Leaping into the unknown? The role of job search in migration decisions*

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Abstract

I present evidence of a new barrier to internal migration: thin cross-regional labour markets. Because in general workers prefer to move with a job rather than speculatively, the inability to find a job remotely translates into lower mobility. This has important implications for the differences in mobility between the less and more educated in the US. Using an augmented discrete choice model, I show that the less educated move less because they tend to work in sectors and occupations where cross-regional hiring is less commonplace. I then build a structural model of job search across space to estimate the thickness of cross-regional labour markets for different groups of workers and quantify its contribution to the observed patterns in migration behaviour. I find that up to 50% of the education gap in mobility can be attributed to differences in the thickness of cross-regional labour markets. This result suggests a large social return to improving regional search and matching for less educated and the unemployed.

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1 Introduction

What prevents workers from moving for opportunity? Geographic mobility is a potentially powerful way of improving ones income and escape unemployment. Nonetheless, 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[1] (Amior and Manning (2018); Chetty et al. (2016); Moretti (2011); Kline and Moretti (2013); Molloy et al. (2011)). This has significant consequences for the persistence of both individual and regional inequalities.

In this paper, I present evidence of a new barrier to migration: thin cross-regional labour markets. Typically, it has been assumed that migration and job search are two separate actions, whereby workers move first and then look for a job in the new labour market. However, if firms hire across local labour markets, a worker may be able to look for a job in another region remotely, and only move if he receives a sufficiently good offer. Such a move has several advantages compared with moving speculatively. First, it means that the worker can relocate and change jobs without becoming unemployed or prolonging their unemployment. Second, the worker only moves if the actual benefit of doing so is sufficiently high, instead of basing his decisions on expectations. This also makes moving with a job less risky. If workers dislike unemployment, if they are risk averse, or if the costs of migration are high compared to the expected benefits, moving with a job is preferred over moving without one. By restricting workers options to find a job before moving, thin cross-regional labour markets reduce geographic mobility.

I show that while all workers face spatial search frictions, the less educated are particularly affected. This has important implications for the mobility gap between education groups. The first piece of evidence is the data on the type of migration: the less educated not only move less, but they are also less likely to move with a job in

[1]Based on inter-state migration of a sample of US adults, 1996-1999.

hand[2]. To understand this pattern, I estimate a discrete choice model of location and employment, which shows that less-educated workers move less in part because they work in sectors and occupations where cross-regional hiring is relatively rare, which makes it more difficult for them to move with a job. In order to quantify this effect, I estimate a structural model of cross-regional job search. I find that the less educated are half as likely to find a job in another region, which corresponds to almost 50% of the mobility gap between the less- and more-educated workers.

The main challenge to identifying this effect is that workers migration options are not directly observable. Instead, I have to infer them from workers actual employment and location decisions. Another issue is that the relationship between the type of migration and migration propensity could be confounded by other factors such as differences in preferences for moving and job search activity between workers with different education levels. My identification strategy is to use differences in recruitment practices across sectors and occupations as a source of exogenous variation in workers probability of finding a job remotely in another region. Of course, the firms hiring strategy is a decision in itself, one that likely depends on the beliefs about workers willingness to move as well as local and overall labour market conditions. However, from an individuals perspective, the recruitment strategy is fixed and can thus serve to identify the role of thin cross-regional labour markets on migration propensity.

The data on employment and migration decisions comes from the Survey of Income and Program Participation (SIPP), a panel survey of US inhabitants. The SIPP does not include information on job search, but the monthly data on employment and location combined with the fact that it follows respondents when they move allows me to classify all moves as either *speculative* (move-search) or *non-speculative* (search-move). I augment this information on within-US mobility with data on workers labour market history, regional indicators, and most importantly proxies of the thickness of cross-regional labour markets. I use three measures to capture the likelihood of firms searching for workers across regions: average firm size, an index of spatial concentra-

[2]Basker (2018) finds a similar pattern in the CPS questionnaire on the stated motivation to move.

tion by sector, and the propensity to post vacancies online. This allows me to test whether thin cross-regional labour markets limit workers migration options.

I test my hypothesis by estimating a discrete choice model of employment and location outcomes. The important and novel feature of the model is that it explicitly models the workers option set. The idea of option set heterogeneity originates from the literature on empirical industrial organisation (such as Abaluck and Adams (2017); Goeree (2008)), where it has been used to demonstrate how consumers purchases depend on the set of products of which the consumer is aware. My model allows me to control for the income, amenities, living and migration costs of different options, as well as whether the option is actually available to the worker, which depends on whether the labour market makes it possible for him to find a job remotely.

I find that the variation in workers migration options is statistically significant in explaining migration behaviour. Controlling for job differences, cross-regional labour markets are thinner for the less educated. Moreover, these workers are also more likely to work in sectors and occupations where cross-regional hiring is less common.

The estimates of the discrete choice model also show that controlling for option set heterogeneity is important for obtaining correct estimates of workers' preferences for migration and their responsiveness to regional differences in income, living costs, amenities and labour market conditions. Ignoring the differences between moving speculatively and with a job leads to erroneously attributing *all* of the reluctance to move to regional differences and migration costs. As a result, I show that we are likely to underestimate workers' sensitivity to regional income differences, and overestimate their migration costs.

To understand the economic significance of thin cross-regional labour markets, I estimate a structural model of job search across space based on McCall (1970)[3]. Workers search for jobs both at home and remotely, and they can move with or without a job. The behaviour of firms is summarised by a distribution of wage offers, and by

[3]Similar models albeit for a single type of migration are estimated by Schmutz and Sidibe (2018); Ransom (2019); Gemici (2011); Wilemme and Schluter (2019).

how many vacancies they create. The model describes equilibrium behaviour in which local and cross-regional job-finding probabilities not only depend on exogenously-given labour market thickness, but also on firms and workers optimal responses to their environment and to each other. I use this model to quantify the overall impact of thin cross-regional labour markets on migration propensities of the less- and more-educated workers in the US.

The structural estimates suggest that speculative migration can explain almost 50% of the gap in migration propensity and 75% of the difference in the type of migration across the education groups. The estimates also reveal considerable heterogeneity in cross-regional job-finding rates. The gap between the probability of finding a job locally and remotely is about twice as large for the less educated compared with college graduates. Remote job search when unemployed is even less likely, with individuals of any education having less than 1% probability of finding a job compared to searching locally[4].

The main contribution of this paper lies in documenting that the way in which individuals move with or without a job matters for within-country mobility. The underlying mechanism complements and exacerbates the barriers to migration established in the literature. One of the robust findings in the literature is that the lower mobility of the less educated is due to relatively high migration costs (Glaeser and Gottlieb (2008); Moretti (2011)). I replicate this finding, but also show that thin cross-regional labour markets amplify their impact. Workers are reluctant to move speculatively if the costs of migration are high because these costs have to be paid upfront, before the worker is able to find a job in another region. Consequently, thin cross-regional labour markets in conjunction with large upfront costs of moving reduce migration by more than what one might expect by simply considering the costs alone; this may help to rationalise the often very large estimates of migration costs presented in the literature.

This paper also builds on the research on spatial search frictions. Schmutz and

[4]Ransom (2019) estimates search frictions by employment and migration status for less educated workers. Although his model does not differentiate between moving with and without a job, his estimates of heterogeneity are in line with those reported here.

Sidibe (2018), Wilemme and Schluter (2019) and Ransom (2019) provide estimates of spatial saerch frictions[5], showing that it is more difficult to find employment between rather than within regions, and that these frictions are an important form of migration costs. This paper establishes similar patterns for regions of the US and workers of different education, sector, and occupation. However, more importantly, I show that the main impact of thin cross-regional labour markets on migration is that they restrict workers option to move non-speculatively. In other words, spatial search frictions can only reduce migration if moving speculatively is not as attractive as moving with a job. Assuming that all migration is the same as is the case in the existing literature does not allow us to make this distinction[6]. It also means that the estimated spatial search frictions are likely biased downwards, since some fraction of workers move speculatively even if cross-regional labour markets are thin.

The findings of this paper offer several lessons for policy. The main implication is that improving search and matching across regions should have a significant impact on both mobility and employment rates, especially for the less educated (see also Schmutz and Sidibe (2018)). The structural estimates of job-finding rates suggest that the greatest room for improvement is among the less-educated unemployed, for whom remote job search is particularly difficult, and who are often the focus of various left behind regional and active labour market policies. However, crucially it is insufficient to simply improve the information flow between regions. Although there is some evidence that information about opportunities may translate into moves[7], the mechanism at the heart of this paper emphasises the ability to form a contract before moving. This distinction seems to be reflected in the studies on the various active labour mar-

[5]Their estimates are for France and the less educated in the US, respectively.

[6]The seminal works of Harris and Todaro (1970), Kennan and Walker (2011) and Kline and Moretti (2013) assume that all migration is speculative, namely that workers can only search after they move. By contrast, a host of papers often focusing on the role of labour markets in migration model all migration as being conditional on finding a job; for example Beaudry et al. (2014); Lutgen and der Linden (2015); Amior (2015); Epifani and Gancia (2005); Lutgen and der Linden (2015). This is also the assumption in the spatial search frictions literature (Schmutz and Sidibe (2018); Wilemme and Schluter (2019); Ransom (2019)). The discrete choice and structural models presented in this paper nest the existing models in the literature by allowing for both types of migration in equilibrium.

[7]As the literature on networks in migration argues to be the case, see for example Patacchini and Zenou (2012); McKenzie and Rapoport (2007); Wilson (2017).

ket policies in developing countries, where interventions that help workers to make a match with the employer such as job application workshops deliver relatively larger improvements in the overall employment and mobility (Abebe et al. (2016); McKenzie (2017); Jensen (2012); Franklin (2018); see Caliendo et al. (2017) for similar work in the context of a developed country).

On the other hand, migration subsidies are unlikely to have a significant impact on within-country migration because they do not make it easier to move with a job[8]. One option is to tweak this policy to include subsiding the return home, thus making it easier for speculative migrants to reverse an unsuccessful move. Another way to lessen the burden of speculative migration would be for workers automatically to carry their unemployment benefits across regions, which is particularly relevant for the US.

The remainder of this paper proceeds as follows. I start with a brief description of data in section 2. In section 3, I present the facts about conditional and speculative migration that motivate this paper. In section 4, I estimate a discrete choice model of migration as a function of cross-regional hiring. I then present a structural model of the joint employment-location decision (section 5), which allows me to quantify the impact of thin cross-regional labour markets on overall mobility, and evaluate the impact of alternative migration policies (section 6). Finally, section 7 concludes.

2 Data

I use two main types of data, on workers and firms. The worker data comes from the 1996 panel of the SIPP, and it describes the migration and employment behaviour, as well as a host of demographic characteristics. The data on firms comprises average sector characteristics that are associated with cross-regional recruitment, and it is taken from the County Business Patterns dataset for a period corresponding to the SIPP. I augment this with data on region-specific characteristics such as house prices

[8] Reducing migration costs – for example, via migration subsidies – encourages both types of migration. However, the subsidy would likely have to be large to significantly reduce the unattractiveness of speculative migration.

and unemployment rates. The full list of variables and their sources is summarised in Table A1 in the Appendix.

SIPP The Survey of Income and Program Participation (SIPP) tracks a nationally-representative sample of US inhabitants over a four-year period, providing monthly data on their income, employment, and residence, as well as their education and household structure. I use the SIPP because of its three key features: it is (i) a panel with (ii) monthly data that (iii) follows its respondents when they move. These three features are necessary to analyse the relationship between cross-regional job search and migration[9]. I use the 1996 panel because of its length, data quality, and because it avoids any major recession (see section A in the Appendix).

I estimate the models on a subsample of men[10] between the ages of 25 and 50 who had at least one month of employment over the duration of the panel. This reflects the paper's focus on the role of job search in migration decisions.

I work with three education categories: high school dropouts, high school graduates (which includes workers with some post-secondary education), and college graduates. There are 16,683 working-age males in my sample, about 12% of whom did not finish high school, while a quarter of the sample have attained a four-year college degree or higher. The three groups are similar in terms of their age, racial and urban profile, while varying considerably in their income, employment, and migration behaviour. The descriptive statistics are summarised in Table A2 in the Appendix.

Data on recruitment strategies In the absence of direct information on cross-regional recruitment, I draw on the findings of the human resources literature to construct three proxies: firm size, spatial concentration, and online vacancy posting. The literature suggests that a firm's search radius increases with the size of the company, the education requirements of the vacancy, and the relative position of the company in

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

[10] 75% of respondents in the data live in households where the primary earner is male and is thus likely to have a disproportionate influence on the migration decision.

the local labour market[11].

I calculate the average firm size by sector, and sectoral geographic concentration[12], from the County Business Patterns dataset for 1996-1999. Online vacancy posting is aggregated by occupation categories, and it captures the proportion of all vacancies advertised on the internet in 2010-2014 (taken from Hershbein and Kahn (2018)). I match these proxies with the industry and occupation variables in the SIPP, creating a measure of cross-regional employment opportunities for each worker.

Defining migration The publicly-available SIPP files record an individual's state and metropolitan area. To maximise the sample of migrants, I define migration as moving across US states. This corresponds to about 907 instances of moving, or 5.4% of the adult working men in my sample.

To reduce the dimensionality of the discrete location-employment problem, I focus on moves between the four large census regions of the US: the Northeast, Midwest, South and West (see Figure A1 in the Appendix). Due to the larger geographic areas, this type of migration is somewhat rarer: just above 50% of all the inter-state moves are also moves between regions. This leaves me with 473 instances of migration.

3 Motivating facts

In this section, I document some of the features of migration that motivate this paper. First, I replicate the stylised fact that internal migration increases with education. Second, I show that there is considerable heterogeneity in how individuals move speculatively and non-speculatively and that the type of migration is also correlated with education. Finally, I compare labour market outcomes of speculative and non-speculative migrants. This shows that moving with a job is not only correlated with higher migration propensity, but also with better labour market outcomes after the move.

[11]See section C in the Appendix for more detail.
[12]Calculated as a Gini index based on Ellison and Glaeser (1997).

3.1 The propensity to migrate

Migration is a rare event. The probability that an adult in my sample of US inhabitants moves into a different state in a given year is about 2%; the annual inter-state migration propensity reported in the literature ranges between 3 and 7%, and has been in decline since the 1980s (Molloy et al. (2011)).

Despite this, a permanent feature of the migration statistics is the large gap in migration propensity between the more and the less educated (Greenwood (1997)). In my core sample of working-age men, college graduates are more than three times more likely to move into another states than high school dropouts (Figure 1). These numbers are in line with the estimates in other studies: for example, Hernández-Murillo et al. (2011) report the migration propensity to be 2.6% for high school dropouts and 5.7% for college graduates. As I show in Table 1 and Figure A2, this education gradient is robust to demographic characteristics, household composition, employment status, and distance migrated.

Figure 1 here.

3.2 Speculative and non-speculative migration

There are two types of migration: speculative, moving without a job (move-search), and non-speculative, moving with a job in hand (search-move). In the data, I categorise non-speculative migrants as those who are employed in the month after moving (one month after recording a change in residence), and speculative migrants as those who are out of work in that month. Overall, the majority of inter-state moves in the US are with a job. However, this leaves space for a significant minority of moves that are speculative: 35% against 65% who move with a job in a sample of all adults. Working-age men in my core sample are even more likely to move with a job compared with the general population (80% of migrants move non-speculatively), which likely reflects their status as primary earners in most households.

There is also considerable variation across education groups. Figure 1 shows that less-educated working men not only move less, but they are also less likely to move with a job in hand when they do. The data shows that in my subsample of working-age men, the share of migration with a job is 58% for high school dropouts, and 86% for college graduates. Migrants with a college degree are thus up to 1.5 times more likely to move non-speculatively compared with high school dropout migrants. This education gradient holds across different age groups and for both genders, as well as after controlling for past employment history and whether the individual is married or has children (Table 1 and Figures A3, A4 and A5 in the Appendix).

Table 1 here.

Do different types of migration lead to different outcomes? To explore this, I look for systematic variation in migrants labour market outcomes and migration destinations. In panel (a) of Figure 2, I plot the migration wage premium the difference between workers average monthly earnings before and after moving separately for those who move with and without a job. In panel (b), I look at the difference in employment probability between the two groups for up to two years after migration. These figures show that non-speculative migrants are less likely to suffer a pay cut and are more likely to remain employed than speculative migrants. The two types of migrants also differ in where they are most likely to settle: non-speculative migrants move to a wider range of locations than speculative migrants (see Figure A7 in the Appendix). This suggests that speculative and non-speculative migration are substantially different.

Figure 2 here.

3.3 Misclassification of migration type

One caveat of this approach is the lack of direct data on workers job search behaviour. Speculative migrants who find a job quickly (within a month) of moving, and non-speculative migrants who delay the start of their employment by a month or more will be misclassified. I try to control for this in two ways. First, I re-classify the type of migration based on 2, 3, and 4 months after the move (Figure A6). While the less educated gradually catch up with college graduates in terms of their post-migration, the positive relationship between education and conditional migration remains positive. 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 A8 shows, the bias of miscategorisation 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 my data suggests.

4 A discrete choice model of speculative and non-speculative migration

In the previous section, I have shown that both the probability of moving and the probability of moving non-speculatively increase with a workers education level. To test whether this relationship is causal, I build an augmented discrete choice model of location and employment. This model allows me to control for attributes of each option, such as income, amenities, and migration costs, as well as linking a workers option set to the thickness of cross-regional labour markets. The results show that the frequency of firms cross-regional hiring has a significant impact on workers migration decisions: less-educated workers move less in part because they have fewer opportunities to move non-speculatively. I contrast my model with alternative models in the literature, and demonstrate that modelling the interaction between the type of migration and the thickness of cross-regional labour markets is important for producing unbiased estimates of workers preferences.

4.1 The model

In every period, the worker decides where to live and whether to work. Because income varies across locations, and because job offers may come from different regions, the location and employment decisions are made jointly. The location decision depends on the current draw of job offers, the characteristics of the different regions, migration costs, and location preferences. The employment decision represents a standard optimal stopping problem. There are eight potential outcomes, corresponding to the four large census regions of the US: $s \in \{\text{employment, unemployment}\} \times \{\text{West, South, Northeast, Midwest}\}$.

Workers differ in their wage distribution, migration costs, and the probability of receiving job offers from outside their home region. They have stochastic idiosyncratic location preferences, drawn every period from a common distribution. Wage offers are also drawn randomly in every period from a region- and worker-specific wage distribution.

The probability that the outcome of a worker i is option s, P_{is}, is a weighted average of conditional choice probabilities, where the weights are the probability that a given option is in his option set. I assume that each worker may face one of two option sets. A full option set, f, includes all possible values of s, which means that the worker has an employment (and unemployment) opportunity in each region, including speculative as well as non-speculative migration. Alternatively, the worker may only be able to search locally, in which case his restricted option set, r, includes five options: employment in his home region, and unemployment in all four regions[13]. This option set includes speculative but not non-speculative migration. An example of the option sets for a worker residing in the West is given in Table A4.

The conditional choice probability describes the probability that an option is se-

[13] I assume that local employment is in r because the regions are sufficiently large to allow any worker to find a job, i.e. the sectoral and occupation composition is sufficiently rich. Any worker can decide to quit their job and move.

lected from a given option set. C^f_{is} and C^r_{is} are the conditional probabilities for option s and individual i in the full and restricted option sets, respectively. They depend on option attributes X_{is}, which may vary across regions and individuals: monthly income, local rent, house prices, regional unemployment rate, and states of migration and unemployment. Together they capture the regional variation in local labour market and living conditions, as well as differences in income and utility across employment states. There are also unobservable factors, ϵ_{is}, such as location preferences, family ties and social networks, and the disutility of work[14]. The worker chooses the option that maximises his utility:

$$C^f_{is} = \text{Prob}(\beta X_{is} + \epsilon_{is} > \beta X_{is'} + \epsilon_{is'} \ \ \forall \ \ s' \neq s; \ \ s, s' \in f) \tag{1}$$

$$C^r_{is} = \text{Prob}(\beta X_{is} + \epsilon_{is} > \beta X_{is'} + \epsilon_{is'} \ \ \forall \ \ s' \neq s; \ \ s, s' \in r) \tag{2}$$

A worker is able to choose from the full choice set f with probability μ_i, and from the restricted option set r with probability $1 - \mu_i$. μ_i depends on a variety of factors: search technology, the thickness of cross-regional labour market, and workers search effort and ability. To identify the role of cross-regional labour markets in workers option sets, I instrument for μ_i with Z_i, proxies for the likelihood that the workers employer hires cross-regionally. I use three proxies: sector-specific average firm size and spatial concentration, and occupation-specific measure of online vacancy posting. The expression for the overall choice probability P_{is} are:

$$P_{i,s\in f} = \mu_i C^f_{is} \tag{3}$$

$$P_{i,s\in r\cup f} = C^r_{is} - \mu_i(C^r_{is} - C^f_{is}) \tag{4}$$

μ_i increases the choice probability of conditional moves, but decreases the proba-

[14]This specification is based on the seminal model of migration by Sjaastad (1962), which argues that a worker decides to move if the the benefits (income, amenities) outweigh the costs (living costs and migration costs). Note that the model setup is relevant even if not all of the migration in my dataset is job related, although Amior (2015) shows that more than a half of cross-state moves are primarily for employment reasons.

bility of speculative migration for all workers for whom $C^r_{is} - C^f_{is} > 0$ (e.g. risk-averse individuals). The overall change in migration propensity thus depends on the relative size of these effects, and in particular on $C^r_{is} - C^f_{is}$. If the addition of the option to move with a job makes speculative migration very unattractive, the magnitude of the difference in conditional probabilities would be large, potentially outweighing the increase in non-speculative migration and reducing migration propensity. On the other hand, if speculative migration is relatively unattractive regardless of the option set, its choice probability will remain more or less unchanged, and higher μ_i will lead to higher migration by increasing non-speculative migration.

