# Education, Job Search and Migration

Emek Basker*

University of Missouri - Columbia

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**Abstract**

Job-search and migration behavior differ across educational groups. In this paper, I explore several differences between the migration and search behavior of workers with different levels of education, both theoretically and empirically. I start with two stylized facts. First, the propensity to migrate increases with education. Second, conditional on migration, the probability that a worker moves with a job in hand (rather than moving to search for a job in the new location) also increases with education. I present a simple model that captures these facts and generates a number of predictions about differential sensitivity of migration to observed variables by education. Predictions include a non-monotonicity of migration elasticities with respect to business-cycle conditions by educational group, and less-educated groups' higher sensitivity to local economic conditions in the migration decision. These predictions are verified using CPS data.

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# 1 Introduction

Most labor-market models, including search models, abstract from geographical concerns and implicitly assume that there is only one region within which search is possible. But in the United States, between two and three percent of adults move their residence across state lines every year, many of them for work-related reasons. Another 3-4% of Americans annually move across counties without changing their state of residence. Some move to search for work in a new location, though most interstate migrants move to take jobs they have already secured.[1]

A few papers have recently gone beyond this abstraction but assume either that migration must precede search or – less often – that search must precede migration. McCall and McCall (1987) assume that migration (between cities) must precede job search. The classic paper by Topel (1986) allows workers to move but not to search in any meaningful sense. Coulson, Laing, and Wang (2001) model search in a single metropolitan area, and allow agents to search in either the central business district or the suburbs, but not both simultaneously (though they may search – and work – in either market with a commuting cost); they argue that global search will never occur. Fahr and Sunde (2002) adapt a search model to allow for endogenous inter-regional migration, but, as with the above papers, assume that migration must precede search. Spilimbergo and Ubeda (2002a) develop a model of migration in which they focus on double matching in the labor market and the marriage market. They assume that unemployed workers can find a job with certainty upon migration (and with probability less than 1 locally), so there is no job search following a move. Finally, Kennan and Walker (2003) use an econometric model to analyze migration empirically, but again assume that migration must precede search.

The purpose of this paper is to explore the relationship between education

[1] I use the terms "migrant" and "mover" interchangeably throughout the paper. Unless otherwise noted, both refer to interstate moves, which are taken to be moves from one labor market to another. I also use the terms "high-skill", "high-education" and "high-wage" interchangeably.

and the timing of job-search and migration. Why do some people move first, before they have found a job? How do employment outcomes vary by the type of move? How sensitive are movers to local and overall economic conditions? I focus on the ways in which education changes workers' incentives, and therefore the migration process. I start by reviewing the evidence on the relationship between education and migration. I then document a previously unexamined relationship between education and the *purpose* of migration, showing that more-educated workers tend move after they have found a job, rather than to look for work.

It has long been established that the propensity to migrate decreases with age and increases with education (see Greenwood 1975 and 1993). There is also evidence that the unemployed are more likely to migrate than the employed (Schlottmann and Herzog 1981), and that the unemployed are more sensitive than the employed to the overall unemployment rate in their migration decision (DaVanzo 1978; Bartel 1979). Since the incidence of unemployment is higher among less-educated workers, this effect may mitigate the direct positive effect of education on migration. Table 1 shows some summary statistics on the differential rates of migration across education categories, computed from the March Current Population Survey (CPS) from 1981-2000.[2] While the overall rates of migration are small, the differences between groups are striking: college educated workers are 82% more likely to migrate in any given year than are high-school dropouts.[3]

In recent years the CPS questionnaire has solicited information about movers' main reason for their move. Approximately half of all migrants over the period 1997-2000 moved for job-related reasons. Of these, 90% moved to take a new

[2] See Section 3 for a description of the data.

[3] Mauro and Spilimbergo (1999) redo the classic analysis of Blanchard and Katz (1992) using Spanish data, and compute separate estimates by education level of the population. They find that, following an adverse regional employment shock, adjustment for highly-educated workers occurs quickly via out-migration, whereas adjustment for low-education workers is much slower and involves high unemployment and low participation rates for a prolonged period. The implication of these findings is that highly-educated workers migrate away in response to a negative idiosyncratic regional shock, whereas low-education workers do not.

job or for a job transfer, and the remaining 10% moved to search for work.[4,5] This fraction varies substantially by education level, as shown in Table 2. The probability that a migrant is moving to take a job increases monotonically with her education level; the probability that she moves to look for work or for non-job related reasons decreases monotonically with her education. Strikingly, of the high-school dropouts who moved either to take a job or to look for a job, nearly a third moved to search for a job. Fewer than 3% of college graduates who moved for one of these two reasons (to take a new job or search for a job) moved for the purpose of searching.[6,7]

The focus of this paper is on the interaction of the migration decision with job search, and the ways in which this interaction depends on a worker's level of education. I start with a simple consumer-choice model in which workers have the choice of searching for a job locally, searching for a job globally (in multiple regions simultaneously), or moving to another region and searching for a job there. I derive conditions under which each strategy dominates; these depend on the worker's expected wage (a proxy for her education or skill) as well as on economic conditions, both aggregate and local. The model predicts that high-skilled workers will be more likely to search globally (and therefore to migrate for job-related reasons) than low-skilled workers; that high-skilled workers will engage in less labor-market arbitrage in the sense of moving from high-unemployment states to low-unemployment states; and that migration will be pro-cyclical, with the cyclicality of migration greatest for workers with intermediate skill (education) level.[8]

[4] Unfortunately, the *ex-ante* labor-force status (employed, unemployed, not in labor force) of these workers is not known.

[5] Since this question was only asked in the last four years of a long economic expansion, results may not generalize. For example, a larger fraction of moves may be for the purpose of looking for a job in leaner years.

[6] The order of job search and migration has implications for employment outcomes: workers who move to take a job they have already found are up to 13% more likely to be employed the following March than workers who move first and search later.

[7] The educational differences in migration motives are larger than differences in migration motives along other demographic dimensions, such as race, sex and age.

[8] The intuition of my model is most closely related to the model by Topel (1986), although the models are quite different. Topel uses a dynamic model in which workers are heterogeneous with respect to age, and shows that workers late in life will be less likely to move because

Table 1: Education and Migration Statistics

| | Fraction of Population | Propensity to Migrate | Fraction of Migrants[a] |
|---|---|---|---|
| All | 100% | 2.69% | 100% |
| HS Dropouts | 12.52% | 2.03% | 9.45% |
| HS Graduates | 35.06% | 2.16% | 28.23% |
| Some College | 25.18% | 2.70% | 25.27% |
| College Grads + | 27.24% | 3.66% | 37.06% |

[a] May not add to 100% due to rounding

Source: Author's calculations from CPS, 1981-2000

Table 2: Main Reason for Migration by Education

| Main Reason for Move[a] | All Movers[b] | HS Dropouts | HS Grads | Some College | College Grads + |
|---|---|---|---|---|---|
| | | *Panel A: Full Sample* | | | |
| New job / job transfer | 46.43% | 26.76% | 32.30% | 39.29% | 60.46% |
| Looking for work / lost job | 5.47% | 12.81% | 9.28% | 6.79% | 1.78% |
| Other job-related reason[c] | 8.13% | 7.71% | 7.99% | 8.84% | 7.84% |
| Non-job related reason[d] | 39.97% | 52.72% | 50.44% | 45.09% | 29.92% |
| | | *Panel B: Men Only* | | | |
| New job / job transfer | 49.70% | 31.58% | 33.29% | 38.92% | 66.02% |
| Looking for work / lost job | 6.26% | 15.48% | 11.21% | 8.79% | 1.21% |
| Other job-related reason[c] | 8.81% | 7.73% | 9.41% | 9.81% | 8.15% |
| Non-job related reason[d] | 35.22% | 45.21% | 46.10% | 42.49% | 24.62% |

[a] May not add to 100% due to rounding

[b] Includes only movers whose moving status and reason for moving are not imputed

[c] Includes retirement, easier commute, and miscellaneous job-related reasons

[d] Includes family reasons (e.g., move for spouse), health reasons, etc.

Source: Author's calculations from CPS, 1997-2000

Using pooled cross-section individual-level data spanning two decades, from the Current Population Survey (CPS), I estimate individual migration equations. I find that, as predicted, migration is pro-cyclical in the aggregate and counter-cyclical with respect to state-level conditions, so that for fixed aggregate economic conditions, workers tend to move out of high-unemployment states. When I allow the effect of economic variables to differ across education categories, I find that high-school graduates are more sensitive to aggregate business-cycle conditions than are workers with both higher and lower education levels. Workers with low education levels are the most sensitive to arbitrage opportunities in unemployment rates across states.

In contrast to the existing literature I do not assume a fixed order of migration and job search. Instead, I derive conditions under which an unemployed worker will search locally and globally, and the corresponding conditions under which a worker will move to search for a job or to take a job. Critically, the higher propensity of high-skilled workers to search for work in other regions (and to move) is derived as their optimal strategy, not forced by assuming that different types of workers have access to different search technologies or are constrained in different ways. The intuition for the result is that the expected return on more intense job search (such as a global, rather than local, search) is higher for higher-skilled (therefore higher-wage) workers. As a result more-skilled workers are willing to make larger investments in their job search than are low-skilled workers.

The remainder of the paper is organized as follows. Section 2 presents the model. Section 3 describes the data used in the analysis, and Section 4 discusses the empirical strategy. Results are presented in Section 5. Section 6 concludes.

they will only earn a return for a few years (until retirement at a fixed and exogenous age), whereas young workers have many years over which to reap the benefits. Topel's model does not allow any unemployment *per se* (involuntary unemployment), but allows regions to vary with respect to wages (due to productivity shocks). In my model wages (net of amenities) are assumed constant across regions, but unemployment rates are allowed to vary. Workers vary across a static ability dimension rather than a dynamic (age) dimension, allowing me to write down a static model. The key intuition, however, is similar: workers with more to gain from investing in migration (Topel) or job search and migration (this paper) will be more likely to move.

# 2 Model

## 2.1 Setup

Consider a worker, who, if employed, earns a (fixed) wage $w$. If unemployed, the worker earns zero. The worker may live in one of two regions, Region 1 or Region 2.

There is one period. At the beginning of the period, the worker resides in Region 1 and is unemployed and searches for a job. The worker is risk-neutral and seeks to maximize expected income net of search costs. She has several alternative technologies for job search. Local search in the worker's region of residence (Region 1) is costless, but yields a job with lower probability than global search. Global search, in all regions simultaneously, yields a job with higher probability, but at a cost ($c$); if the job is found in the other region (Region 2), moving costs need also to be incurred. Finally, the worker may choose to move preemptively to Region 2, incurring the moving cost with certainty, but searching only locally once she arrives. A worker who moves incurs a cost of moving $m$, whether to search for a job or to take a job found in a global search.

