# Why Did People Move During the Great Recession? The Role of Economics in Migration Decisions



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Labor migration offers an important mechanism to reallocate workers when there are regional differences in employment conditions. Whereas conventional wisdom suggests migration rates should increase during recessions as workers move out of areas that are hit hardest, initial evidence suggested that overall migration rates declined during the Great Recession, despite large regional differences in unemployment and growth rates. In this paper we use data from the American Community Survey to analyze internal migration trends before and during the economic downturn. First, we find only a modest decline in the odds of adults leaving distressed labor market areas during the Great Recession, which may result in part from challenges related to the housing price crash. Second, we estimate conditional logit models of destination choice for individuals who migrate across labor market areas; we find a substantial effect of economic factors such as labor demand, unemployment, and housing values. We also estimate latent class conditional logit models that test whether there is heterogeneity in preferences for destination characteristics among migrants. Over all, the latent class models suggest that roughly equal percentages of migrants were motivated by economic factors before and during the Great Recession. We conclude that fears of dramatic declines in labor migration seem to be unsubstantiated.

Keywords: migration, Great Recession, latent class conditional logits

As the Great Recession (from late 2007 to mid-2009) was concluding and the sluggish recovery was beginning, many researchers and federal officials bemoaned the lack of internal migration for jobs (Fletcher 2010; Moretti 2012). Labor migration during a downturn is an important mechanism for local labor markets to cope with employment declines and regional differences

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in economic vitality (Blanchard and Katz 1992; Gallin 2004). Moreover, the extent to which individuals are willing to relocate for employment during an economic downturn has important implications for two common policy response strategies: income replacement programs such as unemployment insurance (Rothstein 2011) and employment-incentivizing programs such as public service employment (Ellwood and Welty 2000; Wiseman 1976) and hiring or worker credits (Neumark 2011). Specifically, the relative investment in each strategy, as well as the mix of funding allocated to specific programs, should depend on the manner in which individuals respond to employment shocks.

The widespread concern about declining migration arose as data from the Current Population Survey (CPS) revealed a substantial drop in interstate migration starting in 2006 and holding throughout the recession (Frey 2009). This drop would accord with previous research on recessionary migration that finds a limited response to poor economic conditions (Gordon 1985; Greenwood 1997; Pissarides and McMaster 1990). Since the Great Depression, seven of the nine recessions have seen declines in migration, and migration since 1948 has been strongly pro-cyclical (Saks and Wozniak 2011). During the Great Recession, declining equity in owners' homes had an especially strong impact by locking homeowners into their local areas and potentially preventing interregional migration (Karahan and Rhee 2012; Modestino and Dennett 2012). Recent analyses, however, question the accuracy of fears that migration declined in response to the downturn. The large drop in migration occurred between May 2006 and May 2007, before the Great Recession (Saks and Wozniak 2011). Further, in the context of a steady decline in migration since the 1980s (Molloy et al. 2014), the drop during the Great Recession is unremarkable and consistent with long-term trends (Kaplan and Schulhofer-Wohl 2011). Thus, it remains important to assess whether or not economic migration declined during the Great Recession.

A central challenge for empirical analyses of migration is the heterogeneity in preferences of migrants. On the one hand, the increased migration that federal officials expected in response to the recession evokes a labor migration model. Classic labor economic theory posits that job availability should be a salient factor, with differences in regional economic conditions as drivers of migration (Hicks 1932, as cited in Greenwood 1975). A large body of research highlights the general salience of economic factors for migration (Davies, Greenwood, and Li 2002; Fishback, Horrace, and Kantor 2006; Greenwood 1997; Hornbeck 2012; Kennan and Walker 2011; Mare and Choy 2001; Milne 1993; Treyz et al. 1993). On the other hand, some migrants certainly move for non-economic reasons. In fact, Mark D. Partridge and colleagues (2012) find that although across-county migration for better geographic amenities remained roughly constant from 1990 to 2007, migrants were less responsive to differences in labor demand from 2000 to 2007 than they were from 1990 to 2000.

Extant analyses adopt a choice framework for migration decisions that constrain preferences to be constant across individuals, which might be problematic if there is heterogeneity in the basic types of movers and their preferences for destination locations. In this paper, we estimate choice models that allow for variation in preferences; specifically, we analyze migrants' destination preferences using latent class conditional logit (LCCL) models, which allow coefficient estimates to vary across class categories. Not only does this better align our empirical estimation with current theories of migration, but it also allows us to classify individuals as migrating for economic or other reasons based on an interpretation of the set of coefficients for each latent class and the relative probabilities of class membership.

We use the large scale of the American Community Survey (ACS) to investigate the determinants of migration decisions before (2005 to 2007) and during (2008 to 2011) the economic downturn associated with the Great Recession. The ACS allows us to analyze migration with greater geographic precision, at the labor market level, than previous nationally representative analyses, which examine interstate migration. This is important, as we later demonstrate, because the types of individuals likely to migrate and the destination characteristics attracting migrants vary between state and substate models. We estimate logit and multinomial

logit models of the decision to remain in one's labor market or migrate to a new area. These models describe the composition of migrants, whether the types of individuals likely to migrate changed during the recession, and the push factors associated with the decision to leave a labor market. Next, we analyze migrants' destination preferences using latent class conditional logit models. These models make a methodological contribution to the study of migration by relaxing the traditional independence of irrelevant alternatives (IIA) assumption and exploring heterogeneity in destination preferences among migrants. We discuss changes in the composition and preferences of migrants during the Great Recession and conclude by considering whether or not economic migration truly declined.

#### PREVIOUS LITERATURE

Everett Lee (1966) argues that both origin push and destination pull factors affect migration decisions, although individuals respond to these factors differently. Moreover, as obstacles to out-migration increase—such as housing lock during the Great Recession (Modestino and Dennett 2012)—pull factors become increasingly important. The pushpull theory predicts that out-migrating individuals will be relatively advantaged compared to their non-migrating peers at their origin location, which serves to push them toward migration. Conversely, migrants are relatively disadvantaged when compared with individuals at their destination location. and the advantages of the destination pull them to migrate. Thus, individuals migrate to achieve improved conditions. Although originally applied internationally, this perspective offers a useful lens for examination of American internal migration during the Great Recession. Specifically, when an individual's community experiences a negative economic shock, he or she becomes more likely to migrate and will be attracted to destinations with strong economic conditions.

#### **Economic Conditions and Migration**

Previous research generally notes a strong link between economic conditions and migration flows, although this relationship may weaken during recessions as workers become less willing or able to migrate (Greenwood 1997; Gordon 1985; Pissarides and McMaster 1990). A common measure of economic conditions is unemployment. Empirical findings are not always consistent, but most show that personal unemployment and regional unemployment are associated positively with out-migration, and relative regional advantages in economic conditions are associated within in-migration. Departures from this trend are more common in research based on aggregate-level data rather than individual-level studies (Greenwood 1997; Herzog et al. 1993; Mare and Choy 2001). Paul S. Davies, Michael J. Greenwood, and Haizhenz Li (2002) find that the relationship between unemployment and interstate migration is stronger during years with a high mean unemployment that has a large variance; higher levels of unemployment may raise the salience of economic concerns for migration decisions, and larger variance may provide better information to migrants.

Other measures of economic conditions also suggest that migrants are more likely to relocate to economically advantaged locations, whether measured by changes in gross domestic product (Milne 1993) or government spending on public works and relief jobs during the Great Depression (Fishback, Horrace, and Kantor 2006). Although regional differentials in wages and wage growth are correlated with migration (Barro and Sala-I-Martin 1992; Kennan and Walker 2011; Pissarides and McMaster 1990; Treyz et al. 1993), labor migration is three times as responsive to unemployment as it is to wages (Beaudry, Green, and Sand 2014; Blanchard and Katz 1992). In sum, previous research using various measures of economic conditions generally finds a positive relationship between economically advantaged locations and inmigration, and both the most common measure of economic conditions and the measure with one of the strongest relationships to migration is the unemployment rate.

Recent research, however, suggests that this pattern may have changed—or at least become more nuanced. Mark D. Partridge and colleagues (2012) find that although positive labor demand shocks were associated with greater in-migration to a county from 1990 to 2000, this

pattern had disappeared and perhaps even turned slightly negative from 2000 to 2007. The authors argue that local labor supply absorbed a greater degree of labor shocks in the recent period, a pattern that would resemble European labor market dynamics. Moreover, longdistance migrations have been declining for several decades (Molloy, Smith, and Wozniak 2011), and recent evidence suggests that relevant job offers have made such transitions less desirable, perhaps due to fewer job openings with high wage premiums (Molloy, Smith, and Wozniak 2014). In fact, those who migrated from a distressed origin to a more advantaged destination during the Great Recession fared no better on economic outcomes than those who stayed behind (Yagan 2014).

If there was little to no benefit to migrating to an economically advantaged destination, this would explain why fewer people might be willing to undertake such a move. Still, it would not explain any increase in migration to economically distressed areas. Atif Mian and Amir Sufi (2014) observe that the counties hit hardest during the Great Recession did not experience net out-migration and actually saw their populations rise. If this increase results from growing preferences for distressed locations among migrants, this would indicate movement away from a labor model of migration. Actually, the increase likely resulted from the diminished influence of origin economic conditions on out-migration decisions; that is, fewer people moved away from economically depressed areas. In-migration to areas hit hardest by the crash did not rise during the recession (Mian and Sufi 2014; Monras 2015). Thus, among migrants, a labor migration model may have persisted.

Over all, the evidence, particularly the recent evidence, on the relationship between economic conditions and migration decisions is mixed. Generally, unemployment is positively related to out-migration and negatively related to in-migration, which is consistent with a push-pull model of migration. Still, the direction and magnitude of these relationships in the context of the Great Recession are unclear. With the potential for increased obstacles to migration during a recession, we argue that destination-specific economic characteristics

might be especially important. Thus, we hypothesize:

H1: Better-destination economic (pull) conditions attract more migrants. Theory suggests the relationship will strengthen during the recession as individuals make economically efficient moves informed by greater variance in economic conditions.

H2: Worse-origin economic (push) conditions encourage migration.

#### **Housing and Migration**

Although a location's housing stock is generally thought of as an amenity (Ritchey 1976), with affordable housing attracting internal migrants to destinations (Sasser 2010), the housing market played a prominent role in the Great Recession. Two unique economic features of the recent recession were the pronounced role of the housing market collapse in the onset of the recession and the persistence of high and prolonged unemployment. Some research posits a link between these phenomena, indicating that housing values and the housing market may have functioned as an economic factor during the Great Recession. Homeowners experienced much sharper declines in their migration rates than renters from 2005 to 2010; in fact, renter migration during the period is statistically indistinguishable from its long-term trend (Kothari, Saporta-Eksten, and Yu 2012).

