UNEMPLOYMENT DURATION AND GEOGRAPHIC MOBILITY: DO MOVERS FARE BETTER THAN STAYERS?

by

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Abstract

This study uses a sample of unemployed workers constructed from the American Community Survey and the LEHD database, to compare the unemployment durations of those who find subsequent employment by relocating to a metropolitan area outside of their originally observed residence, versus those who find employment in their original location. Results from a hazard analysis confirm the importance of many of the determinants of migration posited in the literature, such as age, education, and local labor market conditions. While simple averages and OLS estimates indicate that migrating for a new job reduces the probability of re-employment within a given time frame and lengthens the spell of unemployment in the aggregate, after controlling for selection into migration using an IV approach based on local house price changes, the results suggest that out-migrating for employment actually has a large and significant beneficial effect of shortening the time to re-employment. This implies that those who migrate for jobs in the data may be particularly disadvantaged in their ability to find employment, and thus have a strong short-term incentive to relocate.

1 Introduction

The ability to relocate to a different labor market has long been viewed as an important means by which the unemployed can improve their search process and ultimately escape joblessness. This issue was highlighted during the Great Recession, which was accompanied by a dramatic and well-documented decline in internal migration. While much of this decline was certainly due to the lack of employment opportunities in general, researchers have argued that other factors, such as declining house prices, further deterred unemployed workers from leaving the most distressed labor markets and thus helped prolong the economic recovery. Implicit in these discussions, however, is the assumption that workers who move are better off for having done so, yet there is scant empirical evidence that this is the case. While many models focus on the resulting equilibrium in unemployment rates and wages across regions that migration helps enable, fewer studies have looked at whether the individual outcomes of the actual migrators are better than if they had stayed. Thus, the literature is largely silent on whether migration by the unemployed is "micro-efficient", in the sense that every individual actor increases their utility, as discussed by Herzog (1993).

The migration literature has generally focused on measuring the influence of various factors in the migration decision, with DiLanzo (1978) being the first to focus on unemployment as a key determinant, providing evidence that the unemployed moved at high rates. Structural models of migration and unemployment, such as Harris and Todaro (1970), Sato (2004), Rogerson and McKinnon (2005) and Zenou (2009) have shown how the interaction of unemployment and wages lead to equilibrium locational placement of workers.

Less attention has been paid, however, to the actual outcomes of the individual workers who move, especially in comparison to how they could have expected to fare by remaining in the same location. Kennan and Walker (2011) employ a structural estimation using the NLSY, and show that workers migration decisions are consistent with maximizing lifetime wages, but the model does not specifically consider the unemployed. Those papers that have focused on the jobless population have generally failed to show any evidence of improved outcomes through relocating. Bailey (1994) uses the NLSY and finds that workers who migrate have somewhat longer spells of unemployment on average. Pekkala and Tervo (2002) study workers in Finland and find that employment rates of movers was much lower than that of stayers after the issue of self-selection into migration is controlled for. This last study addresses the selection issue with an instrumental variables method that uses regional house prices as instruments – a strategy that I will follow here.

In this paper, I use a large sample of unemployed workers in the American Community Survey, combined with information about their employment outcomes from the Longitudinal Employer-Household Dynamics (LEHD) database, to measure the difference in unemployment durations between those who move to another metropolitan area for new employment, and those who remain in the same metro area for their next job. To address the biases associated with selection into migration, I use information on local house price changes since the individual moved in to their home, which should influence the individual migration decisions but not be correlated with employability in general. Results from two-stage IV estimates show that those who move for new jobs have more success in becoming re-employed within a shorter time frame, a feature of the data that is not evident in more simple comparisons. These results imply that those who select into

migration are relatively disadvantaged in terms of their ability to find work compared to those who stay, and stand to gain greatly by relocating.

The discussion proceeds as follows. Section 2 describes the data and the method for measuring labor migration and unemployment spells. Section 3 explores the differences between those who move for new jobs versus those who stay, and motivates the role of housing-related factors. Section 4 shows the results from the OLS and instrumental variable regressions that are designed to test the causal effect of moving on unemployment durations, compared to becoming employed in the same area. Section 5 concludes.

2 Measuring Migration and Time to Re-employment

The sample used in this analysis comes primarily from the American Community Survey at the U.S. Census Bureau, a cross-sectional survey of approximately 1% of US households, collected throughout the year. The large size of the sample is advantageous for this analysis, because the data sources more typically used to study migration, such as the NLSY, CPS, and SIPP, do not allow enough observations of unemployed people to generate very precise estimates for this group. By merging in the employment histories of these same individuals from the Longitudinal-Employer-Household-Dynamics (LEHD) database, I can measure labor mobility in the ACS and exploit the variation that the large sample affords.

