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Understanding the Long-Run Decline in Interstate Migration*

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ABSTRACT

We analyze the secular decline in interstate migration in the United States between 1991 and 2011. Gross flows of people across states are about 10 times larger than net flows, yet have declined by around 50 percent over the past 20 years. We argue that the fall in migration is due to a decline in the geographic specificity of returns to occupations, together with an increase in workers' ability to learn about other locations before moving there, through information technology and inexpensive travel. Micro data on the distribution of earnings and occupations across space provide evidence for the decrease in the geographic specificity of occupations. Other explanations, including compositional changes, regional changes, and the rise in real incomes, do not fit the data. We develop a model to formalize the geographic-specificity and information mechanisms and show that a calibrated version is consistent with cross-sectional and time-series patterns of migration, occupations, and incomes. Our mechanisms can explain at least one-half of the decline in gross migration since 1991.

Keywords: Interstate migration; Labor mobility; Gross flows; Information technology; Learning
JEL classification: D83, J11, J24, J61, R12, R23

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1. Introduction

In the early 1990s, about 3 percent of Americans moved between states each year. Today, that rate has fallen by half. Micro data rule out many popular explanations for this change, such as aging of the population or changes in the number of two-earner households. But the data do support two novel theories. The first theory is that labor markets around the country have become more similar in the returns they offer to particular skills, so workers need not move to a particular place to maximize the return on their idiosyncratic abilities. The second theory is that better information — due to both information technology and falling travel costs — has made locations less of an experience good, thereby reducing the need for young people to experiment with living in different places. We build a model that makes these ideas precise and show that a plausibly calibrated version is consistent with cross-sectional and time-series patterns.

Many policymakers have worried that the decline in migration heralds a less-flexible economy where workers cannot move to places with good jobs. In such an economy, the labor market might adjust more slowly to shocks, potentially prolonging recessions and reducing growth. Low migration has thus been proposed as an explanation for the slow recovery from the 2007–’08 financial crisis (see, for example, Batini et al., 2010). But the causes of decreased migration that we identify suggest that the economy may not be less flexible after all. Rather, low migration means that workers either do not need to move to obtain good jobs or have better information about their opportunities. In either case, the appropriate policy response may differ from the appropriate response to a decrease in workers’ ability to move. Thus, understanding the causes of the decline in gross migration is an important goal for economists.

Figure 1 shows gross and net interstate migration rates over the past six decades. The gross rate — the fraction of U.S. residents at least 1 year old who lived in a different state one year ago — comes from the Annual Social and Economic Supplement to the Current Population Survey, commonly known as the March CPS. The net rate comes from the Census Bureau’s annual state population estimates (U.S. Census Bureau, 1999, 2009a). Several key patterns are immediately apparent. First, net flows are an order of magnitude smaller than gross flows. Second, while the gross flows exhibit some cyclical fluctuations, these fluctuations are much smaller than the overall decline over the past 20 years. Third, the trend in gross flows is virtually identical when we restrict the analysis to a sample of working-age adults in

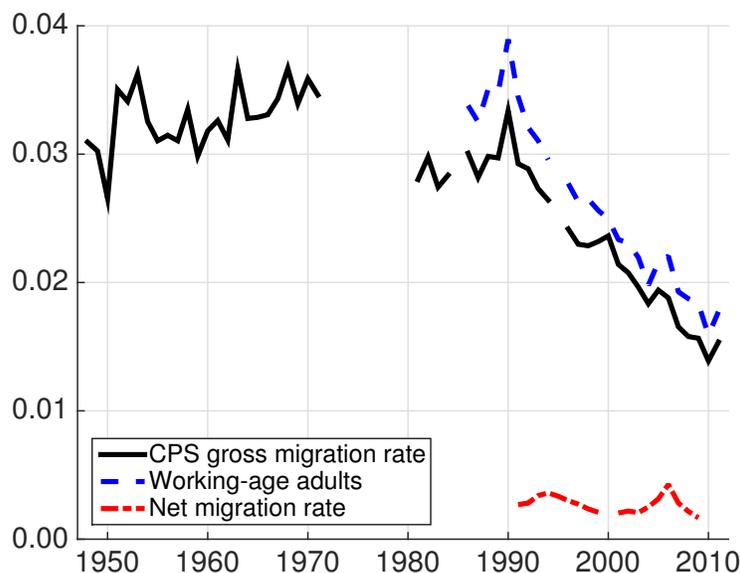


Figure 1: Gross and net interstate migration.

Source: U.S. Census Bureau (gross migration rate, 1948–1967); authors’ calculations from CPS micro data (gross migration rate, 1967–2011) and Census Bureau population estimates (net migration rate). The numerator of the net migration rate is one-half of the sum of absolute values of inflows minus outflows in each state. (This number is the minimum number of moves that would have to be prevented to set net migration to zero in every state.) The denominator of the rate between years t and $t + 1$ is the U.S. population at t minus deaths between t and $t + 1$.

civilian households. These patterns suggest that to understand the decline in migration, we must look for factors that affect gross flows rather than net flows; that vary over long time horizons rather than at business cycle frequencies; and that affect working-age people, rather than only people making life cycle–related transitions such as retiring or moving for college.

Two additional patterns guide our focus on information and on workers. Figure 2(a) shows that even among recent immigrants to the United States, the fraction who move between states after arriving has fallen over time. This decline is broadly consistent with both theories we propose. Improved information may make immigrants better able to choose a good initial destination. Alternatively, if immigrants choose their initial destinations based on family or ethnic ties (e.g., MacDonald and MacDonald, 1964), and later move to places where their idiosyncratic job matches are better, then a decline in interstate migration by new immigrants is consistent with the hypothesis that locations have become more similar in the jobs they offer, so that there is less reason for immigrants to change their initial locations.

Figure 2(b) examines the dimensions of information that may matter by showing the fraction of Americans who say they moved between states for various reasons. Job-related

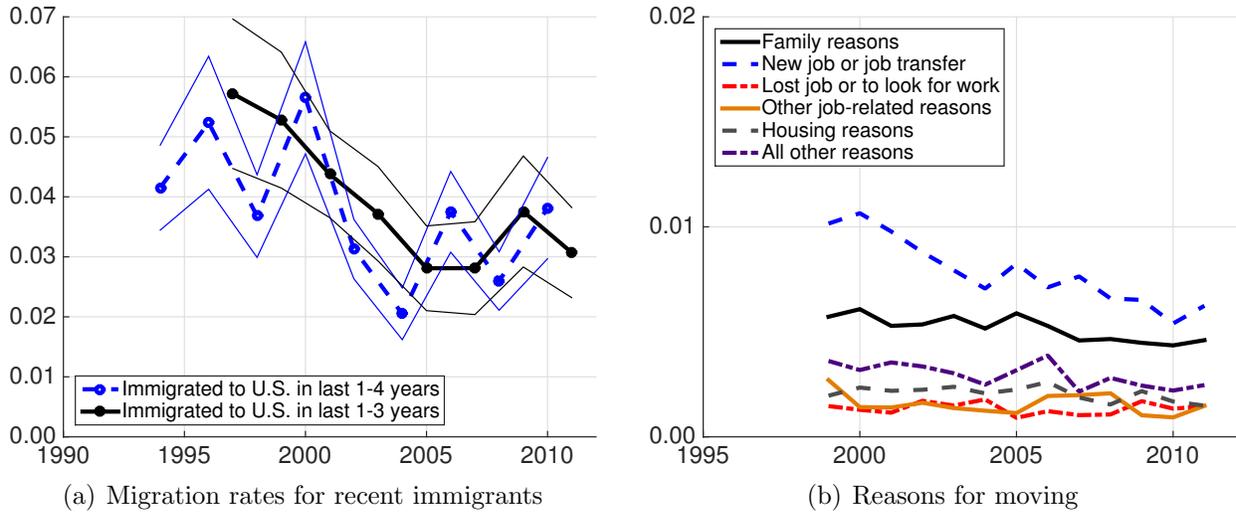


Figure 2: Key patterns in migration rates.

Source: Authors' calculations from CPS micro data. The sample is restricted to working-age adults. Estimates are shown for all years when variables are available. In Figure 2(a), the sample is further restricted to individuals with non-imputed data on number of years in the United States, estimates are standardized to the mean age distribution for new immigrants over the years shown, and thin lines show 1-standard-error confidence bands around point estimates.

reasons — primarily moves for new jobs or job transfers — have declined sharply, while other types of moves have declined more slowly. Of course, the reasons people give in a survey may not be their true reasons for moving. However, when a survey respondent says she moved for a new job, we think it is highly likely that she changed jobs around the time of the move — even if other factors, such as local amenities, motivated the desire to search for a job in a new location. Thus, to understand why migration is falling, we need to understand why people have become less likely to make moves that happen around the same time as job changes. Notably, there has been little change in the fraction of people who move to look for work or because they lost a job. Thus, it does not appear that better information has made it easier for workers to find jobs in faraway places before actually moving there: In that case, we would see an increase in moves for new jobs and a decrease in the number of people who move to look for work. Nonetheless, because moves for a new job or job transfer are much more common than moves to look for work, the ability to search for jobs in remote locations appears to be an important component of migration decisions.

The decline in job-related moves suggests that the potential improvements in job opportunities from moving are smaller than they were in the past. However, any decline in the

impact of moving on job opportunities cannot come simply from convergence of mean incomes across states: Such a change would reduce net migration, not gross migration. Rather, there must be a change in the importance of the match between a particular worker and a particular location. In our model, workers choose between two locations and two occupations. Each worker has different skills in the two occupations, and each occupation is more productive in one location. Changes in this occupation-location premium, which we call the *geographic specificity of occupations*, have no effect on net flows but do change gross flows by reducing workers' need to sort into the places where their particular skills are most productive.

A decrease in the geographic specificity of occupations cannot be the whole story, however. If locations offer more similar jobs, workers will be less likely to move for work but more likely to move for amenity-related reasons, because a smaller difference in amenities is now required to overcome the difference in earnings. But as Figure 2(b) shows, amenity-related moves have not risen. Thus, some other factor must also be at play.

In our model, this other factor is information. The two locations in our model differ in both the job opportunities and the local amenities they offer. Based on evidence that most workers who move for job-related reasons do so with a new job in hand, we assume that workers can search remotely for a job and know the distribution of job opportunities in remote locations. However, we assume that amenities are an experience good: Workers do not know how much they will like the sun in California until they live there. If workers in one location are sufficiently uncertain about amenities in the other location, they may move simply to acquire information. We call this a move for *experimentation* purposes. If the new location proves to be good, an experimenting worker will stay there; if not, she may return to her original location. We model an increase in information as an increase in the precision of workers' priors about the amenities in each location. Tighter priors have two opposing effects on migration. First is a "news" effect: Some workers discover that they would prefer a different location and decide to move. Second is an experimentation effect: Some workers who would have made experimental moves no longer do so because the tighter prior reduces their need to acquire information. Because people who move for experimentation purposes often dislike the new location and return to the origin, the reduction in experimental moves is larger than the increase in news-driven moves, and more information leads to lower migration overall.

We provide direct empirical evidence for the theory that migration has fallen because

job opportunities have become more similar across locations. We show that occupations have become more evenly spread across the country. Further, this change appears to result from a decrease in the dispersion of productivity rather than from a change in the supply of workers willing to take jobs in particular places, because we also find that the variance across states of the average income for a given occupation has fallen. (If, instead, workers increasingly desired jobs in unproductive places — for example because of an exogenous decrease in mobility — the dispersion of incomes would rise.) In addition, we show that migration decreased more in occupations where the cross-state income variance fell by a larger amount. Finally, we show that migration responds to the geographic specificity of occupations: On average, workers move to states where their particular occupations are better paid.

Recent advances in information technology and decreases in travel costs clearly make it easier for workers to learn about faraway places.¹ The hypothesis that increases in information have reduced the need to migrate also has a testable prediction: Rates of repeat migration should have declined because migrants will be more likely to be satisfied with their destinations. We turn to panel data to test this prediction and find that repeat migration indeed has declined, although the estimates are imprecise and a decrease in repeat migration could also be consistent with other theories of reduced migration.

We use a calibrated model to demonstrate that our theories not only are consistent with the data but also can explain a substantial portion of the decline in gross migration. The decrease in geographic specificity of occupations explains half of the fall in migration since 1991. An increase in information can explain as much as all of the remaining decrease.

Our work is related to a substantial literature. Molloy, Smith, and Wozniak (2011) survey research on internal migration in the United States and describe important patterns in the decline in interstate migration, finding, as we do, that compositional changes cannot explain much of the decline. Our analysis of compositional changes extends theirs by considering more fine-grained measures of some variables and by formally calculating counterfactual migration rates that hold composition fixed.²

¹In principle, lower travel costs might raise migration by making it easier to move. However, much of the cost of moving is a time cost — the migrant must find a new home, pack and unpack belongings, and find local services such as doctors and schools — that lower airfares cannot offset. Moreover, if lower travel costs should have increased migration, the observed decline is simply a larger puzzle; our mechanisms then explain less of the decrease relative to the appropriate counterfactual, leaving more room for other explanations.

²One factor that has received much attention but that we do not consider here is fluctuations in the housing market. The trend we document is a secular decline in migration over at least 20 years, during which house

Theories of migration, such as the classic models by Harris and Todaro (1970) and Roback (1982), generally focus on net flows. In related empirical work, Ganong and Shoag (2012) analyze the relationship between income convergence, net flows, and housing regulation, while Partridge et al. (2012) study the response of net migration to demand shocks.

Kennan and Walker (2011) structurally estimate a model in which workers choose locations to maximize their expected lifetime income. Differences in expected income across locations imply that the model features both gross and net flows. However, Kennan and Walker (2011) allow workers to choose among many locations, which means the model has many state variables and must be highly simplified along many dimensions to remain tractable. By studying only gross flows, we can reduce our model to two locations and add realism along other important dimensions, such as utility from amenities, learning, and geographic specificity of skills. Bayer and Juessen (2012) similarly study gross flows in a two-location model but focus on how the autocorrelation of income affects selection into migration; their model does not include amenities or learning, and they investigate cross-sectional patterns rather than the change in migration over time. Coen-Pirani (2010) builds a model to explain gross and net flows but does not analyze the decline in gross flows. Lkhagvasuren (2014) uses a two-location model of matches between workers and locations to study the relationship between education and gross mobility but does not examine utility from amenities or the decline in migration over time.

Our analysis is also connected to the literatures on agglomeration effects, city growth rates, and the concentration of industries in particular regions. To our knowledge, the decrease in the geographic specificity of occupations has not been described previously in the economic literature; it is distinct, for example, from the shift of aggregate employment toward less-dense areas described as “deconcentration” by Carlino and Chatterjee (2002). Our finding that workers move to states where their occupations are better paid is similar to Borjas, Bronars, and Trejo’s (1992) conclusion that high-skill workers tend to move to places with higher returns to skill, although they focus on one-dimensional measures of skill such as education or aptitude test scores rather than on a multitude of occupations. The New

prices and homeownership rose and then fell. If house prices and homeownership are important determinants of gross migration, it is difficult to explain why the decline in migration was monotonic while the housing market fluctuated sharply. In addition, Molloy, Smith, and Wozniak (2011) show that the decline in house prices since the mid-2000s plays at most a small role in the drop in migration over that period.

Economic Geography literature, starting with Krugman (1991), studies how transportation costs and local economies of scale lead workers and firms to concentrate in one location. In the typical model, these effects largely result in net flows: Workers move toward the more populated region. Empirically, Crozet (2004) tests the ability of a New Economic Geography model to explain labor migration. More broadly, changes in agglomeration effects could help explain the changes in the geographic dispersion of wages that we take as exogenous; Duranton and Puga (2004) review a variety of mechanisms that generate agglomeration effects and, hence, might affect the geographic dispersion of wages. The literatures on city population growth, industry concentration, and concentration of skilled workers in particular cities also essentially analyze net rather than gross flows. Again, though, the theoretical mechanisms proposed in these literatures, such as learning through interaction with other workers (Glaeser, 1999), linkages between human capital and entrepreneurship (Berry and Glaeser, 2005; Glaeser, Ponzetto, and Tobio, 2014), or technological diffusion and knowledge spillovers (Desmet and Rossi-Hansberg, 2009), could help explain changes in the geographic dispersion of wages.

