Moving to look or looking to move? The role of job search in migration decisions

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Abstract

I document a new stylized fact about inter-state mobility: a third of inter-state moves in the US are speculative. This finding contradicts the standard assumption that all moves are tied to a job match, and raises the question whether spatial search frictions limit mobility even when workers can move without a job. To answer it, I build a theoretical model of moving and job search which allows for both speculative and non-speculative migration. Workers decide whether to search first or move first. The search-first strategy leads to better labor market outcomes but is constrained by inter-regional search frictions. Estimating the model parameters on US data, I find that spatial search frictions account for about a fifth of the differences in the moving propensity between the less and more educated workers, and they are larger than in alternative models without speculative moving.

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1 Introduction

What prevents workers from moving to opportunity? Geographic mobility is a potentially powerful way of improving one's income and escaping unemployment, but, despite the large and persistent regional differences within countries, individuals do not move much. Indeed, those who may benefit the most – the less-educated, low-pay individuals – seem to move the least: compared to their college-educated counterparts, they are up to three times less likely to move to another region of the same country (Amior and Manning, 2018; Moretti, 2011; Kline and Moretti, 2013; Molloy et al., 2011). This has significant consequences for the persistence of inequality at an individual as well as a regional level (Fogli and Guerrieri, 2019; Chetty et al., 2016; Monras, 2018).

Recent work has pointed toward spatial search frictions as one of the explanations for low regional mobility (Schmutz and Sidibe, 2018; Ransom, 2022; Wilson, 2021; Fujiwara et al., 2021). Broadly defined, spatial search frictions refer to the relative difficulty of finding a job in another region compared to searching locally. They are particularly interesting from a policy perspective because, in contrast to moving costs or preferences for living in a particular region, a reduction in spatial search frictions would unambiguously lead to a welfare-improving increase in mobility. In this paper, I define spatial search frictions as the lower probability of matching with an employer from another region compared to matching locally, but they may also include incomplete information about job opportunities, workers' small search radius, and the local nature of their social networks.

It is unclear, however, how much spatial search frictions actually limit within-country moves. The existing estimates are based on the assumption that all moves are tied to a cross-regional job match: workers only move if they receive a job offer from their destination region, so frictions in the cross-regional matching technology automatically reduce mobility (Schmutz and Sidibe, 2018).[1] Using data on inter-state moves in the US, I show that

[1]Schmutz and Sidibe (2018) allow workers to move both with and without a job, but moving without a job is not an equilibrium strategy in their model, and their data doesn't allow them to distinguish between the two types of moves. Ransom (2022) also estimates the role of spatial search frictions on US mobility, but in his setup workers always move without a job, and spatial search

this assumption does not correspond to the migration patterns on the ground. While most moves are with a job in hand, about a third of individuals move speculatively. This raises the question of whether spatial search frictions limit mobility even when workers can move without having found a job. For example, if utility differences between regions are large, workers might not find it optimal to wait for a cross-regional job offer to move. At the same time, lower spatial search frictions – by increasing the chance of moving with a job – might encourage workers to wait *more*, potentially reducing mobility.

To answer this question, I develop a new model of job search and moving which makes it possible to study the relationship between spatial search frictions and mobility when workers can move both with and without a job. I use this model to derive the theoretical relationship between spatial search frictions and mobility and to estimate spatial search frictions for inter-regional mobility in the US. I find that spatial search frictions reduce mobility even when workers can move speculatively, both empirically and theoretically. Moreover, estimating spatial search frictions in two stylized standard models of migration shows that not allowing for speculative migration *underestimates* the size of spatial search frictions.

I start by presenting a set of new empirical facts about within-country mobility. I draw on a US panel data set, Survey of Income and Program Participation, which allows me to distinguish between workers moving speculatively and with a job. I show that the two types of moving co-exist in the labor market: 19% of all adult male movers in the labor force, and 38% of all adult movers move speculatively. I also find a strong education gradient in the type of moving which correlates with the education differences in overall migration propensity. The less educated workers, who are less likely to move overall, are significantly more likely to move speculatively. Finally, I present evidence that these two types of moving lead to substantially different outcomes: non-speculative moves are associated with higher wages and a lower probability of being unemployed even several years after the move.

In the second part of the paper, I develop a dynamic structural model in which workers can move both with and without a job. I extend the stan-

frictions correspond to their lower job-finding rates in the destination region compared to locals.

dard partial equilibrium model of search (McCall, 1970) by adding a spatial dimension: workers decide which labor market to live in (potentially moving speculatively), and they receive local and cross-regional job offers (giving them the option to move with a job). We might hypothesize that, when it is difficult to find a job in another region (spatial search frictions are large), workers will switch to moving speculatively, offsetting the negative impact of frictions on mobility. However, this is not the case, primarily because moving speculatively and with a job are not perfect substitutes. I show that as long as the economy is in a spatial equilibrium, and employers satisfy standard assumptions about job-creation, workers will on average prefer to move with a job rather than speculatively. As a result, larger spatial search frictions will lower mobility even if speculative moves are possible.

This also means that spatial search frictions have implications for welfare that go beyond their direct impact on mobility. When moving speculatively, workers have to pay the cost of moving upfront and base their decision on the expected utility in the other region. When the move is linked to a specific job offer, on the other hand, workers only pay the moving cost if the job offer is good enough. In other words, speculative moves are *ex ante* optimal, while moves with a job are *ex post* optimal. As a result, the higher the share of non-speculative moves, the higher the share of workers for whom moving increases their welfare.

To understand how allowing for speculative moving changes our estimates of the size and impact of spatial search frictions, I estimate a simplified version of US spatial labor market using data on moves between the four Census regions of the US. I identify the model parameters – region-specific labor market characteristics, such as job-finding and job-destruction rates, moving costs, and workers' regional preferences – from the worker flows within and between regional labor markets. The estimated parameters suggest that US labor markets suffer from substantial search frictions, which in turn significantly lower mobility. These frictions are particularly high for the less educated and the unemployed. An employed college graduate receives 0.57 job offers from another region for every local offer; this share is 0.49 for employed high school graduates, only 0.004 for college-educated unemployed and 0.001 for unemployed high-school graduates. The small cross-regional job-finding probabilities for the unemployed rationalize the fact that the unemployed are significantly more likely to move speculatively, even though their return to finding a job in another region is relatively higher. In a series of counterfactual exercises, I show that reducing spatial search frictions by 1 percentage point would increase overall mobility by 41% and reduce the share of workers moving speculatively. This effect is almost entirely driven by an increase in non-speculative moves by the unemployed. Similarly, making cross-regional matching work as well for the less educated as it does for college graduates could close a fifth of the gap in migration propensity, and two thirds of the difference in the type of moving.

In the final part of the paper, I estimate two alternative models of migration to evaluate the implications of different assumptions about job search and moving. Both models are nested versions of the model developed in this paper, and correspond to standard models of migration. The first model assumes that all moves are non-speculative; the second model additionally assumes that there are no spatial search frictions. Comparing the different model estimates shows that assuming that all moves are non-speculative leads to underestimating the size of spatial search frictions by almost a half, the effect being particularly large for the unemployed. The estimates of moving costs vary across the models, too. I replicate the result by Schmutz and Sidibe (2018), who show that some of the conventional estimates of moving costs can be explained by spatial search frictions. However, adding speculative moving into the model partly reverses this pattern: moving cost estimates in the full model are higher than the moving costs in the absence of spatial search frictions but lower than costs in the model without speculative moving. Intuitively, not allowing for speculative moves attributes all moves to cross-regional hiring, underestimating spatial search frictions. At the same time, the moving costs in the full model have to rise to account for the fact that workers don't take up the option to move speculatively.

This paper makes several contributions to the literature on within-country migration. First, I provide empirical evidence that within-country migration decisions lie somewhere between the two paradigms followed in the literature, that of speculative moving (Harris and Todaro, 1970; Kennan and Walker, 2011; Kline and Moretti, 2013; Ransom, 2022) and moving tied to a job (Beaudry et al., 2014; Lutgen and der Linden, 2015; Amior, 2015; Epifani and Gancia, 2005; Schmutz and Sidibe, 2018). Building on the work by Basker (2018) who documented a similar mobility pattern in stated preference data in CPS, I show that this holds for actual moves, with a significant heterogeneity along employment and education dimensions. Second, I develop a new framework that bridges these two types of models, and estimate a new set of values for spatial search frictions and moving costs in the US (Schmutz and Sidibe, 2018; Schluter and Wilemme, 2019; Ransom, 2022; Porcher, 2021). Methodologically, I follow a growing set of dynamic structural models of internal migration, some of which also use SIPP data (Ransom, 2022; Oswald, 2019; Baum-Snow and Pavan, 2012).

More broadly, this paper expands our understanding of the interaction between the functioning of the labor market and geographic mobility. This is relevant for several important questions within labor and migration economics. For example, Molloy et al. (2017) argue that the steady fall in interstate mobility between 1980-2013 is driven by a fall in job transitions, with the latter falling more steeply than the latter. My theoretical framework shows how a deterioration in the matching between workers and jobs across space would potentially generate this patter. Another example is the question of the role of information provision on migration decisions. While there is some evidence that more information encourages geographic mobility (Wilson, 2021; Fujiwara et al., 2021)[2], we don't know whether the increase in mobility comes from more efficient matching between firms and workers across space, or from a larger number of workers simply moving to search in other labor markets. By focusing on the former, I show that simply improving information flows between regions is unlikely to be sufficient to increase within-country mobility.

The remainder of this paper proceeds as follows. I start by presenting

[2]See also the literature on networks in migration, for example Patacchini and Zenou (2012); McKenzie and Rapoport (2007). In contrast, Kaplan and Schulhofer-Wohl (2017) find that cheaper and more easily available information likely *reduced* inter-state mobility in the US over the past 30 years.

several new facts about within-country mobility in Section 2. In Section 3, I build a joint model of job search and migration and derive the theoretical equilibrium relationships between spatial search frictions and mobility. In Section 4, I estimate the model parameters and run a series of counterfactual exercises to quantify the size and impact of spatial search frictions. In section 5, I estimate two alternative models of migration to evaluate the impact of speculative moving on the existing measures of spatial search frictions and moving costs. Section 6 concludes.

2 Empirical patterns of moving with and without a job

In this section, I present several new stylized facts about mobility between US states using the Survey of Income and Program Participation for the years 1996-1999. I define speculative and non-speculative moves and show that the type of moving matters for labor market outcomes after the move. I also document that some individuals are much more likely to move speculatively than others, especially the unemployed and the less educated.

2.1 Data

I draw on the 1996 panel of Survey of Income and Program Participation (SIPP). The data set tracks a nationally-representative sample of US inhabitants over four years (1996-1999), providing monthly data on their income, employment, and residence, as well as their education and household structure. Unlike other panel data sets, SIPP provides relatively high-frequency (monthly) labor market and residence information and tracks its respondents when they move.[3] The combination of these two attributes makes it possible to distinguish between speculative and non-speculative moves from the mover's employment status in the month immediately following the move. I use the

[3] To my best knowledge, SIPP is the only major data set that combines these features (for a detailed comparison of the different data sources, see Hernández-Murillo et al. (2011)).

1996 panel because of its length, data quality, and because it avoids any major recessions.[4]

My core sample consists of men aged 25-60 who were employed for at least one month over the duration of the panel. I focus on individuals in the labor force[5] because the aim of the paper is to study the relationship between moving and job search, and I select the 25-60 age bracket to avoid moves related to retirement or education (moving to and from college). I exclude women because their migration and labor market decisions tend to be driven more by factors other than their labor market prospects: 75% of respondents in SIPP live in households where the primary earner is male, and the existing literature shows that women are more likely to be tied movers than men (Gemici, 2011; Venator, 2021). This latter point is particularly important if tied movers move speculatively: not excluding them from the sample would lead to an over-estimation of the share of speculative moves among job-seekers. Restricting the sample to men helps to avoid this issue, and sidesteps the household dimension of the moving decision in general.[6,7] For comparison and completeness, I present the key stylized facts for the whole population of adults aged 25-60 alongside the core sample.

The core sample consists of 19,354 male workers who completed 1032 interstate moves. The average man is 40 years old, and the employment rate of the group is 92% (note that I define as "unemployed" anyone who is not employed). About 12% of the individuals did not finish high school, while 27% completed

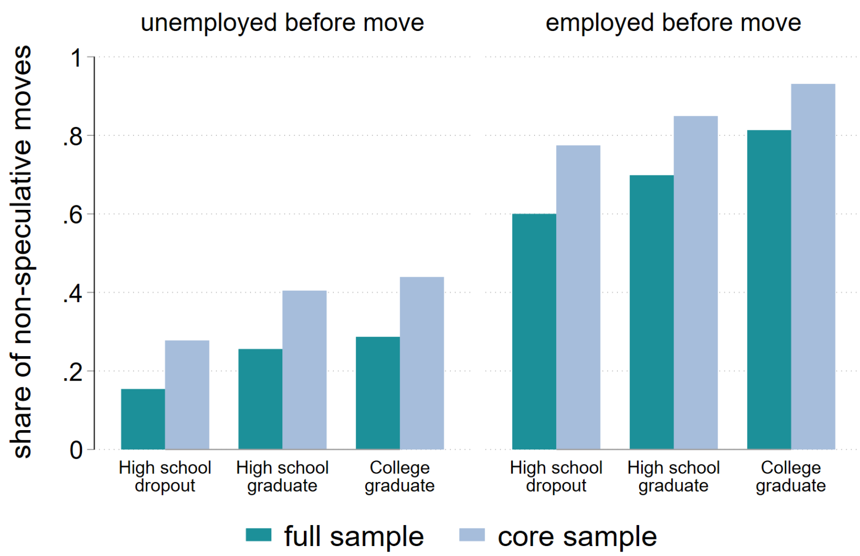
[4]In particular, later SIPP panels include less detailed geographic information: starting with the 2004 panel, there is no information on the city of residence.

[5]SIPP does offer a variable coding the labor market status of the respondent, i.e. whether he is employed, unemployed (actively searching for a job), or out of the labor force. However, I choose to classify all individuals who were observed working for at least 1 month as being in the labor force, even if they are not officially classified as such. This is because the observed job-finding rate for those out of the labor force and the unemployed is often relatively similar (Kudlyak and Lange, 2017). Relatedly, I define unemployment as not being employed.

[6]I explore the differences in mobility patterns by gender and marital status in my data in Appendix B. I find that the main differences in moving are between men and women, while married and single men move relatively similarly. I do find that household structure matters for some post-mobility outcomes, e.g. men's migration wage premium varies with the labor force status of their spouse.