My sample comprises all respondents i (reference person or spouse) of prime working age (age 25-54) during any quarter t during the sample period 2002-2012, who are labeled as unemployed according to ACS definitions and who also have no observed earnings in the LEHD database during quarter t. Note that because the ACS data is monthly and

the LEHD data is quarterly, the restriction that the individual have no LEHD earnings during the entire quarter is more stringent than the requirement that the respondent be called unemployed during the month of the ACS interview. Approximately two-thirds of the unemployed in the ACS meet this restriction of zero LEHD earnings in t.

I also limit the sample to those residing in a Core Based Statistical Area (CBSA) j. CBSAs are defined as areas surrounding an urban core, in which the workforce also resides, providing a convenient definition of labor markets for the purpose of studying migration. The house price data on which my instrumental variable strategy is based are available for 356 of the largest metropolitan areas, and my sample is thus restricted to respondents living in these labor markets. These individuals are then matched via a personal identifier to the LEHD database, which provides their earnings history at all unemployment insurance (UI) covered jobs in 49 states up through 2013q2.

To determine whether an unemployed ACS respondent becomes re-employed in a subsequent time period, I search for the first new LEHD job to begin after the observed date of unemployment. The next job with positive earnings beginning in a quarter $t+k$ is determined to be the new job. In case of multiple new jobs starting in the same quarter, the one with the greatest earnings is chosen (i.e. the "dominant" job). Since a new job in a different CBSA may theoretically be accompanied by another new job beginning in the original CBSA, the concept of migration is somewhat clouded in this case, but the focus on the dominant job is meant to capture the most economically meaningful employment outcome.

The location of the job is given by the LEHD-assigned geographical information for the employer establishment, according to QCEW sources, thus allowing us to determine whether the new job is located in same CBSA as reference CBSA j, or else a different

CBSA $-j$. Moving to a job located in an adjacent CBSA that is considered to be part of the same "Combined Statistical Area", or else to a rural area in the same state as j, is not counted as a move. The LEHD database employs multiple imputations of a worker's workplace establishment when their employer has multiple establishments, in which case I use the first imputation of a worker's establishment. This introduces error in my measurement of migration, although note that the LEHD imputation system is largely based on proximity of the worker's residence to the employer establishment. This mitigates the concern that migration will be spuriously observed due to the imputation process.

The time to re-employment is simply defined as the number of quarters k between the observed reference period of unemployment t in the ACS survey, and the first quarter of subsequent employment in the LEHD data $t + k$. Note that the true beginning of the unemployment spell is not observed, because the ACS survey is cross-sectional and does not contain information about when the unemployment spell actually started. While this means that the length of unemployment spells will be underestimated, assuming that the ACS interview occurs at a random point during an individual's unemployment spell, there is no concern that certain observations will be systematically more mis-measured than others. Also, because I do not observe jobs that are not covered by the LEHD database, the end of unemployment spells may also be measured with error. The LEHD data was available through 2013q2 at the time of this analysis, therefore spells not completed by this time are right-censored.

Table 1 displays summary measures of re-employment in my sample, both for those who become employed in the same CBSA j as their residence in the original ACS reference period t ("stayers"), as well as for those who become re-employed in a different

CBSA $-j$ ("movers"). Of the approximately 243,000 unemployed individuals observed in the sample, about 48% are observed being subsequently employed in the same CBSA j as their ACS residence, while another 16% are next employed in a different CBSA $-j$. The mean number of quarters to re-employment is slightly longer for movers than for stayers, with average times to re-employment of about 4.9 quarters to 4.5 quarters respectively. The re-employment rate within 1 quarter is about 20% overall, with stayers outnumbering movers at about a 3-1 ratio. This ratio remains fairly consistent for the re-employment rates within 2 quarters and within 4 quarters, at which point about 33% of the sample is re-employed at a job in their home CBSA and 10% has migrated for employment.

While the focus of our analysis is on the individual benefits from relocating for employment, it is worth noting whether the aggregated out-migration rates in our data appear to be related to external factors like local labor market conditions. Many empirical studies have noted a relationship between local unemployment rates and migration, such as Basker (2003), Nakosteen et. al. (2008) and Haurin and Haurin (1998). To detect this phenomenon in our sample, Table 2 calculates the observed out-migration rate for four categories of CBSAs, grouped by their average unemployment rate in 2009 according to BLS. The four bins are centered around the mean national unemployment rate of roughly 10%. The fact that the out-migration rate is monotonically increasing across the categories implies that the areas that experienced higher unemployment during the Great Recession also experienced higher rates of out-migration. This is consistent with previous empirical studies and theoretical models which highlight the role of migration in restoring equilibrium in the labor market during economic downturns.