Wang (2013) offers an alternative explanation for decreases in mobility based on changes in the relative returns to experience in large versus small cities. In Wang’s model, workers begin their careers in large cities and move to small ones after accumulating experience; when the return to experience rises in large cities relative to small ones, workers delay the move to small cities and the aggregate migration rate falls. Whether this mechanism mostly affects gross interstate migration, net interstate migration, or within-state moves depends crucially on how large and small cities are distributed across states. Wang shows that her model is consistent with evidence from a sample of white men who are full-time workers, have a bachelor’s degree (but no more education), and were born in 1964 to 1977. In addition, Wang considers five-year rather than one-year migration rates. We view Wang’s hypothesis as complementary to our model, which considers migration rates at the higher one-year frequency and addresses declines in migration for the entire population rather than for just a particular cohort of white, college-educated workers.

The paper proceeds as follows. In section 2, we describe the CPS data and compare migration rates in the CPS, other datasets and other countries. We show that the data are incompatible with many demographic and economic theories of falling migration. Section 3 presents direct evidence for the geographic specificity mechanism: We show that the returns to

working in particular occupations have become less geographically dispersed and that repeat migration rates have declined. We also review evidence for the falling costs of learning about distant locations. Section 4 lays out our model of information, occupational specialization, and migration. Section 5 calibrates the model, examines its success in fitting the data, and quantifies how much of the decline in migration our mechanisms can explain. Section 6 concludes.

2. Empirical Patterns in Migration Rates

We focus our analysis on working-age adults in civilian households in the March CPS from 1991 to 2011.³ (We start the analysis in 1991 because, as shown in Figure 1, the CPS migration rate spikes in 1990, but the cause of this spike is unclear and we do not want it to unduly influence our results. Figure 1 shows that the migration rate was roughly flat during the 1980s and that it fell sometime during the 1970s, although the exact timing is uncertain because data for most of that decade are unavailable.) We define a civilian household as one where no household member is in the military; excluding military households is important because military households move frequently and the military has become smaller (Pingle, 2007). We define a working-age adult as one who is no more than 55 years old and either (a) has a bachelor’s degree and is at least 23 years old or (b) does not have a bachelor’s degree, is not currently enrolled in school, and is at least 19 years old.⁴ Thus, we concentrate on people who have completed their education but are not yet approaching retirement. From 1996 onward, we follow Kaplan and Schulhofer-Wohl (2012) and exclude observations with imputed migration data so that changes in CPS imputation procedures do not produce spurious fluctuations in the migration rate. (The imputation rate before 1996 is negligible.) We obtain most of the data from the Integrated Public Use Microdata Series (King et al., 2010) but identify imputed observations with the imputation flags on the original public-use files from the Bureau of Labor Statistics.⁵

The CPS measures migration with retrospective questions: Did the respondent live in

³Our data omit 1995 because the CPS did not measure one-year migration that year.

⁴The CPS measures current school enrollment only for people ages 16 to 24. We treat all people over age 24 as not currently enrolled in school.

⁵Because the CPS is a very large sample, the standard errors of our estimates are typically on the order of one-tenth of a percentage point, and we omit them from most of the graphs in the interest of legibility. However, we show standard errors when their magnitude is meaningful. The online appendix (Kaplan and Schulhofer-Wohl, 2015) gives technical details of how we calculate standard errors.

the same home one year ago, and if not, where did he or she live? We drop respondents who did not live in the United States one year ago so that fluctuations in immigration do not affect our results. Since we are interested in how internal migration affects the labor market, ideally we would measure migration between distinct labor markets, such as the commuting zones defined by the Bureau of Labor Statistics (Tolbert and Sizer, 1996). However, we cannot identify migrants' origin and destination commuting zones because commuting zones are groups of counties and origin counties are not available in the CPS public-use files. Instead, we examine migration between states. In most parts of the country, states are large enough that labor markets do not cross state borders. Of course, by looking at interstate migration, we miss some migration between distinct labor markets within a state and include some migration that does not entail changing labor markets, such as when a worker in Manhattan moves to a New Jersey suburb. We show in the online appendix (Kaplan and Schulhofer-Wohl, 2015) that our results are robust to controlling for the latter bias by excluding states where the problem is particularly severe.

It is unlikely that the long-run decline we describe is a mechanical result of under-sampling people who move to newly built homes. First, the CPS sample frame is designed to capture new construction (U.S. Census Bureau, 2006, chap. 3).⁶ In addition, if a bias associated with new construction were the main driver of changes in the CPS migration rate, the rate would have fallen sharply during the housing boom of the mid-2000s and risen during the housing bust; it did not.

A. Comparisons with other datasets and countries

We use the CPS data because they cover many years and contain a myriad of covariates that allow us to test hypotheses about the decline in migration. However, the decline in measured annual interstate migration rates appears in other data as well. Figure 3(a) compares migration rates in the CPS, in micro data from the Census Bureau's American Community Survey (ACS) (Ruggles et al., 2010), in Internal Revenue Service (IRS) data, and in data from the Survey of Income and Program Participation (SIPP). The ACS migration rate parallels the CPS rate from 2005 to 2011 but is about one-half of a percentage

⁶The CPS technical documentation (U.S. Census Bureau, 2006, chaps. 3, 15) does report that the sample may miss some newly built group quarters. However, excluding group quarters residents from the sample does not change the gross interstate migration rate by more than 0.01 percentage point in any year.

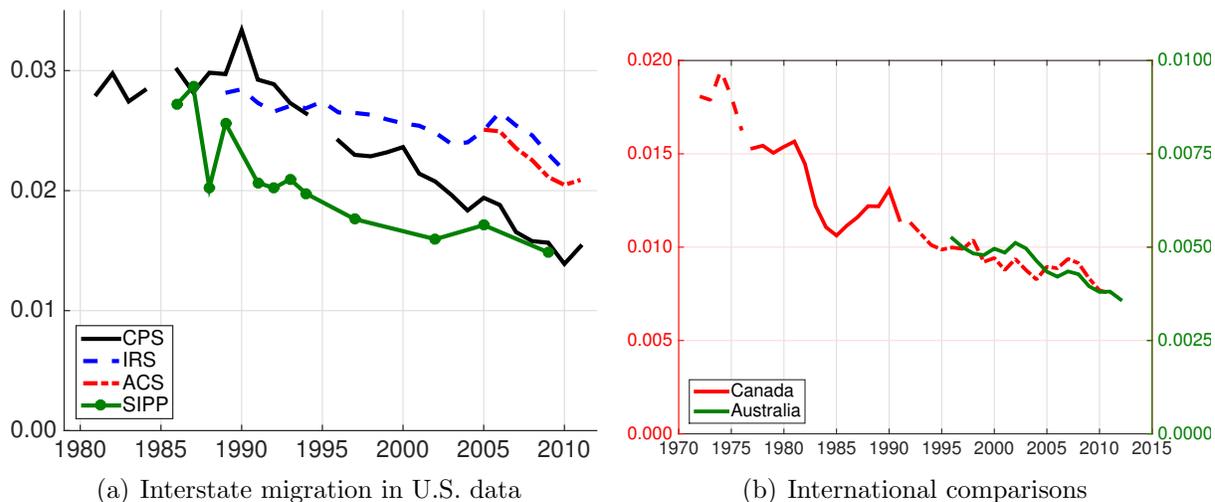


Figure 3: Gross long-distance migration measured from various data sources. Source: Authors’ calculations from CPS, ACS, and SIPP micro data and IRS state-to-state migration tabulations in the United States; Statistics Canada interprovincial migration and total population data (1972–1976: based on Family Allowance data, with Yukon Territory, Northwest Territories, and Nunavut treated as one geographic area; 1977–2011: based on Canada Revenue Agency data, with Northwest Territories and Nunavut treated as one geographic area before 1992); Australian Bureau of Statistics (based on Medicare registration data; annual averages of quarterly migration rates; data pre-1996 are not comparable because of a change in methodology).

point higher in each year, likely because the ACS pursues nonrespondents more intensively (Koerber, 2007). We do not examine earlier ACS data because, before 2005, the ACS was a pilot project and, as we describe in the online appendix, occasional changes in survey procedures may have affected the estimated migration rate. The IRS data cover more years; they, too, show a decline, albeit smaller than in the CPS. However, the IRS data are not a perfect measure of migration: They cover only people with incomes high enough to file taxes, track mailing addresses rather than home addresses, and can be distorted by changes in household formation, in the time of year when people file their returns,⁷ and in changes in the tax code or the economy that affect whose income is high enough to have to file a return (Internal Revenue Service, 2008). In particular, low-income workers who are near the margin of being required to file a tax return tend to have relatively high migration rates; thus, small changes in the tax code that move the margin of filing or economic fluctuations that push some of

⁷Based on IRS news releases reporting the number of returns filed each week during the filing season from 1996 to 2010, the median filing date of individual income tax returns appears to be shifting earlier by about one day every two years. However, the news release data are too imprecise to allow us to measure the second derivative of the median filing date, which is what determines the timing bias, if any, in the IRS data.

Table 1: Trends in migration rates in various datasets

	1989–2010		2005–2011		1986–2009	
	IRS	CPS	ACS	CPS	SIPP	CPS
Trend	-0.00022 (0.00003)	-0.00078 (0.00005)	-0.00085 (0.00012)	-0.00082 (0.00021)	-0.00050 (0.00010)	-0.00069 (0.00005)

Source: Authors' calculations from CPS, IRS, ACS, and SIPP micro data. Robust standard errors are in parentheses.

these workers across the margin could substantially change the migration rate in the IRS data.

One limitation of the CPS is that it does not follow migrants over time and thus does not let us see how earnings and other outcomes change when a particular person moves, nor does it even let us see how likely a migrant is to migrate again. When we examine repeat migration, we turn to panel data from the SIPP. However, for most purposes, panel data are not ideal for measuring migration because results will depend on the survey's success rate in tracking respondents who move, and this success rate could change over time independent of any changes in actual behavior. Thus, we focus most of our analysis on the CPS, which is not subject to attrition bias precisely because it is cross-sectional. Nonetheless, we show the migration rate in the SIPP in Figure 3(a) for completeness. The level is similar to the migration rate in the CPS, and although it shows a decline, the drop is less marked.

Table 1 compares the trends in migration rates in the CPS, IRS, ACS, and SIPP datasets. For each dataset other than the CPS, the table reports the slope coefficient in a time-series regression of the migration rate on the year in that dataset, using all years for which we can calculate a migration rate in that dataset. This slope coefficient is compared with the same coefficient obtained from the CPS, for the comparable set of years. Compared with the CPS data, the estimated trend is notably flatter in the IRS data, slightly flatter — although not statistically significantly so — in the SIPP data, and essentially the same in the ACS data.

The two countries that are most similar to the United States in terms of geography, culture, economic development, and political and economic integration are Australia and Canada. Since it is natural to conjecture that the two mechanisms we emphasize may be at

work in other countries, one might expect to observe a decline in long-distance migration in these countries, too. Figure 3(b) shows the interprovincial migration rate in Canada and the interstate migration rate in Australia. Although the levels of migration are different from those in the United States, both countries show a clear downward trend.⁸

It is also possible to measure migration over horizons longer than a year, for example by asking whether individuals lived in a different state five years ago or were born in a different state than the one where they live now. Molloy, Smith, and Wozniak (2011) show that the five-year interstate migration rate measured in the U.S. census fell from 9.9 percent in 1980 to 9.6 percent in 1990 and then 8.9 percent in 2000. We find that data restricted to a sample of working-age adults in civilian households show a similar downward trend. No nationally representative data on five-year migration are available after 2000.

B. Key patterns of migration

This subsection describes demographic and economic patterns in migration over the past two decades. We use these patterns both to learn which dimensions are important to model and to show that various common beliefs about the fall in migration do not match the data.

Figure 4 shows the age profile of migration rates separately for college graduates and nongraduates in our sample of working-age adults. Migration rates decline sharply with age, but this decline is steeper for college graduates, who migrate much more than nongraduates up to about age 40. Since 1991, the migration rate has fallen at all ages. Thus, although the population is aging and older people migrate less, the aggregate decline in migration cannot be due solely to a mechanical effect of population aging; the aggregate rate would have fallen even if the age distribution had remained the same. Importantly, however, the decline in migration is larger for the young — a fact we will ask our calibrated model to reproduce.

Figure 5 quantifies the importance of population aging by calculating what the interstate migration rate would have been in each year if the age distribution had not changed

⁸Molloy, Smith, and Wozniak (2011) examine the trends in within-country migration in Great Britain and continental Europe. Although they find a drop in migration in Great Britain, we think that the comparison with the United States is not entirely apt because of Britain's smaller land area and labor market concentration in a single large city (London). The mechanisms driving migration in Continental Europe are likely to be different from those in the United States because the continent as a whole is neither linguistically nor culturally homogeneous and has only recently begun the process of economic and political integration, and because individual countries are geographically much smaller than the United States.

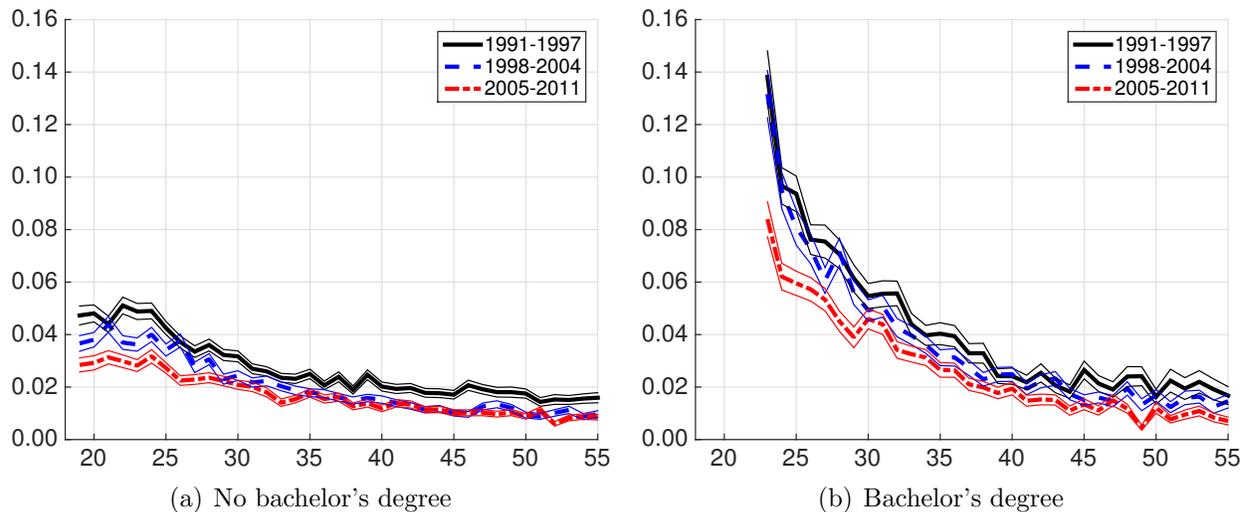


Figure 4: Age profile of interstate migration.

Source: Authors' calculations from CPS micro data. The sample is restricted to working-age adults. Thin lines show 1-standard-error confidence bands around point estimates.

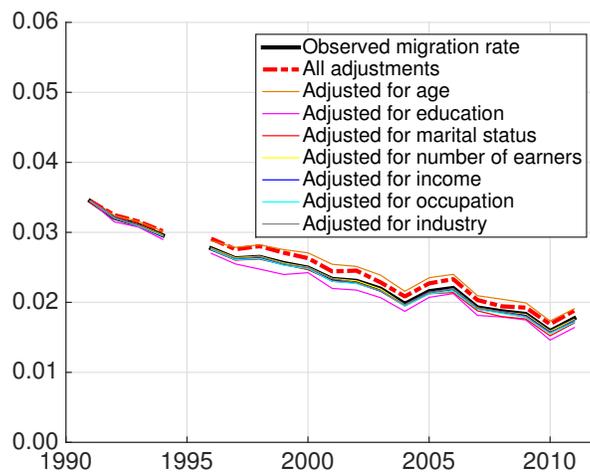


Figure 5: Composition-adjusted migration rates.