Some research proposes negative equity and housing lock as an explanation for this pattern of migration (Karahan and Rhee 2012; Modestino and Dennett 2012). When living in states with greater shares of underwater nonprime mortgages (Modestino and Dennett 2012) or metropolitan areas with declining home prices (Karahan and Rhee 2012), individuals are less likely to out-migrate. At the individual level, findings are mixed. Using the American Housing Survey, Fernando Ferreira, Joseph Gyourko, and Joseph Tracy (2012) find that underwater homeowners are one-third as likely to migrate as similar homeowners who are not underwater on their mortgage. On the other hand, studies using credit report data and the Panel Study of Income Dynamics find a positive relationship between negative equity and migration (Coulson and Grieco 2013; Demyanyk et al. 2014). Ultimately, extant research identifies at most a modest role for housing lock in inhibiting moves that would reduce the unemployment rate (see Modestino and Dennett 2012). Neighborhood or community lock, wherein falling housing values of a labor market area keep individuals from moving (even if they are not underwater), is a possibility, but the extent of its impact remains in question.

Unfortunately for all individuals who live in areas with declining housing values, the declines are strongly correlated with reductions in nontradable employment in a potentially causal manner (Mian and Sufi 2014). Along with fewer jobs, the housing bust accounts for half a point's worth of the rise in unemployment during the Great Recession (Karahan and Rhee 2012). Adam Herkenhoff and Lee E. Ohanian (2011) further argue that half of a point of the persistently high unemployment rate is due to mortgage modification programs and their reduction of economic incentives for migration.

The relationship between housing conditions and migration may be best detected when housing is operationalized at the labor market level rather than the household level. Alicia Sasser (2010) finds that incomes and labor market conditions had larger impacts than the housing market on interstate migration over the past three decades; from 1997 to 2006, however, housing affordability had an impact comparable to that of labor market conditions, indicating growing salience of housing at the labor market level for out-migration decisions.

Given the importance of the housing sector for the economic health of labor market areas (LMAs) immediately before and during the recession (Charles, Hurst, and Notowidigdo 2012), we argue that strong housing markets discourage out-migration and encourage inmigration. In the lead-up to the Great Recession, LMAs with booming housing prices exhibited greater economic vitality. Areas that aggressively built new homes during the housing bubble were left with an oversupply of housing stock following the economic collapse, however, and these same boom LMAs became bust LMAs. The excess supply depressed demand for building new homes, and both home prices

and housing-related employment crashed. Thus, we hypothesize:

H3: Growth in housing prices retains and attracted residents prior to the Great Recession, but during the downturn, previously booming housing markets busted and beca me a push factor encouraging outmigration and discouraging in-migration.

#### Socioeconomic Differences in Migration

There is very limited evidence on group-level differences in population adjustment to changes in economic conditions (Bound and Holzer 2000). Racial minorities are less responsive to economic differences across metropolitan areas (Martin 2001), but at least part of this relationship is explained by the lower responsiveness of less-educated or lower-skilled individuals (Bound and Holzer 2000) to changes in the labor market. Individuals with greater educational attainment and greater skills are more responsive to economic shocks and regional disparities (Notowidigdo 2011; Wozniak 2010; Yankow 2003). Thus, we hypothesize:

H4: Adults with college degrees will be more responsive economic conditions, particularly during a recession.

#### DATA

In this paper we use ACS data from 2005 to 2011 to model migration before and during the Great Recession. The ACS is conducted by the Census Bureau and is an annual national random sample of 1 percent of the American population. The survey gathers data on a range of demographic and economic topics and provides annual, representative estimates of populations at the Public Use Microdata Area (PUMA) level. PUMAs are groups of census tracts and counties that contain between 100,000 and 200,000 individuals. Although the Census Bureau has been fielding the ACS every year since 2000, it was expanded to become a full 1 percent national sample starting in 2005, which was the same year that it began reporting migration information and PUMA data on the current residence and, for movers, their PUMA of residence from the prior year. To analyze migration at the labor market area—a unit of analysis bet-

Table 1. Migration and Unemployment Rates, by Year, for Migration Decision Models

	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
Unemployment rate	4.90	4.90	5.00	8.27	9.15	8.53
Migrants						
New labor market area	4.20%	3.93%	3.82%	3.57%	3.49%	3.64%
New state	2.57%	2.42%	2.31%	2.17%	2.12%	2.21%
Distance						
0-100 miles	1.2%	1.13%	1.12%	1.05%	1.04%	1.07%
100-300 miles	1.08%	1.01%	0.98%	0.9%	0.89%	0.94%
300-1,000 miles	1.21%	1.12%	1.07%	1.02%	0.96%	1.00%
1,000+ miles	0.7%	0.67%	0.64%	0.59%	0.59%	0.62%

ter suited to capturing meaningful economic differences-we transform PUMAs to LMAs when possible. Specifically, we transform PU-MAs to metropolitan statistical areas (2000 definition) using a crosswalk available from the Missouri Census Data Center;1 for rural PUMAs that do not correspond to a metropolitan labor market, we define the labor market as the migration PUMA (see migpuma1 at Ruggles et al. 2010). The ACS is uniquely suited to analyze migration during a period of rapid economic change because it measures annual migration flows and a rich set of economic covariates (for example, employment, industry of occupation, and housing value). Moreover, because the majority of migration occurs within a state, analyzing flows within and across LMAs permits measurement of migration dynamics with much more precision than do interstate models.

In addition to the 2005-to-2011 ACS microdata samples, we also use the 5 percent Census 2000 sample from the Integrated Public Use Microdata Series (IPUMS) database developed by Steven Ruggles et al. (2010). The Census 2000 sample provides controls for base level flows between LMAs. For analyses, we restrict our sample to repeated cross-sections of adults ages twenty-five to sixty-four who did not report living abroad during the past twelve months. We

weight all analyses using the relevant person or household weight. We similarly weight and restrict the tabulations of LMA characteristics, but we calculate these on the sample of all individuals residing in an LMA, regardless of age.

#### Migration

In our analysis, our main dependent variable is a categorical variable measuring whether or not an individual has moved across (LMAs) in the past year (either across or within states), although we also run a parallel analysis for cross-state mobility to make our results compatible with previous research. We further subclassify cross-LMA mobility by the distance of the move (less than one hundred miles, one hundred to three hundred miles, three hundred to one thousand miles, and more than one thousand miles). We do not consider within-LMA moves as migration because such movers' economic prospects are unlikely to change appreciably. Table 1 shows how moves are distributed over our study period. Specifically, we find an appreciable drop in migration throughout most of the study period followed by a small recovery beginning in 2010-2011. The steepest declines for moves of all types correspond tightly with the official timing of the Great Recession (2008 to 2009) and the more protracted rise in unemployment (2008 to 2011). Long-

<sup>1.</sup> The crosswalk is available at Missouri Census Data Center, http://mcdc2.missouri.edu/websas/geocorr2k.html (accessed August 6, 2016).

distance moves—especially those of three hundred to one thousand miles—experienced the greatest relative declines over time. Although our definition of the recession window (2008 to 2011) is longer than the official federal definition, the protracted effects of the downturn on unemployment lasted long past the end of the decline in gross domestic product (GDP) that officially defines a recession. Moreover, it is precisely these types of high-unemployment conditions under which a standard model would predict labor migration as a response.

#### **Unemployment Rate**

As a general measure of the economic vitality of an area, we calculate the unemployment rate as the percentage of individuals in the labor force who are not employed. In our models of destination choice, unemployment is likely to be partly endogenous to migration decisions. Thus, despite the unemployment rate providing a general measure of an area's economy, it is limited by both the potential endogeneity and its inability to isolate sector-specific shocks that may have been especially important during the Great Recession. As a result, we calculate two instrumental variables for sector-specific economic changes.

#### Labor Demand Shocks

A key challenge in estimating the effect of labor demand on migration is that observed changes in employment are endogenous to labor supply changes such as in-migration. In this paper we use an instrumental variable approach to estimate changes in labor demand for tradable goods using the Timothy Bartik (1991, 2013) shift-share approach. The idea is that in industries that produce tradable goods, local employment responds to national-level changes in the demand for those goods. In other words, whereas changes in labor demand at a factory that produces refrigerators reflect aggregate national changes in the demand for refrigera-

tors, changes in labor demand in nontradable industries such as construction, hotels, or restaurants are a function of local demand for those products because they are not tradable across geographic areas. Consequently, an instrumental variable for labor demand shocks in tradable goods that is not correlated with local labor supply changes can be constructed by using employment trends in specific industrial employment at the national level. Our instrument uses the lagged local manufacturing employment mix combined with the weighted national-level changes in industry-specific employment over the past year. By removing the portion of labor demand endogenous to local factors, the instrument captures labor demand shocks resulting from macroeconomic forces. We calculate manufacturing labor demand as

$$\hat{L}_{it} = \sum_{j=1}^{N} e_{ijt-1} \left( \frac{\tilde{e}_{ijt} - \tilde{e}_{ijt-1}}{\tilde{e}_{ijt-1}} - \frac{e_t - e_{t-1}}{e_{t-1}} \right)$$
(1)

where  $e_{ijt-1}$  is the share of an LMAs' (i) jobs that are in industry² j in time period t-1,  $\tilde{e}_{ijt}$  is national employment in industry j excluding the LMA, and  $e_t$  is the national employment. Removing each LMA's employment from the national employment components of that LMA's instrument avoids correlation between the instrument and the error term.³ The use of this shift-share instrument based on local industry mix and national employment changes is widespread in the literature (Blanchard and Katz 1992; Wozniak 2010; Notowidigdo 2011; Charles, Hurst, and Notowidigdo 2012).

It is important to note that, by construction, this measure is intended to capture changes in labor demand in the manufacturing sector. At the same time, an increase in local employment in this sector should have spillover effects on local employment in the nontradable sector, as the demand for housing and services increases to fulfill the needs of new manufacturing employees. Enrico Moretti (2010) uses the

- 2. We operationalize industry of employment using three-digit industry codes, which offers substantial precision in measuring changes in industry demand.
- 3. In addition, because the ACS does not provide representative data at the LMA level for 2004, we estimate 2004 LMA industry composition using the 2005 industry mix for each LMA. The 2004 ACS does provide nationally representative estimates of employment by industry, and we use the change from 2004 to 2005 to calculate 2005 manufacturing labor demand changes by LMA.

Bartik measure of labor demand changes in manufacturing to estimate these spillover effects and finds that for each new job in manufacturing, approximately 1.6 additional jobs are created in the nontradable sector. Nonetheless, although this instrumental variable approach will arguably capture exogenous changes in labor demand for manufacturing industries, a key aspect of the regional variation in the Great Recession's impact was the depth of the bust in construction, which is what we turn to next.