3 Exploring the Determinants of Migration

I begin by exploring the determinants of out-migration by the unemployed, and motivating the role of house prices in the migration decision. While many studies have looked at the characteristics of those who migrate, the large sample from the ACS will allow us to more explicitly control for the alternative of being re-employed in their original home location. To this end, I employ a hazard analysis framework that has been common in the study of unemployment duration since Meyer (1990). As discussed above, the duration of the unemployment spell can be defined as the number of quarters between the observed date of unemployment in the ACS and the next quarter of positive LEHD earnings. Because in our data I am only able to follow individuals until 2013q2 (the last quarter of LEHD data available), unemployment spells that have not been completed by this date are censored. The hazard function will nonparametrically estimate the dependence in unemployment durations, allowing us to test the relationship between certain explanatory variables and the moving decision, while taking into account the alternate option of becoming re-employed in the same metropolitan area.

Using the definition of migration described above, I define the concept of an unemployment spell to be the span of time elapsing between the quarter t in which the individual reports being unemployed according to the ACS, until the quarter $t+k$ when they are next observed earning wages according to the LEHD data. If and when the unemployment spell ends, it does so due to one of two reasons: Either a new job is started in the same location as the ACS reference location, CBSA j, or the new job is located in a CBSA $-j$. Those who are never again observed working in the LEHD database by 2013q2 are treated as censored spells. As shown above, in my sample of about 243,000

people, approximately 48% are observed becoming re-employed in the same CBSA as their ACS-observed residence, 16% are next observed as being re-employed in another CBSA, and 36% are censored.

This setup lends itself to a "competing risks" hazard analysis, which measures the determinants of out-migrating for employment while accounting for the alternative option of taking a job in the same area by effectively treating the competing risk as another form of censoring. In this way I can determine whether the factors that influence out-migrating for employment are different than those that impact re-employment in the same location.

3.1 Hazard Model

I estimate a proportional-hazard, competing-risks regression that models separate semi-parametric hazard functions for the alternate ways that an unemployment spell can end. The sample consists of ACS respondents who are reported to be unemployed at the interview date between 2002-2012, and who have no observed LEHD earnings in the corresponding quarter. Each unemployed individual i is therefore associated with a reference CBSA j and year-quarter time period t.

The hazard function expresses the probability that an unemployment spell for person i terminates at time $t+1$, conditional on the fact that the spell has survived until time t. A separate cause-specific hazard function exists for each of the two ways that an unemployed individual can end his or her spell: Either by finding a new job in the same CBSA j as where they are currently located, or by outmigrating and gaining employment in another CBSA $-j$. Generally, the hazard rate for the rth hazard is:

$$\lambda_i^r(t) = \lim_{\Delta \to 0} \frac{P(t < T_i^r < t + \Delta t | T_i^r \geq t)}{\Delta t} \tag{1}$$

where the unemployed individual i either moves for new employment ($r = M$), or stays in their home area for their next job ($r = S$).

Termination of unemployment spell i occurs at time T, when an individual is observed beginning a new job in the LEHD database, either inside or outside of the reference CBSA. Let T^M and T^S denote discrete random variables representing the time period of re-employment in CBSA $-j$, or CBSA j, respectively. Also let T^C denote censoring due to the unemployment lasting through the end of the LEHD database in 2013q2. Therefore, the realized termination is $T_i^* = \min\{T_i^M, T_i^S, T_i^C\}$. The probability that the spell i lasts until T_i^*, conditional on a vector of covariates $X_i(t)$, is expressed in the survival function:

$$S(T_i^* | X_i) = exp\left[- \int_{t=1}^{T_i^*} (\lambda_i^M(t|X_i) + \lambda_i^S(t|X_i)) dt \right]$$

$$\text{where } \lambda^r(t|X_i) = \lambda_0^r(t) exp(X_i' * \beta^r), r \in \{M, S\}$$

where X_i is a vector of covariates, β^r is a set of corresponding parameter, and $\lambda_0^r(t)$ is called the baseline hazard. The key assumption of the proportional hazard approach is that for each risk $r \in \{M, S\}$, there is such a baseline hazard function that is common to all unemployment spells. The parameters β^r thus express the effects of the covariates X_i on unemployment termination as a proportion of the baseline hazard. The baseline

hazard will be estimated non-parametrically using the common Cox specification (Cox, 1973).

I use the typical likelihood function originally specified in Meyer (1986), which accounts for the fact that the unemployment spells are only observed in discrete intervals and not continuously. The final key observable is how the unemployment spell ends, so let $\delta_i^r = 1$ if spell i terminates because of the rth risk, either moving (M) or staying (S) for a new job, and $\delta_i^r = 0$ otherwise. Therefore, these δ_i^r are represented by two sets of dummy variables, for which only one of them is set equal to 1 unless they are both censored by the end of the LEHD sample period in 2013q2.