[7]For papers that model the moving decisions of households explicitly, see for example Gemici (2011); Foged (2016); Braun et al. (2021); Venator (2021).

Figure 1: Share of non-speculative moves by education and prior employment status



The bars correspond to the share of moves which are non-speculative for each education-employment-sample group. The full sample includes all individuals between the ages 25 and 60. Core sample includes men between the ages 25 and 60 who are attached to the labor force. Employment status before moving refers to whether the individual was employed or unemployed in the month before the move. The education categories are dropout (did not finish high school), high school graduate (graduated high school but did not graduate 4-year college), and college graduate (graduated 4-year college or more). Migration is defined as moving between the 50 US states.

a four-year college degree or more. The full descriptive statistics for the core sample are summarized in Table A1 in the Appendix.

2.2 Patterns in mobility

Migration, even in a relatively mobile country like the US, is a rare event. Between 1996 and 1999, the annual cross-state migration propensity between US states in my core sample of working men was 2%.[8] This is in line with other estimates reported in the literature, which range between 2 and 3% (Molloy et al., 2011). In Table A5, I show that SIPP also replicates the usual

[8]The average migration propensity of the full sample of adults aged 25-60 was 1.9%.

demographic patterns: younger individuals, the unemployed, and those with more education are more likely to move (Greenwood, 1997; Hernández-Murillo et al., 2011). The mobility gap between the less and the more educated is particularly large: college graduates are 2.5-times more likely to move than those without a college degree.

In this paper, I distinguish between two types of migration: speculative and with a job (non-speculative). When moving speculatively, a worker moves first and then searches for a job in his new labor market of residence. A non-speculative move, on the other hand, happens when the worker first searches for jobs from his home labor market and then moves for a specific job offer. Ideally, speculative and non-speculative moves would be identified from information on the mover's job search and job offers around the time of moving. In the absence of this data, I base the classification on the mover's employment status the month after moving: if the mover is employed in $t+1$ after moving, I assume that he has found this job before the move, and categorize the move as non-speculative. If the mover is not employed after the move, the move is categorized as speculative.

I find that the majority (62%) of inter-state moves of all adults in the US are with a job, but there is a significant share (38%) of moves that are speculative. In my core sample of men, the share of speculative moves is smaller, reflecting their higher likelihood of being employed or searching for a job, but it is still non-negligible: every fifth working male adult moves speculatively.

Importantly, the type of move is not simply an extension of the mover's employment status before the move. Employed workers are more likely to move non-speculatively (and unemployed workers are more likely to move speculatively), but there is a crossover between the two categories. I demonstrate this in Figure 1, which plots the share of non-speculative moves for the employed and unemployed of different education levels and across the full and core samples. The graph shows that about 7% of employed workers move speculatively, and about 37% of unemployed workers move with a job. This also means that speculative moves are crucial to understanding the mobility of the unemployed since the majority (63%) of their moves are without a job.

Figure 1 also documents significant differences in the type of moving across education groups. College graduates are significantly more likely to move non-speculatively: only 13% of college graduates move speculatively, in contrast with 27% of those without a college degree, and the difference between education groups is larger when we also include women and those outside of the labor force. Table A5 confirms that this education gradient holds regardless of employment status before the move, gender, and other demographic characteristics.

There are two main sources of measurement error arising from my categorization approach. First, speculative movers who find a job quickly, within a month of moving, will be falsely classified as non-speculative movers. At the same time, non-speculative movers who delay the start of their job by more than a month will be falsely classified as speculative movers. The overall share of speculative moves will be under- or over-estimated depending on which of these two scenarios happens more often. Furthermore, if different groups of workers find jobs at different speeds, or have different preferences and options to decide the start of their employment, these measurement errors will also bias my estimates of heterogeneity in the type of moving.

In Appendix D, I perform two robustness checks to address these potential measurement errors. I re-estimate the share of non-speculative moves for alternative timing cutoff points (employment status after 2, 3, 4 months after the move), and show that it stays relatively flat over time (Figure A5). Next, I calculate the job-finding and job-delaying rates of the stayers in the data and use these to estimate "corrected" shares of non-speculative moves for workers of different education levels. As Figure A6 shows, the bias of miscategorization likely leads to *underestimating* the true extent of the education differences in the type of migration. This is because it is the more educated that are more likely to delay the start of their job (being falsely classified as speculative movers), while the less educated have a relatively higher 1-month job-finding rates (so their moves are more likely to be falsely classified as non-speculative).

Finally, while the *type* of moving is different from the *reason* for moving[9], the CPS questionnaire on the reasons for moving provides corroborative

[9] An individual might be primarily moving to be closer to his family, but he might still choose to search for a job offer and move non-speculatively. Similarly, a worker might move speculatively

evidence for the patterns presented here. As shown in a paper by Basker (2018), about 90% of individuals who moved for job-related reasons over the period 1997-2003 moved for a job, and this share is significantly higher for more-educated movers (97% for college graduates vs. 70% for high school dropouts). Given the difference in time periods covered, and the fact that some of those who state their main reason for moving is not job-related might still move *with* a job, the similarity between the patterns in CPS and SIPP is remarkable.

2.3 Moving with and without a job

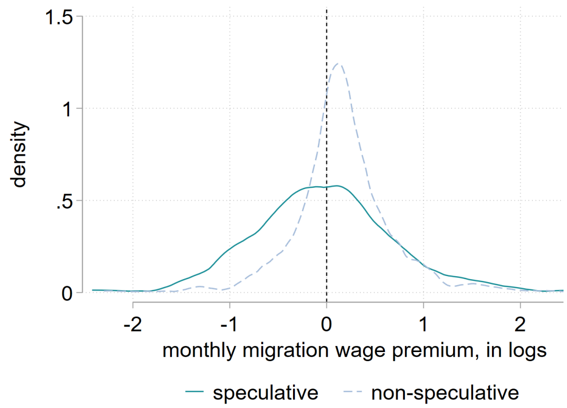
In theory, the different timing of moving and job search has significant implications for the mover's labor market outcomes. Speculative moves are *ex ante* optimal: workers decide based on the expected return of the move and have to pay the cost of moving before the return is realized. Non-speculative moves, on the other hand, are also *ex post* optimal, because workers only choose to move if the realized return (the specific job offer) is high enough to outweigh the cost of moving. In this section, I show that there is suggestive evidence that this theoretical difference between speculative and non-speculative moving translates into differences in observed labor market outcomes.

I start by calculating the migration wage premium separately for speculative and non-speculative movers. For each mover in the sample, I estimate the difference between average nominal pre- and after-move earnings, conditional on being employed. I plot the distribution of these within-individual migration premia in panel (a) of Figure 2. The wage premium of speculative movers is approximately symmetric around 0: half of speculative movers end up earning more than they did in their previous employment, and half end up earning less. In contrast, non-speculative movers have on average higher wages after moving and are significantly less likely to suffer a relative wage cut compared to speculative movers. Overall, the average migration wage premium for non-speculative movers is 10 percentage points higher than for those who move

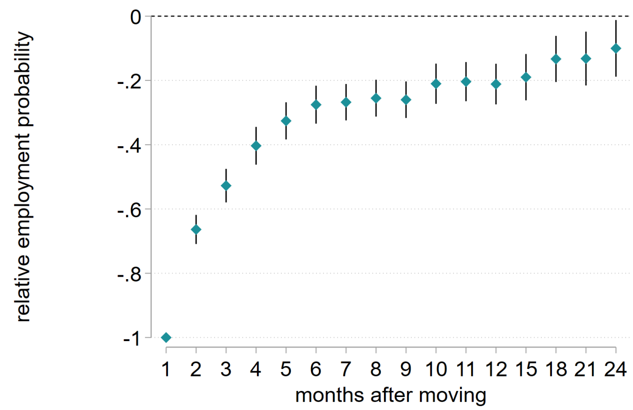
to another city, but this move might be driven by his desire to find a better job.

Figure 2: Differences in outcomes after speculative and non-speculative migration

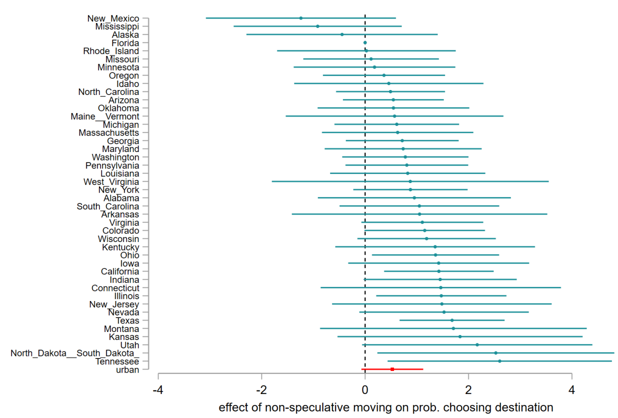
(a) Wage premium



(b) Relative employment probability for speculative movers



(c) Destinations



Panel (a): the distribution of the individual-specific difference between average pre- and post-move nominal wages, conditional on being employed. Panel (b): the monthly probability of being employed for speculative movers, relative to non-speculative movers. Panel (c): differences in destination state between speculative and non-speculative movers. The panel plots the coefficient of moving non-speculatively (as opposed to speculatively) to a particular US state, using Florida as the baseline. The last coefficient refers to a separate regression of whether the move is to an urban destination. In panel (a), the underlying regression controls for individual fixed effects. In panels (b) and (c), the underlying regressions control for age, education, marital status, the number of children, industry, and employment status before the move. Sample: men between the ages 25 and 60 who are in the labor force. Migration is defined as moving between the 50 US states.

speculatively.[10]

In panel (b) of Figure 2 I show that the two types of moving also differ in their employment probabilities. Given the inherent difference between moving speculatively and with a job, it is not surprising that speculative movers have a relatively lower chance of being employed after the move than non-speculative movers. However, this probability remains lower for up to 21 months after moving, suggesting a systematic difference between speculative and non-speculative moves.

Finally, in panel (c), I plot the probability of moving into one of the 50 states for non-speculative movers relative to speculative ones.[11] The figure shows that speculative and non-speculative movers do not differ in their destinations: the dummy for non-speculative moving is statistically significant only for 4 states. Similarly, the coefficient plotted at the bottom of the figure shows that the two groups are equally likely to move to urban areas. While interesting in their own right, these results also suggest that the observed differences in labor market outcomes between speculative and non-speculative movers cannot be fully explained by differences in destinations. In other words, speculative movers are less likely to be employed and are paid relatively less than non-speculative movers not because they move to states with better amenities or lower living costs, but because some of the *ex ante* speculative moves turn out to be suboptimal *ex post*.

[10] I discuss selection into moving, and the differences in migration premia for different groups of workers, in Appendix B and C. The pattern described here is driven mostly by single men and men whose wives are not in the labor force. Men in dual-earner households see on average no wage change when moving non-speculatively, and suffer a migration penalty when moving speculatively. Table A7 shows that speculative movers tend to be negatively selected, while non-speculative movers are, before moving, paid on average the same as stayers.

[11] Because SIPP is representative at the national (but not state) level, these results are only informative about the different destinations of the workers within the sample. They do not mean that the destinations of speculative and non-speculative movers are the same for the whole of the US.

3 A theoretical model of job search and moving

In this section, I build a new model of job search and moving that incorporates the new stylized facts presented in this paper. Workers can move both with and without a job, but the differences in the relative timing of job search and moving have implications on individuals' choices and labor market outcomes. I start by outlining the model of how workers decide to move. I then use the model to derive the theoretical relationship between spatial search frictions and moving, showing that search frictions reduce mobility even when workers do not have to wait for a job offer to move.

3.1 Setup

This model is an extension of the partial equilibrium model of job search by McCall (1970). In the standard model, there is an exogenous distribution of wage offers and some constant rate at which workers receive wage offers. Workers search by waiting to receive these random wage offers; they decide whether to accept or continue searching based on an optimal stopping rule.

I extend the model by adding a location dimension, combining a partial equilibrium job search across multiple locations with the decision where to live. The workers can choose which region to reside in, and they can receive job offers from different regions. Their decisions about where to live and whether to accept a particular job offer may lead to speculative or non-speculative migration.

There are J regions in the model. They correspond to local labor markets so that accepting a job in another region requires the worker to move. Each region has its own wage offer distribution $F_j(z)$, job-finding probabilities (θ_j and λ_j for off- and on-the-job search, respectively), and the probability that the match will be exogenously dissolved, δ_j. Regions also differ in other characteristics, such as weather, location, and amenities. Worker i forms idiosyncratic preferences over these non-labor characteristics γ_{ji}, which are drawn from a probability distribution $g_j(\gamma_i)$ with region-specific mean $\bar{\gamma}_j$ and a common variance σ_γ. The cost of moving to another region is K.[12]

A worker is either employed or unemployed at the start of each period. All workers search, and since search in this model is passive and costless, they search across all regions simultaneously, although, as is standard in this type of models, a worker can receive at most one wage offer each period. The probability of receiving a job offer from region j when residing in (searching from) region m is θ_m^j for the unemployed and λ_m^j for the employed. This set-up could potentially result in a $J \times J$ different job-finding probabilities for the employed and the unemployed each. To compress the parameter space, I assume that the probability of receiving a wage offer from region j when searching from region m depends on the local job-finding probability in m and the relative difficulty of finding a job in another region, which is the same across all labor markets.[13] This relative difficulty is represented by job search wedges ζ_θ and ζ_λ for the unemployed and employed job seekers, respectively. The overall job-finding probability across regions is:

$$\theta_m^j = \zeta_\theta \theta_m \qquad \forall j \neq m \tag{1}$$

$$\lambda_m^j = \zeta_\lambda \lambda_m \qquad \forall j \neq m \tag{2}$$

ζ_λ and ζ_θ fall on the unit interval. They are an inverse measure of spatial

[12] I assume that moving costs are homogenous across space rather than e.g. depending on the distance between regions. This assumption considerably simplifies the estimation procedure but at the cost of reducing the accuracy of the model. However, given the large geographic units used for estimation, the bias from not distinguishing between the cost of moving from the Midwest to the South vs. to the West is likely small. A second concern is that by not allowing K to vary across space, this variation is soaked up by the spatial friction parameters $\zeta_\theta, \zeta_\lambda$, effectively making them capture more variation than moving costs. However, as I explain in the following paragraph, $\zeta_\theta, \zeta_\lambda$ are also homogenous across space. Any spatial variation in search frictions thus comes from the spatial variation in job-finding probabilities themselves, rather than from direct variation in the spatial parameters.