#### **Housing Prices**

On a theoretical level, variation in housing prices across metropolitan statistical areas represents a major source of cost-of-living differences and should be included in any model of interregional migration. Moreover, since the collapse of the U.S. housing market catalyzed the Great Recession, LMA housing prices are likely to provide a key indicator of an LMA's economic health, construction sector vitality, and thus its attractiveness to potential movers and stayers. Just like the problem described earlier with respect to changes in employment levels, however, observed changes in housing prices reflect not only the increased cost of housing per se but also the inflows of migrants who are drawn to particular metropolitan areas because of sustained high levels of labor demand or desirable amenities. In other words, variables measuring changes in housing prices will be endogenous to migratory flows and including them as explanatory variables in individual level models of migration may result in a situation of reverse causality.

To circumvent this endogeneity problem, we again employ an instrumental variable approach. Following Albert Saiz (2010) and Charles, Hurst, and Notowidigdo (2012), we use

the lagged share of land available for development within an LMA as a proxy for the sensitivity of housing prices to changes in housing demand. Housing prices tend to be higher in LMAs with limited land available for development for two reasons. First, areas with low land availability tend to be more productive, pay higher wages, and have greater amenities, which is what draws people to live in the area, raises housing prices, and reduces the level of land availability.4 Second, the geographic and topographical features of the land—a sizable share of developable land already built up, large internal water bodies, undevelopable wetlands, and excessively sloped areas—reduce the price elasticity of housing supply. This GIS and satellite-based measure of exogenous land availability relies solely on preexisting characteristics of local housing markets, making it an ideal choice of instrumental variable for housing prices. See Saiz (2010) for an in-depth explanation of the construction of this variable and the motivation for using it as a measure of the price elasticity of housing supply.

In a study of employment trends in the runup to the Great Recession, Charles, Hurst, and Notowidigdo (2012) find that a lagged measure of land availability strongly predicts changes in MSA-level housing prices and construction employment. We use data on land availability at the county level for 2006 from Guangqing Chi and Hung Chak Ho (2013), which we aggregate up to the LMA level to match the geographic data used in our paper. Chi and Ho use satellite data from the 2006 National Land Cover Database to calculate the percentage of land available for development by excluding area that is already built up or consists of surface water, wetlands, public land, or has a slope greater than 20 percent.5 Table 2 shows the re-

- 4. In other words, low levels of land availability reflect specific factors that make an urban area attractive for migrants. Otherwise, there would be no reason to live in an area with higher housing prices.
- 5. To generate a land availability index for 2000, we adjust the 2006 data from Chi and Ho (2013) by subtracting the estimated amount of land used in new construction in each county between 2000 and 2006. We calculate the land use of new construction by first estimating the average lot size of new construction in the 2011 American Housing Survey as a function of county-level land availability using a regression model. Then, we predict the average lot size of new construction for each county using the 2006 land availability levels, and multiply this by the number of new homes constructed in the county between 2000 and 2006. Data on residential construction at the county level is available from the Census state and county data base: https://www.census.gov/support/USACdataInfo.html (accessed October 10, 2016).

Table 2. Relationship Between the 2000 Land Availability Index and the Change in Housing Values

Variables	(1) 2005	(2) 2006	(3) 2007	(4) 2008	(5) 2009	(6) 2010	(7) 2011
	ch_valueh						
Land availability index	-0.543***	-0.777***	-0.816***	0.0579***	0.134***	0.209***	0.242***
	(0.0497)	(0.0591)	(0.0533)	(0.0160)	(0.0187)	(0.0210)	(0.0231)
Constant	1.773***	2.052***	2.156***	0.950***	0.879***	0.832***	0.798***
	(0.0353)	(0.0420)	(0.0379)	(0.0114)	(0.0133)	(0.0149)	(0.0164)
Observations R <sup>2</sup>	666	666	666	666	666	666	666
	0.152	0.206	0.261	0.019	0.072	0.130	0.142

*Notes:* For 2005–2007, the change in value is the ratio of the average housing value in the labor market area to the value in 2000. For 2008–2011 it is the ratio of the current value to the value in 2007. Coefficients are log odds. Standard errors in parentheses.

sults from a preliminary regression of the change in housing prices in LMAs on this land availability index.6 For the years 2005 to 2007, the dependent variable is the ratio of the current average housing value in the LMA to the value in 2000. For 2008 to 2011 the dependent variable is the ratio of the current value to the value in 2007. During the housing boom years from 2005 to 2007, land availability is negative correlated with housing price changes; LMAs that had preexisting constraints on the amount of land available for development such as San Francisco or New York had the largest increases in prices. During the housing bust from 2008 to 2011 the situation was reversed, and land availability in 2000 is positively correlated with housing price changes.

#### MODELS OF THE DECISION TO MIGRATE

We begin by modeling the decision to migrate. For comparability to previous state-level analyses, we first estimate a logit of the decision to migrate to a new state based on individual demographics and origin contextual variables. For this state-level model, we tabulate our origin contextual variables at the state level as opposed to the LMA level. Next, we leverage the geographic precision of the ACS data to estimate a logit of the decision to migrate to a new LMA based on individual demographics and

origin LMA contextual variables. Finally, to analyze potential differences in migration correlates by distance, we estimate a multinomial logit of the decision to remain in one's origin LMA, migrate to an LMA within one hundred miles, migrate to an LMA between one hundred and three hundred miles away, migrate three hundred to one thousand miles, and migrate over one thousand miles.

Because the ACS surveys respondents at only one point, we rely on a question asking residence one year prior to survey date to establish origin location in the year prior to the ACS wave and destination location (potentially the same as the origin location) during the ACS wave year. These models pool all years of data, and to assess whether or not the origin and individual characteristics of migrants changed during the recession, we interact a recession dummy variable (survey years 2008 to 2011) with all independent variables. Thus, the logits and multinomial logit shed light on H2 and H3. Further, to explore socioeconomic variation in recessionary migration decisions that we predict in H4, we estimate separate models for adults with and without a bachelor's degree.

Adults do not make these migration decisions in a vacuum based only on their origin locations. The characteristics of potential destinations also play a role. Theoretically, all

6. These data are available for download at Population Research Institute, "Land Developability, www.land developability.org (accessed August 6, 2016).

<sup>\*</sup>p < .05; \*\*p < .01; \*\*\*p < .001

adults have the same choice set of potential migration destinations; in our models, these choices are all LMAs (or states) in the continental United States. Nevertheless, for many individuals, it is easier to move to a nearby LMA than to one across the country. Thus, we test the sensitivity of our migration decision models to the inclusion of distance-weighted spatial lags that capture the economic characteristics of potential destinations. We take the natural log of distance (in miles) between the centroids of an LMA (or state) and all other areas (or states). We then use the log distances to create inverse distance weights, which we row normalize to sum to 1 for each LMA or state. The spatial lags of economic variables are the weighted means of those variables for all other LMAs or states.

### CHOICE MODELS OF DESTINATION LOCATIONS

We estimate conditional logit and latent class conditional logit models of destination choice for individuals who migrate. Both models are motivated by a discrete choice framework with utility maximization, and the difference between the two models revolves around whether or not we allow for individual heterogeneity in the preferences for locational characteristics. In equation 2 we represent the utility of choosing to migrate to destination *j* as a function of observed characteristics, fixed and random preferences for those characteristics, and a random error term:

$$U_{ij} = (\gamma_j)Z_{ij} + (\beta_j + \nu_{ij})X, \qquad (2)$$

where  $U_{ij}$  is the utility of destination option j for individual i,  $\varepsilon_{ij}$  is the iid-distributed random error term, and  $Z_{ij}$  and  $X_{ij}$  are sets of destination-specific variables (or individual-specific variables interacted with destination variables). The  $Z_{ij}$  and  $X_{ij}$  terms differ in terms of whether their coefficients are fixed or allowed to vary across individuals. The coefficient on  $Z_{ij}$ ,  $\gamma_{ij}$ , is assumed to be constant across all individuals, while the coefficient on  $X_{ij}$ , has a fixed component  $(\beta_{ij})$  and a random component  $(\nu_j)$  that varies across individuals.

In the conditional logit model, we assume that individuals have identical preferences for these characteristics. In terms of equation 2, this means that all of the explanatory variables are of type Z rather than X, and the choice framework reduces to equation 3:

$$U_{ij} = (\gamma_j) Z_{ij} + \varepsilon_{ij} \tag{3}$$

The assumption of fixed preferences in equation 3 is another way of saying that the conditional logit model, like the multinomial logit model, makes the independence of irrelevant alternatives (IIA) assumption, which is that the error term  $\varepsilon_{ii}$  is not correlated across choice categories for the same person (Train 2003, 144). IIA assumes that one's relative preference between two alternatives is independent of what other alternatives are available. This assumption is problematic in a migration context, wherein specific destinations are often comparable to one another. IIA would require, for example, that an aspiring gambler mulling a move from rural Kentucky to Reno would have the same relative preference for Reno regardless of whether other gambling hubs like Las Vegas or Atlantic city were included among the choices.

One of the advantages of the IIA assumption in the conditional logit model is that it allows for the sampling of alternative choices, because the pairwise choice probability is assumed to be unaffected by the inclusion or exclusion of alternative choices (McFadden 1978; Bruch and Mare 2012). For each individual, the researcher can keep the choice that was actually chosen along with a random sample of the alternative choices that were not selected. For models with large numbers of choices, this greatly increases the computational efficiency (Nerella and Bhat 2004).

In the context of our analysis of economic pull factors and migration, an illustration of how the IIA assumption might be violated in migration models is provided by the following example. Imagine that there are two different types of movers: "economic" movers who have strong preferences for regions with high levels of economic growth, and "amenity" movers, who are not motivated by economic considerations. As a result of heterogeneity in mover type, forcing the coefficient on destination growth rates to be the same for these two groups

(as in equation 3) means that the effect of mover type on the preference for economic growth enters the model as unobserved heterogeneity in the error term, which will be correlated across high- and low-growth-rate destinations. In other words, economic movers will have positive error terms—that is,  $E(\varepsilon_{ij} > 0)$ —for high-growth destinations because the coefficient on the variable measuring destination growth rates is constrained to be the same for both mover types and only partially reflects economic movers' preferences for economic growth.

The upshot of this discussion of heterogeneity in preferences for locational characteristics for migration models is that the arbitrary division of cartographic space into a set of mutually exclusive destination choices (such as states or LMAs) may affect the results of the analysis. This is the familiar "red bus, blue bus" problem familiar to discussions of violations of the IIA assumption where a division of the bus category into two choices based on color creates a problem with correlated error terms across choices (McFadden 1974). In terms of our migration example with a conditional logit and heterogeneity in mover types, the estimated effect of economic growth rates will depend on the distribution of growth rates across the destinations. If a change in growth rates over time alters the relative number of high- and low-growth destinations, then this will affect the estimated coefficient on growth rates just as in the example of dividing the "bus" category into additional categories based on a potentially irrelevant characteristic such as color.