Let $h$ be the probability that the worker finds a job anywhere; $h$ proxies for aggregate business-cycle conditions. Let $ph$ be the probability that a worker finds a job in Region 1, and let the probability of finding a job in Region 2 be $(1-p)\,h$. The variable $p$ therefore represents the relative favorableness of a job-search in Region 1. For a worker in Region 1, searching locally involves a cost of zero and a probability of getting a job of $ph$. Searching globally involves a cost of $c$ and a probability of getting a job of $h$, with an additional cost of moving $m$ with probability $(1-p)\,h$. Moving to Region 2 and searching there involves a moving cost $m$ with certainty, and a probability of finding a job $(1-p)\,h$. The worker's expected utility, conditional on each of these three actions, are:

$$U^L = phw \tag{1}$$
$$U^G = hw - c - (1-p)\,hm \tag{2}$$
$$U^M = (1-p)\,hw - m. \tag{3}$$

where $U^L$ is her expected utility from conducting a local search, $U^G$ is her expected utility from conducting a global search, and $U^M$ is her expected utility from moving to Region 2 and conducting a local search there.

For simplicity, we start by focusing on the case where $h = 1$ (i.e., global search yields a job with certainty, and local search yields a job with probability $p$). In that case

$$U^L = pw \tag{4}$$
$$U^G = w - c - (1-p)\,m \tag{5}$$
$$U^M = (1-p)\,w - m. \tag{6}$$

Given these expected utilities, workers in Region 1 will choose

$$A = \begin{cases} G & \text{if} \quad w > \overline{w} = \max\left\{\frac{1}{1-p}c + m, \frac{1}{p}c - m\right\} \\ L & \text{if} \quad w < \underline{w} = \min\left\{\frac{1}{1-p}c + m, \max\left\{\frac{1}{1-2p}m, 0\right\}\right\} \\ M & \text{if} \quad w \in [\underline{w}, \overline{w}] \end{cases} . \tag{7}$$

The probability that a worker moves from Region 1 is therefore

$$P\,(\text{move}) = \begin{cases} 0 & \text{if} \quad w < \underline{w} \\ 1 & \text{if} \quad w \in [\underline{w}, \overline{w}] \\ 1-p & \text{if} \quad w > \overline{w} \end{cases} . \tag{8}$$

Figure 1 shows the decision space for the worker in $(p, w)$ space if $m = c = 2$ and $h = 1$. For low $w$, searching locally dominates for sufficiently low $p$.

Searching globally dominates for sufficiently high wages regardless of $p$. For an intermediate set of wages and sufficiently low probability of finding a job locally, moving to Region 2 to search there dominates.

Extrapolating to a population of workers facing similar problems (perhaps with idiosyncratic values of $w$, corresponding to ability, and $m$, corresponding to local attachment or the "psychic cost" of moving), we can make the following predictions. When local conditions are very bad – $p$ is very low – all but the lowest-skilled workers migrate to search for work elsewhere. As $p$ increases, and local conditions improve, high-wage workers turn to global search, which decreases the probability that they will migrate, and low-wage workers turn to local search. At very high levels of $p$, when local conditions are very favorable, high-wage workers too eventually switch to local search. As $p$ increases, therefore, the probability of migration decreases for two reasons. First, for high wage workers, the nature of the search changes discretely: from certain or possible migration (if $M$ or $G$ dominate) to certain non-migration. Second, in the region where $G$ dominates, the probability of migration decreases as $p$ increases since the probability that a global search will result in a job outside the region declines with $p$.

Note that the above results do not depend on the one-period specification, but would carry through (with obvious modifications) to a dynamic setting in which jobs may be lost and the decision to move may be revisited. The key assumption driving the results is that the costs of search and moving ($c$ and $m$, respectively) are fixed, whereas the wage increases with ability. A high-skilled worker has a high opportunity cost associated with unemployment, and is therefore willing to spend more resources – in the form of $c$ and $m$ – to increase the probability of finding a job. In contrast, a worker whose wage, and therefore opportunity cost of unemployment, is low, will not spend as many resources on job search.

## 2.2 Comparative Statics

As $m$ decreases (i.e., the workers becomes less migration-averse), all thresholds shift down, so that both $M$ and $G$ dominate on larger regions. Figure 2 shows decision space for the case of $m = h = 1$ and $c = 2$; as $m \to 0$ local search exists only when $p \geq \frac{1}{2}$.

As the cost of global search, $c$, decreases, global search becomes relatively more attractive. Figure 3 shows decision for $m = 2$ and $c = h = 1$; at the limit as $c \to 0$, global search always dominates moving to search, so the relevant choice margin is between local search and global search.

Finally, consider the case where the probability of finding a job anywhere is $h < 1$. For $m = c = 2$ and $h = \frac{1}{2}$, the regions are then as shown in Figure 4. As $h \to 0$, $L$ dominates in an ever-increasing region; at the limit, all workers search locally since there is no expected return to a global search or move.

## 2.3 Extensions

The model can be readily extended in several directions.

Though they were derived in a 2-region setting, these results hold for the case in which there are $n > 2$ regions as well. In the simplest case, the regions can be ranked by their relative economic conditions, so workers who move to search (M) will only move to the most favorable region, while global searchers could move to any region. The model can be amended to accommodate simultaneous preemptive migration to multiple regions by adding heterogeneous individual preferences for different regions, or by building a spatial regional structure and allowing the cost of moving to depend on distance.

Dynamics can also be incorporated into the model, resulting in substantial notational complication but leaving the intuition unchanged. In a two-period model, workers may have some probability of losing their job at the end of the first period, leading to repeated search, and possibly repeated migration. If economic conditions are expected to be unchanged in the second period, then workers' incentive to be in the "best" region in the second period increases,

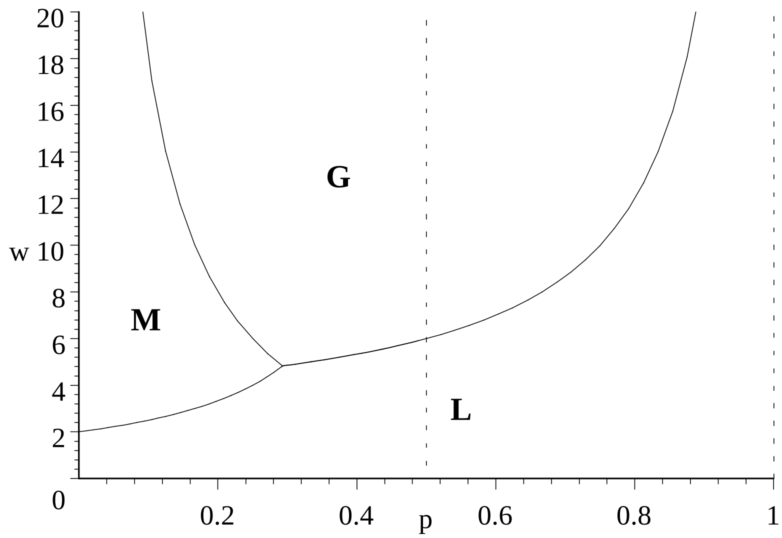


Figure 1: Decision Space for $m = c = 2, h = 1$

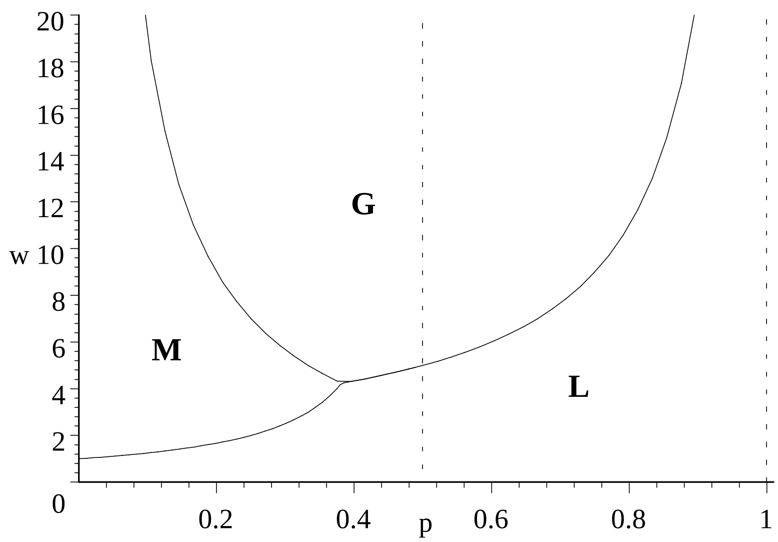


Figure 2: Decision Space for $m = 1, c = 2, h = 1$

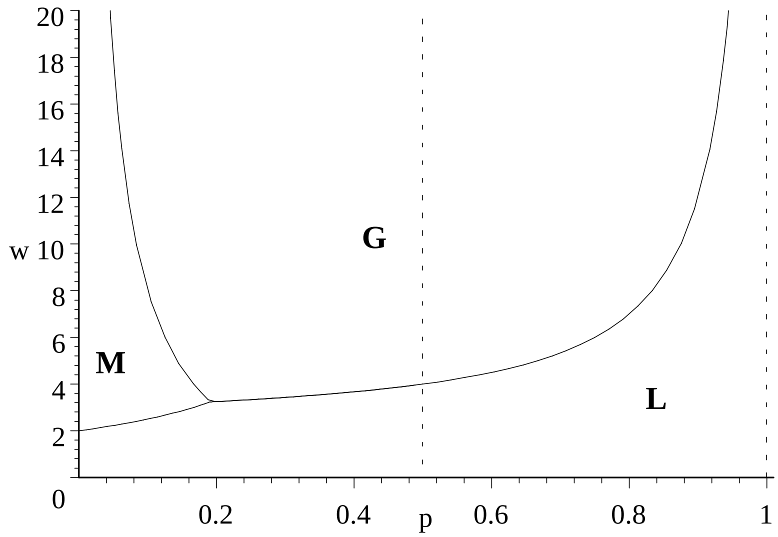


Figure 3: Decision Space for $m = 2, c = 1, h = 1$

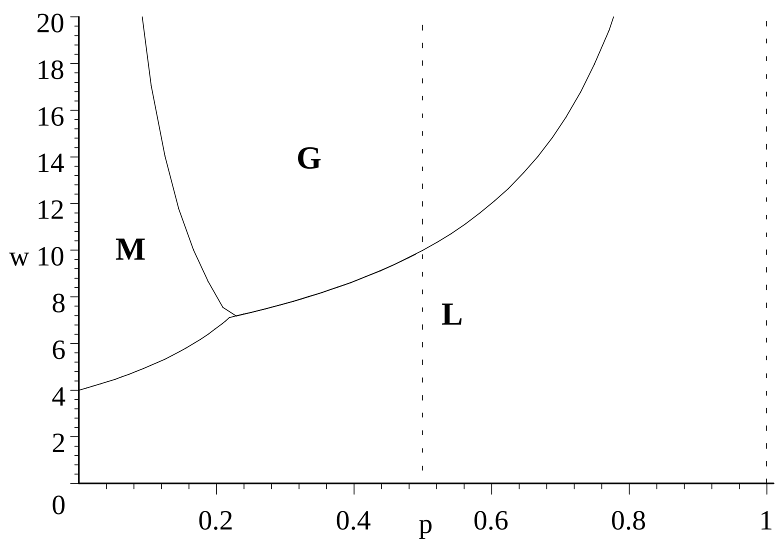


Figure 4: Decision Space for $m = c = 2, h = \frac{1}{2}$

increasing the range of $p$ and $w$ in which M will be the optimal action.

