heads of household are more procyclical than male heads (Panel A). We find no differences across these groups when the cycle is measured using the employment gap. Panel C suggests that less educated workers may be more procyclical in their migration, particularly when conditions are measured using unemployment rates. Panel D shows that young household heads who are in the labor force (i.e. employed or unemployed) have strongly procyclical migration patterns. By contrast, the migration patterns of those who are not in the labor force are largely unaffected by the cycle. Panel E shows that migration patterns of childless homeowners are similarly procyclical to those of childless renters, the omitted group.

[43]As we found with the IRS data, the impact of national business cycle conditions on migration is unaffected by the inclusion of state level controls; the coefficients were little changed in regressions omitting controls for relative state conditions.
[44] Results in panel D are robust to excluding younger individuals—18-25 year olds—who might still be in the process of obtaining higher education.
[45] We include homeownership and the presence of children in the same regression because they are highly correlated with one another.

The presence of children dampens, but does not eliminate, the cyclical fluctuations in migration.[46]

Turning to the results for the 36-65 year old subsample, the main effects indicate that most older individuals do not respond to the aggregate business cycle in making their migration decisions. However, like younger individuals, older blacks, female heads of household, and less-educated individuals–specifically high school dropouts and graduates—tend to have procyclical migration patterns. The acyclicality of highly educated individuals' migration patterns is even more pronounced for this older group than it was for the younger subsample. This acyclicality is somewhat surprising, since other authors have found higher levels of migration and a greater responsiveness to wage arbitrage opportunities among more educated workers (Bound and Holzer 2000, Gregg, Machin and Manning 2004, Malamud and Wozniak 2008, Wozniak 2008). Because migration of more educated workers is *less* procyclical than for other groups, our results suggest that the factors that cause cyclical migration likely differ from those that cause migration rates to be higher for more educated workers.

Several findings in Table 6 point to a role for the national labor market in explaining procyclical migration patterns. First, the migration choices of individuals who are not in the labor force are acyclical. Second, homeownership status has no important impact on the cyclicality of migration, echoing our findings in the IRS data that cyclical fluctuations in migration are unrelated to the housing market. Third, the procyclicality of migration is strongest for groups for whom employment fluctuations also tend to be more sensitive to the national

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[46] Homeownership, employment status, and the presence of children are only observed after the migration decision is made, and these variables might be influenced by migration. However, in unreported analysis using the Panel Study of Income Dynamics (PSID), we find that homeownership and the presence of children in the year prior to the migration decision have the same effects on migration as the post-migration effects found in the CPS. The PSID data also allow us to observe both prior-year and current year employment status, which we use to divide individuals into categories by their employment status transitions. Migration is most procyclical for individuals who are employed in both periods, unemployed in both periods, those making not-in-the-labor-force to unemployed transitions (job seekers), and those making unemployed to employed transitions (job finders). It is acyclical for individuals who are not in the labor force in both periods. Thus, these results also confirm the estimates based on the CPS.

business cycle: the young, non-whites and African Americans in particular, and the less educated. Female heads of household also have more cyclical migration patterns than males, although it is more difficult to relate this result to evidence on the cyclicality of female employment.[47] Additionally, we estimated the specifications shown in Table 5 on the group of CPS respondents aged 65 and older. As this group is generally not active in the labor market, so it is unlikely that their migration choices respond to labor market factors. Consistent with our hypothesis that labor market factors drive observed migration cyclicality, all coefficients on the aggregate cycle were insignificant and close to zero in these specifications.

VI. Conclusion

This paper has shown that migration within the United States is positively correlated with the national business cycle. References to the cyclicality of internal migration have appeared before in the literature, but none have undertaken a thorough investigation of this relationship over multiple business cycles in a large economy widely known for its mobile labor force. We found evidence of procyclical migration patterns in aggregate time series, data on inter-state and inter-metropolitan population flows, and individual-level microdata. The cyclicality of migration is not driven by variation in the geographic dispersion of economic opportunity over the business cycle. Hence, cyclical worker flows across locations are not related to changes in relative local economic conditions but rather to factors that are common to all locations. We interpret these results to imply that the net benefit of moving fluctuates systematically over the business cycle.

The procyclicality of migration is strongest for young individuals. Among this group, migration is strongly procyclical for those in the labor force but acyclical for those not in the

[47] Unemployment of all females tends to be less cyclical than male unemployment. However, the behavior of female household heads may be different from other women, who likely drive the unemployment statistics for all females. The best evidence that employment of female household heads experience procyclical employment comes from the period around welfare reform, although no studies we know of compare cyclicality in this group to men. See Hoynes (2007), Meyer (2002), and Meyer and Rosenbaum (2001).

labor force. Moreover, demographic groups for whom employment tends to be more procyclical also exhibit more procyclical migration. We also find that cyclical fluctuations in migration are similar for homeowners and renters. Thus, cyclical migration patterns appear to be closely related to labor markets with little role for housing markets.