4.2 Estimation and identification

Estimation Under the assumption that ϵ_{is} is type-I extreme value distributed, C^f_{is} and C^r_{is} take on the form of choice probabilities in a standard conditional logit (Rust (1987)). Since μ_i corresponds to the probability that the worker is choosing from the full option set, it can be modelled similarly, as the outcome of a binary logit function of Z_i. This gives P_{is} a closed form solution. The likelihood function assumes the standard form:

$$L(\beta, \gamma) = \prod_i \prod_s (P_{is})^{d_{is}} \tag{5}$$

The model is estimated by maximum likelihood.

The reported standard errors are calculated from a bootstrap, drawing 100 random subsamples of 4,000 individual-month observations from my core sample of working-age men. Each draw contains all instances of migration, and a random subsample of monthly observations of stayers. This reduces the skewness of the choice distribution in the sample, i.e. it increases the number of moves in each estimation subsample. I control for the potential bias of choice-based sampling by including a set of option-specific constants (Manski and Lerman (1977)).

The model is estimated as a pooled panel. Each individual-month is treated as an independent observation but carries the relevant information from the past, chiefly the previous months location. In the subsampling procedure, each individual is represented at most once, i.e. there are no repeated individual observations within a subsample, although there is no limitation on how many subsamples in which an individual may be drawn.

The assumption about the error distribution in conditional choice probabilities and the option set probabilities, the subsampling, and collapsing US geography into four large regions considerably improve the speed and ease of estimation. Despite its standard functional form, the likelihood function contains considerable non-linearity due to the composite expressions of P_{is}, and reducing the dimensions of the option set and the sample size on which the model is estimated significantly reduces the computation time. There are two main downsides. First, type-I extreme value distributed errors imply that shocks to an individuals location preferences are independent of each other and over time[15]. Second, the use of census regions means that this paper analyses migration across relatively large distances, which may make it less representative of the average move[16].

In order to estimate the model, it is necessary impute the missing parts of the monthly income variable: the counterfactual wage offers in regions where the worker decided not to reside, and his unemployment income. A worker's non-labour income and the expected future benefits of job search are captured in individual-specific reservation wage. I sort workers into bins based on their region and characteristics (experience, education, occupation, and year), and I impute the reservation wage as the smallest observed wage in a given bin (Keane et al. (2011)). The unobserved wage offers are extrapolated from the observed monthly earnings using a model in the vein of Dahl (2002), which links wages to worker characteristics, controlling for selection into employment and region of residence[17]. I estimate a separate wage model for each

[15]This is a strong assumption, but it is made less restrictive by the addition of option-specific constants, which capture the common part of location preferences, e.g. general relative popularity of employment in the South.

[16]Migration propensity decreases, and non-speculative migration increases, with distance travelled. Despite this, the positive correlation between conditional migration and migration propensity is robust; see also Figures A2 and A3.

[17]Appendix D for more details, and Tables A6 and A7 for comparison with standard selection controls a

region, and add white noise to simulate the observed wage distribution.

Identification This model decomposes the variation in workers choices into variation in the utility of the options, and variation in their option sets. Workers preferences are identified from the variation in attributes across options, as in any random utility model[18]. The role of option set heterogeneity and hence of the role of thin cross-regional labour markets in migration is identified from the variation in the proxies for firm recruitment, Z_i.

To examine the first-stage relationship between Z_i and option set heterogeneity, I plot the average values of Z_i for migrants and stayers, and for speculative and non-speculative migrants (Figure 3). It shows that migrants work on average in more spatially concentrated sectors, in sectors with larger average company size, and in occupations that are more likely to be advertised online. Furthermore, there is considerable variation in the recruitment proxies by the type of migration, and education.

Figure 3 here.

The identification strategy places two exclusion restrictions on Z_i: workers who are better at job search or have a stronger preference for moving do not self-select into sectors and occupations where cross-regional hiring is more commonplace. To test the first restriction, I show that workers in sectors with more cross-regional hiring are not more likely to also move speculatively, i.e. the recruitment proxies are not predictive of speculative migration (Figure A9). Testing the second exclusion restriction is more complicated because I do not observe any direct measures of search behaviour. Instead, I demonstrate that non-speculative migrants are not more likely to transition between jobs more often, or have higher or faster-growing wages, before the move (Table A5).

la Heckman (1979).

[18]Normalisation of the scale of utility is done implicitly by assuming that the unobserved part of utility, ϵ_{it}, is type-I extreme distributed with variance equal to $\pi^2/6$.

4.3 Alternative models of migration

To better understand the role of thin cross-regional labour markets in migration behaviour, I also estimate three alternative models of migration nested in the model presented in section 4.1.

First, I estimate a simple baseline model mimicking the standard migration models in the literature. The model does not distinguish between speculative and non-speculative migration and there are no search frictions. All workers have the same option set[19] ($\mu_i = 1$ for all workers): f' contains four alternatives, corresponding to employment in each of the four regions of the US[20]. The probability that a worker i is observed in option s is equal to the option's conditional choice probability:

$$P'_{i,s \in f'} = C_{is}^{f'} \tag{6}$$

The second alternative model is a simplified version of Schmutz and Sidibe (2018)[21]. I build on the baseline above and add my proxies for the thickness of cross-regional labour markets. . Because the model does not distinguish between speculative and non-speculative migration, the spatial search friction proxies enter the model additively as option attributes. The unconditional choice probability for worker i of option s has the same functional form as in the baseline model, but with a different set of option

[19] The less and more educated choose from the same option set, but the option attributes and their preferences over these may vary.

[20] Migration in this model is neither speculative nor non-speculative. Under the assumption that all workers find jobs immediately in the new region, regional incomes are calculated as if migration was non-speculative. Unemployment only enters the utility function via a measure of local labour market conditions (regional unemployment rate); since there is no distinction between speculative and non-speculative migration, the model does not include a dummy for being unemployed.

[21] Although the basic framework is the same, the identification of the two models is different. Schmutz and Sidibe (2018) estimate a rich structural model of within-country mobility in France, using the relative distance and location of French cities to identify the search frictions between them. I rely on individual-specific proxies for the frequency of cross-regional hiring, and estimate their effect in a discrete choice model of migration.

attributes:

$$P''_{i,s\in f'} = C_{is}^{f'} \tag{7}$$

$$C_{is}^{f'} = \text{Prob}(\beta X_{is} + \gamma Z_{is} + \epsilon_{is} > \beta X_{is'} + \gamma Z_{is'} + \epsilon_{is'} \;\; \forall \;\; s' \neq s; \;\; s, s' \in f') \tag{8}$$

In the third alternative model, I allow for different types of migration, but shut down any effects of spatial search frictions. The unconditional choice probabilities for all options are equal to the conditional choice probabilities in option set f in the full model:

$$P'''_{i,s\in f} = \mu_i C_{is}^{f} \tag{9}$$

The difference between the baseline and the second model will demonstrate the importance of modelling spatial search frictions separately from migration costs. The difference between the baseline and the third model will determine whether distinguishing between speculative and non-speculative migration can in itself add to our understand of migration behaviour. Finally, comparing the estimates of the second and third models against the full model will allow us to evaluate the role of the interaction between these two mechanisms.

4.4 Results

In this section, I present the estimates of the augmented discrete choice model outlined in section 4.1. It decomposes workers employment and location outcomes into variation in the attributes of their options, and differences in the availability of these options. I also estimate three nested versions of this model to isolate the role of spatial frictions and different types of migration and their interaction in understanding migration behaviour. I estimate these models first on the core sample of all working-age men, and then separately for working-age men with and without college education. Both sets of results show that thin cross-regional labour markets have a significant impact on workers migration behaviour, and that this channel primarily operates via changing the probability of non-speculative moving.

4.4.1 Full-sample estimates

The results of the full model are summarised in columns (4) and (5) of Table 2.

The top part of the table presents estimates of workers' preferences over the different option attributes. They are in line with standard behaviour: workers prefer options offering higher income and better amenities (as captured by house prices), lower rents, and more attractive local labour markets (as captured by regional unemployment rates). The coefficient on the unemployment dummy shows that local unemployment and speculative migration cause disutility beyond the lower income they imply. In line with other migration studies, migration is costly and its total cost decreases with education. The location and employment switching cost is large and negative, which accounts for the large degree of persistence in workers' month-to-month outcomes.

Table 2 here.

The bottom part of Table 2 looks at the role of thin cross-regional labour markets. The proxies for cross-regional hiring, firm size, spatial concentration, and online vacancy posting are positive and statistically significant: individuals working in sectors and occupations where cross-regional hiring is more commonplace are more likely to choose from a full option set (i.e larger μ_i).As a result, they are more likely to move with a job, but less likely to move speculatively. Because the magnitude of the former is much larger than that of the latter for the average worker, the overall impact on migration propensity is positive. The relative size of these effects, and the predicted impact of μ_i on migration behaviour, is plotted in Figure A10. As a robustness check, I also re-estimate this model with data adjusted to reflect the possible misclassification of speculative and non-speculative migration. The alternative estimates either fall within the confidence intervals of the headline coefficients, or exceed them in terms of magnitude (see also section 3.3 for my treatment of potential misclassification and Figures A11 - A22 for the results of the robustness test.).

This result can help to explain the gap in migration propensity between the less and more educated. Using the coefficient estimates in column (5), I predict μ_i for all workers, whereby the distribution of $\hat{\mu_i}$ for each education group is plotted in Figure 4. As education increases, the mean of $\hat{\mu_i}$ increases and its variance falls[22]. The median dropout worker has a 70% chance of being able to select employment away. The median $\hat{\mu_i}$ rises to 75% for high school graduates, and to 84% for college graduates. Fewer than 5% of college graduates face less than a 70% chance of being able to choose from the full choice set. The less educated move less because they have fewer opportunities to move non-speculatively.

Figure 4 here.

Columns (1) - (3) of Table 2 summarise estimates of the three alternative models of migration outlined in section 4.3. The preference estimates for most attributes are in line with expectations, and are not qualitatively different from the full model estimates in columns (4) and (5). The only exception is the coefficient on preferences over regional unemployment rate: the alternative models of migration suggest that workers prefer to reside in places with a higher unemployment rate. Regarding the coefficients on the interaction between migration and the index of spatial concentration and online vacancy posting in column (2), the model qualitatively replicates the results of Schmutz and Sidibe (2018). The estimates are positive, suggesting that workers who face less thin cross-regional labour markets are more likely to move.

Comparing model estimates across the five columns allows us to understand the roles and interactions of spatial search frictions, speculative and non-speculative migration. The main takeaway is that in order to model migration behaviour correctly, it is important to both distinguish between the different types of migration and control

[22]These differences are driven by the variation in firm size, online vacancy posting, and sectoral spatial concentration across education groups (see Figure 3).

for option set heterogeneity. Looking at the magnitudes of the preference coefficients (such as income), the largest difference compared to the baseline model in column (1) is due to allowing for two types of migration (column (3)). However, the coefficient on the regional unemployment rate only turns negative when we allow for the interaction between the type of migration and option set heterogeneity (column (5)). Controlling for spatial search frictions alone (column (2)) brings the coefficients closer to the estimates of the full model, although this specification alone just like the one in column (3) falls short of the full model estimates.

These model comparisons carry several implications for our understanding of migration behaviour. Moving from column (1) to (5), we see that the income coefficient increases and the estimated migration costs decrease for all education groups. This suggests that the alternative models of migration omit variables that prevent workers from moving, some of which are positively correlated with variation in income across employment-location options. For example, moving with a job offers higher income on average than moving speculatively, but if we do not control for the fact that thin cross-regional labour markets make non-speculative moving difficult, we will conclude instead that workers are not very sensitive to income differences across options. The estimated migration costs are much lower in the full model for similar reasons. First, we control for spatial search frictions, which would otherwise be included in the overall migration cost estimate. Second, distinguishing between speculative and non-speculative migration allows us to add controls for switching cost and the disutility of migration, both of which are separate to migration costs, but would otherwise be a confounding factor. The same happens when we introduce option set heterogeneity: the estimates of the fixed cost of migration fall further when we specify that some workers do not move because they cannot move non-speculatively.

As a result, not modelling the role of thin cross-regional labour markets in migration leads to biased estimates of workers preferences, and overestimating the fixed costs of migration. This point is demonstrated visually in Figure 5. It comprises two panels, each comparing the marginal effect of a given variable in the baseline model (column

(1)) and the full model (column (5)). The panel on the left shows how choice probability of a particular option increases with the income of that option, whereby the slope is steeper in the full model. The right-hand-side panel plots the impact of removing the cost of migration on choice probability. Here, the slope estimated in the full model is much flatter, implying a very different migration response.

Figure 4 here.

4.4.2 Education-specific results

The estimates in Table 2 suggested that the less-educated workers move less because they face thinner cross-regional labour markets. To further investigate the differences between education groups, I estimate the discrete choice models of location-employment outcomes separately for those with and without a college degree[23]. In the model estimated in Table 2, I allow migration costs to vary by education; here I allow other preferences to vary too. This provides further evidence on the sources of education differences in migration behaviour, and tests whether my estimated thin cross-regional labour market effects are robust to the inclusion of taste-based differences between the more and less educated.

The full estimation results are summarised in Tables A8 and A9. There are three main takeaways.

First, the variation in coefficients across alternative models of migration displays the same patterns as the full-sample estimates in Table 2. Allowing for education-specific income or amenity preferences or disutility of unemployment does not reduce the contribution of controlling for spatial search frictions and distinguishing between speculative and non-speculative migration.

Second, the results show that thin cross-regional labour market effects matter even when we hold education constant. The coefficients on proxies for cross-regional hiring

[23]I pool the high school graduates and dropouts in this way because the dropout subsample is not sufficiently large to identify all of the variables in the model.

are positive and statistically significant even within education groups. In other words, individuals with the same education who work in sectors and occupations with different cross-regional hiring strategies will exhibit different migration patterns.

The final takeaway is that not controlling for spatial search frictions and different types of migration can lead to overestimating the differences in preferences between education groups. To make this point, I plot marginal effects of income and migration costs for those with and without a college degree, as estimated in the baseline and full models. The left-hand-side panels of Figures 6 and 7 show that according to the baseline model the less educated are somewhat more responsive to income differences, but they also face much higher costs of moving[24]. However, looking at the right-hand-side panels paints a different picture, in which the education groups are much more similar in terms of both income preferences and migration costs. Instead, the less educated move less due to their restricted opportunities to move with a job in hand. Modelling the interaction between migration and labour market hence offers a different narrative of why the less educated do not move much.

Figure 6 here.

Figure 7 here.

5 A structural model of cross-regional job search

The empirical results in section 4 demonstrated that thin cross-regional labour markets matter for migration behaviour. In this section, I build a theoretical model of job search across space to formally capture the role of spatial search frictions, speculative and non-speculative migration. In every period, a worker decides where to live and whether to work there, responding to job offers from various regions and the utility of the different

[24]Comparing the coefficients in Tables A8 and A9, the less educated also exhibit a stronger preference for regional unemployment and a somewhat weaker preference for local amenities.

options. The probability of receiving an offer depends on both the region of origin of the vacancy and the worker, which allows me to model the thickness of cross-regional labour markets. The model pins down the equilibrium employment, location, and wage of the workers, and hence their migration behaviour. I then estimate the model parameters by matching the migration and employment flows in the model with those observed in the US between 1996 and 1999. The results indicate that cross-regional labour markets are thinner than the local ones for all workers, and the probability of finding a job in another region is particularly low for the less educated and the unemployed.

5.1 Setup

The point of departure is a standard partial equilibrium model of job search (McCall (1970)), where workers wait to receive random wage offers and follow an optimal stopping rule in deciding whether to accept them or not. I add a location dimension: workers may receive wage offers from different regions, and they may choose to move to another region even in the absence of a specific job offer. There are three endogenous variables in this model: a worker's employment status, his wage, and his region of residence.

The focus of the model is equilibrium analysis. I assume that a steady-state equilibrium exists, and then describe and determine its properties. Although the model analyses dynamic and forward-looking behaviour, the environment is stationary: the model parameters and distributions (of location preferences and wage offers) are constant over time.

I define a region as an area that is sufficiently large so that a move outside of the region necessarily implies moving to a new labour market. All of the workers within a region are assumed to be subject to the same labour market conditions. There are J regions in the model, denoted $j = 1, 2, ..., J$. They can differ in their labour market characteristics: wage offer distributions ($F_j(z)$), job-finding probabilities off- and on-the-job (θ_j, λ_j respectively), and the probability of exogenous job destruction (δ_j).

Regions may also differ in features unrelated to the labour market, such as weather, landscape, local amenities, geographic links to other regions, etc. Workers may value these differently; their individual-specific preferences over regions are captured by the vector $\boldsymbol{\gamma} = \begin{bmatrix}\gamma_1 & \gamma_2 & ... & \gamma_J\end{bmatrix}$. Each γ_j is a random variable drawn from a fixed multivariate distribution G with variance g^2 and region-specific means $\bar{\gamma}_j$[25].

Migration is costly. The financial, social and psychological burden of moving is captured by a catch-all fixed cost of migration K.

All workers search. I denote θ as the job-finding probability when unemployed, and λ for the employed. The job-finding probability follows a Poisson process, in which the probability of receiving more than one job offer is 0. The employed and unemployed draw from the same regional wage distributions. The job-finding probabilities vary by geography in two ways: first, some regional labour markets have relatively more jobs than others; and second, the job-finding probability may depend on the region from which the worker is searching, as searching locally is easier than searching across regions. I denote θ_k^m as the probability of finding a job in region k when searching from region m, and θ_k^k as the local probability of finding a job in region k. This spatial structure gives rise to up to $J \times J$ job-finding probabilities. To compress the parameter space, I define two wedges, ζ_λ and ζ_θ, which denote the ratio of cross-regional to local job-finding probability for search on the job and when unemployed, respectively. The probability of finding a job in region k when the worker resides in region m is then:

$$\theta_k^m = \zeta_\theta * \theta_m^m \tag{10}$$

$$\lambda_k^m = \zeta_\lambda * \lambda_m^m \tag{11}$$

In every period, worker draws new location preferences $\boldsymbol{\gamma}$ from distribution G. Moreover, one of the following two things may happen: with probability δ_j, the worker may be fired; or, as given by θ_j^k and λ_j^k, he may find a new job, with the wage being drawn from the relevant region-specific wage offer distribution $F_j(z)$. In reaction to

[25]This allows some regions to be generally more attractive to all workers than others.

these stochastic events, the worker re-optimises his location and employment decision, and he may choose to move.

5.2 Utility maximisation

The worker is a rational utility maximiser. He decides where to live and which job offers to accept based on all of the information available to him so that his expected lifetime utility is maximised. All workers are infinitely-lived, risk-neutral, and identical up to their idiosyncratic location preferences. The worker has perfect information about the aggregate characteristics of the local labour markets and his own current location preferences.

The worker's optimal decision is based on the present discounted utility stream from employment and unemployment in different regions. There are J Bellman equations that describe the discounted expected value of employment as a function of wage, $V_j(w)$, and J Bellman equations for unemployment, U_j. The worker's choice also depends on his options, i.e. whether he has received a job offer, or has been fired. The option sets determine which utility streams the worker compares to make his optimal choice. They are embedded in the recursive forms of the values of employment and unemployment defined below[26].

