

The Impact of State Borders on Mobility and Regional Labor Market Adjustments*

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Abstract

I document a new empirical pattern of internal migration in the US. Namely, that county-to-county migration drops off discretely at state borders. People are three times as likely to move to a county 15 miles away, but in the same state, than to move to an equally distant county in a different state. This gap remains even among neighboring counties, or counties in the same commuting zone. This pattern is not explained by differences in county characteristics, is not driven by any particular demographic group, and is not explained by pecuniary costs such as differences in state occupational licensing, taxes, or transfer program generosity. However, I find that county-to-county commuting follows a similar pattern as does social connectedness (as measured by the number of Facebook linkages). Although the patterns in social networks would be consistent with information frictions, non-pecuniary psychic costs, or behavioral biases, such as a state identity or home bias, the data suggest that state identity and home bias play an out-sized role. This empirical pattern has real economic impacts. Building on existing methods, I show that employment in border counties adjusts more slowly after local economic shocks relative to interior counties. These counties also exhibit less in-migration, suggesting the lack of migration leads to slower labor market adjustment.

Keywords: Internal Migration, Commuting, Social Networks, Border Discontinuities

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1 Introduction

Across the country, there is significant heterogeneity in local economic conditions. Seventy percent of counties are within 60 miles of another county with average wages that are at least 20 percent higher and 75 percent of counties are within 60 miles of another county with average house prices at least 20 percent lower. Almost 30 percent of counties are within 60 miles of another county with both 20 percent higher wages and 20 percent lower house prices (see Table 1). For a majority of counties, these employment or housing “opportunities” are in a different, but close, commuting zone. Although there might be other local characteristics that offset these raw differences in equilibrium, it seems plausible many individuals could encounter better opportunities by moving a short distance.

The United States has traditionally been seen as a highly mobile country, with 18-20 percent of people changing their county of residence in a five year period. Even with the steady decline in internal migration over the last 40 years, the United States still exhibits higher internal mobility than most European countries (Molloy et al., 2011). Migration is traditionally seen as an opportunity for individuals to encounter better labor market opportunities and a mechanism through which local labor markets adjust to both positive and negative shocks (Blanchard and Katz, 1992). It is an important component of labor market fluidity that contributes to economic dynamism (Molloy et al., 2016). Frictions that reduce or limit internal migration could lead to less dynamic local economies.

Theoretical models predict that people will move then the utility gain associated with a move exceeds the cost of moving. Consistent with these predictions, migration rates tend to fall with distance, as moving costs increases and places become more dissimilar. However, I document a previously undocumented aspect of US internal migration that potentially limits labor market fluidity. Using the Internal Revenue Service (IRS) migration data, I show that even conditional on distance, county-to-county migration flows drop significantly when there is a state border between the two counties. People are three times as likely to move to a

different county in the same state, than an equally distant county in a different state. In this paper, I document the extent of this empirical pattern, explore potential explanations for why this cross-border drop in migration exists, and evaluate how this empirical migration friction impacts the way local labor markets adjust to cyclical economic shocks.

The canonical migration choice model suggests a discontinuous drop in migration rates at state borders could be due to either differences in location specific characteristics and utility, or differences in moving costs. The gap in migration rates associated with state borders does not appear to be driven by differences in local characteristics or utility. The cross-border migration gap does not close if I control for origin and destination fixed effects or even if I control for differences between the origin and destination in labor markets characteristics, industry composition, demographic composition, natural amenities, political leaning, or home values. Furthermore this gap persists when I focus on counties that we would traditionally think of being more inter-connected or similar, such as counties in the same Metropolitan Area (MSA) or Commuting Zone (CZ) or even neighboring counties.

Differential changes in pecuniary costs at state borders from state-level regulation, such as differences in occupational licensing, state income taxation, or state transfer policy also do not explain the gap. In fact, a similar discontinuity is present when examining county-to-county commute flows, suggesting the discontinuity is not driven by pecuniary adjustment costs associated with moving from one state to another (e.g., updating vehicle registration or drivers' licenses). In American Community Survey (ACS) microdata, the share of migrants that cross state borders do not statistically differ across most demographic groups (e.i., age, race/ethnicity, gender, employment, or family structure) suggesting differences in the preferences or costs across these groups do not explain the pattern. There are, however, distinct differences based on whether or not the individual was initially residing in their birth state. Conditional on moving in the last year, migrants originally living in their birth state are about 30 percent more likely to move to a different county in the state, but over 60 percent less likely to move out of state than individuals originally living away from their

birth state.

Consistent with origin ties playing a role, I find a similar geographic discontinuity in Facebook friendship rates across state borders, as captured by the social connectedness index (Bailey et al., 2018). On average, people have twice as many Facebook friends in a same-state county 15 miles away than in a cross-border county 15 miles away. When I control for the origin-destination Facebook network, the decrease in migration associated with state borders falls by 86 percent, suggesting that most of the migration discontinuity is empirically explained by social network strength or something correlated with the social network.