Worker and job heterogeneity on dimensions other than $w$ may also play an important factor in explaining migration behavior. The assumption that, for a given worker, expected wages are equal in the two regions is also strong; the wage may depend on variable match quality. In practice, workers make trade-offs between expected wages and unemployment rates. Empirical evidence suggests that unemployment rates matter more than wages for the migration decision, so these assumptions seem to be a good first-order approximation. Borjas, Bronars and Trejo (1992) use the National Longitudinal Survey of Youth (NLSY) to show that internal migrants' wages tend to fall with migration but to increase over time relative to the wages of similar non-migrants. Also using the NLSY, Kennan and Walker (2003) find that geographic differences in the wage distribution cannot explain migration behavior.

These different migration technologies can also be incorporated into a general-equilibrium model (such as a search model) in which firms decide on their optimal location based on the initial distribution of workers of different skill levels and their anticipated job-search behavior. Such an extension could help shed light on the "chicken-and-egg" question of whether workers follow jobs or firms follow workers (Partridge and Rickman 2003). Since the focus of this paper is on *ceteris-paribus* individual decision-making, I leave this extension to future work.

## 2.4 Implications

The model yields the following testable empirical implications:

1. High-skilled workers are more likely to migrate than are low-skilled workers. Although the propensity to migrate is, in general, not monotonic in skill – at low $p$ workers with intermediate wages may migrate with higher probability than high-wage workers (because of the discreteness of the $M$ vs. $G$ choice) – it is monotonic when evaluated at the average region's conditions (i.e., at $p = \frac{1}{2}$).

2. The propensity to migrate may be non-monotonic in skill for sufficiently depressed regions, where intermediate-skilled workers will migrate at higher rates than high-skilled workers. This situation corresponds to the case where $p$ is very close to zero in the model.[9]

3. Since intrastate (inter-county) moves are associated with lower costs (conceivably, both $c$ and $m$), intrastate moves should be less sensitive to education.

4. Migration will tend to arbitrage unemployment-rate differentials:

   (a) Workers in regions (states) with bad economic conditions will be more likely to move than those living in regions with good economic conditions.

   (b) A mover's destination will have better economic conditions than her origin region.

5. On average, low-skilled workers who move will experience larger differences between their destinations' unemployment rates and their origins' unemployment rates than high-skilled workers who move. This is because destination economic conditions figure directly in the selection of a location for low-skilled workers who move first and search later ("search migrants"), but only indirectly – by affecting the probability that a job is found – in the location choice of workers who search first and move later ("job migrants").

6. Migration is pro-cyclical: as $h$ falls, migration decreases.

7. The effect of fluctuations in aggregate economic conditions will not be uniform across skill groups. Low-skilled workers, never very likely to move, and high-skilled workers, who search globally for a wide range of local conditions, will change their behavior only slightly. The marginal

[9] This non-montonicity, while theoretically relevant, may be a stretch empirically because at low levels of $p$ the probability of moving following global search, $(1-p)$, approaches 1.

workers will be intermediate-skilled; they are likely to be most sensitive to such business-cycle fluctuations. In other words, we expect to find a non-monotonic relationship between skill and elasticity of migration with respect to business-cycle conditions.

8. For given state-level economic conditions ($p$ and $h$), migrants who move before finding a job should be less skilled than those who move after finding a job. This implication, of course, is part of the motivation for the model (see Table 2), but needs to be confirmed in a regression with controls for other observable characteristics.

9. The relative shares of search migrants in the migrant pool will decrease as $p$ increases: As local economic conditions improve, the share of out-migrants who moved to search for work will decline.

10. Among migrants, even after controlling for skill, the probability of being employed is higher for those who searched globally and moved only after they found a job than for "searching migrants" who move first and search for work later. This is a direct consequence of the fact that global searchers move only if they find a job in the destination state, whereas searching migrants move in order to search.

These hypotheses are tested in Section 5 below.

# 3 Data

I use March Current Population Survey (CPS) data from 1982-2001 (excluding 1985 and 1995). For many variables, including migration, I attribute the variable values to the previous calendar year: for example, the 1982 survey supplies 1981 data. I therefore distinguish between the *survey year* (the calendar year in which the survey was administered) and the *reference year* (the year preceding the survey year). Respondents have been asked whether they moved in the last year (and where from), almost every year since 1982; exceptions are the 1985 and 1995 surveys. Since 1997 movers have also been asked for the main reason for their move.

The Census Bureau selects residential addresses (dwelling units), not their occupants, for inclusion in the CPS; each dwelling unit is included in the March CPS twice, one year apart. By construction, then, non-movers are interviewed twice, whereas movers are interviewed only once – the address is visited twice but two different households respond to the survey. While the CPS questionnaire is quite thorough, most variables – labor force status (employed, unemployed, or not in the labor force), marital status, student status (full- or part-time student), and homeownership status – are available only on a current basis (i.e., for the survey year) and not on a lagged basis (for reference year). This means that these data are never available for movers.[10]

To eliminate as many non-labor-market-related moves as possible, I limit my sample to civilian adults ages 25-60 in the reference year (thereby eliminating as much as possible retirement-related moves) who were not students during the survey year.[11] This restriction provides me with approximately 60,000 observations per year.[12]

As with many surveys, data accuracy is a concern. Questions that are not answered during a survey are replaced by imputed ("allocated") values, which are generated from other ("donor") records. Allocations can be common for some variables and can have a large effect on mean values of some variables, notably migration status. Unfortunately, records with altered or imputed data were not flagged by the Census Bureau until the 1996 survey (referring to 1995 migration data). Since the time series for which allocated values are properly flagged is very short (and migration is a rare event), the analysis presented here cannot be repeated using only non-allocated values. More details on CPS

[10] For further information about CPS design and methodology, see Current Population Survey (2000).

[11] In 1981-1983, I could not eliminate students due to incomplete data.

[12] Because the interpretation of interstate migration is ambiguous for individuals living in Washington D.C., I omit both current D.C. residents and individuals who moved out of D.C. in the past year. None of the results reported here are sensitive to this omission.

allocation procedures are presented in Appendix A.1.[13]

# 4 Empirical Methodology

## 4.1 Migration Regressions

### 4.1.1 Binary Choices

Because migration is a relatively rare event, even a large sample such as the CPS contains only a small number of migrant observations in any given year. In most specifications, I pool the data across all years to estimate the individual-level migration probit equation

$$\mathbb{P}\left(\text{migrate}_{it}\right) = \Phi\left(\alpha + \boldsymbol{\beta} x_{it} + \sum_{s} \sigma_s \text{state}_{ist} + \sum_{t} \delta_t \text{year}_t\right) \tag{9}$$

where $\text{migrate}_{it}$ is an indicator equal to 1 if individual $i$ moved between years $t$ and $t+1$ (and 0 otherwise), $\Phi(\cdot)$ is the standard normal CDF, $\text{state}_{ist}$ is an indicator equal to 1 if individual $i$ lived in state $s$ in year $t$, $\text{year}_t$ is a year indicator, and $x_{it}$ is a vector of additional explanatory variables. For regressions with only individual-level demographic variables, the error term $\text{u}_{it} \equiv \text{migrate}_{it} - \mathbb{P}\left(\text{migrate}_{it}\right)$ is clustered at the household level, allowing correlation between the migration decisions of spouses, as well as across the two interviews of each dwelling unit. For regressions where the coefficient of interest varies only by state and year, $\text{u}_{it}$ is clustered at the state level. All regressions are estimated using the final CPS weights.[14,15]

When the vector $x_{it}$ includes economic variables, such as the unemployment

[13] To complicate matters further, allocation procedures changed in 1988. More details on this change are in Appendix A.2.

[14] For completeness, I also estimate the equivalent OLS regressions
$\text{migrate}_{it} = \alpha + \boldsymbol{\beta} x_{it} + \sum_{s} \sigma_s \text{state}_{st} + \sum_{t} \delta_t \text{year}_t + \text{u}_{it}$.
Results from these regressions are uniformly extremely similar to the probit results, and are therefore not reported.

[15] The individual characteristics for which I control are sex, race, age and education. Though the workers' *ex ante* employment status (employed or unemployed) is not elicited in CPS questionnaires, I attempt to control for it indirectly, as explained in Section 4.3 below.

rate in individual $i$'s state of residence in year $t$, the coefficients $\beta$ are of direct interest in answering the first question posed. The sign, magnitude, and statistical significance of these coefficients gives us a measure of the importance of the explanatory variables in the migration decision.

Year fixed effects are included in some, but not all, of the regressions. Year-to-year fluctuations in the migration rate due to unobservable changes will be captured by these year fixed effects, when included. Year fixed effects are omitted when aggregate economic conditions are included in the regression. I assume, critically, that the effect of specific characteristics, such as education, on the propensity to migrate is not time-varying.