I start by defining *the best unemployment option*, U_m^*, as the highest value of unemployment less migration costs, given the worker's current location m and the vector of idiosyncratic preference draws $\boldsymbol{\gamma}$:

$$U_m^*(\boldsymbol{\gamma}) = \max_j [U_j + \gamma_j - K] \tag{12}$$

The value of unemployment in the region of residence, U_m, comprises the current period payoff, and the expected utility of future optimisation (equation (13)). For every period the worker spends as unemployed in region m, his non-labour income net of living costs is b_m. With probability θ_m, the worker receives a local wage offer z; with

[26] I visualise the relationship between the worker's potential options and his possible outcomes in Figures A23 and A24.

probability $\zeta_\theta \theta_m$ he is offered a job in region j, which comes with the migration cost K. He compares either offer against his best unemployment option U_m^*. Alternatively, with probability $1-(J-1)\zeta_\theta\theta_m-\theta_m$, he receives no job offers and simply picks his best unemployment option. The expectations of the future payoffs are taken over both the values of wages z and idiosyncratic location preferences $\boldsymbol{\gamma}$, since these are the elements unknown to the worker when making a choice today. The utility flow is discounted at the rate i.

$$\begin{aligned} U_m = &\frac{1}{1+i}\left[b_m + \theta_m E_{z,\gamma}\max[V_m(z)+\gamma_m, U_m^*] + \sum_{j\neq m}^{J}\zeta_\theta\theta_m E_{z,\gamma}\max[V_j(z)+\gamma_j-K, U_m^*]\right] \\ &+ \frac{1}{1+i}\left[(1-(J-1)\zeta_\theta\theta_m-\theta_m)\,E_\gamma U_m^*\right] \end{aligned} \tag{13}$$

The value of employment in home region, $V_m(w)$, similarly comprises current and future payoffs, although the expression is more complex because an employed worker can also be fired, as is summarised in equation (14). All $V_j(w)$ for a given region are stacked in vector $\mathbf{V_j}$.

$$\begin{aligned} V_m(w) = &\frac{1}{1+i}\left[w + \lambda_m E_{z,\gamma}\max[V_m(w)+\gamma_m, V_m(z)+\gamma_m, U_m^*]\right] \\ &+ \frac{1}{1+i}\left[\sum_{j\neq m}^{J}\zeta_\lambda\lambda_m E_{z,\gamma}\max[V_m(w)+\gamma_m, V_j(z)+\gamma_j-K, U_m^*]\right] \\ &+ \frac{1}{1+i}\left[\delta_m E_\gamma U_m^* + (1-(J-1)\zeta_\lambda\lambda_m-\lambda_m-\delta_m)\,E_{z,\gamma}\max[V_m(w)+\gamma_m, U_m^*]\right] \end{aligned} \tag{14}$$

The specific optimal choice of a worker will depend on his option set in the given period. For example, if the worker is unemployed and has not received any job offers, his optimal choice is:

$$U_m^*(\boldsymbol{\gamma}) = \max_j[U_j+\gamma_j-K]$$

The optimal choice of an employed worker who has found a job in another region is:

$$\max[V_m(w) + \gamma_m, V_k(z) + \gamma_k - K, U_m^*(\boldsymbol{\gamma})]$$

5.3 Equilibrium

I define an equilibrium as where the endogenous variables of the model, regional unemployment rates $\{\mu_j\}_1^J$, population shares $\{\alpha_j\}_1^J$, and accepted wage distributions $\{H_j(z)\}_1^J$, are constant[27].

Equilibrium conditions A general J-region model requires $J(2+\omega)$ equilibrium conditions (equations (15) - (17)). They pin down the J local unemployment rates μ_j, the J regional population shares α_j, and the J equilibrium wage distributions $H_j(z)$, where ω denotes the size of the discrete wage support. They are all based on imposing a balance of flows between different parts of the labour market or different regions. The size of the specific flows is derived from theutility-maximising worker behaviour, as outlined in the previous section.

$$\textit{flows into regional unemployment in } k = \textit{flows out of regional unemployment in } k \tag{15}$$

$$\textit{migration into region } k = \textit{migration out of region } k \tag{16}$$

$$\textit{new workers who are paid } w \textit{ in region } k = \textit{workers who used to be paid } w \textit{ in } k \tag{17}$$

Finding the equilibrium The model is solved numerically.

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

[27] I normalise the total population to 1, the regional unemployment rates correspond to the worker's employment status, the regional population share depends on his optimal location choice, and the wage distribution on his wage.

which expectations need to be taken over both wage offer distributions and location preferences. The assumption that γ_j are type-I extreme distributed considerably simplifies this step. As Rust (1987) demonstrated, under this assumption the expected future utility has a closed-form solution, so the expression becomes:

$$E_{z,\gamma}\max[V_j(z)+\gamma_j-K,U_m^*]=f_j(z)^T[ln(exp(\mathbf{V_j}(z)-K)+exp(U_m^*))] \qquad (18)$$

Next, I can use $\mathbf{V_j}$ and U_j to find the probabilities that a worker makes a particular choice, given his option set[28]. 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 belonging to different options.

The final step is solving the system of flow equations for the equilibrium endogenous variables $\{\mu_j\}_1^J$, $\{\alpha_j\}_1^J$, and $\{H_j(z)\}_1^J$. I do this using value function iterations in two stages. First, I use the wage offer distribution $F_j(z)$ instead of the endogenous distribution of wages $H_j(z)$ and solve for equilibrium population shares and unemployment rates. I then plug in these first-stage solutions to calculate the equilibrium wage distribution. I repeat the iteration until the values from the two stages converge.

5.4 Estimation

Modelling the US as a four-region economy ($J=4$) requires estimating 20 parameters: job-finding probabilities $\{\theta_j\}_4^1$ and $\{\lambda_j\}_4^1$, job destruction probabilities $\{\delta_j\}_4^1$, job-finding wedges ζ_λ and ζ_θ, migration cost K, and the means and variance of location preference distribution, $\{\bar{\gamma}_j\}_4^1$ and g^2. I normalise non-labour earning, b_j to 0; it will be subdued in the regional mean of location preferences. I further normalise the location preferences by making West the baseline.

I set the distribution of location preferences, γ_j, to be type-I extreme value distribution[29]. The parameters of the regional wage distributions – which are exogenous to

[28]An example of such a probability is equation (21) in Appendix E.
[29]This allows me to find closed-form solutions for model moments.

the model – are taken from the data[30]. The equilibrium outcomes $\{\alpha_j\}_4^1$ and $\{\mu_j\}_4^1$, are also taken directly from the data. The model is estimated separately for those with and without a four-year college degree.

The model is identified from data moments on the worker movement between regions and in and out of employment, which results in 63 free moments[31]. ζ_λ is identified from the between-region employment-to-employment transition rates. The region-specific domestic job-finding probabilities for the employed and unemployed are backed out from the within-region employment-to-employment and unemployment-to-employment transitions, respectively. The regional job destruction probability is determined by the local employment-to-unemployment moves. Overall migration rates pin down migration costs, while the region-specific flows identify average location preferences.

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 labour markets more accurately.

The model parameters are recovered using the method of simulated moments (McFadden (1989)): I find model parameters that minimise 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:

$$\rho = \{\delta_1, \delta_2, ..., \delta_4, \theta_1, ..., \theta_4, \lambda_1, ..., \lambda_4, \zeta_1, \zeta_2, K, \bar{\gamma_1}, ..., \bar{\gamma_3}, g\} \tag{19}$$

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

$$\hat{\rho} = \text{argmin}(\mathbf{M}(\rho) - \mathbf{D})^T \mathbf{W}(\mathbf{M}(\rho) - \mathbf{D}) \tag{20}$$

[30] I approximate it using a two-point support separately for each region: log wages at the 25th and the 75th percentile, attributing a 50% probability density to both.

[31] They are calculated from from the 1996 SIPP panel and presented in Tables A10 and A11 in the Appendix.

$\mathbf{W}$ is the weighting matrix[32].

5.5 Results

The structural estimates are presented in Table 4, separately for the less and more educated. The model's goodness of fit is summarised in Table 3.

Table 3 here.

Table 4 here.

The main parameters of interest are the cross-regional job-finding wedges, ζ_θ and ζ_λ. A number close to 1 means that cross-regional job-finding probability is almost as high as the local one, while a number close to 0 signals relatively thin cross-regional labour markets. I find that the wedges are sizeable and vary by education. An employed college individual is 35% less likely to find a job in another region compared with doing so locally. The wedge is even larger for those without a college degree, who find on average four cross-regional jobs for ten local ones. There are also differences between searching on-the-job and when unemployed. The latter is virtually infeasible: workers of either education level find less than one remote job for one hundred local ones.

The differences in the estimated migration costs are similarly large. Converted to US dollars, the total moving costs for a college graduate are almost $100,000, and they rise to $300,000 for those without a college degree. Despite the large range, these estimates are in line with the literature: Kennan and Walker (2011) estimate the migration cost of high school graduates at more than $300,000, while Amior (2015) arrives at a much more modest $13,000.

The education variation in the rest of the model parameters are much smaller. In general, in line with the greater churn in the labour markets for less-skilled labour, the regional job-finding and job-destructing variables are somewhat larger for those without

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

a college degree. On the other hand, the distributions of their location preferences are very similar, suggesting that variation in location preferences is unlikely to account for much of the migration differences, as further explored in the next section.

6 Explaining the education differences in migration

In this section, I use the estimates of the structural model of cross-regional job search to evaluate the role of thin cross-regional labour markets. I also compare the impact of two migration policies: migration subsidies and improving cross-regional hiring. I show that thin cross-regional labour markets account for almost half of the observed gap in migration propensity between the less and more educated, as well as 75% of the differences in the type of migration. As a result, while migration subsidies may be more effective in increasing migration propensity, almost all of this would be due to increased speculative migration. On the other hand, measures aimed at easier cross-regional hiring could increase migration via non-speculative moving, especially for the lees educated and the unemployed.

6.1 Decomposing the migration propensity gap between the less and more educated

The less and more educated vary along many dimensions: labour market variables, wage distribution, location preferences, migration costs, and the thickness of their cross-regional labour markets. These factors combine to give rise to differences in migration propensity and non-speculative migration, as described in section 3 of this paper. I decompose these gaps in the variation of individual factors using the structural estimates in Table 4.

The decomposition shows that about 80% of the education gap in migration propensity can be explained by the higher migration costs of the less educated. The second most important factor is thin cross-regional labour markets. The relative difficulty of finding jobs cross-regionally for employed and unemployed workers accounts for 41% and 5% of the migration gap, respectively[33]. On the other hand, wage differences play an insignificant role, partly because higher mean and higher variance have opposing effects on migration. However, it also reflects the notion that the observed regional wage differences are not sufficiently large to motivate migration flows. Finally, some parameters such as regional job-finding and job destruction probabilities increase the migration gap.

The education differences in the share of migration with a job (non-speculative) are predominantly determined by the relative thickness of cross-reginal labour markets: almost 75% of the education gap in non-speculative migration can be attributed to the relative difficulty of finding jobs cross-regionally. Similarly to migration propensity, most of this effect is driven by on-the-job search. Migration costs a prominent factor behind their lower migration propensity play a minor role, because they have to be paid regardless of the circumstances in which the worker migrates. The education differences in wage distributions are virtually insignificant, for the same reason as above.

This decomposition suggests that the effectiveness of cross-regional labour markets in matching workers and firms across space is an important determinant of migration behaviour, and can explain a significant portion of the education differences. Overall, the structural model not only replicates the findings of the discrete choice model that the less educated move less because thin cross-regional labour markets make it more difficult for them to move non-speculatively, but it also quantifies the magnitude of this effect on migration behaviour, and estimates the size of spatial search frictions for different groups of workers.

[33]These numbers do not necessarily sum up to 100%, because some parameters (such as job-finding and job destruction rates) and their interactions increase rather than decrease the migration gap. The contribution of each parameter is calculated keeping everything else constant. The detailed results are plotted in Figures A27 and A28.

6.2 Policy implications: the role of job search frictions

Understanding why and how the less educated move is vital for addressing several policy questions. There is evidence that migration is an important buffer to local demand shocks (Bartik (2018), Blanchard and Katz (1992)), but research also shows that the less educated, low-income households that are more exposed to these shocks are also least likely to move (Bound and Holzer (1996), Wozniak (2010), Hoynes (1999)). The implications are potentially strong: Amior and Manning (2018) argue that this lack of mobility leads to the persistent and substantial regional disparities in unemployment and welfare. Governments intervene in these regions, although the impact of their policies is often ambiguous and largely depending on workers migration response (**?**, Glaeser and Gottlieb (2008)).

Assuming that policy-makers wish to increase the mobility of workers especially those who are economically vulnerable what are the implications of this paper? To answer this question, I construct a series of counterfactuals evaluating the possible impact of reducing job search frictions on migration behaviour. I compare them to the effect of the frequently-floated solution to low mobility: migration subsidies.

First, I explore would happen if the relative thickness of cross-regional labour markets was equalised across education groups. The first set of bars in both panels in Figure 8 plots the observed migration behaviour (migration propensity and non-speculative share of migration). The last set depicts a scenario in which I set the cross-regional job-finding wedges of the less educated as equal to those of college graduates, for both the employed and unemployed[34]. In the central set of bars, I close the education gap in migration costs instead (a migration subsidy policy). Comparing the migration behaviour of the less educated under both policies, we can see that migration subsidies are more effective in simply getting people moving. However, they do not change the discrepancy in the type of migration: in other words, the less educated are moving more, but virtually all of these extra moves are speculative. On the other hand, thicker cross-

[34] I leave the regional job-finding probabilities unchanged, setting $\zeta_\theta(nocollege) = \zeta_\theta(college)$ and $\zeta_\lambda(nocollege) = \zeta_\lambda(college)$.

regional labour markets close about 75% of the gap in the type of migration, which also significantly increases migration.

Figure 8 here.

What would happen if we could remove spatial search frictions entirely? I answer this question with a second set of counterfactuals, depicted in Figure 9. I compare outcomes in three scenarios: everyone faces the spatial search frictions of the more educated; everyone faces the spatial search frictions of the less educated; and spatial search frictions are removed for all, i.e. cross-regional job search becomes as easy as it is locally. The graph has two main messages. First, the migration behaviour of the less educated becomes very similar to that of college graduates once they face the same cross-regional labour markets. Second, even in the most efficient markets, spatial search frictions remain very large: the last set of bars predict that migration propensity would increase by an order of magnitude if all thin-market effects could be removed. Indeed, in the absence of thin cross-regional labour markets, only a very small number of workers of any education would choose to move speculatively[35].

Figure 9 here.

Why does it matter whether policy incentivises speculative or non-speculative migration? As long as workers dislike unemployment, are risk averse, or the costs of migration are relatively large, they will prefer to move non-speculatively rather than speculatively. This suggests that it is not sufficient to simply judge policies on how well they can encourage migration, but rather policy-makers should also be concerned about what type of migration they are incentivising. Moreover, migration subsidies and policies aimed at removing spatial search frictions affect the economy via different

[35]Of course, these counterfactuals estimate the upper bound of the search friction effect. The analysis ignores any negative spillover and general equilibrium effects, such as equilibration of rents and wages, changes in firms' vacancy posting strategies, and negative search externalities among the workers. All of these would likely reduce the overall effect estimated here.

channels. By changing migration costs, the policy-maker is changing the cost-benefit balance of migration, while by addressing search frictions the policy-maker also improves the functioning and efficiency of the market[36]. Finally, given the magnitude of migration costs estimated in section 6, improving cross-regional labour market efficiency may be a cheaper alternative.

An active labour market policy aimed at thicker cross-regional labour markets would probably focus on two mechanisms. First, there is the cost of vacancy posting across large geographic areas. It may seem that this would be sufficiently lowered with the advancement of the internet, although the actual impact on the labour market is ambiguous. Data on online vacancy posting (Hershbein and Kahn (2018)) reveals that significant differences remain in the likelihood of different jobs being posted. However, advertising of vacancies is only a small portion of the "black box" of spatial search frictions discussed in this paper. The human resources literature points out that larger, more specialised firms not only advertise more widely, but they also interview more candidates and use different selection procedures. The second part of labour market intervention may thus consider the factors that determine the firm's recruitment strategy. For example, interview transportation subsidies for the unemployed could make it feasible for workers to not only apply but also actively pursue job search in distant regions.

7 Conclusion

The main message of this paper is that job opportunities matter for understanding migration behaviour. I use a combination of discrete choice and structural evidence to show that differences in the thickness of cross-regional labour markets can explain up to half of the gap in migration propensity between more and less educated workers. The less educated are more likely to move speculatively, and less like to move overall,

[36]Of course, the matter is not as simple. Kline and Moretti (2013) demonstrate that in a second-best world and/or in the presence of agglomeration forces, distribution policies such as migration subsidies may both redisitrbute and increase welfare.

because they find it about relatively twice as difficult to find a job in another region before they move.

I motivate the paper by establishing a new, previously-undocumented fact about the relative timing of migration and job search. The less educated are not only less likely to move, but they are also significantly less likely to move with a job in hand. I then analyse what drives this behaviour first by estimating a conditional logit of employment-location with an unobserved option set heterogeneity. In the second step, I model thin cross-regional labour markets formally by adding a location dimension to a standard partial equilibrium model of search. The estimates of both models lend support to the hypothesis that cross-regional search is more difficult for the less educated. The structural model also allows me to simulate a set of counterfactuals looking at the possible impact of different policies focused on improving mobility.

More broadly, the patterns in migration behaviour presented in this paper have implications for how we model within-country migration. I show that 65% of migration is non-speculative namely with a job in hand which is at odds with the standard assumption in the literature that migration and job search are two separate, consecutive decisions.

The policy implications of this paper are two-fold. The discrete choice model shows that in order to correctly interpret workers responsiveness to regional variation in income, living costs, and migration costs, it is necessary to control for the fact that not all of them choose from the same set of options. The counterfactuals based on the structural model suggest that improving the efficiency of cross-regional labour market could not only have a potentially large impact on overall mobility, but it could also improve individuals welfare by allowing them to migrate after the job search uncertainty has been resolved.

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Tables in the main text

Table 1: Relationship between education and the propensity and type of migration

	migration	migration	non-speculative migration	non-speculative migration
education	1.0329***	1.0552***	0.8052***	0.7591***
	(0.0897)	(0.0909)	(0.2217)	(0.2256)
employed in previous month	-0.3731**	-0.3409**	1.4111***	1.4375***
	(0.1578)	(0.1589)	(0.3315)	(0.3385)
married		0.0353		0.2499
		(0.1258)		(0.3305)
kids		-0.1496		0.3065
		(0.1244)		(0.3386)
young		-0.6590***		-0.3978
		(0.1052)		(0.2725)
prob. of unemployment			-1.5825***	-1.6437***
			(0.5448)	(0.5542)
Observations	16473	16473	473	473

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
The sample is restricted to working men between the age of 25 and 50. Columns (1) and (2) model the probability of moving into a different census region. Columns (4) and (5) explain the likelihood that, conditional on moving, the migration is speculative (as opposed to for a specific job). "Employed in previous month" is a dummy variable equal to 1 if the worker was in employment the month before migration. "Prob. of unemployment" refers to individual-specific probability of being unemployed in any given month.

Table 2: Discrete choice models of location and employment, allowing for spatial search frictions and different types of migration

	(1)	(2)	(3)	(4)	(5)
	baseline	search frictions	two types of migration	two types of migration and search frictions	
utility					
Dependent variable (1) and (2): probability of choosing one of the 4 regions					
Dependent variable (3) - (5): probability of choosing one of the 8 employment-location options					
income	0.174***	0.177***	0.283***	0.227***	0.297***
	(0.019)	(0.019)	(0.025)	(0.030)	(0.027)
regional unemp. rate	0.794***	0.784***	0.999***	-0.312***	-0.136***
	(0.065)	(0.075)	(0.076)	(0.020)	(0.035)
unemployment dummy			-0.985***	-1.198***	-0.798***
			(0.094)	(0.068)	(0.087)
regional house price	6.000***	6.000***	6.001***	9.868***	6.001***
	(0.000)	(0.000)	(0.000)	(0.661)	(0.001)
regional rent	-0.010***	-0.010***	-0.010***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
mig. cost (dropouts)	-4.273***	-4.147***	-2.207***	-2.141***	-1.916***
	(0.059)	(0.067)	(0.117)	(0.055)	(0.103)
mig. cost (high school)	-3.580***	-3.527***	-1.398***	-1.207***	-1.133***
	(0.015)	(0.019)	(0.102)	(0.081)	(0.080)
mig. cost (college)	-2.494***	-2.561***	-0.226**	-0.237***	-0.046
	(0.030)	(0.032)	(0.102)	(0.044)	(0.063)
switching cost			-2.568***	-2.628***	-2.546***
			(0.106)	(0.052)	(0.090)
spatial index (sector)		0.040***			
x migration		(0.013)			
online vacancies (occupation)		0.131***			
x migration		(0.020)			
choice set					
Dependent variable (latent): probability of choosing from a full option set					
firm size (industry)				0.812***	
				(0.001)	
spatial index (sector)				0.003	0.436**
				(0.089)	(0.206)
online vacancies (occupation)				(0.088)	0.560***
				(0.355)	(0.048)
constant				0.036	1.278***
				(0.062)	(0.230)

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ *All models contain option-specific constants. Model (1): conditional logit assuming all migration is for a specific job (4 options). Model (2): model (1), allowing for cross-regional job search frictions, which are identified through sectoral and occupation variation in spatial concentration of forms and online vacancy posting. Model (3): model (1) which distinguishes between the two types of migration (8 options). Model (4): allows for both different types of migration (8 options) and for individual-specific spatial search frictions.*

Table 3: SMM estimates of the structural model: goodness of fit.