Causality potentially run in both direction; a lack of friends and acquaintances could limit cross-border migration, but a drop in migration at the state border (for any reason) could limit the number of cross-border friendships. Regardless of the direction of causality, people are less socially connected to people just across state borders. This empirical relationship between cross-border commuting and network strength is consistent with three augmentations of the simple migration model. First, weaker social networks across state lines could impose additional non-pecuniary, psychic costs associated with moving (such as leaving personal ties to community, friends, and family). Existing work supports this notion that local ties (Zabek, 2020) and non-monetary costs (Kosar et al., 2020) keep people rooted. Second, weaker social networks across the border could also lead to more information frictions, leaving individuals less informed about the potential costs and benefits of moving across state lines. In particular settings, access to information about local conditions affect migration flows (Kaplan and Schulhofer-Wohl, 2017; McCauley, 2019; Wilson, 2020). Finally, discontinuous drops in social ties across the state border could also arise if behavioral biases, such as home-bias or state identity, keep people from moving or making social connections across state lines. A strong state identity could affect migration, regardless of the presence of local ties.

Both non-pecuniary costs and information friction explanations would imply that state

borders reduce migration flows because their placement is correlated with people’s network borders. Based on analysis by Bailey et al. (2018), I construct contiguous, connected communities based on the strength of county-to-county friendship links. Although these connected community borders often approximate state borders, there are places where the state borders and network borders deviate. In a horse race regression allowing both the actual state border and the pseudo network border to have separate impacts, most of the effect loads on the actual state borders, explaining 3-6 times as much as the pseudo network borders. This would suggest that the non-pecuniary cost of abandoning personal ties and information frictions do not drive the drop in migration precisely at state borders.

Analysis of Pew Research Center data on mobility (Pew Research Center, 2009), suggest as much as 68 percent of people “identify” with their birth state, meaning birth state identity could play a significant role. In fact, among survey participants, exhibiting a birth state identity reduces the likelihood of ever leaving one’s birth state by 35.3 percentage points (or nearly 64 percent) and people with a birth state identity are 28.1 percentage points (80 percent) more likely to say they would prefer to live in their state of birth than any other state. When asked about opinions towards moving, people with birth state identity are no less likely to consider a move overall, but people with birth state identity that currently reside in their birth state are significantly less likely to consider a move. This would be consistent with birth state identity keeping people from considering moves across state borders. Importantly, these patterns persist even when controlling for individuals’ personal ties to an area (through friends, family, and community involvement) suggesting birth state identity is a factor independent of other local ties.

Regardless of the mechanism behind the empirical pattern, this feature of US internal migration affects the dynamic adjustment of labor markets to local shocks. Following existing methods exploring the persistence and recovery from the Great Recession (Hershbein and Stuart, 2020), I show that counties on a state border, where migration to and from neighboring counties is lower, see slower recoveries in employment. Ten years after the ini-

tial cyclical shock, employment measures in border counties have recovered approximately 50 percent less than other counties in the same state. Border counties also see significantly less in-migration after the recession, leading to persistently worse labor market outcomes. This difference in recovery is similar in size to the penalty that states along the national border experienced. This suggests that state border lead to differences in local labor market dynamism and impact the ability of labor markets adjust to local cyclical shocks. Cross-state labor markets appear to be less connected than we might a priori expect, potentially contributing to the persistent geographic heterogeneity in labor market conditions observed across the United States.

The most closely related work is new evidence that local ties and non-money moving costs significantly impact migration behavior (Kosar et al., 2020; Zabek, 2020). Using a spatial equilibrium framework, Zabek (2020) finds that local ties tend to keep people near their birth place, leading to muted migration responses to local economic shocks. In this work “local ties” is a conceptual term, meant to capture that people tend to live near their birthplace for unexplained reasons, with less evidence of what creates the local tie. As I document, people not only tend to stay near their birthplace, but they are significantly less likely to leave their birth state, even if they live close to the state border. Although local ties could reflect the psychic cost of leaving friends and family, the analysis here suggests that this is not what drives hesitancy to cross state borders. Rather, state borders seem to have a separate effect, potentially driven by home bias or state identity. This identity appears to have a distinct effect from family and other personal ties. Kosar et al. (2020) used stated-preference survey methods to document how various costs, including non-money costs, affect people’s preferences about migration. They find that non-money moving costs are large, especially for individuals who self-identify as “rooted” to their location. These empirical patterns are consistent with state identity affecting migration flows across state borders and suggest that state borders impose large frictions that keep labor markets from quickly adjusting to mitigate economic shocks.