The IIA assumption can be relaxed by allowing variation in preferences across individuals as depicted in equation 2, where the coefficients on the *X* variables are assumed to have fixed and random components. The mixed logit model (Hensher and Greene 2003) is an alternative to the conditional logit model that allows the coefficients to vary across individuals according to some specific parametric distribution. The problem with the mixed logit model for migration, however, is that it does not allow for the sampling of alternative choices (Domanski 2009), which makes it computationally prohibitive to estimate in models with large choice sets.

In this paper we estimate latent class conditional logit models, which are an extension

of the basic mixed logit model that allow the coefficients to vary across a finite set of discrete categories (Train 2008). Because the coefficients are constrained to be the same within the latent categories, they allow for the sampling of alternatives while still providing the benefit of relaxing the IIA assumption across the latent classes (Domanski 2009). The LCCL model is estimated in an iterative process where class membership probabilities are calculated indicating the likelihood of each individual belonging to a particular latent class based on the coefficients estimates for each class, and then the coefficients are updated by running separate conditional logit models for each latent class using the class membership probabilities as weights (Train 2008). The process continues back and forth between calculating the membership weights and estimating the coefficients until the combined likelihood of the conditional logit models for each class are maximized. Appendix A provides more details on the estimation procedures. For the purposes of our discussion here the key benefits of the LCCL models is that they allow for variation in the coefficients of destination characteristics across latent classes, and that membership in the latent classes is not determined a priori but by the estimation procedure itself.

For all CL and LCCL models we include several control variables in addition to our focal economic variables. First, we include destination population and the distance between origin and destination as controls for a basic gravity model of migration. Distance also proxies for psychic and informational costs in migration decisions (Greenwood 1975). In addition, we control for baseline flows between LMAs (or states) using Census 2000 by calculating the percentage of migrants in each origin LMA who move to every other LMA. Although these base flows are not origin-destination-pair fixed effects, which are computationally infeasible in most of our preferred models, their logic is similar. Census 2000 flows are a proxy for certain time-invariant characteristics for which migrants have a consistent preference over time. One such characteristic could be cultural ties that encourage migration between two specific LMAs. In the LCCL models, we constrain the coefficients of our control variables to be constant across latent classes to ensure that our latent classes capture variation in preferences on economic variables. This tests the specific improvement in explanatory power of our LCCL models over the CL models for the focal variables. Finally, we test the sensitivity of our LMA-level models to state fixed effects. State effects provide greater control for unobserved, persistent flows to certain destinations that are not attributable to economic shocks.

#### **RESULTS AND DISCUSSION**

Table 3 presents the results from our logit models of the decision to migrate. We begin with a state-level logit for comparability to previous research. Model 1 estimates an adult's odds of moving to a new state based on origin-state manufacturing labor demand and unemployment, as well as a host of controls. Surprisingly, adults in states with positive manufacturing shocks were more likely to out-migrate prior to the recession, but they were significantly less likely to out-migrate during the recession. In contrast, state-level unemployment is marginally related to reduced odds of out-migration during the recession, suggesting mixed impacts of origin economic conditions for migration decisions during the recession. Model 2 adds the land availability instrument for the housing market, and the recessionary changes in the relationships of manufacturing labor demand and unemployment with out-migration disappear. Individuals residing in areas with greater land available for development-locations that did not experience a housing boom prior to the recession—were less likely to outmigrate prior to the crash, but they were more likely to out-migrate following the crash. This could provide evidence that housing lock inhibited migration, or it could indicate that adults in states with stronger economies have the resources necessary to move across states.

Model 3 adds controls for distance-weighted characteristics of potential destinations, which play an important role in migration decisions and mask the impact of some origin characteristics. The housing market relationship with migration observed in Model 2 persists, but new patterns for unemployment and manufacturing shocks emerge. Adults living in states with stronger economies, as measured by un-

employment and manufacturing labor demand, were more likely to out-migrate prior to the recession, but these patterns attenuated substantially or even reversed during the Great Recession. This suggests that our second hypothesis, that worse origin economic conditions encourage migration, is realized in the context of the recession. That we continue to observe greater out-migration from states with stronger housing markets suggests that, in contrast to H3, negative equity might actually be inhibiting migration during the crash and driving the observed relationship.

Next, we use the geographic detail of the ACS to estimate comparable logits at the LMA level. Results reveal important differences in the role of origin push factors for the decision to migrate between state- and LMA-level models. Unlike the significant relationship between origin-state manufacturing labor demand and migration to a new state, the association of origin manufacturing shocks with migration to a new LMA is explained entirely by the economic characteristics of potential destinations. Moreover, the negative association between unemployment and out-migration before the recession decreases substantially in magnitude in the LMA-level model, and origin unemployment further discourages out-migration to a new LMA during the recession. The only consistent finding between the state- and LMA-level models is the direction and magnitude of the relationship between housing market vitality and out-migration. In sum, whereas the state models provided qualified support for H2 in the context of the recession, the LMA models provide no support for origin economic conditions directly affecting out-migration decisions before or during the recession.

Why might we observe these differences between the state and LMA models? A potential explanation is that state moves are a different type of migration than within-state, across-LMA moves. State moves are generally greater in distance and may require more resources, which could affect the role of origin push factors. Table 4 presents our multinomial logits of migration distance, which reveal systematic variation in the determinants of migration decisions by the distance of moves. Findings from model 1 (without potential destination spatial lags) and

Table 3. Logit Models of the Decision to Migrate

	Panel	1: State-Leve	l Models	Panel	2: LMA-Leve	el Modelsª
	Model 1: All Adults	Model 2: All Adults	Model 3: All Adults with Spatial Lags	Model 1: All Adults	Model 2: All Adults	Model 3: All Adults with Spatial Lags
Origin characteristi	cs					
Labor demand	1.779*** (0.388)	2.442*** (0.419)	4.554*** (0.643)	0.415*** (0.121)	0.418*** (0.121)	-0.076 (0.134)
R*labor demand	-3.079** (0.962)	-0.666 (1.147)	-6.709*** (1.393)	-0.324 <sup>†</sup> (0.182)	-0.542** (0.185)	0.108 (0.194)
Unemployment	0.387 (0.61)	-0.709 (0.631)	-4.78*** (0.899)	-0.101 (0.27)	-0.206 (0.276)	-0.643* (0.282)
R*unemployment	-1.052 <sup>†</sup> (0.635)	0.111 (0.657)	3.029** (0.961)	-1.112*** (0.291)	-1.01*** (0.296)	-0.692* (0.322)
Land availability		-0.363*** (0.054)	-0.268*** (0.057)		-0.146*** (0.024)	-0.229*** (0.028)
R*land availability		0.402*** (0.067)	0.301*** (0.07)		0.238*** (0.03)	0.283*** (0.035)
Potential destinatio	n spatial lag	S				
Labor demand			112.705*** (22.767)			-12.243*** (2.512)
R*labor demand			-71.593** (23.344)			4.429 <sup>†</sup> (2.623)
Unemployment			-85.346*** (19.621)			106.17*** (18.633)
R*unemployment			84.406*** (19.627)			-104.022*** (18.635)
Land availability			8.253***			5.907*** (1.187)
R*land availability			-2.475 (2.92)			-3.656* (1.465)
N	9,543,506	9,479,425	9,479,425	9,538,260	9,474,179	9,466,831

*Notes:* Base outcome is staying in the same state (models 1 and 2) or LMA (models 3 and 4). Coefficients are log odds. Standard errors in parentheses. All models include controls for the recession (dummy), individual race or ethnicity, gender, age, education, marital status, and disability status, as well as previous year's LMA's population size, racial composition, nativity composition, educational composition, and age composition.

model 2 (including destination lags) are broadly consistent, so we will discuss the results from model 2. Consistent with H2, weak origin economic conditions are positively related to likelihood of short-distance migration. High unemployment, declining manufacturing labor demand, and non-booming housing markets

prior to the recession all are associated with increased odds of migrating to a new LMA that is less than one hundred miles away. None of these associations changed during the Great Recession. Medium- and long-distance moves, however, are negatively related to origin LMA economic vitality. Since short-distance moves

<sup>&</sup>lt;sup>a</sup> LMA = labor market area.

 $<sup>^{\</sup>dagger}p$  < .1;  $^{*}p$  < .05;  $^{**}p$  < .01;  $^{***}p$  < .001

**Table 4.** Multinomial Logit Models of Migration Distance (N = 9,465,700)

	Σ	Model 1: All Adults (No Spatial Lags)	(No Spatial L	ags)	Model 2: All	Model 2: All Adults with Potential Destination Spatial Lags	ntial Destination §	Spatial Lags
			Moved					
	Moved < 100	Moved	300-1,000	Moved 1,000+	Moved < 100	Moved 100-	Moved 300-	Moved 1,000+
	Miles	100-300 Miles	Miles	Miles	Miles	300 Miles	1,000 Miles	Miles
Origin characteristics								
Labor demand	-0.271	0.46*	1.157***	1.796***	-0.592**	-0.074	0.577*	1.597***
	(0.194)	(0.222)	(0.243)	(0.357)	(0.215)	(0.246)	(0.266)	(0.406)
R*labor demand	-0.667*	0.523	-0.814*	0.044	-0.172	1.019**	-0.036	-0.031
	(0.292)	(0.346)	(0.372)	(0.565)	(0.308)	(0.363)	(0.388)	(9.0)
Unemployment	3.231***	-2.006***	$-1.02^{\dagger}$	0.904	3.041***	-2.536***	-1.893***	0.597
	(0.433)	(0.511)	(0.554)	(0.872)	(0.444)	(0.522)	(0.567)	(0.885)
R*unemployment	-1.929***	-0.576	-1.305*	-3.27***	-0.706	$-1.086^{\dagger}$	-0.853	-3.601***
	(0.472)	(0.551)	(0.592)	(0.919)	(0.509)	(0.603)	(0.648)	(1.005)
Land availability	0.388***	-0.162***	-0.22***	-0.733***	0.483***	-0.199***	-0.558***	-0.569***
	(0.041)	(0.048)	(0.05)	(0.067)	(0.05)	(0.055)	(0.056)	(0.077)
R*land availability	0.099	0.425***	0.362***	-0.016	0.082	0.47***	0.406***	0.052
	(0.051)	(0.059)	(0.061)	(0.082)	(0.061)	(0.069)	(0.07)	(0.095)
Potential destination spatial lags	patial lags							
Labor demand					-35.89***	-16.099***	-7.827	38.773***
					(4.444)	(4.687)	(4.862)	(6.736)
R*labor demand					32.134***	3.197	-0.965	-49.779***
					(4.649)	(4.901)	(2.06)	(2.009)
Unemployment					278.514***	137.538***	75.537*	-278.647***
					(33.118)	(34.711)	(36.036)	(49.583)
R*unemployment					-279.961***	-132.166***	-72.535*	282.433***
					(33.122)	(34.715)	(36.04)	(49.59)
Land availability					-7.224***	3.523	27.543***	-11.965***
					(2.127)	(2.293)	(2.197)	(3.12)
R*land availability					1.667	4.257	-4.525	-6.458
					(2.595)	(2.851)	(2.728)	(3.888)

Notes: Base outcome is staying in the same labor market area (LMA). Coefficients are log odds. Standard errors in parentheses. All models include controls for the recession (dummy), individual race or ethnicity, gender, age, education, marital status, and disability status, as well as previous year's LMA's population size, racial composition, nativity composition, educational composition, and age composition.