Source: Authors' calculations from CPS micro data. The sample is restricted to working-age adults. Composition-adjusted rates hold the following variables constant at their 1991 distribution: respondent's age (single years), respondent's education (single years), respondent's marital status (four categories), number of labor force participants in respondent's household (two categories), real income per capita of respondent's household (20 equal-population bins in 1991), occupation (one-digit categories), and industry (one-digit categories). See online appendix for category definitions.

after 1991. The effect is tiny: Holding the age distribution fixed, the migration rate would have been 0.1 percentage point higher in 2011. We find similar results when we adjust for changes in the distribution of education, marital status, number of labor force participants in the household, real household income per capita, occupation, or industry — and when we adjust for changes in the joint distribution of all of these variables. (The online appendix describes the precise categories we use to define the distributions.) Thus, although the composition of the U.S. population has changed in many ways since 1991, these changes have no power for explaining the decline in interstate migration. The main reason, which we illustrate in detail in the online appendix, is that — just as with the age distribution — migration rates have fallen in parallel within each subgroup of the population. (For a contrasting view, see Karahan and Rhee, 2014, who argue that population aging can reduce the migration rate of young workers in general equilibrium.)

Many potential theoretical explanations for reduced migration run aground on the finding that composition effects do not matter and that migration rates have declined similarly across population subgroups:

- The findings on marital status and number of earners indicate that the fall in migration is not due to changes in the number of “tied stayers” (Gemici, 2011; Guler, Guvenen, and Violante, 2012; Mincer, 1978) who cannot move because their partners cannot move.
- The findings on industry and occupation composition suggest that the fall in migration is not due to the rise of the service sector (whose workers theoretically could, but empirically do not, have different migration patterns) or to the availability of new technologies that facilitate telecommuting in some occupations.
- The findings on income distribution show that the fall in migration does not result from increases over time in mean incomes or in the degree of income inequality.

The online appendix examines these and other compositional explanations in more detail.

3. Direct Evidence for Our Mechanisms

Our theory relies on two mechanisms to generate a decrease in migration: an increase in the similarity of job opportunities in different parts of the country and a decrease in the cost of learning about amenities in faraway locations. This section presents evidence for each mechanism.

A. Increases in the similarity of job opportunities

We test whether job opportunities around the country have become more similar and whether geographic differences in job opportunities are related to migration by examining both prices and quantities. First, we show that the dispersion of incomes across states and metropolitan areas within occupations has fallen. In other words, the earnings of workers in a given occupation have become more similar across space. This convergence in the *price* of workers in various occupations might result from a change in either demand (e.g., an increase in the productivity of certain occupations in places where those occupations used to be unproductive) or supply (e.g., workers moving from places with low productivity to places with high productivity until marginal productivity is equated across space). A change in demand would reduce migration in the model we present later in the paper; a change in supply is merely a consequence of migration and would not itself cause migration to fall. To distinguish between demand and supply effects, we examine the distribution of the number of workers in each occupation around the country. If productivity in particular occupations becomes less geographically specific, occupations will become less geographically segregated — that is, the distribution of occupations in each state will become more similar to the national average. By contrast, if workers move to places where their occupations are more productive, each location will become more specialized and occupations will become more geographically segregated. We find that occupations have become less geographically segregated across states and metropolitan areas, supporting the view that occupations’ productivity levels have become less geographically specific. The change in productivity dispersion, as measured by the change in income dispersion, will be a key input to our model later on. We then connect productivity dispersion to migration by showing that, on average, a migrant’s occupation brings higher pay in the destination state than in the origin state. Thus, migrants tend to move toward states where their occupations earn higher pay, a key mechanism in our model.

The dispersion of incomes within occupations

We study the geographic specificity of occupations’ income levels by computing residuals from a Mincer regression and examining how the means of these residuals vary across occupations and states. (We focus here on a simple and transparent analysis but briefly describe below some more complex methods that give qualitatively similar results.) First, in

each year t , we estimate the regression

$$\ln y_{iost} = a_{st} + b_{ot} + \mathbf{x}'_{iost} \boldsymbol{\beta}_t + u_{iost}, \quad (1)$$

where y_{iost} is the wage, salary, and self-employment income of worker i in occupation o , state s , and year t ; a_{st} is a state-year fixed effect; b_{ot} is an occupation-year fixed effect; and \mathbf{x}_{iost} is a vector of controls, including sex, dummy variables for single year of education, and a quartic polynomial in potential experience. Second, we assume that the error u_{iost} depends on a component that is common to all workers in a given occupation, state, and year, and a second component that varies idiosyncratically across workers:

$$u_{iost} = \xi_{ost} + \epsilon_{iost}, \quad (2)$$

where we assume ϵ_{iost} is independently and identically distributed across workers with mean zero. Let \hat{u}_{iost} denote the estimated residual from (1) for worker i in occupation o , state s , and year t . Then we can estimate the occupation-state-year interaction ξ_{ost} by the mean of \hat{u}_{iost} in each occupation-state-year cell. We let $\hat{\xi}_{ost}$ denote this cell mean. We weight the regression in (1) and the calculation of mean residuals within cells according to the survey weights. Finally, we characterize the behavior of $\hat{\xi}_{ost}$ both in the cross section and over time. Our estimation approach imposes no a priori restrictions on the persistence of the occupation-state interaction ξ_{ost} , so we can allow the data to tell us whether these interactions persist in a way that could plausibly induce workers to migrate.

To keep the number of parameters manageable, we use the single-digit occupation categories shown in Table 2. Although detailed occupation coding in Census Bureau datasets has changed over time, these changes should have had little impact on how workers are classified at the one-digit level, so we think it is unlikely that our results are driven by changes in occupation coding.

Cross-sectional variation in cell mean incomes. Cross-sectionally, in each year, we calculate the variance of the cell means, $\hat{\sigma}_{\xi,t}^2 = \text{Var}[\hat{\xi}_{ost}|t]$. When $\hat{\sigma}_{\xi,t}^2$ is smaller, the variance of incomes across states within an occupation is smaller, after controlling for individual demographics \mathbf{x}_{iost} and factors b_{st} that affect all occupations in a state. Thus, if occupations'

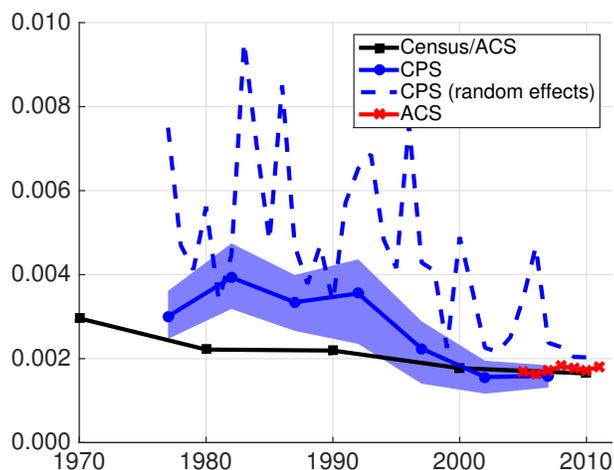


Figure 6: Cross-sectional variance of cell mean incomes across states.

Source: Authors’ calculations from CPS micro data, 1977–2011; ACS micro data, 2005–2011 one-year and 2006–2010 combined five-year samples; and decennial census micro data (1970, 1980, 1990, and 2000). Thick lines marked “Census/ACS,” “CPS,” and “ACS” show bootstrap bias-corrected point estimates from cell mean model. Shaded area shows bootstrap bias-corrected 90 percent confidence intervals around CPS point estimates from cell mean model. The 90 percent confidence intervals for the Census/ACS estimates are too small to be visible. Dashed line shows point estimates from parametric random-effects model. CPS estimates in cell mean model are averaged over five-year periods. The sample is restricted to employed civilians ages 16 and over.

productivity becomes less geographically specific, $\hat{\sigma}_{\xi,t}^2$ will fall. We weight the calculation of the cross-sectional variance of cell means by the population in each cell, so that small states and rare occupations do not unduly influence the results. We use a bootstrap bias correction to remove the upward finite-sample bias in $\hat{\sigma}_{\xi,t}^2$, which arises because $\hat{\xi}_{ost}$ varies across cells for two reasons: true variation in incomes across states within occupations as well as random differences in which workers were sampled in each cell. Removing the upward bias from random sampling is crucial because the magnitude of the bias depends on the sample size, and the size of the sample size changes over time. Therefore, estimates that ignore the bias would not be comparable over time and could not be used to determine the true trend in the variance of incomes across space within occupations.

We estimate $\hat{\sigma}_{\xi,t}^2$ year by year in data from the CPS, the decennial census, and the ACS.⁹ Figure 6 shows estimates of $\sigma_{\xi,t}^2$ for each year. A clear decline from 1970 to 2000

⁹We use the 1 percent form 1 and form 2 state samples from the 1970 census, the 5 percent samples from the 1980 and 1990 censuses, the 5 percent and 1 percent samples from the 2000 census, and annual samples from the ACS, as well as a combined 2006–2010 ACS sample that we use for a 2010 estimate that can be compared with the census results in earlier years. We obtain all census and ACS data from Ruggles et al. (2010).

can be seen in the decennial census data. The downward trend also appears in the CPS, although the CPS estimates are volatile from year to year. (We average the CPS estimates over five-year periods to reduce this volatility.) In the ACS, the cross-sectional variance of cell means has a slight upward trend, but the upward trend is not statistically significant.

Our approach treats ξ_{ost} as a random effect that is orthogonal to the demographic and experience controls \mathbf{x}_{iost} . The model can also be estimated more parametrically by modeling the distribution of the random effect and estimating the variance of this distribution. The dashed line in Figure 6 shows that when we use this more parametric approach, we obtain a similar decline in the variance of occupation-state interactions in the CPS. The online appendix provides technical details on the parametric random-effects estimation method. Alternatively, we could relax the orthogonality assumption by estimating ξ_{ost} as the coefficient on occupation-state interaction dummy variables. The online appendix shows that we obtain similar trends but less precise estimates when we do so. Finally, the online appendix also shows that we obtain similar results when we define geographic locations by metropolitan statistical areas (MSAs) rather than states.

Table 2 shows the change from 1970 to 2010 in the variance of earnings across states, within each of the nine one-digit occupations, and compares this change with the change in the interstate migration rate from 1991 to 2011 among workers in that occupation. The variance of earnings is measured in the 1970 census and in the 2006–2010 combined ACS sample. The geographic variance of earnings declined within six of the nine occupations. The correlation between the change in the variance of earnings and the change in the migration rate is 0.62. Thus, migration fell more among workers in occupations where the geographic variance of earnings fell more. This is the correlation that our theory predicts, although the test of the theory is imperfect because the correlation does not measure a causal relationship and because occupation is measured at the destination of a move.

We interpret the downward trend in geographic dispersion of incomes as reflecting convergence across states in productivity within occupations. In this view, a worker with given skills faces more similar wages across states now than he did several decades ago. However, another possible interpretation is that unobserved differences across states in worker quality may have gotten smaller, which would mean that a worker with given skills does not necessarily face more similar wages across states now than in the past. Econometrically distinguishing differences across states in unobservable worker quality from differences across states in skill

Table 2: Changes in geographic variance of earnings and in migration rate by occupation

Occupation	$\sigma_{\xi,t}^2$			interstate migration rate			1990 fraction of workers
	1970	2010	change	1991	2011	change	
Executive/admin/ managerial	0.0006 (0.0001)	0.0012 (0.0001)	0.0006 (0.0001)	0.036 (0.003)	0.023 (0.002)	-0.012 (0.004)	0.1259 (0.0002)
Professional specialty	0.0015 (0.0002)	0.0011 (0.0001)	-0.0004 (0.0002)	0.047 (0.003)	0.028 (0.003)	-0.019 (0.005)	0.1417 (0.0002)
Technician/related support	0.0014 (0.0004)	0.0012 (0.0001)	-0.0002 (0.0004)	0.035 (0.005)	0.027 (0.006)	-0.008 (0.008)	0.0376 (0.0001)
Sales	0.0026 (0.0003)	0.0009 (0.0001)	-0.0017 (0.0003)	0.042 (0.003)	0.019 (0.002)	-0.023 (0.004)	0.1168 (0.0002)
Admin support	0.0022 (0.0001)	0.0003 (0.0000)	-0.0018 (0.0002)	0.028 (0.002)	0.014 (0.002)	-0.014 (0.003)	0.1662 (0.0002)
Service	0.0054 (0.0003)	0.0019 (0.0001)	-0.0035 (0.0003)	0.033 (0.002)	0.014 (0.002)	-0.019 (0.003)	0.1268 (0.0002)
Farming/forestry fishing	0.0224 (0.0013)	0.0047 (0.0005)	-0.0177 (0.0014)	0.040 (0.006)	0.017 (0.004)	-0.023 (0.008)	0.0227 (0.0001)
Precision production/ craft/repair	0.0016 (0.0001)	0.0025 (0.0001)	0.0008 (0.0002)	0.028 (0.002)	0.013 (0.002)	-0.015 (0.003)	0.1117 (0.0001)
Operator/fabricator/ laborer	0.0023 (0.0001)	0.0041 (0.0001)	0.0018 (0.0002)	0.023 (0.002)	0.015 (0.002)	-0.009 (0.003)	0.1507 (0.0002)

Source: Authors' calculations from decennial census micro data (1970 earnings variance and 1990 fraction of workers), 2006–2010 ACS combined sample micro data (2010 earnings variance), and CPS micro data, 1991 and 2011 (migration rates). The sample is restricted to working-age employed civilians. Migration rates are adjusted to hold the age distribution constant at the 1991 distribution. Standard errors are in parentheses.

returns is a complicated task, and we do not attempt it here.¹⁰ But it is common in the literature to treat workers with identical education, living in the same state but educated in different states, as facing identical wages (see, e.g., Dahl, 2002); even papers that study the effect of local school quality on wages, such as Card and Krueger (1992), acknowledge large differences across space in the returns to education for workers with identical quality.

Behavior of cell mean incomes over time. Workers would not migrate in response to changes in occupation- and state-specific earnings if these changes were transitory. Thus, we need to establish that variation across states in ξ_{ost} is persistent. We cannot simply look at serial correlation because the decrease in the cross-sectional variance over time reduces the serial correlation of ξ_{ost} even if the ranking of states and occupations is persistent. We could examine the rank serial correlation, but it is sensitive to noise in the estimation of ξ_{ost} . To obtain a measure that is more robust to imprecise estimates, we group our estimates of $\hat{\xi}_{ost}$ into terciles and examine the probability that a cell moves from the lowest tercile in one year to the highest tercile in the next year or vice versa. We use a bootstrap bias correction to remove the upward bias in these transition probabilities that is due to sampling variation. Our estimates suggest that the variation across states in ξ_{ost} is indeed very persistent. For example, in the census, the average 10-year conditional transition probability of moving from the highest tercile to the lowest tercile or vice versa is only 3 percent, whereas the conditional probability of remaining in either the highest or the lowest tercile is 75 percent. In the CPS, the analogous transition probabilities across five-year subperiods are 11 percent and 61 percent.

The dispersion of quantities of workers

In Figure 7, we compute the Theil information-theory index of segregation (Theil and Finizza, 1971) for various categories of occupations. The Theil index is commonly used to measure racial segregation, and Reardon and Firebaugh (2002) show that it has many desirable properties that other indices lack, especially when measuring segregation of more than two groups. The Theil index compares the distribution of occupations in each location with the distribution for the nation as a whole. The index ranges from 0 to 1, with higher

¹⁰For example, reestimating (1) with state-specific returns to education would not allow us to rule out differences in worker quality because state-specific returns to education could reflect either differences in the wages for identical workers or differences in the quality of education.

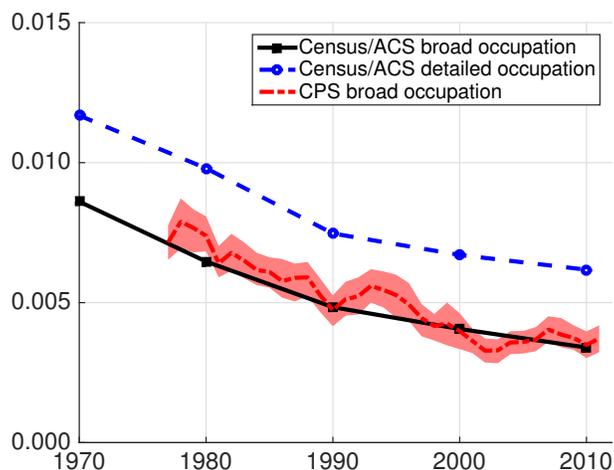


Figure 7: Theil indices of segregation of occupations across states.