2 Data to Document US Internal Migration

Unlike many other developed countries, the United States does not maintain administrative residential histories. To document patterns of internal migration and related trends, I use several sources, which I briefly outline here, with full detail in the data appendix. Most of my analysis relies on the annual IRS Statistics of Income (SOI) county-to-county migration flows. This data is constructed by tracking the number of tax units and tax exemptions (to proxy for households and people) that change their individual tax return form 1040 filing county from one filing year to the next. I divide the number of exemptions by the county population (in thousands) to measure the number of migrants per 1,000 people.

Because the IRS data does not provide migration flows for subpopulations, I supplement this data with migration microdata from the annual American Community Survey (ACS). The ACS is approximately a one percent sample of households in the US and documents individual and household measures ranging from household structure and demographics to employment and place of residency in the previous year. I use the ACS microdata to examine migration differences across individual characteristics, like demographics, occupation, and estimated income tax burden. I use microdata from the 2012-2017 waves.¹ I also exploit individual-level data from a Pew Research Center survey on mobility (Pew Research Center, 2009). This sample includes about 2,000 individuals across the country who were asked about where they were born, where they live, whether they have moved, why they have or have not moved, whether they would move, and what place they identify with.

I also explore commuting mobility using county-to-county commute flows constructed from the LEHD Origin Destination Employment Statistics (LODES), which link where workers live and work, meaning annual cross-county and cross-state commute flows can be constructed. To understand the impact of state borders on social networks I use the Social Connectedness Index (SCI) which maps county-to-county Facebook friendship networks

¹I do not use data from earlier years, because the smallest geographic measure, public use micro-areas (PUMA) definitions were updated in 2012.

Bailey et al. (2018). This data takes a snapshot of active Facebook users in 2016 and reports the number of Facebook friends in each county pair, scaled by an unobserved scalar multiple to maintain privacy. I supplement this data with annual Surveillance, Epidemiology, and End Result (SEER) county population counts and state policy data from various sources. Each of these sources are documented in full in the data appendix.

3 The Empirical Pattern

3.1 Relationship between State Borders and County-to-County Migration

Even in the raw IRS migration data there are distinct patterns in county-to-county migration by both distance and state borders. For all county pairs in the contiguous US with population centroids 15-60 miles apart, I plot the average number of migrants per 1,000 people in 2017 in one mile bins for counties in the same state, and counties in different states in Figure 1. I focus on these “close” county pairs because there is sufficient coverage of both within-state and cross-state pairs.² For both series migration rates fall as distance increases. However, at the same distance migration rates to same-state counties are approximately three times as high as migration rates to cross-state counties.

Throughout the analysis to more easily test the significance of the discontinuity and evaluate the mediating impact of various measures, I parameterize the above relationship as follows

$$\text{Mig. Rate}_{od} = \sum_{b=15}^{59} \beta_b(\text{Diff. State} * b \text{ Miles Apart}) + \gamma_b(b \text{ Miles Apart}) + \varepsilon_{od} \quad (1)$$

The outcome is the origin destination specific number of migrants per 1,000 people at the origin, and the explanatory variables are the interactions between an indicator for whether

²There are no cross-border county pairs that have population centroids less than 6 miles apart. I restrict to county pairs at least 15 miles apart to avoid comparisons with few observations. I also limit to counties 60 miles or less apart to avoid a compositional shift from typical sized counties to large states and counties in the West. The pattern is similar if I include county pairs that are closer or further away (Appendix Figure A1).

the counties are in different states and a vector of one mile distance bins. The 60 mile bin is omitted as the reference group. Average migration rates among counties 60 miles apart are quite low, with only about one migrant per 10,000 people. The γ_b coefficients trace out the migration rates for counties in the same state, while the β_b coefficients indicate how much lower the migration flows are for counties that are in the same distance bin, but in a different state. Standard errors are corrected for clustering at the origin county level. Throughout, I present the coefficients in figure form, with the γ_b coefficients and the total effect for counties in different states ($\beta_b + \gamma_b$) plotted with 95 percent confidence intervals. I use the final year of IRS migration data, 2017, so there is only one observation per origin/destination pair. As I show in the appendix, the state-border discontinuity is similar through all the years of data since 1992 (see Appendix Figure A2).

This flexible parameterization does not impose strong assumptions on the way distance impacts migration rates, but it also does not provide a concise estimate of how state borders reduce migration. To distill the impact of state borders on migration rates into a single parameter, I will estimate the area under the curve for cross-state county pairs relative to the area under the curve for within state county pairs using Riemann integration across the one mile distance bins. From the baseline estimates in Figure 1, state borders reduce migration rates by 72 percent for county pairs between 15 and 60 miles apart. This gap is significant, with 95 percent confidence intervals of 68 and 76 percent.