 $^{+}$ p < .1;  $^{*}$ p < .05;  $^{**}$ p < .01;  $^{***}$ p < .001

account for less than a third of all moves, the extent to which weak origin economic conditions spur migration (H2) is quite modest.

Appendices B through D present the results of our re-estimation of the migration decision models from tables 3 to 4, stratified by collegedegree status. There is some evidence that adults without college degrees may be less likely than college graduates to move from origin LMAs with high unemployment rates, which aligns with our hypothesis that college graduates would be more responsive to economic conditions (H4). This difference arises because college graduates are more likely to make short-distance moves in response to high origin unemployment, and adults without college degrees are less willing to make mediumdistance moves under such conditions. Generally, however, we observe few systematic differences in response to origin economic conditions by education level.

Turning to the destination choices and the pull characteristics that attract migrants, we begin by estimating several CL models of destination selection—the traditional approach to analyzing migration choices. In these models, we estimate separate effects of destination characteristics before and during the recession, which allows for a direct test of whether or not they are statistically different than 0 (and which is mathematically equivalent to estimating a model with main effects for destination characteristics combined with interaction terms for the recession). We do not include a recession dummy variable because it is a constant characteristic of individuals and drops out of the model unless interacted with destinationspecific variables. Table 5 presents the results of the CL models.

Panel 1 presents the results of a state-level analysis of migrants' destination choices. Before the Great Recession, migrants generally preferred to move to economically strong destinations. Migrants tended to select states with lower unemployment rates that had housing markets likely to be booming, both of which are indicative of a preference for strong economies (H1). Still, migrants were less likely to select states with increasing manufacturing labor demand, which could indicate mixed preferences or a declining importance of manufacturing as a po-

tential source of employment for movers. Although they may have attenuated slightly, these preferences did not change dramatically during the Great Recession, which is consistent with H1. In addition, there are few systematic differences between college graduates and adults without a college degree. If anything, the former were more sensitive to variations in the unemployment rate, particularly during the downturn, which is consistent with H4 and our findings from the origin push models.

Panel 2 presents the results of our LMA-level analysis of destination selection. Model 1 presents the results without state fixed effects, and most findings are consistent with the state-level models—with the exception of a change in the direction of the relationship between destination labor demand and in-migration. Leveraging the greater geographic detail available in the ACS, we find that migrants prefer destinations with increasing manufacturing labor demand both before and during the recession. This suggests that state-level models may not have the geographic precision necessary to properly estimate destination selection. For all three economic variables, migrants prefer destinations with stable, growing economies prior to the recession, and only our measure of land availability, which identifies booming housing markets that busted during the crash, runs counter to this story during the recession. In general, then, economic characteristics of an LMA play a critical role in destination selection (H1).

Model 2 adds state fixed effects to model 1 to help control for unobserved persistent flows to destinations that are not attributable to our economic variables. The magnitudes of the unemployment and manufacturing demand parameters are substantively unchanged, but the importance of the land availability instrument declines by roughly half during both the prerecession and recession time periods. This suggests that a meaningful portion of the persistent flows to LMAs with housing booms prior to the recession that subsequently busted are actually due to non-economic factors. These results provide even stronger evidence for a pattern of economic migration that persisted during the Great Recession (H1), at least the pattern of destination selection. Finally, we again find little variation in destination preferences

Table 5. Alternative-Specific Conditional Logits (CLs) of Migrants' Destination Choices—All States and Labor Market Areas with Sampled Destinations

Model 1:         Model 2: College         Model 3:           Census 2000 flows         9.014***         7.417***         10.005***           Census 2000 flows         9.014***         7.417***         10.005***           (0.059)         (0.093)         (0.076)         (0.076)           In(population)         (0.058)***         0.696***         0.518***           (0.003)         (0.004)         (0.005)         (0.004)           In(distance)         (0.003)         (0.005)         (0.004)           Pre-recession preferences         -1.824***         -0.547***         -0.625***           Labor demand         (0.273)         (0.459)         (0.03)           Unemployment rate         -2.078***         -2.078***           (0.019)         (0.03)         (0.024)           Recessionary preferences         -6.575***         -1.825         -9.325***           Labor demand         -6.575***         -1.825         -9.325***           Unemployment rate         -6.575***         -1.825         -9.325***           Land availability         -0.213***         -0.513***         -0.515***           Coll (0.02)         (0.029)         (0.024)           Coll (0.029)         (0.029)         (0.024	Φ				
Model 1: Model 2: College All Adults Graduates O flows 9.014*** 7.417*** (0.059) 0.589*** 0.696*** (0.003) 0.589*** 0.0059 -0.589*** 0.0050 -0.589*** 0.0050 -0.589*** 0.0050 -0.589*** 0.0050 -0.589*** 0.0050 -0.004) 0.006 (0.073) 0.0459) ment rate 0.273 0.459 ability 0.069*** 0.0718*** (0.019) 0.039 ment rate 0.326*** 0.038*** (0.03) 0.032 ment rate 0.032*** 0.038*** (0.018) 0.029	Ф				Model 4:
All Adults Graduates  0 flows 9.014*** 7.417***  (0.059) (0.093)  (0.589*** 0.696***  (0.003) (0.005)  -0.589*** 0.696***  (0.004) (0.005)  -0.589*** -1.272**  (0.004) (0.006)  (0.273) (0.459)  -4.019*** -1.272**  (0.045) (0.051)  -0.69*** -0.718***  (0.019) (0.03)  ry preferences  -6.575*** -1.825  nand (0.019) (0.03)  (0.032) (1.346)  ment rate (0.2326*** -0.772***  (0.018) (0.029)		Model 1:	Model 2:	Model 3: College	Non-College
0 flows 9.014*** 7.417*** 0.059) (0.093) 0.589*** 0.696*** 0.003) 0.589*** 0.696*** 0.004) (0.005) 0.004) (0.006) 0.0073		All Adults	All Adults	Graduates	Graduates
(0.059) (0.093) (0.093) (0.089*** (0.003) (0.005) (0.005) (0.005) (0.005) (0.004) (0.006) (0.004) (0.006) (0.004) (0.006) (0.0273) (0.459) (0.273) (0.459) (0.24** (0.345) (0.019) (0.03) (0.019) (0.019) (0.03) (0.019) (0.03) (0.019) (0.03) (0.019) (0.03) (0.019) (0.03) (0.019) (0.03) (0.019) (0.03) (0.019) (0.03) (0.019) (0.019) (0.03) (0.029) (0.018) (0.029)		23.353***	20.28***	17.871***	19.796***
on)  0.589*** 0.003) -0.589*** 0.005) -0.589*** 0.006) 0.004) 0.004) 0.006) 0.006)  and 0.273 0.459) -4.019*** 0.459) -4.019*** 0.459) -4.019*** 0.045) -4.019*** 0.0561) ability 0.019) 0.03)  ry preferences -6.575*** -1.825 -1.825 -2.326*** 0.03)  ment rate 0.03 (0.832) 0.03) -2.326*** -0.778*** -0.072*** -0.613*** -0.072***		(0.188)	(0.18)	(0.317)	(0.216)
(0.003) (0.005) -0.589*** -0.547*** (0.004) (0.006) -0.589*** -0.547*** -0.589*** -0.547*** -1.824*** -1.272** -4.019*** -6.905*** (0.345) -6.905*** -0.69*** -0.718*** (0.019) (0.03)  ry preferences -6.575*** -1.825 -6.575*** -5.38*** (0.832) (1.346) ment rate (0.2) (0.317) ability -0.613*** -0.772***		0.827***	0.852***	1.021***	0.763***
-0.589*** -0.547*** -0.547*** -0.547*** -0.547*** -0.547*** -0.006)  on preferences		(0.002)	(0.002)	(0.004)	(0.003)
(0.004) (0.006)  -1.824*** -1.272** (0.273) -6.905*** (0.345) -0.69*** (0.345) -0.718*** (0.019) (0.03)  -6.575*** -1.825 (0.832) -5.38*** (0.02) (0.03) -0.613*** -0.772***		-1.242***	-1.312***	-1.127***	-1.407***
-1.824*** -1.272** (0.273) (0.459) -4.019*** (0.459) -4.019*** (0.561) -0.69*** (0.019) (0.03) (0.03) (0.019) (0.03) (0.03) (0.832) (1.346) -2.326*** (0.029) (0.018) (0.029)		(0.003)	(0.003)	(0.006)	(0.004)
-1.824*** -1.272** (0.273)					
(0.273) (0.459) -4.019*** -6.905*** (0.345) (0.561) -0.69*** -0.718*** (0.019) (0.03) -6.575** -1.825 (0.832) (1.346) -2.326*** -5.38*** (0.018) (0.029)	1	0.896***	0.598***	0.541**	0.701***
-4.019*** -6.905*** (0.345) -0.69*** (0.019) (0.03) -6.575*** -1.825 (0.832) (1.346) -2.326*** -5.38*** (0.2) (0.317) -0.613*** -0.772***		(0.1)	(0.102)	(0.197)	(0.12)
(0.345) (0.561) -0.69*** -0.718*** (0.019) (0.03) -6.575** -1.825 (0.832) -2.326** -5.38** (0.2) (0.317) -0.613*** -0.772***		-4.54***	-3.978***	-9.809**	-1.984***
-0.69*** -0.718*** (0.019) (0.03) -6.575** -1.825 (0.832) (1.346) -2.326** -5.38** (0.2) (0.317) -0.613*** -0.772***		(0.193)	(0.195)	(0.372)	(0.231)
(0.019) (0.03) -6.575*** -1.825 (0.832) (1.346) -2.326*** -5.38*** (0.2) (0.317) -0.613*** -0.772***	,	-0.928***	-0.276***	-0.121***	-0.36***
-6.575*** -1.825 (0.832) (1.346) -2.326*** -5.38*** (0.2) (0.317) -0.613*** (0.029)		(0.016)	(0.016)	(0.028)	(0.019)
-6.575*** -1.825 - (0.832) (1.346) -2.326** -5.38** (0.2) (0.317) -0.613*** -0.772***					
(0.832) (1.346) -2.326** -5.38** (0.2) (0.317) -0.613** -0.772*** (0.018) (0.029)	'	0.733***	0.576***	0.573	0.614**
ate		(0.159)	(0.16)	(0.304)	(0.189)
(0.2) (0.317) -0.613*** -0.772*** (0.018) (0.029)		-2.24***	-3.104***	-7.413***	-1.598***
-0.613*** (0.018) (0.029)		(0.127)	(0.128)	(0.237)	(0.153)
(0.018) (0.029)	l v	-0.855***	-0.241***	-0.236***	-0.267***
State fived effects		(0.015)	(0.015)	(0.026)	(0.018)
			×	×	×
N 10,665,931 4,458,591 6,207,340		4,150,666	4,150,666	1,393,468	2,757,198
Log likelihood -733,993 -295,531 -437,363		-429,073	-419,870	-134,834	-278,812

Source: Authors' calculations.