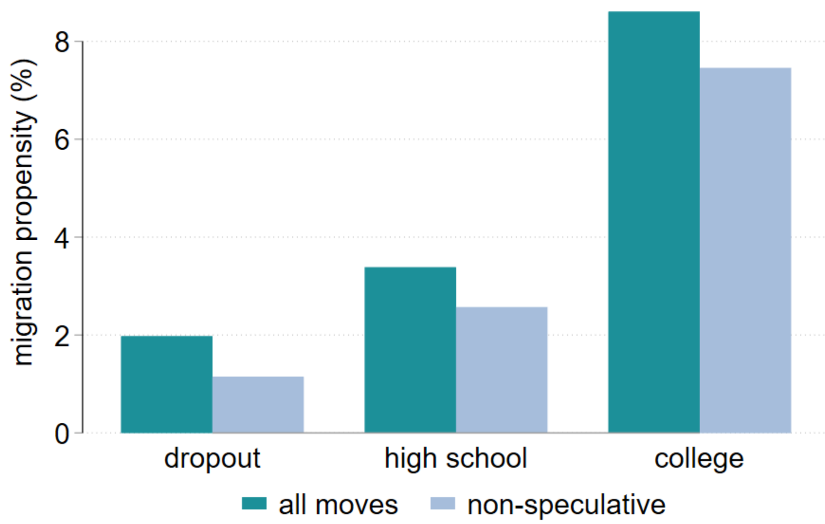
	less educated		more educated	
	data	model	data	model
employed to ...				
... employed home	98.27%	98.31%	98.95%	98.98%
... employed away	0.04%	0.04%	0.11%	0.11%
... unemployed home	1.67%	1.65%	0.93%	0.91%
... unemployed away	0.01%	0.00%	0.00%	0.00%
unemployed to ...				
... employed home	10.47%	10.22%	11.15%	10.81%
... employed away	0.02%	0.00%	0.07%	0.03%
... unemployed home	89.43%	89.68%	88.56%	88.93%
... unemployed away	0.08%	0.10%	0.22%	0.23%

Table 4: SMM estimates of the model parameters, by education.

description	parameter	less educated	more educated
job offer arrival rate, on-the-job, Northeast	λ_1	0.857	0.660
job offer arrival rate, on-the-job,Midwest	λ_2	0.907	0.514
job offer arrival rate, on-the-job, South	λ_3	0.869	0.644
job offer arrival rate, on-the-job, West	λ_4	0.998	0.619
job offer arrival rate, unemployed, Northeast	θ_1	0.096	0.110
job offer arrival rate, unemployed, Midwest	θ_2	0.102	0.113
job offer arrival rate, unemployed, South	θ_3	0.096	0.102
job offer arrival rate, unemployed, West	θ_4	0.116	0.110
job destruction probability, Northeast	δ_1	0.016	0.008
job destruction probability, Midwest	δ_2	0.015	0.008
job destruction probability, South	δ_3	0.017	0.009
job destruction probability, West	δ_4	0.019	0.012
job search wedge, on-the-job	ζ_1	0.399	0.674
job search wedge, unemployed	ζ_2	0.0001	0.001
migration cost (log)	K	12.626	11.485
std. dev. of location preferences	g	1.609	1.627
mean location preference, Northeast	$\bar{\gamma}_1$	-0.162	-0.037
mean location preference, Midwest	$\bar{\gamma}_2$	0.004	0.108
mean location preference, South	$\bar{\gamma}_3$	0.289	0.240

Figures in the main text

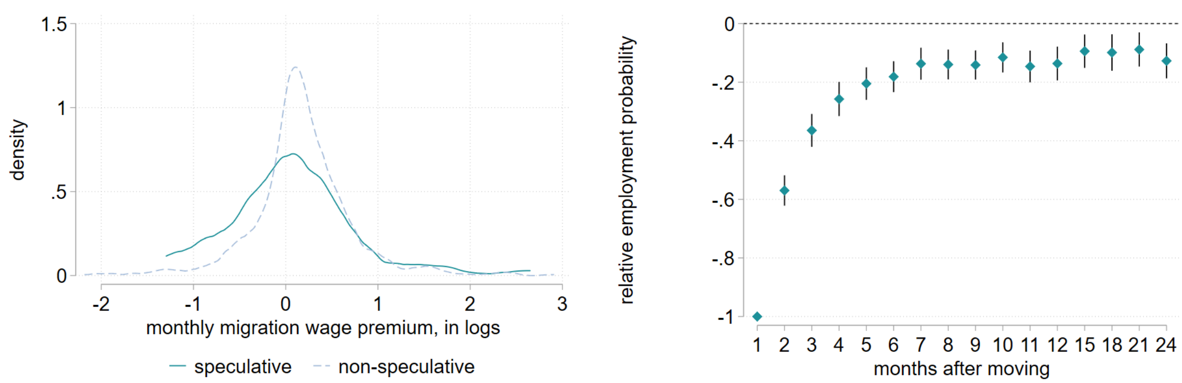
Figure 1: Propensity to migrate into another state, US, 1996-1999.



Calculated from the Survey of Income and Program Participation, 1996-1999 panel. Sample: men between the age of 25 and 50 who are a part of the labour force. States refer to the 50 US states. Bars represent the number of moves (all and non-speculative) as a fraction of the number of workers in a given education group.

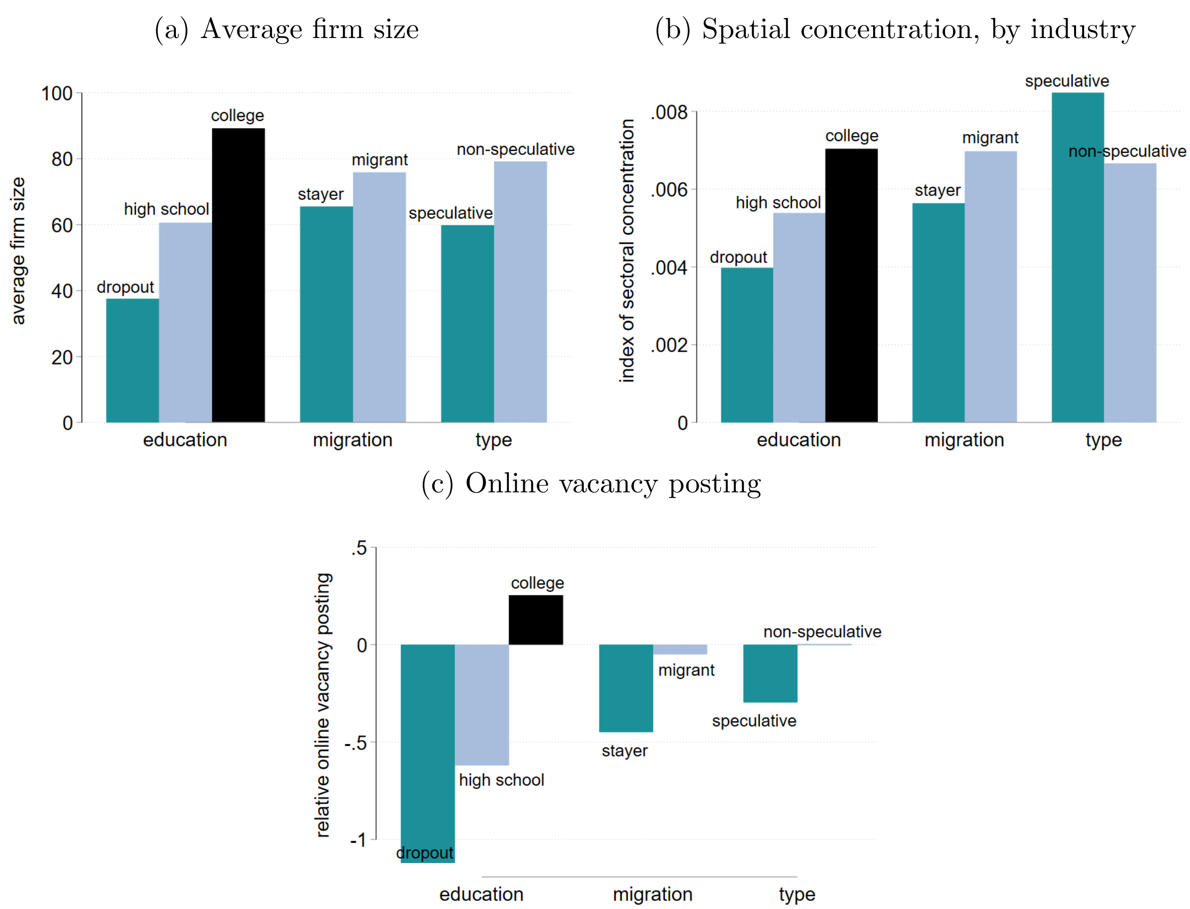
Figure 2: Differences in outcomes after speculative and non-speculative migration

(a) Wage premium (b) Relative employment probability



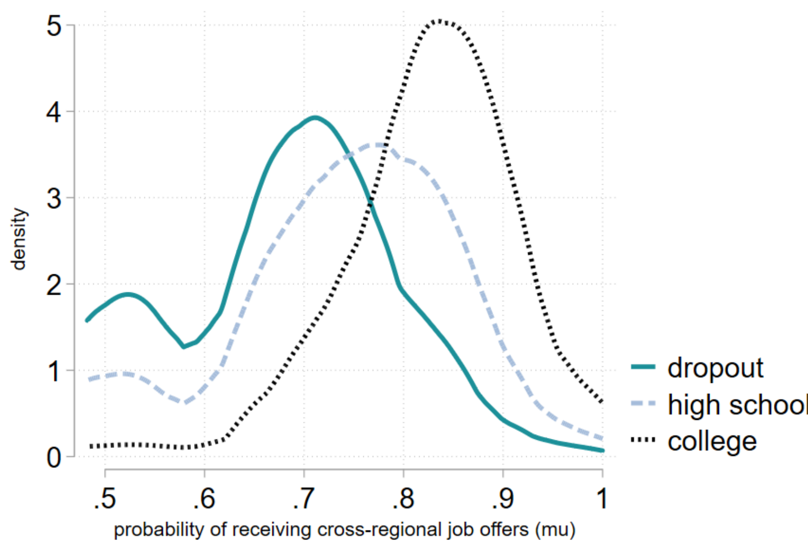
Calculated from the Survey of Income and Program Participation, 1996-1999 panel. Sample: men between the age 25 and 50 who are in the labour force. Migration is defined as moving between the 50 US states. Wage premium measures the differences in average monthly log wage before and after migration. Relative employment probability refers to the probability of a speculative migrant being employed the given number of months after moving compared with non-speculative migrants.

Figure 3: Recruitment proxies and migration



Recruitment behaviour and worker characteristics. Panel (a) summarises average firm size by education, migration propensity, and type of migration (conditional on migration). Panel (b) plots average index of spatial concentration by education, migration propensity, and type of migration (conditional on migration). The higher the value of the index, the more spatially concentrated the industry. Panel (c) summarises the gap between all vacancies and those posted online. The variable is calculated as the log odds ratio of the probability density mass of each occupation category in the two datasets. A negative number means that the vacancies are under-represented in the online data, and vice versa. Data sources: SIPP (1996-2000), County Business Patterns (1996-1999), JOLTS (2007-2014), Burning Glass (2007-2014).

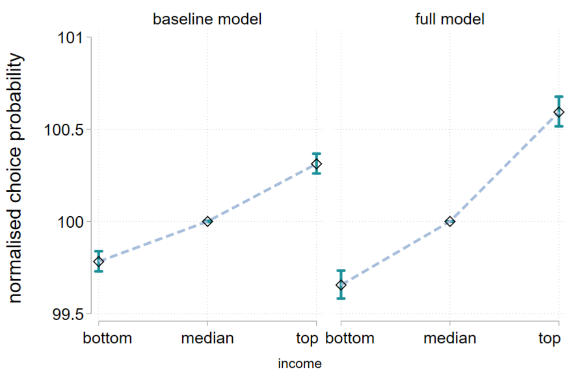
Figure 4: Estimated distribution of the probability of choosing from a full option set (the probability of receiving a cross-regional job offer), by education.



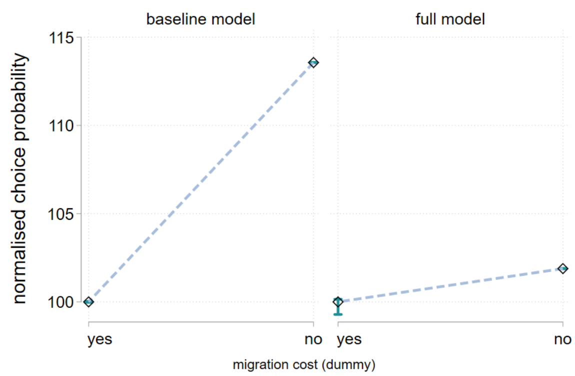
Kernel density plot of estimated μ_i, by education. Solid line: dropouts. Dashed line: high school graduates. Dotted line: college graduates. Based on specification (5) in Table 2.

Figure 5: Marginal effects of income and migration costs on the probability that an average high school graduate in the Northeast chooses employment in the South (option 5).

(a) income



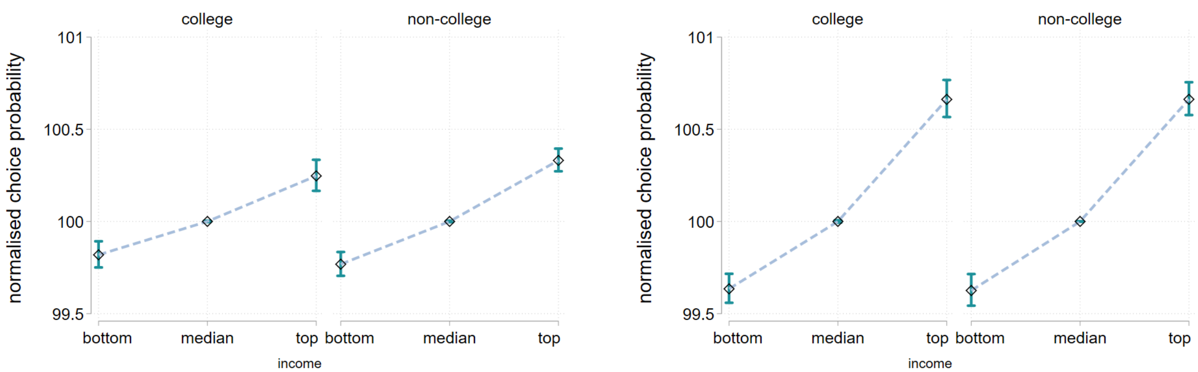
(b) migration costs



The figures plot the estimated probability that average high school graduate in the Northeast chooses employment in the South. Baseline model (column (1) in Table 2) assumes that all workers always choose from all options, all migration is with a job in hand, and there are no spatial search frictions. Preferred specification (column (5) in Table 2) allows for spatial search frictions and both types of migration, and explicitly models choice set heterogeneity. Left-hand panel shows how this choice probability changes as the income offered in this option increases. Bottom = bottom 1% of the wage distribution in the South. Median = median wage. Top = top 1% of the wage distribution. Right-hand-side panel shows how this choice probability changes between a case with and without migration costs. The diamond represent the point estimates; the solid lines depict 95% confidence intervals.

Figure 6: Marginal effects of income on the probability that an average worker chooses employment in the South (option 5), by education.

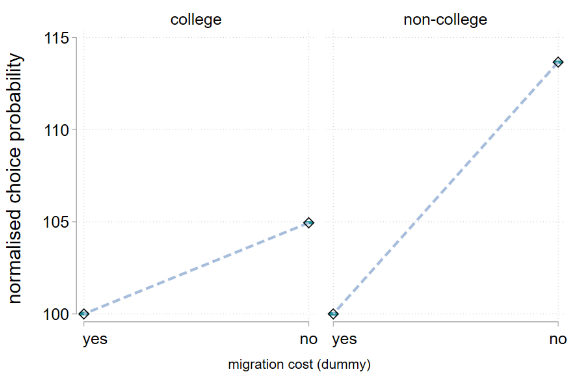
(a) baseline model (b) full model



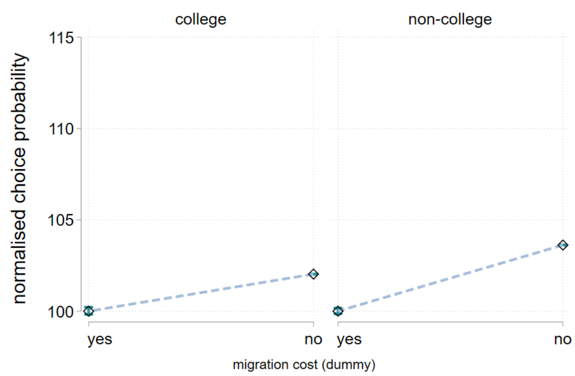
The figures plot the estimated probability that average worker chooses employment in the South, if she currently resides in the Northeast, as the income offered in this option increases. The probabilities are calculated separately for workers with and without college education, using estimates from Table A8 and Table A9. Left-hand side panel: baseline model (column (1)) assumes that all workers always choose from all options, all migration is with a job in hand, and there are no spatial search frictions. Right-hand-side panel: preferred specification (column (4)) allows for spatial search frictions and both types of migration,a and explicitly models choice set heterogeneity. Bottom = bottom 1% of the wage distribution in the South. Median = median wage. Top = top 1% of the wage distribution.The diamond represent the point estimates; the solid lines depict 95% confidence intervals.

Figure 7: Marginal effects of migration cost on the probability that an average worker chooses employment in the South (option 5), by education.

(a) baseline model



(b) preferred specification

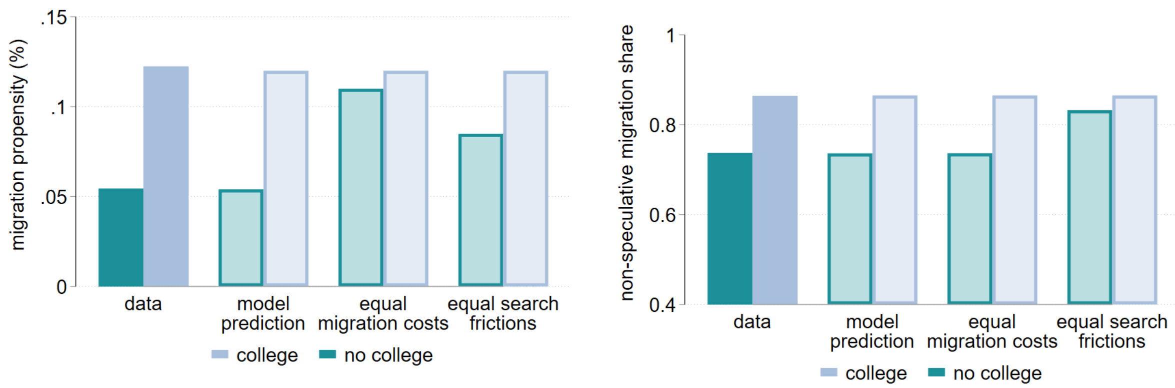


The figures plot the estimated probability that average worker chooses employment in the South, if she currently resides in the Northeast, in cases with and without migration costs. The probabilities are calculated separately for workers with and without college education, using estimates from Table A8 and Table A9. Left-hand side panel: baseline model (column (1)) assumes that all workers always choose from all options, all migration is with a job in hand, and there are no spatial search frictions. Right-hand-side panel: preferred specification (column (4)) allows for spatial search frictions and both types of migration,a and explicitly models choice set heterogeneity. Bottom = bottom 1% of the wage distribution in the South. Median = median wage. Top = top 1% of the wage distribution.The diamond represent the point estimates; the solid lines depict 95% confidence intervals.