3.2 Sensitivity of Pattern to Controls and Samples

Counties across the country differ on many dimensions, potentially explaining the cross-border difference in migration. To test the sensitivity of the state-border discontinuity I adjust equation (1) to include origin fixed effects to control for characteristics of the origin, destination fixed effects to control for characteristics of the destination, and observable origin/destination pair specific differences in local labor market, population, and housing

market measures to control for pairwise differences as follows

$$\text{Mig. Rate}_{od} = \sum_{b=15}^{59} \beta_b(\text{Diff. State} * b \text{ Miles Apart}) + \gamma_b(b \text{ Miles Apart}) + X'_{od}\Gamma + \phi_o + \delta_d + \varepsilon_{od} \tag{2}$$

The X_{od} vector includes differences in origin and destination labor markets (unemployment rates, employment to population ratios, average weekly wages, and industry shares); differences in the population, as well as the gender, racial, ethnic, and age composition of the origin and destination; differences in natural amenities such as the average temperature in January and July, average sunlight in January, average humidity in July, and USDA natural amenity score; differences in the 2016 presidential Republican vote share; and differences in average home values. As seen in Figure 1, controlling for demographic, economic, and housing market differences between the origin and destination does not close the gap. State borders are associated with a 67 percent reduction in migration rates.

In equation (1), all county pairs between 15 and 60 miles apart are included. As such, some counties like those in central Texas, central Michigan, or Maine, which are over 60 miles from the nearest state only have within state county pairs. To ensure that patterns are not driven by compositional differences in the counties with and without cross-border county pairs, most of analysis is limited to origin counties that have at least one cross-border county within 60 miles (see the map in Figure A3).³ As seen in Figure 2, the distance gradient and state-border penalty is essentially unchanged. Conditional on distance, migration state borders reduce migration by 72 percent.

3.3 Sensitivity to Measure of Distance

Perhaps comparing the direct distance between counties does not provide a reasonable comparison. If cross-state road networks are more sparse, or if state borders correspond with rivers or other natural features (as is the case for counties in 41 states), travel across state

³Patterns throughout are unchanged if we include all county pairs within 60 miles of each other.

lines might be more challenging, even if equidistant. Using geocoding travel time software, I construct the travel time between each county pair. I then replicate equations (1) and (2) but measure distance in terms of minutes of travel. As seen in Figure 3, the role of state borders is similar, lowering migration rates by 62 percent.⁴

This is a pattern that has not been documented previously and is perhaps unexpected given beliefs about high US mobility (Molloy et al., 2011). Given that this empirical pattern exists, the first goal of this paper is to identify potential mechanisms that help explain the state-border discontinuity in migration or that can be ruled out as an important driving force. The second goal of this paper is to document to what extent this migration friction impacts the dynamism of local labor markets and the persistence of local economic shocks.

4 Potential Explanations

To codify potential explanatory mechanisms, I turn to the canonical model of migration choice model that builds on the early work of Sjaastad (1962). In its simplest form, the decision to migrate is characterized as a comparison between the utility gain and the cost associated with moving from origin o to destination d as follows

$$Move_{od} = \begin{cases} 1 & \text{if } u_i(X_d) - u_i(X_o) \geq c_{iod} \\ 0 & \text{else} \end{cases} \quad (3)$$

where utility is a function of location specific characteristics. The migration rate from o to d can be captured as the share of the population at o for whom

$$c_{iod} < c_{iod}^* = u_i(X_d) - u_i(X_o). \quad (4)$$

For state borders to influence migration rates, the model would suggest that either (1)

⁴As seen in Appendix Figure A4, the state border penalty is similar for counties separated by land or by rivers.

local characteristics that contribute to utility differences between the origin and destination d or (2) moving cost change discontinuously at state borders. Although spatial equilibrium models (Roback, 1982; Rosen, 1979) highlight the role of migrants in equalizing differences across places, there is empirical evidence that there is still substantial heterogeneity in labor market and housing market conditions across geography (Bartik, 2018) and that for many individuals moving costs are prohibitively large (Bartik, 2018; Kosar et al., 2020). Both of these channels are potentially relevant.⁵ Beyond differences in characteristics and monetary moving costs, it will also be important to consider alternative mechanisms, such as psychic non-monetary moving costs, frictions, or biases that might change the migration decision relative to equation (3). Building on this theory and previous work exploring the drivers of migration behavior, I next explore the role of leading potential mechanisms.