Notes: Coefficients are log odds. Standard errors are in parentheses.

 $<sup>^{\</sup>dagger}p < .1; ^{*}p < .05; ^{**}p < .01; ^{***}p < .001$ 

**Table 6.** Latent Class Conditional Logits of Labor Market Area Destination Choice with Sampled Destinations

	Pre-recession	n (2005–2007)	Recession Yea	rs (2008-2011)
	Latent Class 1	Latent Class 2	Latent Class 3	Latent Class 4
Census 2000 flows [constrained]	20.082***			
	(0.181)			
In(population) [constrained]	0.853***			
	(0.002)			
In(distance) [constrained]	-1.310***			
	(0.003)			
Labor demand	0.454***	1.147***	-0.058	1.878***
	(0.018)	(0.022)	(0.052)	(0.048)
Unemployment rate	-0.698**	-6.563***	-0.691***	-4.084***
	(0.065)	(0.088)	(0.036)	(0.029)
Land availability	2.138***	-2.831***	-2.652***	2.021***
	(0.001)	(0.001)	(0.000)	(0.000)
Latent class weight	0.2348	0.2072	0.2576	0.3004
Percentage of migrants by period	53.13	46.87	46.16	53.84

*Notes:* Coefficients are log odds. Standard errors in parentheses. N = 4,150,650. Log likelihood = -394,431. Models include state fixed effects. Census 2000 flows, log population, and log distance are constrained to be constant across latent classes.

$$^{\dagger}p$$
 < .1;  $^{*}p$  < .05;  $^{**}p$  < .01;  $^{***}p$  < .001

by college degree status except for the moderately stronger responsiveness of college graduates to the unemployment rate of potential destinations (models 3 and 4).

Although the LMA-level CL model offers an improvement on the state-level CL, we want to test whether the assumption of fixed preferences for economic pull factors may be masking heterogeneity in mover types. As described in the methods section, if there are two types of movers—"economic" movers, who are strongly affected by economic conditions, and "amenity" movers, who are not—then this would violate the IIA assumption and potentially affect the parameter estimates. Thus, we

estimate an LCCL model of LMA destination choice with state fixed effects that relaxes the IIA assumption by allowing destination preferences to vary across latent classes. We include four latent classes in the model—two classes for adults migrating prior to the recession and two classes for adults migrating during the recession.<sup>7</sup> In addition to comparing parameter estimates across the latent classes, we can examine the share of adults in each latent class to assess the change in the distribution of migrants between the periods, conditional on the estimated latent classes. Table 6 presents the results of our LCCL model.<sup>8</sup> These models offer a substantial improvement in explanatory

<sup>7.</sup> We accomplish this as a pooled model that includes all observations (2005 to 2011) by restricting the latent class weights for adults migrating prior to the recession to be zero for the two recessionary latent classes, and vice versa. Our rationale for including two latent classes for each period is to attempt to isolate migrants motivated by economic considerations from those motivated by other considerations.

<sup>8.</sup> The results presented in model 5 are those of the best-fitting model based on twenty replications. The log likelihood, coefficients, and weights of the latent classes do not differ substantially across the other models (results available upon request).

power over the traditional CL as evidenced by comparing the log likelihood of model 2 in panel 2 of table 5 (-419,870) with the log likelihood of our LCCL model in table 6 (-394,431).

Examining the pre-recession period (2005) to 2007), adults in latent class 2 (LC2) are clearly more motivated by economic considerations than adults in LC1. Adults in LC2 are significantly more likely to choose destinations with increasing manufacturing labor demand and low levels of unemployment. In addition, these adults chose LMAs with less land available for development, which proxies for areas experiencing a housing boom and strong housing sector prior to the recession. By comparison, adults in LC1 are at most marginal economic migrants, given their modest preferences for lower unemployment and higher manufacturing demand. Moreover, LC1 adults were more likely to choose destinations with comparatively weak housing sectors.

Turning to migrants during the economic downturn (2008 to 2011), we again observe a clear distinction between migrants motivated by economic considerations (LC4) and those motivated by other considerations (LC3). The same differences for unemployment and manufacturing labor demand observed prior to the recession persist during the recession. If anything, the intraperiod difference in preferences by LC for manufacturing demand widens during the recession, but the difference in labor demand preferences shrinks during the recession. Although the coefficient on land availability switches signs for economic migrants between the periods, this is entirely consistent with our expected pattern of economic migration. Economic migrants were more likely to select LMAs with booming housing markets prior to the recession. Once the crash hit and such areas busted, however, economic migrants were more likely to select LMAs that never boomed and thus experienced less of a bust.

Examining the shares of adults in each of the latent classes—the latent class weight—allows us to draw inferences regarding the extent to which motivations for migration changed during the economic downturn. Prior to the Great Recession, roughly 47 percent of migrants were motivated by economic considerations in selecting their destination LMA, whereas dur-

ing the downturn, 54 percent of migrants exhibited economic preferences in destination selection. This seven-percentage-point increase suggests that, if anything, the share of migrants motivated by economic factors in selecting destinations increased during the Great Recession, which is confirmatory of H1.

#### CONCLUSION

The past few decades have seen declines in migration as well as a drop in salience of economic characteristics for migration decisions. These declines, coupled with the typical reductions associated with recent recessions (Saks and Wozniak 2011), led to strong concern among policymakers about the lack of migration for jobs during the Great Recession (Fletcher 2010; Moretti 2012). A recessionary drop would negate an important mechanism through which labor markets cope with employment shocks and differentials in economic vitality (Blanchard and Katz 1992; Gallin 2004). Hopes were buoyed somewhat by research suggesting that migration during the Great Recession did not decline at a faster rate than recent trends (Kaplan and Schulhofer-Wohl 2011), but research has yet to disentangle the changes in labor migration during the recession from non-economic migration. Heterogeneity in preferences among migrants poses a severe challenge for traditional empirical models of migration.

We provide new evidence on the extent to which economic migration did or did not decline during the Great Recession. Using the geographic detail and large scale of the American Community Survey, we analyze the push and pull factors (Lee 1966) at play in the migration process before (2005 to 2007) and during (2008 to 2011) the economic downturn. Specifically, we estimate logit and multinomial logit models of the decision to migrate, as well as CL and LCCL models of destination preferences among migrants. These models make several methodological contributions to the migration literature. First, estimating many of our models at both the state and LMA level reveals significant differences in the economics-migration relationship by level of analysis, demonstrating the importance of the precision available with the ACS. Second, incorporating state fixed effects into our LMA-level destination selection

models highlights the importance of controlling for unobserved, persistent flows. Third, the heterogeneity in preferences allowed by our LCCL models relaxes the IIA assumption of traditional CL models, and perhaps more importantly it allows us to classify migrants as motivated by economic or non-economic destination characteristics.

Exploring migration push factors, we find that adults living in LMAs with weaker origin economic conditions are less likely to outmigrate. Adults in economically weak LMAs are more likely to make short-distance moves (as opposed to not migrating to a new LMA), but they are less likely to make medium- and longdistance moves. The latter types of moves account for over two-thirds of all moves, so weak economic origin conditions do not generally seem to push adults to migrate (contrary to H2). Some of this effect may be the result of housing lock as adults in labor market areas whose housing markets experienced larger crashes during the recession were less likely to out-migrate, particularly for a medium- or longer-distance move (contrary to H3). We find few systematic differences by college degree status, but college graduates seem to respond to origin unemployment with slightly more outmigration (H4). Over all, our results highlight modest differences with previous research finding increased out-migration from areas with high unemployment (Greenwood 1997; Pissarides and McMaster 1990), but these differences may result from our analysis at the LMA-level. Our state-level estimates provide greater support for a labor migration model during the recession.

Turning to destination pull factors, the CL model demonstrates that migrants are generally responsive to the economic vitality of potential destinations (H1), and this responsiveness was substantively unchanged during the economic downturn. Adults are more likely to choose LMAs with broadly strong economies as measured by unemployment and manufacturing labor demand, but they persist in their likelihood of migrating to LMAs with previously booming housing markets that have busted during the crash (contrary to H3). The positive relationship between labor demand and desti-

nation selection that we find suggests a reversal of the decline in importance of potential destination economies over the past two decades found by Mark D. Partridge and colleagues (2012). College graduates may be more responsive to differences in unemployment between potential destinations, but again we find only modest evidence of variation in migration decisions by education level (H4).

Our LCCL models, however, reveal substantial heterogeneity in migration preferences among adults, and the models offer an improvement upon traditional CL estimation for two reasons. First, the models relax the traditional IIA assumption, and second, the models substantially improve our explanatory power for destination selection. On the basis of the results of our LCCL models, we are able to conclude that the number of economic migrants remained stable or even increased during the economic downturn. Roughly 47 percent of adult migrants were economic movers before the recession, and nearly 54 percent of adult migrants were economic movers during the downturn. This aligns with our expected increase in labor migration during the recession (H1).

Ultimately, although adults are generally less likely to out-migrate from an economically distressed LMA, their odds of leaving such labor markets did not decline dramatically during the Great Recession. In addition, more migrants were motivated by economic considerations during the recession than prior to it. Our findings offer suggestive evidence that policymakers' fears during the downturn may not have been warranted. Nevertheless, we did not observe dramatic, large-scale changes in migration behavior that would indicate a widespread shift toward labor migration. Instead, the United States experienced—perhaps even continues to experience—a protracted adjustment to employment equilibrium between labor markets. In a previous downturn in Great Britain, Christopher A. Pissarides and Ian McMaster (1990) found that it can take over twenty years to achieve equilibrium. Thus, during future large-scale recessions, policymakers may consider legislation that incentivizes and supports labor migration of the workforce.

#### **APPENDIX A**

## Estimation of the Latent Class Conditional Logit Models

As described earlier, the latent class conditional logit (LCCL) model presents a viable alternative to the mixed logit model. Incorporating correlation in migration preferences between some individuals, the LCCL uses discrete latent classes of individuals to allow for variation in the coefficients ( $\beta_i$ ) across individuals and yields the following modification to basic equation for the conditional logit model:

$$P_{ic}(j) = \frac{\exp(\beta_c x_{ij})}{\sum_{\nu} \exp(\beta_c x_{ij})}, \qquad (4)$$

where *c* represents a number of latent classes. In equation 4, whereas parameter estimates can vary across latent classes, they are forced to be constant within latent class. Equation 4 does circumvent the IIA assumption of constant preferences across individuals, but it accomplishes this in a much more computationally feasible way than the mixed logit. A LCCL model also allows the sampling of choices, which adds to the computational feasibility. Along with these advantages, the LCCL model preserves the multilevel structure of random effects and random coefficients from the mixed logit model by allow-

ing intercepts and parameter estimates to vary across the latent classes.