Given this, the probability that an unemployment spell i will end due to the rth hazard in the interval from t to $t+1$ is expressed as:

$$\begin{aligned} P(T_i^{(r)} \geq t+1 | T_i^{(r)} \geq t] &= exp[-\int_t^{t+1} \lambda_i^r(s|X_i(s))ds] \\ &= exp\{-exp[\gamma_r(t) + X_i(t)'\beta^r]\} \end{aligned}$$

$$\text{where } \gamma^r(t) = ln\{\int_t^{t+1} \lambda_0^r(s)ds$$

It then follows that the resulting likelihood function is:

$$\begin{aligned} L(\gamma, \beta) = \prod_{i=1}^{N} ([1 - exp\{-exp[\gamma^M(k_i) + X(k_i)'\beta^M]\}]^{\delta_i^M} \\ *[1 - exp\{-exp[\gamma^S(k_i) + X(k_i)'\beta^S]\}]^{\delta_i^S} \\ *H(k_i|X_i) \end{aligned}$$

$$\text{where } H(k_i|X_i) = \prod_{t=0}^{k_i-1} exp\{-(exp[\gamma^M(t) + X_i(t)\beta^M] + exp[\gamma^S(t) + X_i(t)'\beta^S])\}$$

3.2 Hazard Results

The Cox hazard functions for movers and stayers, evaluated at the mean of the covariates, is shown in Figure 1. While shown on separate scales, the two hazards track each other fairly closely, thus appearing to satisfy the proportional hazard assumption of the Cox model. While there is some divergence in the later time periods, the hazards are likely measured with less precision on this part of the curve since very few unemployment spells are observed as persisting this long.

Aside from the standard demographic variables such as age, sex, education, etc., I will also include measures of local house prices in order to determine their impact on the hazards. House prices are likely to have a strong impact on the decision to move for many reasons. First of all, they represent changes in the relative cost of living, which makes one's home location more or less affordable. Second, local house prices represent changes in the desirability of an individual's neighborhood, due to amenity values or similar factors. Finally, house price movements determine the amount of equity that homeowners have in their homes, which has been hypothesized to have an impact on the ability to move. Specifically, those who have experienced nominal price declines are likely to be in a position of negative equity, (owing more on a mortgage than the value of the home), and be unable to move due a lack of liquidity, as in Genesove and Meyer (2001).

In order to incoporate house price information into the analysis, I define the variable

$\Delta HousePrice = ln(HouseValueIndex_{tz_t}/HouseValueIndex_{mz_m})$, where t is the reference period and m is the date when the individual moved into their home according to the ACS, and $HouseValueIndex$ comes from Zillow's house value index for the individual's zip-code of residence z during the corresponding points in time. The Zillow index represents the estimated value of the median home in the given zip code and time period, according to a proprietary algorithm based on sales records, dating back to 1996 for most metropolitan areas. If the move-in date of the respondent pre-dates the beginning of the Zillow data, the first available figure for that zip-code is used. Since Census data do not define geography based on postal zip codes, I determine the zip code of residence using a crosswalk between the Census tract of an individual's residence and the corresponding Zip Code Tabulation Area (ZCTA), as constructed by the Census Bureau.

Results from estimating the model are shown in Table 3, with coefficients expressing the percentage impact of the covariate on the baseline hazard (i.e. the hazard evaluated at the point where all covariates are set equal to 0). Coefficients greater than one indicate an increased risk due to the covariate, while a coefficient less than one represents a decreased risk. While the magnitudes of the baseline mover and stayer hazards are different, the proportionality of the risks allow us to compare the coefficients between the two risk specifications. The results reveal that the out-migration risk is significantly lower for women, minorities and homeowners, is decreasing in age, and is increasing in education level, all consistent with the findings of previous studies. Note, however, that in almost of all of these cases, the effects of the covariates on the "moving" hazard are not substantially different than the corresponding effects on the "staying" hazard. This means that while certain demographic categories are clearly associated with higher out-migration propensities, they are often the same characteristics that are associated

with re-employment in general. The most notable exceptions are the $SomeCollege$ and $College+$ categories, for which the impact on moving is much stronger than the corresponding impact on staying for employment. This agrees with the results of Wozniak (2010), who finds that each additional year of higher education is associated with a higher likelihood to relocate.

In contrast, the coefficients on the house-price related variable are noticeably different between the two hazards. The coefficient of .809 on $\Delta HousePrice$ in the first column shows that an increase in house prices has a negative and highly significant effect on the hazard of moving, while the corresponding coefficient of .967 on the staying hazard in the second column is very close to 1 and not significant at the 1% level. The fact that the house price variable is strongly correlated with the propensity to move to a different CBSA for a new job, but uncorrelated with the likelihood of finding employment in the same area, motivates the use of $\Delta HousePrice$ as an instrument for migration.