Source: Authors’ calculations from CPS micro data, 1981–2011; ACS micro data, combined 2006–2010 sample; and decennial census micro data (1970, 1980, 1990, and 2000). Detailed occupation categories are three-digit codes for the OCC1990 variable in Ruggles et al. (2010). Broad occupation categories are the categories shown in Table 2. The sample is restricted to employed civilians ages 16 and over and is weighted by the number of workers. Point estimates are bootstrap bias corrected. Shaded areas show bootstrap bias-corrected 90 percent confidence intervals around CPS point estimates. The 90 percent confidence intervals for census and ACS estimates are too small to be visible.

values indicating more segregation; the index is 1 when each occupation is found in only one location and 0 when each location has the same distribution of occupations as the nation as a whole.¹¹

Figure 7 shows that, over time, states’ distributions of workers across occupations have become more similar. This pattern holds whether we look at single-digit occupations or more detailed categories. (To examine more detailed categories, we must go to decennial census and multiyear ACS data,¹² because the CPS contains too few observations to reliably

¹¹The formula for the index is

$$H = \frac{1}{E} \sum_{s=1}^S \frac{N_s}{N} (E - E_s), \quad E = - \sum_{j=1}^J \pi_j \ln \pi_j, \quad E_s = - \sum_{j=1}^J \pi_{js} \ln \pi_{js},$$

where s indexes states, N_s is the number of workers in state s , N is the national number of workers, j indexes occupations, π_j is the fraction of U.S. workers who are in occupation j , and π_{js} is the fraction of state s ’s workers who are in occupation j . We compute confidence intervals for the index by bootstrapping, taking account of the survey sample designs in constructing the bootstrap samples, and use a bootstrap bias correction to remove the upward finite-sample bias that is due to random sampling.

¹²We use the same census samples as for the income dispersion analysis. For the ACS, we use the 2006–2010 combined dataset, which is equivalent to a 5 percent sample. Despite the large size of these samples, some occupations are not observed in all years. We combine occupations that are not observed in all years into an “all other” category so that the groups over which the index is calculated are constant over time.

estimate, say, the number of meter readers in Vermont in 2010.) The online appendix shows that results are similar when we define locations by MSAs rather than states and when we examine segregation of industries rather than occupations.

Migration and the geographic specificity of occupations

Our geographic-specificity mechanism assumes that workers tend to migrate to states where their occupations bring higher pay. We now test that assumption by examining whether the state-occupation interaction ξ_{ost} in equation (2) is larger in the migrant's destination state than in the migrant's origin state. Specifically, for a migrant i who moved from state s to state s' and is currently working in occupation o , we define

$$\Delta_{it} = \hat{\xi}_{o,s',t} - \hat{\xi}_{ost}, \quad (3)$$

where $\hat{\xi}_{ost}$ is our estimate of the state-occupation interaction ξ_{ost} . The quantity Δ_{it} is the difference between i 's predicted income from equation (1) at the destination state and i 's predicted income at the origin state, holding constant i 's occupation and demographics and controlling for differences in incomes that affect all occupations in a given state. That is, Δ_{it} represents i 's within-occupation income gains from moving, net of any difference in the average income across all occupations between the origin and destination states. If migrants move toward states where their occupations are better paid, we expect Δ_{it} to have a positive mean.

Figure 8 shows the mean of Δ_{it} in each year in the CPS, ACS, and decennial census. The CPS estimates begin in 1986 because that is the earliest year when we can identify working-age adults, and we average the CPS estimates over five-year periods to smooth out the volatility that results from the small sample size. We define occupations by one-digit codes, we estimate ξ_{ost} using data on all workers, not just migrants, and we estimate the mean of Δ_{it} using data on all interstate migrants, even if they are not currently employed. The results show that, on average, Δ_{it} is positive: Migrants move toward states where their occupations are higher paid. In the census and ACS, we can reject at least at the 10 percent level the hypothesis that the gain from moving is zero. In the CPS, the estimates are much less precise but nonetheless positive except in the final five-year period.

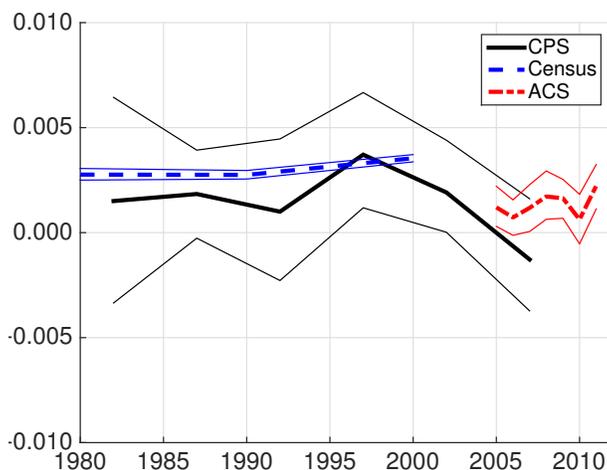


Figure 8: Mean within-occupation income gains from moving.

Source: Authors' calculations from CPS, ACS, and decennial census micro data. Samples are restricted to interstate migrants who are working-age adults in civilian households and report an occupation. The CPS sample is further restricted to those with non-imputed migration data, and estimates are averaged over five-year periods. The ACS sample is further restricted to those not living in group quarters. Estimates are shown for all years when variables are available. Point estimates are bootstrap bias corrected; thin lines show bootstrap bias-corrected 90 percent confidence intervals.

B. Decreases in the cost of information

If people have better information about distant locations, they will be less likely to move somewhere only to find it unsatisfactory and move again soon afterward. Thus, a decrease in the cost of information about faraway places should reduce the rate of repeat and return migration. Further, while many mechanisms that would reduce migration in general would mechanically reduce repeat and return migration as well, a unique prediction of our information theory is that it should reduce repeat migration more than total migration, because fewer people make experimental or mistaken moves that result in a return trip. Thus, under our theory, the ratio of repeat or return migration to total migration should fall.

We cannot measure repeat and return migration in the cross-sectional CPS, so we turn to panel data from the U.S. Census Bureau's Survey of Income and Program Participation (SIPP) as well as data on place of birth and residence five years ago from the decennial census. Each of these data sources has drawbacks, but given the need for repeated measures of migration, the SIPP and the decennial census are the best available datasets for our purpose.

As we discuss in section 2, panel survey data are not ideal for measuring migration because results can depend on the survey's procedure for finding migrants at their new loca-

tions, and any changes in measured migration might result from changes in survey procedures. However, the SIPP makes significant efforts to locate respondents who move (see U.S. Census Bureau, 2009b, chap. 2) and starts with a large sample, about 50,000 households in recent years, so that the population at risk of repeat migration is large enough to obtain reasonably precise estimates. (Overall interstate migration rates in the SIPP are similar in magnitude to those in the CPS, although the downward trend is less pronounced.) The SIPP consists of a series of independent panels that started in various years and were each followed for several years. Respondents are interviewed every four months. For each panel, we calculate repeat and return annual interstate migration rates in the first two years that the panel was followed. Specifically, for a panel first interviewed in year t , the repeat migration rate is the probability of living in a state at the seventh interview (year $t + 2$, 24 months after the first interview) that is different from the state at the fourth interview (year $t + 1$, 12 months after the first interview), conditional on making an interstate move between the first and fourth interviews (years t and $t + 1$). The return migration rate is the probability of returning to the year- t state at $t + 2$, conditional on making an interstate move between t and $t + 1$. These definitions ignore moves that happen within a single year — even though the SIPP measures such moves — so that we are measuring annual rates that can be compared with the annual rates in the CPS. In some panels, the SIPP public-use data files combine certain small states to protect respondents’ anonymity. We use these combinations of states in all panels to ensure that our results are not driven by changes in the state coding.

Because the census is collected cross-sectionally, it is not affected by panel attrition. Long-form census questionnaires ask respondents where they were born and where they lived five years ago. We calculate the repeat migration rate as the probability of living in a state at the time of the census that is different from the state of residence five years earlier, conditional on making an interstate move between birth and five years ago. The return migration rate is the probability of currently living in the birth state, conditional on not living in the birth state five years ago. These rates are not directly comparable to the one-year migration rates among workers that are the focus of our paper, because they include some moves by children and some moves in the distant past, and ignore some moves at frequencies higher than five years.¹³ Nonetheless, these rates are useful indicators because decreases in high-frequency

¹³For example, a person who is born in Minnesota, moves to Wisconsin at age 1, returns to Minnesota at

return migration by workers should lead, all else equal, to decreases in the return migration rate that we measure in the census.

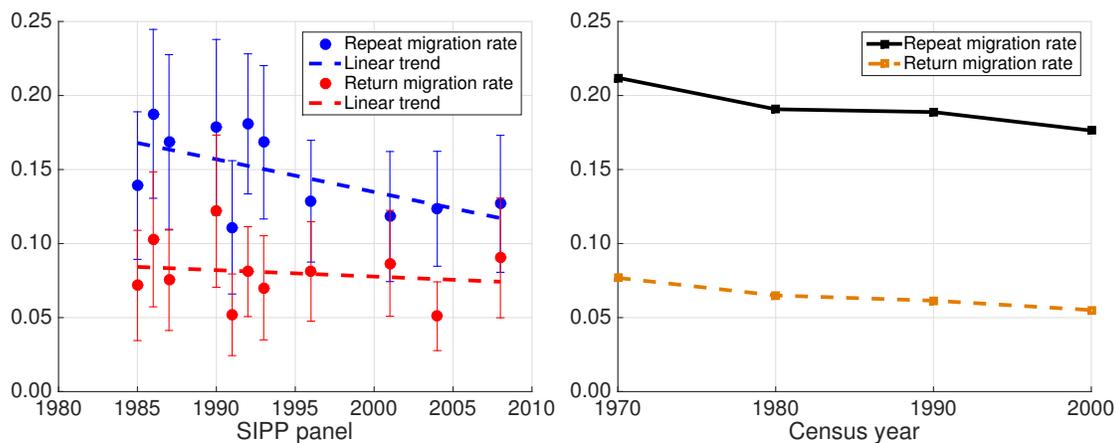
To make the SIPP and census data as comparable as possible to our results from the CPS, we limit the SIPP and census samples to people who are working-age adults in civilian households. Additional details on sample selection and the calculation of confidence intervals are in the online appendix.

Figure 9 shows the results. Repeat and return migration rates are high: The SIPP data show that someone who leaves a state in one year has roughly a 7 percent chance of returning the next year and a similar chance of moving to a third state the next year. But these rates have fallen over time. In particular, the annual repeat migration rate in the SIPP appears to have fallen by about 5 percentage points in the past two decades. The census data also show high but declining repeat and return migration. The SIPP dataset is too small to precisely estimate the ratio of repeat or return migration to total migration. In the much larger census dataset, we find a clear decrease in these ratios, consistent with our theory.

Several important caveats apply to these findings. First, the estimates from the SIPP are very imprecise. The reason is that respondents are part of the sample used to estimate repeat or return migration only if they migrate in the initial year; because interstate migration is rare to begin with, this sample is small even though the overall SIPP sample is large. The downward trends in the SIPP repeat and return migration rates are not statistically significant at conventional significance levels. Second, the changes we observe in the SIPP could theoretically be due to changes in procedures for following respondents who move, although we are not aware of any such changes. Third, in the census, the timing of the changes in moving behavior is unclear because the estimated rates are a function of migration over the entire life cycle, and the observed changes could result from changes in moving rates among families with children rather than from changes in moving rates among workers.

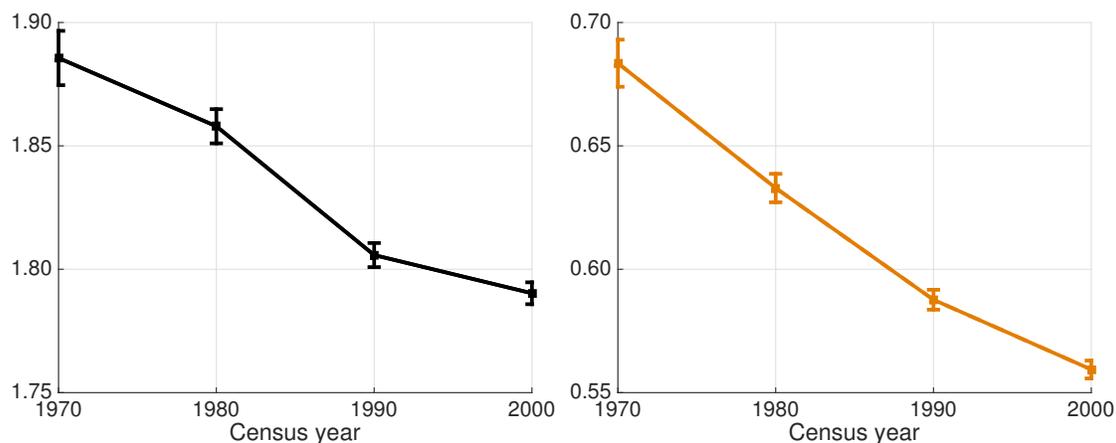
There are also reasons beyond the decline in repeat and return migration to believe that people have more information about distant locations than in the past. The past several decades have seen dramatic changes in several technologies and markets that help people to gather this information. Most obvious, of course, is the development of the Internet, which

age 29, and is a census respondent at age 30 will count as a return migrant; a person who lives in Minnesota up to age 27, moves to Wisconsin at age 28, returns to Minnesota at age 29, and is a census respondent at age 30 will not count as a return migrant.



(a) Repeat migration in the SIPP

(b) Repeat and return migration in the census



(c) Ratio of repeat to total migration in the census

(d) Ratio of return to total migration in the census

Figure 9: Repeat and return interstate migration rates.

Source: Authors' calculations from SIPP and decennial census micro data. Samples are restricted to working-age adults in civilian households; additional sample selection details are in the online appendix. Dashed lines in Figure 9(a) are predicted values from a linear regression of the repeat or return migration rate on the initial year of the SIPP panel. Vertical bars in Figures 9(a), 9(c), and 9(d) show 95 percent confidence intervals for point estimates. Confidence intervals for census estimates in Figure 9(b) are too small to be visible.

allows people to inexpensively and rapidly learn about life in other cities. But other changes have also sharply reduced the cost of information. Following the breakup of AT&T in 1984, competition in the market for long-distance telephone calls rose, prices fell by 50 percent in seven years, and demand for long-distance services doubled (Taylor and Taylor, 1993). Thus, even before the Internet, the cost of learning about distant places by picking up the telephone was decreasing.

Travel costs are also an important influence on the cost of gathering information. A person who wants to learn whether she will like the weather in California can best do so by vacationing in California. After the United States deregulated the airline industry in 1978, airfares fell significantly (though the exact size of the decrease is difficult to calculate) and airlines offered more flights to more destinations (Borenstein and Rose, 2014). A decrease in the cost of air travel reduces the cost of gathering information both by reducing actual outlays on travel and, for workers who substitute to air travel from other modes of transportation, by reducing the time required to reach the destination. Indeed, air travel is increasingly common: U.S. domestic airline passenger enplanements per capita increased by 23 percent from 1990 to 2012, according to the U.S. Bureau of Transportation Statistics.

These examples of improvements in individuals' abilities to learn about their preferences for living in remote locations need not be restricted to the United States. Hence, if changes in information are an important factor for understanding changes in migration, one would expect to observe a decline in migration in other geographically large countries whose level of economic development and cultural homogeneity is similar to the United States. In Figure 3(b), we showed that this is indeed the case for the two countries that are most similar to the United States along these dimensions: Canada and Australia.

Ideally, we would provide direct evidence for the effect of information on migration by relating migration behavior to an observable measure of information that varies exogenously in the population. Unfortunately, we have found no such measures of information in the United States. The best available evidence of this type that we are aware of is from Indonesia. Farré and Fasani (2013) use a differences-in-differences design to estimate the causal effect of media exposure (as measured by access to TV networks) on internal migration. They find a significant effect: an increase of one standard deviation in access to TV as an adolescent causes a reduction in the inter-provincial migration rate of around 2 percentage points. Despite the obvious differences between Indonesia and the United States, these results lend additional

support to the hypothesis that improvements in information have played a role in the decline in migration in the United States.

