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**Why are Higher Skilled Workers More Mobile
Geographically? The Role of the Job Surplus**

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Abstract
The skill gap in geographical mobility is entirely driven by workers who report moving for a new job. A natural explanation lies in the large expected surplus accruing to skilled job matches. Just as large surpluses ease the frictions which impede job search in general, they also help overcome those frictions (specifically moving costs) which plague cross-city matching in particular. I reject the alternative hypothesis that mobility differences are driven by variation in the moving costs themselves, based on PSID evidence on self-reported willingness to move. Evidence on wage processes also supports my claims.

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1   Introduction

It has long been known that better educated individuals are more mobile geographically; see Greenwood (1975) for a survey. Recent evidence suggests the effect is causal (Malamud and Wozniak, 2012; Machin, Salvanes and Pelkonen, 2012[1]). Figure 1 plots US cross-county mobility rates for household heads[2], by age[3] and education[4], based on the March waves of the Current Population Survey[5] (CPS). The skill mobility gap is driven by the under-35s; and among this group, college graduates are about one third more mobile than non-graduates.

But, this obscures much starker patterns. Figure 2 shows the gap is entirely driven by workers who report moving county for job reasons. Among those aged 25-34s, 2 percent of high school dropouts make job-motivated moves annually, compared to 7 percent of the postgraduate-educated. There are also positive education effects among older workers. This steep skill gradient is swamped by a large quantity of "non-job" moves[6] (primarily family and housing-related), whose frequency is (if anything) decreasing in education. The fact that low skilled workers so rarely move for job reasons is concerning, given that they suffer disproportionately from local business cycle volatility (Hoynes, 2002).

I argue the obstacle to low skilled mobility is exactly that which impedes low skilled job finding more generally: meager job surpluses (or returns to a match), irrespective of geography. Table 1 confirms that workers with limited education do suffer lower job finding rates.[7] And I claim the impact on *cross-city* job finding is particularly debilitating: the small surpluses in low skilled matches are usually insufficient to fund the cost of migrating. This effect is reinforced by slim investment in cross-city search by both workers and firms, as well as limited job creation. The overall impact is larger for the young, as they make more job transitions.

For the most part, the previous literature has relied on a location choice framework. This yields two possible explanations for the skill mobility gap. Either the low skilled face large moving costs, whether due to financial constraints, lack of information or home attachment (Greenwood, 1973; Topel, 1986; Bound and Holzer, 2000; Wozniak, 2010; Kennan, 2015).[8]

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[1] These studies exploit randomness from the Vietnam war draft in the US and a Norwegian compulsory schooling reform respectively.

[2] In each household, I define the head as the individual with the greatest predicted earnings power. Earnings power is predicted using a Mincer regression of log weekly wages on a detailed set of characteristics (see Appendix A for further details). In households with multiple predicted top-earners, I divide the person weights by the number of top-earners.

[3] I restrict attention to the over-25s. This helps ensure my results are not conflated by individuals leaving college. In any case, I exclude those who explicitly report moving primarily to attend or leave college: these account for 2 percent of the remaining cross-county migrant sample.

[4] I define five education groups: high school dropout (less than 12 years of schooling), high school graduate (12 years of schooling), some college (between 1 and 3 years of college), undergraduate (4 years of college) and postgraduate (5 or more years of college).

[5] I use the March CPS files organized by IPUMS (King et al., 2010).

[6] The prevalence of other reasons for moving is consistent with Yagan's (2014) finding that migration is largely "undirected": a large fraction of migrants do *not* move to cities with better employment opportunities.

[7] The difference is moderate among the unemployed, as documented by e.g. Mincer, 1991, and more substantial among the inactive.

[8] Gregg, Machin and Manning (2004) suggest that college graduates have weaker home attachment, having

Or they face narrow geographical differentials in expected disposable income, whether due to transfer payments and housing costs (Notowidigdo, 2011) or labor productivity (Lkhagvasuren, 2014; Davis and Dingel, 2012). See also Moretti (2011) for a survey.

My hypothesis also emphasizes the role of productivity and out-of-work income. But, I consider migration in the context of broader job search. This approach follows an early study by Schwartz (1976), later echoed by Wildasin (2000). Given the specialized skills of better educated workers, they argue both applicants and recruiters *search in more locations* (including their own) for the ideal match. This is irrespective of any complementarities between particular skills and locations.

I build on these ideas in two ways. First, I study these processes using an equilibrium model[9]. This yields new insights. Rather than just emphasizing match dispersion in productivity (or skill specialization), the model show it is the expected job surplus more generally which matters. In particular, the average productivity of labor (relative to out-of-work income) and job tenure are also important contributors to the expected surplus and therefore mobility (Table 1 documents a steep negative skill gradient in separation rates; see also Mincer, 1991). This point illustrates the common determinants of immobility and joblessness. My second contribution is to test the mechanisms outlined in the model using new empirical evidence.

The model is a multi-city version of the Diamond-Mortensen-Pissarides framework set out in Pissarides (2000). There are many identical cities, each with its own matching function over local unemployed workers and vacancies. But, workers and firms can also participate in a *national* matching function involving agents in *all* cities: this is the source of migration. Once a match is made (in either market), a random productivity parameter is drawn independently of geography; and the match is consummated if both parties accept. Importantly, workers pay a fixed matching cost (or "migration cost") on accepting a national market job offer.

While matching is random within markets, search is somewhat directed: workers and firms choose how intensively they search (or advertise) in both the local and national market. Local markets are effectively integrated geographically, with the extent of this integration driven by the national search intensity, which itself is endogenously determined. This set-up contrasts with Moen's (1997) textbook directed search model, which restricts agents' search activities to a *single* submarket (there is no national market). The same can be said of the competitive model of urban labor markets developed by Roback (1982). There also, workers are restricted to operating in one of many *distinct* local labor markets, with migration interpreted as "spatial arbitrage" between them. Molho (2001) makes a similar point.[10]

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already left home to study, though Malamud and Wozniak (2012) dispute this hypothesis. Both these studies propose that long-distance job search is more costly for lower skilled workers, whether due to a lack of information or fewer social contacts in other cities. In addition to these ideas, Bound and Holzer (2000) suggest a lack of assets may constrain the set of location choices, especially if house prices are higher in desirable cities.

[9]Schwartz (1976) does not present an equilibrium model, and Wildasin's (2000) argument is descriptive.

[10]Recent work by Beaudry et al. (2012; 2014*a*; 2014*b*) has integrated job matching into urban frameworks, with each city having its own matching function. But, they do not allow for matching across cities. In contrast, Jackman and Savouri (1992) argue that internal migration should be interpreted as cross-city job matching. More

I do not include multiple skill groups in the model. Instead, I explore the effects of changing key parameters on the cross-city mobility of homogeneous workers. The model offers two explanations for the skill mobility gap. Either skilled workers face lower cross-city matching costs. Or larger job surpluses facilitate more cross-city matching, despite prohibitive moving costs. Larger surpluses arise in the model from higher average productivity (relative to out-of-work income), larger dispersion in match quality, or a lower separation rate.

On assuming identical cities, notice I rule out the possibility that the mobility gap is driven by large net flows of skilled workers to particular locations.[11] I show in Appendix A that this is consistent with the evidence: even in comparisons across detailed occupation groups, net flows across states in (self-reported) job-motivated migration vary little with skill level.[12] For example, net flows of bankers across states are not much greater than net flows of hairdressers.

It is notoriously difficult to evaluate the role of moving costs in the skill mobility gap, and the debate in the literature attests to this. Some studies have inferred moving costs in different skill groups from a structural model, whether by estimation (Kennan, 2015) or calibration (Lkhagvasuren, 2014). I take an alternative approach, imputing moving costs directly from subjective responses in the Panel Study of Income Dynamics (PSID).

In the 1970s, the PSID asked respondents whether they would move away for the sake of a "good" job. 50 percent of employed and 73 percent of unemployed workers answered yes, and these fractions vary little with education. Among those answering yes, the PSID asked for the lowest wage offer which would tempt them to move. I impute migration costs by taking the difference between this wage and the average wage the worker earned through the previous year. Again, it turns out this imputed cost varies little with education. Of course, this exercise is only valuable if these subjective responses are informative about true costs; and I show they do have explanatory power for future migration decisions. Also, I find no evidence that lower skilled workers systematically overstate the likelihood of a job-motivated move.

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recently, Manning and Petrongolo (2011) have studied the geographical extent of labor markets, using a model where workers simultaneously apply to jobs in multiple locations. Using British data from public employment agencies on applicants and vacancies, they find that labor markets are very local: the utility of job offers declines exponentially at around 0.3km from a worker's residence. But, they argue higher skilled markets are likely to be broader. Marinescu and Rathelot (2014) estimate the model using job application data from the US. Also, Lutgen and der Linden (2013) have developed a cross-city search model to explore the implications of more efficient online job search.

[11]Such a view might sit comfortably with evidence on various agglomeration effects. For example, Wheeler (2001) argues that skilled workers benefit from larger urban wage premia arising from market size externalities and complementarities in production. Costa and Kahn (2000) suggests instead that large cities offer better opportunities to college educated couples (it is more likely that both spouses will find a good job match). And Diamond (2013) argues that college graduates are attracted by the amenities (such as better schools and low crime) which endogenously arise in skill-intensive cities.

[12]It has long been known that gross migration flows dominate net flows across locations (Shryock, 1959; Schwartz, 1971; Jackman and Savouri, 1992; Wildasin, 2000; Coen-Pirani, 2010). Indeed, this fact is central to Wildasin's contention that migration is driven primarily by the specializations of *individual* workers and firms: these idiosyncratic matches dominate aggregate adjustments between local areas. It has also been documented that the ratio of net to gross migration is smaller for better educated individuals (Folger and Nam, 1967; Schwartz, 1971; Lkhagvasuren, 2014). In Appendix A, I show this result is driven by job-motivated migration in particular, and it also holds for comparisons across detailed occupation groups (not just broad education groups).

If moving costs do not account for the mobility gap, what does? The PSID also asked whether there were better jobs available in other cities. Higher skilled workers were more likely to say yes; and fewer of them reported not knowing. This suggests skilled mobility is driven by greater availability of valuable job matches *and* better information on these matches: these are corollaries of larger surpluses in the model. Indeed, I present more direct evidence in Appendix B of intensive (and geographically broader) search by firms and workers in skilled markets, based on employer and labor force surveys respectively. And I also show that vacancy-unemployment ratios tend to be larger.

While job surplus cannot be observed directly, it can be inferred from the dispersion of wages accepted by an individual over time. Using the Survey of Income and Program Participation (SIPP), Fitzgerald (1999) shows that skilled workers are indeed subject to larger innovations in hourly wages[13]; and I report similar findings below. I also attempt a simple calibration exercise: given the distribution of imputed moving costs from the PSID, my estimates of skill differences in expected surplus are of sufficient magnitude to explain the skill mobility gap.

Advocates of cost-based explanations for the mobility gap have often emphasized evidence of a spatially inelastic supply of low skilled labor. In particular, Bound and Holzer (2000), Wozniak (2010), Notowidigdo (2011) and Amior and Manning (2014) find that the low skilled are less likely to leave their city following a slump in local demand.[14] This view is also supported by results from Kennan (2015). On estimating a dynamic structural model of migration[15], he finds that much of the observed mobility gap is not explained by geographical wage dispersion, whether aggregate-level or individual-specific. His model assigns the residual to unspecified "costs".

But, these findings are not at odds with my claims: my definition of "moving costs" is somewhat limited. For example, Gregg, Machin and Manning (2004) and Malamud and Wozniak (2012) argue that cross-city job search is more costly for the low skilled. But, I exclude these "information costs" from my moving cost definition. Rather, I interpret such frictions as an endogenous response to a small expected surplus, mediated by meager investment by firms in long-distance advertising. Fundamentally, it is the small gains to employment (irrespective of geography) which discourage low skilled workers from leaving cities suffering local shocks. I show how this result can be derived from my model.

One particular piece of evidence, relating to speculative migration, lends credibility to this emphasis on search intensity. In the main exposition of the model, I rule out the possibility

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[13]This finding is not well known, because much of the literature on earnings processes has focused on monthly or annual earnings, rather than hourly wages. As it happens, there is little systematic effect of skill on the volatility of monthly earnings.

[14]Topel (1986) and Bound and Holzer (2000) suggest this explains the large local wage volatility suffered by the low skilled (as documented by Hoynes, 2002). And Gregg, Machin and Manning (2004) relate this inelastic supply to the large local differentials in low skilled jobless rates.

[15]The model is based on Kennan and Walker (2011), who use it to measures the responsiveness of cross-state migration to expected gains in lifetime income.

of moving to look for work without a job in hand. Given the risk involved (as Molho, 2001, emphasizes), such speculative moves only account for 3 percent of cross-county migration.[16] But, despite the steep skill gradient in job-motivated migration in Figure 2 (largely driven by moves for *specific* jobs), the lower skilled are *more* likely to make speculative moves. As I show in an extension to the model in Appendix C, this is a natural consequence of a small expected surplus and meager investment in cross-city search. Given the poor integration of national markets, the low skilled are forced into this risky strategy.

The key point is that low skilled immobility is less a *cause* of joblessness, and more a *symptom* of the low returns to work associated with limited human capital. This matters for the policy debate, given growing calls for relocation assistance for the unemployed (see e.g. Ludwig and Raphael, 2010; Moretti, 2012).

In the following section, I set out my cross-city matching model. And in Section 3, I show how match productivity and the job separation rate affect cross-city mobility and other outcomes of interest. As I show in Section 4, there is little support in the PSID for claims that moving costs vary by skill. But, wage processes from the SIPP are consistent with large skilled job surpluses. I also document the evidence on speculative job moves; and I argue the negative skill gradient in non-job motivation (illustrated in Figure 2) casts further doubt on the moving costs explanations. I conclude in Section 5.

2 Model

2.1 Overview

I set the model in continuous time. The economy consists of a measure 1 of workers and J identical cities, where J is large. Each worker is characterized by an "origin city", with an equal measure of workers assigned to each city. These origins determine workers' access to local job markets, as I explain below. Origins are fixed, irrespective of migration histories.

Workers are either employed or unemployed, and the latter receive a flow utility b. For simplicity, I assume that only the unemployed search for work. But, I sketch an extension with on-the-job search in Appendix C: the key results are unaffected. Firms are homogeneous and are free to open vacancies in any city. Each firm employs a single worker to produce a single output good, with price normalized to 1.

There are two frictions which impede job matching. The first is the cost of search. In this model, agents can engage in both local and national search. There are $J+1$ job markets, each characterized by a distinct Cobb-Douglas matching function: J local markets and one national market. Only workers of origin j and local firms have access to city j's local market; but all agents have access to the national market. Unemployed workers of origin j choose local and national search intensities s_{Lj} and s_{Nj}, at a cost $\frac{1}{2}\gamma_{sX}s_{Xj}^2$ in market $X = \{L,N\}$. And similarly,

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[16]Based on the March CPS between 1999 and 2013.

firms choose advertising intensities a_{Lj} and a_{Nj}, at a cost $\frac{1}{2}\gamma_{aX}a_{Xj}^2$. I allow the search cost parameters γ_{sX} and γ_{aX} to vary by agent type and market X[17], though this is unnecessary for the main results. Notice that an origin j worker and a firm located in j can meet through *both* the local and the national market. But, since there are many cities, the likelihood of the latter is negligible.

The second friction is a matching cost $m > 0$, paid by workers on acceptance of a *national* market match. Assuming there is no cross-city commuting, m can be interpreted as a one-off moving expense. Once a worker loses his job, he returns to his origin city at no cost.

When a worker and firm are matched, a productivity y is drawn from some distribution F, where F is independent of city. Matches are consummated if the job surplus exceeds zero, and the wage is set according to a Nash bargain.[18] Matches are separated at an exogenous rate δ, though I show in Appendix C that the key results are merely reinforced if δ is endogenous.

2.2 Matching

The flow of matches in the national market is:

$$z\left(\bar{s}_N u, \bar{a}_N v\right) = \left(\bar{s}_N u\right)^\alpha \left(\bar{a}_N v\right)^{1-\alpha} \tag{1}$$

where u and v are the total measure of unemployed workers and vacancies, and $\bar{s}_N$ and $\bar{a}_N$ are the average national search and advertising intensities. This approach of integrating search and advertising intensity into the matching function follows Pissarides (2000): the two arguments of z represent the aggregate search intensity of workers and firms respectively.

The local matching function in city j is identical:

$$z\left(\bar{s}_{Lj} u_j, \bar{a}_{Nj} v_j\right) = \left(\bar{s}_{Nj} u_j\right)^\alpha \left(\bar{a}_{Nj} v_j\right)^{1-\alpha} \tag{2}$$

where u_j is the stock of origin j workers and v_j the stock of local vacancies. $\bar{s}_{Lj}$ and $\bar{a}_{Lj}$ are the average local search and advertising intensities, among city j's workers and firms. Since cities are identical, $u_j = \frac{u}{z}$, $v_j = \frac{v}{z}$, $\bar{s}_{Lj} = \bar{s}_L$ and $\bar{a}_{Lj} = \bar{a}_L$ for all j.

And so, per unit of search in market $X = \{L,N\}$, the matching rates for workers and firms are $\left(\frac{\bar{a}_X}{\bar{s}_X}\theta\right)^{1-\alpha}$ and $\left(\frac{\bar{a}_X}{\bar{s}_X}\theta\right)^{-\alpha}$ respectively, where $\theta = \frac{v}{u}$ denotes the market tightness.

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[17]For example, search might be more costly in the national market because of costly travel and costly advertising in national media outlets.

[18]The precise rent sharing rule is not important, as long as both wages and profits are increasing in job surplus: this ensures that both workers and firms invest resources in search effort.

2.3 Worker and firm values

Let U_j be the unemployment value of workers of origin j. Given the symmetry of the model, $U_j = U$ for all j.[19] Specifically:

$$rU = b + \sum_{X=\{L,N\}} \max_{s_X} \left\{ s_X \left(\frac{\bar{a}_X}{\bar{s}_X} \theta \right)^{1-\alpha} \hat{U}_X - \frac{1}{2} \gamma_{sX} s_X^2 \right\} \tag{3}$$

where, for each market $X = \{L,N\}$, workers choose the optimal search intensity s_X. Assuming cities are large, workers take the average search intensity $\bar{s}_X$ as given. r is the discount rate, and $\hat{U}_X$ is the expected value to the worker (before the match quality is revealed) of a match in market X. Specifically:

$$\hat{U}_X = \int_y \max \left\{ E_X(y) - U - m_X, 0 \right\} dF \tag{4}$$

On discovering the productivity of a type X match, the worker accepts if $E_X(y) - U \geq m_X$, where E_X is the employment value and m_X is the matching cost. As described above, $m_L = 0$ for local matches, and $m_N = m > 0$ for national matches. The employment value is:

$$rE_X(y) = w_X(y) + \delta(U - E_X(y)) \tag{5}$$

where $w_X(y)$ is the negotiated wage, given match type X and a productivity draw of y. This equation also accounts for the expected loss of value from a random job separation, arriving at rate δ.