In conclusion, fluctuations in long-distance migration rates add to a growing body of evidence that labor market churning is procyclical (Caballero and Hammour 2005, Fallick and Fleischman 2004). Understanding cyclical fluctuations in labor markets is important as there is an emerging consensus that labor market mechanisms are likely important to understanding fluctuations in aggregate output and growth (King and Rebelo, 1999; Hall, 1999). By studying labor reallocation through the lens of migration, we introduce a new empirical tool to business cycle analysis. Migration data provide a useful alternative to the limited number of annual labor market measures available in long time series and the short time series in which detailed data on job creation, destruction and worker turnover are available. Our paper provides a starting point for studying the cyclicality of geographic worker reallocation by presenting a benchmark against which business cycle theories that incorporate migration might be measured.[48]

Although we have documented a clear correlation between migration and business cycle, our analysis does not address whether migration has a causal effect on the business cycle. The cyclicality of migration might be a cause, a consequence, or one step in a feedback loop driving aggregate fluctuations. Despite this uncertainty, the cyclicality of migration can still reveal something important about the connection between the labor market and the business cycle. For one, our results imply that the timing and efficacy of local economic adjustment may differ between national booms and recessions as low levels of migration are less likely to alleviate local disparities. Procyclical migration patterns also imply that the scale of the job applicant

[48] Shimer (2005b) provides a step in this direction by presenting a theory of geographic mismatch between workers and firms. However, worker migration in his model is the result of random exogenous shocks, leaving no role for endogenous movements of workers between locations.

pool is larger in booms. Thus, employer-employee match quality might be procyclical if match quality is increasing in the size of the pools from which firms and workers are drawn. [49] This result runs contrary to a standard prediction of labor search models and suggests that other mechanisms, such as assortative matching, may be important for understanding business cycle fluctuations.[50] Finally, our results showing that younger workers and those more marginally attached to the labor force have the most procyclical migration suggests that this particular cyclical labor market flow differs from other cyclical flows in the labor market, like employer-to-employer transitions, that are comprised of workers more strongly attached to the labor force.

[49] Recent work by Pries (forthcoming) shows that a larger fraction of low productivity workers are in the pool of unemployed during downturns, which could discourage employers from listing new vacancies during these periods.
[50] The countercyclical property of match quality is due to the need for higher idiosyncratic (i.e. worker-firm specific) values of productivity in order to meet reservation wages in times of low aggregate productivity. Barlevy (2002) proposes alternative mechanisms that result in procyclical match quality.

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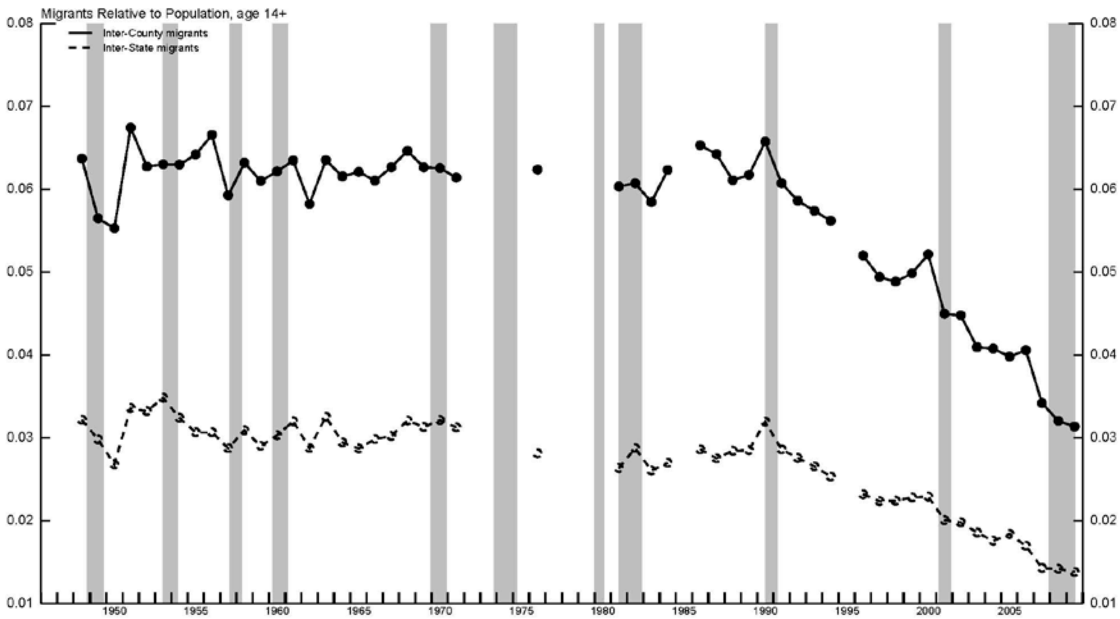
Figure 1
Internal Migration Rates Over the Business Cycle



Note. The shaded areas show NBER recessions.