Figure 8: Counterfactuals comparing the role of migration costs and cross-regional search frictions in migration behaviour.

(a) migration propensity

(b) non-speculative migration (conditional on moving)

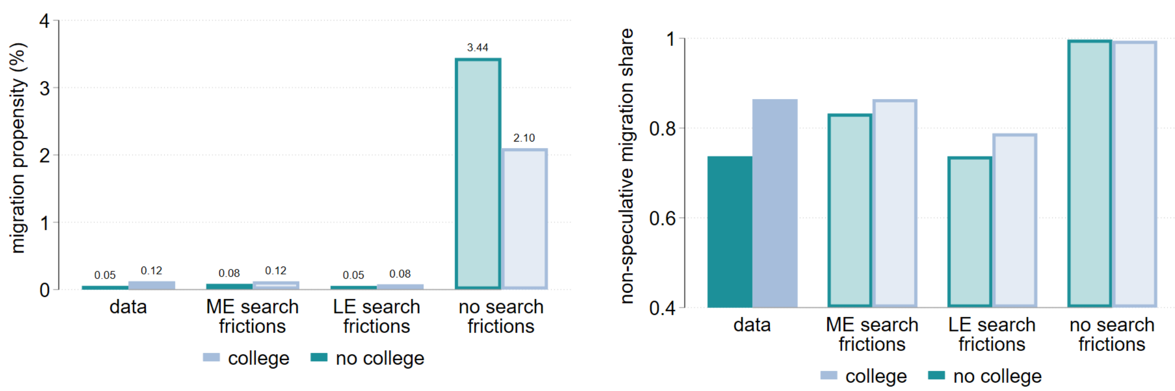


Calculated using the structural estimates in Table 4. The two leftmost bars represent observed behaviour. The next set from the left plot the values predicted by the model. The other bars plot the counterfactual migration behaviour of the less educated if the given parameters were equal to that of the more educated. For example, the rightmost bars show that if the less educated faced the same search frictions in their cross-regional job search as the more educated, about half of the migration propensity gap, and almost all of the migration type gap, would disappear. The search frictions scenario changes the search wedge for both on-the-job and unemployed search.

Figure 9: Counterfactuals evaluating the role of cross-regional search frictions on migration behaviour.

(a) migration propensity

(b) non-speculative migration (conditional on moving)



Calculated using the structural estimates in Table 4. The two leftmost bars represent observed behaviour. The other bars plot migration behaviour when cross-regional search frictions change. For example, the "ME search frictions" cluster represents the migration behaviour if both education groups faced the cross-regional search frictions of the more-educated group. The rightmost bars consider what would happen if there were no cross-regional frictions, i.e. if it was as easy to find a job elsewhere as it is to find a job locally. The job-finding probabilities (and other labour market variables) remain education-specific.

A Data

I use the Survey of Income and Program Participation (SIPP) because of its three key features: it is a (i) panel with (ii) monthly data that (iii) follows its respondents when they move. These three features are necessary to analyse the relationship between cross-regional job search and migration. I need panel data in order to observe the outcomes of the worker's job search, and I need information on her geographic movement to be able to study migration. Finally, the data needs to be of sufficiently high frequency to allow me to link the two, i.e. to be able to see the worker's labour market outcomes just after the move. SIPP is, to my best knowledge, the only major dataset that combines these three features (for a detailed comparison of the different data sources, see Hernández-Murillo et al. (2011)). High-level monthly data on employment and wages is often a snapshot of the economy, missing the panel dimension. On the other hand, the available panel data at a similarly high frequency (such as the Current Population Survey) does not track respondents when they move; or, when it does (such as the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics), the data is collected at low frequency (annual, bi-annual, or every ten years in the case of census data), making it hard for me make reasonable inference about whether the worker migrated with a job in hand or not. The SIPP combines all these features at a large enough sample size to allow me to conduct meaningful empirical analysis.

The data collection for SIPP occurs every four months, when the respondents provide monthly retrospective data. There are several consecutive SIPP panels, each lasting between three and four years, so that there is potentially up to four years of monthly data on each participating individual. The first SIPP panel started in 1984, but I focus on the data collected after the major re-design in 1996. There are five such panels: 1996, 2001, 2004, 2008, and 2014 (ongoing).

I use the 1996 panel, which covers data from December 1995 to February 2001, for two reasons. First, it covers a "normal" period with no large downturns or recessions. Second, it follows a large redesign of the survey aiming to improve the data quality and extend the length of the survey, and manages to avoid some of the budget cuts and complications that plagued the later surveys (a 2000 panel had to be cancelled after 8 months due to budget restrictions, while the 2004 panel ran for less than 3 years).

Each SIPP panel contains between 14,000 and 52,000 interviewed households, but like in all panel datasets, this number changes over time due to sample attrition. In the SIPP, individuals may exit the sample by becoming unresponsive, through entering the army or an institution (such as prison), or migrating overseas. At the same time, the panel sample can grow: because the SIPP is based on households, new individuals may enter the survey any time by becoming a member of the respondent household, e.g. via marriage. This results in a degree of flux in and out of the panel sample. Of the total of 115, 996 individuals surveyed in the 1996 panel, a fifth (21%) remained in the survey for a year or less.[37] Just over a half of the sample (52,558 individuals), remained in the dataset for the full 4 years. The descriptive statistics on the subsample used in my analysis are summarised in Table A2. The distribution of individuals' outcomes on a monthly basis is given in Table A3.

Data on regional house prices, rents, and unemployment rates are drawn from supplementary datasets. The rent data is taken from the 5% sample of the 2000 census. I calculate median rent by state and then aggregate it up to the census regions used in the model. I also include data on quarterly data on median house price sales by region, for two reasons. First, rent and house price data correlate with both living costs and local amenities, which is why it makes sense to include two variables. Second, unlike the rent data, house prices vary over time. The third variable, monthly regional unemployment rate, is taken from the Bureau of Labor Statics. The full list of variables and their sources is summarised in Table A1.

[37] This may be due to inflow of new respondents as well as sample attrition.

B Robustness to the misclassification of migration type

The type of migration (speculative and non-speculative) may be misclassified because the dataset used (SIPP) does not directly ask movers whether they are moving with a job in hand or to search. Instead, I infer it from whether the individual is employed the month after moving. This gives rise to two potential misclassification errors:

- **error I**: migrant moves with a job in hand and starts this job later than 1 month after the move: non-speculative migration falsely classified as speculative migration
- **error II**: migrant moves speculatively, searches in the new labour market, and finds and starts a new job within 1 month after the move: speculative migration falsely classified as non-speculative migration

These two types of misclassification affect my results in different ways. Error I underestimates non-speculative migration, while error II overestimates it. Insofar as the prevalence of the two errors varies by education groups, they have an ambiguous impact on the relationship between education and non-speculative migration that lies at the core of this paper. If their combined effect overestimates the migration differences between different education groups (i.e. the true education slope for the share of non-speculative migration is flatter than my original classification makes it to be), the estimated role of thin cross-regional labour markets will be biased upwards. If the opposite is true – the real differences in non-speculative migration between the less and more educated are larger than my data suggests – the paper underestimates the importance of cross-regional labour markets.

The direction of the bias depends on which error is more likely to appear in different education groups. Conventional wisdom suggests that the workers in manual and routine occupations (which tend to overlap with lower education) should find it easier job look for jobs in a new labour market, and hence are more likely to be misclassified as non-speculative even if they moved without a job. This would mean I have underestimated the true extent of the education differences in non-speculative migration. At the same time, one would expect the probability of error I to be higher among the more educated: recruitment for their jobs may start further in advance of the actual start date, and they are more likely to have the savings to be able to postpone working in order to settle in the new region, etc. If this holds, the true number of non-speculative moves among the more educated is higher than what it appears in the data, underestimating the true extent of the education differences in the type of migration.

In sum, according to conventional wisdom, potential misclassification leads to underestimating the positive relationship between education and non-speculative migration. This would lead to a downward bias in the estimated role of thin cross-regional labour markets in migration. In the rest of this section, I explore this hypothesis using empirical evidence and robustness checks.

B.1 Empirical evidence on the extent of misclassification

Unfortunately, I am not aware of any study examining the average time spent waiting (not looking) between jobs. Similarly, to the best of my knowledge, there is not a study that reports first-month job-finding rates by education or occupation groups for the US; the available evidence does not present a specific set of estimates that could be used to fix the misclassification issue in this paper. The state of the literature is briefly summarised below.

Looking beyond the below one-month cutoff, the literature offers a wide range of estimates on the job-finding rate, spanning between 6% and 45%[38]. Moreover, most of these papers agree that job-finding probability is sensitive to the duration of

[38] Hall and Schulhofer-Wohl (2018) find the job-finding rate varies between 34% and 6% depending on the worker's part employment history and whether they are in the labour force. Veracierto (2011); Osberg (1993); Shimer (2012) argue that the distinction between unemployment and out-of-labour-force is mostly arbitrary, and Kudlyak and Lange (2017) shows that the duration of joblessness, rather than self-reported unemployment duration, is the best predictor of job-finding success. The estimates presented by these authors range between 45% (Shimer (2012)) and 30% (Kudlyak and Lange (2017))

unemployment, which means that the < 1 month probability of finding a job is not a representative estimate of the average job-finding probability, and hence gets rarely reported. An exception is a study by Hobijn and Sahin (2009) who use a semi-structural approach to calculate the "initial" job-finding rate to be 75.5%, much higher higher than the estimates given elsewhere.

Breakdowns of job-finding probability by education or occupation groups are similarly rare and pointing in opposite directions. Kudlyak and Lange (2017) calculates the first-month job-finding rate at 45%, but finds no differences by education. Graversen and van Ours (2006) provide one of the few breakdowns by occupation category, showing that, compared to Danish blue collar workers, white collar workers are significantly less likely to exit unemployment within the first 5 weeks compared to construction workers. These results suggest that error II is more likely among the less educated, but the results reported in the paper do not lend themselves to retrieving actual job-finding probabilities for different education groups. A study by Hedtrich (2019) claims the opposite. He calculates average job-finding probability from unemployment for the 1990s, showing that the more educated workers find jobs faster on average (35% vs. 28% for college graduates and high school graduates, respectively), although it is not clear whether this relationship also holds within the first month of unemployment. Riddell and Song (2011) reach similar conclusion in their study on long-term re-employment probability: about 52% of low-education workers were employed a year after being unemployed, but this share increased to 70% among college graduates. These education differences hold even after controlling for the grater probability of the more educated to quit voluntarily.

B.2 Evidence from SIPP

In the absence of conclusive empirical literature on the prevalence of error I and II, I draw on the data on stayers in SIPP.

Using the SIPP data to understand the prevalence of error I, i.e. waiting for the job to begin, suggests that the more educated workers are more likely to wait before starting a job. However, the dataset provides various ways to capture this, and these do not necessarily point in the same direction. The broadest measure of inactivity before employment is the fraction of joblessness spell spent out of labour force. This is 27.5% for those without a college degree, and 36.7% for college graduates. In other words, there is about a one-to-three chance that a worker spends the months preceding employment out of labour force. However, as discussed above (Veracierto (2011)), there is a good reason to believe that the inactivity/unemployment margin is not an accurate measure of the worker's actual labour market status. Instead, I look at the fraction of the joblessness spell (preceding employment) spent reportedly not searching for work: 36.2% of the joblessness spell of the less educated, and 51.2% of that of college graduates is reportedly spent not searching for work. However, these numbers seem inflated when compared to the variable *rnotake*, which allows workers to state that the reason for their joblessness is waiting for a job to begin. Only 0.1% of the joblessness spell of the less educated workers is marked this way; it is 0.2% for the more educated. This evidence thus suggests that the more educated are indeed more likely to spend some time "waiting" before the commencement of employment.

Looking at the the probability of finding a job in less than a month also appears to weakly increase in education: it is 23.2% vs. 29.5% for less than college and college graduates, respectively. However, this is most likely a reflection of job-to-job transitions and greater search on the job practised by college graduates. I attempt to control for this in several ways: excluding those who report quiting to take up another job (which brings the figures to 19.7% and 20.9%, respectively); those who report not looking for work prior to becoming unemployed (24.3% vs. 32.9%); as well as making use of all the information in SIPP variables on labour market status and reasons for leaving past employment (19.5% vs. 20%). In all of these cases, the more educated workers were at least as much, if not marginally more likely, to find employment within 1 month of becoming jobless. The only exception to this pattern is the subsample of workers who were made redundant: there the first-month job-finding rate is 21.1% for those without a college degree, but only 10.4% for those with it.

B.3 Adjusting for micslassification

To understand how robust are the headline results of this paper to misclassification, I adjust the education-specific shares of non-speculative migration to reflect the two misclassification errors, using the SIPP evidence on the probability of finding a job in less than a month and delaying the start of a new job. I re-estimate the discrete choice model of location and employment on this adjusted data. In general, this robustness check shows that the misclassification likely biases my estimates towards 0: the headline results present a lower bound of the true impact of thin cross-regional labour markets on migration behaviour.

I consider five models of misclassification:

- **model A**: observed data (the original classification)
- **model B**: type of migration is random, with a 50-50 chance that a move is speculative
- **model C**: correcting for error II
- **model D**: correcting for error I
- **model E**: correcting for both errors

To adjust for error II, I make use of the SIPP data on the job-finding probabilities of workers who were made redundant. This probability is 21.1% for those without a college degree, but only 10.4% for those with a degree. This means that 21.1% of all non-speculative movers without a college degree in fact moved speculatively and found a job within the fist month of their arrival. I use this to adjust the share of non-speculative migrants downwards. In practice, I randomly changed the type of migration in 21.1% of moves to speculative (and analogously for college graduates). This gives me the education-specific migration types for model C.

The adjustment for model D (error I) is similar. I use the SIPP data on the number of months individuals claimed they were not looking for work as a fraction of their overall spell of joblessness; note that I take this particular data because it results in the largest misclassification: 36.2% of the joblessness spell of the less educated, and

51.2% of that of college graduates is reportedly spent not searching for work. This means that I randomly change more than a half of the speculative moves by college graduates to non-speculative migration (and similarly for the less educated).

In model E, I allow for both types of misclassification simultaneously. The adjusted shares of non-speculative migration are plotted in Figure A8. There are two benchmarks: the original classification (model A) and a random even split (model B), which corresponds to the hypothesis that the type of migration does not matter. The figure shows that adjusting for error II increases the difference in migration type between education groups while error I adjustment reduces it. As a result, adjusting for both types of misclassification simultaneously leaves the shares of non-speculative migration virtually unchanged compared to the original classification.

B.4 Robustness checks

I re-estimate the augmented discrete choice model from section 4 using the migration type data from models A – E above. The estimated coefficients and their 95% confidence intervals are plotted in Figures A11 - A22. Comparing the original estimates with those from models C – E allows us to evaluate the likely direction of bias due to misclassification, while comparison with the random classification in model B helps to visualise how much the classification of migration matters overall.

While there is some heterogeneity in the bias implied by these plots, very few estimates fall outside of the confidence intervals of the original (model A) coefficient. This suggests that my results are robust to misclassification error as specified here.

C Capturing variation in choice sets: firm recruitment strategies

In order to identify the importance of choice set heterogeneity in workers' employment-location decisions, I need to collect variables that capture this heterogeneity. Ideally, I would use detailed occupation- and industry-specific information on the geographic radius within which the representative employer advertises their vacancies and searches for employees.

To my best knowledge, no such large-scale recruitment dataset exists. Instead, I draw on the findings of the human resources literature and then use firm data to construct proxies to recruitment behaviour.

The literature suggests that firms that hire across a wide geographic radius are likely to fall into one of two categories. They may be looking for workers of specific skill that may be hard to find in their local labour market. The studies by Barron, Bishop and Dunkelberg (1985) and Russo, Nijkamp and Rietveld (1996) have demonstrated that firms that are looking for more educated workers search across greater distance, using more resources. Second, the search radius is also going to increase with the size of the firm itself. Tardos and Pedersen (2011) and Russo et al. (1996) show that larger firms spend more money on recruitment, interview more applicants, and reach out into more distant regions. Moreover, these studies point out that larger companies are more likely to use formal recruitment channels, such as job board or newspaper postings, and professional recruitment agencies, that are more likely to reach outside of the local labour market. Small companies, on the other hand, are much more likely to rely on informal channels, such as referrals and word of mouth, as well as using only one recruitment channel (Barber et al, 1999).

Based on these findings, I construct three proxies for the geographic radius of recruitment. Using firm data from the County Business Patterns dataset for the years 1996-1999, I calculate the average company size (as measured by the number of employees) by industry. I use the firm location information in this dataset to calculate an index of spatial concentration of each industry. The index (based on Ellison and Glaeser (1997)) compares the total employment in a sector in a county against the total population in each county of the US. The higher the number, the more clustered the given industry is. Finally, I use a more recent data on online vacancy posting that looks at what proportion of all vacancies, within each occupation, are advertised on the Internet (Kahn and Hershbein, 2016). Even though the data in question is from a more recent period (2007, 2010-2014), this variable provides a more direct evidence on the willingness of a firm to disseminate their vacancy information as widely as possible.

D Imputing wage offers

The mean of the wage offer distribution is smaller than the mean of the observed wage because workers do not accept wages that are not large enough. This is a well-known problem in labour economics that is usually solved following a selection control approach introduced by Heckman (1979). It consists of first parametrically estimating the probability that a given worker would be employed, and then adding this selection correction term into a regression that explains observed wages as a function of worker characteristics. The coefficients from this second-stage regression then allow me to calculate average wage offer for a worker, conditional on her characteristics.

For the purposes of this model, however, I also have to control for the probability of observing wage from a particular region. Because the worker's decision is along two dimensions (employment and location), I have to explicitly control for both workers choosing highest possible wages, and workers rejecting high wages in favour of living in anther region. One way to solve this problem is to add variables to the Heckman control function that determine workers' migration decision. The disadvantage of this approach is that, by relying on a rich set variables to capture both types of bias, the overall wage regression become difficult to estimate and convergence of results is challenging.

My preferred way of estimating wage offers follows Dahl (2002). In his estimates of state-level education premium, Dahl faces the same multinomial selection bias. His solution is to calculate, for each region, the probability that a local worker becomes employed there, and the probability that a worker moves into employment from elsewhere. He then uses a polynomial of these probabilities as a proxy for the correction function, adding it to the wage regression in the same way as the Heckman correction term.

The results of the Heckman wage regressions are presented in Table A6; Dahl estimates are summarised in Table A7. The wage regression, using the given correction function, is estimated separately for each region, using the wage data on workers working and living in the region at the time. I use race as exclusion restriction in the Heckman specification. Overall, the coefficients across the two regressions are quite similar, as is the (unreported) standard deviation of the error term, suggesting that both models can explain similar mount of variation in the observed wages. The Dahl specification is my preferred one because, thanks to the lower demands on estimation, it allows me to add more worker characteristics in the wage regression.

E Equilibrium in the structural model: a 2-region example

To see how the equilibrium flows equations link to the structural model, consider a two-region example with a single wage. Figure A25 illustrates all the possible stocks and flows between regions, employed and unemployed in this economy. The boxes represent stocks of workers, employed and unemployed, in each region, while arrows depict the flows between these stocks, in and out of employment and between and within regions. The economy is in equilibrium when the size of the flows is such that the size of the stocks stays the same. For example, the equilibrium condition for regional population shares would specify that the magnitude of the flows in and out of each region must perfectly offset each other. Figure A25 makes it clear that this implies equality between the flows from employment to employment, employment to unemployment, unemployment to employment, and unemployment to unemployment from B to A, and the same flows in the opposite direction, from A to B.

Figure A26 shows how the model pins down the size of these flows. For example, the flow of employed in A to employment in B is $\alpha_A(1-\mu_A)\zeta_\lambda\lambda_A P_1$. There are $\alpha_A(1-\mu_A)$

employed workers in region A. Fraction $\zeta_\lambda \lambda_A$ of them receive a job offer in the other region, which is necessary in order to move for a specific job. Conditional on that, P_1 denotes the probability that the worker accepts the offer:

$$
\begin{aligned}
P_1 &= \Pr(V_B \text{ is the optimal choice out of } \{V_A, U_A, V_B, U_B\}, \text{ given preferences } \boldsymbol{\gamma}) \\
&= f_B(z) \left[\Pr(V_B(z) + \gamma_B - K > \{V_A(w) + \gamma_A, U_A + \gamma_A, U_B + \gamma_B - K\})\right] h_A(w)
\end{aligned}
\tag{21}
$$

where $f_j(z)$ and $h_j(z)$ are probability density functions of $F_j(z)$ and $H_j(z)$, respectively. The expression of the overall flows thus depends on the optmisation of the worker, which is in turn the function of employment and unemployment values in different locations, and her choice set.