The problem faced by firms is similar. Unlike workers though, firms choose the city j that yields the largest vacancy value:

$$V = \max_j V_j \tag{6}$$

In a spatial equilibrium, $V_j = V$ for all j, where:

$$rV = \sum_{X=\{L,N\}} \max_{a_X} \left\{ a_X \left(\frac{\bar{a}_X}{\bar{s}_X} \theta \right)^{-\alpha} \hat{V}_X - \frac{1}{2} \gamma_{aX} a_X^2 \right\} \tag{7}$$

The intuition is identical to above: for each market X, firms choose the optimal advertising intensity a_X. Assuming cities are large, firms take the average advertising intensity $\bar{a}_X$ as given. $\hat{V}_X$ is the expected value to the firm of a match in market X, where:

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[19]I do not grant workers a choice over origin cities. But despite this, the value of unemployment is still invariant across origins in equilibrium (because of the symmetry of the model). Consequently, an equilibrium with $U_j = U$ would still exist if I allowed workers to choose their origin. But, that equilibrium would be unstable because workers and firms would be better off if they all clustered at a single location, minimizing search and matching costs. In this framework, I could ensure stability by incorporating diminishing returns to locations (whether through the local production function, congestion externalities or imperfectly elastic housing supply). But since this is not my focus, I keep the model simple and assume fixed origins.

$$\hat{V}_X = \int_y \max\{J_X(y) - V, 0\} \, dF \qquad (8)$$

The match is consummated if $J_X(y) \geq V$. The value of a filled job $J_X(y)$ varies with market X, because the wage bargain is affected by the matching cost:

$$rJ_X(y) = y - w_X(y) + \delta(V - J_X(y)) \qquad (9)$$

The intuition behind this equation is identical to (5). Conditional on the draw of y, I define the match surplus gross of the matching cost as:

$$\begin{aligned} S(y) &= E_X(y) - U + J_X(y) - V \\ &= \frac{1}{r+\delta}(y - rU - rV) \end{aligned} \qquad (10)$$

A match in market X is accepted if $S(y) \geq m_X$, or equivalently if $y \geq \tilde{y}_X$, where:

$$\tilde{y}_X = rU + rV + (r+\delta)m_X \qquad (11)$$

If so, the surplus net of the matching cost is shared according to a Nash bargain:

$$E_X(y) - U - m_X = \phi[S(y) - m_X] \qquad (12)$$

where ϕ denotes the bargaining power of workers. The equilibrium wage can be derived by substituting equation (5) for $E_X(y)$ in the Nash bargain:

$$w_X(y) = \phi(y - rV) + (1 - \phi)(m_X + rU) \qquad (13)$$

2.4 Search effort choices

For market X, the first order conditions for search and advertising intensity are:

$$s_X = \frac{\phi}{\gamma_{sX}}\left(\frac{\bar{a}_X}{\bar{s}_X}\theta\right)^{1-\alpha}\int_y \max\{S(y) - m_X, 0\} \, dF \qquad (14)$$

and

$$a_X = \frac{1-\phi}{\gamma_{aX}}\left(\frac{\bar{a}_X}{\bar{s}_X}\theta\right)^{-\alpha}\int_y \max\{S(y) - m_X, 0\} \, dF \qquad (15)$$

respectively. Clearly, search and advertising intensity are larger in local markets. This is because (1) the search cost is smaller ($\gamma_{sL} < \gamma_{sN}$ and $\gamma_{aL} < \gamma_{aN}$) and (2) no matching cost m is paid.

In equilibrium, all workers and firms choose the same search and advertising intensities, so

$\bar{s}_X = s_X$ and $\bar{a}_X = a_X$. The first order conditions then yield a simple expression for the relative search effort of workers and firms:

$$\frac{s_X}{a_X} = \sqrt{\frac{\phi}{1-\phi} \frac{\gamma_{aX}}{\gamma_{sX}} \theta} \tag{16}$$

This varies with market X if either workers or firms have a comparative advantage in national search. Substituting this back into the first order conditions yields:

$$s_X = \frac{\phi}{\gamma_{sX}} \left(\frac{1-\phi}{\phi} \frac{\gamma_{sX}}{\gamma_{aX}} \theta \right)^{\frac{1-\alpha}{2}} \int_y \max \{S(y) - m_X, 0\} \, dF \tag{17}$$

and

$$a_X = \frac{1-\phi}{\gamma_{aX}} \left(\frac{1-\phi}{\phi} \frac{\gamma_{sX}}{\gamma_{aX}} \theta \right)^{-\frac{\alpha}{2}} \int_y \max \{S(y) - m_X, 0\} \, dF \tag{18}$$

Also, notice that applying the first order conditions to equation (3) gives:

$$rU = b + \frac{1}{2} \left(\frac{1-\phi}{\phi} \theta \right)^{1-\alpha} \sum_{X=\{L,N\}} \frac{1}{\gamma_{sX}^{\alpha} \gamma_{aX}^{1-\alpha}} \left[\phi \int_y \max \{S(y) - m_X, 0\} \, dF \right]^2 \tag{19}$$

in equilibrium. Similarly, applying them to (7):

$$rV = \frac{1}{2} \left(\frac{1-\phi}{\phi} \theta \right)^{-\alpha} \sum_{X=\{L,N\}} \frac{1}{\gamma_{sX}^{\alpha} \gamma_{aX}^{1-\alpha}} \left[(1-\phi) \int_y \max \{S(y) - m_X, 0\} \, dF \right]^2 \tag{20}$$

And combining equations (19) and (20):

$$\frac{rU - b}{rV} = \frac{\phi}{1-\phi} \theta \tag{21}$$

where the ratio of the unemployment to vacancy value is increasing in market tightness θ.

2.5 Job finding and migration rates

Let ρ be the job finding rate. This can be decomposed into local and national components: $\rho = \rho_L + \rho_N$, where:

$$\begin{aligned} \rho_X &= s_X \left(\frac{a_X}{s_X} \theta \right)^{1-\alpha} [1 - F(\tilde{y}_X)] \tag{22} \\ &= \frac{\phi}{\gamma_{sX}^{\alpha} \gamma_{aX}^{1-\alpha}} \left(\frac{1-\phi}{\phi} \theta \right)^{1-\alpha} \int_y \max \{S(y) - m_X, 0\} \, dF \cdot [1 - F(\tilde{y}_X)] \end{aligned}$$

for $X = \{L, N\}$, after substituting (16) and (17). The equilibrium unemployment rate is:

$$u = \frac{\delta}{\delta + \rho} \tag{23}$$

And since I have assumed that only the unemployed search for jobs (and migrate), the migration rate μ is:

$$\mu = \rho_N u = \frac{\delta \rho_N}{\delta + \rho} \tag{24}$$

2.6   Equilibrium

I have so far described three key equations: (10), (19) and (20). But, these contain four unknowns: U, V, $S(y)$ and θ. To complete the system, I impose a free entry condition. Suppose the cost of opening a vacancy is fixed at $\bar{V}$, so firms have an incentive to enter the economy as long as $V \geq \bar{V}$. In equilibrium, the following condition must be satisfied:

$$V = \bar{V} \tag{25}$$

The equilibrium wage $w_X(y)$, search intensity s_X, advertising intensity a_X, finding rate ρ_X and migration rate μ can then be solved as a function of the unknowns above using (13), (17), (18), (22) and (24) respectively.

3   Impact of job surplus

3.1   Impact on local matching

In this section, I show how larger job surpluses (driven by the match productivity distribution or separation rate) ease both the frictions which impede job search in general *and* cross-city matching in particular. I first focus on the implications for local job finding, ignoring migration. To this end, I suppress the national market to ease the exposition. This effectively collapses the model to a single city.

To simplify the exposition, I assume the productivity distribution F is uniform with $y \in [\bar{y} - \sigma, \bar{y} + \sigma]$. The expected surplus accruing to a random match is then:

$$\int_y \max \{S(y), 0\} dF = \frac{1}{4\sigma(r + \delta)} \left(\bar{y} - b + \sigma - r\breve{U} - r\bar{V} \right)^2 \tag{26}$$

where $r\breve{U} = rU - b$ is the expected return to job search activities.

It is simple to show that the expected surplus is increasing in $\bar{y} - b$ and σ and decreasing in δ. Notice first that, according to (26), this must be true if $\breve{U}$ is held constant. In particular, the impact of σ follows from an option value argument: since all jobs with negative surplus are rejected anyway, only the upside from growing dispersion will affect the expected match value.

Next, notice the expression for $\check{U}$ in (19) can be simplified by substituting (21) for θ:

$$r\check{U} = \left[\left(\frac{1-\phi}{\phi} \right)^2 \frac{1}{r\bar{V}} \right]^{\frac{1-\alpha}{\alpha}} \left[\frac{1}{2\gamma_{sL}^{\alpha} \gamma_{aL}^{1-\alpha}} \left(\phi \int_y \max\{S(y), 0\} dF \right)^2 \right]^{\frac{1}{\alpha}} \tag{27}$$

This shows that $\check{U}$ is increasing in (and fully determined by) the expected surplus. It then follows that both $\check{U}$ and the expected surplus are increasing in $\bar{y} - b$ and σ and decreasing in δ. I set out the complete derivations in Appendix D.

A larger expected surplus also materializes in a tighter labor market. This can be seen in equation (21), as θ is increasing in $\check{U}$, with the vacancy value fixed at $\bar{V}$. Intuitively, given the free entry condition, firms respond to larger surpluses by creating more vacancies. And in equilibrium, firms trade off larger job surpluses with smaller hiring probabilities. I confirm in Appendix B that vacancy-unemployment ratios are indeed larger in skilled markets, using data from the Conference Board.

What is the impact on search effort? Consider first the decision of firms. Substituting the first order condition (18) into (20) gives:

$$rV = \frac{1}{2}\gamma_{aL}a_L^2 \tag{28}$$

Notice that $\frac{1}{2}\gamma_{aL}a_L^2$ is the instantaneous advertising expenditure by individual firms. Since V is fixed in equilibrium, (28) shows that this expenditure depends only on the advertising cost γ_{aL}, and not on the productivity parameters. Intuitively, firms exhaust the rents from the larger surplus through *entry*, as manifested by tighter labor markets, and not through advertising.[20] Having said that, I show in Appendix D that vacancy durations must be longer when surpluses are larger (as markets are tighter[21]), so firms do spend more on advertising *over the life* of each vacancy. I also present evidence in Appendix B from employer surveys that skilled vacancy durations are longer, with more human resource hours invested.

In contrast, the number of workers is fixed by assumption; so they do increase their instantaneous search expenditure in response to larger surpluses. To see this, substitute the worker's first order condition (17) into (19):

$$r\check{U} = \frac{1}{2}\gamma_{sL}s_L^2 \tag{29}$$

where $\frac{1}{2}\gamma_{sL}s_L^2$ is total search expenditure. I have shown above that $\check{U}$ is increasing in $\bar{y} - b$ and σ, so the same must be true of s_L. This effect is driven fundamentally by the larger expected surplus and amplified by the increase in θ. I present supporting evidence on workers' search

---

[20]In a world where entry is somewhat restricted, the effect on market tightness will be smaller, and firms will spend more on advertising as the expected surplus grows.

[21]As I show in the Appendix, this dominates any countervailing influence of increasing search intensity and match acceptance probability.

effort from the CPS in Appendix B.

Finally, I study the impact on the job finding rate ρ. Equation (22) shows ρ is a function of (1) firms' advertising intensity, (2) workers' search intensity, (3) market tightness and (4) the job acceptance probability. The final three are increasing in $\bar{y} - b$, and therefore so is ρ. But, the overall effect of σ and δ are ambiguous (and depend on the parameter values) because of the acceptance probability. I leave the complete derivations to Appendix D, but the intuition is simple to see. Notice the acceptance probability can be expressed as:

$$
\begin{aligned}
1 - F(\tilde{y}_L) &= \frac{\bar{y} - b + \sigma - r\check{U} - r\bar{V}}{2\sigma} \\
&= \sqrt{\frac{r+\delta}{\sigma} \int_y \max\{S(y), 0\} \, dF}
\end{aligned}
\tag{30}
$$

This is increasing in the expected surplus, all else equal. But controlling for the expected surplus, it is decreasing in σ and increasing in δ. This is because the valuations of individual jobs become more dispersed with larger σ and longer job tenures, so workers have an incentive to hold out for a better match.

In practice, as Table 1 shows, better educated workers do benefit from higher job finding rates. So, in comparing skill groups, the overall impact of the expected surplus on ρ dominates any countervailing influence of growing match dispersion.

3.2 Impact on job-motivated migration

To study the impact on migration, I bring back the national market into the model. The expected surplus accruing to a random match in market X is:

$$
\int_y \max\{S(y) - m_X, 0\} \, dF = \frac{1}{4\sigma(r+\delta)} \left[\bar{y} - b + \sigma - r\check{U} - r\bar{V} - (r+\delta)m_X\right]^2
\tag{31}
$$

where $m_L = 0$ in local markets and $m_N = m$ in the national market.

Notice the migration rate μ in (24) can be expressed as a function of (1) the flow of accepted matches $\eta = \frac{\delta\rho}{\delta+\rho}$ and (2) the odds ratio of national to local job finding $\frac{\rho_N}{\rho_L}$:

$$
\mu = \eta \frac{\rho_N}{\rho} = \frac{\eta}{1 + \frac{\rho_L}{\rho_N}}
\tag{32}
$$

How does the flow of accepted matches η vary with education? On the one hand, skilled workers benefit from higher finding rates ρ, driven partly by tighter markets and more intensive search. But as it happens, this is entirely offset in η by longer job tenures (that is, smaller δ). In Figure 3, I report the annual flow of accepted matches (as a share of all individuals in each cell,

12

including the inactive), based on the 2004 panel[22] of the SIPP. The flow of matches is larger among the young, and this can explain much of the age differentials in job-motivated migration documented in Figure 2.[23] But, there is little skill variation within age groups.

Therefore, any variation in mobility across skill groups must be manifested empirically in the finding rate odds ratio, $\frac{\rho_N}{\rho_L}$. It is simple to show this is increasing in $\bar{y} - b$ and σ and decreasing in δ. Notice $\frac{\rho_N}{\rho_L}$ can be expressed as a function of the national-local ratios of search and advertising intensity and acceptance probability; and these in turn are all functions of the national-local ratio of expected surplus:

$$
\begin{aligned}
\frac{\rho_N}{\rho_L} &= \left(\frac{s_N}{s_L}\right)^{\alpha} \left(\frac{a_N}{a_L}\right)^{1-\alpha} \left[\frac{1 - F(\tilde{y}_N)}{1 - F(\tilde{y}_L)}\right] \\
&= \left(\frac{\gamma_{sL}}{\gamma_{sN}}\right)^{\alpha} \left(\frac{\gamma_{aL}}{\gamma_{aN}}\right)^{1-\alpha} \left[\frac{\int_y \max\{S(y) - m, 0\}}{\int_y \max\{S(y), 0\}}\right]^{\frac{3}{2}} \\
&= \left(\frac{\gamma_{sL}}{\gamma_{sN}}\right)^{\alpha} \left(\frac{\gamma_{aL}}{\gamma_{aN}}\right)^{1-\alpha} \left[1 - \frac{m}{2}\sqrt{\frac{r+\delta}{\sigma} \frac{1}{\int_y \max\{S(y), 0\} \, dF}}\right]^3
\end{aligned}
\tag{33}
$$

Clearly, $\frac{s_N}{s_L}$, $\frac{a_N}{a_L}$, $\frac{1-F(\tilde{y}_N)}{1-F(\tilde{y}_L)}$ and $\frac{\rho_N}{\rho_L}$ are all decreasing in the cross-city matching cost m. But the job surplus also matters. The final line of equation (33) shows all these national-local ratios are increasing in the expected surplus from a local match, $\int_y \max\{S(y), 0\} \, dF$. And so, given the results above, these ratios must also be increasing in $\bar{y} - b$ and σ and decreasing in δ. Notice that $\bar{y} - b$, σ and δ have a larger impact if m is larger.[24]

Intuitively, larger surpluses make the fixed cost m increasingly inconsequential. So, the gap between national and local search intensity narrows; and relatively more national market matches are consummated. In the particular case of the separation rate δ, the fixed cost m is more likely to discourage cross-city matches if job tenures are expected to be short.

3.3 Migratory response to local shock

So far, I have considered the impact of aggregate-level parameter changes on gross migration. Next, I consider the migratory response to a *local* shock: how does this response vary with the expected job surplus? Based on (22), the rate of national market job finding ρ_{Nj} for workers of origin j is:

$$\rho_{Nj} = s_{Nj} \left(\frac{\bar{a}_N}{\bar{s}_N} \theta_N \right)^{1-\alpha} \left[1 - F_{-j} \left(\tilde{y}_{Nj} \right) \right] \tag{34}$$

$$= \frac{\phi}{\gamma_{sN}^{\alpha} \gamma_{aN}^{1-\alpha}} \left(\frac{1-\phi}{\phi} \theta_N \right)^{1-\alpha} \int_y \max \left\{ \frac{y - rU_j - r\bar{V}}{r + \delta_{-j}} - m, 0 \right\} dF_{-j} \cdot \left[1 - F_{-j} \left(\tilde{y}_{Nj} \right) \right]$$

where $\bar{a}_N$ and $\bar{s}_N$ are the average firms' and workers' search intensities in the national market, and θ_N is the national market tightness. F_{-j} and δ_{-j} are the match productivity distribution and separation rate respectively outside city j. And finally, U_j is the unemployment value of origin j workers, and $\tilde{y}_{Nj}$ is their cutoff for accepting a national market job.