4. A Model of Information, Specialization, and Gross Migration

Guided by our empirical findings, we construct a model in which broad-based changes in information technology and the structure of labor markets impel all workers to migrate less. Our model contains five features that make it suitable for our purposes.

First, our model features only two symmetric locations, which can be thought of as “here” and “there.” By formulating a model with only two locations, each of which contains half of the population, rather than multiple locations with different populations, we limit our ability to make inferences about net population movements to or from particular locations. However, since it is gross migration rates and not net migration rates that have changed, this modeling choice does not come at any cost. Instead, it imparts some important benefits. Unlike existing models (e.g., Davis, Fisher, and Veracierto, 2010; Kennan and Walker, 2011) that have multiple locations, our model is simple enough to allow for the inclusion of richer environmental features that are at the heart of theories of the decline in migration.

Second, agents in our model can be employed in one of two distinct occupations or be nonemployed. Each occupation commands a higher wage in one of the two locations. One could think, for example, of banking in New York and acting in Los Angeles. Individuals in our model have occupation-specific skills that evolve stochastically, so that there is heterogeneity across households in their comparative advantage at working in an occupation, and thus their labor market incentives for living in each location.

Third, locations in our model are an experience good. This means that individuals have imperfect information about the non-labor market (amenity) values that they derive from living in each location. Only by living in a location do individuals learn about their preferences for living there.

Fourth, the labor market in our model is frictional, in the sense that individuals must search for employment opportunities. Moreover, living in one location does not preclude an individual from searching for a job in the other location. The possibility of remote search is important because it allows us to capture the notion that even if the fundamental reason for a move is a change in amenity-related preferences, the move may not take place until the individual finds a job opportunity in the desired location.

Finally, our model has a life cycle element, since we showed in section 2B that the likelihood of migration varies greatly with age.

A. Environment

Demographics and preferences Individuals (which we will also refer to as households or agents) live for T periods, $t = 1, \dots, T$. In each period, they live in one of two locations, $j \in \{a, b\}$, and either work in one of two occupations, $k \in \{A, B\}$, or are nonemployed, $k = u$. They choose locations, occupations, and job search strategies to maximize expected discounted utility,

$$\mathbb{E} \sum_{t=1}^T \beta^{t-1} (y_t + u_t),$$

where y_t is income and u_t is utility derived from non-labor market features of the location where the individual lives at age t . We let $n_t^j \in [0, t]$ denote the number of periods that the individual has lived in location j , up to and including period t . Note that $n_t^a = t - n_t^b$, since in any period an individual who is not in location a must be in location b , and vice versa.

Information and amenities Agents' preferences for local amenities, $v = (v^a, v^b)'$, are fixed over time. However, individuals do not know these preferences and must learn them over time, through living in the two locations. Each period, an individual who lives in location j_t receives non-labor market utility $u_t = v^{j_t} + \epsilon_t$, that is, the sum of his underlying unknown preference for the location and an i.i.d. random preference shock. The individual observes only u_t and must use this information to update his belief about v^{j_t} . We denote the initial prior mean and precision of beliefs by m_0^j and τ_0 . We assume that the ϵ shocks and the v values are normally distributed with precisions τ_ϵ and τ_v , respectively:

$$\epsilon \sim N\left(0, \frac{1}{\tau_\epsilon^2}\right), \quad v^j \sim N\left(0, \frac{1}{\tau_v^2}\right).$$

We assume that v^a and v^b are independent so that a strong preference for living in either location imparts no information about the *absolute* preference for living in the other location.

Labor markets Labor markets are arranged according to an island structure in each location, in the spirit of Lucas and Prescott (1974). There are two islands, one on which production takes place and one populated by nonemployed households who receive a nonem-

ployment benefit. To find the production island, nonemployed households are required to search. On the production island, there is a competitive labor market for each occupation. Technology is constant returns to scale in skills, and labor is the only input for production. Thus, the wage rate per unit of skill equals the marginal product of skills in each occupation; we take this marginal product as exogenous.

An individual at age t is characterized by his skills in each of the two occupations, $s_t = (s_t^A, s_t^B)'$, which evolve according to an exogenous Markov process normalized so that $E[e^{s_t}] = 1 \forall t$. These skills are revealed to the individual at the beginning of period t . (That is, while our model features learning about amenity preferences, there is perfect information about skills. We abstract from learning about skills because observed occupational mobility is much higher than long-distance geographic mobility — implying that people will learn faster about their skills than about their geographic preferences — and because explaining occupational mobility within geographic locations is not our goal.) We also assume that skills have a deterministic life cycle component ψ_t to capture the evolution of average wages over the life cycle.

We denote the price of skills for occupation k in location j by p_k^j and assume that

$$p_B^a = p_A^b < p_A^a = p_B^b.$$

This specification encodes two assumptions. First, islands and occupations are symmetric. Second, there is a geography-occupation interaction in the price of skills: An occupation commands a higher price per unit of skill when it is performed in the location where it has a comparative advantage. We normalize $p_B^a = p_A^b = 1$ and define $\theta = p_A^a = p_B^b$. Thus, $\theta > 1$ is the wage premium for working in a matched location and occupation.

Incomes depend on skills s_t , the life cycle component ψ_t , and a time cost of moving. Specifically, income is

$$y_t(j_t, k_t, s_t) = \begin{cases} (1 - \kappa \mathbf{1}_{\text{migrate}}) \psi_t e^{s_{k_t}} p_k^j & \text{employed agent} \\ (1 - \kappa \mathbf{1}_{\text{migrate}}) q & \text{nonemployed agent,} \end{cases}$$

where κ is the time cost of moving, q is the nonemployment benefit, and a worker who migrates between periods t and $t + 1$ loses a fraction κ of his work time during period t .

Both nonemployed and employed workers can choose to search for the production island in either location (but not both), regardless of where they are currently located. Search is costless and equally efficient for employed and nonemployed agents. Searches succeed with probability λ .¹⁴ In addition, employed workers randomly lose their jobs and are forced to move to the nonemployment island with probability δ .

Timing An individual enters period t with the following relevant information: the location where he resides (j_t); his current island, that is, production or nonemployment (i_t); his skills in the two occupations at the end of the previous period (s_{t-1}); his beliefs about his preferences for living in the two locations, conditional on information at the end of period $t - 1$ (m_{t-1}); and the number of periods he has lived in location a (n_{t-1}^a). Recall that $n_{t-1}^b = t - 1 - n_{t-1}^a$.

Within each period, the timing of events is as follows:

1. The individual's skills in each of the two occupations, s_t , are realized.
2. The individual receives his non-labor market utility, $u_t = v^{j_t} + \epsilon_t$.
3. The individual updates the number of periods he has lived in location a , n_t^a , and his beliefs about his utility from living in location j_t , $m_t^{j_t}$. He does not update his beliefs about utility from living in the other location because he has no new information about that parameter. We give a formal description of the learning problem and formulas for updating beliefs later on.
4. If the individual is on the production island ($i_t = 1$), he chooses his occupation for the current period k_t . He may also choose to quit to the nonemployment island.
5. The individual works (if employed) and receives his earnings or nonemployment benefit.
6. After working, an employed worker may randomly lose his job with probability δ .
7. The individual decides whether to search for the production island in either location, and the results of search are realized.
8. Conditional on the outcome of search, the individual makes his migration decision, that is, he chooses his location for $t + 1$. This consists of the choice of a location-island pair (j_{t+1}, i_{t+1}). Migrants pay a moving cost κ , proportional to income. There is no cost for switching occupations.

¹⁴Although we could introduce search costs and differences in search efficiency, we do not need to do so to explain the decrease in migration.

Table 3: Updating formulas for beliefs

$j_t = a$		$j_t = b$	
n_t^a	$= n_{t-1}^a + 1$	n_t^a	$= n_{t-1}^a$
m_t^a	$= \frac{(\tau_0^2 + n_{t-1}^a \tau_\epsilon^2) m_{t-1}^a + \tau_\epsilon^2 u_t}{\tau_0^2 + n_t^a \tau_\epsilon^2}$	m_t^a	$= m_{t-1}^a$
m_t^b	$= m_{t-1}^b$	m_t^b	$= \frac{[\tau_0^2 + (t-1-n_{t-1}^a) \tau_\epsilon^2] m_{t-1}^b + \tau_\epsilon^2 u_t}{\tau_0^2 + (t-n_t^a) \tau_\epsilon^2}$

B. The learning problem

Because the prior and the signal are both normally distributed, the posterior after any number of signals will also be a normal distribution and can be completely described by its mean and variance. Let $m_{t,n}$ and $\frac{1}{\tau_{t,n}^2}$ be the mean and variance of the posterior at date t after n signals. Using Bayes' theorem and the definitions of normal densities, we have the following relationship between the kernels of the posterior, signal, and prior after one signal:

$$\exp\left(-\frac{1}{2}\tau_{t,1}^2(v - m_{t,1})\right) \propto \exp\left(-\frac{1}{2}\tau_\epsilon^2(u_t - v)\right) \exp\left(-\frac{1}{2}\tau_0^2(v - m_0)\right),$$

which implies

$$\tau_{t,1}^2 = \tau_0^2 + \tau_\epsilon^2, \quad m_{t,1} = \frac{\tau_0^2 m_0 + \tau_\epsilon^2 u_t}{\tau_0^2 + \tau_\epsilon^2}.$$

Repeating the same analysis given priors with mean $m_{t,n-1}$ and precision $\tau_{t,n-1}^2$, we arrive at the following general updating formulas for the moments of the belief distribution:

$$\begin{aligned} \tau_{t,n}^2 &= \tau_{t-1,n-1}^2 + \tau_\epsilon^2 = \tau_0^2 + n\tau_\epsilon^2, \\ m_{t,n} &= \frac{[\tau_0^2 + (n-1)\tau_\epsilon^2]m_{t-1,n-1} + \tau_\epsilon^2 u_t}{\tau_0^2 + n\tau_\epsilon^2}. \end{aligned}$$

Because there are only two locations, we only need to keep track of n_t^a , the number of periods lived in location a up to time t . The number of periods lived in location b is then given by $t - n_t^a$, and the precision of beliefs can be expressed as a function of n_t^a . The updating formulas conditional on the location j_t where the agent lives in period t are thus as shown in Table 3.

The conditional distribution of the time $t + 1$ signal, u_{t+1} , given information available

at the end of period t , is normal with mean and variance given by

$$\begin{aligned} \mathbb{E} \left[u_{t+1}^{j_{t+1}} | j_{t+1}, n_t^{j_{t+1}}, m_t^{j_{t+1}} \right] &= m_t^{j_{t+1}}, \\ \text{Var} \left[u_{t+1}^{j_{t+1}} | j_{t+1}, n_t^{j_{t+1}}, m_t^{j_{t+1}} \right] &= \frac{1}{\tau_0^2 + n_t^{j_{t+1}} \tau_\epsilon^2} + \frac{1}{\tau_\epsilon^2}, \end{aligned}$$

where we have used the fact that the time $t + 1$ location decision is known at the end of period t .

C. Recursive formulation of the model

The timing just described and the updating formulas allow us to express the worker's maximization problem recursively. We consider the expected present value of an individual in period t just before making his location and island choice for $t + 1$, (j_{t+1}, i_{t+1}) . The state variables at this point are $x_t = (j_t, s_t, m_t, n_t, o_t)$, where j_t is the current location, s_t is the vector of skills in the two occupations, m_t is the vector of beliefs about preferences over the two locations, n_t is the number of periods lived in location a , and $o_t = (o_t^a, o_t^b)'$ are indicator variables denoting whether the individual has an offer to work in each location. Because employed workers are free to choose either occupation, the current occupation is not relevant when deciding the future location once we condition on o_t ; hence, k_t is not a state variable. Furthermore, because individuals are always free to quit to nonemployment, an individual will never choose a pair $(j, 0)$ over $(j, 1)$ if he has an offer at location j . Nonetheless, even if j_{t+1} is the only choice at a given state, it is convenient to define the value functions in terms of location-island pairs. We will denote this choice as $y_t \equiv (j_{t+1}, i_{t+1})$. Consequently, let $J_t(x_t, y_t)$ be the expected present value of an individual in period t who has state variables x_t and chooses the location-island pair y_t .

Agents make two other decisions in each period: occupation and search choices. It is useful to define a beginning-of-period value function. Let $V_t(j_t, i_t, s_t, m_t, n_t^a) \equiv V_t(\Omega_t)$ be the expected present value of an individual who begins period t on island i_t at location j_t with state variables (s_t, m_t, n_t^a) , and who makes optimal occupation, search, and migration choices from then onward.

The choice-specific value functions are then given by

$$\begin{aligned} J_t(x_t, y_t) &= \sum_{s_{t+1} u_{t+1}} \int [u_{t+1} + \beta V_{t+1}(\Omega_{t+1})] dF(u_{t+1}|m_t, j_{t+1}) \Pr(s_{t+1}|s_t) - \kappa_t(x_t, y_t) \\ &= \sum_{s'} \int_{u'} [u' + \beta V'(\Omega')] dF(u'|m, n, j') \Pr(s'|s) - \kappa(x, y), \end{aligned}$$

where in the second line we have used primes to denote $t + 1$ variables. The migration cost $\kappa_t(x_t, y_t)$ for individuals who migrate is $\kappa p_k^j \psi_t e^{s_t}$ for those who worked in period t and κq for those who were unemployed, where $p_A^a = p_B^b = \theta$ and $p_A^b = p_B^a = 1$.

Using the conditional distribution of u_{t+1} derived earlier, we then have

$$J(x, y) = m^{j'} + \beta \sum_{s'} \int_{u'} V'(\Omega') dF(u'|m, n, j') \Pr(s'|s) - \kappa(x, y),$$

where u' shows up inside the integral in the m' component of Ω' . This holds because $m' = E[u'|j', n, m]$.

We now derive the value function V . Define

$$L_t(x_t) = \max_{y_t} J_t(x_t, y_t).$$

The available choices y_t are determined by the offers o_t . Expanding $y_t = (j_{t+1}, i_{t+1})$ and making use of the fact that $J(x, (j, 1)) \geq J(x, (j, 0))$ always, we have

$$L_t(x_t) = \max \{ J_t(x_t, a, o_t^a), J_t(x_t, b, o_t^b) \}.$$

For ease of notation, we suppress the rest of the state space x_t and the time subscript because these choices are made within one time period, and we denote this value function as $L(o^a, o^b)$.

Now consider the search decision. Let ζ denote the search decision, with $\zeta = 0$ being no search, $\zeta = 1$ being search in the opposite location, and $\zeta = 2$ being search in the current location (which is relevant only for unemployed households). Let $H_e(\zeta)$ and $H_u(\zeta)$ be the expected present values of employed and unemployed agents who choose search strategy ζ .

For an agent at location a , these search-specific value functions are

$$\begin{aligned}
H_e(0) &= L(1, 0) \\
H_e(1) &= \lambda_e L(1, 1) + (1 - \lambda_e) H_e(0) - c_e \\
H_u(0) &= L(0, 0) \\
H_u(1) &= \lambda_{u,1} L(0, 1) + (1 - \lambda_{u,1}) H_u(0) - c_{u,1} \\
H_u(2) &= \lambda_{u,2} L(1, 0) + (1 - \lambda_{u,2}) H_u(0) - c_{u,2},
\end{aligned}$$

where again we have suppressed the dependence on the state variables (j, s, m, n) . These functions are analogously defined for agents in location b .

Finally, let $K(j, k)$ be the expected present value of an agent in location j who works in occupation k . These occupation-specific value functions are

$$K(j, k) = \begin{cases} p_k^j \psi e^{s^j} + (1 - \delta) \max_{q \leq 1} H_e(q) + \delta \max_q H_u(q) & \text{if employed } (k \in \{A, B\}) \\ q + \max_q H_u(q) & \text{if unemployed } (k = u). \end{cases}$$

The beginning-of-period value function V can thus be written as

$$V_t(j_t, i_t, s_t, m_t, n_t^a) = \begin{cases} \max_k K(k, j_t, i_t, s_t, m_t, n_t^a) & \text{if } i_t = 1 \\ K(u, j_t, i_t, s_t, m_t, n_t^a) & \text{if } i_t = 0, \end{cases}$$

where the second line reflects the fact that if $i_t = 0$, the individual is unemployed and so $k_t = u$.