4.1 Differences in Utility

Discrete changes in labor market opportunities, demographic characteristics, natural amenities, or housing markets at state borders could result in discrete differences in utility across state borders. To rule out discrete changes in local characteristics, I present evidence similar to a regression discontinuity design plotting how average characteristics in 2017 change as the distance between origin and destination decreases. If average origin/destination differences in characteristics for same-state pairs and cross-state pairs diverge as the distance between the origin and destination decreases, this could be a potential mechanism. For each county pair there are flows in two directions, so by construction differences between the origin and destination by distance will be mean zero. For this reason, I examine absolute differences in county pair characteristics. I examine origin/destination differences in measures that are frequently used as controls (or outcomes) in labor market and demographic research. I examine labor market measures (the unemployment rate, employment to population ratio, average

⁵Adding multiple potential destination turns the decision into a multinomial decision where the individual chooses the destination where $u_i(X_d) - u_i(X_o) - c_{iod}$ is the largest. For state borders to matter, the same potential channels are present, but the relative importance of these channels in other potential destinations will also matter.

weekly wages); industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others); demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20-34, 35-49, 50-64, and 65 and older); natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale); the 2016 presidential Republican vote share; and the county housing price index, converted to dollars using the median house value from 2000. These plots are presented in Appendix Figures A5 and A6. Because there are few county pairs less than 15 miles apart my analysis focuses on county pairs that are between 15 and 60 miles apart. For each measure I shade in gray origin/destination pairs that are less than 15 miles apart. Consistent with few observations within 15 miles of each other, the spread increases and standard errors on the local linear polynomials become large as we approach zero.

Otherwise, differences in average local labor market, demographic, natural amenity, vote share, or housing market measures appear similar regardless of a state border separating the counties, especially if we focus on counties 15 to 60 miles apart. Once again as we saw above in Figures 1 and 2, controlling for these differences does not impact the discontinuity in migration rates at the state border.⁶

Another way to determine if the discontinuity is driven by differences in utility is to focus on county pairs that are “close” or believed to be more connected, such as counties that border each other or are in the same commuting zone (CZ) or metropolitan area (MSA). These counties are more likely to be in the same markets (e.g., housing and labor markets) and face more similar conditions. in Figure 4, we see the same distance gradient and cross-border penalty for counties in the same CZ, in the same MSA, or that border each other. These significantly smaller samples exhibit less precision, but nonetheless, state borders

⁶Appendix Figure A7 documents how the impact of state borders affects migration rates as we add various groups of controls on either a constrained sample that has all non-missing control measures or an unconstrained sample.

are associated with a significant 69 percent decline in migration for same commuting zone counties, while the decline is 56 percent in same-MSA counties.⁷ People are at least twice as likely to move to a neighboring county in the same state than move to a neighboring county in a different state.⁸ As seen in Appendix Figure A8, this pattern also holds for individual MSA when we focus on counties in well-known cross-state MSAs like New York City, Washington DC, or Kansas City.

4.2 Differences in Pecuniary, Adjustment Costs

The drop in migration across state borders does not appear to be driven by differential changes in the utility of migration, but there might be differential changes in the cost. There are many pecuniary costs associated with moving (e.g., renting a moving truck, or hiring movers). Most of these would be incurred whether the move was across a state-border or not. However, there are some pecuniary costs associated with moving that differentially impact in-state and cross-state moves. For example, you are required to renew your license and car registration when you moved to another state, but not if you move to a different county in the same state. State laws, policies, and requirements might also lead to differential pecuniary costs associated with cross-state moves. I explore several potential themes that have been highlighted in the internal migration literature.

Occupational Licensing

Some states require licenses, certificates or education/training requirements for someone to work in pre-specified occupations.⁹ In some cases, these requirements do not include state reciprocity, meaning a qualification in one state is void in another. Johnson and Kleiner (2020) show that among 22 universally licensed occupations where licensing exams are ei-

⁷These impacts are based on the estimates not controlling for differences between the origin and destination. The specifications controlling for these differences produce even larger but equally significant impacts.

⁸Among the sub-sample of neighboring counties standard errors are large when using one mile bins. This is because there are relatively fewer observations in each one mile bin. The differences are more precisely estimated when larger bins, that contain more observations, are used.

⁹See Kleiner and Soltas (2019) for a full treatment of the welfare impacts of occupational licenses.

ther state-specific or nationally administered, state-specific licensing rules reduce interstate migration by approximately 7 percent. However, they note that these effect sizes can only explain a small share of the aggregate trends in interstate migration. To determine if occupational licenses produce the drop in migration across state borders I explore total and cross-state migration rates by occupation in the ACS in Figure 5. First I plot the share of individuals in each non-licensed occupation that moved in the last year on the x-axis, and the share that moved out-of-state on the y-axis. Each occupation is weighted by the summed sampling weights for all of the workers in that occupation. The linear relationship between these two migration shares is plotted in black with 95 percent confidence intervals. In general, occupations that have a higher migrant share have a higher out-of-state migrant share. Using occupational licensing measures from the State Policy Index and the National Conference of State Legislatures, I then overlay the plot for occupations that have a recorded occupational license. If low out-of-state migration was caused by occupation licenses, we would expect licensed occupations to be systematically lower on the y-axis. However, this is not the case, licensed occupations are not outliers and the linear relationship (in gray) for licensed occupations is not significantly different than the relationship for unlicensed occupations.