Figure 2: Inter-County Migration Over the Business Cycle

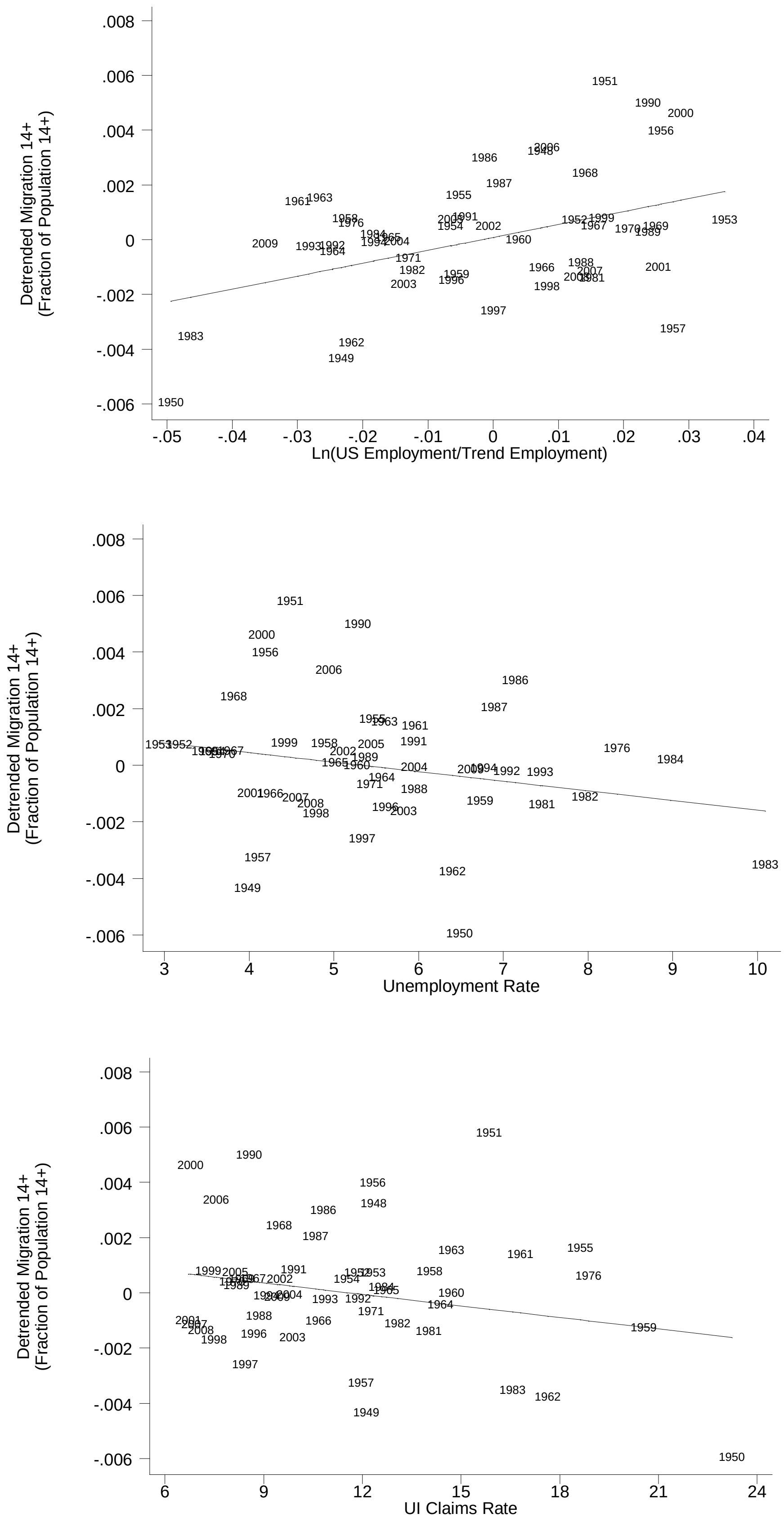


Figure 3: Dispersion of Relative State Economic Conditions in Peak and Trough Years of the National Business Cycle