In this exercise, I study the response of ρ_{Nj} to a shock to U_j (driven by a change in local productivity or job separation), taking parameters in other cities F_{-j} and δ_{-j} as given. Since there are many cities, I assume that $\bar{a}_N$, $\bar{s}_N$ and θ_N are unaffected by the local shock. To ease the exposition, I assume an initial equilibrium where all cities are identical: that is, the equilibrium described in Section 2 above. Imposing the same uniform distribution of match productivity as above, ρ_{Nj} can be expressed as:

$$\rho_{Nj} = \frac{\phi}{\gamma_{sN}^{\alpha} \gamma_{aN}^{1-\alpha}} \left(\frac{1-\phi}{\phi} \theta_N \right)^{1-\alpha} \frac{\left[\bar{y} + \sigma - rU_j - r\bar{V} - (r+\delta)m \right]^3}{8\sigma^2 (r+\delta)} \tag{35}$$

And differentiating with respect to U_j:

$$\frac{d\rho_{Nj}}{drU_j} = -\frac{\phi}{\gamma_{sN}^{\alpha} \gamma_{aN}^{1-\alpha}} \left(\frac{1-\phi}{\phi} \theta \right)^{1-\alpha} \frac{3 \left[\bar{y} + \sigma - rU_j - r\bar{V} - (r+\delta)m \right]^2}{8\sigma^2 (r+\delta)} \tag{36}$$

$$= -\frac{3\phi}{2\gamma_{sN}^{\alpha} \gamma_{aN}^{1-\alpha} \sigma} \left(\frac{1-\phi}{\phi} \theta \right)^{1-\alpha} \int_y \max \left\{ S(y) - m, 0 \right\} dF$$

The response is of course negative. Clearly, all else equal, the impact on ρ_{Nj} is decreasing in the national matching cost m. Indeed, much of the literature has attributed the spatially inelastic supply of low skilled labor to high moving costs (see e.g. Bound and Holzer, 2000; Wozniak, 2010).

But, this empirical fact can also be explained by the job surplus. As equation (36) shows, for given match dispersion σ, $\frac{d\rho_{Nj}}{drU_j}$ is increasing in the expected surplus. This is for three reasons. First, for given σ, larger surpluses are associated with a larger job acceptance probability. Second, larger surpluses generate a tighter national market (larger θ), which yields more potential cross-city matches for origin j workers. And third, larger surpluses encourage more intensive search by both workers and firms in the national market.[25] As a result, local workers are more

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[25]It is simple to show that both workers' and firms' *national* search intensity is increasing in the expected

likely to respond to a decline in U_j by taking up work in other cities.

Notice though that an aggregate change in match dispersion σ has an ambiguous impact on the the migratory response $\frac{d\rho_{Nj}}{drU_j}$. Intuitively, while the expected surplus is increasing in σ, a given change in the outside option U_j will have a smaller effect on the job acceptance probability (for given expected surplus). Without knowledge of the precise parameter values, it is not clear which effect dominates. But certainly, skill differences in $\frac{d\rho_{Nj}}{rdU_j}$ can theoretically be explained by job surplus alone, without resorting to skill differences in m.

4 Empirical evidence

4.1 Evidence on moving costs

The model offers two possible explanations for the skill mobility gap: differences in moving costs or job surplus. I next attempt to discriminate between these using evidence from the PSID and the SIPP.

Since the study began in 1968, the PSID has asked respondents why they changed residence. Also, between 1970 and 1980, there were more detailed questions about migration intentions which give some indication of moving costs. In the 1970-80 sample, qualitative patterns among household heads[26] in job-motivated migration by age and education[27] (in the first panel of Figure 4) are similar to those of recent years (as reported in Figure 1 above, based on the CPS).[28]

Below, I compare subjective willingness to move (and imputed moving costs) across skill groups. In making these comparisons, it is first necessary to confirm the low skilled are realistic about their limited job-motivated migration prospects. This is the purpose of the second panel of Figure 4. The PSID asks: "Do you think you might move in the next couple of years?" and "Why might you move?" Based on the responses, I plot the share of respondents who claim they might make a job-motivated move. The patterns clearly reflect the migration outcomes depicted in the first panel. This yields some credibility to the analysis which follows.

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surplus. Substituting (17) into (19) gives: $r\breve{U} = \frac{1}{2}\sum_X \gamma_{sX} s_X^2$, which is a version of (29) including the national market. Similarly, for firms: $r\bar{V} = \frac{1}{2}\sum_X \gamma_{aX} a_X^2$. Given that (1) the national-local search intensity ratios $\frac{s_N}{s_L}$ and $\frac{a_N}{a_L}$ are increasing in the expected surplus (see (33)) and (2) neither of $r\breve{U}$ and $r\bar{V}$ contract, it must be that both s_N and a_N grow.

[26]Household heads in the PSID are always male, unless there is no husband (or cohabiting partner) present or the husband is too ill to respond to the survey.

[27]Given the relatively small samples of the PSID, I have collapsed those with undergraduate and postgraduate education into a single category in Figure 4.

[28]Migration rates in Figure 4 (PSID 1970-80) are somewhat higher than in Figure 1 (CPS 1999-2013). This is for two reasons. First, Figure 1 reports cross-county rates, while Figure 4 includes within-county job-motivated moves also. Based on the CPS, cross-county moves account for about two-thirds of all job-motivated moves. And second, migration rates have declined since the 1980s. This has been documented by, for example, Molloy, Smith and Wozniak (2011). Kaplan and Schulhofer-Wohl (2012) argue the trend is driven by a decline in the geographical specificity of returns to occupations, together with improving communications technology. I show in Appendix A that CPS and PSID time series of job-motivated migration are quantitatively consistent.

In the years 1970-2 and 1979-80, employed respondents to the PSID were asked: "Would you be willing to move to another community if you could get a good job there?" Unemployed respondents were asked the same question in all years between 1970 and 1980 excluding 1976. Also, in most of these years[29], those who answered affirmatively were asked: "How much would a job have to pay for you to be willing to move?"

In interpreting the responses, it helps to set out a simple model. Let w_i^M be the minimum wage required to tempt a worker i to move, and let m_i be a one-off individual-specific moving cost. Then, for an employed worker, w_i^M satisfies:

$$E\left(w_i^M\right) = E\left(w_i\right) + m_i \tag{37}$$

where w_i is the worker's current wage, and $E\left(w\right)$ is the discounted value of a job paying wage w. This is a reformulation of the job acceptance decision embedded in equation (4), for workers engaged in on-the-job search. In this simplified version, I have expressed the employment value as a function of wages w_i rather than productivity y_i. Workers only disclose their reservation wage w_i^M if:

$$w_i^M \leq w_i^G \tag{38}$$

where w_i^G is what worker i expects to earn in a "good job". Of course, the definition of a "good job" is entirely subjective.[30] But, it seems reasonable to assume w_i^G approximates the best wage that can be "realistically" attained, so workers with $w_i^M > w_i^G$ face only a remote probability of moving.

As it happens, the share of heads who are willing to move for a "good job" does not vary systematically with education. This is illustrated in Figure 5. I plot responses separately by employment status. 50 percent of employed and 73 percent of unemployed workers answer yes: intuitively, the latter are more willing to bear the cost of moving.[31] Notice also that older workers are less willing to move, and this can help explain the age differentials in mobility (together with differences in job churn reported in Figure 3). But, despite this intuitive variation by work status and age, there is no such variation by education. In Table 2, I disaggregate those unwilling to move by reported reason. The most common reasons are family/location ties and financial; and together with age/health reasons, these account for the bulk of the age differences. However, with the exception of health, none of these categories exhibit substantial variation by education.

Next, I impute moving costs for workers who disclose w_i^M. For simplicity, suppose the current job value $E\left(w_i\right)$ can be expressed as $\frac{w_i}{r+\delta}$, where r is the discount rate and δ the job

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[29]Excluding 1979-80 for the employed.

[30]Clearly, if respondents were offered a million dollar salary, the vast majority would move.

[31]In the context of equation (37), for unemployed workers, the reservation wage for a long-distance move w_i^M satisfies $E\left(w_i^M\right) = U + m_i$, where U is the value of unemployment. Unemployed workers will be more willing to move if $U < E\left(w_i\right)$.

separation rate. Then, for workers with $w_i^M \leq w_i^G$, the one-off moving cost m_i can be imputed as $\frac{w_i^M - w_i}{r+\delta}$. The numerator, $w_i^M - w_i$, is the flow-equivalent cost over the duration of the job.

In Figure 6, I plot the distribution of $w_i^M - w_i$ in hourly wage terms for employed heads aged 25 to 64. I also plot differentials in log wages, that is $\log w_i^M - \log w_i$: this may be more relevant for migration decisions if utility is non-linear. I proxy w_i with the average hourly wage earned over the previous year. Notice there is large variation in imputed moving costs. This is consistent with findings from Kennan and Walker (2011). Part of the variation however is presumably driven by reporting error or mismeasurement of the expected wage w_i, and this may explain the large quantity of observations (9 percent) falling below zero.

In Table 3, I report sample means of $w_i^M - w_i$ and $\log w_i^M - \log w_i$, by education and age for employed workers. I also present estimates separately for the unemployed[32]: these can be interpreted as the moving cost net of the value of finding work. Given the small samples of unemployed workers, I use just two education groups (no college and at least some college). And I omit the education disaggregation entirely for the over-35s: the samples are too small to be informative.

The average flow-equivalent cost for employed workers is \$7.46 or 40 log points. And for the unemployed, this number is \$2.33 or 23 log points: they require less compensation for a long-distance move. These costs vary little with age, conditional on being willing to move. More importantly, Table 3 suggests they vary little with education, whether costs are measured in dollar or log terms. An exception is the 45-64 age group (in which college graduates face relatively low costs), though the 45-64s account for little of the mobility gap overall. Of course, the standard errors which accompany these estimates are large, but the results are still compelling. My interpretation is predicated on the assumption that lower skilled workers do not systematically overstate their willingness to move. And to this end, I rely on the evidence in the second panel of Figure 4.

To derive the one-off cost $m_i = \frac{w_i^M - w_i}{r+\delta}$, the estimates in Table 3 must be discounted at rate $r + \delta$. Consider a simple calibration. The average hourly dollar wage gap ($w_i^M - w_i$) is \$7.46 for the employed. Given a sample average of 190 working hours per month, the monthly equivalent is \$1,420. Moving to the denominator, Shimer (2012) estimates a month-to-month job separation rate of about 0.04 in the 1970s. Since the monthly interest rate is negligible in comparison, I approximate $r + \delta$ as 0.04. This suggests an average one-of cost m_i of \$35,500,[33] among workers who are willing to move if offered a "good job".[34]

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[32]As with the employed, I proxy w_i with the average hourly wage over the previous year. Consequently, my unemployment sample necessarily excludes those workers reporting no earnings over the previous year.

[33]How does this compare with moving cost estimates in the literature? Bayer and Juessen (2012) estimate a cross-state moving cost of \$34,000, using a dynamic structural model. And based on a calibrated Roy model, Lkhagvasuren (2014) suggests a cost of crossing census divisions of between \$28,000 and \$54,000. Kennan and Walker (2011) find a much larger average (unconditional) cost of \$312,000, though the cost for people who actually move is typically negative: this is because most moves are motivated by idiosyncratic amenity payoffs, which Kennan and Walker factor into the cost. It should be emphasized that my estimate relates to hypothetical *job-motivated* moves, based on the sample of individuals who are willing to move for a "good job".

[34]It is well known that job separation rates are larger for low skilled workers (see Table 1 above). But, this

Given that these results are based on the subjective judgments of respondents, there may be doubts over accuracy. But, the cost measures do have significant predictive power for future migration decisions. Consider the following empirical model. Suppose the instantaneous job-motivated migration rate $\mu(x_i)$ of an individual with characteristics x_i is invariant over time and can be expressed as $\exp(x_i'\beta)$, where x_i is a vector of covariates including a subjective cost measure, lagged by one year. Define M_i^τ as a binary indicator taking 1 if the individual i moves before time τ. The probability of moving before t is:

$$\Pr(M_i^\tau = 1, t < \tau | X) = 1 - \exp\left(-\exp\left(x_i'\beta\right)\tau\right) \tag{39}$$

I normalize τ to one year in this exercise, to correspond with the PSID data interval. Equation (39) is a complementary log-log model, and the vector β can be estimated by maximum likelihood. The advantage of this model is that the estimates have an intuitive interpretation: β defines the log point change in the migration rate $\mu(x_i)$, for a given change in x_i. This interpretation is independent of the time t associated with the migration variable.

Of course, the cost measure in the x_i vector may be correlated with the wage offer distribution facing workers, which clearly influences migration decisions. In an attempt to address this problem, I include a range of controls in x_i which can partially proxy for wage offers: employment status (lagged by one year), a set of demographic controls[35], fixed effects denoting the individual's census division of residence one year ago, and year fixed effects.

I report results in Table 4 separately by lagged employment status. Based on column 1, a (binary) stated willingness to move adds 101 log points to the job-motivated migration rate the following year. Column 4 shows that a $10 increase in the dollar imputed cost adds 24 log points to the migration rate. And column 7 identifies an elasticity of the migration rate to the log imputed cost of -0.52. In the conditional sample, the effects are much larger for the unemployed, presumably because employed workers are not necessarily seeking a new job. The key point to take from this table is that the moving cost estimates *do* have predictive power.

4.2   Evidence on job surplus

If moving costs do not explain the skill mobility gap in Figure 4, what does? Subjective responses to another PSID question point to the job surplus. In the 1976 wave (alone), employed workers were asked: "Are there better jobs you could get if you were willing to move and live somewhere else?" Since the question conditions on willingness to move, it speaks to job quality rather than costs.

I report results by education in Table 5. There are three possible answers to the question: yes, no or do not know. 50 percent of college graduates responded affirmatively, compared with

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suggests the statistics in Table 3 *underestimate* the one-off moving costs for low skilled workers, relative to the high skilled.

[35]Specifically: age, age squared, four education indicators (high school graduate, some college, undergraduate and postgraduate), and gender and black dummies.

29 percent of high school dropouts. Interestingly, skilled workers also have better information: 14 percent of college graduates cannot answer, compared to 28 percent of high school dropouts. This suggests mobility differences can be explained by both the availability of quality matches and information on those matches. This is consistent with the model's predictions, as well as the evidence in Appendix B on search intensity and market tightness.

Job surplus can also be studied using wage realizations. Consider worker i's return on the surplus (or flow-equivalent surplus), conditional on accepting a job. This can be expressed as the gap between the accepted and reservation wage, $w_i - w_i^R$. Unfortunately, survey data on reservation wages is sparse.[36] But, a useful proxy for the surplus is the variance over wages in an individual worker's history. Intuitively, if a worker is willing to accept a broader range of wages, he must be receiving a larger surplus on average.

In particular, suppose the wage offer distribution facing worker i is uniform, with a worker-specific and time-invariant range of $\left[w_i^{min}, w_i^{max}\right]$. And suppose the reservation wage w_i^R is also time-invariant, with $w_i^R \in \left(w_i^{min}, w_i^{max}\right)$. Then, for individual i, the variance in (accepted) wages over time t is:

$$\mathrm{Var}_i\left(w_{it} | w_{it} \geq w_i^R\right) = \frac{1}{12}\left(w_i^{max} - w_i^R\right)^2 \tag{40}$$

This is an increasing function of the maximum flow-equivalent surplus $w_i^{max} - w_i^R$ (and hence expected surplus) accruing to the worker. Given my distributional assumptions, the variance must therefore be increasing in both $\bar{y} - b$ and σ, the mean match productivity (net of out-of-work-income) and dispersion respectively.

However, this variance may not be a good measure of surplus if there are worker-specific trends in w_i^{max} and w_i^R. One approach is to remove worker-specific linear time trends by estimating:

$$w_{it} = \alpha_i + \beta_i t + \varepsilon_{it} \tag{41}$$

for each worker by OLS, and studying worker-specific variances in the residuals ε_{it}. In this case, the variance formula (40) will still be correct if w_i^{max} and w_i^R are subject to common worker-specific linear trends, such that $\Delta w_{it}^{max} = \Delta w_{it}^R = \beta_i$. Then, conditional on accepting a job, worker i's flow-equivalent surplus $w_i - w_i^R$ will be subject to a uniform distribution with range $\left[0, w_i^{max} - w_i^R\right]$, so $\mathrm{Var}_i\left(\varepsilon_{it} | w_{it} \geq w_i^R\right) = \frac{1}{12}\left(w_i^{max} - w_i^R\right)^2$.

Should this variance be estimated over dollar wages or logarithms? In the model above, I assume linear utility; so larger surpluses in dollar terms are sufficient to ensure larger mobility.[37] But, in other settings, a log specification might be more appropriate; and indeed, this

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[36]The PSID does record reservation workers of unemployed workers between 1980 and 1987, but I have found the samples are too small for statistical inference.

[37]As well as being analytically simpler, this approach has some foundation in the literature: Grogger and Hanson (2011) show that a Roy model with linear utility and skill-invariant migration costs can better explain the observed selection of high and low skilled migrants across countries than an alternative specification with log utility and migration costs which are proportional to income. However, it is not clear whether this result for *international* migration is generalizable to *internal* migration in the US.

is standard in the earnings process literature. In any case, I show the results are qualitatively robust to this specification choice.

Of course, there is already a mature literature on earnings processes, and several studies have estimated these separately by education. The focus is usually on changes in earnings instability over time, distinguishing between permanent and transitory components. In the simplest specification, implemented by Gottschalk et al. (1994), the permanent component is estimated as an individual's average earnings over an extended period; and transitory earnings are the log deviation from this mean. In the empirical model in equation (40), I am effectively identifying job surplus with the "transitory earnings" variance of this literature.

The evidence has been mixed on whether transitory earnings instability is increasing in skill.[38] But, Fitzgerald (1999) shows that better educated workers face much larger transitory instability in hourly wage rates (as opposed to monthly earnings). And the hourly wage rate is the relevant variable for my application, as it describes the value of *jobs* to workers (when in employment). Since this result may not be widely known, I present similar findings here. For this purpose, I use the 2004 panel of the SIPP, covering the period from February 2004 until January 2008.[39] I construct a longitudinal data set using reported wages[40] at the end (specifically the final month) of each four-month wave.[41]

In Figure 7, I plot averages of the worker-specific wage variances (with wages in dollar terms) across individuals, within education and age groups. The first panel reports estimates for basic wage variances, and the second panel after extracting worker-specific trends. In each panel, there is a steep positive education gradient, ranging from under $10 (on average) for high school dropouts to over $50 or $30 for postgraduates, in the basic and detrended specifications respectively. The effect of education is larger for younger workers, though only when moving from undergraduate to postgraduate level.

These large effects for dollar wages are perhaps unsurprisingly, given that wages are significantly higher for skilled workers. But, as I show in Figure 8, there is also a strong positive

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[38]Gottschalk et al. (1994) find that lower skilled workers in the PSID faced *larger* transitory fluctuations in the 1970s and 1980s; though this pattern was reversed thereafter (Gottschalk and Moffitt, 2009).