D. Incentives to migrate

Why might an individual in this model decide to migrate? First, consider a shock to skills in one or both occupations. When $\theta > 1$, so that each location has a comparative advantage in one of the two occupations, a shock to an individual's relative abilities in the two occupations changes his relative earnings potential in the two locations. If θ is large enough that the effect on earnings dominates any difference in the locations' perceived amenity values, this shock to the worker's skills will lead him to migrate. Second, consider a low realization of non-labor market utility u_t . Such a realization causes an individual to revise downward his

beliefs about his underlying preference for the current location, and hence to revise upward his beliefs about his relative preference for living in the other location. If this change in beliefs is big enough to overcome any difference in potential earnings across the two locations, then the individual will choose to migrate. The likelihood of such a move depends on both the tightness of individuals' prior beliefs about their preferences for each location τ_0 and the information content of the signals that they obtain through living in a location, τ_ϵ .

The two reasons for migration just described can be considered the fundamental reasons for moving in the model, since it is the exogenous shocks to either skills or beliefs that change individuals' relative desire to live in the two locations. However, because of the frictional labor market, the proximate cause of migration may differ from the fundamental cause. Consider an individual who desires to migrate because he has received a series of bad draws for his amenity-related utility in the current location. Knowing that he desires to live in the other location, this individual will search for a job there, yet may move only once he finds a job. The proximate reason for this individual's migration is the outcome of search — a job offer in the remote location. Hence, if asked in a survey about his reason for migrating, he may well answer that it was to take a new job. However, the fundamental reason for migrating was actually the shock to his beliefs about his non-labor market preferences.

Finally, the model generates one additional type of migration, which we refer to as *experimentation*. Consider a worker in location a who believes that he prefers the amenities in a (i.e., $m_t^a > m_t^b$) but is quite uncertain about his beliefs regarding location b (i.e., has a small precision τ_t^b). This worker may migrate to location b , even though in expectation the amenities there are worse, simply because the information gained from the move is valuable. However, a move made for reasons of experimentation may lead to return migration if, once the worker learns more about b , he becomes relatively certain that he prefers location a . Increases in initial information will reduce both the initial experimental moves and the subsequent return migration.

5. Quantifying our proposed mechanisms' effect on migration

Earlier, we showed *qualitatively* that our proposed explanations for the secular decline of gross interstate migration fit the facts, whereas many other theories do not. This section shows that our explanations succeed *quantitatively*: Given the size of the observed fall in the geographic specificity of returns to skills, and for plausible improvements in information, the

decline in migration that our model predicts is consistent with what has been observed in the data.

Our quantitative exercise compares steady states of the model under different parameter values. We start by fitting the model to cross-sectional data from the period 1991–’97.¹⁵ Our parameterized model for this period closely fits the salient features of the migration and labor market data. We then reduce the geographic concentration of returns to skills and increase the available amount of information, compute the model’s new steady state, and compare it with data from 2005–’11.

We emphasize that the purpose of the quantitative analysis is not to attempt a full structural estimation of a life cycle model of migration, occupation choice, and labor market flows, as in, for example, Kennan and Walker (2011). Rather, our goal is to provide some confidence that the two mechanisms we propose as the source of the decline in migration not only are qualitatively consistent with the evidence, but also generate the right quantitative drop in migration rates.

A key element in our quantitative exercise is the size of the change in our two proposed mechanisms that we feed into the model. For the decline in the geographic specificity of skill prices, we can measure the change directly because there is a one-to-one mapping between the wage premium for working in a matched location-occupation in the model, θ_t , and the measured state-occupation interaction in earnings regressions, $\sigma_{\xi,t}^2$.¹⁶ We measure θ in the same years as the other data; thus, our comparison of steady states assumes that the economy will quickly converge to a new steady state after a change in θ . The online appendix analyzes transition dynamics in our model and shows that, under reasonable assumptions, convergence is indeed rapid. In addition, our results are not particularly sensitive to this assumption because, if convergence were slow, the solution would be to calibrate the model to lagged changes in θ , such as the change from 1970 to 1990, that are similar in magnitude to the contemporaneous changes.

For the increase in information, there is no direct analogue in the data. The increase in information that our mechanism emphasizes is an increase in the precision of initial beliefs

¹⁵We choose 1991–’97, rather than just 1991, as our initial condition because pooling several years of data gives us sharper estimates of the empirical moments that we want our model to match.

¹⁶If we ran the earnings regressions from section 3A in simulated data from the model and included skills as one of the controls, we would obtain $\sigma_{\xi,t}^2 = (\theta_t - 1)^2/4$. Thus, $\theta_t = 1 + 2\sigma_{\xi,t}$.

about local amenities, τ_0 , because this precision reflects what individuals know about a place without living there. It is difficult to say exactly how much the technological changes we described earlier have increased this precision. However, we think it is unlikely that technologies such as the Internet and low-cost travel could give people more information than what they could learn by actually living in a location. Therefore, it is natural to measure the improvement in information as a fraction of the precision of the annual signals, τ_ϵ . We experiment with improvements in initial information that are equivalent to a range of fractions of τ_ϵ . If we had a precise estimate of the change over time in the return or repeat migration rate, we could use this estimate to discipline the increase in information. However, as Figure 9 shows, we cannot estimate this rate precisely even in the largest available suitable dataset. Although we do not directly target the change in return or repeat migration, we do show later that our model generates a decline in repeat migration that is consistent with the empirical evidence.

Our quantitative analysis features an important asymmetry: We change the geographic dispersion of returns to skills but not the geographic dispersion of the value of amenities. We make this choice because a decrease in the geographic dispersion of amenity values would not fit the data. In particular, the model predicts that job-related moves will rise when amenity values become more similar, but in the data, job-related moves fell.

In section 3, we showed that the age profile of migration is very different for college-educated and non-college-educated workers. We therefore perform all of the quantitative analysis separately for these two education groups. We do not have a theory of how well people are matched with their initial locations, so we drop from our simulations the first model period — when many agents move because of initial conditions — and match the age profile starting with migration between the second and third model periods.

A. Initial steady state: 1991–1997

Parameterization

The model period is annual.¹⁷ We fix the annual discount factor, β , at 0.96 and the arrival probability of a job offer, λ , at 0.5. Given our available data, these parameters are

¹⁷We solve the model with a horizon of $T = 40$ years. When calibrating the model, we target moments for the first 37 model periods for the non-college sample (corresponding to ages 19 to 55), and for the first 33 model periods for the college sample (corresponding to ages 23 to 55).

Table 4: Calibrated parameters

Parameter	Description	Non-college	College
q	value of nonemployment ^a	2.10	0.40
δ	separation rate	0.088	0.131
ρ	skills process: autoregressive coefficient	0.923	0.885
σ_0^2	skills process: initial variance	0.024	0.007
σ_η^2	skills process: innovation variance	0.154	0.143
κ	moving cost	0.53	0.22
τ_0	amenities: precision of initial prior beliefs	10.2	11.4
τ_ϵ	amenities: precision of preference shocks	6.8	61.0

^aAs multiple of average earnings conditional on working in the first model period.

difficult to separately identify from the remaining model parameters and have little impact on our ultimate findings.¹⁸ Also, we set the dispersion in amenity values across locations, $\frac{1}{\tau_v}$, equal to 1. This choice is essentially a normalization. Migration decisions are determined by beliefs about amenity values, not by the true values, so the dispersion of true values influences decisions only by influencing the dispersion of beliefs.

The wage premium for working in a matched location-occupation, θ , is set to 1.15, consistent with the average measured state-occupation interaction in earnings in the CPS from 1991 to 1997. This value implies that an identical worker earns 15 percent higher wages in the matched location-occupation than the unmatched one.

Ten parameters remain: the cost of moving, κ ; the parameters describing the learning process for amenity values (τ_0, τ_ϵ); the value of nonemployment, q ; the separation rate, δ ; and the parameters describing the stochastic process for skills (a quadratic in t for the deterministic component ψ_t , and an AR(1) process with initial variance σ_0^2 , innovation variance σ_η^2 , and autoregressive parameter ρ for the stochastic component s_t). We choose these parameters to match the age profiles of migration, employment, mean log earnings, and the variance of log earnings, as well as two scalar moments: the autocorrelation of log earnings and the average log earnings difference between migrants and non-migrants.¹⁹ Although we cannot formally

¹⁸In particular, the arrival probability of a job offer is difficult to separately identify from the value of nonemployment and the separation rate without data on flows in and out of employment. Since our focus is on understanding migration, not labor market flows, we fix λ exogenously.

¹⁹The earnings variable for the age profiles and the migrant–non-migrant earnings difference is usual weekly earnings. The CPS measures this variable at the time of the survey — that is, after any migration — in

Table 5: Scalar targeted moments

Moment	Non-college		College	
	Data	Model	Data	Model
Autocorrelation of log earnings	0.767	0.809	0.780	0.829
Migrant vs. non-migrant log earnings difference	-0.084	-0.076	0.012	0.006

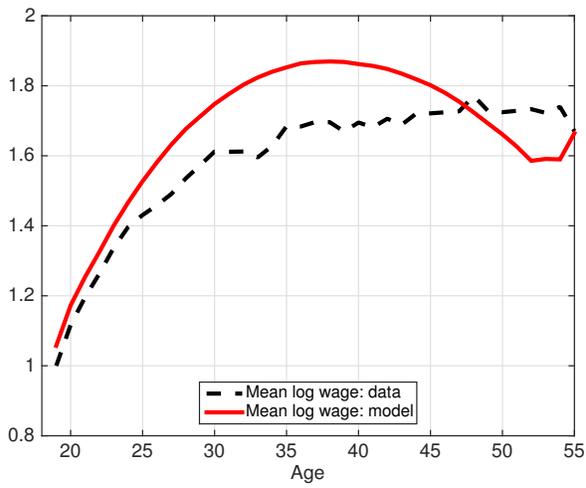
prove that these moments identify the parameters, later we provide an intuitive argument for why the parameters are identified, alongside our discussion of the model fit. Table 4 shows the calibrated parameter values.

Model fit

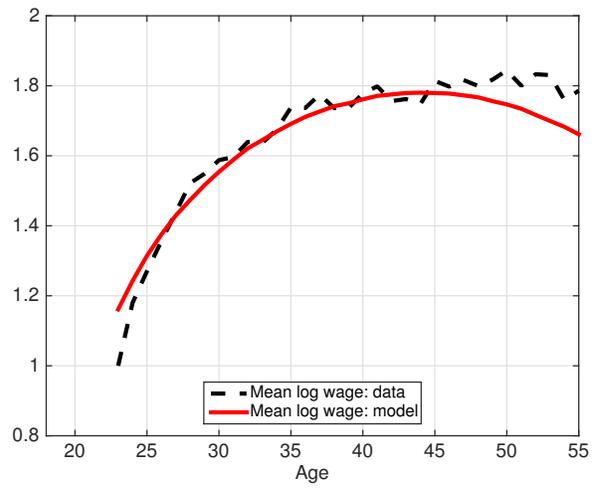
Figure 10 shows how the model fits the age profiles of labor market moments. The graphs in the left column of Figure 10 refer to the non-college sample, and those in the right column refer to the college sample. Figures 10(a) and 10(b) show the fit for mean log earnings conditional on working. Conditional on migration and occupation decisions, which affect mean earnings through the geographic specificity parameter, θ , the age profile of mean log earnings pins down the quadratic age profile for ψ_t . Earnings grow over the life cycle both because of this deterministic age component and because workers move toward locations that match their occupations as they age. (The fraction of workers in a matched location-occupation varies from 67 percent to 76 percent for the non-college group and from 69 percent to 79 percent for the college group.)

Figures 10(c) and 10(d) show the model fit for the variance of log earnings. Together with the autocorrelation of log earnings, this profile pins down the parameters that govern the stochastic process for skills $(\rho, \sigma_0^2, \sigma_\epsilon^2)$. The variance among the young determines the initial variance σ_0^2 . Conditional on ρ , the variance among the old determines the innovation variance σ_ϵ^2 , because with $\rho < 1$ the variance among the old will be that of the stationary distribution

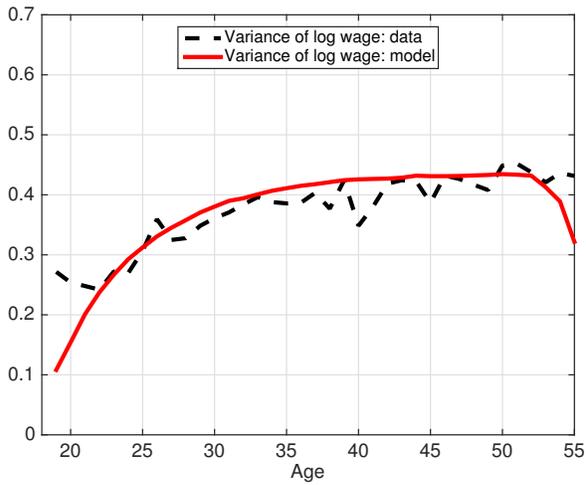
contrast to other income variables that are for the previous year and may include income before or after migration. We calculate the migrant–non-migrant earnings difference as the coefficient on a migration indicator in a regression of log earnings on the migration indicator and age indicators. For the autocorrelation of log earnings, we cannot use cross-sectional CPS data, so we turn to the Panel Study of Income Dynamics and calculate the autocorrelation of residuals from a regression of log labor income on experience, experience squared, and year indicators. (We make the PSID samples comparable to our CPS samples by including only people ages 23 to 55. We use PSID data for 1968 to 1997.) When we ask the model to match the earnings difference and autocorrelation, we run the same regressions in the model as in the data.



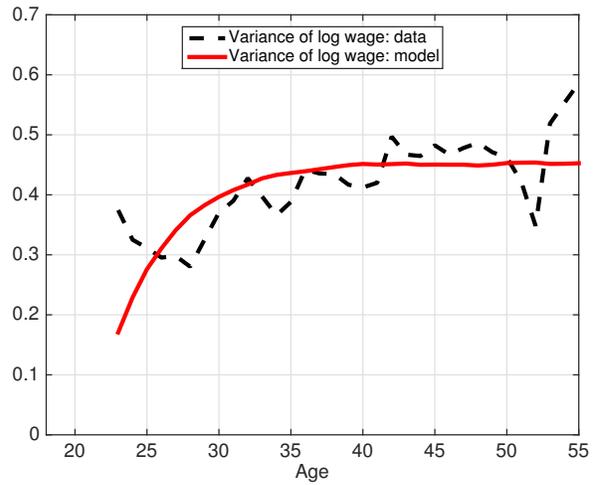
(a) Mean log wage, non-college sample



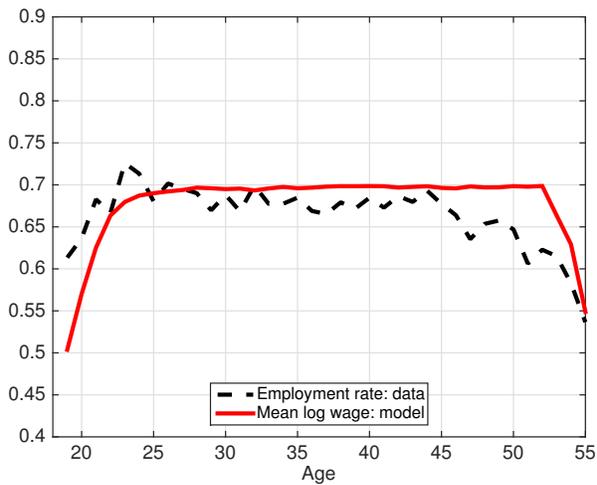
(b) Mean log wage, college sample



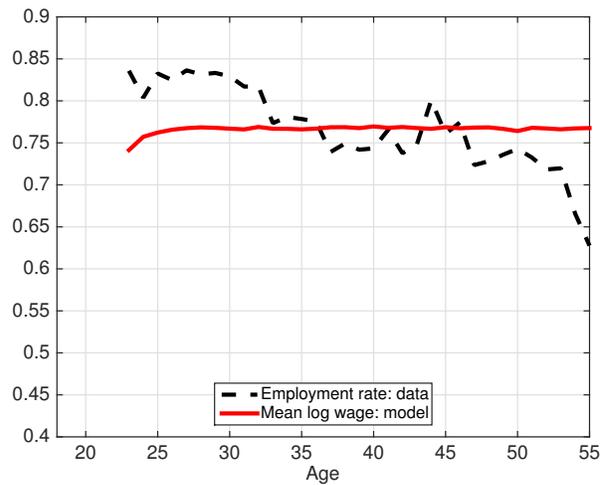
(c) Variance of log wage, non-college sample



(d) Variance of log wage, college sample



(e) Employment rate, non-college sample



(f) Employment rate, college sample

Figure 10: Model fit, labor market moments.