[13] My region-of-residence simplification implies that workers in a thick labor market find it relatively easier to find jobs anywhere. One can also imagine an alternative set-up in which the probability of receiving a job in region j only depends on the job-finding probability in that region, regardless of where the worker is searching from. The underlying structure of spatial search frictions likely includes both of these mechanisms; however, the existing evidence for cross-city job search in France by Schmutz and Sidibe (2018) suggests that spatial search frictions are smaller in cities that are relatively larger and better connected. The authors conclude that "cities with higher local job-finding rates are also better at sending their workers to other cities".

search frictions: the closer they are to 1, the smaller the frictions. While ζ_λ and ζ_θ are taken as exogenous parameters in this model, they also capture the real-life endogenous decisions of workers and firms about how broadly to search across space. Marinescu and Rathelot (2018) and Manning and Petrongolo (2017) both show that workers search within relatively limited geographic space, partly because most workers are located close to vacancies, and partly because of the cost of commuting and migration. ζ_λ and ζ_θ in addition also capture firms' preferences and beliefs about hiring workers outside of their local labor market, as well as any geographic costs and barriers inherent in the spatial matching function.

Employed workers face a non-zero probability that their match will be destroyed. The probability of job destruction is region-specific and denoted δ_j. A worker cannot become unemployed and re-employed in the same period, so a worker whose job has been just destroyed has to be unemployed for at least one period.

Workers are *ex ante* identical and normalized to 1. They have perfect information about the aggregate characteristics of each local labor market, are risk-neutral and infinitely lived.[14] Wealth and home ownership, while important for both employment and location decisions, are modelled only indirectly.[15] Oswald (2019) models the self-selection into renting vs. house-ownership, and the migration behaviour of both groups, also using the SIPP panel. He shows that house-owners are less mobile, partly because individuals with greater distaste for moving sort into house ownership, but mostly because owning a house makes moving significantly more expensive. Insofar as house ownership rates differ significantly between the less and the more educated, these differences in moving costs due to the housing market will be captured by the general differences in moving costs across education groups in this model. The more educated workers, who are more likely to own a house, will be less likely to move speculatively partly because the selling (and buying) of a house is a costly and time-consuming process that they wouldn't want to undertake unless they've

[14]The life-cycle aspect of the migration decision is the focus of Schluter and Wilemme (2019).

[15]The process of selling and buying a house might be complementary to cross-regional job search. A joint model of property and job search is an interesting topic for further research.

received a sufficiently good job offer.

This is a partial equilibrium model, so the wage offer distributions, the job-finding and job-destruction probabilities, and worker preferences over regions are exogenous. The environment is stationary. As a consequence, the spatial equilibrium condition (Roback, 1982; Kline and Moretti, 2013) must hold: the marginal worker is indifferent between regions. In this model, this condition will apply to speculative movers. In equilibrium, the differences in the value of unemployment (value of search) across regions must be smaller than the cost of moving K:

$$U_m(\bar{\gamma}_m) \geq U_j(\bar{\gamma}_j) - K \quad \forall\, j \neq m \tag{3}$$

This means that speculative migration is *ex ante* suboptimal in equilibrium: the best region to be unemployed in is always the worker's home region. Any speculative moves will be the result of very high (or very low) draws from the distribution of idiosyncratic location preferences. Non-speculative moves are also the result of stochastic shocks (job offers), but they are not subject to the same spatial equilibrium condition. In other words, the lack of systematic utility differences between regions for speculative movers does not imply that movers are indifferent about moving non-speculatively.

3.2 Workers' decisions

The worker starts each period living in the region he chose and earning the wage he accepted in the previous time period. At the end of each period, the worker draws his location preferences for the next period: $\boldsymbol{\gamma_i} = \begin{bmatrix}\gamma_{1i} & \gamma_{2i} & \dots & \gamma_{Ji}\end{bmatrix}$, and he is subject to labor market shocks. If he is unemployed, he might receive a wage offer from one of the J regions with probability θ_m^j. If he is employed, he might receive a wage offer with probability λ_m^j, and with probability δ_m his job might get destroyed. Upon observing these random draws, the worker compares the discounted utilities of each of his options, and chooses the highest one. His choice comes into force at the start of the next period.

The value of being unemployed in region m depends on the flow utility of residing in this region and the expected value of searching from here. Suppressing the i subscript, the corresponding Bellman equation is:

$$
\begin{aligned}
(1+r)U_m(\gamma_m) = \gamma_m & \\
& + \theta_m E_{z,\gamma} \max[V_m(z,\gamma_m), U_m(\gamma_m), U_j(\gamma_j) - K \,\forall\, j \neq m] \\
& + \sum_{j\neq m}^{J} \zeta_\theta \theta_m E_{z,\gamma} \max[V_j(z,\gamma_j) - K, U_m(\gamma_m), U_j(\gamma_j) - K \,\forall\, j \neq m] \\
& + (1 - (J-1)\zeta_\theta\theta_m - \theta_m)\, E_\gamma \max[U_m(\gamma_m), U_j(\gamma_j) - K \,\forall\, j \neq m]
\end{aligned} \tag{4}
$$

The flow utility of being unemployed in region m is γ_m[16]. With probability θ_m, he receives a local wage offer, z, and with probability $\zeta_\theta\theta_m$ the worker receives a wage offer from another region. There is also a $1-(J-1)\zeta_\theta\theta_m - \theta_m$ chance that he receives no wage offers at all. In each case, he compares the value of staying unemployed at home, $U_m(\gamma_m)$, against the values of moving to be unemployed in another region, $U_j(\gamma_j) - K$, and the value of the specific job offer (if he received one), and chooses the highest one. The expectations about the future payoffs are taken over both the wage offers z and the worker's future draws of regional preferences $\boldsymbol{\gamma_i}$. The utility flow is discounted at the rate r.

The value of being employed in region m at wage w is defined similarly:

$$
\begin{aligned}
(1+r)V_m(w,\gamma_m) = w + \gamma_m & \\
& + \lambda_m E_{z,\gamma} \max[V_m(w,\gamma_m), V_m(z,\gamma_m), U_m(\gamma_m), U_j(\gamma_j) - K \,\forall\, j \neq m] \\
& + \sum_{j\neq m}^{J} \zeta_\lambda \lambda_m E_{z,\gamma} \max[V_m(w,\gamma_m), V_j(z,\gamma_j) - K, U_m(\gamma_m), U_j(\gamma_j) - K \,\forall\, j \neq m] \\
& + \delta_m E_\gamma \max[U_m(\gamma_m), U_j(\gamma_j) - K \,\forall\, j \neq m] \\
& + (1 - (J-1)\zeta_\lambda\lambda_m - \lambda_m - \delta_m)\, E_{z,\gamma} \max[V_m(w,\gamma_m), U_m(\gamma_m), U_j(\gamma_j) - K \,\forall\, j \neq m]
\end{aligned} \tag{5}
$$

The first line of this expression captures the per-period utility of being employed at wage w in region m. The second line describes the expected value

[16]Non-labor income is a part of $\bar{\gamma}_m$, the mean idiosyncratic preference for region m

of receiving a new local job offer z, and the third line describes the expected value of receiving a job offer from another region. In each case, the worker can decide whether to leave his current job and accept the new offer, or leave employment altogether. With probability δ_m, the worker's job is exogenously destroyed, and he has to decide whether to remain unemployed at home, or move speculatively to another region (line 4). The last line captures the expected value of no labor market shocks.

The complex structure of the Bellman equations is driven by the relatively large number of options a worker might face.[17] An unemployed worker might be offered a job at home or in another region, and he can always decide to be unemployed in another region. Similarly, an employed worker might receive local and cross-regional wage offers, his job could be destroyed, and he also always has the option to quit and be unemployed in any of the J regions. Lower spatial search frictions (high ζ_λ and ζ_θ) increase the likelihood that a worker has a larger option set, but the variation in the option set is also stochastic because it depends on the specific realizations of the random matching mechanism. The worker's choice will be the product of the value of his options, and which options are available to him.

3.3 Spatial search frictions and moving

Spatial search frictions impact equilibrium migration in two ways: directly, by changing the probability that a worker can move with a job, and indirectly by changing the worker's option set and hence the relative attractiveness of speculative moving. These two channels have opposing effects on mobility. On one hand, lower frictions translate into a greater probability that a worker will be able to move non-speculatively, which increases (non-speculative) mobility. However, lower search frictions also make speculative moving relatively less attractive, decreasing (speculative) mobility. The overall impact on mobility depends on the relative size of these two effects. Lower spatial search frictions will attract some workers who would not have moved speculatively but would

[17] I visualize the relationship between the worker's potential options and his possible outcomes in Figures A2 and A3.

move with a job, increasing mobility. At the same time, however, the shift from speculative moving to waiting for a cross-regional job offer reduces mobility because not all who search receive an offer and move. This introduces the theoretical possibility that lower spatial search frictions might in some cases reduce mobility.

In this section, I explore these two channels and their overall impact on mobility theoretically. I summarize my findings in three propositions. The first two formalize the intuition laid above: lower spatial search frictions increase non-speculative moving and reduce the number of speculative moves. In the third proposition, I combine these two results to show that the overall impact of spatial search frictions on mobility is negative: the increase in non-speculative movers always outweighs the fall in speculative moving.

To sketch the proofs of these three propositions, I assume that workers' idiosyncratic location preferences γ_{ij} are drawn from Type-I extreme value distribution, and that the economy consists of 2 regions only, A and B. This allows me to derive succinct closed-form solutions for workers' choice probabilities, which makes the link between frictions and decisions more explicit. The full proofs do not depend on any assumption about the distribution of local preferences or the number of regions. They can be found in Appendix G.

Proposition 1. *Lower spatial search frictions increase the probability that a worker will move non-speculatively.*

The mechanism behind this result is somewhat mechanical: lower frictions increase the probability that a worker receives a cross-regional job offer, and since there is a positive probability he will choose this offer, non-speculative moves become more likely. To see this, note that the probability that an unemployed worker chooses to move non-speculatively in a 2-region economy is the product of the job search wedge, the job-finding probability in his region of residence, and of the conditional choice probability for non-speculative moves:

$$\text{Prob(non-specul. move)} = \zeta_\theta \theta_A \frac{exp(E_B - K)}{exp(E_B - K) + exp(U_A) + exp(U_B - K)} \tag{6}$$

We can see that a derivative of this expression with respect to ζ_θ at around equilibrium simply equals the logit-style conditional choice probability times the job-finding rate, which is a positive expression. In other words, if there is a non-zero probability that the worker accepts a cross-regional job offer, a decrease in spatial search friction, holding everything else constant, will increase the probability of the worker making a non-speculative move.

Proposition 2. *Lower spatial search frictions decrease the probability that a worker will move speculatively.*

The relationship between spatial search frictions and the probability that a worker moves speculatively is somewhat more complicated. It equals the sum of three separate conditional choice probabilities for speculative moving, under the scenario of a local job offer, a cross-regional job offer, and no job offer:

$$\begin{aligned}\text{Prob(specul. move)} = {} & \theta_A \frac{exp(U_B - K)}{exp(U_B - K) + exp(U_A) + exp(E_A)} \\ & + \zeta_\theta \theta_A \frac{exp(U_B - K)}{exp(E_B - K) + exp(U_A) + exp(U_B - K)} \\ & + (1 - \theta_A - \zeta_\theta \theta_A) \frac{exp(U_B - K)}{exp(U_A) + exp(U_B - K)} \end{aligned} \tag{7}$$

An increase in ζ_θ (lower spatial search frictions) shifts the weight from the probability of moving speculatively under no job offers (third line) to the probability of moving speculatively despite a cross-regional job offer (second line). As long as *some* local job offers are preferred to local unemployment[18]:

$$\exists z : \; E_j(z) > U_j \tag{8}$$

lower search frictions will shift probability mass from a situation where speculative moving is relatively more attractive to a situation where it is less attractive, reducing the overall probability that it will be chosen.

Proposition 3. *Lower spatial search frictions increase overall mobility.*

[18]This condition is about *local* employment vs *local* unemployment because we are comparing the probability that the worker chooses to be employed or unemployed in the same region (in this case, B).

The overall impact of spatial search frictions on mobility depend on which of the two effects described so far dominates: an increase in non-speculative moving, or a decline in moving speculatively. Using ζ_θ-derivatives of the unconditional choice probabilities, it can be shown that lower search frictions increase mobility if:

$$\frac{exp(U_A)}{exp(E_B - K) + exp(U_A) + exp(U_B - K)} > 1 - \frac{exp(U_A)}{exp(U_A) + exp(U_B - K)} \tag{9}$$

i.e. if the probability of staying unemployed at home despite a cross-regional job offer is greater than the probability of *not* staying unemployed at home when the worker receives no job offers. In other words, the probability of staying unemployed at home with no offers must be larger than the probability of making the same choice when presented with a cross-regional job offer. This will hold if there are *some* cross-regional job offers that are preferred to being unemployed:

$$\exists z, k \neq j : \; E_k(z) - K > U_j \tag{10}$$

To summarize, these propositions will hold if the following two conditions are satisfied: first, the wage offer distribution $F_j(z)$ and local job-finding probabilities are such that local employment is preferred to local unemployment for at least some wage offer z; second, there is some wage offer at which employment away is preferred to local unemployment. In other words, there must be some firms willing to hire locally, and there must be some firms willing to hire cross-regionally. Since these correspond to standard assumptions about the recruitment behavior of firms, Propositions 1-3 are likely to hold.

4 Estimation and results

In this section, I describe how the structural model from the previous section is identified and estimated using the 1996 SIPP data on within- and across-region mobility. After presenting the parameter estimates, I use them to construct several counterfactuals, quantifying how much spatial search frictions reduce mobility, and to what extent they can explain the observed differences in mobility between the more and the less educated workers.

4.1 Estimation, identification and data

Estimation strategy I estimate the model parameters by inverting the model: I take the observed unemployment rates, regional populations shares, mobility flows and wages as given, and use them to back out the underlying labor market parameters.

The model is estimated separately for the less and more educated, generating a set of parameters for each group including education-specific spatial search frictions and moving costs. I implicitly assume that the labor markets for those with and without college degree operate independently.

I estimate the model for the four US Census regions[19]. These regions are too large to correspond to actual local labor markets, but estimating the model at the level of commuting zones would be computationally prohibitive.[20] The model estimated here is best described as a stylised simplification of the actual spatial labor market which allows us to evaluate the importance of allowing for both speculative and non-speculative moving. Since mobility declines in distance, the estimated spatial search frictions (and moving costs) correspond to an upper bound on the frictions governing cross-regional job search between smaller geographic units.