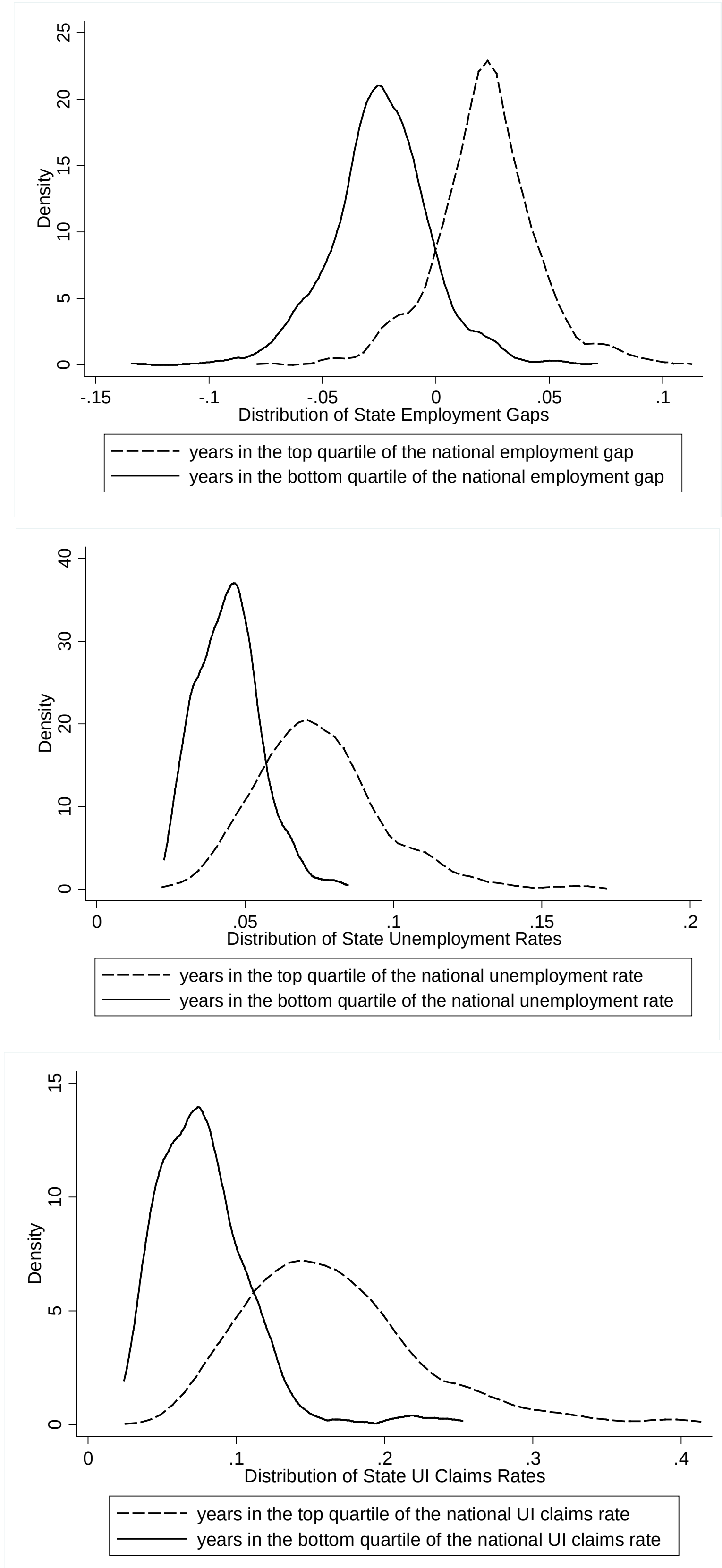


Table 1
Correlation of Inter-County Migration with National Economic Conditions
Controlling for Variation in State Economic Conditions
(Dependent Variable= Migrants 14+ / Population 14+, detrended with an HP filter)

	(1)	(2)	(3)	(4)
	Employment Gap			
	sample = 1948-2009		sample = 1948-2005	
National employment gap	0.0010**	0.0010**	0.0011**	0.0011**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Standard deviation of state employment gaps		-0.0000		-0.0001
		(0.0003)		(0.0003)
	Unemployment Rate			
	sample = 1976-2009		sample = 1976-2005	
National unemployment rate	-0.0006	-0.0012	-0.0006	-0.0013*
	(0.0004)	(0.0007)	(0.0004)	(0.0007)
Standard deviation of state unemployment rates		0.0008		0.0008
		(0.0009)		(0.0007)
	UI Claims Rate			
	sample = 1948-2009		sample = 1948-2005	
National UI claims rate	-0.0005*	-0.0007	-0.0005*	-0.0007
	(0.0003)	(0.0004)	(0.0003)	(0.0005)
Standard deviation of state UI claims rates		0.0003		0.0002
		(0.0005)		(0.0005)

Note. Each column of each panel shows the result of a separate regression where the dependent variable is the detrended migration rate for the population ages 14 and up. Migration trends are estimated using a Hodrick-Prescott filter; regressions ending in 2005 also use a trend estimated only through 2005. Regressions are based on annual data with missing data in 1972-75, 1977-80 and 1995. All covariates are rescaled to have a mean of zero and variance of 1. Aggregate and state employment gaps are defined as the logarithm of employment relative to a Hodrick-Prescott trend, and the values for each year are averages from April to March. All regressions using the unemployment rate are limited to 1976-onward due to the availability of state unemployment rate data. * indicates significance at the 10% level and ** indicates significance at the 5% level.

Table 2
Correlation of State-to-State Migration with National and State Economic Conditions

	Migrants / Initial Population$_{ijt}$ in 1000's			Ln(Migrants$_{ijt}$)		
	Emp. Gap	Unemp. Rate	UI Claims Rate	Emp. Gap	Unemp. Rate	UI Claims Rate
Aggregate BC conditions$_t$	0.017**	-0.018**	-0.024**	0.025**	-0.029**	-0.024**
	(0.002)	(0.004)	(0.004)	(0.004)	(0.006)	(0.009)
Relative BC conditions in origin state$_{it}$	-0.075**	0.076**	0.050**	-0.103**	0.108**	0.089**
	(0.015)	(0.017)	(0.010)	(0.022)	(0.018)	(0.011)
Relative BC conditions in destination state$_{jt}$	0.059**	-0.069**	-0.042**	0.097**	-0.105**	-0.088**
	(0.013)	(0.016)	(0.005)	(0.018)	(0.017)	(0.010)
Relative house prices in origin state$_{it-1}$	0.203**	0.098**	0.119**	0.363**	0.214**	0.241**
	(0.031)	(0.020)	(0.022)	(0.046)	(0.032)	(0.039)
Relative house prices in destination state$_{jt-1}$	-0.202**	-0.119**	-0.140**	-0.367**	-0.239**	-0.250**
	(0.026)	(0.029)	(0.021)	(0.036)	(0.031)	(0.030)
Relative income in origin state$_{it-1}$	0.999**	0.522**	0.004	1.241**	0.650**	-0.009
	(0.242)	(0.163)	(0.121)	(0.365)	(0.200)	(0.096)
Relative income in destination state$_{jt-1}$	0.198	0.471**	1.012**	0.546	1.099**	1.730**
	(0.265)	(0.161)	(0.098)	(0.336)	(0.200)	(0.128)

Note. Migration is defined as the number of exemptions moving from state *i* to state *j* in year *t*. Initial population is the total number of non-migrants plus out-migrants in the origin state. Regressions include a separate fixed-effect and time trend for each origin and destination state and are estimated on annual data from 1977 to 2008. The aggregate and relative business cycle conditions are normalized to have a mean=zero and standard deviation=1. We instrument for the origin and destination relative business cycle conditions with a Bartik shock and oil shock; see Appendix Table A1 for first stage estimates. Standard errors are clustered by year. * indicates significance at the 5% level, ** at the 1% level.