[39]Fitzgerald (1999) also takes his data from the SIPP, though covering the 1980s and early 1990s. For my purposes, the SIPP has three attractive features. First, it is nationally representative. Second, the samples are very large: the 2004 panel covers 132,000 individuals. In comparison, the PSID covered 9,000 families in its latest wave; and the National Longitudinal Survey of Youth (NLSY) followed 13,000 individuals. And third, the SIPP waves are just four months apart (waves are annual in the PSID and NLSY). This is useful in years with job changes, and it should also reduce the measurement error attributable to memory recall.

[40]My sample consists of employees aged 25 to 64 and still working in the final week of the wave. I exclude those with second jobs or businesses. I use hourly wage data for workers paid by the hour, and I impute hourly wages for salaried workers using monthly earnings and hours. Finally, I drop wage observations under $5 in 2000 prices and top-coded values, as well as any remaining observations over $100. Top-coded values account for 3 percent of the remaining sample.

[41]Respondents to the SIPP do report monthly changes in earnings, but I do not exploit this variation. This monthly data is likely to be subject to large measurement error due to poor recall, as information is only collected at the end of each 4-month wave. In particular, it is known that the SIPP suffers from severe seam bias (see e.g. Marquis and Moore, 2010): monthly changes in individuals' outcomes (whether employment status or wages) tend to be larger between months at the seam of two waves than between months within the same wave.

gradient for variances over log wages. The variances are about twice as large for postgraduates compared to dropouts in both the basic and detrended specifications, but are similar across age groups.

4.3 Calibrating the job surplus

Using the variance estimates, it is possible to impute the size of workers' surplus in different education groups. Specifically, rearranging equation (40) gives:

$$w_i^{max} - w_i^R = \sqrt{12 \cdot \text{Var}_i\left(w_{it} | w_{it} \geq w_i^R\right)} \tag{42}$$

Assuming a uniform offer distribution, this can be interpreted as the maximum flow-equivalent surplus that worker i can receive.

In Panel A of Table 6, I report estimates of the mean of $\text{Var}_i\left(w_{it} | w_{it} \geq w_i^R\right)$ and $w_i^{max} - w_i^R$ across workers aged 25-64 within each education group. The variance estimates are based on *dollar* wages, as the assumptions behind equation (42) require this. Based on the basic wage data (not detrended), the average maximum flow-equivalent surplus ranges from \$5 for dropouts to \$16 for postgraduates. The estimates from the detrended specification are slightly smaller, ranging from \$4 to \$13. In comparison, the average imputed moving cost from the PSID is \$7.46. While this exceeds the average maximum surplus received by lower skilled workers, Kennan and Walker (2011) do emphasize that migrants tend to face much lower moving costs than the average.

Are these surplus differences sufficient to explain the mobility gap? To address this question, I calibrate (for each worker) the ex ante relative probability of accepting a national market offer compared to a local offer, equivalent to $\frac{1-F(\tilde{y}_N)}{1-F(\tilde{y}_L)}$ in the model above. Unlike the model, I allow the productivity distribution F to vary across workers. Let $\hat{m}_i = (r+\delta)m_i$ be the flow-equivalent of the matching cost m_i. Again, unlike the model, I assume $\hat{m}_i$ is random, drawn from a distribution M common to all workers (when a national match is made). The relative acceptance probability (or odds ratio) for worker i is then:

$$\frac{\text{Pr}\left(w_i - \hat{m}_i \geq w_i^R\right)}{\text{Pr}\left(w_i \geq w_i^R\right)} = \frac{\int_{\hat{m}} \max\left\{w_i^{max} - w_i^R - \hat{m}, 0\right\} dM}{w_i^{max} - w_i^R} \tag{43}$$

I calibrate the distribution M in the following way. I assume a worker draws an infinite matching cost with probability 0.5, commensurate with the proportion of employed individuals in the PSID who are reportedly unwilling to move for a "good job" (see the first panel of Figure 5). And with probability 0.5, $\hat{m}_i$ is drawn from the dollar moving cost distribution in Figure 6.

I report estimates of the mean odds ratio (43) across workers, by education group, in columns 5 and 6. Results are very similar for the basic and detrended variance specifications. The odds ratio ranges from about 0.1 for dropouts to 0.2 for postgraduates. That is, dropouts

are on average ten times less likely to accept a national match compared to a local one, and postgraduates five times less likely.

To check whether these numbers of reasonable, I compare these odds ratios with the relative propensities of national and local job finding, $\frac{\rho_N}{\rho_L}$. Notice from equation (33) that these ratios are not the same: the relative search intensity $\frac{s_N}{s_L}$ also matters for $\frac{\rho_N}{\rho_L}$, though $\frac{s_N}{s_L}$ is unobserved.

I present estimates of $\frac{\rho_N}{\rho_L}$ by education in Panel B. These are computed from (1) the job-motivated migration rate $\mu = \frac{\rho_N \delta}{\rho + \delta}$ and (2) the flow of all accepted matches $\eta = \frac{\rho \delta}{\rho + \delta}$, reported in the first two columns. The relative finding rate $\frac{\rho_N}{\rho_L}$, in column 3, is equal to $\frac{\mu}{\eta - \mu}$. I estimate μ and η for individuals aged 25-64 in the CPS 1999-2013 and SIPP 2004 samples respectively, following the procedures outlined in the notes under Figures 2 and 3.

$\frac{\rho_N}{\rho_L}$ ranges from 0.05 for dropouts to 0.16 for postgraduates. Therefore, skill differences in my estimates of the job acceptance odds ratio (in Panel A) can explain the bulk of the variation in $\frac{\rho_N}{\rho_L}$.[42] Of course, my estimates of the job surplus in national and local matches are based on some brave assumptions. But, this back-of-the-envelope calibration does suggest the skill gradient in the job surplus (as estimated from observed wage processes) can plausibly generate the mobility gap observed in the data. This lends some credibility to my hypothesis.

4.4 Evidence from disaggregated reasons for moving

Until now, I have focused my attention on job-motivated mobility. I show here that a more detailed disaggregation of reported reasons for moving can provide further (suggestive) evidence for the job surplus explanation.

Table 7 presents estimates from complementary log-log models for annual incidence of cross-county migration, by reported reason. The empirical model takes the form of equation (39), with the x_i controls consisting of education indicators, year effects and a detailed range of demographic characteristics.[43] The reported β coefficients give the log point effect of a particular level of education on the instantaneous migration rate, relative to high-school dropout (the omitted category). For simplicity, I pool all age groups (25-64) together.

There are two pieces of evidence which are of particular interest to the surplus/cost debate. The most stark is the patterns in speculative migration. Among job-motivated moves (columns 2-5), the positive skill gradient is almost entirely driven by those moving for a new job or transfer: such moves account for two thirds of job-motivated migration (see the bottom row), and the effect of education is particularly large.[44] But interestingly, higher skilled workers

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[42]Since my estimates of $\frac{\rho_N}{\rho_L}$ are smaller than the job acceptance odds ratios, this would imply $\frac{s_N}{s_L}$ lies below 1 (based on equation (33)). Also, since $\frac{\rho_N}{\rho_L}$ is somewhat more steeply increasing in education than the job acceptance odds ratio, this would suggest $\frac{s_N}{s_L}$ is larger in skilled markets, though the effect is small. But, these results should be interpreted in the light of the strong assumptions underlying this exercise.

[43]Specifically: age, age squared, black and Hispanic race dummies, immigrant status, marital status, a range of indicators for number of own children, and a gender indicator which is also interacted with all previously mentioned variables.

[44]Commuting-motivated moves also have a positive education slope, though the effect is smaller than for new

are *less* likely to move to *look* for work (speculatively, without a job in hand): a postgraduate education reduces the speculative migration rate by 58 log points, relative to dropouts.

This result may appear puzzling, but it is entirely consistent with skill differences in expected job surplus. Skilled mobility is enabled by large surpluses, which fund cross-city search by both firms and workers. Low skilled workers on the other hand, facing large local employment disparities and meager investment in cross-city search, are forced to make (costly) speculative moves. Their engagement in this risky strategy (rather than cross-city search) is testament to the relatively poor integration of national markets. While I have excluded speculative moves from the model above, I sketch an extension illustrating these mechanisms in Appendix C.

The second piece of evidence is the negative skill gradients in non-job migration. This is somewhat visible in the unconditional migration rates of Figure 2, but the effect is much stronger once I control for demographic characteristics (and this is true for all age groups, as I show in Appendix A). These negative effects appear in migration motivated by family, housing and neighborhood quality.[45]

If the mobility gap were driven by costs, this negative skill slope might seem strange. But again, it is a natural consequence of the surplus explanation. The large surpluses in skilled markets are more resilient to amenity shocks of a given size, so skilled workers are less likely to break these matches for non-job reasons. I sketch an extension to the model with non-job migration in Appendix C.

On the other hand, low skilled workers may also face larger family, housing and amenity shocks. For example, they tend to be more credit constrained, so housing costs may be a more important contributor to migration decisions. Or they may suffer more from family instability (see e.g. McLanahan, 1985).

5   Conclusion

Low skilled workers make fewer long-distance moves, and they are less likely to migrate following slumps in local demand. I argue that the obstacles to low skilled mobility are exactly those which impede low skilled job finding more generally: a small expected job surplus, irrespective of geography. These small surpluses have a particularly debilitating effect on *cross-city* search intensity and job finding.

I have outlined a cross-city matching model to illustrate these mechanisms. The model offers two explanations for the mobility gap: differences in moving costs or expected surplus, arising from mean productivity (net of welfare income), match dispersion or job tenure. I reject

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jobs.

[45]The CPS does provide more disaggregated categories of reasons for moving. I show in Appendix A that the negative non-job skill gradients are largely driven by the categories labeled "other family reasons", "other housing reasons" and "cheaper housing".

the costs hypothesis, based on evidence from the PSID: self-reported willingness to accept long-distance job offers is invariant with skill. However, I report large skill differences in expected surplus, based on observed wage processes. And given the moving costs I impute from the PSID, these surplus differences are quantitatively sufficient to explain the mobility gap. These conclusions are also consistent with patterns in speculative and non-job migration.

Steep cross-city search costs in low skilled markets are an endogenous *outcome* of the model, as firms invest fewer resources in seeking match partners. But, this is just one symptom of the *underlying* problem of meager returns to work. In this sense, the issue of low skilled immobility is intimately tied to broader concerns about high rates of joblessness, loose markets and limited search effort. These findings suggest that policy interventions which address migration costs exclusively (such as relocation vouchers) may only have a limited effect on employment.

Tables and figures

Table 1: Job transition rates (%), over 4 month intervals

| | FINDING | | | SEPARATION | |
	Unemp to emp	Inactive to emp	Emp to emp	Emp to unemp	Emp to inactive
HS dropout	34.52	6.43	9.92	2.24	3.84
HS graduate	40.66	8.43	9.04	1.49	2.90
Some college	42.34	10.48	9.09	1.33	2.55
Undergraduate	45.43	11.66	8.12	0.79	2.15
Postgraduate	45.35	13.41	7.46	0.54	1.73

This table reports job finding rates by education for individuals aged 25 to 64 in the SIPP panel of 2004. "Unemp (inactive) - Emp" is the percentage of unemployed (inactive) workers at the end of wave *t-1* who are employed at the end of wave *t* (four months later). "Emp - emp" is the percentage of workers, employed at the end of *t-1*, who left their primary job and found new work in *t*. A primary job is the wage/salary job paying the most in monthly earnings; self-employed jobs are excluded from this definition. The total sample amount to 405,000 observations.

Table 2: Disaggregation of those unwilling to move by reported reason

| | Unwilling to move | By reported reason for separation: | | | | | Observations |
		Family/location ties	Financial	Age/health	Other	Not recorded	
Education							
HS dropout	50.67	29.75	10.49	5.56	3.14	1.75	7,115
HS graduate	46.54	27.65	10.68	3.39	3.31	1.51	5,815
Some college	43.60	26.73	9.59	2.76	2.89	1.64	2,390
College graduate	46.14	27.77	9.57	1.94	4.23	2.62	2,919
Age group							
25-34	33.66	22.02	7.53	0.14	2.66	1.31	7,171
35-44	48.35	30.67	11.18	0.89	3.85	1.75	4,465
45-64	62.39	33.64	12.64	10.04	3.71	2.35	6,603

In the 1970s, the PSID asked individuals: "Would you be willing to move to another community if you could earn more money there?" In this table, I report the percentage responding negatively, and disaggregate these individuals by their stated reason for being unwilling to move. Statistics in this table are pooled across employed and unemployed individuals. These questions were posed to the employed in the waves of 1970-2 and 1979-80, and to the unemployed in every wave between 1970 and 1980 excluding 1976. The column labelled "not recorded" refers to the small number of individuals who claim to be unwilling to move, but who are coded as N/A for the reason why; these include retirees, students and housewives, among others.

Table 3: Flow-equivalent cost moving costs (in hourly wage terms)

	Employed					Unemployed		
	All	HS d/out	HS grad	Some coll	Coll grad	All	Non-coll	Coll
Aged 25-34								
Dollar gap ($ 2000)	7.83	6.97	8.01	8.07	8.61	2.33	2.13	3.16
	(7.76)	(6.60)	(7.21)	(10.45)	(7.86)	(8.12)	(8.28)	(7.45)
Log gap	0.43	0.45	0.42	0.40	0.41	0.23	0.23	0.22
	(0.37)	(0.37)	(0.35)	(0.43)	(0.36)	(0.49)	(0.50)	(0.46)
Observations	1,329	400	459	197	273	402	323	79
Aged 35-44								
Dollar gap ($ 2000)	7.61	7.00	7.76	7.98	8.83	2.53	-	-
	(7.87)	(6.82)	(6.96)	(10.11)	(10.19)	(5.76)		
Log gap	0.40	0.43	0.39	0.35	0.35	0.25	-	-
	(0.35)	(0.34)	(0.33)	(0.38)	(0.40)	(0.43)		
Observations	956	433	276	93	154	133	-	-
Aged 45-64								
Dollar gap ($ 2000)	6.86	6.21	8.21	9.93	4.38	2.12	-	-
	(8.24)	(6.95)	(8.26)	(9.82)	(10.67)	(8.64)		
Log gap	0.37	0.39	0.39	0.43	0.20	0.21	-	-
	(0.39)	(0.39)	(0.37)	(0.45)	(0.32)	(0.49)		
Observations	1,044	562	254	106	122	135	-	-

This table reports mean imputed migration costs by age, education and employment status; standard errors are in parentheses. Within each cell, I present two alternative estimates of the imputed cost. The first is the "dollar gap", equivalent to $w_i^M - w_i$, where w_i^M is the minimum hourly wage required to tempt a worker i to take a job in another city, and w_i is the worker's average hourly wage in the previous 12 months (with wages expressed in 2000 dollars). The "log gap" is the log difference between the reservation and current wage: $\log w_i^M - \log w_i$. For employed workers, I report mean imputed costs for five education groups: high school dropout, high school graduate, some college, undergraduate and postgraduate. For the unemployed, I report just two groups (no college and at least some college) because samples are smaller; and I omit the disaggregation entirely for the over-35s because the college-educated unemployed samples are two small to be informative. The sample consists of employed household heads aged 25-64 in the PSID waves of 1970-2, and unemployed heads in all waves between 1970 and 1980 excluding 1976. Household heads in the PSID are always male, unless there is no husband (or cohabiting partner) present or the husband is too ill to respond to the survey. I exclude all workers earning less than $5 or more than $100 per hour (in 2000 dollars) in the previous year; and similarly, I exclude workers whose reported reservation lies below $5 or above $100. The specific question eliciting the reservation wage is: "How much would a job have to pay for you to be willing to move?"

Table 4: Effect of cost measures on job-motivated migration rate

Complementary log-log regressions of job-motivated migration on 1-year lagged cost measures

Emp status (lagged):	Unconditional sample			Conditional sample: individuals willing to move					
	All	Emp	Unemp	All	Emp	Unemp	All	Emp	Unemp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Willing to move (binary)	1.005***	1.020***	0.902**						
	(0.111)	(0.116)	(0.382)						
Dollar gap (imputed cost)				-0.024***	-0.022**	-0.041**			
				(0.008)	(0.009)	(0.021)			
Log gap (imputed cost)							-0.524**	-0.385	-0.909**
							(0.207)	(0.255)	(0.395)
Employed (lagged)	-0.547***			-0.548			-0.558		
	(0.209)			(0.352)			(0.354)		
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census div FEs (lagged)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,219	15,815	1,404	3,814	3,205	609	3,814	3,205	609
Job-motivated mig rate	0.029	0.029	0.040	0.047	0.045	0.060	0.047	0.045	0.060

This table reports the impact of (1-year) lagged subjective cost measures on job-motivated migration incidence, based on complementary log-log regressions. I report results separately for all labor force participants and disaggregated by lagged employment status. I study three subjective cost measures: the binary indicator of willingness to move (for a "good job"), the dollar gap moving cost, and the log gap moving cost. The latter two are available only for individuals who report being willing to move. These measures are described in greater detail in the notes under Figure 5 and Table 3. Coefficients should be interpreted as the log point effect of each measure on the instantaneous job-motivated migration rate, conditional on the empirical model described by equation (39). The sample consists of household heads aged 25-64 who were employed in the PSID waves of 1970-2, and who were unemployed in any wave between 1970 and 1980 excluding 1976. Household heads in the PSID are always male, unless there is no husband (or cohabiting partner) present or the husband is too ill to respond to the survey. The sample is further restricted for the dollar gap and log gap measures, as described in the notes under Table 3. All specifications control for (1) demographic controls, specifically age, age squared, four education indicators (high school graduate, some college, undergraduate and postgraduate), and gender, black and Hispanic dummies; (2) fixed effects denoting the census division of residence one year ago; and (3) year fixed effects. I also control for lagged employment status in the pooled employment status specifications. Errors are clustered by individual, and robust SEs are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Are there better jobs available in other cities?

	HS dropout	HS graduate	Some college	College graduate
Yes	0.294	0.379	0.420	0.495
No	0.431	0.427	0.396	0.368
Don't know	0.275	0.194	0.184	0.138
Observations	1,134	1,151	450	639

Employed workers in the PSID wave of 1976 were asked: "Are there better jobs you could get if you were willing to move and live somewhere else?" In this table, I report the fraction of respondents answering "yes", "no" and "do not know". The sample consists of household heads aged 25-64 who are currently employed.