The model is estimated using the method of moments. The theoretical moments are closed-form expressions for within- and cross-regional transition rates derived from the model (see Appendix F for full derivation). I use value function iteration to calculate the values of employment and unemployment across regions, $\mathbf{V_j}$ and U_j. The challenging part of this procedure is to find the expected maximum value of future decisions, such as $E_{z,\gamma}\max[V_j(z) + \gamma_j - K, U_m^*]$, in which expectations need to be taken over

[19]See Figure A1 in the Appendix. In Appendix E, I replicate the stylized facts presented in section 2 on Census region level.

[20]Schmutz and Sidibe (2018) estimate a model of spatial search frictions for 100 largest cities in France, allowing for heterogeneous spatial search frictions and moving costs, but they only allow for non-speculative moves which considerably simplifies the structure of the model.

both wage offer distributions and location preferences. The assumption that γ_j are type-I extreme distributed implies that the expected future utility has a closed-form solution (Rust, 1987). As a result, I can use $\mathbf{V_j}$ and U_j to find the probabilities that a worker makes a particular choice conditional on her option set. The unconditional probabilities are then calculated in the standard way, using model parameters and the equilibrium population shares and regional unemployment rates as the weights.

The model parameters are recovered using the method of moments (McFadden (1989)): I find model parameters that minimize the squared distance between the data moments and the corresponding moment expressions as derived from the structural model. Define $\mathbf{D}$ as a 63x1 vector of data moments and $\mathbf{M}(\rho)$ the 63x1 vector of moment expressions, where ρ is the set of the 19 unknown parameters:

$$\rho = \{\delta_1, \delta_2, ..., \delta_4, \theta_1, ..., \theta_4, \lambda_1, ..., \lambda_4, \zeta_1, \zeta_2, K, \bar{\gamma_1}, ..., \bar{\gamma_3}, g\} \tag{11}$$

The MM estimates of ρ, $\hat{\rho}$, is then a 19x1 vector of variables that can be defined as:

$$\hat{\rho} = \text{argmin}(\mathbf{M}(\rho) - \mathbf{D})^T \mathbf{W}(\mathbf{M}(\rho) - \mathbf{D}) \tag{12}$$

$\mathbf{W}$ is the weighting matrix.[21]

Identification Modelling the US as a four-region economy ($J = 4$) requires estimating 20 parameters: 8 job-finding probabilities $\{\theta_j\}_4^1$ and $\{\lambda_j\}_4^1$, 4 job destruction probabilities $\{\delta_j\}_4^1$, 2 job-finding wedges ζ_λ and ζ_θ, the migration cost K, and the 5 parameters that describe the distribution of location preferences, namely the means $\{\bar{\gamma_j}\}_4^1$ and variance σ_γ. I normalize the location preferences by making the West the baseline. This leaves 19 parameters to estimate.

I set the distribution of location preferences, γ_j, to be type-I extreme value distribution. This makes the estimation process much easier by allowing me to find a closed-form solution for the expression for the expected maximum value of future decisions, leading to closed-form model moments (I discuss the details

[21] I use an identity matrix (see Altonji and Segal (1996)).

of the estimation procedure in the next section). The region-specific wage distributions $\{F_j(z)\}_4^1$ are approximated as discrete distributions with two-point support corresponding to wages at the 25th and 75th percentile. The equilibrium outcomes, regional population shares $\{\alpha_j\}_4^1$ and unemployment rates $\{\mu_j\}_4^1$, are taken directly from the data.

The model is identified from data moments on the worker movement between the four regions and in and out of employment, which results in 63 free moments. I use transitions in and out of employment within each region to back out local job-finding and job-destruction rates. This allows me to identify spatial search frictions as the difference between cross-regional and within-region job-finding rates for the employed and the unemployed. Speculative moves to individual regions identify workers' preferences over the regions, while overall mobility pins down the moving cost. The education-specific parameters are the result of estimating the model separately for workers with and without a college degree.

With 19 unknowns and 63 equations, the order condition is satisfied. This is particularly helpful in my case because migration is a relatively rare event. Some off-diagonal elements of the moment matrices are small and close to 0, so having multiple observations on between-region unemployment-to-employment flows allows me to estimate the relative thickness of cross-regional labor markets more accurately.

Data and the goodness of fit The data moments used to estimate the model parameters are the two transition matrices (for the less and more educated) between employment and unemployment and across the four US Census regions. They are calculated from from the 1996 SIPP panel using the sample of working-age men attached to the labor force. I present the summary version of these moments in Table 1. The full version is in Tables A2 and A3 in the Appendix.

The model's goodness of fit in terms of the summary data moments is presented in Table 1.

Table 1: Data and model moments (%)

	less educated		more educated	
	data	model	data	model
employed to ...				
... employed home	98.07	98.09	98.83	98.84
... employed away	0.05	0.04	0.13	0.13
... unemployed home	1.87	1.87	1.03	1.02
... unemployed away	0.01	0.00	0.01	0.00
unemployed to ...				
... employed home	16.63	16.76	18.49	18.58
... employed away	0.023	0.05	0.09	0.25
... unemployed home	83.24	83.07	81.15	80.86
... unemployed away	0.10	0.12	0.28	0.31

4.2 Results

Search frictions and overall mobility The goal of the structural estimation is to quantify spatial search frictions in the presence of speculative moving. I present these estimates in Table 2.

The estimated spatial search frictions between US regions are significant. For the employed, the spatial search wedges are 0.57 and 0.49 for those with and without a college degree, respectively. This means that an employed college graduate receives 0.57 cross-regional job offers for every local job offer, and the ratio is below 0.5 for those without a college degree.

The estimated search frictions are even larger for the unemployed. The estimates of ζ_θ show that cross-regional job search is two orders of magnitude more difficult for the unemployed compared to those searching on the job. An unemployed college graduate receives 0.4 cross-regional job offers for every 100 local ones, while an unemployed individual without a college degree only receives 1 away offer for 100 local ones. This difference between the employed and unemployed is further exacerbated by the fact that the job-finding rate is

Table 2: Estimated model parameters

description	parameter	less educated	more educated
job search wedge, on-the-job	ζ_1	0.4963	0.5784
job search wedge, unemployed	ζ_2	0.0010	0.0044
migration cost	K	8.5981	7.5986
as share of employment utility		9.4%	8.3%
as share of unemployment utility		14.4%	12.7%
std. dev. of location preferences	g	1.0870	1.0937
mean location preference, Northeast	$\bar{\gamma}_1$	0.3350	-0.1017
mean location preference, Midwest	$\bar{\gamma}_2$	0.0647	-0.2771
mean location preference, South	$\bar{\gamma}_3$	0.4437	0.1502

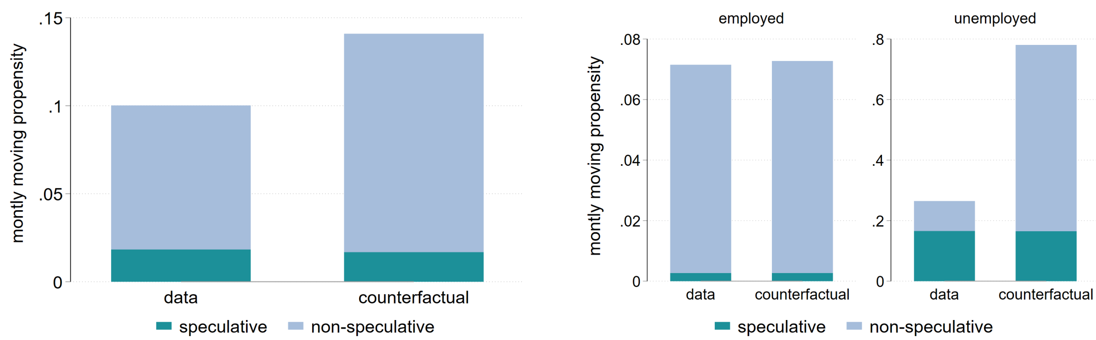
much higher for the employed (I present the estimates of all model parameters in Table A4). Put together, the low job-finding rates and the large spatial search wedge mean that an unemployed worker is very unlikely to have the option to move with a job. This finding can rationalize the fact that unemployed workers move predominantly speculatively, despite their larger return to finding a job.

To quantify the impact of spatial search frictions on mobility, I use the estimated model to calculate the change in the propensity and type of moving when spatial search frictions are reduced by 1 percentage point for all workers.[22] These counterfactual mobility patterns are plotted in panel (a) Figure 3. The left bar shows the observed moving behavior: the average monthly moving propensity is 0.1%, with 82% of these moves being non-speculative. Lowering spatial search frictions leads to an overall 41% increase in moves. This increase is driven entirely by an increase in workers moving with a job. Non-speculative moves increase both proportionally (to 88% of all moves), and

[22]The spatial search wedge ζ lies somewhere between 0 and 1. Increasing the parameter by 1 percentage point means e.g. increasing ζ_λ of the college educated from 0.5784 to 0.5884.

Figure 3: Counterfactual: mobility under 1 percentage point reduction in spatial search frictions

(a) All workers (b) By employment status before the move



The bars correspond to actual (left bar) and simulated (right bar) monthly moving propensities between US Census regions. In the counterfactual, I increase ζ_θ, ζ_λ for both education groups by 1 percentage point. These results are averages for the entire population.

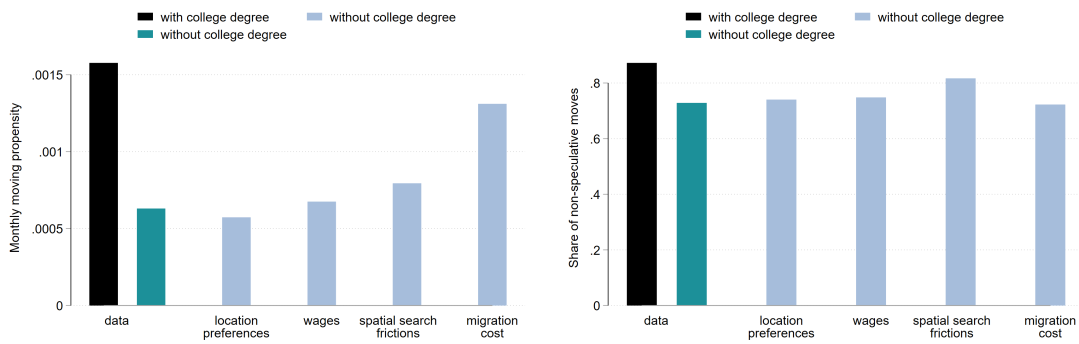
in absolute numbers, more than compensating for the 8% fall in speculative moves as their relative attractiveness declines. Overall, this exercise implies a relatively large elasticity of moves to spatial search frictions.[23]

Next, I focus on the differential impact of spatial search frictions on the employed and the unemployed. It is a well-known fact that unemployed workers are more likely to move than the employed; the estimated search frictions show that this is the case despite the fact that cross-regional job search is much more difficult for the unemployed. As a result, an intervention that could lower the barriers to cross-regional search for the unemployed would have a large positive impact on the mobility of this group. I demonstrate this in panel (b) of Figure 3, in which I revisit the impact of a 1 percentage point reduction in spatial search frictions separately for the employed and unemployed. The figure shows that the mobility of the employed increases only marginally, by 2%. The large increase in mobility shown in panel (a) is driven almost entirely by the unemployed, whose propensity to move almost triples. Furthermore, the

[23]The actual impact of reducing spatial search frictions would most likely be smaller, since we would expect several general equilibrium effects, such as adjustments in wages, job-finding rates, and local cost of living, which would likely reduce the overall effect estimated here.

Figure 4: Counterfactual: decomposition of the difference in mobility by education

(a) propensity to move (b) share of non-speculative moves



Black bar: actual moves by more educated workers. Teal bar: actual moves by less educated workers. Pale blue bars: counterfactual mobility of the less educated workers when the given model parameters are set to equal parameter values of the more educated. Location preferences refer to the variance of the distribution of idiosyncratic location preferences. Spatial search frictions refer to both job search wedges.

gap in non-speculative moving between employed and unemployed workers is significantly reduced, as the unemployed take up the opportunity to move with a job that comes from lower spatial search frictions. In the data, only 37% of unemployed workers move non-speculatively, compared to 96% of employed movers; in the counterfactual, this share for the unemployed increases to 79%. The intuition for this result draws on fundamental nature of non-speculative moving where a move is tied with employment. Even though the unemployed face smaller opportunity cost of moving (and are thus more likely to move speculatively), they value employment relatively more, and would be more likely to move with a job if given the opportunity. This is the case despite the fact that the estimated moving costs are larger, in relative utility terms, for the unemployed than for the employed.

Search frictions and education differences in mobility The structural model can also shed light on the education differences in moving. As I showed in section 2, the less educated move less. This result is traditionally rationalized by a combination of lower wage returns, higher costs of moving, and differences in location preferences. I present my estimates of these parameters in Table 2. The estimated distributions of location preferences have nearly identical standard deviation, suggesting that the less and more educated are equally likely to have very strong preferences over different regions. In contrast, I estimate that moving costs of the less educated are larger, both in absolute terms and relative to their lifetime utility, than those of college graduates. These differences are even starker when we take into account the differences in employment probabilities between this group: moving costs are 14.4% of the utility of less educated unemployed, but only 8.3% of the utility of employed college graduates.[24]

To quantify the relative importance of frictions vs moving costs (and other factors) on mobility, I run a counterfactual exercise in which I set the different model parameters for the less educated workers equal to the parameters for college graduates. The resulting mobility patterns are summarized in Figure 4. Each pale blue bar plots the moving propensity (in panel (a)) or the share of non-speculative moves (in panel (b)) when setting a different set of parameters equal to the values of the more educated. The counterfactuals show that the difference in moving costs has the largest impact on the mobility gap, closing 72% of it. Spatial search frictions are second most effective, reducing it by a fifth (17%), while equalizing the wage structure and the variance of location preferences has only minimal impact.

However, the different parameters have different impact on the gap in the type of moving. The large increase in mobility thanks to subsidizing the moving costs of the less educated is driven entirely by an increase in speculative moves. On the other hand, the reduction in spatial search friction allows the less educated to move non-speculatively, closing almost two thirds (61%) of the gap in the type of moving. Equalized wages would also improve the share

[24]To calculate migration cost as a share of utility, I compare the estimated K parameter to the (lifetime) utility value of employment and unemployment, as defined by expressions (4) and (5). An alternative way to to understand the estimated value of K is to compare it to g, the estimated standard deviation of idiosyncratic location preferences. Moving costs are 7.9-times greater than the unexplained part of utility flow for the less educated, and 6.9-times for the more educated. For comparison, this ratio is an order of magnitude smaller than that estimated in Kennan and Walker (2011).

of non-speculative moving, highlighting an interaction between wage returns and the opportunity to move with a job. The role of variance of location preferences in minimal.