Table 3
Correlation of State Inflows and Outflows with National and State Economic Conditions

	Migrants / Initial Population$_{it}$ in 1000's		Ln(Migrants$_{it}$)	
	Inflows	Outflows	Inflows	Outflows
Employment Gap				
Aggregate BC conditions$_t$	0.831**	0.787**	0.026**	0.028**
	(0.164)	(0.135)	(0.004)	(0.005)
Relative BC conditions in own state$_{it}$	4.440**	-3.051**	0.088**	-0.081**
	(0.842)	(0.930)	(0.016)	(0.025)
Average BC conditions in other states$_{it}$	-0.994	-0.132	-0.015	-0.018
	(0.880)	(1.14)	(0.016)	(0.036)
Relative house prices in own state$_{it-1}$	-17.2**	10.8**	-0.345**	0.405**
	(2.58)	(1.97)	(0.039)	(0.056)
Average house prices in all other states$_{jt-1}$	4.70	-12.0**	0.051	-0.455**
	(3.74)	(4.04)	(0.071)	(0.112)
Relative income per capita in own state$_{it-1}$	0.216	33.9*	0.314	0.810*
	(16.2)	(14.6)	(0.321)	(0.407)
Average income per capita in all other states$_{jt-1}$	87.6	64.2	1.90*	2.92
	(49.7)	(62.3)	(0.938)	(2.02)
Unemployment Rate				
Aggregate BC conditions$_t$	-1.54**	-0.687**	-0.041**	-0.023**
	(0.199)	(0.211)	(0.005)	(0.006)
Relative conditions in own state$_{it}$	-4.12**	2.92**	-0.090**	0.084**
	(1.14)	(0.761)	(0.019)	(0.014)
Average conditions in other states$_{it}$	0.006	0.626	0.002	0.023
	(0.665)	(0.904)	(0.014)	(0.034)
Relative house prices in own state$_{it-1}$	-9.67**	6.50**	-0.189**	0.293**
	(1.08)	(1.13)	(0.027)	(0.039)
Average house prices in all other states$_{jt-1}$	-5.38*	-10.9**	-0.164**	-0.454**
	(2.47)	(2.61)	(0.060)	(0.076)
Relative income per capita in own state$_{it-1}$	32.9**	13.9*	0.886**	0.350**
	(9.72)	(5.7)	(0.202)	(0.114)
Average income per capita in all other states$_{jt-1}$	53.1	70.0*	1.51*	2.50
	(29.6)	(35.3)	(0.717)	(1.37)
UI Claims Rate				
Aggregate BC conditions$_t$	-1.10**	-1.39**	-0.029**	-0.039**
	(0.366)	(0.264)	(0.009)	(0.009)
Relative BC conditions in own state$_{it}$	-2.62**	2.18**	-0.065**	0.067**
	(0.263)	(0.544)	(0.007)	(0.012)
Average BC conditions in other states$_{it}$	-0.493**	0.389**	-0.012*	0.015
	(0.214)	(0.186)	(0.006)	(0.005)
Relative house prices in own state$_{it-1}$	-10.7**	6.72**	-0.205**	0.293**
	(0.915)	(0.843)	(0.023)	(0.026)
Average house prices in all other states$_{jt-1}$	-2.81	-11.7**	-0.099	0.452**
	(3.14)	(2.72)	(0.082)	(0.083)
Relative income per capita in own state$_{it-1}$	62.9**	-7.10	1.50**	-0.229*
	(4.65)	(4.77)	(0.108)	(0.098)
Average income per capita in all other states$_{jt-1}$	37.1*	72.8**	1.01*	2.423
	(17.6)	(11.4)	(0.446)	(0.371)

Note. The dependent variable is the total number of migrants entering or leaving state *j* in year *t* from all other 47 continental states. Average conditions in other states are weighted by the inverse of the distance between states. Regressions include a separate fixed-effect and time trend for each state and are estimated on annual data from 1977 to 2008. The aggregate and relative business cycle conditions are normalized to have a mean=zero and standard deviation=1. We instrument for the own-state and other-state relative business cycle conditions with a Bartik shock and oil shock; see Appendix Table A2 for first stage estimates. Standard errors are clustered by year. * indicates significance at the 5% level, ** at the 1% level.