In Table 2, I estimate the impact of facing a state occupational license on the probability of moving out of state in the ACS microdata relative to other individuals in your occupation but a different state. Occupational licenses do not increase the probability of moving out of state for the full sample or even when conditioning on making a move in the last year. Controlling for state and year fixed effects to capture persistent differences or aggregate shocks does not change the relationship. State occupational licenses do not seem to drive the drop in migration at the border, consistent with previous work suggesting licensing only explains a small share of aggregate state-to-state migration trends (Johnson and Kleiner, 2020).

State Taxation

Taxation also varies across state lines, leading to large differences in tax burden across state borders. State income tax rates vary between 0 and 13.3 percent (Loughead, 2020). Moretti and Wilson (2017) find that star scientists are sensitive to these income tax differences. Differences in tax burden and state income taxes could lead to discontinuous changes in migration at state borders. However, if it is driven by tax burden, we would expect asymmetric behavior across borders with different state tax policy. I will estimate the following equation to determine if cross-border county-to-county migration rates differ when the tax burden is larger, when the tax burden is smaller, or when the counties are in the same state.

$$\begin{aligned}
 Mig. Rate_{od} = & \sum_{b=15}^{59} \beta_b (Higher * Diff. State * b \text{ Miles Apart}) + \theta_b (Lower * Diff. State * b \text{ Miles Apart}) \\
 & + \gamma_b (b \text{ Miles Apart}) + X'_{od} \Gamma + \phi_o + \delta_d + \varepsilon_{od} \quad (5)
 \end{aligned}$$

Where *Higher* indicates that the state income tax burden in the potential destination county is greater than the state income tax burden in the origin county. *Lower* indicates that the state income tax burden in the destination is less than or equal to the burden at the origin. The β_b represent the differential migration to counties in different states with a higher tax burden, while the θ_b represent the differential migration to counties in a different state with a tax burden less than or equal to the origin. Spatial equilibrium models (Roback, 1982; Rosen, 1979) would suggest that long-standing differences in tax rates would lead to differential sorting causing the utility value of areas to equilibrate across all dimensions. As such, we might not observe differences when examining equilibrium migration rates. However, as tax burdens vary across the income distribution, it is possible we would observe differences for certain groups that faced larger differences in tax burdens. For this reason, we will examine tax burdens for various family types at multiple income levels. Using tax burden estimates from the NBER TAXSIM I examine how the role of state borders differ in

Figure 6 when I split by the tax burden for households that are married and filing jointly with two children, and income of either \$25,000, \$50,000, \$75,000, or \$100,000.¹⁰

Across all income levels, the tax burden split yield similar migration patterns to counties in states with higher or lower income tax burdens. For county pairs between 15 and 25 miles apart, the point estimates are slightly larger when the state income tax burden in the destination state is weakly less than the origin, but these estimates are not statistically different than those for destinations with a higher income tax burden. Conditional on distance, migration to both cross-border groups is still less than half the level within state.

Unfortunately the IRS migration data does not allow me to link households to their individual income tax burden. To focus on household specific tax burden I turn to the ACS microdata. For family units in the 2012-2017 ACS microdata I use TAXSIM to calculate their income specific state and federal income tax burden. By moving the focus to a household, rather than a county-to-county migration flow, identifying the potential destination is not straightforward. To focus on the origin/destination decisions that ex ante are the most likely, I limit the sample to families originally living in commuting zones that cross state lines, and then calculate the average income tax burden the family would face in the other state(s) in the commuting zone.¹¹ I then calculate the percent change in total federal and state tax burden between the original state and the other state in the commuting zone.¹² In Appendix Figure A9 I plot the share of migrants who move out-of-state in one percentage point bins of the change in the total tax burden. If state income tax policy led to the reduction in migration across the state border, we would expect the share of migrants that move out-of-state to decrease as the income tax burden increases with a cross-state move. Consistent with state taxes playing a role, the share of migrants that move across state

¹⁰Income details for the TAXSIM calculations are available in Appendix C. Estimates for households with \$10,000 of income are also available in Appendix Figure A10. Estimates for single head of households and married filing jointly (with no children) households at the same income levels are available in Appendix Figure A11 and A12.

¹¹For commuting zones with multiple states, I compare the tax burden in the origin state to the average tax burden in the other states.