The LCCL model is estimated using the expectation-maximization (EM) algorithm, and the probability of individual membership in the various latent classes is estimated through an iterative process as part of the model. The probability of a worker (i) choosing destination j is

$$P_i(j) = \sum_k [s_c * P_{ic}(j)], \qquad (5)$$

where  $S_c$  is the share of individuals in latent class c. The probability of individual i being in latent class c is

$$h_{ic} = \frac{s_c P_{ic}(k)}{P_i(k)} , \qquad (6)$$

where k is the destination that is chosen.

The application of the LCCL technique to the migration literature is novel but demonstrates promise. A recent paper (Liao, Farber, and Ewing 2014) uses LCCL to analyze community preferences within a few counties of Utah. Still, there is yet to be a large-scale application of this method to analyze migration. We offer such an application by estimating LCCL models of migration for individuals migrating to a new LMA from 2005-2011 in the ACS.

APPENDIX B

Table B1. Logit Models of the Decision to Migrate Stratified by College Degree Status

		State-Lev	State-Level Models			LMA-Leve	LMA-Level Models <sup>a</sup>	
Origin Characteristics	College	College, with SL	No College	No College, with SL	College	College, with SL	No College	No College, with SL
Labor demand	1.477*	3.204***	2.956***	5.224***	0.774***	0.244	0.315*	-0.157
R*labor demand	(0.638 <i>)</i> -1.66	(0.974) -8.28***	(0.541) -0.082	(0.839) -5.736**	(0.233) -0.982**	(0.237) -0.289	(0.14 <i>2</i> ) -0.438*	0.183
	(1.717)	(2.103)	(1.539)	(1.859)	(0.354)	(0.371)	(0.217)	(0.228)
Unemployment	$-1.652^{\dagger}$	-5.242***	0.149	-4.011***	0.83	0.264	-0.519	-0.891**
	(0.943)	(1.367)	(0.852)	(1.196)	(0.517)	(0.533)	(0.326)	(0.332)
R*unemployment	1.3	3.787**	-0.917	2.084	-1.711**	$-1.051^{\dagger}$	-0.867*	-0.655⁺
	(0.984)	(1.458)	(0.885)	(1.279)	(0.553)	(0.61)	(0.352)	(0.381)
Land availability	-0.479***	-0.403***	-0.271***	-0.163*	-0.256***	-0.315***	-0.116***	-0.208***
	(0.084)	(0.087)	(0.072)	(0.076)	(0.043)	(0.05)	(0.03)	(0.034)
R*land availability	0.359***	0.28**	0.427***	0.308***	0.274***	0.307***	0.221***	0.274***
	(0.103)	(0.107)	(0.087)	(0.092)	(0.053)	(0.063)	(0.036)	(0.042)
Potential destination spatial lags		×		×		×		×
Z	2,919,471	2,919,471	6,559,954	6,559,954	2,918,096	2,916,632	6,556,083	6,550,199

models include controls for the recession (dummy), individual race or ethnicity, gender, age, education, marital status, and disability status, as well as previous Notes: Base outcome is staying in the same state (left models) or labor market areas (right models). Coefficients are log odds. Standard errors in parentheses. All year's LMA's population size, racial composition, nativity composition, educational composition, and age composition.

a LMA = labor market area.

 $^{\dagger}p < .1$ ;  $^{*}p < .05$ ;  $^{**}p < .01$ ;  $^{***}p < .001$ 

# APPENDIX C

Table C1. Multinomial Logit Models of Migration Distance for College Graduates (N = 2,916,458)

	Co	llege Graduates	College Graduates (No Spatial Lags)	(s	College Gradu	lates (with Pote	College Graduates (with Potential Destination Spatial Lags)	Spatial Lags)
	Moved	Moved	Moved	Moved	Moved	Moved	Moved	Moved
	< 100	100-300	300-1,000	1,000+	< 100	100-300	300-1,000	1,000+
Origin Characteristics	Miles	Miles	Miles	Miles	Miles	Miles	Miles	Miles
Labor demand	-0.353	0.657	2.199***	0.615	-1.022*	-0.074	1.925***	0.287
	(0.399)	(0.44)	(0.4)	(0.736)	(0.445)	(0.486)	(0.417)	(0.807)
R*labor demand	-0.592	-0.158	-2.374***	1.223	0.201	0.439	-1.585*	1.116
	(0.62)	(0.686)	(0.618)	(0.995)	(0.655)	(0.719)	(0.628)	(1.054)
Unemployment	4.622***	-0.662	-0.187	2.772*	4.238***	-1.4	-1.072	2.34
	(606.0)	(966.0)	(0.938)	(1.327)	(0.935)	(1.037)	(0.974)	(1.373)
R*unemployment	-2.872**	-1.188	-1.47	-4.391**	-1.502	-1.392	0.133	-4.58**
	(0.992)	(1.067)	(0.999)	(1.393)	(1.081)	(1.182)	(1.109)	(1.563)
Land availability	-0.016	-0.077	-0.138	-0.704***	0.222*	-0.069	-0.613***	-0.48***
	(0.079)	(0.085)	(0.08)	(0.103)	(0.095)	(0.102)	(0.092)	(0.12)
R*land availabilility	0.298**	0.435***	0.317***	-0.004	$0.216^{\dagger}$	0.492***	0.4***	0.007
	(0.1)	(0.107)	(0.099)	(0.126)	(0.121)	(0.127)	(0.114)	(0.148)
Potential destination spatial lags					×	×	×	×

Source: Authors' calculations.

Notes: Base outcome is staying in the same labor market area. Coefficients are log odds. Standard errors in parentheses. All models include controls for the recession (dummy), individual race or ethnicity, gender, age, education, marital status, and disability status, as well as previous year's LMA's population size, racial composition, nativity composition, educational composition, and age composition.

 $^{\dagger}p < .1; ^{*}p < .05; ^{**}p < .01; ^{***}p < .01$ 

APPENDIX D

Table D1. Multinomial Logit Models of Migration Distance for Adults Without a College Degree (N = 6,549,242)

	Non-	College Gradua	Non-College Graduates (No Spatial Lags)	.ags)	Non	-College Gradu Destination (	Non-College Graduates (with Potential Destination Spatial Lags)	tial
		:		-	:	:	:	-
	Moved	Moved	Moved	Moved	Moved	Moved	Moved	Moved
	< 100	100-300	300-1,000	1,000+	< 100	100-300	300-1,000	1,000+
Origin Characteristics	Miles	Miles	Miles	Miles	Miles	Miles	Miles	Miles
Labor demand	-0.248	0.372	0.725*	2.355***	-0.471	-0.091	-0.024	2.277***
	(0.221)	(0.261)	(0.308)	(0.373)	(0.243)	(0.287)	(0.346)	(0.43)
R*labor demand	-0.691*	0.669	-0.199	-0.589	-0.29	1.118**	0.601	-0.693
	(0.33)	(0.403)	(0.467)	(0.68)	(0.347)	(0.421)	(0.493)	(0.718)
Unemployment	2.952***	-2.411***	-1.353*	0.075	2.835***	-2.845***	-2.252**	-0.151
	(0.491)	(965.0)	(0.687)	(1.152)	(0.505)	(0.608)	(0.7)	(1.156)
R*unemployment	-1.758**	-0.504	-1.367	-2.961*	-0.565	-1.106	$-1.528^{\dagger}$	-3.302*
	(0.536)	(0.645)	(0.736)	(1.216)	(0.576)	(0.704)	(0.802)	(1.313)
Land availability	0.509***	-0.22***	-0.276***	-0.762***	0.565***	-0.277***	-0.539***	-0.643***
	(0.048)	(0.057)	(0.064)	(0.087)	(0.058)	(0.066)	(0.071)	(0.1)
R*land availabilility	0.042	0.419***	0.378***	-0.028	0.043	0.459***	0.417***	0.094
	(0.059)	(0.07)	(0.078)	(0.108)	(0.071)	(0.081)	(0.088)	(0.124)
Potential destination spatial lags					×	×	×	×

sion (dummy), individual race or ethnicity, gender, age, education, marital status, and disability status, as well as previous year's LMA's population size, racial Notes: Base outcome is staying in the same labor market area. Coefficients are log odds. Standard errors in parentheses. All models include controls for the recescomposition, nativity composition, educational composition, and age composition.

 $100. > q^{***}$ ;  $10. > q^{**}$ ;  $10. > q^{*}$ 

#### REFERENCES

- Barro, Robert J., and Xavier Sala-I-Martin. 1992. "Regional Growth and Migration: A Japan-United States Comparison." *Journal of the Japanese and International Economies* 6(4): 312–46.
- Bartik, Timothy J. 1991. Who Benefits from State and Local Economic Development Policies? Kalamazoo, Mich.: W. E. Upjohn Institute for Employment Research.
- ——. 2013. "Social Costs of Jobs Lost Due to Environmental Regulations." Upjohn Institute Working Paper 13-193. Kalamazoo, Mich.: W. E. Upjohn Institute for Employment Research.
- Bartik, Timothy J., and Randall W. Eberts. 2006. "Urban Labor Markets." In *A Companion to Urban Economics*, edited by Richard J. Arnott and Daniel P. McMillen, pp. 389–403. Malden, Mass.: Blackwell.
- Beaudry. Paul, David A. Green, and Benjamin M. Sand. 2014. "Spatial Equilibrium with Unemployment and Wage Bargaining: Theory and Estimation." *Journal of Urban Economics* 79(January): 2–19.
- Blanchard, Olivier Jean, and Lawrence F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity* 1992(1): 1–75.
- Bound, John, and Harry J. Holzer. 2000. "Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s." *Journal of Labor Economics* 18(1): 20–54.
- Bruch, Elizabeth E., and Robert D. Mare. 2012. "Methodological Issues in the Analysis of Residential Preferences, Residential Mobility, and Neighborhood Change." Sociological Methodology 42(1): 103–54.
- Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo. 2012. "Manufacturing Busts, Housing Booms, and Declining Employment: A Structural Explanation." NBER Working Paper 18949. Cambridge, Mass.: National Bureau of Economic Research.
- Chi, Guangqing, and Hung Chak Ho. 2013. "Land Developability: A Measure of the Proportion of Lands Available for Development and Conversion." Available at
  - http://www.landdevelopability.org.website /index.html; accessed August 6, 2016.
- Coulson, N. Edward, and Paul L. E. Grieco. 2013. "Mobility and Mortgages: Evidence from the PSID." *Regional Science and Urban Economics* 43(1): 1–7.