Table 4
Correlation of Metropolitan Area Inflows and Outflows with National and Local Economic Conditions

	Migrants / Initial Population$_{it}$ in 1000's		Ln(Migrants$_{it}$)	
	Inflows	Outflows	Inflows	Outflows
Employment Gap				
Aggregate BC conditions$_t$	0.344*	0.197	0.013**	0.010
	(0.159)	(0.307)	(0.004)	(0.007)
Relative employment gap	0.836**	0.043	0.024**	0.011**
in own MSA$_{it}$	(0.161)	(0.156)	(0.003)	(0.003)
Relative house prices in	-7.60**	6.39**	-0.129**	0.142**
own MSA$_{it-1}$	(1.12)	(2.13)	(0.025)	(0.50)
Relative income per capita	43.1**	-10.2*	0.717**	-0.298**
in own MSA$_{it-1}$	(6.32)	(5.11)	(0.010)	(0.085)
Unemployment Rate				
Aggregate BC conditions$_t$	-0.438	-0.195	-0.014*	-0.008
	(0.315)	(0.516)	(0.007)	(0.011)
Relative employment gap	0.828**	0.024	0.024**	0.010**
in own MSA$_{it}$	(0.164)	(0.177)	(0.004)	(0.003)
Relative house prices in	-7.76**	6.39**	-0.132**	0.145**
own MSA$_{it-1}$	(1.30)	(1.99)	(0.033)	(0.044)
Relative income per capita	42.0**	-11.0**	0.692**	-0.346**
in own MSA$_{it-1}$	(4.65)	(3.98)	(0.086)	(0.109)
UI Claims Rate				
Aggregate BC conditions$_t$	-0.431	-0.344	-0.010	-0.007
	(0.267)	(0.633)	(0.008)	(0.015)
Relative employment gap	0.788**	0.009	0.023**	0.010*
in own MSA$_{it}$	(0.167)	(0.168)	(0.003)	(0.004)
Relative house prices in	-7.46**	6.45**	-0.124**	0.152**
own MSA$_{it-1}$	(1.15)	(1.95)	(0.30)	(0.051)
Relative income per capita	42.2**	-11.2*	0.681**	-0.344**
in own MSA$_{it-1}$	(6.23)	(5.28)	(0.071)	(0.111)

Note. The dependent variable is the total number of migrants entering or leaving MSA *j* in year *t* from all other 358 continental MSAs (defined using the 2005 Census definitions). Regressions include a separate fixed-effect and time trend for each MSA and are estimated on annual data from 1981 and 1984-2008. The aggregate and relative business cycle conditions are normalized to have a mean=zero and standard deviation=1. Coefficients are estimated with median regression due to the skewed distribution of migration across metropolitan areas. Standard errors are clustered by year using a bootstrap method with 50 iterations. * indicates significance at the 5% level, ** at the 1% level.

Table 5
Linear Probability Models of Migrant Status using CPS Microdata

	Household Heads 18 to 35			Household Heads 36 to 65		
	Emp. Gap	Unemp. Rate	UI Claims Rate	Emp. Gap	Unemp. Rate	UI Claims Rate
	Dependent Variable: Inter-County Move in Last Year					
Aggregate Business Cycle Conditions	0.0028	-0.0040	-0.0047	0.0011	-0.0015	-0.0005
	(0.0012)*	(0.0017)*	(0.0017)**	(0.0005)*	(0.0007)*	(0.0007)
Relative Conditions in Residence State	0.0046	0.0102	-0.0091	0.0012	0.0058	-0.0033
	(0.0088)	(0.0126)	(0.0007)**	(0.0037)	(0.0041)	(0.0004)**
Observations	425682	411484	520544	825294	802230	1041239
R^2 (Uncentered)	0.14	0.13	0.14	0.04	0.04	0.04
	Dependent Variable: Inter-State Move in Last Year					
Aggregate Business Cycle Conditions	0.0017	-0.0029	-0.0044	0.0004	-0.0007	-0.0004
	(0.0009)*	(0.0013)*	(0.0010)**	(0.0004)	(0.0006)	(0.0005)
Relative Conditions in Residence State	0.0056	0.0007	-0.0063	0.0013	0.0023	-0.0023
	(0.0041)	(0.0071)	(0.0006)**	(0.0017)	(0.0025)	(0.0002)**
Observations	425682	411484	520544	825294	802230	1041239
R^2 (Uncentered)	0.07	0.07	0.07	0.02	0.02	0.02