Table 6: Calibration of surplus and relative probability of accepting national offers

PANEL A: *Imputing relative national/local acceptance probability (SIPP)*

	Mean over dollar wage variance, $\text{Var}_i\left(w_{it}\mid w_{it}\geq w_i^R\right)$		Mean over maximum surplus flow, $w_i^{max}-w_i^R$		Mean over relative N/L acceptance prob: equ (43)		Sample
	Basic spec	Detrended	Basic spec	Detrended	Basic spec	Detrended	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
HS dropout	9.74	4.94	4.69	3.50	0.10	0.09	2,476
HS graduate	9.93	6.29	5.97	4.49	0.12	0.10	7,756
Some college	16.12	11.23	7.68	5.92	0.13	0.12	11,520
Undergraduate	33.28	22.77	12.41	9.87	0.17	0.15	6,149
Postgraduate	50.88	34.38	15.83	12.66	0.19	0.17	3,195

This panel imputes the relative national/local job acceptance probability. I first estimate $\text{Var}_i\left(w_{it}\mid w_{it}\geq w_i^R\right)$ for individual workers, based on wages recorded at the end of each 4-month wave in the SIPP panel of 2004, separately using the basic wage data and after extracting worker-specific linear trends. The first two columns report means of these variances across workers within education groups. For each worker, based on the variance estimates and assuming worker-specific uniform surplus distributions, I calibrate the maximum surplus using equation (42); and I report means of this maximum surplus across workers in columns 3 and 4. I then calibrate each worker's relative national/local acceptance probability using equation (43). This requires knowledge of the distribution of the flow-equivalent matching cost $\hat{m}_i = (r+\delta)m_i$. As I describe in the main text, I assume that each worker draws an infinite matching cost with probability 0.5, commensurate with the proportion of employed individuals in the PSID who are reportedly unwilling to move for a good job (see the first panel of Figure 5). And with probability 0.5, $\hat{m}_i$ is drawn from the dollar moving cost distribution in Figure 6. After computing the relative probabilities for each worker, I report the education group means in columns 5 and 6. Column 7 gives the sample of employees aged 25 to 64 in the SIPP data by education group. See the notes under Figure 7 for further sample restrictions.

PANEL B: *Imputing relative national/local job-finding propensity*

	Job-motivated cross-county migration rate (CPS): μ	Flow of accepted matches (SIPP): η	Relative N/L job finding propensity: $\frac{\rho_N}{\rho_L}=\frac{\mu}{\eta-\mu}$
	(1)	(2)	(3)
HS dropout	0.010	0.218	0.050
HS graduate	0.011	0.230	0.051
Some college	0.015	0.249	0.064
Undergraduate	0.023	0.231	0.109
Postgraduate	0.027	0.192	0.164

The first column of Panel B reports the annual rate of job-motivated cross-county migration μ among all those aged 25-64 in each education group, based on the CPS sample described in the notes under Figure 2. The flow of accepted matches η among 25-64s by education is given in column 2, based on the SIPP 2004 panel sample described in the notes under Figure 3. This is the average number of times a worker of given education is hired for a new job each year. The relative national/local job finding propensity, reported in column 3 is a function $\frac{\mu}{\eta-\mu}$ of the statistics in columns 1 and 2.

Table 7: Log point responses of migration rate, by reported reason

	ALL	JOB REASONS				NON-JOB REASONS				
		New job/ transfer	Commute	Look for work	Other job reasons	Family	Housing	Better n/hood	Climate, health retirement	Other reasons
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High-school graduate	-0.074***	0.172**	0.046	-0.351***	0.047	-0.106**	-0.078*	-0.138	-0.139	-0.097
	(0.025)	(0.070)	(0.115)	(0.114)	(0.146)	(0.045)	(0.045)	(0.116)	(0.117)	(0.150)
Some college	0.008	0.568***	0.223**	-0.409***	0.203	-0.07	-0.119***	-0.094	-0.071	-0.176
	(0.025)	(0.068)	(0.113)	(0.117)	(0.145)	(0.046)	(0.046)	(0.117)	(0.118)	(0.152)
Undergraduate	0.051**	1.026***	0.282**	-0.496***	0.165	-0.279***	-0.160***	-0.377***	-0.213*	-0.029
	(0.026)	(0.067)	(0.116)	(0.124)	(0.146)	(0.049)	(0.048)	(0.126)	(0.128)	(0.153)
Postgraduate	0.182***	1.496***	0.438***	-0.575***	0.517***	-0.438***	-0.294***	-0.375***	-0.092	0.059
	(0.028)	(0.069)	(0.125)	(0.148)	(0.155)	(0.058)	(0.055)	(0.145)	(0.138)	(0.166)
Migration rate (%)	4.658	1.083	0.273	0.160	0.157	1.236	1.269	0.156	0.180	0.142

This table reports education effects from complementary log-log regressions on annual cross-county migration incidence, by reported reason. Each column reports the effects on moving for the motivation specified, with the first column presenting effects on the overall migration incidence (all reasons). Coefficients should be interpreted as the log point effect of a particular level of education (relative to high-school dropout, the omitted category) on the instantaneous migration rate (for the motivation specified), conditional on the empirical model described by equation (39). Each regression controls for a detailed set of individual characteristics: age, age squared, black and Hispanic race dummies, immigration status, marital status, a range of indicators for number of own children, a gender indicator which is also interacted with all previously mentioned variables, and a set of year fixed effects (for the individual CPS cross-sections). Estimates are based on pooled CPS cross-sections between 1999 and 2013. The sample consists of household heads aged 25-64 and amounts to 900,317 observations in each regression. See the notes under Figure 2 for further details on the sample. Robust SEs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
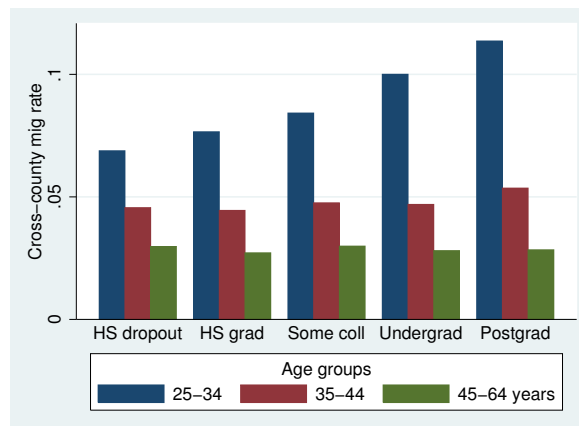

Figure 1: Annual cross-county migration rates (CPS 1999-2013)

The March CPS reports whether individuals moved county or state in the previous 12 months, and I estimate migration rates based on this information. My sample is based on household heads in pooled cross-sections between 1999 and 2013. In each household, I define the head as the individual with the greatest predicted earnings power. Earnings power is predicted using a Mincer regression of log weekly wages on a detailed set of characteristics. In households with multiple predicted top-earners, I divide the person weights by the number of top-earners. I exclude individuals who lived abroad one year previously, individuals who report moving primarily to attend or leave college, and those who report moving because of natural disasters. See Appendix A for further details.
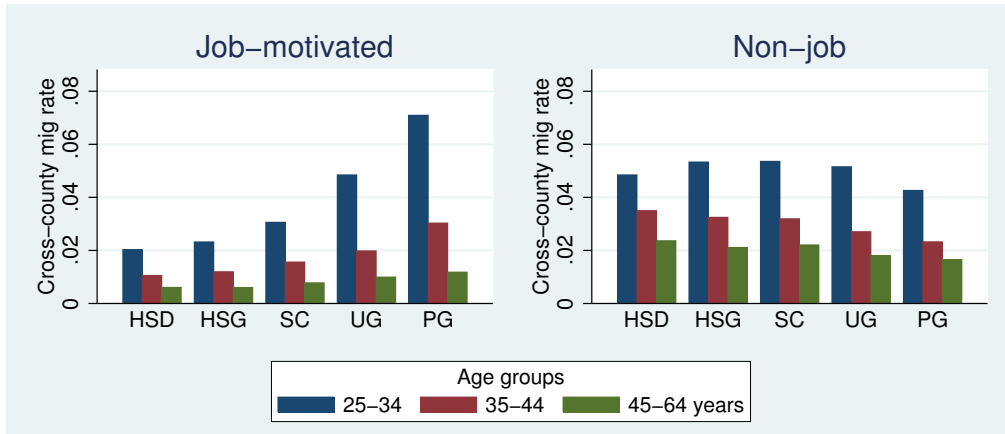
Figure 2: Annual migration rates by reported reason (CPS 1999-2013)

Between 1999 and 2013, the CPS asked migrants for their primary reason for moving. In the first panel, I report rates of migration for all job-related reasons; and in the second panel, for all non-job reasons. See Figure 1 notes for sample details.
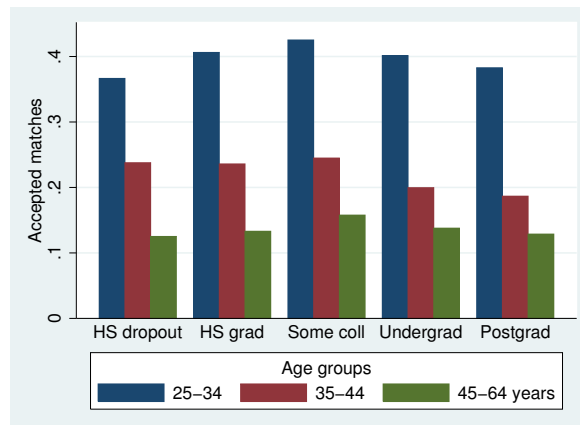

Figure 3: Annual flow of accepted matches per individual (SIPP 2004)

This figure reports the average number of times a worker is hired for a new job each year, across all individuals in each age/education cell. These estimates are based on the 2004 panel of the Survey of Income and Program Participation (SIPP), which covers the period from February 2004 until January 2008. I exclude self-employed jobs from this analysis; and when an individual works has multiple jobs, I restrict attention to the "primary" job, as defined by monthly earnings.
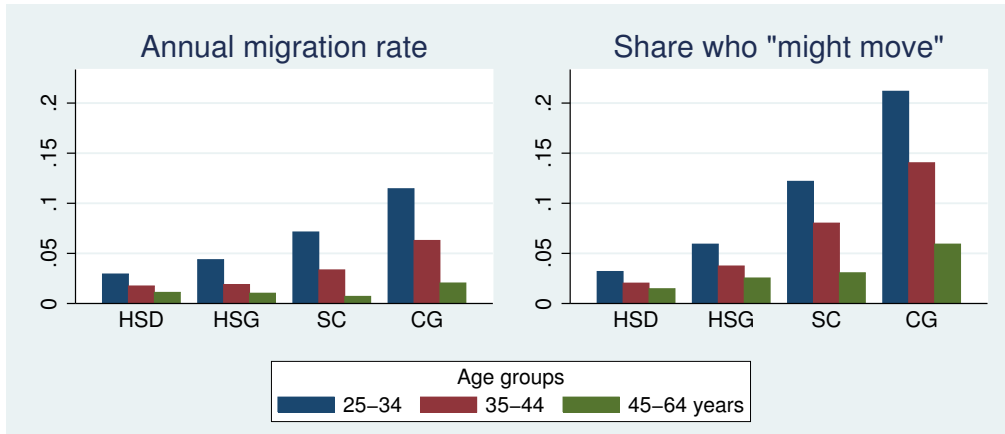
Figure 4: Annual job-motivated migration rates: PSID 1970-80

The first panel reports the proportion of household heads moving residence each year for job-related reasons, based on the PSID sample of 1970-80. Using the same sample, the second panel reports the share of heads who both (1) answer affirmatively to the question "Do you think you might move in the next couple of years?" *and* (2) report job-related reasons in answer to the question "Why might you move?" Household heads in the PSID are always male, unless there is no husband (or cohabiting partner) present or the husband is too ill to respond to the survey.
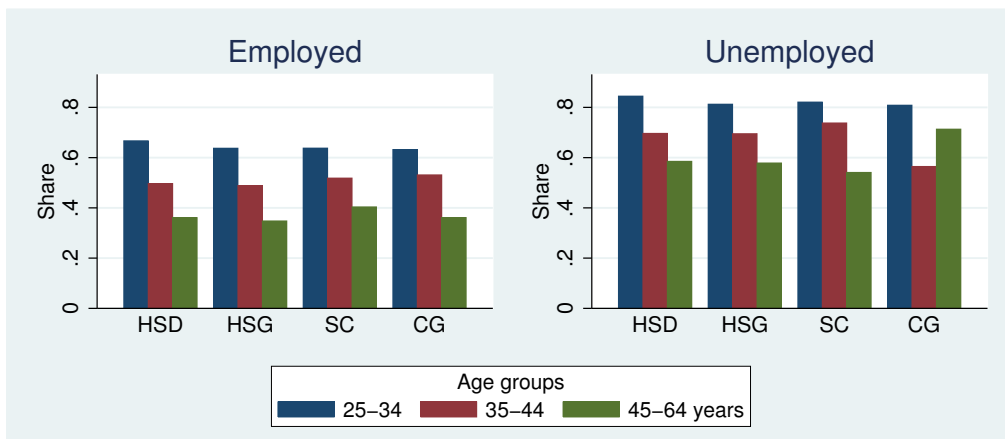

Figure 5: Share who would move for "good job": PSID 1970-80

In the years 1970-2 and 1979-80, employed respondents to the PSID were asked: "Would you be willing to move to another community if you could get a good job there?" Unemployed respondents were asked the same question in all years between 1970 and 1980 excluding 1976. This figure reports the proportion of households heads responding affirmatively, by employment status, age and education. Household heads in the PSID are always male, unless there is no husband (or cohabiting partner) present or the husband is too ill to respond to the survey.
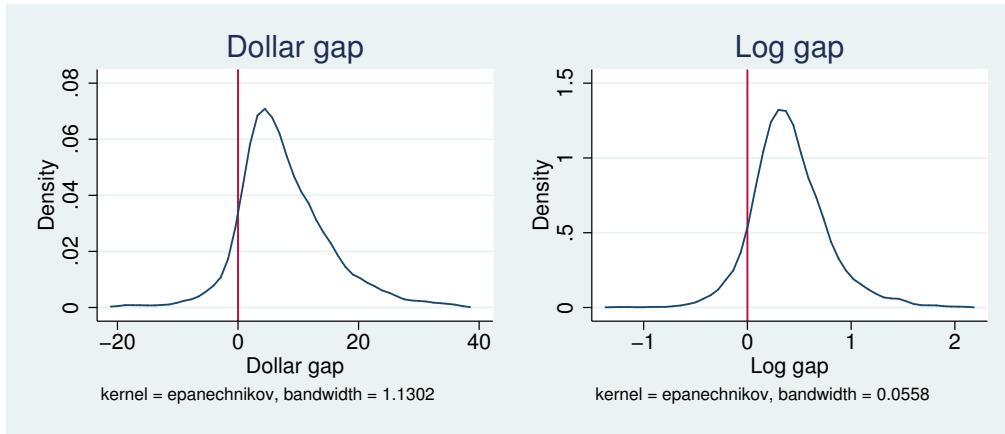
Figure 6: Distribution of flow-equivalent moving costs (hourly wage terms, 2000 $)

This figure plots kernel distributions of imputed flow-equivalent moving costs (in 2000 dollars, inflated by CPI), based on responses of employed household heads (in the PSID, 1970-2) to the question: "How much would a job have to pay for you to be willing to move?" The sample excludes those individuals who report being unwilling to move. Household heads in the PSID are always male, unless there is no husband (or cohabiting partner) present or the husband is too ill to respond to the survey. See notes under Table 3 for further details on the sample and how the cost measures are constructed.
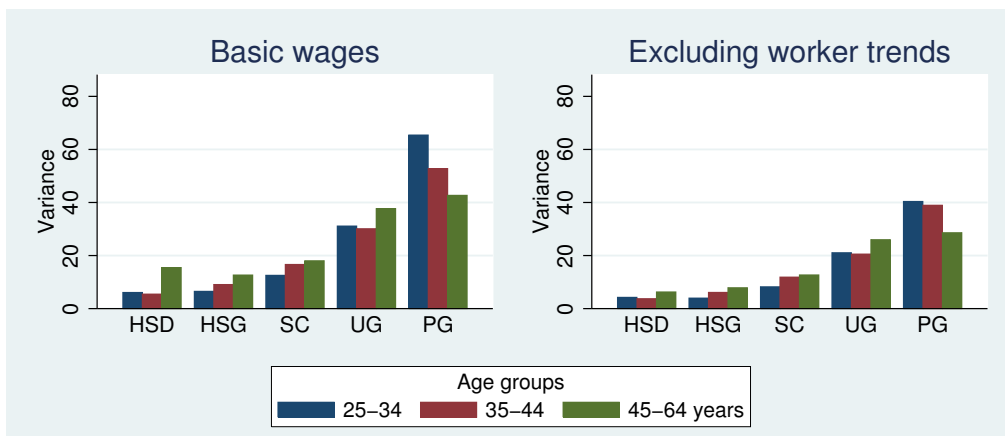

Figure 7: Average worker-specific variance over hourly dollar wages (2000 $)

These estimates are based on the SIPP panel of 2004. For each individual, I estimate variances in dollar wages over 4-month waves; and I report the mean variance within each age/education cell. The first panel uses the basic wage data, and the second uses wages purged of worker-specific linear time trends. The sample consists of employees still working in the final week of the wave. I exclude those with second jobs or businesses. I use hourly wage data for workers paid by the hour, and I impute hourly wages for salaried workers using monthly earnings and monthly hours. Finally, I drop wage observations under $5 in 2000 prices and top-coded values, as well as any remaining observations over $100.
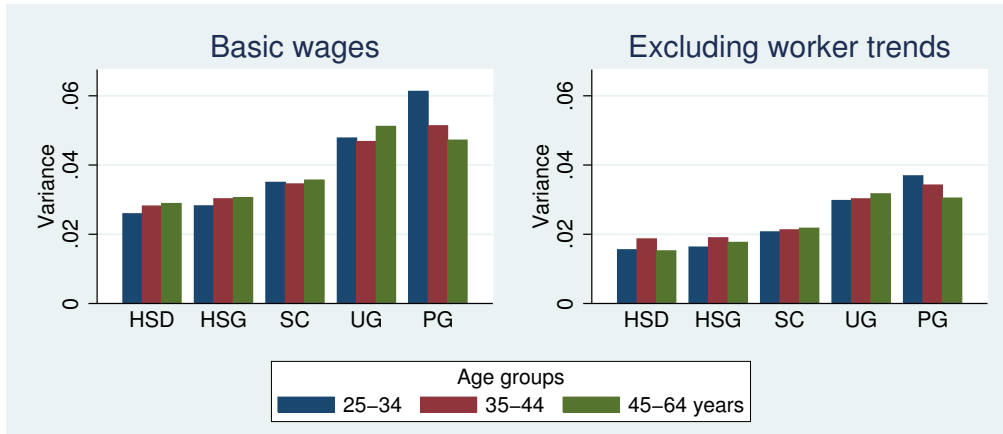
Figure 8: Average worker-specific variance over log hourly wages

This figure replicates the exercise of Figure 7, but estimates variances over log wages rather than dollar wages. See notes under Figure 7 for details on estimation and sample.