The diverging impact of moving cost subsidies and reductions in spatial search frictions on the type of moving carries important implications for policies aimed at increasing mobility. Subsiding moving costs may be more effective at making individuals move, but all these additional moves are speculative. This matters because, as I demonstrated in section 2, the labor market outcomes of speculative movers are on average worse than of non-speculative movers. A policy encouraging non-speculative migration, even if the overall increase in mobility was smaller, would lead to a higher number of moves that are *ex post* optimal.

5 Comparison with nested models of moving

In the final part of this paper, I seek to quantify the impact of removing the assumption that all moves are non-speculative on our understanding of internal migration. I estimate two alternative models of moving that are nested within the full model presented in this paper. They correspond to two types of models existing in the literature – models without any spatial search frictions, and models with frictions that assume that all moves are with a job – which helps me to pin down the relationship between the different assumptions and the size of the estimated barriers to moving. I find that removing the assumption that all moves are non-speculative has important consequences for our understanding of internal migration. The estimated barriers to moving (moving costs and spatial search frictions) are larger than previously thought, but the option to move speculatively means that their impact on mobility is relatively lower.

5.1 Models and estimation

Model of migration with spatial search frictions The existing models of migration with spatial search frictions assume that all moves are non-speculative (Schmutz and Sidibe, 2018; Ransom, 2022; Schluter and Wilemme, 2019; Wilson, 2021; Fujiwara et al., 2021). This kind of model can be easily nested within the model introduced in section 3 by shutting down the option to move speculatively.

Compared to the full model, the worker's decision-making becomes simpler in two ways. First, removing the option to move speculatively means that there are now certain situations, such as when he has received no job offers or when he has been fired, in which the worker has no options and simply remains in his existing state. Second, shutting down speculative moves significantly reduces the role of idiosyncratic location preferences. In the full model, a very high (or very low) draw of location preferences for a particular region means the worker can move speculatively. Here, location preferences alone cannot induce migration, but they can deter the worker from accepting a cross-regional offer if his preferences for the region are not strong enough. (A similar mechanism works for relatively weaker cross-regional job offers from strongly preferred regions.) As a result, the structure of Bellman equations for unemployment and employment become simpler (see Appendix H): the option sets shrink, and I only need to take expectations over both wages and location preferences for the scenario where the worker receives a cross-regional job offer.

While the estimation procedure is the same as in section 4, I adjust the data moments used to reflect the assumption that all moves are non-speculative. The region-to-region (non-speculative) flow becomes the sum of speculative and non-speculative moves observed in the data. In other words, while I distinguish between workers' employment status before the move, I assume that all wo rkers are employed after the move. Within-region employment-unemployment flows are unchanged.

Basic model of migration In the second nested model, I further assume that there are no spatial search frictions. In this basic model, workers can only

Table 3: Estimates of spatial search frictions and moving costs for the main model and the two alternative specifications

parameter		basic model	+ spatial search frictions	++ speculative moves
more educated workers				
job search wedge, on-the-job	ζ_λ	1	0.7458	0.5784
job search wedge, unemployed	ζ_θ	1	0.0073	0.0044
moving cost	K	7.6702	6.9743	7.5986
st. dev. of location preferences	g	1.0081	1.0353	1.0937
less educated workers				
job search wedge, on-the-job	ζ_λ	1	0.5125	0.4963
job search wedge, unemployed	ζ_θ	1	0.0017	0.0010
moving cost	K	8.6496	8.2767	8.5981
st. dev. of location preferences	g	1.0059	1.2608	1.0870

move with a job, and finding a job in another region is as easy as finding one locally. In other words, the regional labor markets are perfectly integrated, the only barrier to a single national labor market being the moving cost K. Estimating this model allows me to quantify, for my data set, a benchmark value for moving costs in the absence of any labor market considerations.

The structure of the basic model is the same as the structure of the first nested model, with the additional assumption that the job search wedges $\zeta_\theta, \zeta_\lambda$ are equal to 1. The data moments are the same as for the first nested model.

5.2 Results

I summarize the main parameter estimates from the full and two nested models in Table 3. The first column corresponds to the most restrictive model, the basic model, which does not allow for spatial search frictions or speculative moving. The model in the second column allows for spatial search frictions. In the third column, I re-print the results from my full model which allows for both. I again estimate all three models separately for the less and the more educated.

The comparison of these parameter values across the three models offers three key insights.

First, starting from the basic model, I replicate the result by Schmutz and Sidibe (2018) who show that some of the large moving costs estimated in the literature partially reflect spatial search frictions. In my model, moving from the baseline to the model of spatial search frictions (without speculative moving) reduced the estimated moving costs by 9% for the more educated and 4.3% for the less educated.

Second, adding speculative moves (comparing columns 2 and 3) increases the estimated spatial search frictions, especially for the unemployed. Assuming that all workers move with a job under-estimates spatial search frictions by up to 43%[25] for certain parts of the labor market. Intuitively, not allowing for speculative moves makes spatial search frictions appear smaller, because we assume that all moves are the result of a cross-regional match. In reality, workers and firms from different regions meet less frequently and some moves are speculative. This bias is greater for the unemployed who are much more likely to move speculatively.

At the same time, the impact of spatial search frictions on mobility is smaller when workers can move speculatively. I demonstrate this in panel (a) of Figure A4 in the Appendix, where I simulate moving propensity under a 10 percentage points reduction in spatial search frictions. The moving propensity in the model with spatial search frictions (but without speculative migration) is about 9.2% higher than in the full model, reflecting the fact that the possibility of moving speculatively makes the moving decision less dependent on cross-regional matches.

The third finding is that adding speculative moves also increases the estimated moving cost, to a value below the estimate from the basic model but higher than in the model with spatial search frictions. Moving costs are higher

[25]Moving from column 2 to column 3, the estimated search frictions increase by 22% for the employed more educated workers, 40% for the unemployed more educated, 3% for the employed less educated, and 43% for the unemployed less educated.

in the full model to rationalize the fact that most workers still move with a job even though they could move speculatively. However, the actual impact of moving costs on mobility does not change much, and remains significantly higher in the basic model compared to the two models of spatial search frictions. To make this point, in panel (b) of Figure A4, I simulate the impact of a 10 percentage point reduction in moving costs on moving propensity across the three models. The resulting increase in moving is an order of magnitude higher in the basic model than in the models with spatial search frictions. This is a direct consequence of the different modeling assumptions across the three models. In the basic model, where cross-regional job search is as easy as local one, moving costs are the only barrier to moving. In the model with spatial search frictions, the estimated frictions are significant: here, workers move infrequently not because moving costs are so large, but because cross-regional job offers arrive so rarely. The full model sits in between these two limiting cases, which is why the estimated moving costs lie between the estimates of the two models.

6 Discussion and conclusion

In this paper, I document a new stylized fact about inter-state mobility in the US: a third of inter-state moves in the US are speculative. This finding contradicts the standard assumption in the migration literature that all moves are tied to a job match, and raises the question whether, in a world where workers do not have to wait for a job offer to move, spatial search frictions are a significant barrier to utility. To answer this question, I build a theoretical model of moving and job search which allows for both speculative and non-speculative migration. I use it to prove that when the economy is in a spatial equilibrium, and as long as the employers satisfy standard assumptions about recruitment, spatial search frictions reduce mobility even in the presence of speculative moving. As the next step, I estimate the model parameters for stylised inter-regional moves in the US. I find that spatial search frictions are large, accounting for about a fifth of the differences in the moving propensity between the less and more educated workers. Moreover, these spatial search frictions are in fact larger than in alternative models without speculative moving.

There are several other open questions. I estimated the model for a simplified four-region economy, even though local labor markets are much smaller; a more complex model, allowing for dyadic spatial search frictions between metropolitan areas or commuting zones, is needed to fully capture the extent of spatial search frictions in the US. Similarly, since I only focus on working men, more research is needed to understand the interaction between intra-household bargaining, job search, and moving decisions of spouses (for recent advances in this area, see Braun et al. (2021)). Another dimension that matters for moving, but was not discussed in this paper, is the role of risk preferences. In the model, I assume that individuals are risk neutral, while empirical evidence suggests that movers are on average more risk-taking than stayers (Jaeger et al., 2010). In a world with spatial search frictions and where workers can move speculatively, risk preferences might play a relatively important role as another barrier to (speculative) moving.

The results in this paper carry several implications for policy. I show that the assumption about the type of moving matters for our estimates of spatial search friction and moving costs, influencing the design and evaluation of policies aiming to encourage regional mobility. More importantly, I document that speculative and non-speculative movers differ in their post-move outcomes, in line with the fact that some speculative moves will not turn out to be optimal *ex post*. While the paper stops shy of full welfare analysis, these findings suggest that policymakers should pay attention to how a given policy influences the type of moving, not just the propensity to move as such. For example, moving costs subsidies, if large enough, have been shown to have positive impact on mobility. However, this paper suggests that these additional moves are likely all speculative, reducing the *ex post* welfare gain of the policy. Instead, the policymaker might want to combine a moving cost subsidy with a policy aimed at improving the integration between local labor markets (lowering spatial search frictions), to make it easier for individuals to move with a job (for some recent evidence, see Caliendo et al. (2022)). Given the large share of unemployed workers who move speculatively, such a policy would also be better targeted than blanket moving cost subsidies.

Perhaps the most straightforward policy intervention would be to make it easier for workers to search for vacancies across space. Of course, this change has in fact taken place thanks to the gradual introduction of the Internet and online job search since late 1990s. The fact that this revolution in search methods across space has not reversed (or halted) the decline in internal mobility in the US reinforces our need to understand spatial search frictions better – and suggests that the question of job search as a barrier to mobility discussed in this paper is still relevant today.

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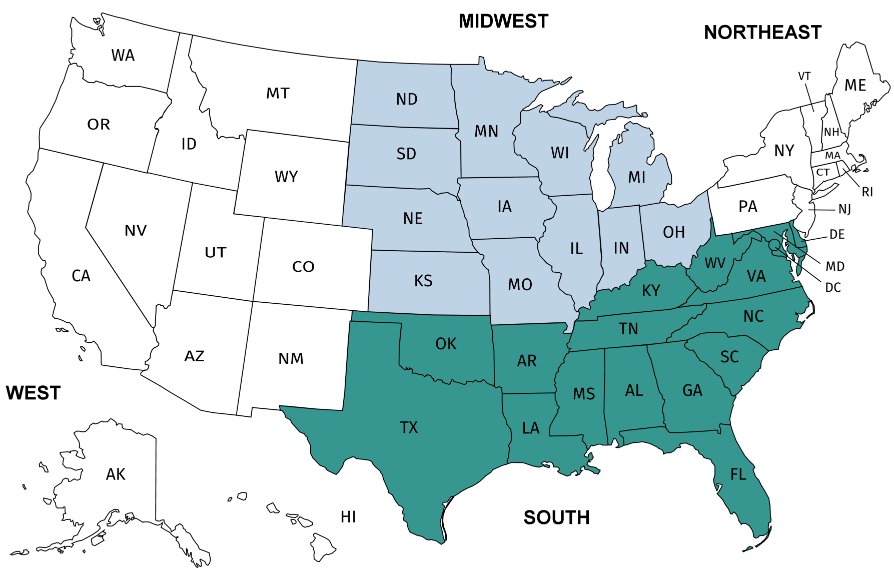
A Figures and tables

Figure A1: The 4 large census regions of the USA.



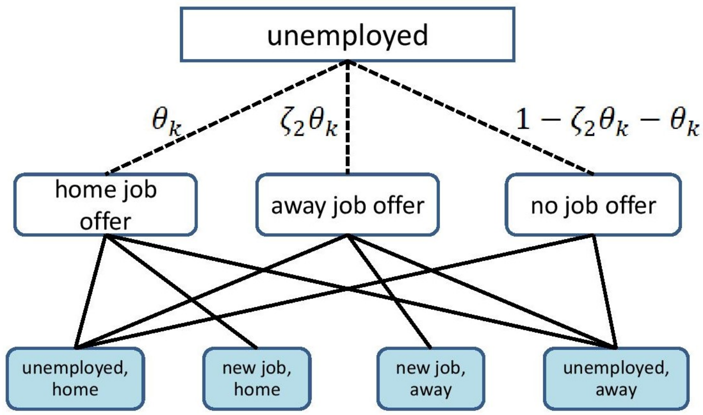
Source: US Census Bureau, Geography Division.

Table A1: Descriptives statics

	All	Stayers	Movers
Age	40.38	40.50	36.50
	(9.306)	(9.302)	(8.602)
High school dropout	0.121	0.123	0.0437
	(0.326)	(0.329)	(0.204)
High school graduate	0.606	0.612	0.427
	(0.489)	(0.487)	(0.495)
College graduate	0.273	0.265	0.529
	(0.445)	(0.441)	(0.499)
Race (white)	0.864	0.862	0.907
	(0.343)	(0.345)	(0.290)
Employed	0.916	0.916	0.910
	(0.278)	(0.278)	(0.287)
Monthly wage ($)	3151.0	3135.3	3688.5
	(3076.7)	(3061.3)	(3520.5)
Total household income ($)	4865.7	4867.8	4797.2
	(4225.9)	(4227.9)	(4158.0)
Urban	0.799	0.799	0.822
	(0.401)	(0.401)	(0.383)
observations	589741	572468	17273
individuals	19348	18322	1026

Demographic descriptives for the core sample. Column (1): all men in the labor force between the age of 25 and 60. Column (2): subsample of men who never moved. Column (3): subsample of men who at some point changed their state of residence. The data for migrants only includes the months before they moved. High school dropout, high school graduate, college graduate, race, employed and urban refer to shares of individuals with the given characteristic. Source: SIPP, 1996-1999.