F Tables in the appendix

Table A1: Definitions and sources of variables.

variable	definition	source
migration	dummy equal to 1 if person changes region of residence	SIPP
speculative migration	dummy equal to 1 if person migrates and is unemployed in the following month	SIPP
income	accepted wage offer: observed monthly wage rejected wage offer: imputed average monthly wage offer reservation wage: imputed average monthly lowest wage	SIPP
unemployment	dummy equal to 1 if person is unemployed in a given month	SIPP
unemployment rate, regional	monthly state-level unemployment rate, aggregated to regions, 1996-1999	Bureau of Labor Statistics
unemployment rate, individual	individual-specific probability that the worker is unemployed in a given month. Excludes months of and after migration.	SIPP
regional rent	median rent calculated from the 5% sample of 2000 Census	IPUMS
regional house price	quarterly median house sale price, by census region, 1996-2000	Federal Reserve Bank of St. Louis
migration cost	dummy equal to 1 if person changes region of residence	SIPP
switching cost	dummy equal to 1 if this month's employment or location differs from previous month	SIPP
young	dummy equal to 1 if individual is less than 35 years old	SIPP
kids	dummy equal to 1 if individual is in a family with at least 1 child	SIPP
married	dummy equal to 1 if individual currently married	SIPP
education	highest achieved education	SIPP
online vacancies	log odds ratio of the probability density mass of a given occupation in online postings and full universe	JOLTS, Burning Glass
spatial concentration	Gini index of distribution of sector-specific employment relative to regional population	County Business Patterns
employees per firm	average number of employees per firm, per sector, 1996-1999	County Business Patterns

Table A2: Descriptive statistics for the sample of working men between the age of 25 and 50

	dropout	high school	college
age	38.48	38.33	39.21
	(7.411)	(7.222)	(7.488)
white	0.835	0.855	0.890
	(0.371)	(0.352)	(0.313)
employed	0.876	0.937	0.962
	(0.329)	(0.243)	(0.191)
monthly wage ($)	1829.9	2677.2	4703.3
	(1207.1)	(1987.5)	(4422.3)
total household income ($)	3115.2	4428.7	6943.6
	(2335.0)	(3074.9)	(5449.3)
urban population	0.789	0.778	0.881
	(0.408)	(0.416)	(0.324)
migration propensity (state), per month	0.000740	0.00141	0.00331
	(0.0272)	(0.0375)	(0.0574)
migration propensity (region), per month	0.000361	0.000688	0.00183
	(0.0190)	(0.0262)	(0.0428)
observations	58143	294990	135801
individuals	2076	10411	4196

Summary descriptive statistics for the sample used in the empirical sections of this paper. The values are averaged over the whole duration of the survey, 1996-1999. Migration propensities are calculated monthly.

Table A3: Observed outcomes

outcome	observations	%
employment, Northeast	84,799	17.34
unemployment, Northeast	5,383	1.10
employment, Midwest	119,443	24.43
unemployment, Midwest	6,577	1.35
employment, South	152,519	31.19
unemployment, South	10,653	2.18
employment, West	101,237	20.71
unemployment, West	8,313	1.70
employment, home	457,644	93.60
unemployment, home	30,817	6.30
employment, away	379	0.08
unemployment, away	84	0.02
Total	488,924	100.00

Summary of individual-month outcomes. The upper panel presents distribution of options from the 8 options in the logit model. The lower panel aggregates these options based on employment/unemployment and migration.

Table A4: Full and restricted choice sets. Example for a worker resident in the West.

options in...	
full choice set	restricted choice set
1 [employed, Northeast]	-
2 [unemployed, Northeast]	2 [unemployed, Northeast]
3 [employed, Midwest]	-
4 [unemployed, Midwest]	4 [unemployed, Midwest]
5 [employed, South]	-
6 [unemployed, South]	6 [unemployed, South]
7 [employed, West]	7 [employed, West]
8 [unemployed, West]	8 [unemployed, West]

The left hand column lists all the employment-location options available to a worker that does receive job offers from other regions. The right hand side column lists the options available to a worker that only receives job offers from her home region (is not capable of cross-regional job search).

Table A5: The relationship between non-speculative migration and proxies for search effort

	wage level	wage growth	unemployment	job-to-job transitions
non-speculative	0.0015	0.0084	0.8870***	0.2322
	(0.0188)	(0.0106)	(0.1485)	(0.2203)
migrant	0.0371**	-0.0050	-1.1053***	0.0410
	(0.0172)	(0.0097)	(0.1218)	(0.2028)
Observations	450513	430421	475031	475031

All regressions control for education, marital status, age, employment history, occupation and sector, region and year. The outcome variables are monthly individual data for all stayers and for migrants before the move.

Table A6: Heckman selection model for monthly regional wages.

	(1) Northeast	(2) Midwest	(3) South	(4) West
wage				
age	280.6687***	278.3296***	219.8698***	263.7825***
	(8.0228)	(5.6201)	(4.9114)	(6.7049)
education	1116.2263***	1021.3983***	1000.2749***	966.8457***
	(23.3704)	(16.8157)	(13.5038)	(18.2518)
_cons	2245.7523***	1741.0617***	2044.4947***	2462.5954***
	(60.8001)	(43.4558)	(36.1614)	(49.1740)
select				
age	0.0319***	0.0228***	0.0257***	0.0052
	(0.0056)	(0.0051)	(0.0041)	(0.0047)
education	0.3023***	0.3506***	0.1887***	0.2267***
	(0.0155)	(0.0138)	(0.0109)	(0.0121)
race	-0.1585***	-0.2641***	-0.1362***	-0.0898***
	(0.0105)	(0.0116)	(0.0089)	(0.0068)
_cons	1.5561***	1.5149***	1.7357***	1.4580***
	(0.0468)	(0.0405)	(0.0347)	(0.0371)
N	78530	108208	144165	95882
ll	-7.152e+05	-9.692e+05	-1.286e+06	-8.572e+05

Standard errors in parentheses

Both stages also include occupation groups and year dummy.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: Dahl selection model for monthly regional wages

	(1) Northeast	(2) Midwest	(3) South	(4) West
age	279.8684***	270.4605***	217.3884***	258.5599***
	(8.2174)	(5.7405)	(5.0433)	(6.8946)
education	1091.7691***	961.5562***	996.4935***	948.8347***
	(24.6079)	(17.5926)	(14.0792)	(19.1049)
year	73.9644***	82.4742***	88.6739***	113.9386***
	(12.0316)	(8.3644)	(7.3824)	(10.0632)
home_prob	-2421.5960*	-3933.6999***	-1485.0401*	262.5190
	(1005.0397)	(727.8249)	(668.3174)	(799.1905)
mig_prob	-4.065e+04***	-1.387e+04***	356.7142	-2.473e+04***
	(5571.2857)	(3179.5752)	(3265.3795)	(4907.0853)
home_prob2	10403.0351***	-901.3914	6360.9951***	-746.5879
	(1842.0758)	(1183.6315)	(1235.7193)	(1155.8361)
mig_prob2	38877.6788***	14905.4679***	-968.5881	23634.7809***
	(5710.3835)	(3239.1183)	(3312.2007)	(4903.5391)
cross_prob1	55462.4511***	14841.3148***	6372.0374	32798.8037***
	(6795.9589)	(4093.9859)	(4091.4949)	(6184.1172)
cross_prob2	-7915.8938***	4587.8734***	-4672.2692***	1460.6144
	(1774.5541)	(1099.2049)	(1186.0104)	(1083.5815)
cross_prob3	-7807.7315*	4440.2111	-4814.0601*	-4116.8270
	(3847.9920)	(2300.8156)	(2205.1413)	(3446.3211)
_cons	2231.6960***	2152.4964***	1894.9275***	1540.6217***
	(408.2322)	(292.2394)	(273.3837)	(323.9317)
N	72852	101648	134390	87900
ll	-6.856e+05	-9.368e+05	-1.241e+06	-8.204e+05

Standard errors in parentheses

The regression also includes occupation groups and year dummy.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: Discrete choice models of location and employment, allowing for spatial search frictions and different types of migration, workers without college degree

	(1)	(2)	(3)	(4)
	baseline	search frictions	two types of migration	two types of migration and search frictions
utility				
Dependent variable (1) and (2): probability of choosing one of the 4 regions				
Dependent variable (3) and (4): probability of choosing one of the 8 employment-location options				
income	0.193***	0.193***	0.330***	0.338***
	(0.023)	(0.022)	(0.029)	(0.031)
regional unemp. rate	0.915***	0.943***	1.105***	-0.109***
	(0.037)	(0.044)	(0.057)	(0.031)
unemployment dummy			-0.806***	-0.574***
			(0.081)	(0.083)
regional house price	6.000***	6.000***	6.000***	6.000***
	(0.001)	(0.001)	(0.000)	(0.000)
regional rent	-0.010***	-0.011***	-0.011***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.001)
mig. cost	-3.687***	-3.603***	-1.921***	-1.639***
	(0.011)	(0.020)	(0.077)	(0.088)
switching cost			-2.535***	-2.525***
			(0.082)	(0.082)
spatial index (sector)		0.041***		
		(0.018)		
online vacancies (occupation)		0.164***		
		(0.018)		
choice set				
Dependent variable (latent): probability of receiving cross-regional job offer				
spatial index (sector)				0.363**
				(0.054)
online vacancies (occupation)				0.414***
				(0.037)
constant				1.072***
				(0.228)

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ *All models contain option-specific constants. Model (1): conditional logit assuming all migration is for a specific job (4 options). Model (2): model (1), allowing for cross-regional job search frictions, which are identified through sectoral and occupation variation in spatial concentration of forms and online vacancy posting. Model (3): model (1) which distinguishes between the two types of migration (8 options). Model (4): allows for both different types of migration (8 options) and for individual-specific spatial search frictions.*

Table A9: Discrete choice models of location and employment, allowing for spatial search frictions and different types of migration, workers with college degree

	(1) baseline	(2) search frictions	(3) two types of migration	(4) two types of migration and search frictions
utility				
Dependent variable (1) and (2): probability of choosing one of the 4 regions				
Dependent variable (3) and (4): probability of choosing one of the 8 employment-location options				
income	0.147***	0.155***	0.300***	0.313***
	(0.028)	(0.029)	(0.027)	(0.030)
regional unemp. rate	0.723***	0.744***	0.953***	-0.112***
	(0.065)	(0.049)	(0.069)	(0.038)
unemployment dummy			-1.107***	-0.893***
			(0.097)	(0.103)
regional house price	6.027***	6.030***	6.000***	6.001***
	(0.264)	(0.298)	(0.000)	(0.000)
regional rent	-0.009***	-0.009***	-0.008***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
mig. cost	-2.477***	-2.548***	-1.348**	-1.158***
	(0.030)	(0.036)	(0.104)	(0.108)
switching cost			-2.900***	-2.894***
			(0.109)	(0.110)
spatial index (sector)		0.046***		
		(0.017)		
online vacancies (occupation)		0.130***		
		(0.040)		
choice set				
Dependent variable (latent): probability of receiving cross-regional job offer				
spatial index (sector)				1.742**
				(0.541)
online vacancies (occupation)				0.787***
				(0.086)
constant				0.906***
				(0.238)

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ *All models contain option-specific constants. Model (1): conditional logit assuming all migration is for a specific job (4 options). Model (2): model (1), allowing for cross-regional job search frictions, which are identified through sectoral and occupation variation in spatial concentration of forms and online vacancy posting. Model (3): model (1) which distinguishes between the two types of migration (8 options). Model (4): allows for both different types of migration (8 options) and for individual-specific spatial search frictions.*

Table A10: 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	19.24984	0.16173	0.00682	0.00038	0.00909	0.00076	0.00492	0.00038
u,1	0.13370	1.05521	0.00000	0.00152	0.00076	0.00189	0.00000	0.00076
e,2	0.00682	0.00000	24.32591	0.20150	0.01477	0.00038	0.00720	0.00076
u,2	0.00000	0.00114	0.15112	1.13361	0.00038	0.00152	0.00076	0.00114
e,3	0.00682	0.00000	0.00985	0.00076	28.57478	0.26361	0.01212	0.00038
u,3	0.00000	0.00038	0.00114	0.00076	0.20188	1.71690	0.00038	0.00152
e,4	0.00682	0.00000	0.00909	0.00076	0.00909	0.00000	20.78645	0.24695
u,4	0.00038	0.00038	0.00000	0.00038	0.00038	0.00227	0.19127	1.47980

The transition probabilities are calculated from the 1996-1999 SIPP data. The sample is working adult males between the age 25 and 50. e = employment. u = unemployment. The numbers denote one of the four census regions of the US (see table **??***).*

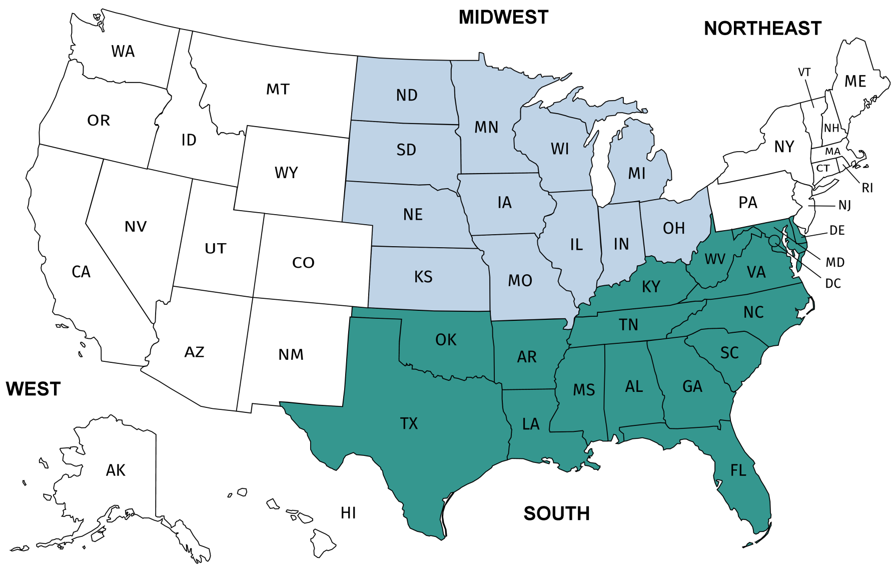
Table A11: Data moments: matrix of transition probabilities for the less educated (in %)

	e,1	u,1	e,2	u,2	e,3	u,3	e,4	u,4
e,1	14.90083	0.23907	0.00048	0.00000	0.00556	0.00097	0.00145	0.00000
u,1	0.20692	1.91083	0.00000	0.00024	0.00000	0.00073	0.00000	0.00000
e,2	0.00073	0.00024	21.64856	0.33382	0.00580	0.00193	0.00338	0.00048
u,2	0.00000	0.00000	0.27508	2.34255	0.00073	0.00169	0.00000	0.00097
e,3	0.00193	0.00024	0.00411	0.00048	31.29649	0.53929	0.00604	0.00024
u,3	0.00000	0.00024	0.00024	0.00097	0.42640	3.87870	0.00097	0.00024
e,4	0.00193	0.00000	0.00218	0.00024	0.00508	0.00121	18.86438	0.36549
u,4	0.00024	0.00000	0.00024	0.00193	0.00000	0.00193	0.32391	2.39162

The transition probabilities are calculated from the 1996-1999 SIPP data. The sample is working adult males between the age 25 and 50. e = employment. u = unemployment. The numbers denote one of the four census regions of the US (see table **??***).*

G Figures in the appendix

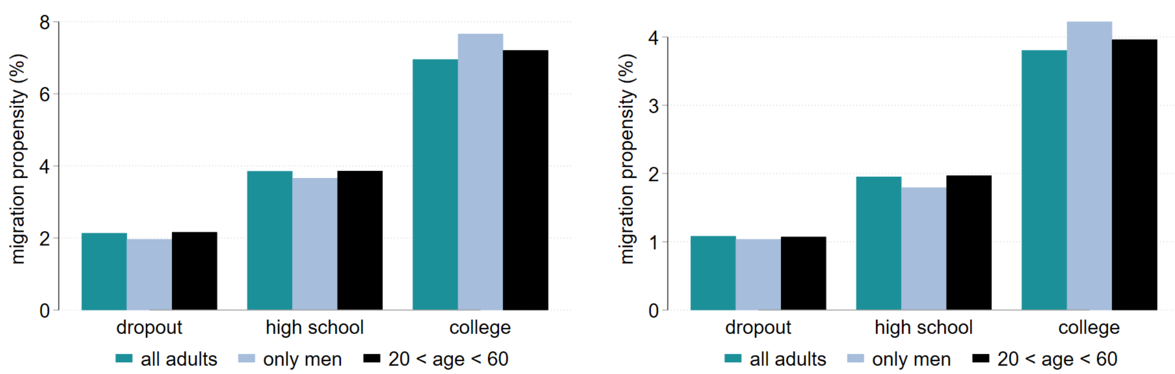
Figure A1: The 4 large census regions of the USA.



Source: US Census Bureau, Geography Division.

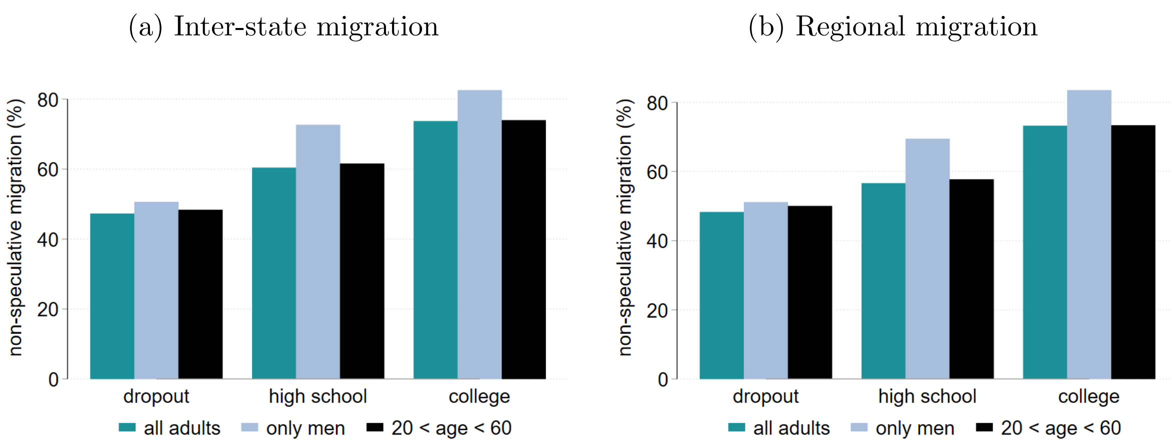
Figure A2: Propensity to migrate, US, 1996-1999.

(a) Inter-state migration (b) Regional migration



Calculated from the Survey of Income and Program Participation, 1996-1999 panel. Adult is defined as anyone over the age of 18. States refer to the 50 US states. Regions refer to the 4 Census regions (see section 3.2 for definition).

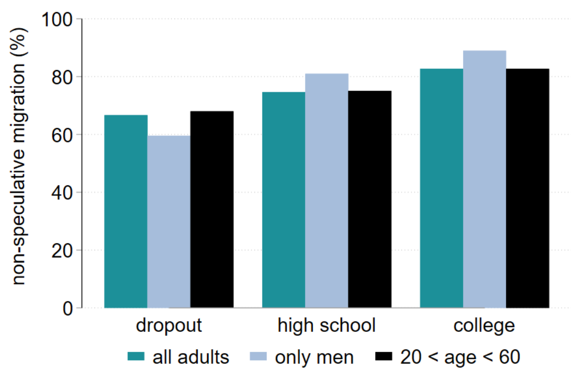
Figure A3: Probability of moving into a specific job (conditional on moving), US, 1996-1999.



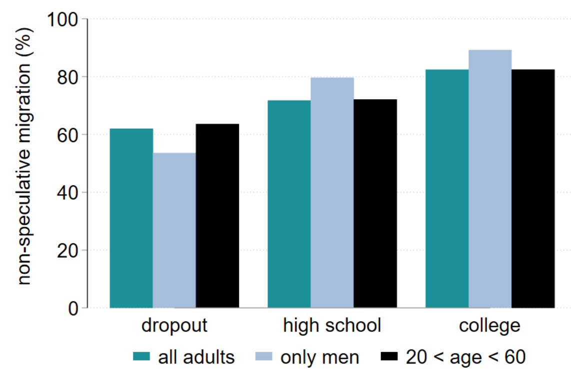
Calculated from the Survey of Income and Program Participation, 1996-1999 panel. Adult is defined as anyone over the age of 18. Migration for a specific job refers to migration followed by employment. States refer to the 50 US states. Regions refer to the 4 Census regions (see section 3.2 for definition).