Appendices

A   Supplementary estimates from the CPS

This appendix presents supplementary estimates on reasons for moving, based on the CPS. First, I present a disaggregation of cross-county and cross-state migration in the CPS by reported reason. Second, I explore in greater detail how migration rates by reported reason vary with education, building on Figure 2 and Table 7 in the main text. Third, I disaggregate job-motivated and non-job migration into net flows across states and residual "excess flows": I show the skill gap in job-motivated migration is largely driven by the former, even within detailed occupation groups. And fourth, I show that CPS and PSID time series on job-motivated migration are quantitatively consistent. I begin by describing the sample I use for these exercises and in the main text.

A.1   Sample description

All estimates from the Current Population Survey (CPS) in this study are based on the March waves, organized by IPUMS (King et al., 2010). The March CPS reports whether respondents moved county or state in the previous 12 months. Since 1999, individuals have also given their primary reason for moving. All estimates below are based on pooled cross-sections between 1999 and 2013.

I restrict the sample to individuals aged 25 to 64 who lived in the US for the previous 12 months. Focusing on the over-25s helps ensure my results are not conflated by individuals leaving college. In any case, I exclude those who explicitly report moving primarily to attend or leave college: these account for 2 percent of the remaining cross-county migrant sample. I

also exclude those who report moving because of natural disasters: the majority of these are responses to Hurricane Katrina.

Importantly, the CPS question on reasons for moving is addressed to *individuals* within households. But of course, migration decisions are made in the context of the household. This ambiguity has resulted in some inconsistencies in the coding of responses: many household dependents simply report the reasons of the breadwinners.[46] My strategy is to restrict the sample to those individuals with the greatest predicted earnings power in each household: I define these as "household heads". This restriction excludes 41 percent of the original sample. I predict earnings power from a Mincer regression of log weekly wages on a detailed set of characteristics.[47] In households with multiple predicted top-earners, I divide the person weights by the number of top-earners.[48]

A.2   Breakdown of migration by reported reasons for moving

Table A1 disaggregates cross-county migration by primary reason for moving, separately for cross-state and within-state moves. The first column gives the percentage of the full sample who changed state for each recorded reason, and the second column reports the percentage of cross-state migrants who moved for each recorded reason. The final two columns repeat this exercise for cross-county moves within states.

The bottom row shows that, each year, about 2 percent of the sample move across states and another 2 percent switch county within states. Almost half of cross-state moves are job-motivated, compared with a third of within-state moves. Job-motivated moves are almost always driven by the needs of a *specific* job. Usually, this is due to a job change or transfer; and among within-state moves, commuting reasons also feature prominently. In contrast, it is rare to move to *look* for work without a job lined up. This sort of speculative job search accounts for just 5 percent of cross-state and 2 percent of within-state moves. This is unsurprising: moving without a job in hand is a costly and risky strategy. In terms of non-job migration, family and housing motivations account for most moves.

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[46]This is most clearly visible among children: in households with at least one adult moving for job-related reasons, 77 percent of under-16s also report moving for job reasons.

[47]Specifically: age, age squared, four education indicators (each of which are interacted with age and age squared), black and Hispanic race dummies, immigrant status, marital status, a range of indicators for number of own children, a gender indicator which is also interacted with all previously mentioned variables, and a set of year fixed effects (for the individual CPS cross-sections).

[48]As it happens, this sample restriction makes little difference to the results which follow: this is presumably because education is correlated across individuals within households. An alternative approach would be to choose those individuals with the greatest current (rather than predicted) earnings within households. But, this strategy is not ideal. Firstly, earnings are endogenous to migration itself. And secondly, this restriction would exclude those households with no current earners from the sample.

A.3   Skill gradients in job-motivated and non-job migration

Next, I show that the positive skill slope in job-motivated migration and negative slope in non-job migration (in Figure 2) are robust to individual demographic controls, within each age group. Specifically, I estimate complementary log-log models for annual incidence of cross-county migration, of the form of equation (39), on a set of education effects.

The β estimates for the education effects are presented in Table A2. I report results both with and without a detailed range of demographic controls.[49] The reported coefficients give the log point effect of a particular level of education, relative to high-school dropout (the omitted category), on the instantaneous migration rate (for the specified motivation).

With regards to job-motivated migration, Table A2 shows there are positive and strongly significant education effects within each age group. The coefficients change little after controlling for demographic characteristics, though the differences between age groups do narrow. Among those aged 25-34, a postgraduate education adds 124 log points to the migration rate (controlling for characteristics), relative to high school dropouts. This effect comes to 98 log points among the 35-44s, and 74 among the 45-64s. As in Figure 2, moving from high school dropout to graduate has little effect; but job-motivated rates grow rapidly thereafter.

Next, consider non-job migration. As in Figure 2, in the specification without demographic controls, the education effects are negative only for the over-35s. But interestingly, after controlling for demographic characteristics, the significant negative effect also extends to the 25-34s. It turns out this is largely due to controlling for Hispanic heritage: Hispanics tend to make relatively few non-job moves, despite having relatively low education levels. When demographic controls are included, the effect of a postgraduate education on the non-job migration rate (relative to dropouts) varies between 26 and 44 log points across age categories.

A.4   Disaggregated skill gradients

In Table 7 in the main text, I disaggregate the job-motivation and non-job skill gradients into nine distinct motivations. And in Table A3 in this appendix, I provide an even finer disaggregation. Again, I estimate complementary log-log models for migration by reported reason, of the form of equation (39), on education effects and a range of demographic controls. In each row of the table, I report education slopes for the individual motivations. I also produce separate estimates for the incidence of cross-state moves (first four columns) and within-state cross-county moves (last four columns). I pool all age groups together in each specification.

The first row reports effects for all motivations combined. Interestingly, the positive education gradient is only present for cross-state moves and not within-state. Mechanically, this is for two reasons. First, the positive education slope of job-motivated migration is much steeper

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[49]Specifically: age, age squared, black and Hispanic race dummies, immigrant status, marital status, a range of indicators for number of own children, and a gender indicator which is also interacted with all previously mentioned variables.

for cross-state than within-state moves (see the second row). Second, the negative education slopes for the various non-job motivations tend to be larger for within-state moves.

A broad range of the non-job motivations exhibit negative skill slopes, which contribute to the negative education effects reported in Table 7 in the main text. These include establishing own household, "other family reasons" (which are likely to include proximity to relatives), cheaper housing, "other housing reasons" and seeking a better neighborhood. There are only two non-job motivations with significant positive skill slopes: the desire to purchase a home, and the residual "other reasons" category (across states only).

A.5 Disaggregating migration into net and excess flows

In my model, I assume cities are identical. This rules out the possibility that the mobility gap is driven by large net flows of skilled workers to particular cities. In this section, I show this assumption is consistent with the empirical evidence. This finding is not entirely new: Folger and Nam (1967) and Schwartz (1971), and more recently, Lkhagvasuren (2014), show the ratio of net to gross migration rates is strongly decreasing in education.[50] I show this result is driven by job-motivated migration in particular, and it also holds for comparisons across detailed occupation groups (not just broad education groups).

Specifically, I estimate the cross-state net migration rate as $\frac{1}{2n}\Sigma_j|n_j^{in} - n_j^{out}|$, where n is the total sample of individuals, n_j^{in} is the number of in-migrants to state j, and n_j^{out} is the number of out-migrants from state j. Dividing the expression by 2 ensures that migrants are not double-counted. Notice the gross migration rate is simply equal to $\frac{1}{n}\Sigma_j n_j^{in}$ or $\frac{1}{n}\Sigma_j n_j^{out}$.

In Table A4, I report gross and net migration rates separately for job-motivated and non-job migration, and separately for each education group. As is well known[51], net flows are small relative to gross flows. Next, consider the skill gradients. As shown in the main text, gross job-motivated migration is strongly increasing in education. But, the skill gradient in net migration is much flatter: the net-gross ratio falls from 0.26 for high school dropouts to just 0.11 for postgraduates. Interestingly though, among non-job moves, there is no systematic pattern in the net-gross ratio.

The evidence in Table A4 shows that net flows within education groups account for only a small portion of the skill differences in job-motivated mobility. But, this does not rule out large *occupation-specific* net flows among college graduates. For example, graduate bankers might move en masse from California to New York, and graduate computer scientists in the other direction, yielding small net flows overall.

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[50]Schwartz (1971) criticizes Folger and Nam (1967) on their interpretation of this fact. Following Shryock (1959), Folger and Nam view the net-gross ratio as reflecting migration "efficiency" (with a small ratio implying many moves in the "wrong" direction). This claim was disputed by Schwartz, who noted that large gross flows can be explained by movements up an idiosyncratic wage distribution. He argues that the small net-gross ratio among skilled workers reflects small local earnings differentials which arise in better integrated markets.

[51]See, for example, Schwartz (1971); Jackman and Savouri (1992); Wildasin (2000); Coen-Pirani (2010).

However, I show that the results above also hold within 80 detailed occupation groups.[52] In Figure A1, I plot annual net and gross migration rates within each occupation group on its "skill" percentile, where skill is identified with an occupation's median wage.[53]

The first panel presents results for job-motivated and the second for non-job migration.[54] Job-motivated gross migration rates increase rapidly after the 30th percentile. But, there is no systematic pattern in the net rates, except perhaps a small increase around the 90th percentile. Among non-job moves though, similarly to Table A4, net-gross ratios appear to vary little with skill.

There is an important caveat in the interpretation of these results. Ideally, I would classify workers according to their occupation 12 months previously; but unfortunately, this information is not reported in the March CPS. Instead, occupations are reported at the time of survey (immediately after the period in which migration is recorded). This is problematic to the extent that occupational skill percentile and migration are co-determined. But, the clarity of the patterns is still compelling.

A.6   Consistency between CPS and PSID

In this study, I have cited evidence from both the CPS and PSID on reported reasons for moving. In this section, I show estimates of the job-motivated migration rate (the key variable of interest) are consistent across these surveys. In Figure A2, I plot time series of the share of households heads[55] making job-motivated moves in the previous 12 months, separately for moves of any distance and cross-state moves.

In the PSID, there has been a clear downward trend since the mid-1980s.[56] Notice that the PSID series is much more volatile: this reflects the smaller sample sizes. Reassuringly though, the CPS rates (beginning in 1999) have similar magnitude to the PSID rates in the same period.

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[52]These are time-consistent groups constructed by IPUMS, based on the census 1990 coding scheme.

[53]The percentiles are employment-weighted. Specifically, I line up workers according to their median occupational wage; and I estimate the "skill percentile" as the average percentile of workers (within each occupation group) along this line.

[54]I exclude individuals reporting no occupation and those in the armed forces. Individuals in the military are unusually mobile, with an annual job-motivated migration rate of 10.7 percent, compared to 0.9 percent for other workers.

[55]The definition of household heads differs between the PSID and CPS. Household heads in the PSID are always male, unless there is no husband (or cohabiting partner) present or the husband is too ill to respond to the survey. In contrast, the CPS might define a husband or wife as the reference person. For the purpose of this exercise, I construct a PSID-equivalent household head definition in the CPS data. Specifically, I use the CPS's definitions, unless there is a female head living with a male partner - in which case I designate the male as the head.

[56]This has been well documented in the literature: see, for example, Molloy, Smith and Wozniak (2011). Kaplan and Schulhofer-Wohl (2012) argue the trend is driven by a decline in the geographical specificity of returns to occupations, together with improving communications technology.

Table A1: Breakdown of migration motivations for individuals aged 25-64

Primary reason	State moves		County moves (within states)	
	% full sample	% state migrants	% full sample	% county migrants
JOB-MOTIVATED	0.94	45.31	0.60	28.78
New job or job transfer	0.69	33.23	0.33	15.61
Easier commute	0.07	3.17	0.17	8.21
Looking for work	0.10	4.62	0.05	2.48
Other job-related reasons	0.09	4.30	0.05	2.48
NON-JOB	1.13	54.69	1.49	71.22
Family	0.52	24.87	0.58	27.57
Change in marital status	0.11	5.51	0.18	8.56
Establish own household	0.08	4.05	0.15	6.97
Other family reasons	0.32	15.31	0.25	12.03
Housing	0.40	19.21	0.71	34.17
Want to own home	0.07	3.53	0.17	8.29
New or better housing	0.13	6.34	0.24	11.59
Cheaper housing	0.08	3.71	0.12	5.76
Other housing reasons	0.12	5.63	0.18	8.54
Amenities	0.18	7.49	0.18	6.47
Better neighborhood	0.05	2.47	0.09	4.16
Climate, health, retirement	0.10	5.02	0.05	2.32
Other reasons	0.06	3.12	0.06	3.01
ALL REASONS	2.07	100	2.09	100

This table presents migration rates for individuals aged 25-64, by primary reason in CPS cross-sections between 1999 and 2013. I exclude individuals living abroad in the previous 12 months, and those who migrated primarily to attend or leave or college or because of natural disasters. The sample is further restricted to the individuals with the greatest predicted earnings power in each household, where this prediction is based on a Mincer wage regression. In households with multiple predicted top-earners, I divide the person weights by the number of top-earners. The first column reports the percentage of the *full sample* who changed state, for each given reason, over the previous twelve months. The second column gives the percentage of *state-movers* reporting each reason. The final two columns repeat the exercise for cross-county moves within states.

Table A2: Log point responses of job-motivated and non-job migration rates

	JOB-MOTIVATED			NON-JOB		
	25-34	35-44	45-64	25-34	35-44	45-64
	(1)	(2)	(3)	(4)	(5)	(6)

Specification 1: no demographic controls

High-school graduate	0.135*	0.122	0.012	0.104**	-0.082	-0.088*
	(0.073)	(0.089)	(0.087)	(0.048)	(0.052)	(0.046)
Some college	0.422***	0.397***	0.275***	0.116**	-0.088*	-0.037
	(0.071)	(0.087)	(0.085)	(0.047)	(0.052)	(0.046)
Undergraduate	0.893***	0.649***	0.524***	0.080*	-0.242***	-0.231***
	(0.069)	(0.087)	(0.085)	(0.048)	(0.055)	(0.050)
Postgraduate	1.300***	1.086***	0.691***	-0.095	-0.384***	-0.330***
	(0.072)	(0.088)	(0.087)	(0.059)	(0.065)	(0.055)

Specification 2: demographic controls

High-school graduate	0.071	0.036	-0.029	-0.013	-0.178***	-0.096**
	(0.076)	(0.093)	(0.089)	(0.050)	(0.054)	(0.048)
Some college	0.353***	0.324***	0.241***	-0.042	-0.192***	-0.046
	(0.075)	(0.092)	(0.087)	(0.050)	(0.056)	(0.049)
Undergraduate	0.755***	0.543***	0.513***	-0.140***	-0.317***	-0.178***
	(0.075)	(0.092)	(0.088)	(0.053)	(0.060)	(0.053)
Postgraduate	1.241***	0.983***	0.737***	-0.256***	-0.440***	-0.256***
	(0.079)	(0.095)	(0.091)	(0.064)	(0.069)	(0.058)
Observations	195,754	264,221	440,342	195,754	264,221	440,342
Migration rate (%)	3.657	1.686	0.811	5.136	3.023	2.039

Each column reports education effects from complementary log-log regressions on job-motivated and non-job migration incidence across counties. I report results separately for three age groups. Coefficients should be interpreted as the log point effect of a particular level of education (relative to high-school dropout, the omitted category) on the instantaneous migration rate, conditional on the empirical model described by equation (39). Estimates are based on a panel of CPS cross-sections between 1999 and 2013; see the notes under Table A1 for the sample description. I include results for specifications both with and without detailed demographic controls: age, age squared, black and Hispanic race dummies, immigration status, marital status, a range of indicators for number of own children, and a gender indicator which is also interacted with all previously mentioned variables. All specifications control for a set of year fixed effects (for the individual CPS cross-sections). Robust SEs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Log point responses of migration rate, by detailed reported reason

Primary reason	CROSS-STATE				CROSS-COUNTY WITHIN STATE			
	HS grad	Some coll	Coll grad	Post grad	HS grad	Some coll	Coll grad	Post grad
All reasons	-0.044	0.047	0.217***	0.504***	-0.097***	-0.027	-0.090***	-0.139***
	(0.038)	(0.038)	(0.039)	(0.041)	(0.033)	(0.033)	(0.035)	(0.040)
JOB-MOTIVATED								
New job/transfer	0.258***	0.647***	1.185***	1.771***	0.062	0.465***	0.775***	0.973***
	(0.092)	(0.090)	(0.089)	(0.090)	(0.107)	(0.104)	(0.104)	(0.113)
Commute	-0.195	0.036	0.046	0.478*	0.118	0.276**	0.369***	0.434***
	(0.231)	(0.226)	(0.228)	(0.244)	(0.132)	(0.131)	(0.133)	(0.144)
Look for work	-0.306**	-0.421***	-0.358**	-0.474***	-0.422**	-0.408**	-0.740***	-0.765***
	(0.148)	(0.147)	(0.151)	(0.181)	(0.176)	(0.189)	(0.212)	(0.254)
Other job reasons	0.362*	0.535**	0.575***	1.057***	-0.288	-0.161	-0.296	-0.229
	(0.208)	(0.209)	(0.207)	(0.213)	(0.206)	(0.200)	(0.210)	(0.239)
NON-JOB								
Change in marital status	0.106	0.133	-0.076	-0.113	0.251**	0.411***	0.081	-0.005
	(0.156)	(0.158)	(0.169)	(0.193)	(0.127)	(0.127)	(0.135)	(0.151)
Establish own household	-0.030	-0.057	0.003	-0.193	-0.237*	-0.128	-0.437***	-0.566***
	(0.168)	(0.169)	(0.178)	(0.212)	(0.122)	(0.122)	(0.130)	(0.162)
Other family reasons	-0.296***	-0.250***	-0.345***	-0.523***	-0.113	-0.202**	-0.483***	-0.741***
	(0.082)	(0.083)	(0.090)	(0.106)	(0.087)	(0.090)	(0.097)	(0.122)
Want to own home	0.211	0.139	0.471**	0.548**	0.197	0.373***	0.542***	0.291**
	(0.195)	(0.203)	(0.202)	(0.223)	(0.129)	(0.129)	(0.130)	(0.145)
New or better housing	0.053	-0.080	-0.100	-0.190	-0.079	-0.056	-0.101	-0.295**
	(0.129)	(0.135)	(0.144)	(0.160)	(0.095)	(0.096)	(0.101)	(0.115)
Cheaper housing	-0.068	-0.238	-0.635***	-0.528**	-0.205*	-0.285**	-0.588***	-0.863***
	(0.168)	(0.174)	(0.193)	(0.223)	(0.124)	(0.128)	(0.140)	(0.176)
Other housing reasons	-0.057	-0.261*	-0.194	-0.217	-0.300***	-0.388***	-0.607***	-0.678***
	(0.149)	(0.150)	(0.154)	(0.173)	(0.099)	(0.102)	(0.112)	(0.130)
Better neighborhood	-0.126	0.031	-0.429**	-0.276	-0.141	-0.152	-0.354**	-0.424**
	(0.196)	(0.193)	(0.213)	(0.240)	(0.143)	(0.147)	(0.155)	(0.181)
Climate, health, retirement	-0.084	0.131	0.006	0.062	-0.200	-0.439**	-0.596***	-0.345
	(0.154)	(0.154)	(0.163)	(0.175)	(0.180)	(0.190)	(0.215)	(0.232)
Other reasons	0.203	0.135	0.572***	0.733***	-0.279	-0.371*	-0.477**	-0.489**
	(0.206)	(0.212)	(0.206)	(0.223)	(0.200)	(0.202)	(0.210)	(0.235)