Figure A2: Choices and possible outcomes for an unemployed worker



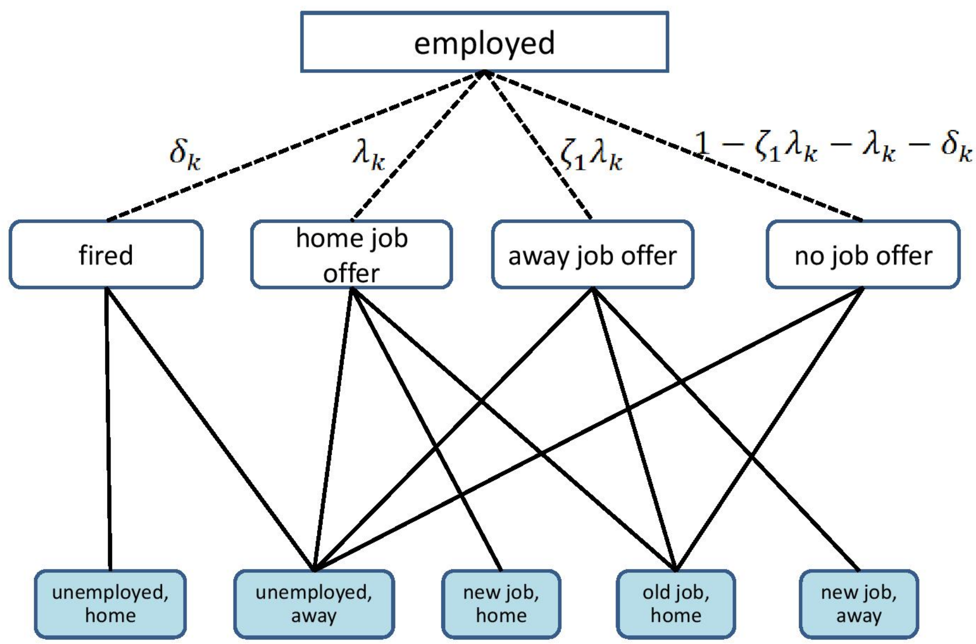
The scheme links the functioning of the labor market with workers' options and their potential outcomes. For instance, with the probability θ^k, the worker receives a job offer in her home region. In that case, she can decide between three outcomes: accept the offer, reject it and stay unemployed at home, or reject it and move into unemployment in another region. On the other hand, migration for a specific job is only possible if she receives a job offer from there first.

Table A2: Data moments: matrix of transition probabilities for the more educated (in %)

	E, 1	U, 1	E, 2	U, 2	E, 3	U, 3	E, 4	U, 4
E, 1	98.968	0.876	0.038	0.002	0.068	0.004	0.044	0.000
U, 1	18.337	81.050	0.000	0.166	0.127	0.243	0.000	0.078
E, 2	0.033	0.002	98.883	0.962	0.070	0.003	0.041	0.005
U, 2	0.000	0.170	20.217	79.339	0.105	0.065	0.000	0.105
E, 3	0.025	0.000	0.041	0.001	98.879	1.002	0.050	0.001
U, 3	0.000	0.024	0.048	0.125	17.120	82.583	0.024	0.077
E, 4	0.034	0.000	0.047	0.008	0.044	0.004	98.584	1.279
U, 4	0.027	0.027	0.000	0.027	0.027	0.089	18.707	81.096

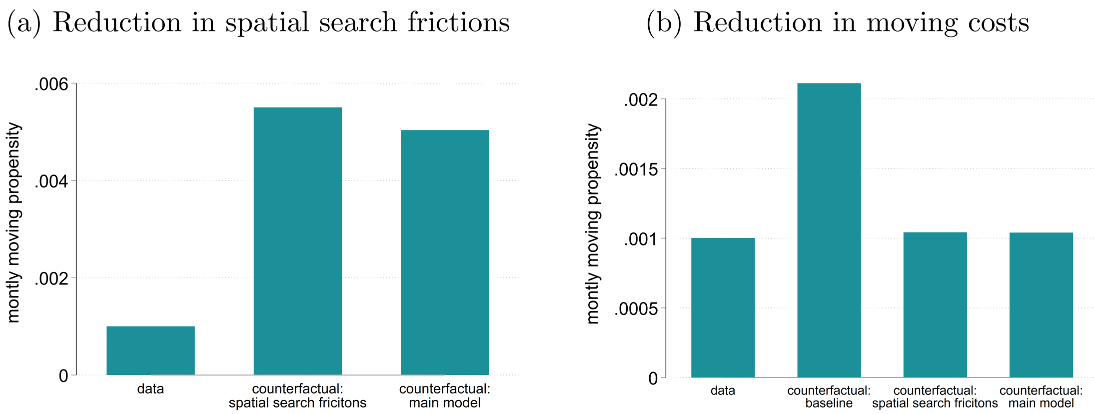
Average monthly transition probabilities for the core sample of men between the age of 25 and 60 who are in the labor force. E = employment. U= unemployment. The numbers correspond to the four large census regions: 1 = Northeast, 2 = Midwest, 3 = South, 4 = West. Rows = state of origin (month t). Columns = destination state (month $t+1$).

Figure A3: Choices and possible outcomes for an employed worker



The scheme links the functioning of the labor market with workers' options and their potential outcomes. For instance, with the probability λ_k, the worker receives a job offer in her home region. In that case, she can decide between three outcomes: accept the offer, reject it and stay employed at home, or reject it and move into unemployment in another region.

Figure A4: The impact of lower search frictions and moving costs across alternative models of migration



Panel (a): moving propensity under a 10 b.p. reduction in spatial search frictions. Panel (b): moving propensity under a 10 b.p. reduction in moving costs. The first column in both panels corresponds to observed mobility. "Counterfactual: baseline" refers to simulated mobility in the model without spatial search frictions or speculative moves. "Counterfactual: spatial search frictions" refers to simulated mobility in the model with spatial search frictions but without speculative moves. "Counterfactual: main model" refers to simulated mobility in the model introduced in this paper, which includes both spatial search frictions and speculative moves. The results are averages for the entire population.

Table A3: Data moments: matrix of transition probabilities for the less educated (in %)

	E, 1	U, 1	E, 2	U, 2	E, 3	U, 3	E, 4	U, 4
E, 1	98.170	1.769	0.003	0.000	0.047	0.005	0.003	0.002
U,, 1	15.674	84.242	0.000	0.026	0.000	0.058	0.000	0.000
E, 2	0.002	0.002	98.242	1.699	0.029	0.006	0.019	0.001
U, 2	0.013	0.000	17.232	82.586	0.034	0.101	0.000	0.034
E, 3	0.010	0.001	0.016	0.001	98.090	1.860	0.019	0.002
U, 3	0.008	0.000	0.008	0.028	15.849	84.088	0.008	0.013
E, 4	0.006	0.000	0.012	0.008	0.022	0.006	97.742	2.205
U, 4	0.013	0.000	0.021	0.092	0.013	0.059	18.094	81.709

Average monthly transition probabilities for the core sample of men between the age of 25 and 60 who are in the labor force. E = employment. U= unemployment. The numbers correspond to the four large census regions: 1 = Northeast, 2 = Midwest, 3 = South, 4 = West. Rows = state of origin (month t). Columns = destination state (month $t+1$).

Table A4: Structural estimates of the model parameters

description	parameter	less educated	more educated
job offer arrival rate, on-the-job, Northeast	λ_1	0.2956	0.5717
job offer arrival rate, on-the-job,Midwest	λ_2	0.6615	0.9966
job offer arrival rate, on-the-job, South	λ_3	0.4846	0.5301
job offer arrival rate, on-the-job, West	λ_4	0.9980	0.6728
job offer arrival rate, unemployed, Northeast	θ_1	0.1595	0.1870
job offer arrival rate, unemployed, Midwest	θ_2	0.1733	0.1996
job offer arrival rate, unemployed, South	θ_3	0.1593	0.1738
job offer arrival rate, unemployed, West	θ_4	0.1820	0.1873
job destruction probability, Northeast	δ_1	0.0177	0.0088
job destruction probability, Midwest	δ_2	0.0170	0.0096
job destruction probability, South	δ_3	0.0186	0.0101
job destruction probability, West	δ_4	0.0220	0.0128
job search wedge, on-the-job	ζ_1	0.4963	0.5784
job search wedge, unemployed	ζ_2	0.0010	0.0044
migration cost (log)	K	8.5981	7.5986
std. dev. of location preferences	g	1.0870	1.0937
mean location preference, Northeast	$\bar{\gamma}_1$	0.3350	-0.1017
mean location preference, Midwest	$\bar{\gamma}_2$	0.0647	-0.2771
mean location preference, South	$\bar{\gamma}_3$	0.4437	0.1502

B Mobility patterns by gender and marital status

The main analysis in this paper focuses on mobility of men in the labor force, implicitly assuming that their moving and employment decisions are independent of their household composition. In this section of the Appendix, I explore whether and how much mobility varies by gender and marital status.

In Table A5, I run a simple reduced-form regression of the propensity to move into another state, and the type of moving, as a function of demographic characteristics. I run this regression first for the full sample of all adults between the age of 25 and 60, and for the core subsample of men in the labor force. Column (1) of Table A5 shows that the propensity to move does not significantly vary by gender and marital status. However, I do find that mothers are less likely to move compared to fathers. Furthermore, column (4) shows that married women – and even more so mothers – are much less likely to move with a job[26]. In contrast, the mobility of men in my core sample is relatively homogenous: their propensity to move and the type of moving do not depend on their parental or marital status. Men who have children or are married are somewhat more likely to move with a job, but this difference (compared to the baseline of single childless men) is not statistically significant.

I do, however, find evidence that married men respond to their wives' labor market status in terms of the jobs they accept. In Table A6, I estimate average migration wage premia for the full sample (which includes women), as well as separately for single and married. For the latter category, I further differentiate by the wife's labor market status. I find that the average migration wage premium is somewhat higher when the sample includes women, and that the household composition matters for the wage premia of men. In particular, married men whose wives are also in the labor force enjoy significantly smaller wage premia in both types of moving. In fact, men in dual-earner households

[26]To some extent, this result likely reflects the fact that married women and mothers are less likely to be in the labor force. The regressions control for employment status in the month before the move, but they do not control for whether the individual was ever employed, which is my proxy for labor force status.

Table A5: Mobility and demographic characteristics

	Prob(move)			Prob(non-speculative move)		
	(1)	(2)	(3)	(4)	(5)	(6)
	all	men	men	all	men	men
HS dropout	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)
High school graduate	0.6922***	0.6958***	0.6844***	0.5524**	0.4889	0.4911
	(0.1014)	(0.1529)	(0.1531)	(0.2379)	(0.3675)	(0.3689)
College graduate	1.6920***	1.8531***	1.8437***	1.0537***	1.1064***	1.1087***
	(0.1034)	(0.1535)	(0.1536)	(0.2437)	(0.3733)	(0.3749)
Below 35 years old	0.4126***	0.3944***	0.3908***	0.1866*	0.2512	0.2514
	(0.0460)	(0.0677)	(0.0677)	(0.1128)	(0.1854)	(0.1854)
past_employed	-1.0815***	-0.7593***	-0.7589***	2.1718***	2.3650***	2.3648***
	(0.0528)	(0.0905)	(0.0905)	(0.1169)	(0.1952)	(0.1952)
Single × Male	0.0000	0.0000		0.0000	0.0000	
	(.)	(.)		(.)	(.)	
Single × Female	0.0668			0.1026		
	(0.0733)			(0.1771)		
Married × Male	0.1282	0.0527		0.4130*	0.3966*	
	(0.0782)	(0.0803)		(0.2111)	(0.2171)	
Married × Female	0.0368			-0.6702***		
	(0.0774)			(0.1826)		
Children × Male	-0.0702	-0.0490	-0.0454	0.3073	0.3377	0.3375
	(0.0768)	(0.0772)	(0.0773)	(0.2237)	(0.2292)	(0.2292)
Children × Female	-0.1381**			-0.4118***		
	(0.0651)			(0.1495)		
No children × Male		0.0000	0.0000		0.0000	0.0000
		(.)	(.)		(.)	(.)
Married × Wife not in labour force			0.0719			0.3936*
			(0.0814)			(0.2215)
Married × Wife in the labour force			-0.1052			0.4219
			(0.1430)			(0.4310)
Observations	39731	19165	19165	2165	1032	1032

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table summarises the differences in the pattern of inter-state mobility by gender, marital status, and household composition. Columns (1) - (3) analyze the propensity to move over the 4-year period of the SIPP survey; columns (4) - (6) do the same for the probability that, conditional on moving, the move is non-speculative. Columns (1) and (4) describe mobility patterns of the entire adult population of the SIPP between the ages 25-60. In columns (2)-(3) and (5)-(6), the sample is restricted to men of the same age who are in the labor force. "Young" is a dummy equal to one if the individual is less than 35 years old. "Children" denote the presence of at least one individual below the age of 18 in the household. "Employed in previous month" is a dummy variable equal to 1 if the worker was in employment the month before migration.

Table A6: Migration wage premium for different subgroups, log(monthly wage)

	Full sample	Working-age men			
		All	Single	Married, wife not in labour force	Married, wife in labour force
Speculative move	0.0459***	0.0419*	-0.00938	0.0727**	-0.903***
	(0.0141)	(0.0237)	(0.0399)	(0.0307)	(0.244)
Non-speculative move	0.159***	0.154***	0.193***	0.139***	0.0542
	(0.00575)	(0.00700)	(0.0124)	(0.00886)	(0.0336)
Observations	55663	28893	10158	16685	2050

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Estimation of the migration wage premium, i.e. the difference between pay before and after the move for an individual, conditional on being employed. Dependent variable is log of monthly wage. The sample consists of movers before and after the move. Each column corresponds to a regression with individual fixed effects and demographic controls (age, marital status, gender, parent dummy, education, industry, occupation). Full sample consists of all adults between the ages 25 and 60. Working-age men refers to a subsample of men who are attached to the labor force.

experience a wage penalty after moving if they move speculatively, suggesting a cost to coordinating with the spouse. On the other hand, the behavior of married men whose wives do not work is much more similar to that of single men.

Overall, this analysis confirms results from the literature (e.g. Braun et al. (2021); Venator (2021) for recent work) that the dual-earner households move differently to the rest of the labor market.

C Selection into moving

Are movers fundamentally different from stayers? To answer this question, I investigate the differences in labor market outcomes of stayers and movers before they moved.

Table A7 describes the differences in wages (conditional on employment). Controlling for age, gender, marital status, parent dummy, education, occupation, industry and the state of residence, I regress individual monthly wage on a dummy for being a mover. In the first two columns, I use the full sample (including women and those outside of the labor force); in the second two

Table A7: Selection into moving: comparing wages of stayers and movers before the move

	Full sample		Working-age men	
	(1)	(2)	(3)	(4)
	Log(wage)	Log(wage)	Log(wage)	Log(wage)
Mover	-0.0580***		0.0163	
	(0.0165)		(0.0210)	
Speculative mover		-0.222***		-0.137**
		(0.0383)		(0.0639)
Non-speculative mover		-0.0131		0.0374*
		(0.0181)		(0.0222)
Below 35 years old	-0.135***	-0.135***	-0.153***	-0.153***
	(0.00615)	(0.00615)	(0.00857)	(0.00857)
HS dropout	0	0	0	0
	(.)	(.)	(.)	(.)
High school graduate	0.240***	0.240***	0.250***	0.250***
	(0.0110)	(0.0110)	(0.0142)	(0.0142)
College graduate	0.535***	0.534***	0.546***	0.545***
	(0.0138)	(0.0138)	(0.0187)	(0.0187)
Male × Single	0	0	-0.197***	-0.196***
	(.)	(.)	(0.0106)	(0.0106)
Male × Married	0.234***	0.234***	0	0
	(0.0100)	(0.0100)	(.)	(.)
Female × Single	-0.146***	-0.145***		
	(0.0112)	(0.0112)		
Female × Married	-0.234***	-0.233***		
	(0.0113)	(0.0113)		
Children	-0.0319***	-0.0319***	0.0403***	0.0403***
	(0.00632)	(0.00632)	(0.00904)	(0.00904)
Observations	1045898	1045898	503610	503610

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table summarises regressions of log of monthly wage on different migration dummies and a series of controls (age, gender, marital status, parent dummy, education, occupation, state of residence, industry). The sample consists of all stayers, and movers before the move. Full sample corresponds to all adults between the age of 25 and 60. Working-age men is a subsample consisting of men who are in the labor force.