Unless otherwise noted, I report the derivatives $\frac{\partial\Phi(x,z)}{\partial x}|_{(\overline{x},\overline{z})}$ (where $z$ is the vector of all explanatory factors excluding $x$) rather than probit coefficients. The numbers reported may therefore be interpreted as the effect of an infinitesimal change in the variable of interest, $x$, on the probability of migration where the independent variables are evaluated at sample means. In cases where $x$ is a binary variable (such as an indicator for race, sex, or education), I report instead the change in the probability of migration associated with a discrete change in $x$:

$$\Phi\left(x=1;\overline{z}\right)-\Phi\left(x=0;\overline{z}\right).$$

#### 4.1.2 Multiple Choices

In some cases I have data on a multinomial, rather than binary, choice. This is the case when I distinguish between interstate moves and intrastate (inter-county) moves, or in regressions using the later (1997-2000) data where I can distinguish between moves for different reasons. In those cases instead of a simple probit model I estimate a multinomial logit model. In the case of a ternary (three-way) migration choice (e.g., stay, move locally, move to another state), the multinomial-logit coefficient vectors $\left(\boldsymbol{\beta}^{A},\boldsymbol{\beta}^{B},\boldsymbol{\beta}^{C}\right)$ is a maximum-likelihood solution to

$$\mathbb{P}\left(\text{migration}_{it}=X\right)=\frac{\exp\left(\boldsymbol{\beta}^{X}\mathbf{x}_{it}\right)}{\exp\left(\boldsymbol{\beta}^{A}\mathbf{x}_{it}\right)+\exp\left(\boldsymbol{\beta}^{B}\mathbf{x}_{it}\right)+\exp\left(\boldsymbol{\beta}^{C}\mathbf{x}_{it}\right)}\quad X=A,B,C.$$

(The same set of explanatory variables is used in these regressions as in the probit regressions.) Since this set of equations is not identifiable, one outcome has to be designated as the base category with coefficient vector normalized to **1**. I always use non-migration as the base category, and estimate

$$\begin{aligned}\mathbb{P}\left(\text{migration}_{it}=A\right) &= \frac{1}{1+\exp\left(\boldsymbol{\beta}^{B}\mathbf{x}_{it}\right)+\exp\left(\boldsymbol{\beta}^{C}\mathbf{x}_{it}\right)} \qquad (10)\\ \mathbb{P}\left(\text{migration}_{it}=X\right) &= \frac{\exp\left(\boldsymbol{\beta}^{X}\mathbf{x}_{it}\right)}{1+\exp\left(\boldsymbol{\beta}^{B}\mathbf{x}_{it}\right)+\exp\left(\boldsymbol{\beta}^{C}\mathbf{x}_{it}\right)}\quad X=B,C\end{aligned}$$

(where I take $A$ here to be non-migration). I report the multinomial logit coefficient vectors $\boldsymbol{\beta}^{X}$. As above, standard errors are always clustered at the household level unless otherwise specified, and all regressions use CPS weights.

#### 4.1.3 Sample Selection

Most regressions use all available observations, with the exception of a few focusing only on movers. Because women are more likely than men to move for reasons other than work (specifically, for a spouse or other family member), I have also estimated results using a male-only sample. The results tend to be qualitatively similar though most effects are magnified because of men's higher sensitivity to labor-market conditions.[16] I report the results for men only when they are sufficiently different from the results for the full sample to be of independent interest.

[16] Of course, since the sample is about half the size, some significance is lost despite the (absolutely) larger estimated coefficients

## 4.2 Unemployment Rates

I compute state-level unemployment rates, as well as state unemployment rates by education category (high-school dropouts, high-school graduates, some college, and college degree or beyond), using records of male non-migrants ages 25-60. For each cell (depending on the regression, unemployment rates are computed for state-year cells, education-year cells, and state-education-year cells) I compute the unemployment rate using the final CPS weights. Because the cells tend to be fairly small, the computed unemployment rates are noisy.[17]

The arbitrage motive in migration, in the model, depends on the difference between the unemployment rate in a worker's current region of residence and the unemployment rate in other regions to which the worker could potentially move. I compute the "target unemployment rate" for a worker in state $s$ as

$$\text{target}_{st} = \sum_{m \neq s} \omega_{sm} \text{unemp}_{mt}$$

where $\text{unemp}_{mt}$ is the unemployment rate in state $m$ in year $t$, and the weights $\omega_{sm}$ are derived from the 1990 Census as follows. Letting $\text{migrants}_{sm}$ represent the number of people in state $s$ at the time of the 1990 Census who give their state of residence for 1985 as state $m$,

$$\omega_{sm} = \frac{\text{migrants}_{sm}}{\sum\limits_{k \neq s} \text{migrants}_{sk}}. \tag{11}$$

The target unemployment rate is therefore the unemployment rate in the "typical" state of destination for state-$s$ out-migrants in the late 1980s.[18]

The relevant variable for arbitrage by migration is the difference between the unemployment rate in the worker's current state and the unemployment rate in

[17] The unemployment rate for state*education cells is measured with more error than the average unemployment rate in the state due to the relatively small number of observations in every state*year*education cell.

[18] I obtain similar results using migration patterns from the CPS over the entire period 1981-2000. The Census weights have the advantage that they represent a much larger sample (this is a long-form question).

the target area, evaluated before migration:

$$\text{arbitrage opportunity}_{st} = \text{unemp}_{st} - \text{target}_{st}. \tag{12}$$

A final issue that warrants mention is measurement error. The predictions of the model in Section 2 have all to do with the *individual's* employment prospects, not with the average employment opportunity in her state. In the empirical analysis, the state unemployment rate is used to proxy for individual employment prospects, but as such it is measured with error. Attenuation bias in the coefficient on the differential unemployment rates is therefore to be expected, both because the unemployment rate is itself measured with error (especially when broken down by education category, where very few observations inform each calculation), and because it is an imperfect proxy for the conditions faced by any individual worker.

### 4.3 Personal Labor-Force Status

As noted in Section 3, the labor-force status of workers (employed, unemployed, out of the labor force) is only available *ex post*, that is, for the survey year, and is not known for the reference year. Unfortunately, it is their *ex ante* employment status – at the time of the decision to stay or migrate – that we want to control for in the migration equations estimated in this paper.

Since more-educated workers are less likely to be unemployed, and since the unemployed may be more likely to migrate, controlling for education without controlling for labor-force status risks biasing the results reported here. In the baseline regressions reported in Section 5.1, omitting workers' employment status may bias the measured effect of education on migration downwards.

On the other hand, in regressions in which workers' education levels are interacted with business-cycle indicators – as in Section 5.4 – the omission is likely to bias *upwards* the differential effect of business cycles by education on migration. To see this, note that the less-educated tend to be more adversely affected by recessions than the more-educated. The aggregate unemployment rate variable, intended to capture business-cycle conditions, is therefore correlated more strongly with the probability that a high-school dropout is unemployed than with the probability that a college graduate is unemployed, and a spurious differential relationship between aggregate conditions and migration, by education, may be estimated as a result.

I attempt to address this concern using two proxies for individual unemployment status in the reference year: the number of weeks worked in the previous year, or – alternatively – an indicator for a worker having been employed at least 50 of the last 52 weeks.[19] These proxies should be correlated with workers' past employment status (prior to their [potential] move), but they are muddied by their equally-strong correlation with the workers' current employment status. More important than the measurement error in these proxies is their possible endogeneity, since the number of weeks worked last year is – in the model presented here as well as in numerous others – endogenous to the migration decision.

When these controls are added to the regressions, the estimated coefficients increase or decrease in the predicted direction. An open – and unanswerable – question is how much the results presented below would change if less-noisy and truly exogenous controls for last year's employment status were used.

# 5 Results

## 5.1 Baseline Regression

In this section I test hypotheses (1)-(2) from Section 2.4. Recall, these are:

1. Evaluated at average regional conditions, high-skilled workers are more likely to migrate than are low-skilled workers.

2. The propensity to migrate may be non-monotonic in skill for sufficiently depressed regions.

[19] The second proxy is simply a discretization of the first.

To test these hypotheses, the baseline regression includes only individual-level explanatory variables: age, sex, race, and education, as well as state and (for some regressions) year fixed effects. I report the coefficients on these demographic variables from probit regressions in Table 3. Coefficients on age fixed effects from Column (1) are plotted in Figure 5. Three education categories are reported (high school diploma, some college, college degree or beyond); the omitted education category is less than high school. As expected, migration increases monotonically with education, and decreases with age.

When the number of weeks worked last year is included in the regression (either as a continuous variable or as an indicator for 50 or more weeks worked), the estimated effect of education increases. Since more-educated workers are less likely to be unemployed, and since the unemployed may be more likely to migrate, controlling for education without controlling for labor-force status biases downward the estimated coefficient on education. Controlling for the number of weeks worked last year therefore increases the measured effect of education on migration. Since the number of weeks worked last year is itself endogenous to the migration decision, however, results with these controls should be interpreted with care. The coefficients on weeks of work should be interpreted with caution, if at all.[20]

To verify the robustness of these results, I repeat the above regressions controlling for the worker's marital status and number of children. As noted in Section 3, data on marital status is only available on an *ex-post* basis, and may be endogenous to the migration decision if workers move when their marital status changes (i.e., when they marry or divorce). The number of children is less likely to be endogenous, but may be if individuals delay having children

[20] To see why the number of weeks worked is endogenous, note that (i) moving takes time, and (ii) workers who move in order to search for work are expected to be unemployed for a time in their new location. The number of weeks worked is also a noisy proxy for the worker's labor-force status the previous year, which is the (unavailable) control variable of interest. While the endogeneity biases the coefficient upwards (in absolute terms), the measurement error biases it towards zero; whether the true effect of having been employed one year ago is larger or smaller than the one estimated is impossible to say.