4 Testing the Impact of Migration on Time to Re-Employment

We next turn to regression analysis in order to more formally compare movers vs. stayers in their propensity to become re-employed within a given length of time. The dependent variable of interest is emp_within_1qtr, an indicator for whether the respondent is re-employed within 1 quarter of the observed date of unemployment t in the ACS and LEHD. I will also use re-employment within 2 quarters (emp_within_2qtr), 4 quarters (emp_within_4qtr), and the total number of quarters before the termination of the un-

employment spell, $Unemp_duration(qtrs.)$, as alternative left-hand-side variables. The independent variable of interest in all specifications is $Mover$, an indicator for whether the worker is observed becoming re-employed in a CBSA $-j$ other than the CBSA j where they were observed in the ACS. The same individual-level controls used in the hazard analysis will be also included, as well as CBSA- and year-level controls.

For this analysis, the sample will need to be limited to completed unemployment spells, since I am only able to identify workers as either movers or stayers if and only if they become re-employed. For the purposes of interpretation, note that because I can not determine whether somebody who fails to get a job is a mover or stayer, this analysis measures the impact of moving on the time to re-employment *conditional* on eventual re-employment. After removing individuals who never receive LEHD earnings subsequent to observed unemployment, the sample size is reduced by roughly one third to approximately 156,000. Summary statistics for the final sample are shown in Table 4.

4.1 Regression Models

For estimation, I begin with an OLS specification that includes dummy variables for the reference CBSA and year in which the individual was observed as unemployed in the ACS. However, since workers are not randomly selected into migration, I also employ an Instrumental Variables technique based on local house price information. Mobility will be instrumented for with the variable representing the change that the individual has experienced since living in their home, $\Delta HousePrice$, as defined in the previous section. The instrument is assumed to be valid because while house prices affect the propensity to move, as discussed above, they should be uncorrelated with general employability

once individual characteristics are accounted for. This assumption is supported by the competing-risk hazard results that showed little impact of $\Delta HousePrice$ on the hazard of finding a job in the reference location, but a strong impact on the hazard of moving for employment. This identification strategy is similar to that of Pekkala and Tervo (2001) in their study using data from Finland. Unlike the Finnish study, I choose not to use homeownership itself as an instrument, because the individual's decision to purchase a home in a given area could be related to their unobservable abilities to find employment in that area. A change in house prices is more plausibly exogenous since it is largely outside of the individual's control.

In this two-stage framework, the moving decision is modeled in the first stage as:

$$Mover_{it} = \alpha' Z_{it} + \epsilon \tag{2}$$

where Z_{it} is a vector of individual characteristics as well as dummy variables for the reference CBSA and year. The second stage expresses the individual's subsequent employment status within a certain period of time $t + k$, conditional on the migration decision, as:

$$Emp_Within_k_{i,t} = \beta' X_{it} + \delta' Mover_{it} + u_{it} \tag{3}$$

where X_{ijt} is the vector of covariates that affect the employment outcomes, which by assumption excludes the house price variable in Z_{it}, $\Delta HousePrice$. This model will be estimated by 2-stage least squares.

4.2 Results

Results from the regression analyses are shown in Table 5. Column 1 displays results from the OLS specification with dummies for the reference CBSA and year. The coefficient on *mover* reveals about a 5 percentage point lower rate of re-employment within 1 quarter of observed unemployment for those who migrate for a new job, compared to those who stay. This slightly negative impact of moving is consistent with the findings of many others, such as Shumway, Bailey, and Pekkala and Tervo. However, the IV results in Column 2 reveal strongly *positive* and significant effects of moving on 1-quarter re-employment, with a coefficient of .587. These IV results stand in contrast to those of Pekkala and Tervo (2001) who employ a similar IV method and find even stronger negative effects than the OLS estimates.

Table 7 shows the results using alternate dependent variables, representing re-employment in 2 quarters, re-employment in 4 quarters, and the total length of the completed unemployment spell (in numbers of quarters). All three specifications reveal the same pattern, with OLS estimates suggesting that moving for employment results in poorer re-employment outcomes, and IV results implying that moving has a beneficial impact on the time to re-employment. All coefficients on $Mover$ are significant at the 1% level, except in the $Unemp_duration$ specification where the p-value is just under 3%.

Table 6 contains results from the first stage regression, and shows a coefficient of -.034 on the excluded instrument $\Delta HousePrice$ that is strongly significant and lies within the unit interval. Also, the F-stat from the first-stage of the IV regressions is over 100, alleviating concerns of weak-instrument bias.