Table A8: Selection into moving: comparing employment rates of stayers and movers before the move

	Full sample		Working-age men	
	(1)	(2)	(3)	(4)
	employed	employed	employed	employed
Mover	-0.0604***		-0.0216***	
	(0.00641)		(0.00702)	
Speculative mover		-0.198***		-0.173***
		(0.0150)		(0.0289)
Non-speculative mover		-0.00288		0.00780
		(0.00589)		(0.00579)
Below 35 years old	-0.0107***	-0.0113***	0.0138***	0.0131***
	(0.00247)	(0.00247)	(0.00279)	(0.00278)
HS dropout	0	0	0	0
	(.)	(.)	(.)	(.)
High school graduate	0.0775***	0.0773***	0.0522***	0.0520***
	(0.00499)	(0.00499)	(0.00577)	(0.00576)
College graduate	0.0995***	0.0983***	0.0729***	0.0719***
	(0.00560)	(0.00560)	(0.00648)	(0.00647)
Male × Single	0	0	-0.0489***	-0.0483***
	(.)	(.)	(0.00357)	(0.00357)
Male × Married	0.0600***	0.0594***	0	0
	(0.00348)	(0.00347)	(.)	(.)
Female × Single	-0.0229***	-0.0224***		
	(0.00419)	(0.00418)		
Female × Married	-0.0441***	-0.0427***		
	(0.00412)	(0.00412)		
Children	-0.0222***	-0.0219***	0.0156***	0.0156***
	(0.00241)	(0.00241)	(0.00279)	(0.00278)
Observations	1283013	1283013	589636	589636

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
The table summarises regressions of monthly employment status on different migration dummies and a series of controls (age, gender, marital status, parent dummy, education, occupation, state of residence, industry). The sample consists of all stayers, and movers before the move. Full sample corresponds to all adults between the age of 25 and 60. Working-age men is a subsample consisting of men who are in the labor force.

columns, I focus on the core sample of working-age men in the labor force. The results show that, in general, movers are negatively selected: they earn less than observationally equivalent stayers living in the same state. This negative selection is entirely driven by speculative movers. The result is similar, albeit less statistically significant, for the core subsample of working men: speculative migrants are weakly negatively selected, but overall movers are not different from stayers before the move.

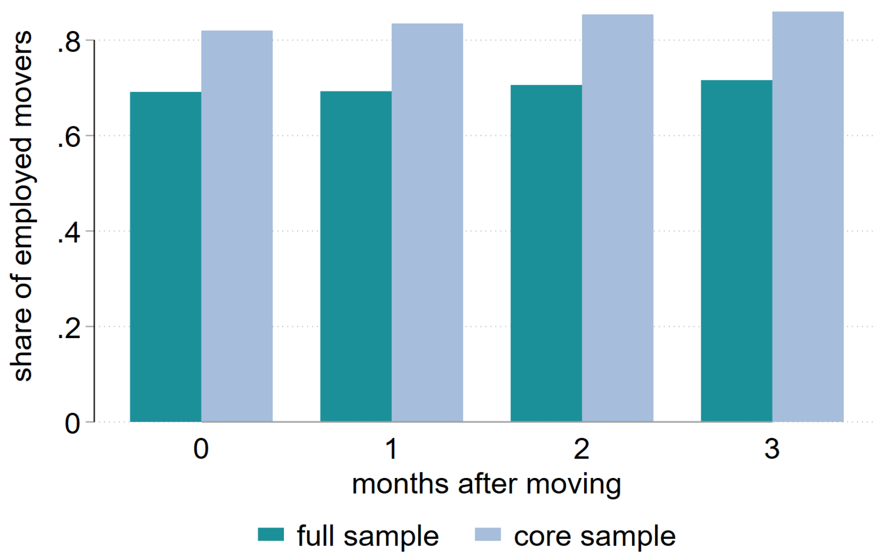
In Table A8 I repeat the analysis for employment rates. The results are very similar: speculative movers are negatively selected, while non-speculative movers have the same employment rates as their peers who stay. Interestingly, this pattern of negative selection holds also for working men, suggesting that speculative moves might be the result of an attempt to escape unemployment (as opposed to receiving a higher wage).

While these results are suggestive, it is unclear whether they should be interpreted purely as evidence of self-selection as such, or rather as a reflection of the adverse labor market conditions that made workers want to move in the first place. To disentangle these two, we would need a much longer panel dataset that would allow us to distinguish between temporary labor market outcomes and worker ability.

D Misclassification of speculative and non-speculative migration

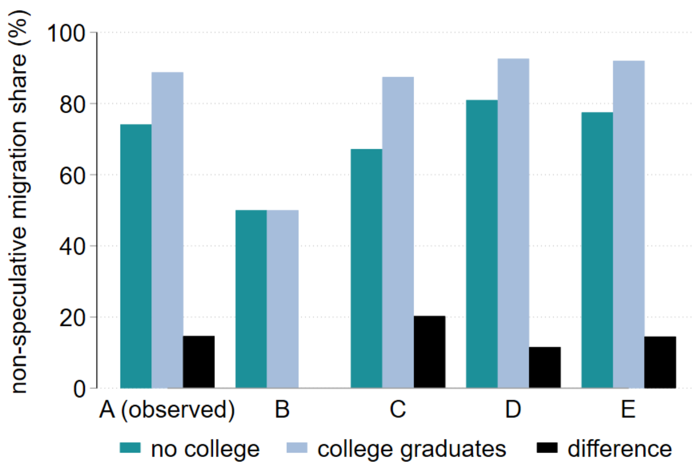
The lack of direct data on job search itself means that the classification of moves into speculative and non-speculative is prone to measurement error. In particular, speculative movers who find a job quickly (within a month) will be falsely classified as non-speculative movers, and non-speculative movers who delay the start of their jobs (by more than a month) will be misclassified as speculative movers. Moreover, if the less educated workers are more or less likely to find a job quickly, or to delay the start of their job, compared to workers with a college degree, this measurement error will impact both the overall estimates of non-speculative moves and our understanding of the

Figure A5: Robustness of the share of moves that are non-speculative to the month the employment status is measured after move



Calculated from the Survey of Income and Program Participation, 1996-1999 panel. Full sample: all individuals between the age of 25 and 60. Core sample: men between the age 25 and 64 who are in the labor force.

Figure A6: The share of non-speculative migration in different models of misclassification



The share of migration that is non-speculative under different scenarios of misclassification. Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified as non-speculative. Model D: observed data corrected for the probability that a worker finds a job but starts working more than a month later, i.e. that non-speculative migration was misclassified as speculative. Model E: observed data corrected for both types of misclassification. Sample: men between the age 25 and 50 who are in the labor force.

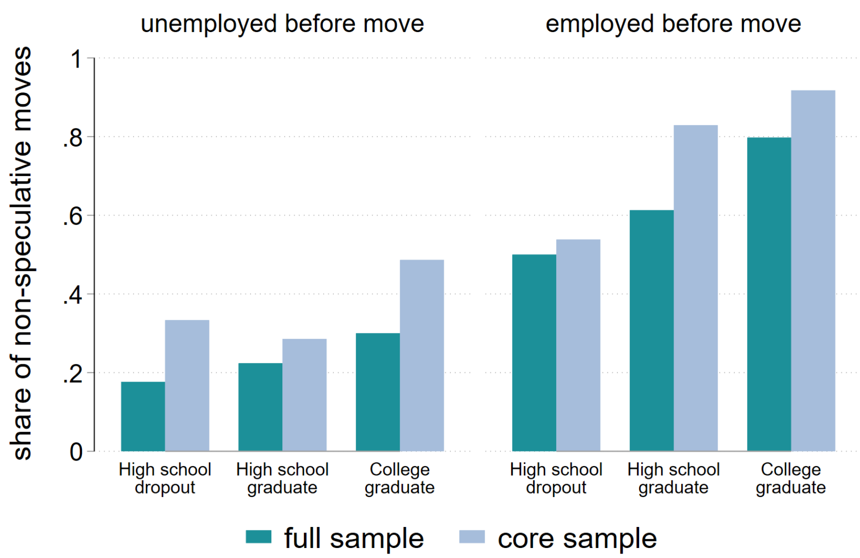
differences in mobility by education.

I address these measurement errors in two ways. First, I plot the employment share of movers at different points after the move to see how much would my estimate of non-speculative moving change with alternative timing. These shares are plotted in Figure A5. It shows that, while the employment share of movers rises in the months since moving as expected, the impact on the estimated share of non-speculative moves is relatively small. In the full sample, it increases from 64% when looking at contemporaneous employment status to 65% when using employment 3 months after the move; the shares are 81% and 85% in the core sample of working men, respectively.

Second, I adjust the education-specific shares of non-speculative migration to reflect the two errors, using the probabilities of finding employment in less than a month and delaying the start of a new job. As Figure A6 shows, the bias of miscategorization likely leads to *underestimating* the true extent of the education differences in the type of migration. Because the less educated may find jobs faster than the more educated, and because college graduates are more likely to be able to afford delay working, the true extent of the differences in the share of migrants with a job is probably larger – rather than smaller – than what the baseline estimates suggest.

E Patterns of mobility between the Census regions

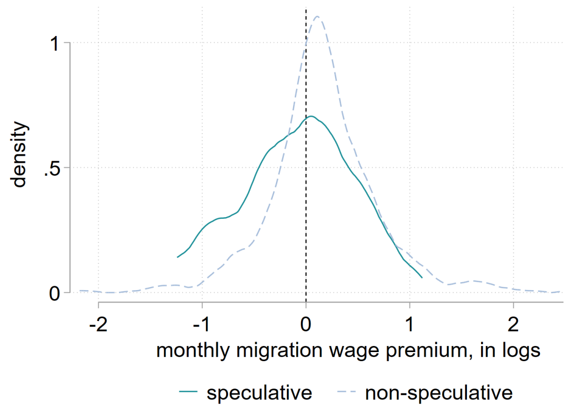
Figure A7: Share of non-speculative moves by education and prior employment status



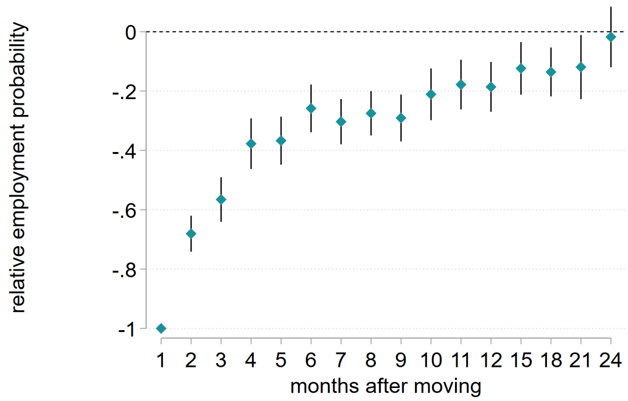
The bars correspond to the share of moves which are non-speculative for each education-employment-sample group. Full sample includes all individuals between the age 25 and 65. Core sample includes men between the age 25 and 60 who are attached to the labor force. Employment status before moving refers to whether the individual was employed or unemployed in the month before the move. The education categorize are dropout (did not finish high school), high school graduate (graduated high school but did not graduate 4-year college), and college graduate (graduated 4-year college or more). Migration is defined as moving between the 4 Census regions.

Figure A8: Differences in outcomes after speculative and non-speculative migration

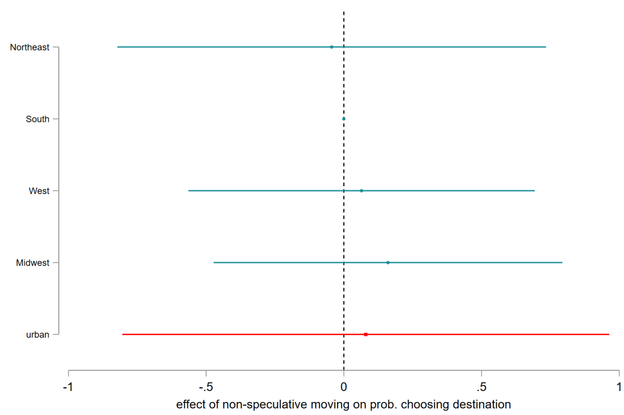
(a) Wage premium



(b) Relative employment probability for speculative movers



(c) Destinations



Panel (a): the distribution of the individual-specific difference between average pre- and post-move nominal wages, conditional on being employed. Panel (b): the monthly probability of being employed for speculative movers, relative to non-speculative movers. Panel (c): differences in destination region between speculative and non-speculative movers. The panel plots the coefficient of moving non-speculatively (as opposed to speculatively) to a particular US region, using South as the baseline. The last coefficient refers to a separate regression of whether the move is to an urban destination. In panels (b) and (c), the underlying regressions control for age, education, marital status, the number of children, industry, and employment status before the move. Sample: men between the ages 25 and 60 who are in the labor force. Migration is defined as moving between the 4 Census regions.