This table reports education effects from complementary log-log regressions on annual migration incidence, estimated separately for cross-state and within-state (cross-county) moves. Each row reports the effects on moving for the motivation specified, with the first row presenting education effects on the overall migration incidence (all reasons). The first four columns gives results for cross-state migration and the final four for cross-county migration within states. Coefficients should be interpreted as the log point effect of a particular level of education (relative to high-school dropout, the omitted category) on the instantaneous migration rate, conditional on the empirical model described by equation (39). Estimates are based on a panel of CPS cross-sections between 1999 and 2013; see the notes under Table A1 for the sample description. The sample size in each regression is 900,317. Each regression controls for a detailed set of individual characteristics: age, age squared, black and Hispanic race dummies, immigration status, marital status, a range of indicators for number of own children, a gender indicator which is also interacted with all previously mentioned variables, and a set of year fixed effects (for the individual CPS cross-sections). Robust SEs in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Net cross-state migration rates by education

	HS dropout	HS graduate	Some college	Under graduate	Post graduate
Job-motivated					
Gross migration rate (%)	0.50	0.58	0.78	1.33	1.84
Net migration rate (%)	0.13	0.11	0.10	0.16	0.20
Net-gross ratio	0.26	0.18	0.13	0.12	0.11
Non-job					
Gross migration rate (%)	1.25	1.19	1.20	1.16	1.00
Net migration rate (%)	0.26	0.15	0.17	0.21	0.19
Net-gross ratio	0.20	0.12	0.14	0.18	0.19
Observations (000s)	90	255	243	197	114

This table reports annual gross and net cross-state migration rates within education groups, based on the CPS March cross-sections of 1999-2013. See notes under Table A1 for sample description. The cross-state net migration rate is estimated as $\frac{1}{2n}\Sigma_j|n_j^{in} - n_j^{out}|$, where n is the total sample of individuals, n_j^{in} is the number of in-migrants to state j, and n_j^{out} is the number of out-migrants from state j. Gross and net rates are estimated separately for workers who report moving for job-related and non-job reasons.
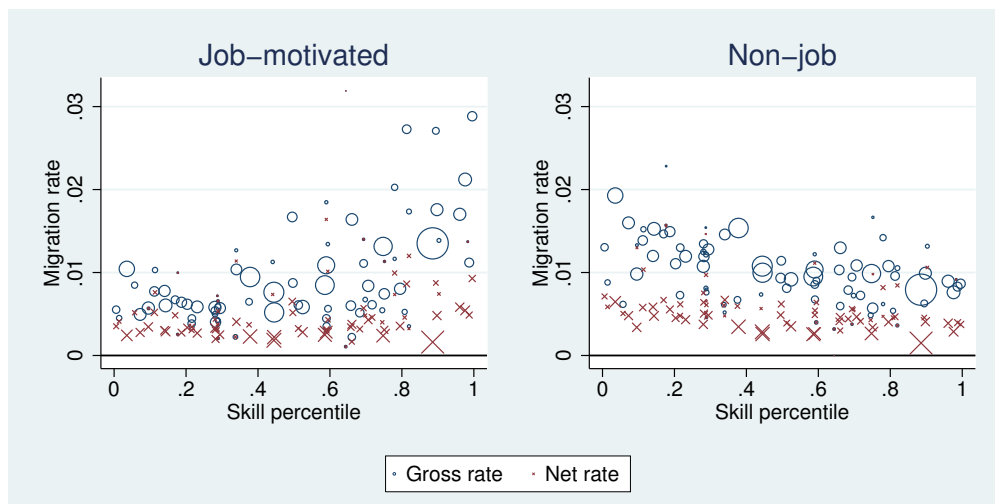

Figure A1: Annual gross and net cross-state migration by occupation

This figure reports annual gross and net cross-state migration rates within 80 occupation groups, based on the CPS March cross-sections of 1999-2013. See notes under Table A1 for sample description. The occupations are time-consistent groups constructed by IPUMS, based on the census 1990 coding scheme. Within each occupation group, the cross-state net migration rate is estimated as $\frac{1}{2n}\Sigma_j|n_j^{in} - n_j^{out}|$, where n is the total sample of individuals, n_j^{in} is the number of in-migrants to state j, and n_j^{out} is the number of out-migrants from state j. Gross and net rates are estimated separately for workers who report moving for job-related and non-job reasons.
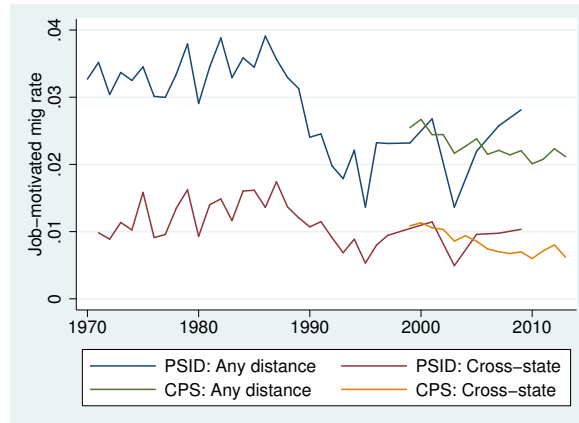
Figure A2: Comparison of job-related migration rates in PSID and CPS

The job-motivated migration rate is the share of household heads aged 25-64, who report changing residence for a job-related reason in the previous year. I plot migration rates of any distance and cross-state rates separately. The "any distance" PSID series can be constructed for all years between 1970 and 2009, excluding even years since 1998 (when no survey was conducted). The cross-state series can be constructed for those same years excluding 1970. I report CPS estimates since 1999, when respondents were first asked why they moved. The definition of household heads differs between the PSID and CPS. Household heads in the PSID are always male, unless there is no husband (or cohabiting partner) present or the husband is too ill to respond to the survey. In contrast, the CPS might define a husband or wife as the reference person. For the purpose of this exercise, I construct a PSID-equivalent household head definition in the CPS data. Specifically, I use the CPS's definitions, unless there is female head living with a male partner - in which case I designate the male as the head.

B   Evidence on market tightness and search intensity

The model predicts that the large expected job surplus in skilled markets is manifested in (1) tight labor markets and (2) intensive job search by both firms and workers. In this section, I document evidence for both claims. Of course, conditional on the model, these measures can also be interpreted as proxies for the expected surplus itself.

B.1   Market tightness

Every month, the Conference Board reports the number of new online job ads and ads reposted from the previous month on 16,000 online job boards,[57] known as the Help Wanted Online (HWOL) series. This data is also disaggregated by occupational SOC classification. I use a (pre-recession) data release from April 2008[58] and take the ratio of these vacancy counts to occupational unemployment estimates from the IPUMS American Community Survey (ACS) of 2007[59]. In Figure B1, I plot this vacancy-unemployment ratio on occupational college employment share[60]. For low skilled occupations (with college share below 40 percent), the ratio ranges from 0.02 to 0.32; and rises to between 0.14 to 3.40 for occupations with more than

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[57]See *http://www.conference-board.org/pdf_free/press/TechnicalPDF_5202_1401797782.pdf* for further details.

[58]*http://www.conference-board.org/pdf_free/HWOnLine043007_PR.pdf*

[59]In the ACS, unemployed workers were asked to report their most recent occupation. The IPUMS ACS data was compiled by Ruggles et al. (2010)

[60]I also estimate college share using data from the ACS of 2007.

40 percent college employment.[61] An important concern with this data is that online job ads clearly do not represent the universe of occupations; and higher skilled jobs are perhaps more likely to be advertised online. However, it does not seem plausible that this can explain the very large effect of skill in Figure B1.

B.2 Firms' search effort

If the free entry condition holds, the model predicts that a firm's instantaneous advertising expenditure is invariant with expected job surplus. But in any case, as vacancy duration is increasing in job surplus (as I show in Appendix D), we should expect firms to spend more over the duration of each vacancy.

I present some evidence on firms' search effort (or "advertising intensity" in the model) from a pair of employer surveys in 1992 and 2001, funded by the Small Business Administration (SBA) and conducted by the Survey Research Center at the University of Kentucky[62] (see Berger, Barron and Black, 2001*b*). Of interest to this study, respondents were asked a number of questions related to the application process of their most recent hire, together with that hire's highest qualification. And I report mean outcomes by education group in Table B1, per individual hired for each advertised position.

All the measures of firm search effort over the hiring process are increasing in education. In 1992, the effects are very large and monotonic across education groups. On average, firms received 35 applications, conducted 8 interviews and spent 34 human resource hours per hire at postgraduate level; but these numbers are just 10, 3 and 5 at high school dropout level. The story is qualitatively similar in 2001, though the monotonicity result does not hold in each case. Also, magnitudes do vary across surveys. In particular, the number of applications received per hire was significantly larger in the earlier survey, with a sample average of 15.1 compared to 6.7 in 2001; though the reported standard errors for this variable were much larger in 1992.

The 2001 survey also reports the time required to fill the vacancy, and I present means by education group in the final column. As predicted by the model (see Appendix D below), durations are significantly longer for higher skilled workers, ranging from 3 weeks for dropouts to 10 weeks for postgraduates (per worker hired). This is consistent with the market tightness patterns in Figure B1: firms respond to the large job surpluses in skilled markets by creating many more vacancies; so in equilibrium, they trade off larger gains per job with lower recruitment rates. These longer vacancy durations may account for much of the variation in applications received and HR hours invested.

---

[61]The dispersion in tightness among skilled occupations is large. It is plausible that the loose markets that characterize the arts/sport/media or education/training categories are attributable to restricted firm entry in those industries, but this is merely speculation: there are certainly many factors at play.

[62]These can be downloaded from *http://harris.uchicago.edu/directory/faculty/dan_black*. In both 1992 and 2001, the investigators contacted a nationally representative sample of establishments. In 1992, 1,288 establishments completed the survey (with a response rate of 55.9 to 60.6 percent, depending on the method used). And in 2001, there were 1,024 completions with a response rate of 47.1 to 48.1 percent.

The model also predicts that firms apply search effort more broadly geographically when recruiting high skilled workers. The SBA survey does not report this sort of information. But, there is some useful evidence in an annual survey of recruitment conducted by the Chartered Institute of Personnel and Development (CIPD) in the UK. In particular, the annual report of 2004 presents data on firms' advertising strategies by occupational rank. In the CIPD sample, 61 percent of firms recruiting managers and professionals posted job ads in national newspapers and 67 percent posted ads in the trade press; this compares to just 8 and 6 percent respectively for firms recruiting manual or craft workers. In contrast, manual/craft recruiters were more likely to post ads in local newspapers: 78 percent compared to 48 percent for manager/professional recruiters.

B.3   Workers' search effort

Despite high skilled markets being much tighter (see Figure B1), Table B1 shows there are still many more applicants per position. This suggests that higher skilled workers are individually applying to many more jobs than the low skilled. This is indicative of greater search intensity, which is consistent with the model's predictions.

More direct evidence on workers' search intensity can be extracted from the CPS. Before 1994, the CPS asked unemployed job-seekers which search methods they used. In Table B2, I report the share of job-seekers in each education group using each search method. I restrict the sample to individuals aged 25-64 in the 1988-93 waves of the March CPS: answers to this question were consistently coded over this period. Higher skilled workers are more likely to have placed or check advertisements (51 percent of postgraduates compared to 32 percent of high school dropouts), used private job agencies (22 percent of postgraduates compared to 6 percent of dropouts) and used other unspecified methods (10 compared to 4 percent). The low skilled are somewhat more likely to have used public job agencies (27 percent of dropouts compared to 20 percent of postgraduates), though this is presumably a reflection of the type of jobs advertised.

Related to this is the role of social networks in job search. Most studies tend to show around half of workers find their job through a personal contact (see Granovetter, 1995, for a survey and original analysis). Since higher skilled workers benefit from larger job surpluses, my model would predict they invest more heavily in developing broader social networks. Indeed, Granovetter finds that higher skilled workers are relatively more likely to have found their job through "work" contacts rather than "family/social" contacts; and it might be presumed that "work" contacts are somewhat more costly to maintain.

Table B1: Evidence on firms' search effort from the SBA survey

Reported statistics are means, per worker hired for advertised position

PANEL A: SBA survey 1992

Education of most recent hire	Applications received	Applicants interviewed	HR labor hours	Sample
HS dropout	9.89	2.61	4.76	72
	(27.15)	(2.84)	(6.94)	
HS graduate	9.91	4.54	9.31	415
	(16.18)	(5.75)	(12.44)	
Some college	12.31	4.83	12.16	290
	(23.05)	(4.92)	(16.60)	
Undergraduate	26.25	5.72	25.89	207
	(54.41)	(5.65)	(43.56)	
Postgraduate	35.49	7.66	33.77	51
	(56.54)	(8.82)	(37.79)	

PANEL B: SBA survey 2001

Education of most recent hire	Applications received	Applicants interviewed	HR labor hours	Weeks to fill	Sample
HS dropout	3.66	3.03	11.19	2.87	85
	(4.49)	(3.79)	(22.55)	(5.96)	
HS graduate	5.30	3.15	8.10	2.52	415
	(12.10)	(3.32)	(11.78)	(7.32)	
Some college	6.21	4.33	13.15	4.89	182
	(7.98)	(5.66)	(21.00)	(17.44)	
Undergraduate	12.36	4.77	23.12	6.98	148
	(23.99)	(8.71)	(37.83)	(16.81)	
Postgraduate	10.51	3.80	40.51	9.51	33
	(13.03)	(3.11)	(76.89)	(23.05)	

These estimates are based on two employer surveys in 1992 and 2001, funded by the Small Business Administration (SBA) and conducted by the Survey Research Center at the University of Kentucky. The data files can be downloaded from *http://harris.uchicago.edu/directory/faculty/dan_black*. Respondents were asked a number of questions related to the application process of their most recent hire, together with that hire's highest qualification. I report mean outcomes by education group, per worker hired for each advertised position. Standard errors in parentheses.

Table B2: Search methods of the unemployed

Reported statistics are percentages of those looking for work, by education group

Search method	HS dropout	HS graduate	Some college	Under graduate	Post graduate
Placed/checked ads	32.19	41.56	47.14	49.19	51.13
Contacted employer	70.87	69.9	68.5	69.95	71.47
Public job agency	26.63	28.87	29.15	24.22	19.77
Private job agency	5.75	8.08	12.44	18.25	22.18
Asked friends/relatives	26.23	20.86	22.36	23.74	22.46
Other method	3.66	5.67	7.09	7.46	10.17
Observations (000s)	4.24	6.51	3.27	1.47	0.71

This table reports, by education group, the percentage of those looking for work (in the last four weeks) using each search method. The sample consists of unemployed individuals aged 25-64, who looked for work during the preceding four weeks, in the CPS March waves of 1988-1993.
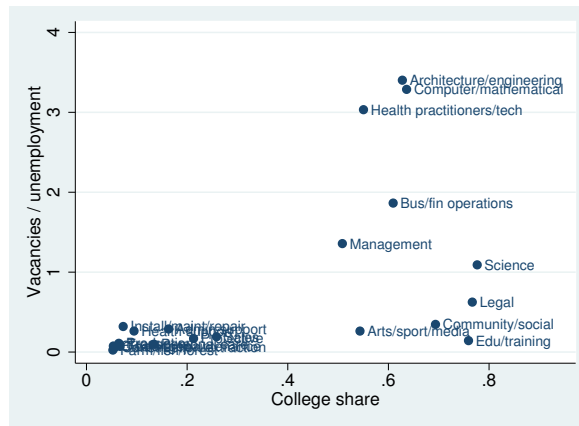
Figure B1: Ratio of online job ads to unemployment (Conference Board, Apr 2007; ACS 2007)

Data on vacancies for 22 SOC occupations are taken from the Conference Board Help Wanted Online series for April 2007. And I estimate unemployment counts using the American Community Survey (ACS) of 2007: in the ACS, unemployed workers were asked to report their most recent occupation. I also use the ACS to estimate occupation-specific shares of college graduates, reported on the x-axis.

C   Extensions to the model

C.1   Endogenous separation rate

In the main text, I have assumed the job separation rate δ is exogenous. But, the fact that skilled workers face lower separation rates (see Table 1) may itself be a consequence of larger job surpluses, driven fundamentally by larger $\bar{y} - b$ and σ. As I have shown in the main text, the expected surplus is decreasing in δ. So, this endogeneity would merely serve to amplify

the effect of given changes in $\bar{y} - b$ or σ on the expected surplus.

Endogeneity in δ can be introduced through randomness in the match productivity, after job formation. Suppose, for example, match productivity follows a random walk:

$$y' = y + \zeta \tag{C1}$$

The initial productivity y (when the match is formed) is drawn from the distribution F as before. But now, i.i.d. draws of ζ arrive at rate ψ from some distribution G. The match is destroyed if the surplus $S(y)$ falls below zero. For given G, the rate of job destruction is clearly lower in markets with larger surpluses.[63]

But of course, the distribution G may vary with education. In particular, skilled jobs may be associated with greater accumulation of firm-specific human capital (see Lillard and Tan, 1992; Mincer, 1991 for evidence on training), so skilled workers would benefit from larger draws of ζ. This would further reduce the probability of separation (see Mincer, 1991).