While these findings are among the first to suggest that moving results in strong

short-term gains for the unemployed, there are reasons to suspect that these results may not be universal, especially given the large magnitude of the coefficients. According to the "local average treatment effect" interpretation of the IV results as discussed in Angrist and Imbens (1995), the estimates are identified off of individuals for whom the moving decision is determined at the margin by the change in their home price. Whether these people are representative of the general population is unknown. Nevertheless, the large difference between the OLS and IV results suggest that the workers who select into migration in our sample may possess unobservable qualities that make them ill-suited to finding employment. This corresponds with a story where the most disadvantaged workers are the ones who have the greatest incentive to move, and while their unemployment duration is longer than their peers who remain in the area, they ultimately become re-employed more quickly than they would have otherwise.

5 Conclusion

This study combines information from the ACS and the LEHD database to measure unemployment duration and out-migration in a sample of the unemployed. The main goal was to test how migrators fare in terms of their time to re-employment compared to those who remain in the same area for their next job. By controlling for selection into migration with an instrumental variable strategy based on changes in local home prices, I find that movers have significantly *higher* probability of re-employment within a given time threshhold, and *shorter* unemployment spells.

While there has been little previous evidence that relocating improves the outcomes of the unemployed, our results should perhaps not be surpising. Moving is costly in

terms of money and time, which the unemployed can often ill-afford to spend. Leaving one's home area may also represent a loss of location-specific capital in the labor market. Therefore, in order to provide a sufficient incentive, the benefit to moving must be large enough to outweigh the costs. This perhaps explains why while I find strongly beneficial effects from moving, the average time to re-employment of observed movers is longer than for those who stay. If the movers that are observed are those who are struggling the most to find employment, it stands to reason that they may have much to gain by moving.

While this paper looks at one specific outcome, namely the time to re-employment, these short-term considerations are not the only ones that the unemployed face in their locational decision. Papers such as Kennan and Walker (2010) have addressed the importance of lifetime earnings in the migration decision, although their study does not explicitly address the unemployed. Thus, further study is warranted on whether the unemployed in particular appear to be motivated by these longer-term income and employment considerations. After all, different priorities may guide the migration decision for the unemployed than for the population at large, and our results suggest that shortening their unemployment spells appears to be one of them.

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A Tables and Figures

Table 1: Re-Employment Statistics for ACS Sample of Unemployed

Variable	Mover	Stayer	All Re-employed
Fraction re-employed within 1 qtr.	0.044	0.152	0.196
Fraction re-employed within 2 qtrs.	0.070	0.236	0.305
Fraction re-employed within 4 qtrs.	0.100	0.332	0.432
Fraction re-employed by end of sample	0.157	0.484	0.640
Mean Time to Re-employment (qtrs.)	4.944	4.469	4.585
N		~243,000	

Table 2: Out-Migration by CBSA-level Unemployment Rate: 2009

Unemployment Rate	Out-Migration Fraction
Under 9%	.148
9%-10%	.159
10%-11%	.208
Over 11%	.228