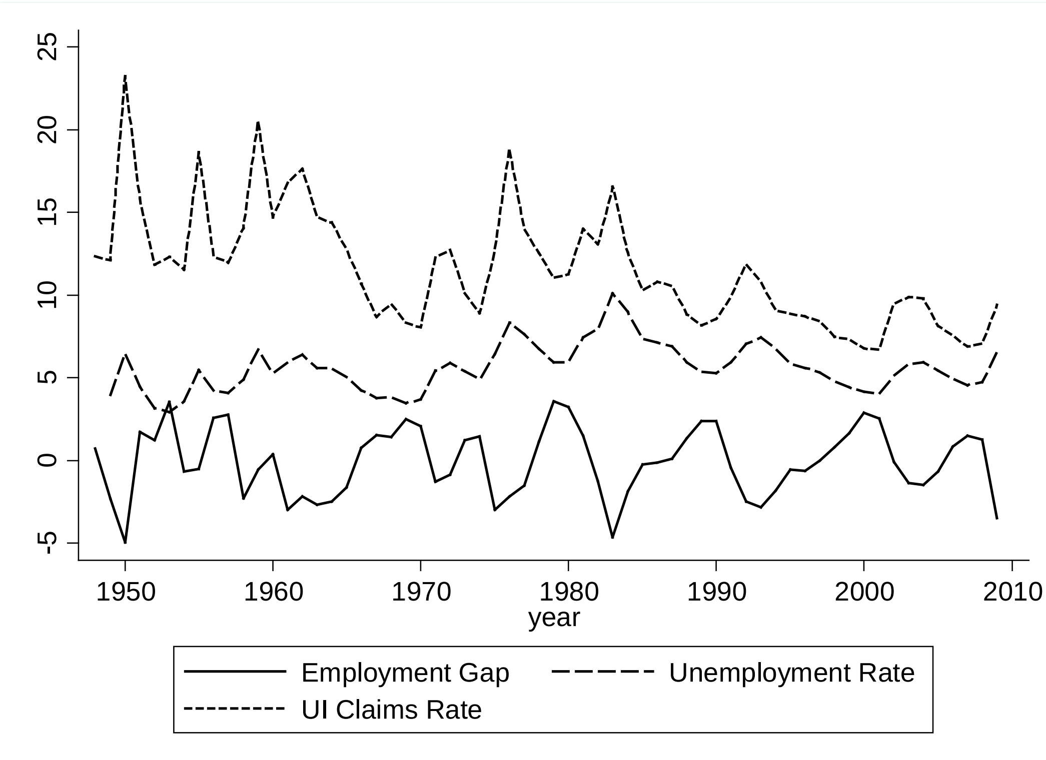
Notes: Method of estimation is 2SLS for specifications using employment gap and unemployment rate; OLS for UI claims rate specification. Data are from IPUMS March CPS, 1964 to 2009. Differences in sample sizes are due to variation in availability of state business cycle measures and instruments for state level conditions. The aggregate and relative business cycle conditions are normalized to have a mean=zero and standard deviation=1. We instrument for the local relative business cycle conditions with a Bartik shock and oil shock; see Appendix Table A3 for first stage estimates. Standard errors are in parentheses and clustered by year. * indicates significance at the 5% level, ** at the 1% level. All specifications include controls for age, education, race and ethnicity, marital status, number of children, employment status, metropolitan area residence, and a quadratic time trend. Observations are unweighted. Construction and years of availability for business cycle measures and instruments given in text.

Table 6
Group Interactions with Aggregate Business Cycle Measures
in Linear Probability Models of Migrant Status

	Ages 18-35			Ages 36-65		
	Employment Gap	Unemp. Rate	UI Claims Rate	Employment Gap	Unemp. Rate	UI Claims Rate
	A. Gender					
Aggregate BC	0.0023	-0.0020	0.0003	0.0006	-0.0004	0.0006
	(0.0012)*	(0.0020)	(0.0024)	(0.0004)	(0.0009)	(0.0010)
x Female	0.0013	-0.0060	-0.0050	0.0010	-0.0030	-0.0034
	(0.0016)	(0.0012)**	(0.0011)**	(0.0010)	(0.0005)**	(0.0004)**
	B. Race and Ethnicity					
Aggregate BC	0.0024	-0.0029	0.0001	0.0007	-0.0009	0.0004
	(0.0014)+	(0.0020)	(0.0027)	(0.0005)	(0.0009)	(0.0010)
x Black	0.0017	-0.0065	-0.0066	0.0013	-0.0039	-0.0045
	(0.0020)	(0.0021)**	(0.0014)**	(0.0013)	(0.0010)**	(0.0007)**
x Hispanic	0.0007	-0.0025	-0.0039	0.0007	0.0000	-0.0030
	(0.0016)	(0.0021)	(0.0014)**	(0.0008)	(0.0002)	(0.0005)
	C. Education					
Aggregate BC	0.0022	-0.0062	-0.0021	0.0013	-0.0026	-0.0012
	(0.0014)	(0.0016)**	(0.0024)	(0.0006)+	(0.0008)**	(0.0010)
x Dropout	0.0011	0.0013	0.0006	0.0005	-0.0002	0.0001
	(0.0015)	(0.0014)	(0.0010)	(0.0004)	(0.0004)	(0.0003)
x Some College	0.0014	0.0013	-0.0002	-0.0011	0.0027	0.0014
	(0.0010)	(0.0010)	(0.0008)	(0.0004)*	(0.0006)**	(0.0005)**
x College	0.0003	0.0059	0.0030	-0.0007	0.0032	0.0019
	(0.0021)	(0.0025)*	(0.0017)+	(0.0007)	(0.0006)**	(0.0005)**
	D. Labor Force Status					
Aggregate BC	0.0031	-0.0044	-0.0055	0.0010	-0.0010	-0.0006
	(0.0012)**	(0.0019)*	(0.0017)**	(0.0004)*	(0.0006)	(0.0006)
x Unemployed	0.0007	-0.0071	-0.0030	0.0020	-0.0040	0.0003
	(0.0033)	(0.0035)*	(0.0030)	(0.0016)	(0.0013)	(0.0021)
x Out of LF	-0.0027	0.0059	0.0087	-0.0003	-0.0013	0.0003
	(0.0026)	(0.0023)**	(0.0030)**	(0.0011)	(0.0008)	(0.0009)
	E. Homeownership and Presence of Children					
Aggregate BC	0.0046	-0.0048	-0.0022	0.0014	-0.0011	-0.0017
	(0.0020)*	(0.0024)**	(0.0033)	(0.0012)	(0.0013)	(0.0013)
x Homeowner	-0.0004	-0.0010	-0.0008	-0.0002	-0.0013	0.0010
	(0.0017)	(0.0014)	(0.0012)	(0.0013)	(0.0011)	(0.0010)
x Kids	-0.0024	0.0013	0.0016	-0.0002	0.0008	0.0006
	(0.0011)*	(0.0011)	(0.0011)	(0.0003)	(0.0003)*	(0.0002)**