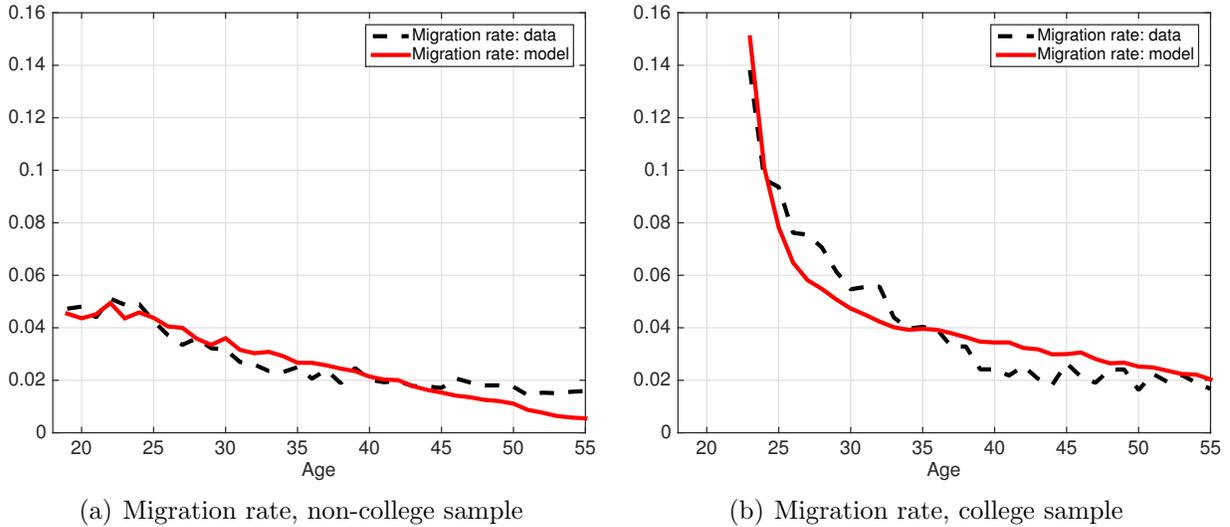


Figure 11: Model fit, migration.

of the stochastic process. Finally, the curvature of the age profile and the autocorrelation of earnings shown in Table 5 determine the autoregressive parameter, ρ . Of course, these parameters are determined jointly with all the other parameters of the model since, for example, more migration and high levels of θ also serve to increase the variance of log earnings.

Figures 10(e) and 10(f) show the fit for the employment rate. The average level of employment over the life cycle pins down the separation rate, δ , because this parameter determines the outflow from employment and hence the steady-state employment rate. The slope and curvature of this age profile pin down the value of nonemployment, q , given migration choices as well as the stochastic process for skills and the mean wage profile ψ_t . This is because the employment rate at a given age depends on where q falls in the distribution of potential earnings, which in turn depends on age through ψ_t .²⁰

Figure 11 shows the age profile of migration in the model. The model closely captures the overall level of migration as well as the way that migration varies with age for the two groups. Our calibrated model yields an average migration rate for the non-college sample of 2.60 percent, compared with 2.69 percent in the 1991–’97 data, and an average migration rate

²⁰Our model cannot match the decrease in employment with age for the college sample because the model does not include any of the mechanisms that could produce such a decline, such as marriage and child-rearing, differential taxation of secondary earners, and disability. We think it is unlikely that including these mechanisms would significantly change the model’s implications for migration.

for the college sample of 4.25 percent, compared with 4.16 percent in the 1991–’97 data.²¹ The age profile of migration can be thought of as encompassing three moments: the level of migration for the old, the level of migration for the young, and the curvature of migration between young and old ages. The stochastic process for skills and the location-occupation match premium θ together pin down the level of migration for the old, because old agents migrate primarily for labor-market-related reasons. (Old agents have largely completed the learning process and have little uncertainty about amenities. In addition, they have higher wages and thus respond more to the location-occupation premium.) Meanwhile, migration rates among the young depend primarily on τ_0 , which describes the tightness of individuals’ initial priors about the amenity value of each location. A tighter prior leads to lower migration for experimentation reasons in the first half of the working life. Finally, the speed with which individuals learn about their preferences, and thus the rate at which migration for experimentation reasons slows with age — the curvature of the age profile — is determined by the precision of the signals, τ_ϵ .

It may seem natural to conjecture that the age profile of migration should also pin down the cost of moving, κ . But while κ affects migration rates, other parameters can adjust to offset changes in κ . Instead, the moving cost in our model is primarily pinned down by the mean difference in log earnings between migrants and non-migrants, which we report in Table 5. Two components determine the size and sign of this difference. First, there is the average increase in earnings that an individual receives by moving, compared with the counterfactual earnings that individual would have if he did not move. Such wage gains arise primarily when individuals move to a matched location-occupation; thus, this component is determined by θ . In the model, this component is strongly positive and yields an earnings difference that is larger than in the data. Second, and offsetting these wage gains, the model generates negative selection into migration because the cost of moving is a time penalty; higher-wage workers pay higher moving costs when measured in units of income. Because the cost of migration rises with income, lower-income workers are more likely to move. This negative selection reduces the cross-sectional average earnings of migrants and increases the average earnings of non-migrants. The larger is κ , the more negative selection occurs. Hence, the moving cost is pinned down by the difference between the wage gains from moving that

²¹We compute these averages weighting all ages equally.

θ alone would imply and the observed earnings gap between migrants and non-migrants.

B. Implications for other features of the data

Before describing the effects of an increase in information and a decline in the geographic specificity of skills in the model, we briefly examine our model's implications for three important features of the data that were not directly targeted in the calibration procedure: return migration, migration rates over longer horizons, and occupational switching rates.

Return migration

We define the one-year repeat migration rate in the model as the fraction of time $t - 1$ migrants who were also migrants at time t . Since the model has only two locations, this is also the one-year return migration rate because it corresponds to the fraction of time $t - 1$ migrants who were living in the same location at time $t + 1$ as they were at time $t - 1$. The two-year and five-year migration rates are defined analogously, that is, as the fraction of time $t - 1$ migrants who were living in the same location at time $t + 2$ or $t + 5$, respectively.

The levels of return migration in the model are lower than those in the data but are not unreasonable. For the non-college group, the one-year return migration rate in the calibrated model is 1.1 percent, the two-year rate is 3.8 percent, and the five-year rate is 16.4 percent. For the college group, the one-year return migration rate in the calibrated model is 8.0 percent, the two-year rate is 15.2 percent, and the five-year rate is 30.4 percent. For the corresponding time period, the average one-year repeat migration rate in the SIPP (shown in Figure 9) was between 10 percent and 15 percent (the imprecision of the estimates makes it difficult to narrow the range), whereas the average one-year return migration rate was between 5 percent and 10 percent.

The most likely reason for the lower rates of repeat migration in the model as compared with the data is the lack of heterogeneity in moving costs κ . Without such heterogeneity, the model cannot reproduce a phenomenon that we think is likely to be important in the real world: Migrants are those with lower moving costs and thus are disproportionately likely to migrate again.

Long-run migration

Our calibration procedure targeted only one-year migration rates. How closely do measures of long-run migration in the model resemble corresponding measures in the data? The five-year migration rate in the model is 11.3 percent for the non-college group and 13.5 percent for the college group. Census data from 1990 and 2000 show average five-year migration rates of 8.6 percent and 7.8 percent, respectively, for the non-college group and 16.5 percent and 15.1 percent for the college group. Thus, the model somewhat overstates five-year migration rates for the non-college group and somewhat understates them for the college group.

An alternative measure of long-run migration is the fraction of individuals who ever migrate and the average number of lifetime moves that these individuals make. In the calibrated model, 76 percent of the non-college group ever migrate, for an average of 1.9 moves per individual, and 80 percent of the college group ever migrate, for an average of 2.4 moves per individual. It is not possible to construct corresponding statistics using available data. The closest measure is the fraction of individuals who currently live in a state other than their state of birth, which we can measure in the Census. In the 1990 Census, around one-third of the non-college group and around one-half of the college group were not living in their state of birth.

Occupational switching rates

In the calibrated model, the annual occupational switching rate conditional on being employed is approximately 6.9 percent for the non-college sample and 12.3 percent for the college sample. Although Kambourov and Manovskii (2008) empirically document a similar overall level for annual mobility between one-digit occupations, they report that workers with more education have lower occupational mobility, contrary to the results in our simulations. A likely explanation for the discrepancy is that our model does not feature occupation-specific human capital, which Kambourov and Manovskii (2008) argue reduces migration among highly educated workers. We think it is unlikely that introducing a complication such as occupation-specific human capital would have a meaningful impact on migration rates in our model. In both the data and the model, occupation switches tend to take place early in the life cycle, but migration among the young in the model is mostly driven by amenity preferences and experimentation, not by occupational switches.

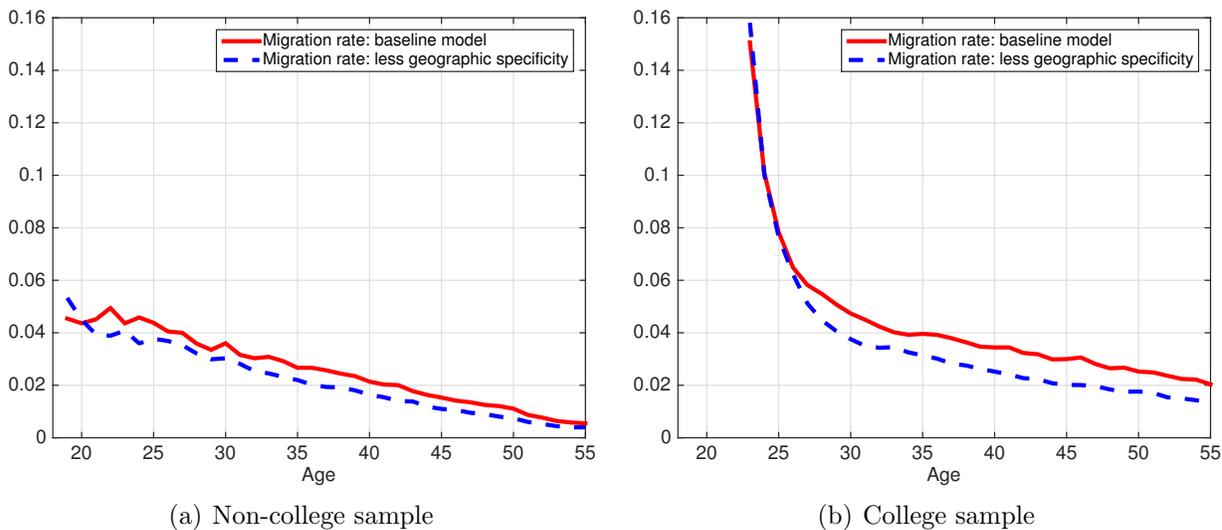


Figure 12: Effects of reduced geographic specificity on migration.

C. Change in gross migration

Decline in geographic specificity of returns to skills

We measure the effect on migration of the fall in geographic specificity of skills by changing θ from 1.15 to 1.10 — consistent with the average measured state-occupation interaction in earnings in 2005 to 2011 — but leaving all other parameters the same and simulating the model’s new steady state. Figures 12(a) and 12(b) show the results for the non-college and college samples, respectively. The solid red line in each figure shows the age profile of migration in the baseline model. The dashed blue line shows the age profile of migration in the model with a lower geographic specificity of returns to skills. On average over all ages, the decline in the geographic specificity of skills reduces the migration rate from 2.60 percent to 2.18 percent for the non-college sample and from 4.25 percent to 3.50 percent for the college sample. These changes are equivalent to 42 percent of the observed drop in migration for the non-college group and 51 percent of the observed drop for the college group from the 1991–’97 baseline to the 2005–’11 period. Thus, the increased similarity of returns to occupational skills across space can account for about half of the total observed decline in migration between 1991–’97 and 2005–’11.

Not surprisingly, the decline in the wage premium for working in a matched location-occupation has a larger effect for the college sample, and the resulting declines in migration are concentrated among older workers. (In fact, for the college sample, this mechanism has

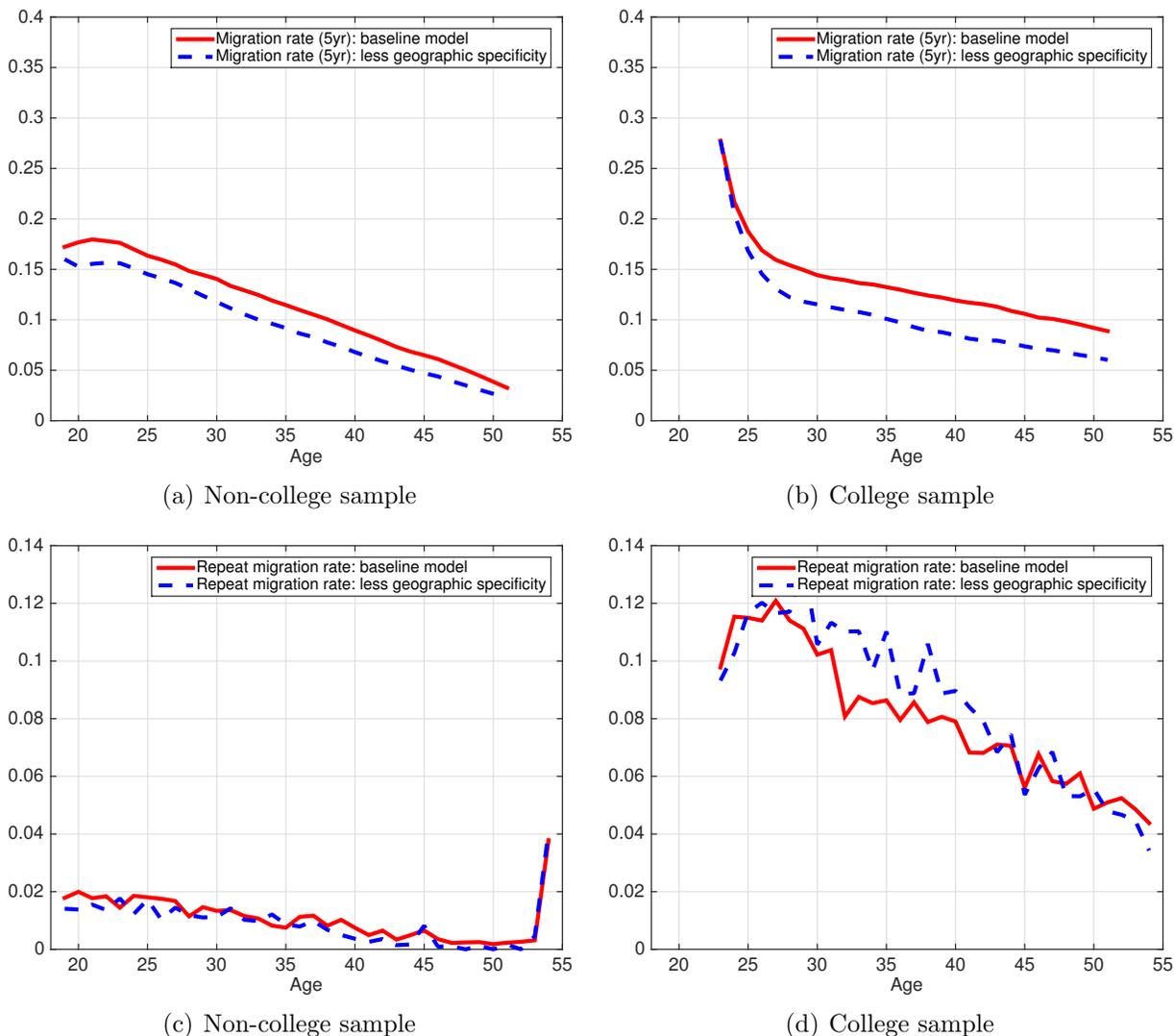


Figure 13: Effects of reduced geographic specificity on five-year migration and repeat migration.

essentially no impact on migration in the first five years in the labor market.) Higher-wage (i.e., older and college-educated) workers respond more to changes in θ because these workers have more to gain in absolute terms from a wage premium that generates a multiplicative increase in wages for being in a matched location-occupation. In addition, older workers have more incentive to move locations to be better matched to their particular skills because they are less likely to want to switch occupations before their careers end.