Figure 1: Hazard Functions

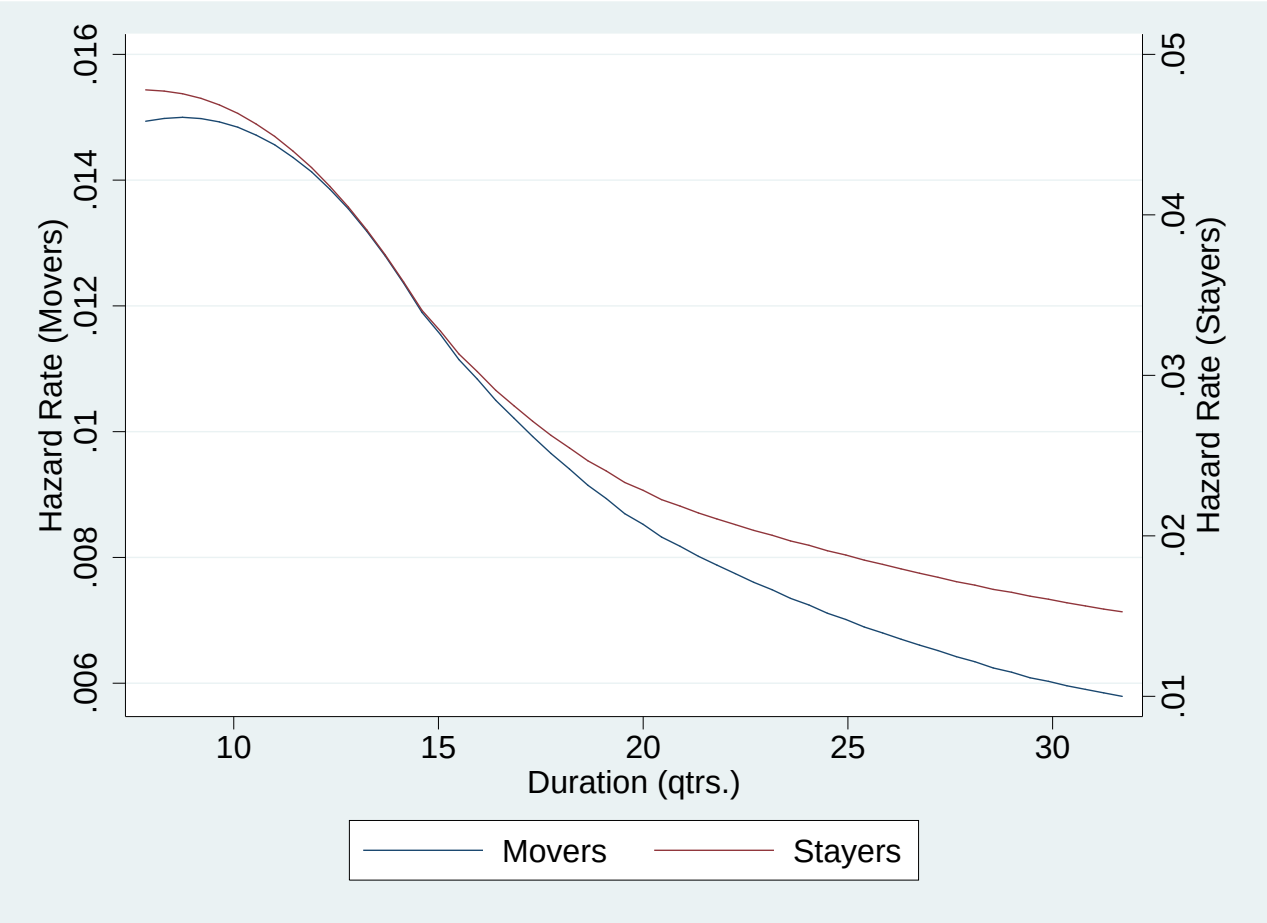

Table 3: Cox Hazards: Competing Risks Regressions

	(Move for new job)	**(Stay for new job)**
$\Delta HousePrice$	0.809*	0.967
	(0.019)	(0.016)
$Homeowner$	0.906*	1.078 *
	(0.014)	(0.010)
$Age35-44$	0.856*	0.901*
	(0.011)	(0.007)
$Age45-54$	0.731*	0.776*
	(0.011)	(0.008)
$Female$	0.832*	1.003 *
	(0.013)	(0.009)
$Nonwhite$	0.891*	0.938
	(0.015)	(0.009)
$Married$	0.979	0.966*
	(0.013)	(0.010)
$Children$	1.001	1.108*
	(0.014)	(0.010)
$Highschool$	1.239*	1.197*
	(0.029)	(0.017)
$SomeCollege$	1.424*	1.286*
	(0.035)	(0.021)
$College+$	1.565*	1.282*
	(0.044)	(0.026)

Star Denotes Significance at the 1% level. Standard errors in parentheses.

Notes: Sample consists of approximately 243,000 unemployment spells of ACS respondents i, age 25-54 and residing in one of 356 CBSAs j during 2002-2012. Results are shown from a competing-risks regressions, which estimate Cox proportional-hazards models separately for the two ways in which an unemployed spell can end: by beginning a new LEHD job in the same CBSA j, or beginning a new job in any CBSA$-j$. In the estimation of a given hazard, the occurence of the competing hazard is treated as another form of censoring. Approximately 38,000 spells end with a job move to another CBSA, while around 118,000 spells terminate with new employment located in the same CBSA j, and the remaining spells are censored by the end of the LEHD sample in 2013q2. All regressions include dummy variables for the reference CBSA and year of unemployment (results omitted for clarity). Individual characteristics are represented by binary indicator variables $Female$, $Nonwhite$, $Married$, $Children$,and $Homeowner$, as well as age groups $35-44$, $45-54$ (25-34 omitted) and education categories $HighSchool$, $SomeCollege$,and $College+$ (less than High School omitted). Coefficients express the impact of the given covariate on the baseline hazard ratio. All standard errors are clustered by CBSA.