¹²As some states do not have an income tax, I consider the federal plus state income tax burden so percentages will be defined.

lines is often higher when there is a large reduction in tax burden, but it is more dispersed. However, it is also higher with more dispersion when there is a large increase in tax burden. There is no significant linear relationship between the change in tax burden and the out-of-state migration share. Although some subpopulations might be sensitive to tax burden changes (such as star scientists (Moretti and Wilson, 2017)), it does not appear to drive the discontinuity at state lines.

State Transfer Policy and “Welfare Migration”

State transfer programs also differ, leading to discontinuities in potential low-income benefits at state lines. This could affect costs, but could also differentially affect the utility associated with a cross-border move. There is a long literature exploring interstate migration in response to state low-income benefit generosity, or “welfare migration.” Gelbach (2004) find that low-income populations that move across state lines tend to move to higher benefit states, while Borjas (1999) documents a similar pattern among non-native immigrants. McKinnish (2007) and McKinnish (2007) find higher welfare expenditures in high-benefit states on the border of high and low benefit states. Welfare reform policy changes in the 1990s reduced interstate migration of less-educated unmarried mothers (Kaestner et al., 2003), while medicaid expansions associated with the Affordable Care Act (ACA) did not increase migration to expansion states (Goodman, 2017). McCauley (2019) finds that migration to health care benefits in the UK depends on access to information.

Based on the existing work, I focus on three state transfer policies that affect low income households and vary across state lines: Temporary Aid for Needy Families (TANF), ACA medicaid expansions, and earned income tax credit (EITC) state supplements. I also examine the role of the effective state or national minimum wage, another policy that impacts the income of low-income households. For each of these policies I estimate a model similar to equation (5), but *Higher* and *Lower* now reference the benefit generosity in the destination state relative to the origin state. These estimates are plotted in Figure 7. Migration

rates to cross-border destinations with higher minimum wages, higher state EITCs, higher TANF benefits, and medicaid expansions were not significantly different than migration rates to cross-border destinations with lower benefits, respectively. In all cases, cross-border migration was significantly lower than within state migration, conditional on distance. For close counties the point estimates among lower EITC states were lower than among higher EITC states, while the point estimates among non-medicaid expansion states were lower than among expansion states, but these differences are not significant. The discontinuity in migration across state borders does not appear to be driven by differences in state transfer policy.

Other Adjustment Costs

There might be other pecuniary moving costs that add up but are difficult to record or measure. Commuters can cross state-lines without incurring many of these adjustment costs associated with moving (such as updating registration), so if there is a similar state-border drop in commuting, it is likely not driven by these factors. I estimate equations (1) and (2), with county-to-county commute flows from the LEHD LODS as the outcome. In Figure 8, we see that county-to-county commute rates follow a similar pattern. Commuting rates decrease with distance, but are significantly lower for cross-state border county pairs, even conditional on distance. This gap remains when controlling for origin and destination fixed effects as well as differences in local characteristics. Because commuters do not face the same adjustment costs but respond similarly, the drop in migration at state borders is likely not solely driven by pecuniary adjustment costs.¹³

Consistent with this evidence, cross-border migration rates are similar across demographic groups that might face different adjustment costs. Using microdata from the 2012-

¹³One potential adjustment cost commuters would still face is the ease with which you can cross the border. This might be particularly challenging if the state border follows a river and there are limited crossings. In Appendix Figure A4 I plot estimates from a specification similar to equation (5), where states with and without river borders are treated separately. Overall the border penalty is similar whether or not there is a river at the border.

2017 American Community Survey (ACS), I calculate the fraction of migrants that move across state lines by age, gender, race/ethnicity, education, living arrangements, and employment (see Figure 9). Among migrants, the share that cross state borders is fairly stable across most groups, between 15 and 22 percent.¹⁴ There is an education gradient, with the share of migrants moving across state lines increasing with education. Migrants that are federal workers are also substantially more likely to move across state borders, at roughly 43 percent.¹⁵ Both of these patterns would work against a drop in migration at state borders. Consistent with the gap not being driven by pecuniary costs, we don't see lower out-of-state migration for families with children, who face adjustment costs when changing school districts, or state and local employees who are more likely to have state-specific pension benefits. The group with the lowest point estimate is migrants that originally resided in their birth state, while migrants originally residing outside their birth state are over twice as likely to move out of state.

Among people in the same local area as captured by Public Use Micro Area (PUMA), individuals born in that state are only 1.3 percentage points (about 8 percent) less likely to move at all relative to individuals who were born in another state. However, conditional on moving at all, individuals born in that state are about 15 percentage points (63 percent) less likely to move out of state than individual born elsewhere (Table 3). Although people appear tied to their birth state, they are about 5 percentage points (31 percent) more likely to move to a different PUMA within the same state state, suggesting the tie is not necessarily to the local area in the state. State borders appear to influence migration decisions for individuals in their birth state, or nearly 52 percent of adults.