Table 3: Probability of Migration: Baseline Regression Estimates

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Male | 0.174 | 0.483 | 0.499 | 0.175 | 0.489 | 0.505 |
| | (0.027) | (0.027) | (0.026) | (0.027) | (0.027) | (0.026) |
| White | -0.055 | -0.009 | -0.041 | -0.053 | 0.004 | -0.026 |
| | (0.065) | (0.061) | (0.061) | (0.064) | (0.061) | (0.060) |
| High School | 0.001 | 0.273 | 0.293 | -0.004 | 0.263 | 0.279 |
| Diploma Exactly | (0.067) | (0.067) | (0.066) | (0.067) | (0.067) | (0.066) |
| Some College, | 0.474 | 0.832 | 0.862 | 0.475 | 0.818 | 0.841 |
| No Degree | (0.076) | (0.079) | (0.078) | (0.076) | (0.079) | (0.078) |
| College Degree | 1.452 | 1.964 | 1.993 | 1.446 | 1.941 | 1.961 |
| or Beyond | (0.086) | (0.092) | (0.091) | (0.086) | (0.091) | (0.090) |
| Weeks Worked | | -0.075 | | | -0.075 | |
| Last Year (Number) | | (0.001) | | | (0.001) | |
| Worked 50+ Weeks | | | -3.209 | | | -3.238 |
| Last Year (Indicator) | | | (0.060) | | | (0.061) |
| $\chi^2_{(3)}$ test for equality of | 793 | 1,100 | 1,145 | 790 | 1,085 | 1,123 |
| education coefficients | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Age Fixed Effects | Y | Y | Y | Y | Y | Y |
| Origin State FE | Y | Y | Y | Y | Y | Y |
| Year Fixed Effects | N | N | N | Y | Y | Y |

Notes: 944,061 observations used. Standard errors are clustered at the household level. All coefficients are multiplied by 100.

as long as they anticipate a high degree of mobility.[21] At the same time, both marital status and the number of children may affect the likelihood of migration. The presence of school-aged children may reduce couples' mobility due to the additional costs involved in the adjustment of children to the new location; in the notation of the model, the moving cost $m$ is likely to increase with children. Even in the absence of children, married workers may be less likely to migrate due to coordination problems if both are in the labor force.[22] This factor may also be modeled in a reduced form as an increase in $m$ due to marriage (though a more structural model would include two potential searchers, not necessarily both unemployed, within a single household).[23] Results with these variables are shown in Table 4. Both marriage and the presence of children (included as an indictor variable in Columns (4)-(6) and as a count variable in Columns (1)-(3)) are associated with lower migration probability, though the discussion above suggests that these coefficients should not be interpreted causally. The coefficients on the other variables are qualitatively unchanged.[24]

Next, I test the prediction that propensity to migrate may not be monotonic in education for regions with sufficiently high unemployment rates. Let $\text{bad}_{st}$ be an indicator for bad economic conditions in the state relative to the "target

[21] Since the number of children given is the number of children living with the parents, another possible mechanism for endogeneity of this variable is that in the case of divorce, the parent with custody is less likely to move out of state. For example, Jim and Mary get divorced and Mary gets the children. Jim, who never liked living in Nebraska in the first place, moves back to California. If Jim get interviewed in the CPS he has moved and has no children in the household – if Mary gets interviewed, she has not moved and has children.

[22] The co-location problem has been examined most notably Costa and Kahn (2000) and more recently by Compton and Pollak (2003). They argue that the problem is most critical for highly-educated two-earner couples, a complication I ignore here.

[23] Perhaps surprisingly, among the 902 married couples who both moved in the period 1997-2000, the reasons for migration given by the two spouses are the same in 98.5% of the time. In 41% of cases, both spouses say they moved to take a job (or for a job transfer), and 3% of couples say they are both moving to look for work. Fewer than 1% of respondends – male or female – whose spouses report moving to take a job report moving either to look for work or for other reasons.

[24] Including homeownership status, another endogenous variable, in the regressions, also has no qualitative impact.

Table 4: Baseline Regressions Estimates with Family-Structure Variables

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Male | 0.185 | 0.474 | 0.485 | 0.163 | 0.452 | 0.463 |
| | (0.027) | (0.026) | (0.026) | (0.027) | (0.026) | (0.026) |
| White | 0.005 | 0.053 | 0.020 | -0.005 | 0.048 | 0.015 |
| | (0.064) | (0.060) | (0.059) | (0.064) | (0.060) | (0.059) |
| Married | -0.488 | -0.402 | -0.381 | -0.404 | -0.334 | -0.313 |
| | (0.050) | (0.047) | (0.046) | (0.050) | (0.048) | (0.047) |
| Children | -0.243 | -0.295 | -0.277 | -0.670 | -0.737 | -0.703 |
| | (0.024) | (0.023) | (0.022) | (0.050) | (0.048) | (0.047) |
| High School | -0.029 | 0.231 | 0.246 | -0.013 | 0.253 | 0.267 |
| Diploma Exactly | (0.066) | (0.066) | (0.065) | (0.066) | (0.066) | (0.065) |
| Some College, | 0.424 | 0.756 | 0.778 | 0.439 | 0.780 | 0.801 |
| No Degree | (0.075) | (0.078) | (0.077) | (0.075) | (0.078) | (0.077) |
| College Degree | 1.362 | 1.835 | 1.854 | 1.367 | 1.853 | 1.871 |
| or Beyond | (0.085) | (0.090) | (0.089) | (0.085) | (0.090) | (0.089) |
| Weeks Worked | | -0.076 | | | -0.076 | |
| Last Year (Number) | | (0.001) | | | (0.001) | |
| Worked 50+ Weeks | | | -3.243 | | | -3.229 |
| Last Year (Indicator) | | | (0.061) | | | (0.060) |
| $\chi^2_{(3)}$ test for equality of | 738 | 1,011 | 1,047 | 729 | 1,009 | 1,046 |
| education coefficients | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Notes: 944,061 observations used. Standard errors are clustered at the household level. All regressions include age, origin-state and year fixed effects. Columns (1)-(3) include the number of children as a count variable, while Columns (4)-(6) use an indicator that equals 1 if the respondent has at least one child under 18 living at home. All coefficients are multiplied by 100.

area" for potential migrants:

$$\text{bad} = \begin{cases} 1 & \text{if arbitrage opportunity} > 0 \\ 0 & \text{otherwise,} \end{cases}$$

where arbitrage opportunity is as defined in Equation (12). Table 5 presents coefficients on *interactions* of education and bad economic conditions, to test whether the effect of education is monotonic in the good regime (when $\text{bad}_{st} = 0$) but non-monotonic in the bad regime ($\text{bad}_{st} = 1$). Each regression is presented in two columns, the first showing coefficients on education for state-year cells with the bad regime, and the second showing the coefficients for state-year cells with the good regime.

The first two columns show coefficients from a regression with no year fixed effects; the last two columns repeat this exercise with year fixed effects. In each column, I show first the coefficients on the interaction terms, followed by a $\chi^2$ test for equality of the coefficients by education for each regime. In every case, equality of the coefficients on education *within* the regime is clearly rejected.

Below this first $\chi^2$ test statistic I show the $\chi^2$ statistic of interest: testing whether changes in the probability of migration change with education *differently* across the two regimes. The prediction that intermediate-skilled workers will migrate more than both low- and high-skilled workers out of states with bad economic conditions clearly fails: there is no statistical difference between the elasticity of migration with respect to education in the bad regime and that in the good regime.

## 5.2 Intrastate (Inter-County) Migration

Inter-county (but intrastate) moves tend to be shorter-distance moves, and are therefore associated with lower "psychic" as well as pecuniary costs. The pecuniary savings include both costs that are monotonic in distance (transportation costs, cost of keeping in touch with friends and family via return visits) as well as costs that depend on the discrete transition across state boundaries (such as


Figure 5: Coefficients on Age Indicators ($\beta_{60} \equiv 0$)

Table 5: Baseline Regression Estimates with *bad* interaction

| | (1) | | (2) | |
|---|---|---|---|---|
| Variable | bad = 1 | bad = 0 | bad = 1 | bad = 0 |
| High-School Dropout | (dropped) | -0.277<br>(0.111) | (dropped) | -0.226<br>(0.122) |
| High School Diploma Exactly | -0.107<br>(0.094) | -0.181<br>(0.099) | -0.071<br>(0.093) | -0.164<br>(0.097) |
| Some College, No Degree | 0.308<br>(0.109) | 0.327<br>(0.114) | 0.369<br>(0.108) | -0.342<br>(0.112) |
| College Degree or Beyond | 1.358<br>(0.134) | 1.320<br>(0.137) | 1.439<br>(0.131) | 1.316<br>(0.135) |
| $\chi^2_{(3)}$ test for equality of education coefficients | 364.55<br>0.0000 | 445.53<br>0.0000 | 398.28<br>0.0000 | 411.25<br>0.0000 |
| $\chi^2_{(4)}$ test for significance of *bad* interactions | 6.54<br>0.1626 | | 5.84<br>0.2113 | |
| Year Fixed Effects | N | | Y | |

Notes: 944,061 observations used. Regressions include all controls from Table 3. Standard errors are clustered at the household level. All coefficients are multiplied by 100.

the cost of obtaining a driver's license in the new state, car registration, and re-licensing in the case of some occupations like doctors, lawyers, and beauticians). Semi-global (meaning state-level, rather than national) job search is also likely to be cheaper than global job search in many cases – perhaps disproportionately so for low-skilled workers who rely on informal networks with more limited coverage.[25] Combined, these observations suggest that intrastate migration rates should be less disparate across educational groups than are interstate migration rates. I break Hypothesis (3) into two parts:

3. (a) Intrastate (inter-county) migration will be less sensitive to education than interstate migration.

   (b) The relationship between education and the ratio of job movers to search movers will be weaker for intrastate (inter-county) migration than for interstate migration.

I first compute the probability of an intrastate, inter-county move over the period 1981-2000 by education, and the reason for these moves over the period 1997-2000. Comparing the figures in Table 6 to the ones shown in Tables 1 and 2, the difference in migration rates between high-school dropouts and college graduates is much smaller. A much larger fraction of intrastate movers – nearly 70% – moved for non-job related reasons, compared with only 40% of interstate movers. This is not surprising since only a fraction of inter-county moves are likely to qualify as "migration" in the sense of a move from one labor market to another; many others are local moves that happen to straddle a county border, and these are outside the model considered here.[26] Conditional on a job-related move, the differences between educational groups appear just as large as in the case of interstate migration.

[25] For theoretical and empirical insights into the importance of networks, see Spilimbergo and Ubeda (2002a, 2002b). Related theoretcial treatments include Bräuninger (2002) and Calvó-Armengol (2003).

[26] The same problem arises to a lesser extent in interstate moves; the difference is of degree. This argument applies also to the "other job-related reason" category, which includes moving for easier commute.

To confirm the first finding, that intrastate migration rates are not as sensitive to education as were interstate rates, I estimate a multinomial-logit model to simultaneously determine whether an individual is a nonmover, intrastate (inter-county) mover, or interstate mover, as in Equation (10). The results are shown in Table 7. Each regression in shown in 2 columns. The first column of coefficients shows coefficient estimates for intrastate (inter-county) moves and the second column shows estimates for interstate migration (nonmovers are the base category). These regressions confirm the results from the previous tables: the positive relationship between education and migration is much stronger for interstate migration than for intrastate (inter-county) migration, and the effect of personal unemployment is smaller.[27,28] The coefficients on the unemployment proxies are about half as large for intrastate movers as for interstate moves (though they remain statistically significant). Also, as expected, the education coefficients decline (relative to the omitted category, high-school dropouts) – although here too large and statistically-significant differences remain, the $\chi^2$-statistics are much smaller than in the interstate regressions.