Figure A4: Probability of moving into a specific job, conditional on moving and employment state before migration, US, 1996-1999.

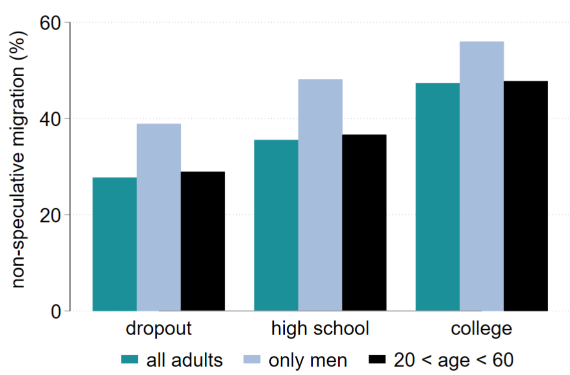
(a) Inter-state, employed before moving



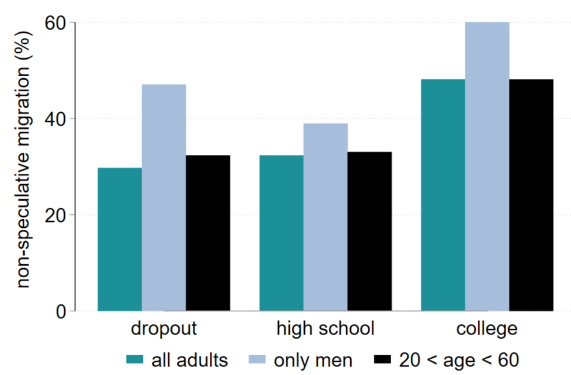
(b) Regional, employed before moving



(c) Inter-state, unemployed before moving

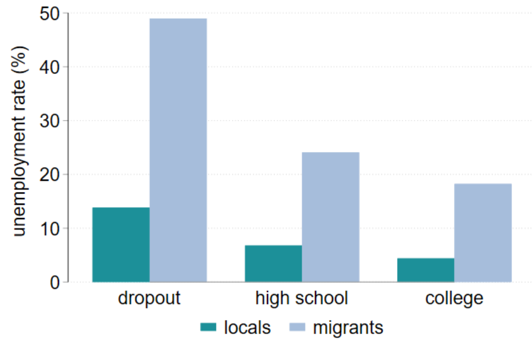


(d) Regional, unemployed before moving



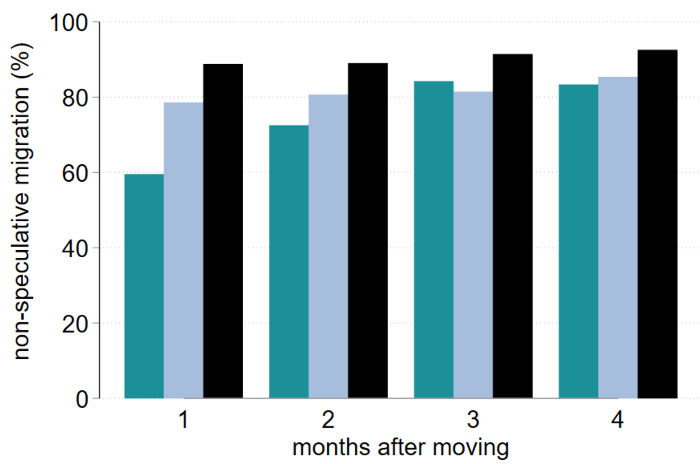
Calculated from the Survey of Income and Program Participation, 1996-1999 panel. Adult is defined as anyone over the age of 18. Migration for a specific job refers to migration followed by employment. States refer to the 50 US states. Regions refer to the 4 Census regions (see section 3.2 for definition).

Figure A5: Unemployment rates for stayers and migrants, US, 1996-1999.



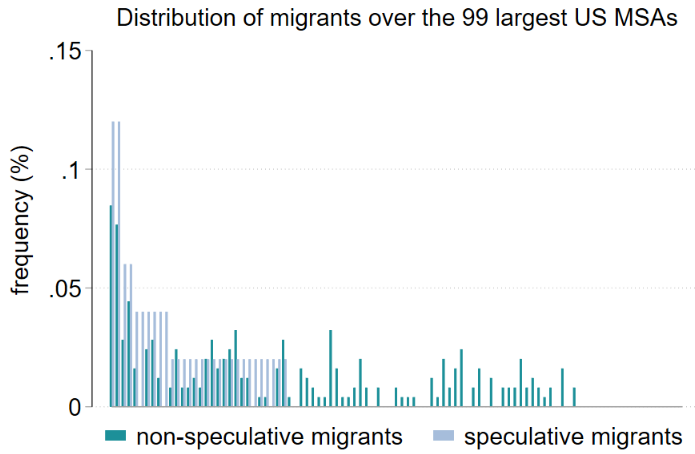
Calculated from the Survey of Income and Program Participation, 1996-1999 panel. Sample: men between the age 25 and 50 who are in the labour force. The bars represent average state-level unemployment rate for the given group.

Figure A6: Probability of moving non-speculatively as a share of all moves, varying the month when employed is measured



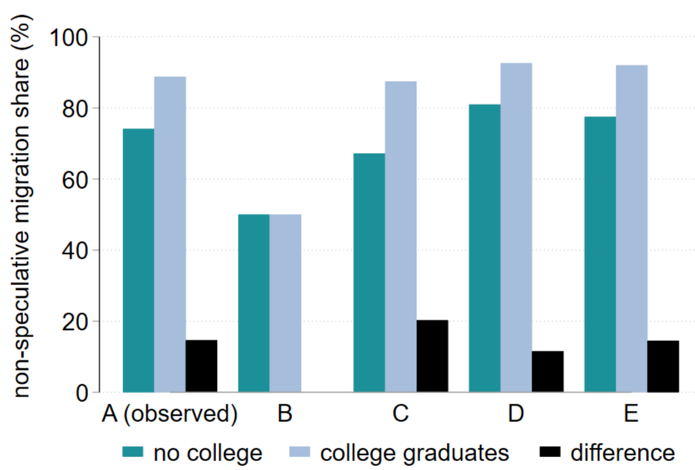
Calculated from the Survey of Income and Program Participation, 1996-1999 panel. Sample: men between the age 25 and 50 who are in the labour force.

Figure A7: Distribution of migrants by destination cities and migration type



Calculated from the Survey of Income and Program Participation, 1996-1999 panel. Sample: men between the age 25 and 50 who are in the labour force.

Figure A8: The share of non-speculative migration in different models of misclassification

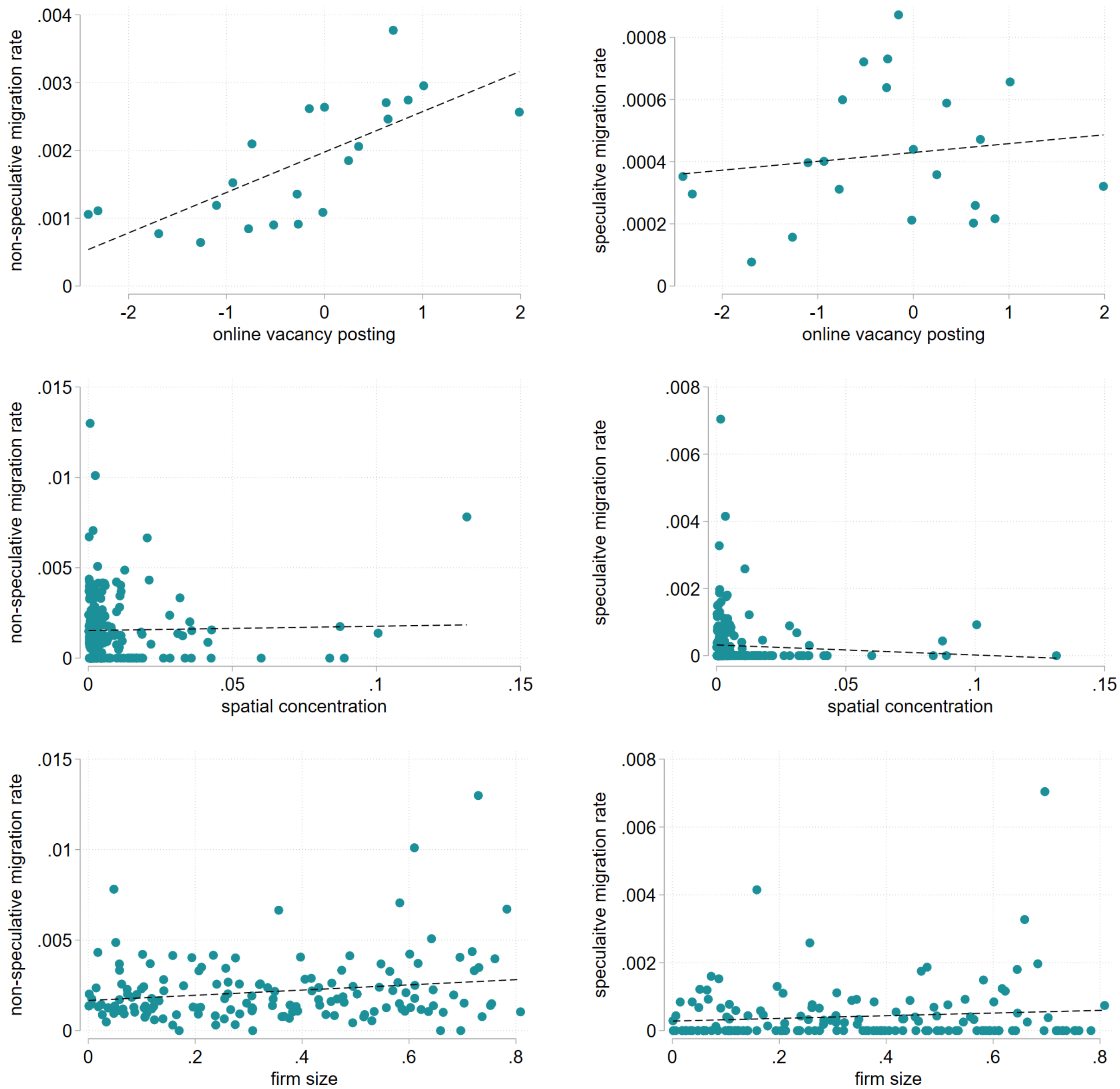


The share of migration that is non-speculative under different scenarios of misclassification. Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability 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 labour force.

Figure A9: Relationship between recruitment proxies and types of migration, by occupation and sector

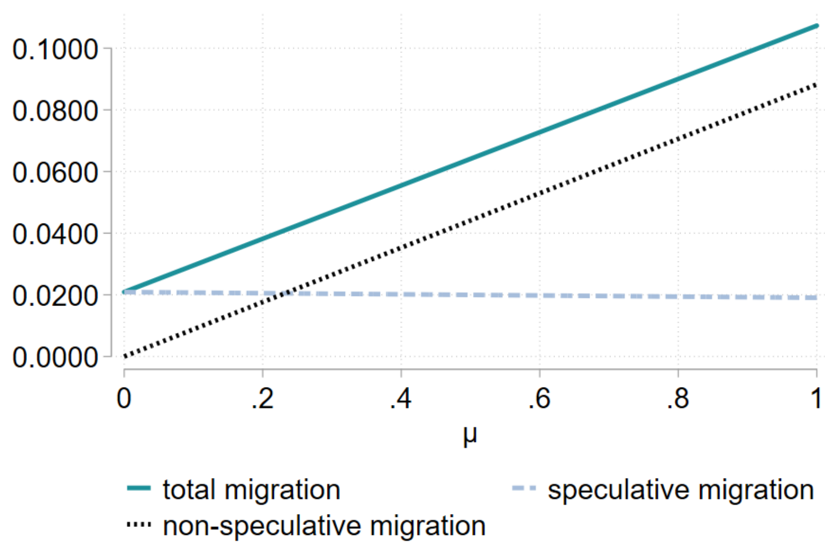
(a) non-speculative migration

(b) speculative migration



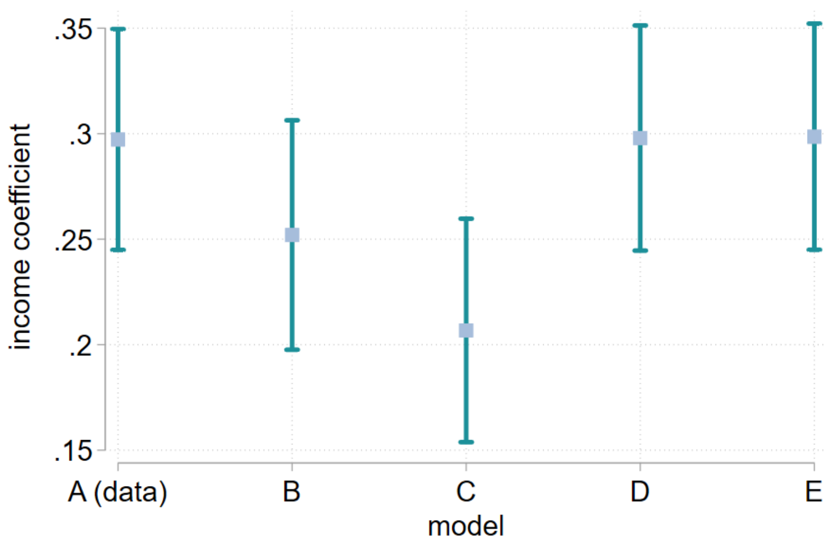
Panels in column (a) plot the correlation between a given proxy for cross-regional hiring and non-speculative migration rate in the given sector or occupation. Panels in column (b) plot this correlation for speculative migration. Online vacancy posting is measured on occupation level; firm size and spatial concentration are by sector.

Figure A10: Estimated relationship between the probability of choosing from a full option set and speculative and non-speculative migration



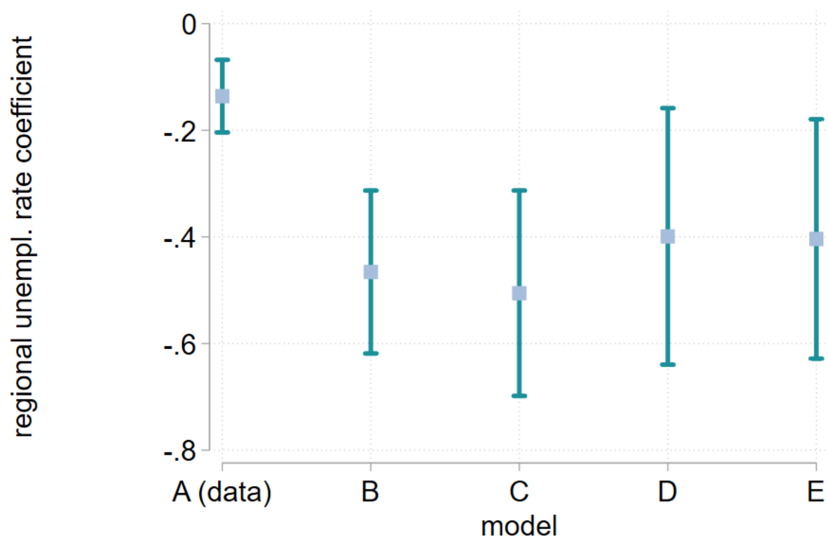
Predicted probability of choosing speculative or non-speculative migration for an average employed high-school graduate living in the Northeast, as a function of μ. Based on specification (5) in Table 2.

Figure A11: Robustness test: estimated income coefficient under different misclassification errors



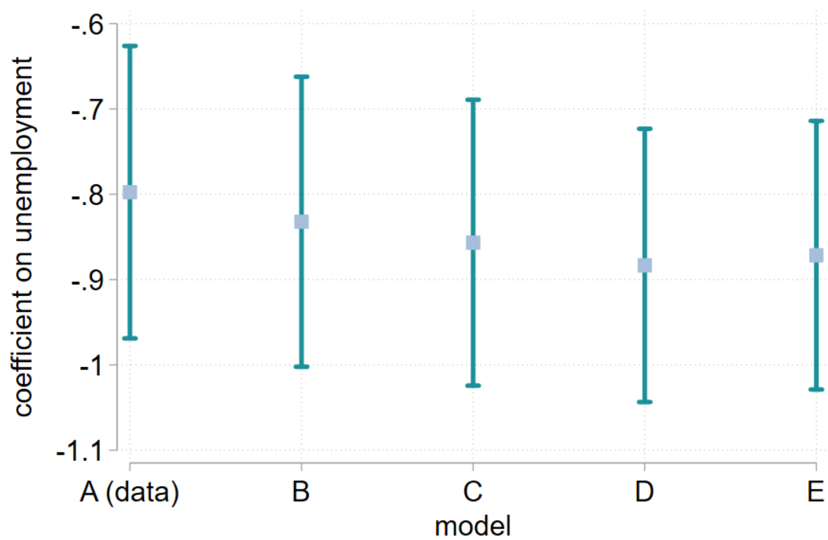
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A12: Robustness test: estimated regional unempl. rate coefficient under different misclassification errors



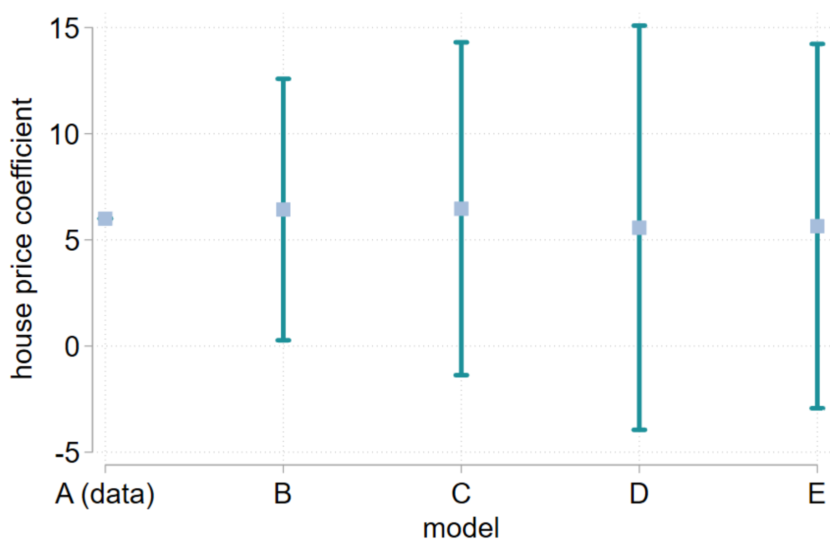
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A13: Robustness test: estimated unemployment coefficient under different misclassification errors



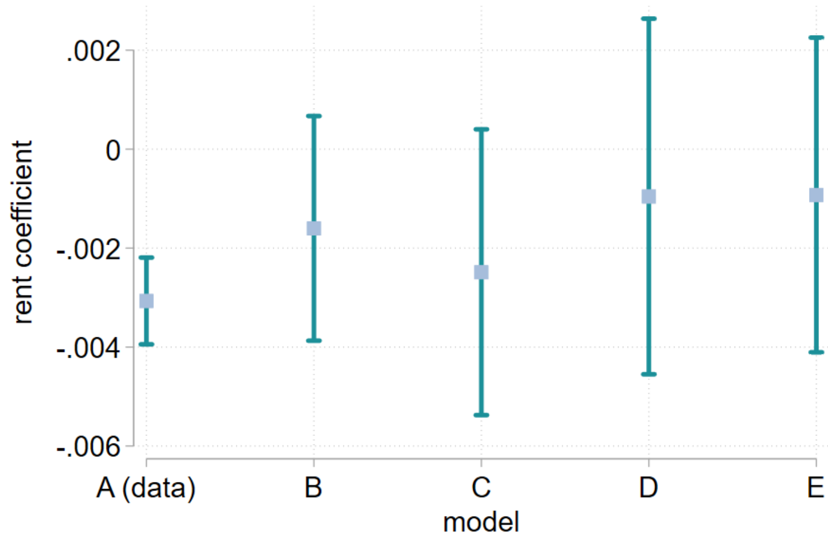
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A14: Robustness test: estimated house price coefficient under different misclassification errors