C.2   On-the-job search

Until now, I have ruled out on-the-job search. While this assumption greatly simplifies the exposition, it does not affect the key results. Consider a world in which workers can search whenever they wish. They make a job-to-job move when they receive an offer with surplus exceeding zero (or exceeding the matching cost in the national market).[64] The surplus accruing to a job-to-job move is defined as:

$$
\begin{aligned}
S(y, w_0) &= E(w_X(y, w_0)) - E(w_0) + J(y, w_X(y, w_0)) - \bar{V} \\
&= \frac{1}{r + \delta}(w_X(y, w_0) - w_0) + \frac{1}{r + \delta}(y - w_X(y, w_0)) - \frac{r}{r + \delta}\bar{V} \\
&= \frac{1}{r + \delta}(y - w_0 - r\bar{V})
\end{aligned} \tag{C2}
$$

where y is the productivity of the new job, and w_0 is the wage of the worker's previous job. The wage offer of the new job $w_X(y, w_0)$ is fully determined by y and w_0, together with the matching cost m_X:

$$w_X(y, w_0) = \phi(y - r\bar{V}) + (1 - \phi)(m_X + rE(w_0)) \tag{C3}$$

with $m_L = 0$ and $m_N = m > 0$. Notice the employment value $E(w)$ must now include the returns to search:

---

[63] See Sengul (2009) for similar reasoning, in the context of skill differences in separation rates.

[64] For simplicity, I rule out the possibility that a worker can renegotiate his wage in his current match after receiving a better offer elsewhere. See Cahuc, Postel-Vinay and Robin (2006) for a search model with this feature.

$$rE(w) = w + \delta(U - E(w)) \tag{C4}$$

$$+ \sum_{X=\{L,N\}} \max_{s_X} \left\{ s_X \left(\frac{\bar{a}_X}{\bar{s}_X} \theta \right)^{1-\alpha} \hat{E}_X(w) - \frac{1}{2} \tilde{\gamma}_{sX} s_X^2 \right\}$$

where s_X is the search effort directed at a vacancy in market X. I assume search is more costly for the employed: $\tilde{\gamma}_{sX} > \gamma_{sX}$; this ensures unemployed workers do not simply accept every offer which pays more than their out-of-work income b. $\hat{E}_X(w)$ is the ex ante expected value to the employed worker of a job offer in market X. Specifically:

$$\hat{E}_X(w) = \int_{y'} \max \left\{ E(w_X(y', w)) - E(w) - m_X, 0 \right\} dF \tag{C5}$$

where w is the worker's current wage, and y' denotes the productivity of the new offer. For employed workers, the first order condition for search intensity is:

$$s_X(w) = \frac{\phi}{\gamma_{sX}} \left(\frac{\bar{a}_X}{\bar{s}_X} \theta \right)^{1-\alpha} \int_y \max \left\{ S(y', w) - m_X, 0 \right\} dF \tag{C6}$$

where $S(y', w)$ is the surplus, gross of the matching cost, which accrues to a match of quality y', involving an employed worker with a job currently paying wage w.

Assuming $y \sim U(\bar{y} - \sigma, \bar{y} + \sigma)$, as in the main text, the expected surplus accruing to a local market job-to-job transition is:

$$\int_y \max \left\{ S(y, w_0), 0 \right\} = \frac{1}{4\sigma(r+\delta)} (\bar{y} + \sigma - w_0 - r\bar{V})^2 \tag{C7}$$

For a given current wage w_0, notice this is increasing in $\bar{y}$ and σ and decreasing in δ. Certainly, the current wage w_0 will tend to be larger in an economy with larger $\bar{y}$ and σ, and this will diminish the expected surplus somewhat. But, this latter effect will not dominate. Intuitively, in the Nash bargain, workers do not receive the entire surplus from changes in $\bar{y}$, σ and δ in their wage w_0; so the expected surplus will grow overall.

And therefore, the ratio of the national to local expected surplus must also be increasing in $\bar{y}$ and σ and decreasing in δ:

$$\frac{\int_y \max \left\{ S(y, w_0) - m, 0 \right\}}{\int_y \max \left\{ S(y, w_0), 0 \right\}} = \left[1 - \frac{m}{2} \sqrt{\frac{r+\delta}{\sigma} \frac{1}{\int_y \max \left\{ S(y, w_0), 0 \right\} dF}} \right]^2 \tag{C8}$$

And based on equation (33) in the main text, the same must be true of the relative national-local search intensity $\frac{s_N}{s_L}$ and finding rate $\frac{\rho_N}{\rho_L}$.

C.3 Non-job migration

The model in the main text deals exclusive with "job-motivated" migration. This is appropriate for this study, given that evidence from the CPS shows the skill mobility gap is entirely explained by moves of this type. Having said that, it is possible to analyze other types of moves within the framework described by the model. In particular, suppose that a worker i's employment value depends on an individual-specific valuation of local amenities a_{ij} in the city of employment j. Building on equation (5) in the main text:

$$rE_{Xij}(y) = w_{Xij}(y) + a_{ij} + \delta \left(U - E_{Xij}(y) \right) \tag{C9}$$

At any point in time, each worker i is associated with a vector of amenity valuations over all cities j: $\{a_{i1},...,a_{iJ}\}$. At random intervals, workers draw a new amenity vector. In particular, suppose an employed worker randomly draws a very large amenity match a_{ij} for some city j, perhaps due to family needs. If the shock is large, the surplus associated with the worker's current job would become small. He would then search intensively (on-the-job) for new employment in city j and would eventually move there. This would be a "non-job" move, in the sense that it was triggered by an amenity draw a_{ij}, rather than a productivity draw y.

What is the effect of a decrease in the national matching cost m? Clearly, workers are more likely to act on local differentials in amenity valuations if moving is cheaper. And consequently, for a given distribution of a_{ij} and arrival rate of amenity shocks, the non-job migration rate would be larger.

And what is the effect of an increase in the expected job surplus, due to changes in $\bar{y} - b$, σ or δ? A given shock to the a_{ij} vector would be less likely to tempt workers away from their current job. So, while the job-motivated rate of migration would grow, the non-job rate would contract. This is consistent with evidence from Table 7 in the main text.

C.4 Move-then-search

The model in Section 2 restricts workers to moving only after coming into contact with a prospective match partner: as Table A1 shows, very few individuals move speculatively to look for work. But in any case, according to Table 7, the incidence of speculative moves is decreasing in skill. I argue this is consistent with my hypothesis.

I interpret a speculative move in the model as a change of worker's origin. Suppose unemployed workers have the the option of switching origin at cost c. I assume c exceeds the national market matching cost m, since it is difficult to move to a new city with no steady income. A worker of origin j will make a speculative move if:

$$U_j < \max_k U_{k \neq j} - c \tag{C10}$$

Clearly, in an equilibrium with identical cities, no workers will choose to make speculative

moves. But, workers of origin j will switch origin following an adverse local productivity shock. In fact, since there are constant returns to production, no workers and firms will remain in city j in equilibrium. To ensure stability in the model, some form of diminishing returns must be injected, whether in the production technology or through an inelastic supply of local housing.

How do changes in moving costs and the expected surplus affect the incidence of speculative moves, given some local productivity shock? Clearly, smaller moving costs (with m and c both affected) will encourage both more cross-city matches *and* more speculative moves. But, a larger expected surplus will *discourage* speculative moves. This is because national market search and speculative migration are substitutes. Larger job surpluses can sustain more intensive cross-city search, obviating the need for costly speculative moves.

D   Derivations of local market results from Section 3

In this appendix, I derive the responses of the local expected job surplus and the local job finding rate to changes in $\bar{y} - b$, σ and δ. As in the main text, I suppress the national market to simplify the exposition. To ease the notation, I define the following terms:

Definition 1. $\Omega = \int_y \max\{S(y),0\}\, dF = \frac{1}{4\sigma(r+\delta)} (\bar{y} + \sigma - rU - rV)^2$ is the expected job surplus.

Definition 2. $\Gamma = F(\tilde{y}) = \frac{1}{2\sigma}(\sigma - \bar{y} + rU + rV)$ is the ex ante probability (before the productivity is determined) of a match being accepted.

Definition 3. $\pi = \frac{1}{\gamma_s^\alpha \gamma_a^{1-\alpha}}$ is an exogenous parameter summarizing the ease of search.

Proposition 1. *The local expected surplus and job finding rate are increasing in $\bar{y} - b$.*

Notice first that:

$$\frac{d\Omega}{d(\bar{y}-b)} = \frac{1-\Gamma}{r+\delta}\left(1 - r\frac{d\breve{U}}{d(\bar{y}-b)}\right) \tag{D1}$$

To make progress, I need to know how $\breve{U}$ responds. Substituting equation (21) for θ in the unemployment value (19) gives:

$$
\begin{aligned}
r\breve{U} &= \frac{1}{2}\left(\frac{1-\phi}{\phi}\theta\right)^{1-\alpha}\pi(\phi\Omega)^2 \tag{D2}\\
&= \frac{1}{2}\left[\left(\frac{1-\phi}{\phi}\right)^2\frac{r\breve{U}}{rV}\right]^{1-\alpha}\pi(\phi\Omega)^2
\end{aligned}
$$

And differentiating with respect to $\bar{y} - b$:

$$r\frac{d\check{U}}{d(\bar{y}-b)} = \left(\frac{1-\phi}{\phi}\theta\right)^{1-\alpha}\pi\phi^2\Omega\frac{d\Omega}{d(\bar{y}-b)} + (1-\alpha)r\frac{d\check{U}}{d(\bar{y}-b)} \tag{D3}$$

$$= \left(\frac{1-\phi}{\phi}\theta\right)^{1-\alpha}\pi\phi^2\Omega\frac{1-\Gamma}{r+\delta}\left(1-r\frac{d\check{U}}{d(\bar{y}-b)}\right) + (1-\alpha)r\frac{d\check{U}}{d(\bar{y}-b)}$$

$$= \frac{\phi\rho}{r+\delta}\left(1-r\frac{d\check{U}}{d(\bar{y}-b)}\right) + (1-\alpha)r\frac{d\check{U}}{d(\bar{y}-b)}$$

$$= \frac{\phi\rho}{\alpha(r+\delta)+\phi\rho}$$

where ρ is the job finding rate, as defined in equation (22). Substituting this back into (D1) gives:

$$\frac{d\Omega}{d(\bar{y}-b)} = \frac{\alpha(1-\Gamma)}{\alpha(r+\delta)+\phi\rho} \tag{D4}$$

which is positive, so the expected surplus is increasing in $\bar{y}-b$. To assess the impact on the finding rate, notice first that:

$$\frac{d(1-\Gamma)}{d(\bar{y}-b)} = \frac{1}{2\sigma}\left(1-r\frac{d\check{U}}{d(\bar{y}-b)}\right) \tag{D5}$$

$$= \frac{1}{2\sigma}\cdot\frac{\alpha(r+\delta)}{\alpha(r+\delta)+\phi\rho}$$

Next, consider the finding rate ρ. After substituting equation (21) for θ in (22), ρ can be expressed as:

$$\rho = \left(\frac{1-\phi}{\phi}\theta\right)^{1-\alpha}\pi\phi\Omega(1-\Gamma) \tag{D6}$$

$$= \left[\left(\frac{1-\phi}{\phi}\right)^2\frac{r\check{U}}{rV}\right]^{1-\alpha}\pi\phi\Omega(1-\Gamma)$$

And differentiating with respect to $\bar{y}-b$:

$$\frac{d\rho}{d(\bar{y}-b)} = (1-\alpha)\frac{\rho}{r\check{U}}r\frac{d\check{U}}{d(\bar{y}-b)} + \frac{\rho}{\Omega}\frac{d\Omega}{d(\bar{y}-b)} + \frac{\rho}{1-\Gamma}\frac{d(1-\Gamma)}{d(\bar{y}-b)} \tag{D7}$$

$$= \frac{(4-\alpha)\rho}{\alpha(r+\delta)+\phi\rho}\cdot\frac{r+\delta}{2\sigma(1-\Gamma)}$$

which is clearly positive.

Proposition 2. *The local expected surplus is increasing in σ, but the effect on the local job finding rate is ambiguous.*

Notice first that:

$$\frac{d\Omega}{d\sigma} = \frac{1-\Gamma}{r+\delta}\left(\Gamma - r\frac{d\check{U}}{d\sigma}\right) \tag{D8}$$

And differentiating (D2) with respect to σ:

$$
\begin{aligned}
r\frac{d\check{U}}{d\sigma} &= \left(\frac{1-\phi}{\phi}\theta\right)^{1-\alpha}\pi\phi^2\Omega\frac{d\Omega}{d\sigma} + (1-\alpha)r\frac{d\check{U}}{d\sigma} \\
&= \left(\frac{1-\phi}{\phi}\theta\right)^{1-\alpha}\pi\phi^2\Omega\frac{1-\Gamma}{r+\delta}\left(\Gamma - r\frac{d\check{U}}{d\sigma}\right) + (1-\alpha)r\frac{d\check{U}}{d\sigma} \\
&= \frac{\phi}{r+\delta}\rho\left(\Gamma - r\frac{d\check{U}}{d\sigma}\right) + (1-\alpha)r\frac{d\check{U}}{d\sigma} \\
&= \frac{\phi\rho\Gamma}{\alpha(r+\delta)+\phi\rho}
\end{aligned}
\tag{D9}
$$

Substituting this back into (D8) gives:

$$\frac{d\Omega}{d\sigma} = \frac{\alpha(1-\Gamma)\Gamma}{\alpha(r+\delta)+\phi\rho} \tag{D10}$$

which is positive, so the expected surplus is increasing in σ. To assess the impact on the finding rate, notice first that:

$$
\begin{aligned}
\frac{d(1-\Gamma)}{d\sigma} &= \frac{1}{2\sigma}\left(2\Gamma - 1 - r\frac{d\check{U}}{d\sigma}\right) \\
&= \frac{1}{2\sigma}\left[\frac{\alpha(r+\delta)\Gamma}{\alpha(r+\delta)+\phi\rho} - (1-\Gamma)\right]
\end{aligned}
\tag{D11}
$$

And differentiating (D6) with respect to σ:

$$
\begin{aligned}
\frac{d\rho}{d\sigma} &= (1-\alpha)\frac{\rho}{r\check{U}}r\frac{d\check{U}}{d\sigma} + \frac{\rho}{\Omega}\frac{d\Omega}{d\sigma} + \frac{\rho}{1-\Gamma}\frac{d(1-\Gamma)}{d\sigma} \\
&= \frac{\rho}{2\sigma}\left[\frac{(4-\alpha)(r+\delta)}{\alpha(r+\delta)+\phi\rho}\cdot\frac{\Gamma}{1-\Gamma} - 1\right]
\end{aligned}
\tag{D12}
$$

The sign of this expression depends on the parameters of the model.

Proposition 3. *The local expected surplus is decreasing in δ, but the effect on the local job finding rate is ambiguous.*

Notice first that:

$$\frac{d\Omega}{d\delta} = -\frac{1-\Gamma}{r+\delta}\left(\frac{1-\Gamma}{r+\delta}\sigma + r\frac{d\check{U}}{d\delta}\right) \tag{D13}$$

And differentiating (D2) with respect to δ:

$$
\begin{aligned}
r\frac{d\check{U}}{d\delta} &= \left(\frac{1-\phi}{\phi}\theta\right)^{1-\alpha}\pi\phi^2\Omega\frac{d\Omega}{d\delta} + (1-\alpha)r\frac{d\check{U}}{d\delta} \\
&= -\frac{\phi}{r+\delta}\rho\left(\frac{1-\Gamma}{r+\delta}\sigma + r\frac{d\check{U}}{d\delta}\right) \\
&= -\frac{\sigma}{r+\delta}\cdot\frac{\phi\rho\left(1-\Gamma\right)}{\alpha\left(r+\delta\right)+\phi\rho}
\end{aligned}
\tag{D14}
$$

Substituting this back into (D13) gives:

$$\frac{d\Omega}{d\delta} = -\frac{\alpha\Omega}{\alpha\left(r+\delta\right)+\phi\rho} \tag{D15}$$

which is negative, so the expected surplus is decreasing in δ. To assess the impact on the finding rate, notice first that:

$$
\begin{aligned}
\frac{d\left(1-\Gamma\right)}{d\delta} &= -\frac{1}{2\sigma}\cdot r\frac{d\check{U}}{d\delta} \\
&= \frac{1}{2\left(r+\delta\right)}\cdot\frac{\phi\rho\left(1-\Gamma\right)}{\alpha\left(r+\delta\right)+\phi\rho}
\end{aligned}
\tag{D16}
$$

And differentiating (D6) with respect to δ:

$$
\begin{aligned}
\frac{d\rho}{d\delta} &= (1-\alpha)\frac{\rho}{r\check{U}}r\frac{d\check{U}}{d\delta} + \frac{\rho}{\Omega}\frac{d\Omega}{d\delta} + \frac{\rho}{1-\Gamma}\frac{d\left(1-\Gamma\right)}{d\delta} \\
&= \frac{\rho}{\alpha\left(r+\delta\right)+\phi\rho}\left[\frac{\phi\rho}{2\left(r+\delta\right)} - 2 - \alpha\right]
\end{aligned}
\tag{D17}
$$

The sign of this expression depends on the parameters of the model.

Proposition 4. *The local hiring rate is decreasing in $\bar{y} - b$ and σ and increasing in δ.*

Let λ denote the instantaneous probability of hiring a worker:

$$\begin{aligned}
\lambda &= \left(\frac{1-\phi}{\phi}\theta\right)^{-\alpha}\pi\phi\Omega(1-\Gamma) \tag{D18}\\
&= \left[\left(\frac{1-\phi}{\phi}\right)^2\frac{r\breve{U}}{rV}\right]^{-\alpha}\pi\phi\Omega(1-\Gamma)\\
&= \frac{4\phi rV}{(1-\phi)^2}\cdot\frac{r+\delta}{\bar{y}-b+\sigma-r\breve{U}-r\bar{V}}
\end{aligned}$$

Given the results above on responses of $r\breve{U}$, it is clear that $\frac{r+\delta}{\bar{y}-b+\sigma-r\breve{U}-r\bar{V}}$ is decreasing in $\bar{y}-b$ and σ and increasing in δ. And so, the same must be true of the hiring rate λ.

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