F Model transition probabilities

Define $\boldsymbol{T}$ as the $J \times 2J$ matrix of transition probabilities between employment and unemployment of the J different regions. The (pairs of) diagonal elements correspond to the overall probability that worker leaves employment or unemployment in the column region, and the off-diagonal elements denote the probability that worker from employment or unemployment in the column region leaves to the row region.

$$\boldsymbol{T} = \begin{pmatrix} T_{1,e1} & T_{1,u1} & \cdots & T_{1,ej} & T_{1,uj} & \cdots & T_{1,eJ} & T_{1,uJ} \\ T_{2,e1} & T_{2,u1} & \cdots & T_{2,ej} & T_{2,uj} & \cdots & T_{2,eJ} & T_{2,uJ} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ T_{J,e1} & T_{J,u1} & \cdots & T_{J,ej} & T_{J,uj} & \cdots & T_{J,eJ} & T_{J,uJ} \end{pmatrix} \tag{13}$$

The diagonal elements, capturing the outflows from employment and unemployment in region m, are:

$$T_{m,em} = -\sum_{j \neq m} \zeta_\lambda \lambda_m P^{1e}_{m,j} - \sum_{j \neq m} \left(\lambda_m P^{2e}_{m,j} + \sum_{k \neq m} \zeta_\lambda \lambda_m P^{3e}_{m,k,j} + (1 - \lambda_m - (J-1)\zeta_\lambda \lambda_m) P^{4e}_{m,j} \right)$$

$$T_{m,um} = -\sum_{j \neq m} \zeta_\theta \theta_m P^{1u}_{m,j} - \sum_{j \neq m} \left(\theta_m P^{2u}_{m,j} + \sum_{k \neq m} \zeta_\theta \theta_m P^{3u}_{m,k,j} + (1 - \theta_m - (J-1)\zeta_\theta \theta_m) P^{4u}_{m,j} \right)$$

and the off-diagonal elements, denoting the inflows from employment and unemployment in region j to region m, are:

$$T_{m,ej} = \zeta_\lambda \lambda_j P^{1e}_{j,m} + \lambda_j P^{2e}_{j,m} + \sum_{k \neq m} \zeta_\lambda \lambda_j P^{3e}_{j,k,m} + (1 - \lambda_j - (J-1)\zeta_\lambda \lambda_j) P^{4e}_{j,m}$$

$$T_{m,uj} = \zeta_\theta \theta_j P^{1u}_{j,m} + \theta_j P^{2u}_{j,m} + \sum_{k \neq m} \zeta_\theta \theta_j P^{3u}_{j,k,m} + (1 - \theta_j - (J-1)\zeta_\theta \theta_j) P^{4u}_{j,m}$$

P correspond to the different choice probabilities for employed (P^e) and unemployed (P^u) with different option sets. P^{0u}_m is the probability that an unemployed worker chooses to accept a local job offer, $P^{1u}_{m,j}$ is the probability she chooses an away job offer, $P^{2u}_{m,j}$ is the probability she chooses unemployment away when offered a local job, $P^{3u}_{m,k,j}$ is the probability she chooses unemployment in j when offered an away job in k, and $P^{4u}_{m,j}$ is the probability she chooses unemployment away when offered no jobs.

The definitions of these probabilities are:

$$
\begin{aligned}
P^{0u}_{m} &= \text{Prob}(V_m(z,\gamma_m) = \text{argmax}[V_m(z,\gamma_m), U_m(\gamma_m), U_j(\gamma_j) - K\,\forall\, j \neq m]) \\
P^{0e}_{m} &= \text{Prob}((V_m(w,\gamma_m) \cup V_m(z,\gamma_m)) = \text{argmax}[V_m(z,\gamma_m), U_m(\gamma_m), U_j(\gamma_j) - K\,\forall\, j \neq m, V_m(w,\gamma_m)]) \\
P^{1u}_{m,j} &= \text{Prob}(V_j(z,\gamma_j) - K = \text{argmax}[V_j(z,\gamma_j) - K, U_m(\gamma_m), U_j(\gamma_j) - K\,\forall\, j \neq m]) \\
P^{1e}_{m,j} &= \text{Prob}(V_j(z,\gamma_j) - K = \text{argmax}[V_m(w,\gamma_m), V_j(z,\gamma_j) - K, U_m(\gamma_m), U_j(\gamma_j) - K\,\forall\, j \neq m]) \\
P^{2u}_{m,j} &= \text{Prob}(U_j(\gamma_j) - K = \text{argmax}[V_m(z,\gamma_m), U_m(\gamma_m), U_j(\gamma_j) - K\,\forall\, j \neq m]) \\
P^{2e}_{m,j} &= \text{Prob}(U_j(\gamma_j) - K = \text{argmax}[V_m(z,\gamma_m), U_m(\gamma_m), U_j(\gamma_j) - K\,\forall\, j \neq m, V_m(w) + \gamma_m]) \\
P^{3u}_{m,k,j} &= \text{Prob}(U_j(\gamma_j) - K = \text{argmax}[V_k(z,\gamma_k) - K, U_m(\gamma_m), U_j(\gamma_j) - K\,\forall\, j \neq m]) \\
P^{3e}_{m,k,j} &= \text{Prob}(U_j(\gamma_j) - K = \text{argmax}[V_k(z,\gamma_k) - K, U_m(\gamma_m), U_j(\gamma_j) - K\,\forall\, j \neq m, V_m(w,\gamma_m)]) \\
P^{4u}_{m,j} &= \text{Prob}(U_j(\gamma_j) - K = \text{argmax}[U_m(\gamma_m), U_j(\gamma_j) - K\,\forall\, j \neq m]) \\
P^{4e}_{m,j} &= \text{Prob}(U_j(\gamma_j) - K = \text{argmax}[U_m(\gamma_m), U_j(\gamma_j) - K\,\forall\, j \neq m, V_m(w,\gamma_m)])
\end{aligned}
$$

G Proofs for Propositions 1-3

Proof 1. Total non-speculative mobility from region m is:

$$
\begin{aligned}
\text{Prob(non-speculative move)} = \alpha_m \mu_m \sum_{j \neq m}^{J} \zeta_\theta \theta_m P^{1u}_{m,j} \\
+ \alpha_m (1-\mu_m) \sum_{j \neq m}^{J} \zeta_\lambda \lambda_m P^{1e}_{m,j} \qquad (14)
\end{aligned}
$$

To see how a fall in spatial search frictions affect non-speculative moves, I differentiate this expression with respect to ζ_θ and ζ_λ, holding the values of employment and unemployment constant. This is equivalent to differentiating the total non-speculative moves around the equilibrium, keeping the endogenous variables constant.

$$\frac{\partial\,\text{Prob(non-speculative move)}}{\partial\,\zeta_\theta} = \alpha_m\mu_m \sum_{j\neq m}^{J} \theta_m P^{1u}_{m,j} > 0 \tag{15}$$

$$\frac{\partial\,\text{Prob(non-speculative move)}}{\partial\,\zeta_\lambda} = \alpha_m(1-\mu_m) \sum_{j\neq m}^{J} \lambda_m P^{1e}_{m,j} > 0 \tag{16}$$

Both of these expressions are positive. Lower spatial search frictions mean greater chance of receiving a job offer from another region, and since there is a non-zero probability that the worker chooses to accept such an offer, non-speculative mobility increases. □

Proof 2. Total speculative mobility from region m is:

$$\begin{aligned}
&\text{Prob(speculative move)} = \\
&\quad \alpha_m\mu_m \sum_{j\neq m}\left(\theta_m P^{2u}_{j,m} + \sum_{k\neq m}\zeta_\theta\theta_m P^{3u}_{m,k,j} + \left(1-(J-1)\zeta_\theta\theta_m - \theta_m\right)P^{4u}_{m,j}\right) \\
&\quad + \alpha_m(1-\mu_m)\sum_{j\neq m}\left(\lambda_m P^{2e}_{j,m} + \sum_{k\neq m}\zeta_\lambda\lambda_m P^{3e}_{m,k,j} + \left(1-(J-1)\zeta_\lambda\lambda_m - \lambda_m\right)P^{4e}_{m,j}\right)
\end{aligned} \tag{17}$$

The effect of lower spatial search frictions on speculative moves, for the unemployed and employed respectively, is:

$$\frac{\partial\,\text{Prob(speculative move)}}{\partial\,\zeta_\theta} = \alpha_m\mu_m \sum_{j\neq m}\left(\sum_{k\neq m}\theta_m P^{3u}_{m,k,j} - (J-1)\theta_m P^{4u}_{m,j}\right) \tag{18}$$

$$\frac{\partial\,\text{Prob(speculative move)}}{\partial\,\zeta_\lambda} = \alpha_m(1-\mu_m) \sum_{j\neq m}\left(\sum_{k\neq m}\lambda_m P^{3e}_{m,k,j} - (J-1)\lambda_m P^{4e}_{m,j}\right) \tag{19}$$

To derive the sign of the partial effect, I start by restating the two probabilities. $P^{3u}_{m,k,j}$ is the probability that the worker chooses speculative moving to region j when offered a job in region k. $P^{4u}_{m,j}$ is the probability that the worker chooses to move speculative to j when offered no jobs. In other words, $P^{3u}_{m,k,j}$ is the probability that speculative move is optimal when the option set includes speculative moving, local unemployment and a job offer, while $P^{4u}_{m,j}$ is the probability that speculative move is optimal when the option set only includes speculative moving and local unemployment. Invoking the Axiom of Independence of Irrelevant Alternatives, the following must be true:

$$P^{3u}_{m,k,j} - P^{4u}_{m,j} \begin{cases} = 0 & \text{if} \quad \forall k \quad V_k(z, \gamma_k) < U_j(\gamma_j) \\ < 0 & \text{if} \quad \exists k \quad V_k(z, \gamma_k) \geq U_j(\gamma_j) \end{cases} \tag{20}$$

As long as there exists a job offer in some region $k \neq m$ which is weakly preferred to unemployment away, adding a job offer into the option set will strictly decrease the probability that the worker chooses speculative migration. Such a job must exist because the value of unemployment reflects the value of job search, and so at least some of the job offers must be more valuable than searching.[27,28] Note that a sufficient condition for this to be true is that local employment is preferred to local unemployment: $V_j(z) > U_j$.

As a result, the probability that the worker chooses speculative move in the presence of *some* away job offer must be smaller than the probability that she chooses to move speculatively in the absence of such an offer:

$$\sum_{k \neq m} P^{3u}_{m,k,j} - (J-1) P^{4u}_{m,j} < 0 \tag{21}$$

[27] In a standard single-region model of the labor market, we'd assume that $V(z) > U$ for all z; there would be no reason for firms to offer wages that would never be accepted. However, no such restriction on $F_m(z)$ applies in this model, because z that would not be accepted in region m might be acceptable in region j where wages are generally lower.

[28] It is possible that $V_k(z, \gamma_k) < U_j(\gamma_j)$ for all k as long as $V_m(z, \gamma_m) > U_j(\gamma_j)$, i.e. the value of home job offer is high. However, in this case speculative moving would be chosen over local unemployment only if the probability of finding a job in m were greater from another region than domestically: $\theta_m < \zeta_\theta \theta_j$. While this is theoretically possible (even under the existence of spatial search frictions), it is empirically unlikely since the positive link between local job-finding rates and wages has been robustly documented (Kuhn et al., 2021).

Plugging this result into (15) shows that lower spatial search frictions decrease speculative moving.

$$\begin{aligned}
\frac{\partial\,\text{Prob(speculative move)}}{\partial\,\zeta_\theta} &= \alpha_m\mu_m \sum_{j\neq m}\left(\sum_{k\neq m}\theta_m P^{3u}_{m,k,j} - (J-1)\theta_m P^{4u}_{m,j}\right) \\
&= \alpha_m\mu_m\theta_m \sum_{j\neq m}\left(\sum_{k\neq m} P^{3u}_{m,k,j} - (J-1)P^{4u}_{m,j}\right) \\
&< 0 \qquad (22)
\end{aligned}$$

The result for speculative moving of the employed can be derived analogously.

□

Proof 3. Lowering spatial search frictions will increase mobility if the positive impact on non-speculative moves exceeds the reduction in speculative moving.

$$\begin{aligned}
\frac{\partial\,\text{Prob(non-speculative move)}}{\partial\,\zeta_\theta} &> -\frac{\partial\,\text{Prob(speculative move)}}{\partial\,\zeta_\theta} \\
\alpha_m\mu_m \sum_{j\neq m}^{J}\theta_m P^{1u}_{m,j} &> -\alpha_m\mu_m \sum_{j\neq m}\left(\sum_{k\neq m}\theta_m P^{3u}_{m,k,j} - (J-1)\theta_m P^{4u}_{m,j}\right) \\
\sum_{j\neq m} P^{1u}_{m,j} &> -\sum_{j\neq m}\left(\sum_{k\neq m} P^{3u}_{m,k,j} - (J-1)P^{4u}_{m,j}\right)
\end{aligned}$$

The sufficient condition for this to be true is:

$$P^{1u}_{m,j} > -\left(\sum_{k\neq m} P^{3u}_{m,k,j} - (J-1)P^{4u}_{m,j}\right) \qquad (23)$$

This condition has a relatively straightforward interpretation. In the proof of Proposition 2, I showed that a job offer from another region reduces the probability that the worker will choose speculative migration: the right-hand side of the inequality above is positive. The condition above tells us that, for lower search frictions to increase mobility, this reduction must be smaller than the probability that the worker accepts the away job offer.

The argument for why this condition holds is similar to the proof of Proposition 2. Condition (23) implies that the other option in the worker's option set – unemployment at home – must also become relatively less attractive when an away job offer becomes a part of the option set. This is equivalent to showing that, for each region $j \neq m$, there are some values of employment that are preferable to unemployment in m: $E_{z,\gamma}\max[V_j(z,\gamma_j) - K - U_m(\gamma_m)] > 0$ In other words, unemployment at home mustn't be strictly preferred to employment away. Just like in Proposition 2, this is not an unreasonable assumption to make given that U_m reflects the value of searching for jobs, so by construction the value of at least some of these jobs must exceed the value of search.

□

H Bellman equations for the nested models of migration

The Bellman equations for the model of spatial search frictions are:

$$\begin{aligned}
(1+r)U_m(\gamma_m) = \gamma_m & \\
&+ \theta_m E_z \max[V_m(z,\gamma_m), U_m(\gamma_m)] \\
&+ \sum_{j\neq m}^{J} \zeta_\theta \theta_m E_{z,\gamma} \max[V_j(z,\gamma_j) - K, U_m(\gamma_m)] \\
&+ \left(1 - (J-1)\zeta_\theta\theta_m - \theta_m\right) U_m(\gamma_m) \qquad (24)
\end{aligned}$$

$$\begin{aligned}(1+r)V_m(w,\gamma_m) = {} & w + \gamma_m \\ & + \lambda_m E_z \max[V_m(w,\gamma_m), V_m(z,\gamma_m), U_m(\gamma_m)] \\ & + \sum_{j\neq m}^{J} \zeta_\lambda \lambda_m E_{z,\gamma} \max[V_m(w,\gamma_m), V_j(z,\gamma_j) - K, U_m(\gamma_m)] \\ & + \delta_m U_m(\gamma_m) \\ & + (1-(J-1)\zeta_\lambda\lambda_m - \lambda_m - \delta_m)\, V_m(w,\gamma_m) \end{aligned} \tag{25}$$

The equations for the basic model of migration are the same, but the job search wedges ζ_θ and ζ_λ are set equal to 1.