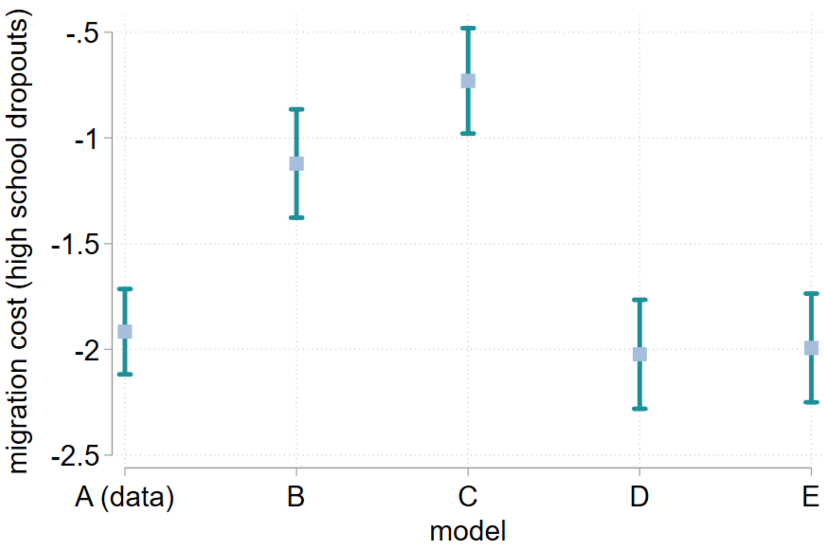
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A15: Robustness test: estimated rent coefficient under different misclassification errors



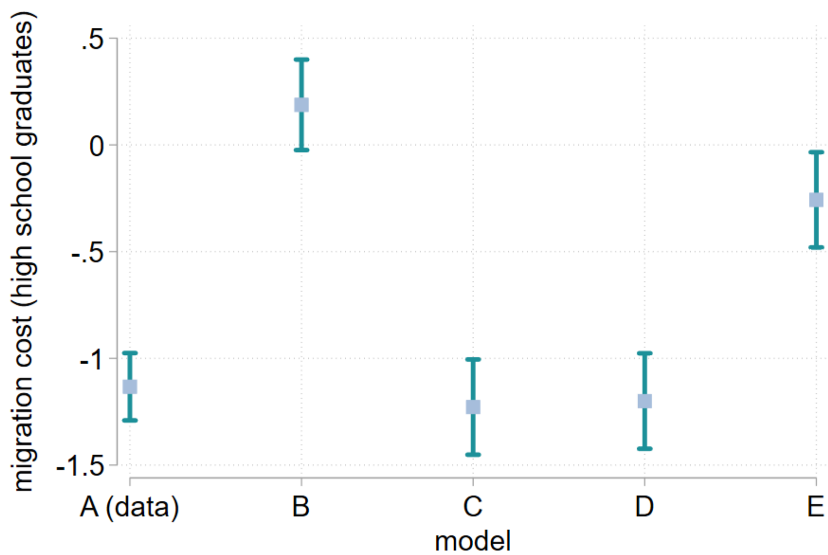
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A16: Robustness test: estimated migration cost (dropouts) under different misclassification errors



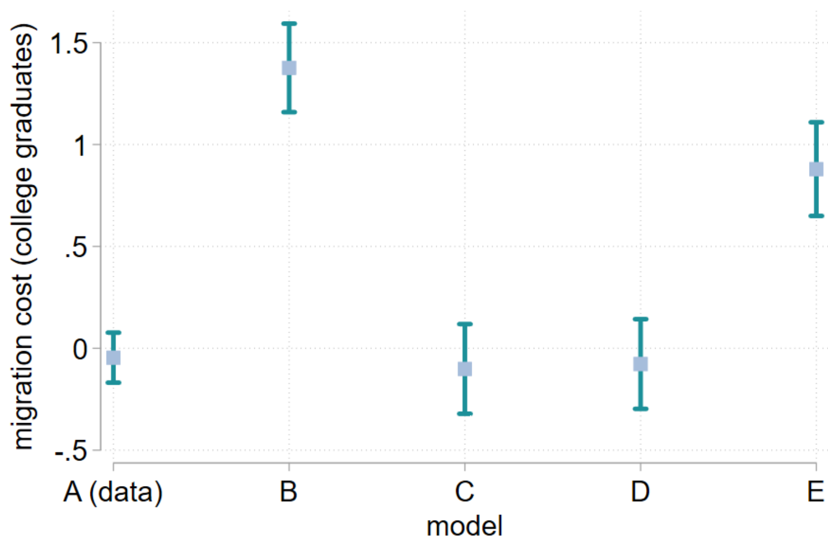
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A17: Robustness test: estimated migration cost (high school graduates) under different misclassification errors



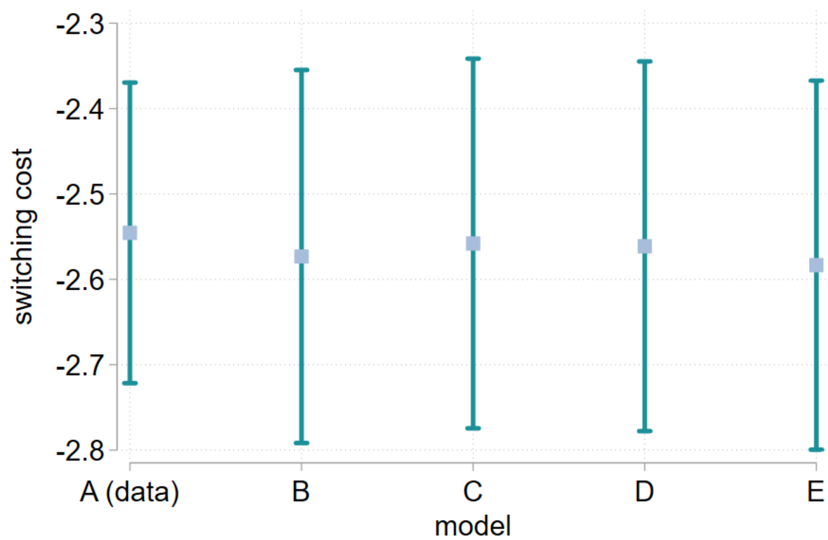
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A18: Robustness test: estimated migration cost (college graduates) under different misclassification errors



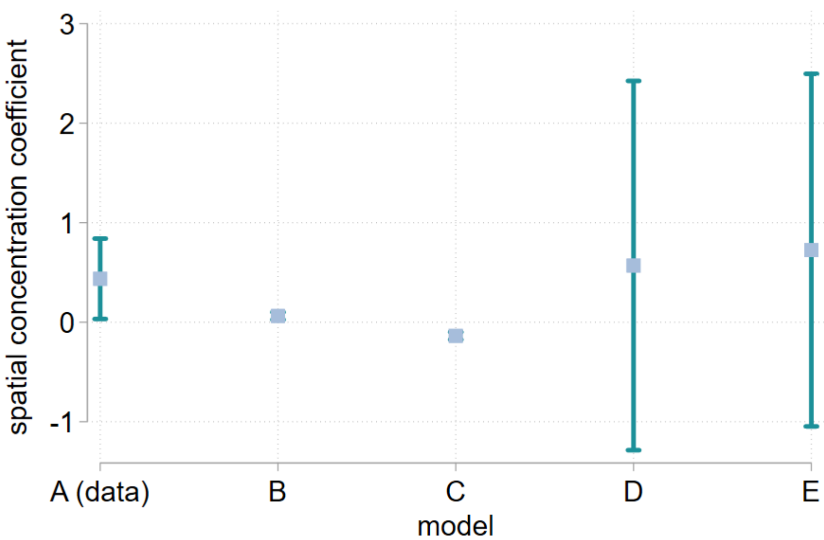
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A19: Robustness test: estimated switching cost under different misclassification errors



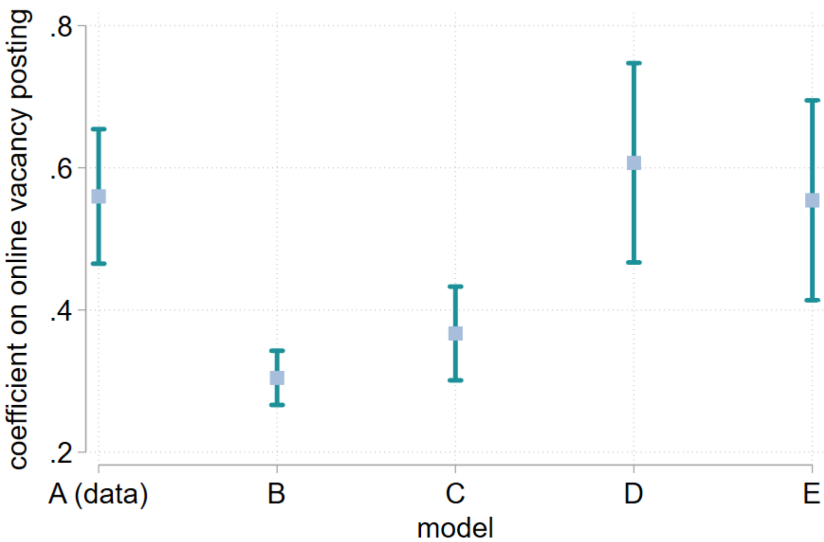
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A20: Robustness test: estimated spatial concentration coefficient under different misclassification errors



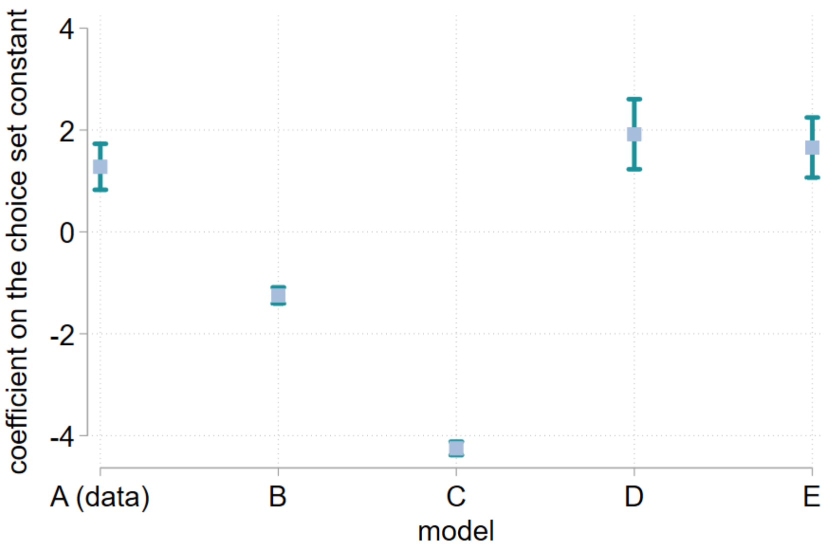
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A21: Robustness test: estimated coefficient on online vacancy posting under different misclassification errors



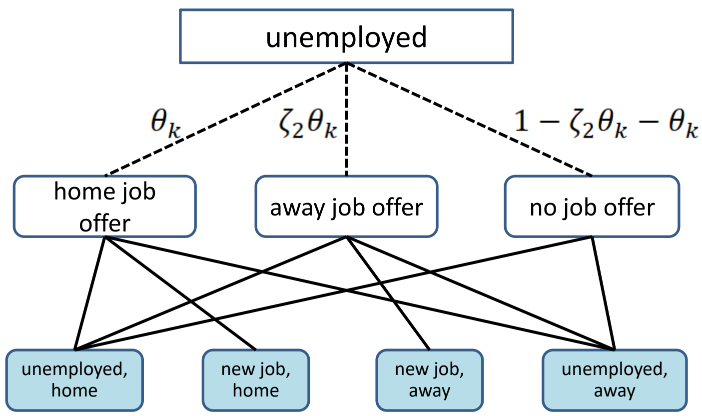
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A22: Robustness test: estimated option set constant under different misclassification errors



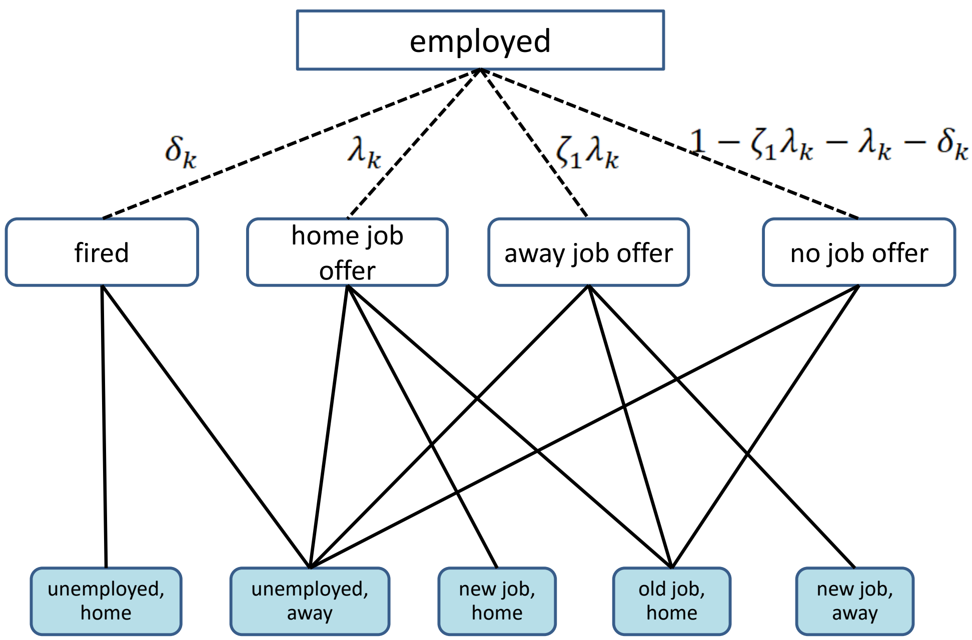
Model A: observed data. Model B: hypothesis that the type of migration is a statistical construct: even split between speculative and non-speculative migration. Model C: observed data corrected for the probability that a worker finds a job within one month, i.e. that speculative migration was mislcassified 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 labour force.

Figure A23: Choices and possible outcomes for an unemployed worker



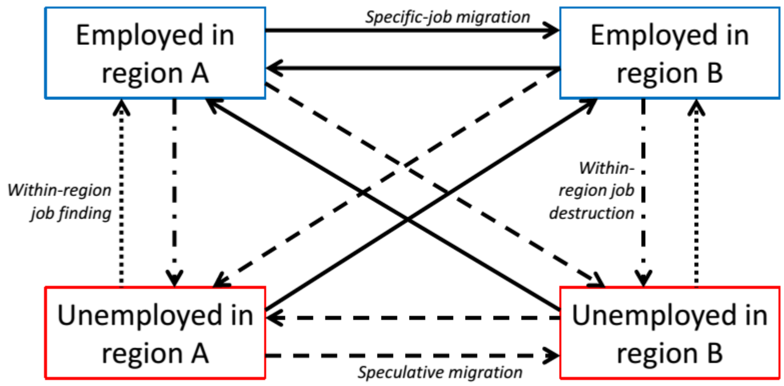
The scheme links the functioning of the labour market with workers' options and their potential outcomes. For instance, with the probability θ^k, the worker receives a job offer in her home region. In that case, she can decide between three outcomes: accept the offer, reject it and stay unemployed at 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.

Figure A24: Choices and possible outcomes for an employed worker



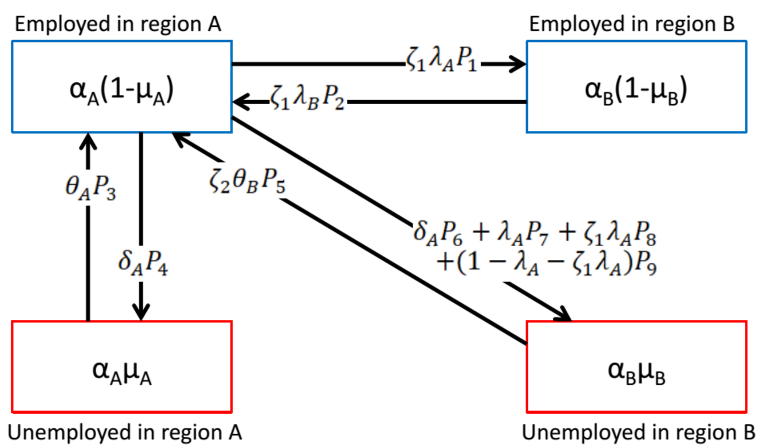
The scheme links the functioning of the labour market with workers' options and their potential outcomes. For instance, with the probability λ_k, the worker receives a job offer in her home region. In that case, she can decide between three outcomes: accept the offer, reject it and stay employed at home,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

Figure A25: Equilibrium in a 2-region model.



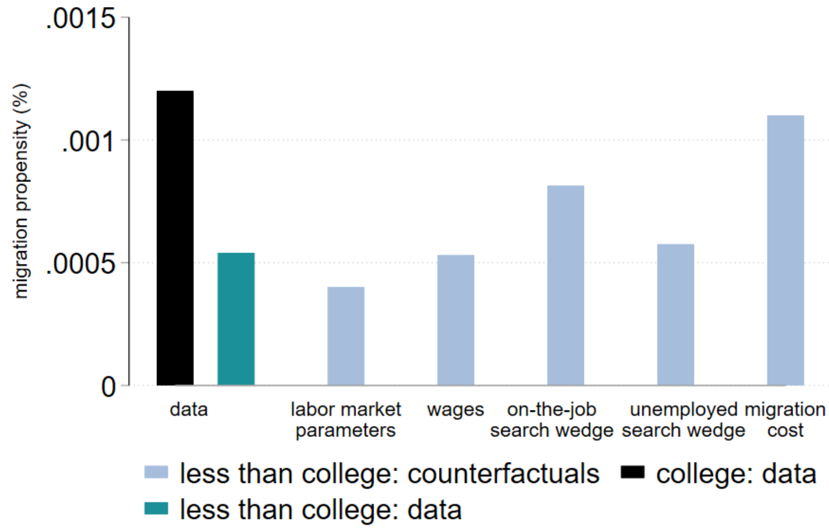
The arrows represent flows between the different employment-region stocks. Solid line: migration for a specific job. Dashed line: speculative migration. Dotted line: flows from unemployment to employment withing the same region. Dotdashed line: flows from employment to unemployment within the same region.

Figure A26: Equilibrium in a 2-region model: constant stock of employed workers in region A.



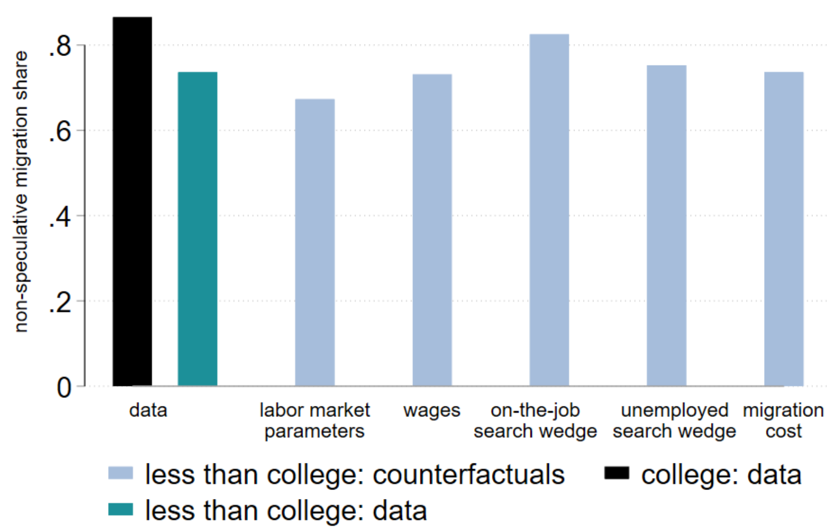
The four boxes represent the 4 different stocks of workers. The arrows demonstrate the possible flows in and out of the stock of employed in A. In equilibrium, these flows must perfectly offset each other. There are 3 inflows (from unemployment in A, unemployment in B, and employment in B) and 3 outflows (into unemployment in A, unemployment in B, and employment in B); the expressions on each arrow denotes the share of the corresponding stock that flows that way, i.e. the probability that a worker in a given stock would move into a different stock.

Figure A27: Decomposition of the education differences in migration propensity.



Calculated using the structural estimates in Table 4. The two leftmost bars represent observed behaviour. The other five bars plot the change in the migration behaviour of the less educated if the given parameters were equal to that of the more educated. For example, the rightmost bar in panel (a) shows that if the less educated faced the same migration costs as the more educated, their propensity to migrate would be almost as high as that of the more educated.

Figure A28: Decomposition of the education differences in migration for a specific job.



Calculated using the structural estimates in Table 4. The two leftmost bars represent observed behaviour. The other five bars plot the change in the migration behaviour of the less educated if the given parameters were equal to that of the more educated. For example, the rightmost bar in panel (a) shows that if the less educated faced the same migration costs as the more educated, their propensity to migrate would be almost as high as that of the more educated.