- Davies, Paul S., Michael J. Greenwood, and Haizheng Li. 2002. "A Conditional Logit Approach to U.S. State-to-State Migration." *Journal of Regional Science* 41(2): 337–60.
- Demyanyk, Yuliya, Dmytro Hryshko, María José Luengo-Prado, and Bent E. Sørensen. 2014. "Moving to a Job: The Role of Home Equity, Debt, and Access to Credit." Federal Reserve Bank of Cleveland Working Paper No. 1305R.
- Domanski, Adam. 2009. "Estimating Mixed Logit Recreation Demand Models with Large Choice Sets." Paper presented at the Agricultural and Applied Economics Association Annual Meeting. Milwaukee (July 26–28, 2009).
- Ellwood, David T., and Elisabeth D. Welty. 2000. "Public Service Employment and Mandatory Work: A Policy Whose Time Has Come and Gone and Come Again?" In *Finding Jobs: Work and Welfare Reform*, edited by David Card and Rebecca M. Blank. New York: Russell Sage Foundation.
- Ferreira, Fernando, Joseph Gyourko, and Joseph Tracy. 2012. "Housing Busts and Household Mobility: An Update." *Economic Policy Review* 18(3): 1–15
- Fishback, Price V., William C. Horrace, and Shawn Kantor. 2006. "The Impact of New Deal Expenditures on Mobility During the Great Depression." Explorations in Economic History 43(2): 179–22.
- Fletcher, Michael A. 2010. "Few in U.S. Move for New Jobs, Fueling Fear the Economy Might Get Stuck, Too." Washington Post, July 30. Available at: www.washingtonpost.com/wp- dyn/content /article/2010/07/29/AR2010072906367.html; accessed September 14, 2012.
- Frey, William H. 2009. "The Great American Migration Slowdown: Regional and Metropolitan Dimensions." Washington, D.C.: Brookings Institution. Available at: at: www.brookings.edu/~/media/research/files/opinions/2011/1/12%20 mig ration%20frey/1 209\_migration\_frey.pdf; accessed September 14, 2012.
- Gallin, Joshua Hojvat. 2004. "Net Migration and State Labor Market Dynamics." *Journal of Labor Economics* 22(1): 1–21.
- Gordon, Ian. 1985. "The Cyclical Interaction Between Regional Migration, Employment, and Unemployment: A Time Series Analysis for Scotland." Scottish Journal of Political Economy 32(2): 135– 58.
- Greenwood, Michael J. 1975, "Research on Internal

- Migration in the United States: A Survey." *Journal of Economic Literature* 13(2): 397–433.
- —. 1997. "Internal Migration in Developed Countries." In Handbook of Population and Family Economics, Volume 1, Part B, edited by Mark R. Rosenzweig and Oded Stark. Amsterdam, Netherlands: Elsevier.
- Hensher, David, and William Greene. 2003. "Mixed Logit Models: State of Practice." *Transportation* 30(2): 133–76.
- Herkenhoff, Kyle F., and Lee E. Ohanian. 2011. "Labor Market Dysfunction During the Great Recession." Cato Papers on Public Policy 1: 173–217.
- Herzog, Henry W., Alan M. Schlottmann, and Thomas P. Boehm. 1993. "Migration as Spatial Job-Search: A Survey of Empirical Findings." *Regional Studies* 27(4): 327–40.
- Hornbeck, Richard. 2012. "The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe." American Economic Review 102(4): 1477–1507.
- Kaplan, Greg, and Sam Schulhofer-Wohl. 2011. "Interstate Migration Has Fallen Less Than You Think: Consequences of Hot Deck Imputation in the Current Population Survey." Working Paper 681. Federal Reserve Bank of Minneapolis. Available at: www.minneapolisfed.org/research/wp/wp681.pdf; accessed September 14, 2012.
- Karahan, Fatih, and Serena Rhee. 2012. "Geographical Reallocation and Unemployment During the Great Recession: The Role of the Housing Bust." Staff report, no. 605. New York: Federal Reserve Bank of New York. Available at: https://www.newyorkfed.org/research/staff\_reports/sr605.html; accessed August 6, 2016.
- Kennan, John, and James R. Walker. 2011. "The Effect of Expected Income on Individual Migration Decisions." *Econometrica* 79(1): 211–51.
- Kothari, Siddharth, Itay Saporta-Eksten, and Edison Yu. 2012. "The (Un)importance of Mobility in the Great Recession." Available at: http://dosen.narotama.ac.id/wp-content/uploads/2012/03/The-Un-importance-of-Mobility-in-the-Great-Recession.pdf; accessed August 6, 2016.
- Lee, Everett S. 1966. "A Theory of Migration." *Demography* 3(1): 47–57.
- Liao, Felix Haifeng, Steven Farber, and Reid Ewing. 2014. "Compact Development and Preference Heterogeneity in Residential Location Choice Behaviour: A Latent Class Analysis." Urban Studies 52(2): 314–37.

- Mare, David C., and Wai Kin Choy. 2001. "Regional Labour Market Adjustment and the Movements of People: A Review." New Zealand Treasury Working Paper 01/08. Wellington, N.Z., December. Available at: http://motu.nz/assets/Documents/our-work/population-and-labour/migration/Regional-Labour-Market-Adjustment-and-the-Movements-of-People-A-Review.pdf; accessed August 6, 2016.
- Martin, Richard W. 2001. "The Adjustment of Black Residents to Metropolitan Employment Shifts: How Persistent Is Spatial Mismatch?" *Journal of Urban Economics* 50(1): 52-76.
- McFadden, Daniel. 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." In *Frontiers in Econometrics*, edited by Paul Zarembka. New York: Academic Press.
- ——. 1978. "Modeling the Choice of Residential Location." *Spatial Interaction Theory and Planning Models* 25(1): 75–96.
- Mian, Atif, and Amir Sufi. 2014. "What Explains the 2007–2009 Drop in Employment?" *Econometrica* 82(6): 2197–2223.
- Milne, William J. 1993. "Macroeconomic Influences on Migration." *Regional Studies* 27(4): 365-73.
- Modestino, Alicia Sasser, and Julia Dennett. 2012. "Are American Homeowners Locked into Their Houses? The Impact of Housing Market Conditions on State-to-State Migration." Working Paper No. 12-1. Boston: Federal Reserve Bank of Boston. Available at: www.bos.frb.org/economic/wp/wp2012/wp1201.htm; accessed September 18. 2012.
- Molloy, Raven, Christopher L. Smith, and Abigail Wozniak. 2011. "Internal Migration in the United States." *Journal of Economic Perspectives* 25(3): 173–96.
- 2014. "Declining Migration Within the US: The Role of the Labor Market." Finance and Economics Discussion Series. Staff Working Paper No. 2013-27. Washington: Federal Reserve Board, Divisions of Research & Statistics and Monetary Affairs. Available at: www.federalreserve.gov/pubs/feds/2013/201327/201327pap.pdf; accessed August 6, 2016.
- Monras, Joan. 2015. "Economic Shocks and Internal Migration." IZA Discussion Paper No. 8840. Bonn, Germany: Institute for the Study of Labor.
- Moretti, Enrico. 2010. "Local Multipliers." *American Economic Review* 100(2): 1–7.
- ---.. 2012. "What Workers Lose by Staying Put."

- Wall Street Journal, May 26. Available at: www .wsj.com/articles/SB1000142405270230361050 4577420701942867414; accessed March 16, 2015.
- Nerella, Sriharsha, and Chandra Bhat. 2004. "Numerical Analysis of Effect of Sampling of Alternatives in Discrete Choice Models." *Transportation Research Record*, vol. 1894, pp. 11–19.
- Neumark, David. 2011. "Direct Job Creation Policies in the Aftermath of the Great Recession and Beyond." Available at: http://50.87.169.168/OJS /ojs-2.4.4-1/index.php/EPRN/article/view/1870 /1868; accessed October 13, 2016.
- Notowidigdo, Matthew J. 2011. "The Incidence of Local Labor Demand Shocks." NBER Working Paper No. 17167. Cambridge, Mass.: National Bureau of Economic Research.
- Partridge, Mark D., Dan S. Rickman, M. Rose Olfert, and Kamar Ali. 2012. "Dwindling U.S. Internal Migration: Evidence of Spatial Equilibrium or Structural Shifts in Local Labor Markets?" Regional Science and Urban Economics 42(1-2): 375-88. DOI: 10.1016/j.regsciurbeco.2011.10.006.
- Pissarides, Christopher A., and Ian McMaster. 1990. "Regional Migration, Wages, and Unemployment: Empirical Evidence and Implications for Policy." Oxford Economic Papers 42(4): 812–31.
- Ritchey, P. Neal. 1976. "Explanations of Migration." Annual Review of Sociology 2: 363-404.
- Rothstein, Jesse. 2011. "Unemployment Insurance and Job Search in the Great Recession." *Brookings Papers on Economic Activity* (Fall): 143–213.
- Ruggles, Steven, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. 2010. "Integrated Public Use Microdata Series: Version 5.0 [Machinereadable database]." Minneapolis: University of Minnesota.

- Saiz, Albert. 2010. "The Geographic Determinants of Housing Supply." *Quarterly Journal of Economics* 125(3): 1253–96.
- Saks, Raven E., and Abigail Wozniak. 2011. "Labor Reallocation over the Business Cycle: New Evidence from Internal Migration." *Journal of Labor Economics* 29(4): 697–739.
- Sasser, Alicia C. 2010. "Voting with Their Feet: Relative Economic Conditions and State Migration Patterns." Regional Science and Urban Economics 40(2-3): 122-35.
- Train, Kenneth E. 2003. *Discrete Choice Methods* with Simulation. New York: Cambridge University Press.
- ——. 2008. "EM Algorithms for Nonparametric Estimation of Mixing Distributions." *Journal of Choice Modelling* 1(1): 40–69.
- Treyz, George I., Dan S. Rickman, Gary L. Hunt, and Michael J. Greenwood. 1993. "The Dynamics of U.S. Internal Migration." *Review of Economics and Statistics* 75(2): 209–14.
- Wiseman, Michael. 1976. "Public Employment as Fiscal Policy." *Brookings Papers on Economic Activity* 1: 67–114.
- Wozniak, Abigail. 2010. "Are College Graduates More Responsive to Distant Labor Market Opportunities?" *Journal of Human Resources* 45(4):
- Yagan, Danny. 2014. "Moving to Opportunity? Migratory Insurance over the Great Recession."

  Available at: http://eml.berkeley.edu/~yagan
  /MigratoryInsurance.pdf; accessed August 6,
  2016.
- Yankow, Jeffrey J. 2003. "Migration, Job Change, and Wage Growth: A New Perspective on the Pecuniary Return to Geographic Mobility." *Journal of Regional Science* 43(3): 483–516.