I return to the second finding, that the type of move – job move vs. search move – is just as sensitive to education in the case of intrastate moves as with interstate moves, in Section 5.5 below. I do not find evidence to support Hypothesis (3b).

## 5.3 Arbitrage

In this section I test hypotheses (4) and (5) from Section 2.4:

4. (a) Workers in states with bad economic conditions will be more likely to move than those living in states with good economic conditions.

   (b) Destinations will have better economic conditions than origin states.

[27] The results shown omit year fixed effects. Results with year fixed effects are extremely similar.

[28] The coefficients in this table are clearly not immediately comparable to the other tables where marginal effects from a probit model were shown. Results from probit regressions with intrastate migration on the LHS are qualitatively similar to those shown here, and available from the author upon request.

5. Low-skilled workers' destinations will, on average, represent a larger improvement over their origins than is the case for high-skilled workers.

Before turning to regression analysis, I first present a simple tabulation of the average improvement in migrants' state-level unemployment rate. Table 8 tabulates the fraction of migrants whose destination-state unemployment rate (measured in year $t$, before the move) is lower than their year-$t$ origin-state unemployment rate, by education. I show results using both average state unemployment rates (Column 1) and education-specific state unemployment rates (Column 2), both constructed from March CPS files using male non-movers ages 25-60.

The table confirms hypotheses (4b) and (5). On average, migrants move to states with lower overall unemployment rates, less so to states with lower education-specific unemployment rates. As the model predicts, the fraction of migrants whose destinations have lower unemployment rates than their origins decreases monotonically with education.

To test Hypothesis (4a), I add the arbitrage opportunity (the difference between the state unemployment rate and the unemployment rate in the state's "target region") to the regressions presented in Table 3. Table 9 shows the estimated effect of an arbitrage opportunity on migration. Column (1) shows results using the average target unemployment-rate differential. Columns (2) and (3) control for weeks worked last year (as a continuous variable and as a discrete variable, respectively); Columns (4)-(6) repeat these regressions with year fixed effects. All other controls from Table 3 are included in all regressions.

When no controls for employment status are included, the effect of an arbitrage opportunity is positive and significant: the higher is a state's unemployment rate, relative to the region to which its residents are likely to migrate, the higher is the probability that they will move. For the regressions with year fixed effects, this result continues to hold when weeks of work are included in the regression; the results are marginally-significant (significant at the 10% confidence level) when no year fixed effects are included. As above, it is important to interpret the results of regressions which control for weeks of work with care, since the number of weeks worked is endogenous to the migration decision.

### 5.4 Cyclical Patterns

I now turn to testing the hypotheses regarding the cyclical behavior of migration:

6. Migration is pro-cyclical.

7. The cyclicality of migration is strongest for workers with intermediate skills (education).

Table 10 shows coefficients on the U.S. unemployment rate **when interacted with education variables**. In Column (1), the US unemployment rate is interacted with individuals' education categories. In Columns (2) and (3), controls are added for weeks worked last year (continuously and discretely, respectively). Column (4) shows results similar to Column (1) with the difference that individuals' education categories are interacted with the unemployment rate *by education category*. Columns (5) and (6) repeat this specification again controlling for weeks worked last year. Standard errors are clustered at the education-category level. Note that education enters into these regressions directly as well as through the interaction terms.

The $\chi^2$ statistic shows a test for equality of the effect of business cycles conditions across educational categories. In all cases a $\chi^2$ test rejects equality of the coefficients across education groups. The estimated effect of the business cycle is non-monotonic: the migration rate of high-school graduates is more sensitive to business-cycle conditions that that of high-school dropouts. This nonmonotonicity is strong in some specifications and almost invisible in others.[29]

[29] The model does not tell us what is the "intermediate" skill level for which migration should be most sensitive to cyclical conditions. Failing to find such a nonmonotonicity would be consistent with the model if the "intermediate" category turned out to be those making \$1-\$2/hour or those making \$1000-\$2000/hour.

### 5.5 Reasons for Migration

In this section I test whether the reasons for migration are sensitive to observable variables. Since questions about the main reason for migration were not asked before 1997, only a small set of observations (fewer than 2,000) is available to answer this question, and some variables (specifically, cyclical ones) cannot be used on the right-hand side. Moreover, the model presented in this paper predicts that workers who search globally migrate with probability $(1-p)\,h < 1$, implying that only a fraction of global searchers will be included in the migrant sample.

With these caveats in mind, I first show that search migrants are more likely to arbitrage unemployment rate differences across states than are job migrants. Table 11 shows the average arbitrage in unemployment rates by type of migration for 1997-2000 (the years for which type of migration is solicited). Strikingly, a statistically-significant 64% of search movers move to states with lower unemployment rates, while only 52% of job movers do so (and for them the fraction is not statistically different from half); the numbers are slightly smaller, but the pattern the same, when education-specific unemployment rates are used.

I next turn to testing the model's predictions about differences between "job movers" and "search movers":

8. For given state-level economic conditions ($p$ and $h$), search migrants will be less skilled than job migrants.

9. The share of search migrants among out migrants will decrease as local economic conditions improve.

I test these hypotheses using a multinomial logit model. For the years 1997-

2000 (when reason for migration is given), I define migration reason as:

$$\text{migreason} = \begin{cases} N & \text{if no migration} \\ J & \text{if job migration} \\ S & \text{if search migration} \\ O & \text{if other migration.} \end{cases}$$

and let non-migrants (who include intrastate movers for this purpose) be the base category. Table 12 shows results from two regressions. In both cases year fixed effects are omitted, but the results are very similar when they are included. Each regression is shown in three columns. The first column shows the maximum-likelihood coefficients for job movers, the second for search movers, and the third for other movers. In each case the comparison (base) group is non-movers. The first set of results shows that job migrants are substantially more likely to be highly-educated (some college or college degree) than non-movers, whereas search movers are *less* likely than non-movers to have a college degree. The third column shows that other movers are somewhat more likely to have a college degree than non-movers.

To test whether the latter two results are due to differential rates of unemployment by education, the second regression adds weeks worked last year to the regression.[30] The estimated under-education of search migrants relative to non-migrants is reduced by a third. Since weeks worked last year is a noisy proxy for the worker's labor-force status one year earlier (as discussed in Section 4.3), it stands to reason that a better measure of labor-force status would further reduce search migrants' estimated differences from non-migrants, possibly to a statistically insignificant level.

Adding arbitrage opportunity (again defined as the difference between the state unemployment rate and the unemployment rate in the target area), we can test whether arbitrage opportunities have different impacts on job migration and search migration. Those results are shown in Table 13. Surprisingly,

[30] Results using the worked 50 weeks or more indicator are very similar.

controlling for observed characteristics, arbitrage opportunities do *not* have a differential effect on search and job moves. In both cases, arbitrage opportunities are negatively, but insignificantly, correlated with moves.

Before turning to outcomes, I return to Hypothesis (3b):

3. b. The relationship between education and the reason for migration will be weaker for intrastate (inter-county) migration than for interstate migration.

To address this question, I estimate a multinomial logit with seven possible outcomes: nonmigration, intrastate migration for each of 3 reasons (job, search, other) and interstate migration for each of those reasons. The results are shown in Table 14.[31] The table shows a single regression with coefficients for six move types: intrastate job, intrastate search, intrastate other, etc. Two $\chi^2$ test statistics for equality of the education coefficients for intrastate job and search migrations, and for interstate job and search migration.

Hypothesis (3b) implies that the $\chi^2$ statistic for interstate migrations will be larger, since it says that the difference between the education levels of interstate movers of different types (job vs. search) will be greater. This is exactly what we see.[32]

It is also worth noting how similar job migrants look whether they move within the state or across state lines. While the coefficients on the education indicators are significantly different across these two move types ($\chi^2_{(3)} = 15.91$, p-value 0.0012), these two groups are much more similar than intrastate movers overall or interstate movers overall. This finding suggests that job movers are likely to be global searchers and therefore share characteristics regardless of where (or whether) they move.[33]

[31] Because of the computational requirements of this regression, age fixed effects were replaced with five age indicators for age groups $(25-30, 31-36, 37-42, 43-48, 49-54, 55-60)$. State of origin fixed effects were replaced with five Census region fixed effects (Northeast, Midwest, South Atlantic, South Central, West).

[32] Results not controling for weeks worked last year or using an indicator for 50 or more weeks worked are extremely similar.

[33] Some of the differences between job movers by destination may be due to their matching

### 5.6 Outcomes

How important is the type of migration to employment outcomes? The final hypothesis is that

10. Among migrants, even after controlling for skill, the probability of being employed is higher for job migrants than for search migrants.

To answer this question, I regress current employment status on type of move, controlling for the same household characteristics:

$$\mathbb{P}\left(\text{employed}_{i,t+1} \mid \text{migrate}_{it}\right) = \Phi\left(\alpha + \boldsymbol{\beta} x_{it} + \kappa \text{jobmove}_{it} + \sum_{t} \delta_t \text{year}_t\right) \tag{13}$$

where $\text{employed}_{i,t+1}$ is an indicator which equals 1 if the worker is employed in year $t+1$, and zero otherwise (i.e., for both the unemployed and non-participants). The results are shown in Table 15. Columns (1) and (2) show results for the full sample of movers, without and with year fixed effects, respectively; Columns (3) and (4) repeat the analysis for men only.

These results suggest that, conditional on migration, male workers who moved to take jobs are 13% more likely to be employed the following March than male workers who moved to search for work. Interestingly, controlling for type of move, education does not significantly change the probability of being employed. Unfortunately, these results are probably driven, at least in part, by an unaddressed endogeneity problem: workers who move to search for a job are more likely to have been unemployed before they moved, whereas workers who move to take jobs (job movers) are more likely to have engaged in on-the-job search before the move. This implies that being a job-mover is probably correlated with other, unobserved, characteristics that make the worker more employable in any location. It is therefore hard to judge how much of the increased probability of being employed is due to the type of migration; the 13% figure (16% for both sexes) should be taken as an upper bound.

ability with firms at different destinations. I am exploring this possibility in another paper.

# 6 Conclusion

This paper presents a stylized one-period consumer-choice model of migration and job search intended to capture two observations: the positive relationship between education and propensity to migrate, and the tendency of more-educated workers to find work before they move, while less-educated workers move first and search for work second. Several predictions about aggregate migration behavior emerge from the model, and are tested empirically, with very good results.