The increase in the geographic specificity of skills also leads to a fall in five-year migration. (See Figure 13, panels (a) and (b).) This reduction is around 17 percent for the

non-college sample and around 22 percent for the college sample. As reported in section 5B, the five-year migration rate declined by 8.4 percent in the non-college group and 8.8 percent in the college group over the 10 years from 1990 to 2000, suggesting that if five-year migration could have been measured in 2010, the decrease over 20 years would have been similar in magnitude to what the model produces. The increase in the specificity of skills, however, leads to essentially no change in the repeat migration rate. (See Figure 13, panels (c) and (d).)

In the quantitative exercise, we feed into the model an exogenous change in skill prices and allow agents' occupation and location decisions to respond endogenously. We can check whether our model features a quantitatively realistic endogenous response to the change in skill prices by comparing the implied change in the distribution of workers across space with the change observed in the data. In the baseline model, the Theil index of occupational segregation is 0.084 for the non-college group and 0.090 for the college group. In the experiment with lower geographic specificity θ , these indices fall to 0.056 and 0.064, respectively.²² The level of the Theil index of occupational segregation depends on the number of occupations. Hence, the level in the simulated model (with two occupations) is quite different from that in the data (where we consider many more occupations). To adjust for this difference in levels, we compare the percent change in the Theil index in the model and the data. In the model, the change in geographic specificity θ reduces the Theil index by 33 percent for the non-college sample and by 29 percent for the college sample. By comparison, Figure 7 shows that in the data, from 1990 to 2010, the Theil index for broad occupations fell by 30 percent and the index for detailed occupations fell by 23 percent. Since our calibration strategy did not target changes in the Theil index, this close mapping between data and model should be taken as evidence that our relatively simple model of migration and occupation decisions does a relatively good job of capturing workers' endogenous responses to changes in the geographic specificity of skills.

Increase in information

Figure 14 shows the decline in migration that the model generates when we give individuals more information about their preferences for living in different locations. The

²²Results are similar in the experiment shown later with more information as well as lower geographic specificity. Adding information alone slightly reduces the index.

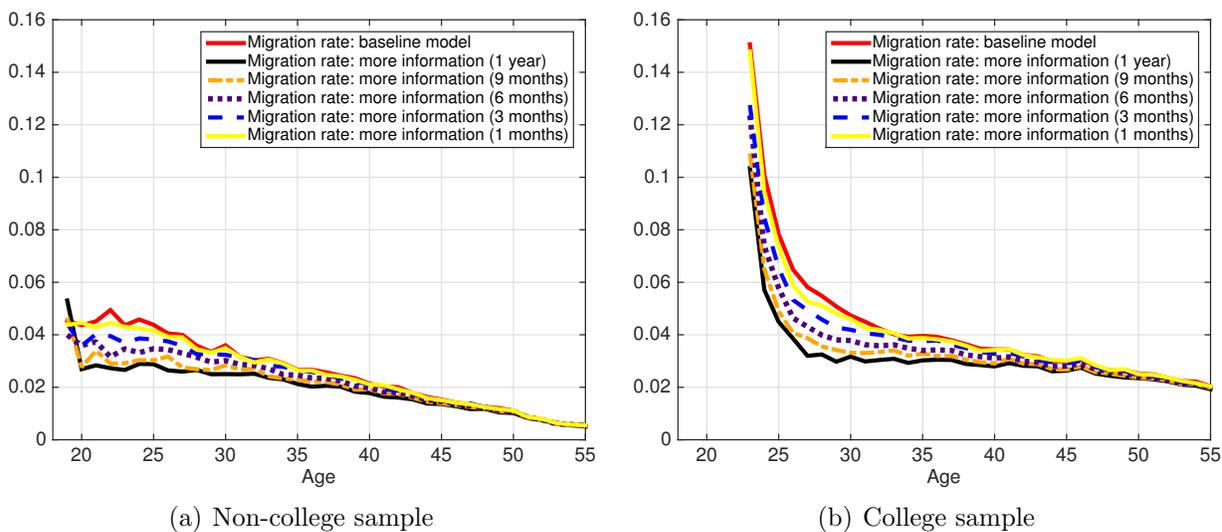


Figure 14: Effects of increased information on migration.

solid red line in each figure is the age profile of migration in the baseline model. The other four lines show the age profile of migration when individuals are better informed about their preferences. As discussed earlier, we model the information change as an increase in the initial precision of beliefs about preferences for amenities, τ_0 , and we set as an upper bound for this increase the improvement in precision that would be obtained by living in a location for one year, τ_ϵ . The figures also report the corresponding reductions in migration if we increase the amount of available information by smaller amounts — the amount of signals in one month, three months, six months, or nine months. The larger the increase in information that we feed into the model, the larger the decline in migration. For the non-college sample, the overall decline ranges from a 3 percent reduction for one month’s worth of information to a 24 percent reduction for one year’s worth of information. For the college sample, the overall decline ranges from a 3 percent reduction for three months’ worth of information to a 28 percent reduction for one year’s worth of information. Expressed as a fraction of the observed decline in migration, this mechanism generates between 7 percent and 63 percent of the decline in the data for the non-college sample, and between 8 percent and 76 percent for the college sample.

Increased availability of information mainly affects young workers. Figure 14 reveals that as retirement approaches, this mechanism has almost no impact on migration rates. This finding is intuitive: By the time individuals reach the second half of their working lives,

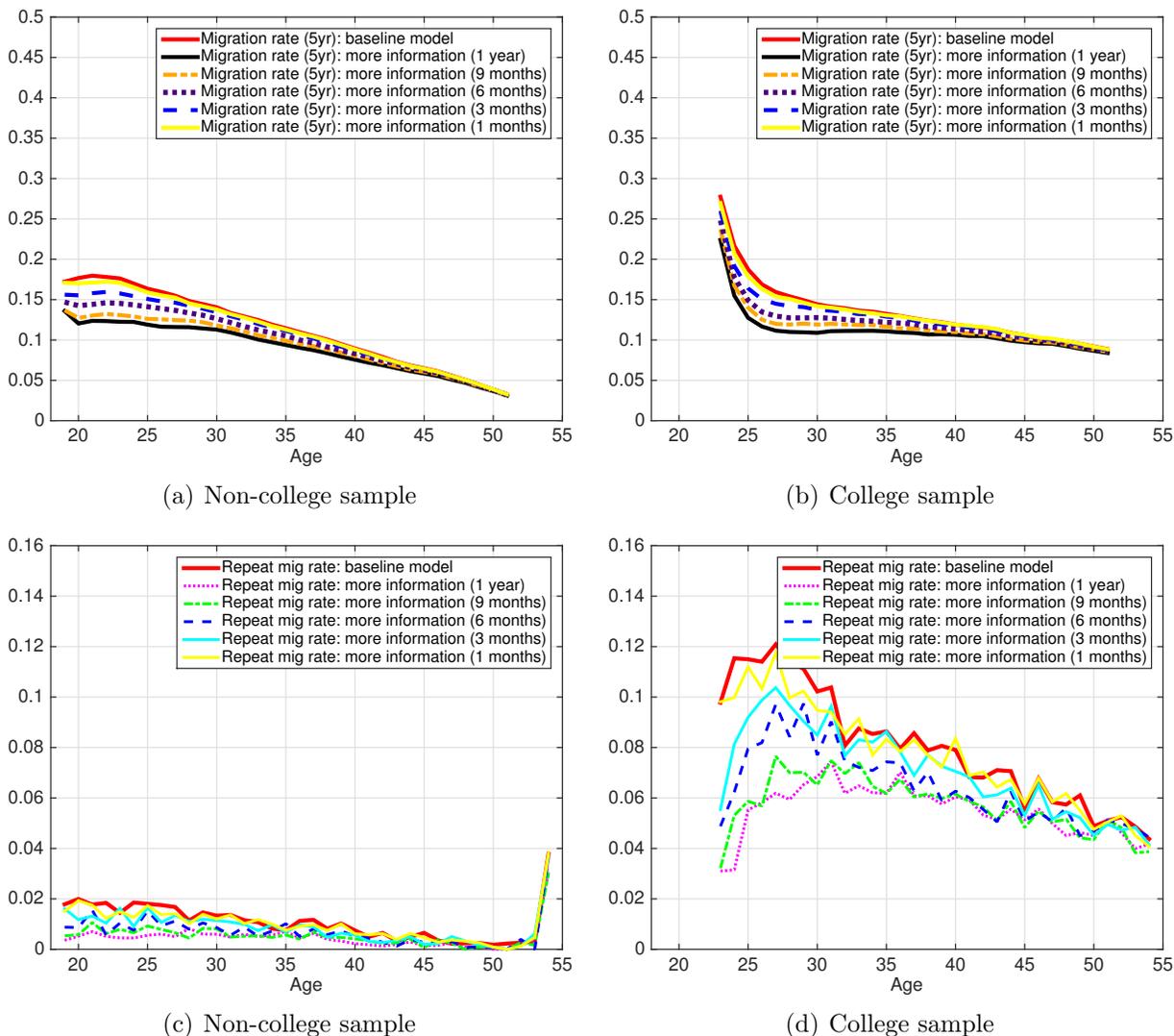


Figure 15: Effects of increased information on five-year migration and repeat migration.

most of the initial uncertainty about their preferences has been resolved, so changes in the precision of initial beliefs have little effect on migration rates at older ages.

We can check whether the informational changes we feed into the model are reasonable by examining their effect on the repeat migration rate. (In the model, repeat and return migration are identical because there are only two locations, so we compare repeat migration in the model with repeat migration in the data.) In the baseline model, the one-year repeat migration rate is 1.1 percent for the non-college group and 8.0 percent for the college group. These rates fall to 0.7 percent and 6.5 percent, respectively, in the experiment with six additional months of information. This result is in marked contrast to the experiment where

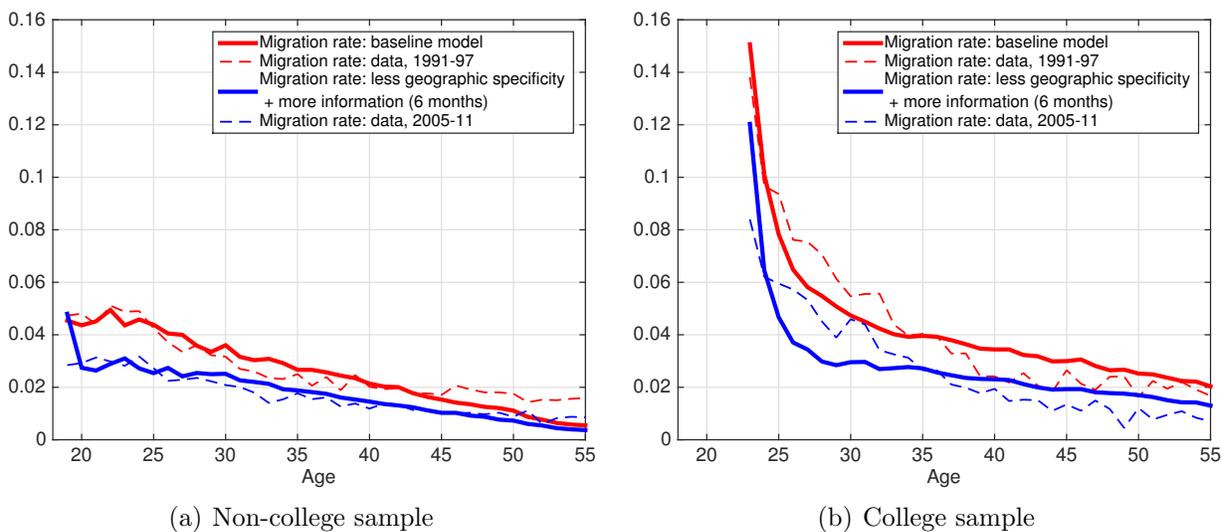


Figure 16: Combined effects of geographic specificity and information on migration.

we change θ . The changes are proportionately larger or smaller when we add more or less information. (See Figure 15.) Adding six months of information reduces repeat migration by a factor of about one-fourth in the model, a change that is broadly consistent with the observed decline in Figure 9.

Combined effect of the two mechanisms

The previous two experiments showed that a reduction in the geographic specificity of returns to skills is quantitatively consistent with the observed decline in migration at older ages, whereas an increase in the availability of information is quantitatively consistent with the observed decline in migration at younger ages. Since the data show that migration has declined at all ages, it is natural to conjecture that the combined effect of our two proposed mechanisms can quantitatively account for the overall observed reduction in migration. Figure 16 shows the results of an experiment in which we increase information by the equivalent of six months' worth of signals and reduce the wage premium for being in a matched location-occupation by the amount observed in the data. As shown in Table 6, the model generates an overall reduction in migration of 0.83 percentage point for the non-college sample, which is equivalent to 83 percent of the corresponding decline in the data, and a reduction of 1.47 percentage points for the college sample, which is equivalent to 101 percent of the corresponding decline in the data. Smaller increases in information would reduce the migration

Table 6: Average migration rates in the data and the model.

	Non-college	College
Data, 1991–'97	2.69%	4.16%
Model, baseline	2.60%	4.25%
Model, less geographic specificity*	2.18%	3.50%
Model, +6 months' information [†]	2.23%	3.60%
Model, +3 months' information [‡]	2.40%	3.88%
Model, +1 months information*	2.53%	4.13%
Model, both mechanisms (6 months)*, [†]	1.77%	2.77%
Model, both mechanisms (3 months)*, [‡]	1.97%	3.11%
Model, both mechanisms (1 month)*,*	2.10%	3.37%
Data, 2005–'11	1.69%	2.69%

*Reduce θ from 1.15 to 1.10. [†]Increase τ_0 by $\tau_\epsilon/2$. [‡]Increase τ_0 by $\tau_\epsilon/4$. *Increase τ_0 by $\tau_\epsilon/12$.

rate by smaller amounts. Since we are somewhat agnostic on the actual size of the increase in information that took place over the period from 1991 to 2011, and since this change is not well disciplined by available data, we conclude that our combined mechanisms can account for at least one-half of the observed reduction in gross interstate migration in the United States.

6. Conclusion

We argue that interstate migration is falling in the United States because of a combination of two factors: a reduction in the geographic specificity of returns to different types of skills and an increase in workers' information about how much they will enjoy living in alternative locations. Micro data reject numerous alternative explanations but do support our two hypotheses. We build a model of migration that makes these hypotheses precise. In the model, workers choose locations on the basis of both income and local amenities, search for jobs both locally and remotely, and learn about the amenities in different locations. The calibrated model provides a good fit to the data and shows that our mechanisms can account for at least one-half of the decline in interstate migration over the past two decades.

Our empirical analysis reveals a novel fact about U.S. labor markets: Returns to occupations have become less geographically specific over time. Although our analysis takes

this change as exogenous and studies its implications for migration, looking into the causes of the decrease in geographic specificity would be a valuable subject for future research. For example, is this decrease related to a change in the nature or magnitude of agglomeration effects, a change in local economic policies, a change in either interstate or international trade costs, or some other factor? Understanding these causes is important for determining what policies, if any, are appropriate in response to the decline in migration. It would also be valuable to know whether similar changes in the geography of work have happened in other parts of the world, and if so, what the effect on migration has been.

The decline in interstate migration is not the only recent change in gross worker flows in the United States: Davis, Faberman, and Haltiwanger (2012) show that job creation and destruction rates have also fallen in the past two decades, and Kambourov and Manovskii (2008) show that occupational and industry mobility increased between 1968 and 1997. Because job-to-job flows and occupational and industry changes are much more common than long-distance migration, we did not ask our model to explain these phenomena, although they may well be related, as Molloy, Smith, and Wozniak (2014) suggest. Future research could examine whether there is a connection between changes in interstate migration and changes in other gross flows, and if so, whether that connection helps explain the fraction of the migration decrease that our mechanisms leave unexplained.

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