Notes: Dependent variable is an indicator for moving across county or state lines in the previous year. Rows preceded by an "x" indicates interactions of the row variable with aggregate business cycle conditions. Method of estimation is 2SLS for specifications using employment gap and unemployment rate; OLS for UI claims rate specification. Data are household heads age 18-65 from IPUMS March CPS, 1964 to 2009. The aggregate business cycle conditions are normalized to have a mean=zero and standard deviation=1. We instrument for the local relative business cycle conditions with a Bartik shock and oil shock; see Appendix Table A3 for first stage estimates. Standard errors are in parentheses and clustered by year. * indicates significance at the 5% level, ** at the 1% level. All specifications include controls for the level of state relative business cycle conditions and interactions of the relevant group dummies with state conditions. Controls for age, education, race and ethnicity, marital status, number of children, employment status, residence in a metropolitan area, and a quadratic time trend are also included.

Appendix Figure 1
Measures of National Economic Conditions



Appendix Table A1
First-Stage Estimates of State-to-State Migration Regressions

	Origin State Employment Gap	Destination State Employment Gap	Origin State Unemployment Rate	Destination State Unemployment Rate
Origin State				
Bartik shock$_{it-1}$	0.130*	0.005	-0.174**	-0.003
	(0.053)	(0.005)	(0.038)	(0.002)
Oil shock$_{it-1}$	0.076	-0.016	-0.043	0.003
	(0.089)	(0.013)	(0.036)	(0.004)
Oil shock$_{it-1}^2$	-0.007	-0.003*	0.004	0.001
	(0.007)	(0.001)	(0.003)	(0.000)
Destination State				
Bartik shock$_{it-1}$	0.005	0.130*	-0.003	-0.174**
	(0.005)	(0.053)	(0.002)	(0.038)
Oil shock$_{it-1}$	-0.016	0.076	0.003	-0.043
	(0.013)	(0.089)	(0.004)	(0.036)
Oil shock$_{it-1}^2$	-0.003*	-0.007	0.001	0.004
	(0.001)	(0.007)	(0.000)	(0.003)
F-test that all 6 instruments = 0	16.7	16.7	73.3	73.3

Note. Each column shows the coefficient estimates on the instruments for the instrumental variable regressions reported in Table 3. All regressions include the other exogenous variables named in Table 3. Standard errors are clustered by year. * indicates significance at the 5% level, ** at the 1% level.

Appendix Table A2
First-Stage Estimates of Gross State Inflow and Outflow Regressions

	Own State Employment Gap	All Other States Employment Gap	Own State Unemployment Rate	All Other States Unemployment Rate
Own State				
Bartik shock$_{it-1}$	0.126*	-0.013	-0.184**	0.022
	(0.053)	(0.025)	(0.038)	(0.020)
Oil shock$_{it-1}$	0.059	-0.072	-0.013	0.049
	(0.098)	(0.039)	(0.022)	(0.033)
Oil shock$_{it-1}^2$	-0.008	-0.012**	0.005*	0.011**
	(0.008)	(0.003)	(0.002)	(0.002)
All Other States				
Bartik shock$_{it-1}$	0.038	0.116	0.018	-0.049
	(0.044)	(0.072)	(0.033)	(0.069)
Oil shock$_{it-1}$	0.041	0.133	-0.063	-0.152
	(0.067)	(0.089)	(0.051)	(0.097)
Oil shock$_{it-1}^2$	0.003	-0.004	-0.002	-0.006
	(0.003)	(0.003)	(0.002)	(0.005)
F-test that all 6 instruments = 0	10.4	11.2	26.1	10.7

Note. Each column shows the coefficient estimates on the instruments for the instrumental variable regressions reported in Table 4. All regressions include the other exogenous variables named in Table 4. Standard errors are clustered by year. * indicates significance at the 5% level, ** at the 1% level.

Appendix Table A3
First-stage Estimates for CPS Microdata Regressions

	Heads 18 to 35		Heads 36 to 65	
	State Unemployment Rate	State Employment Gap	State Unemployment Rate	State Employment Gap
Bartik shock$_{it}$	-0.137**	0.060*	-0.137**	0.056+
	(0.040)	(0.029)	(0.040)	(0.032)
Oil shock$_{it-1}$	-0.085	0.203	-0.102	0.254
	(0.072)	(0.180)	(0.074)	(0.183)
Oil shock$_{it-1}^2$	0.054	0.031	0.023	0.086
	(0.059)	(0.151)	(0.061)	(0.153)
F-test that all 3 instruments = zero	49.51	7.36	29.11	5.90

Notes: Data are household heads from IPUMS March CPS, 1964 to 2004. Each column shows the coefficient estimates on the instruments for the instrumental variable regressions reported in Tables 6 and 7. All regressions include the other exogenous variables named in the notes of Table 6. Standard errors are clustered at the year level. ** indicates significance at the 1% level, * 5% level, + 10% level.