First, I test whether the monotonic relationship between education and migration holds both in below-average and above-average states. I find that the relationship is somewhat more stable in states with worse-than-average economic conditions than in states with better-than-average conditions. The strong prediction of the model, that intermediate-skilled workers will have the highest out-migration rates from worse-than-average states, fails empirically. At the same time, the difference between the out-migration rates of the highly-educated and the low-educated is smaller in these worse-than-average states, as the model predicts.

Second, I show that, *conditional on moving*, low-skilled workers are more sensitive to relative unemployment rates than are high-skilled workers. I also look at the sensitivity of different educational groups to business-cycle conditions, and find, as the model predicts, that intermediate-skilled workers are most sensitive to business-cycle conditions in their migration decision.

Finally, I show that search movers are substantially less likely to be employed following their move than are job movers.

The model presented here is not intended to capture all aspects of the migration decision; as Table 2 (in the Introduction) shows, nearly half of all migrants give reasons other than work for their decision to move. And while the model imposes identical preferences and identical search-and-migration technologies on all workers (allowing them to differ along a single dimension – wages, assumed to increase monotonically with skill), in reality there are many other differences between low- and high-skilled workers. On the preference dimension, workers may care differentially about their career. If skill is acquired, workers who are "career-minded" may choose to acquire skill and, concurrently, be more willing to migrate even when the expected gain is small. In the terminology of the model presented here, this would imply a correlation between the (psychic) cost of moving and skill: $\rho(m, w) < 0$. On the technology dimension, skilled workers may face lower global-search costs, so that $c$ may decrease with skill. Such modifications to the model would increase the migration rate of the high-skilled relative to the low-skilled, and further decrease the sensitivity of high-skilled workers to cyclical patterns.

Additional research is needed into the relationship between job search and migration, both theoretically and empirically.

On the theoretical side, the search literature has tended to ignore the relationship between job-search and migration. Even models that have allowed for migration have completely overlooked the distinction between migration for the purpose of searching and migration that follows searching (search migration vs. job migration, in the language used here). Incorporating these different search technologies into a search model could reveal interesting implications. The model presented here took job location as exogenous and examined workers' best response, but if firms take workers' incentives into account in their location decision, these incentives may be exacerbated by the endogenous determination of firm location.

Empirically, this paper raises questions that cannot be addressed with existing data. Because only a fraction of those who search for a job before they move (global searchers) are observed as moving suggests that observed differences in migration rates across educational groups mask even larger differences in *willingness to move* that are not captured in the data. The degree of this bias cannot be established from the available data, since we do not know what fraction of global searchers in each education category find a job in another region. Current data also do not allow us to distinguish between workers who search globally and workers who search in a specific destination region prior to migration – either because they are engaged in on-the-job search or because they hope to bargain over moving costs. To address these issues we need data on the geographic scope of job-search.

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# A Data Appendix

## A.1 Allocated Values

As mentioned in Section 3, missing data in the CPS are replaced by allocated values, which are generated from other ("similar") records. Unfortunately, records with altered or imputed data were not properly flagged by the Census Bureau before 1995. One variable that is particularly susceptible to allocation is the migration variable. Table 16 lists the number of records with an allocated migration status for each year, their relative weight in the sample, and the propensity of allocated records to be coded as migrations. Beginning with the 1996 survey, over a thousand observations annually are allocated, and the fraction of these observations that are assigned migrant status increases sharply over time, to nearly 60% by the 2001 survey.[34]

## A.2 1988 Processing Changes

Following a change in the CPS processing system in 1988, the 1988 survey data were re-released, having been processed using the new system. There are therefore two files containing 1988 data, the first of which was used by the Census Bureau to produce their reports, and the second, known as the "bridge" file (or, alternatively, as the 1988 rewrite file or the 1988B file), intended to facilitate comparisons to subsequent years. Since the input data – the pool of respondents, the survey questions and answers – are identical across the two 1988 files, one should in principle be able to use either one for analysis. Unfortunately, these processing changes were not completely benign. Among the changes made in the re-processing were changes to the imputation procedures for missing data (Bureau of the Census 1991).

While the demographic characteristics of respondents (age, sex, occupation, marital status, and race) are statistically indistinguishable across the two files, as seen in Table 17, migration data are disconcertingly different in these two

[34] Allocation flags were not included in the data prior to the 1988 bridge file.

surveys, by a statistically significant margin. Note that the p-value is given here only as a reference, since the differences between the two data sets are all due to imputation. As these are not actually two separate samples, it is not clear what interpretation, if any, a t-test can be given in this case.

The change in the migration estimation is due to 445 records which were coded as movers in one file but as non-movers in the other. These include 116 that were coded as movers in the original file (but not in the bridge file), and another 329 that were coded as movers in the bridge file (but not in the original file). A frightening 684 additional records are coded as migrants in both files, but their state of origin differs across files. According to the Census Bureau, these changes had the effect of "making migration recodes [*sic*] more consistent with residence fields" (US Census Bureau 1991). In the data analysis I rely exclusively on the bridge file for 1988 data (1988B), in the hope that the processing changes improved the data quality.

Table 6: Intrastate (Inter-County) Migration Statistics

| | All Movers[b] | HS Dropouts | HS Grads | Some College | College Grads + |
|---|---|---|---|---|---|
| *Panel A: Probability of intrastate move, 1981-2000*[a] | | | | | |
| | 3.37% | 3.01% | 2.97% | 3.62% | 3.83% |
| *Panel B: Main Reason for Move among Movers, 1997-2000*[b,c] | | | | | |
| New job / job transfer | 18.28% | 11.86% | 11.63% | 18.72% | 24.33% |
| Looking for work / lost job | 2.22% | 5.77% | 3.13% | 2.12% | 0.79% |
| Other job-related reason[d] | 11.14% | 11.97% | 10.26% | 11.45% | 11.33% |
| Non-job related reason[e] | 68.36% | 70.39% | 74.99% | 67.71% | 63.55% |

[a] Conditional on no interstate move

[b] May not add to 100% due to rounding

[c] Includes only movers whose moving status and reason for moving are not imputed

[d] Includes retirement, easier commute, and miscellaneous job-related reasons

[e] Includes family reasons (e.g., move for spouse), health reasons, etc.

Source: Author's calculations from CPS, 1997-2000

Table 7: Multinomial Logit Estimates: Simultaneous Determination of Interstate and Intrastate Migration

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| Variable | Intra | Inter | Intra | Inter | Intra | Inter |
| Male | 9.866 | 8.277 | 16.016 | 22.654 | 16.076 | 23.923 |
| | (1.077) | (1.147) | (1.122) | (1.208) | (1.111) | (1.196) |
| White | 8.210 | -1.526 | 9.432 | 1.313 | 8.928 | 1.472 |
| | (2.576) | (2.699) | (2.583) | (2.713) | (2.582) | (2.710) |
| High School | -3.819 | -0.573 | 1.703 | 11.862 | 2.008 | 13.225 |
| Diploma Exactly | (2.627) | 2.915 | (2.635) | (2.945) | (2.633) | (2.941) |
| Some College, | 10.571 | 19.392 | 17.537 | 35.064 | 18.190 | 37.511 |
| No Degree | (2.728) | (2.024) | (2.739) | (2.063) | (2.738) | (2.063) |
| College Degree | 19.865 | 55.598 | 28.758 | 76.167 | 29.457 | 78.881 |
| or Beyond | (2.753) | (2.067) | (2.780) | (3.030) | (2.775) | (3.022) |
| Weeks Worked | | | -1.610 | -3.158 | | |
| Last Year (Number) | | | (0.053) | (0.047) | | |
| Worked 50+ Weeks | | | | | -50.030 | -109.98 |
| Last Year (Indicator) | | | | | (1.564) | (1.590) |
| $\chi^2_{(3)}$: equality of ed coeffs | 158.32 | 849.82 | 222.86 | 1,179 | 231.35 | 1,241 |
| within migration type | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| $\chi^2_{(3)}$: equality of ed coeffs | 176.15 | | 242.59 | | 257.60 | |
| across migration types | 0.0000 | | 0.0000 | | 0.0000 | |
| Age Fixed Effects | Y | | Y | | Y | |
| Origin State FE | Y | | Y | | Y | |
| Year Fixed Effects | N | | N | | N | |

Notes: 944,061 observations used. Standard errors are clustered at the household level. All coefficients are multiplied by 100.

Table 8: Unemployment Rate Arbitrage by Migrants' Education

| | Fraction Moving to States with Lower... | |
|---|---|---|
| | Unemployment Rate | Education*UE Rate |
| All Movers | 53.58% | 52.51% |
| HS Dropouts | 57.57% | 54.59% |
| HS Graduates | 54.28% | 54.20% |
| Some College | 53.19% | 52.81% |
| College Grads + | 52.01% | 50.49% |

Source: Author's calculations from CPS, 1981-2000

Table 9: Arbitrage Regression Estimates

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Arbitrage | 6.398 | 4.768 | 4.533 | 6.582 | 5.024 | 4.825 |
| Opportunity | (2.458) | (2.357) | (2.264) | (1.994) | (1.895) | (1.827) |
| Weeks Worked | | -0.074 | | | -0.075 | |
| Last Year (Number) | | (0.002) | | | (0.002) | |
| Worked 50+ Weeks | | | -3.185 | | | -3.212 |
| Last Year (Indicator) | | | (0.096) | | | (0.093) |
| Year FE | N | N | N | Y | Y | Y |

Notes: 944,061 observations used. Regressions include all controls from Table 3. Standard errors are clustered at the state level. All coefficients are multiplied by 100.

Table 10: Cyclicality of Migration by Education Category

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Unemp Variable | US Average | | | US Average by Education | | |
| High School | -8.889 | -14.531 | -15.869 | -4.370 | -7.750 | -8.553 |
| Dropout | (0.525) | (0.635) | (0.600) | (0.317) | (0.396) | (0.362) |
| High School | -10.491 | -14.925 | -16.104 | -9.063 | -12.690 | -13.588 |
| Graduate | (0.580) | (0.696) | (0.550) | (0.453) | (0.548) | (0.431) |
| Some College, | -1.769 | -6.056 | -7.409 | -4.328 | -9.095 | -10.540 |
| No Degree | (0.820) | (0.948) | (0.847) | (0.854) | (0.987) | (0.874) |
| College Degree | 1.315 | -1.107 | -1.686 | 5.059 | -0.062 | -2.062 |
| or Beyond | (0.786) | (0.856) | (0.830) | (1.309) | (1.467) | (1.397) |
| Weeks Worked | | -0.076 | | | -0.076 | |
| Last Year (Number) | | (0.003) | | | (0.003) | |
| Worked 50+ Weeks | | | -3.249 | | | -3.247 |
| Last Year (Indicator) | | | (0.159) | | | (0.161) |
| $\chi^2_{(3)}$ test for equality | 441,286 | 26,992 | 149,981 | 7,208 | 17,500 | 8,788 |
| of interaction terms | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Notes: 944,061 observations used. Regressions include all controls from Table 3. Standard errors are clustered at the education-category level. All coefficients are multiplied by 100.