Table 4: Regression Sample: Summary Stats

Variable	**Mean**	**Std. Dev.**
$Mover$	0.244	0.430
$Stayer$	0.756	0.430
$Age25-34$	0.277	0.448
$Age35-44$	0.313	0.464
$Age45-54$	0.34	0.474
$Female$	0.547	0.498
$Non-white$	0.282	0.45
$Less_than_Highschool$	0.128	0.334
$Highschool$	0.278	0.448
$SomeCollege$	0.346	0.476
$College+$	0.248	0.432 59
$Married$	0.623	0.485
$Children$	0.566	0.496
$Homeowner$	0.574	0.495
$\Delta HousePrice$	0.235	0.369
Emp_within_1q	0.306	0.461
Emp_within_2q	0.476	0.499
Emp_within_4q	0.674	0.469
$Unemp_duration(qtrs.)$	4.585	5.147
Sample Size:˜156,000		

Table 5: Regressions: New LEHD Employment within 1 quarter

	OLS with MSA and year controls	IV Regression
	$\beta/(s.e.)$	$\beta/(s.e.)$
$Mover$	-.049*	0.587*
	(.004)	(.190)
$Homeowner$	-.010*	.031*
	(0.003)	(.007)
$Age35-44$	-.017*	-.013*
	(.003)	(.004)
$Age45-54$	-.031*	-.026*
	(.004)	(.005)
$Female$	-.017*	.005
	(.003)	(.009)
$Non-white$	-.021*	-.015*
	(.004)	(.005)
$Married$	.011*	.012*
	(.003)	(.003)
$Children$	-.016*	-.004
	(.003)	(.005)
$Highschool$	.017*	.013*
	(.005)	(.005)
$SomeCollege$	.017*	.003
	(0.005)	(.006)
$College+$	.024*	.000
	(.005)	(.009)

Star Denotes Significance at the 1% level. Standard errors in parentheses.

Notes: Sample consists of approximately 156,000 completed unemployment spells by ACS respondents i, age 25-54 and residing in one of 356 CBSAs j during 2002-2012. Approximately 38,000 spells end with new LEHD employment located in another CBSA $-j$, while around 118,000 spells terminate with new employment in the same CBSA j. Results shown are from regressions of the probability of becoming employed at a new LEHD job within 1 quarter of ACS-observed unemployment on migration status. Column 1 reports estimates from an OLS model, and Column 2 shows results from a 2-step Instrumental Variables regression. All regressions include dummy variables for the reference CBSA and year of unemployment (results omitted for clarity). Individual characteristics are represented by binary indicator variables $Female$, $Nonwhite$, $Married$, $Children$, and $Homeowner$, as well as age groups $35-44$, $45-54$ ($25-34$ omitted) and education categories $HighSchool$, $SomeCollege$, and $College+$ (less than High School omitted). Coefficients express the impact of the given covariate on the probability of being employed within the threshold number of quarters. All standard errors are clustered by CBSA.

Table 6: IV - First Stage

	$\beta/s.e.$
$\Delta HousePrice$	-0.034*
	(0.003)
$Homeowner$	-0.029*
	(0.004)
$Age36-45$	-0.005
	(0.003)
$Age46-55$	-0.003
	(0.004)
$Female$	-0.036*
	(0.003)
$Non-white$	-0.008*
	(0.003)
$Married$	-0.002
	(0.002)
$Children$	-0.018*
	(0.002)
$Highschool$	0.007
	(0.005)
$SomeCollege$	0.020*
	(0.005)
$College+$	0.035*
	(0.007)

Star Denotes Significance at the 1% level. Standard errors in parentheses

R-sq.	Adjusted R-sq.	Partial R-sq.	Robust F(3,232)	Prob > F
0.0824	0.0802	0.0006	105.619	0.0000

Table 7: Regressions with Alternate Dependent Variables

Dependent Variable	**Coefficient on *Mover* – OLS**	**Coefficient on *Mover* – IV**
	$\beta/(s.e.)$	$\beta/(s.e.)$
Emp_within_2q	-.061*	0.699*
	(.005)	(.183)
Emp_within_4q	-.062*	.456*
	(.006)	(.169)
$Unemp_duration(qtrs.)$	.725*	-9.22
	(.098)	(4.23)

Star denotes significance at the 1% level. Standard errors in parentheses.

Notes: Sample consists of approximately 156,000 completed unemployment spells by ACS respondents i, age 25-54 and residing in one of 356 CBSAs j during 2002-2012. Approximately 38,000 spells end with new LEHD employment located in another CBSA $-j$, while about 118,000 spells terminate with a job in the same CBSA j. Column 1 displays the coefficient on the *mover* variable from an OLS specification, while Column 2 shows the coefficient on *mover* from the IV specification. Each line of the table represents a specification using a different dependent variable. All regressions include dummy variables for the reference CBSA and year of unemployment (results omitted for clarity). Individual characteristics are represented by binary indicator variables $Female$, $Nonwhite$, $Married$, $Children$, and $Homeowner$, as well as age groups $35-44$, $45-54$ ($25-34$ omitted) and education categories $HighSchool$, $SomeCollege$, and $College+$ (less than High School omitted). Coefficients express the impact of a one unit increase on the probability of being employed within the threshold number of quarters. All standard errors are clustered by CBSA.