Table 11: Unemployment Rate Arbitrage by Migration Type

| | Fraction Moving to States with Lower... | |
|---|---|---|
| | Unemployment Rate | Education*UE Rate |
| All Movers | 52.73% | 52.28% |
| Job Movers | 48.64% | 50.88% |
| Search Movers | 62.62% | 58.86% |

Source: Author's calculations from CPS, 1997-2000

Table 12: Regression Results for Job-Mover Characteristics

| Variable | (1) J | (1) S | (1) O | (2) J | (2) S | (2) O |
|---|---|---|---|---|---|---|
| Male | 26.080 | 42.227 | -9.646 | 37.236 | 71.630 | 9.344 |
| | (4.246) | (14.107) | (4.460) | (4.396) | (15.043) | (4.659) |
| White | 40.903 | -5.859 | 0.695 | 42.250 | 2.811 | 3.893 |
| | (11.277) | (27.464) | (9.242) | (11.276) | (27.747) | (9.277) |
| High School Diploma Exactly | 40.514 | -2.609 | 18.903 | 49.605 | 17.007 | 34.487 |
| | (17.644) | (25.640) | (12.203) | (17.692) | (26.339) | (12.335) |
| Some College, No Degree | 82.300 | -17.179 | 31.202 | 93.603 | 5.908 | 50.582 |
| | (17.268) | (29.410) | (12.339) | (17.363) | (29.918) | (12.492) |
| College Degree or Beyond | 176.030 | -100.561 | 46.977 | 190.083 | -68.792 | 71.254 |
| | (16.753) | (31.789) | (12.422) | (16.909) | (32.679) | (12.668) |
| Weeks Worked Last Year (Number) | | | | -2.737 | -5.385 | -4.056 |
| | | | | (0.191) | (0.465) | (0.165) |
| $\chi^2_{(3)}$: equality of ed coeffs within migration reason | 350.06 | 15.46 | 21.12 | 373.21 | 11.03 | 41.14 |
| | 0.0000 | 0.0015 | 0.0001 | 0.0000 | 0.0116 | 0.0000 |
| $\chi^2_{(3)}$: equality of ed coeffs across migration reasons[a] | | 87.90 | | | 78.67 | |
| | | 0.0000 | | | 0.0000 | |
| Age Fixed Effects | | Y | | | Y | |
| Year Fixed Effects | | N | | | N | |
| Origin State FE | | Y | | | Y | |
| Observations | | 189,543 | | | 189,543 | |

Notes: Standard errors are clustered at the household level. All coefficients are multiplied by 100.
[a] Test is for equality of education coefficients across job and search moves only.

Table 13: Regression Results for Job-Mover Characteristics

| | (1) | | | (2) | | |
|---|---|---|---|---|---|---|
| Variable | J | S | O | J | S | O |
| Male | 26.227 | 43.422 | -10.295 | 37.348 | 73.683 | 9.008 |
| | (4.280) | (14.695) | (4.496) | (4.431) | (15.350) | (4.708) |
| White | 41.562 | -13.881 | -1.862 | 43.021 | -5.290 | 1.323 |
| | (11.448) | (26.081) | (9.180) | (11.454) | (26.483) | (9.219) |
| High School | 39.803 | -1.737 | 19.427 | 48.886 | 18.252 | 35.341 |
| Diploma Exactly | (17.664) | (26.518) | (12.265) | (17.713) | (27.213) | (12.394) |
| Some College, | 80.182 | -13.208 | 32.550 | 91.406 | 10.712 | 52.216 |
| No Degree | (17.311) | (29.828) | (12.402) | (17.406) | (30.258) | (12.548) |
| College Degree | 175.735 | -100.435 | 47.576 | 189.698 | -68.120 | 72.182 |
| or Beyond | (16.751) | (32.546) | (12.505) | (16.916) | (33.293) | (12.748) |
| Weeks Worked | | | | -2.722 | -5.443 | -4.095 |
| Last Year (Number) | | | | (0.194) | (0.467) | (0.165) |
| Arbitrage | -281.173 | -928.339 | 970.262 | -295.544 | -967.794 | 948.820 |
| Opportunity | (475.064) | (1680.01) | (467.447) | (4.753) | (1660.08) | (469.582) |
| $\chi^2_{(1)}$: equality of | | 0.14 | | | 0.15 | |
| arbitrage coeffs[a] | | 0.7109 | | | 0.6969 | |
| Age Fixed Effects | | Y | | | Y | |
| Year Fixed Effects | | N | | | N | |
| Origin State FE | | Y | | | Y | |
| Observations | | 185,265 | | | 185,265 | |

Notes: Standard errors are clustered at the household level. All coefficients are multiplied by 100.
[a] Test is for equality of arbitrage coefficients across job and search moves only.

Table 14: Regression Results for Simultaneous Choice of Move Distance and Reason

| Variable | Intra-J | Intra-S | Intra-O | Inter-J | Inter-S | Inter-O |
|---|---|---|---|---|---|---|
| Male | 36.894 | 102.123 | 13.653 | 37.484 | 72.003 | 9.857 |
| | (6.619) | (20.995) | (3.285) | (4.365) | (15.126) | (4.659) |
| White | 42.755 | 43.163 | 3.554 | 43.408 | 2.837 | 7.096 |
| | (15.498) | (39.453) | (6.773) | (10.806) | (25.864) | (8.841) |
| High School | 13.086 | -27.524 | 4.154 | 54.842 | 22.752 | 38.674 |
| Diploma Exactly | (21.657) | (30.378) | (8.239) | (17.703) | (26.636) | (12.331) |
| Some College, | 80.907 | -43.031 | 21.168 | 99.072 | 19.129 | 56.292 |
| No Degree | (21.284) | (36.691) | (8.345) | (17.378) | (30.473) | (12.443) |
| College Degree | 132.052 | -113.859 | 34.038 | 196.150 | -57.507 | 76.803 |
| or Beyond | (21.086) | (45.201) | (8.537) | (16.856) | (32.810) | (12.590) |
| Weeks Worked | -2.640 | -5.349 | -1.606 | -2.819 | -5.420 | -4.159 |
| Last Year | (0.297) | (0.647) | (0.173) | (0.189) | (0.446) | (0.163) |
| $\chi^2_{(3)}$: equality of | | 33.53 | | | 76.33 | |
| education coeffs[a] | | 0.0000 | | | 0.0000 | |

Notes: Standard errors are clustered at the household level. All coefficients are multiplied by 100. Regression includes 6 age and 5 region fixed effects. 189,543 observations.

[a] Test is for equality of coefficients across job and search moves only.

Table 15: Employment Probability for Migrant Sub-Sample

| | All Movers | | Men Only | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Job Mover | 16.091 | 16.098 | 13.229 | 12.973 |
| | (4.369) | (4.319) | (4.237) | (4.228) |
| Male | 18.280 | 18.379 | | |
| | (1.947) | (1.942) | | |
| White | -1.221 | -1.159 | -0.372 | -0.210 |
| | (2.724) | (2.792) | (2.631) | (2.649) |
| High School Diploma Exactly | 0.652 | 0.467 | 0.243 | 1.647 |
| | (3.703) | (3.752) | (2.940) | (2.915) |
| Some College, No Degree | 1.184 | 1.105 | 1.422 | 1.299 |
| | (3.749) | (3.761) | (2.672) | (2.654) |
| College Degree or Beyond | 3.482 | 3.306 | 3.239 | 3.053 |
| | (3.877) | (3.879) | (3.190) | (3.110) |
| $\chi^2_{(3)}$ test for equality of | 2.26 | 2.16 | 2.51 | 2.39 |
| education coefficients | 0.5203 | 0.5400 | 0.4734 | 0.4959 |
| Age Fixed Effects | 6 | 6 | 6 | 6 |
| Year Fixed Effects | N | Y | N | Y |
| Sex Composition | M & F | | M only | |
| Observations | 1861 | 1861 | 1088 | 1088 |

Notes: Standard errors are clustered at the household level.
All coefficients are multiplied by 100.

Table 16: Allocations and Migration in CPS Data

| Survey | Observations | Migration Allocations | Allocation Weight | Allocated Migration[a] |
|---|---|---|---|---|
| 1988B | 66,828 | 0 | 0 | n/a |
| 1989 | 62,477 | 8 | <0.001 | 0 |
| 1990 | 68,121 | 5 | <0.001 | 0 |
| 1991 | 68,341 | 6 | <0.001 | 0 |
| 1992 | 67,613 | 0 | 0 | n/a |
| 1993 | 67,179 | 0 | 0 | n/a |
| 1994 | 63,822 | 5 | <0.001 | 0 |
| 1996 | 55,000 | 1,125 | 0.023 | 0.213 |
| 1997 | 55,666 | 1,217 | 0.025 | 0.228 |
| 1998 | 56,259 | 1,052 | 0.020 | 0.209 |
| 1999 | 56,524 | 1,160 | 0.023 | 0.409 |
| 2000 | 56,718 | 1,149 | 0.022 | 0.561 |
| 2001 | 54,754 | 1,003 | 0.021 | 0.596 |

[a] Fraction of allocated observations that are assigned migrant status

Table 17: Summary Statistics for 1988 Surveys

| Variable (I=Indicator) | Mean 1988[a] | Mean 1988B | p-Value for Equality |
|---|---|---|---|
| Interstate Migration (I) | 0.025 | 0.028 | 0.002 |
| Age | 39.75 | 39.74 | 0.789 |
| Male (I) | 0.487 | 0.486 | 0.845 |
| White (I) | 0.858 | 0.859 | 0.797 |
| High School Dropout (I) | 0.178 | 0.178 | 0.922 |
| High School Graduate (I) | 0.378 | 0.378 | 0.921 |
| Some College, No Degree (I) | 0.215 | 0.215 | 0.905 |
| College Degree or Beyond (I) | 0.229 | 0.229 | 0.930 |
| Observations | 66,504 | 66,828 | |

Notes: Means include past and present DC residents. All means are weighted. Means are reported for non-student civilian adults ages 25-60. Hypothesis tests assume equal variance across surveys.