¹⁴The patterns are similar if I restrict the sample to migrants originally living in cross-state commuting zones.

¹⁵This share is similar if I exclude people initially in the Washington DC area (DC, MD, and VA).

5 The Correlation Between Cross-Border Social Networks and Migration

As we saw in Figure 9 and Table 3, migrants were much less likely to cross state lines if they originally resided in their birth state. In Figure 10 I explore this further by estimating equation (1) with the scaled number of Facebook friends between each county pair divided by the origin population as the outcome. This measure is known as the SCI and is constructed from a snapshot of active Facebook users in 2016. There is a similar distance gradient in the number of Facebook friends, but once again, friendship rates are significantly lower for cross-border county pairs than for counties in the same state. Including origin and destination fixed effects or differences in labor market, demographic, natural amenities, or housing markets between the origin and destination do no significantly impact the pattern.

In Figure 11 I estimate equation (2) but also control for the origin/destination Facebook friendship rate. The difference between same-state and cross-border county pairs is compressed significantly, but still significant. For close counties (15-25 miles apart) the gap falls from 3-6 migrants per 1,000 people to 0.5-2 migrants per 1,000 people. Interestingly, the distance gradient for cross-state pairs completely disappears when we control for the social network (consistent with Diemer (2020)), but there is still a slight distance gradient for same-state county pairs.

The fact that social network strength can empirically explain part of the state-border discontinuity in migration does not pinpoint a particular mechanism, but is consistent with several channels of effect. First, it must be acknowledged that a causal relationship between migration and social networks could go in either (or both) directions. A lack of social network could imply large non-pecuniary costs or information frictions leading to high migration costs and low levels of migration. Alternatively, low levels of cross-border migration for other reasons, could lead to more regional isolation and lower social network spread across state borders. Given the empirical pattern, I explore three possible explanations for the social

network, migration correlation. First, social network strength might fall at state borders, leading to large non-pecuniary, psychic costs and reduced migration. For example, people might be less will to move 20 miles away across the state border because they have fewer family or friends there. Second, social network strength might fall at state borders leading to less information about circumstances and opportunities across the state border. This information friction could result in less migration if people are risk averse. Finally, people could exhibit local ties (like birth state identity or home bias) that makes them less likely to move away and in equilibrium less likely to have social links across state borders.

5.1 Non-Pecuniary, Psychic Costs

Existing work suggests that the non-money costs associated with leaving social connections are large (Kosar et al., 2020). Local ties to friends and family can keep people in weak labor markets and lead to depressed migration levels (Zabek, 2020). The non-pecuniary, psychic cost mechanism implies a direction of causality. For any number of reasons, social networks are weaker across state borders leading to larger migration costs and lower migration flows.

5.2 Information Frictions

Since social networks become more sparse across state lines, it is plausible information frictions exist that differentially keep people from fully understanding returns and conditions in counties outside of their home state. These frictions could keep people from following the behavior in equation (3). Previous work has found that access to information about government programs increases welfare migration (McCauley, 2019) and information about labor demand shocks increases migration to economic opportunities (Wilson, 2020). Kaplan and Schulhofer-Wohl (2017) argue that improved access to information has allowed people to avoid moves that result in low-quality matches and helped contribute to the decline in internal migration over the last 40 years. The information friction mechanism will imply the same causal channel as the non-pecuniary, psychic cost mechanism. Weaker social networks

across state borders would lead to less information about opportunities in markets across state lines, potentially reducing migration flows. Without an exogenous source of information or change in the social network, we can not disentangle whether the pattern in social networks relates to migration through non-pecuniary costs of social network strength, a lack of information, or some other means.

5.3 Geographic Identity and Home Bias

Other behavioral biases and frictions might also exist. For example, people might exhibit “home bias” and systematically discount the return at non-home locations because they identify with a given location. This would be consistent with less cross-state migration from people in their birth state and more cross-state migration from people originally outside of their birth state. In order for these frictions and biases to explain the state-border discontinuity, they must have differential impacts at state borders and even impact counties that are close or in the same market (CZ or MSA).¹⁶

Importantly, the home bias mechanism would imply a different causal channel. A third factor (home state bias) leads to both lower migration and fewer friendship links across the state border. In general, the SCI does fall across state lines, but this is not universally true. There are cross-border areas with stronger friendship networks. This presents a setting to estimate the relative importance of these mechanisms in a horse race regression. Following Bailey et al. (2018), I construct “Connected Communities” based on the strength of the SCI. Connected Communities are contiguous county clusters where the social ties are stronger within the community than if a county was attached to a different, neighboring community. Based on the pre-specified number of Connected Communities, these clusters are sometimes subsections of states or contain areas across state borders. As seen in Figure 12, when there

¹⁶One mechanism for “home bias” would be the in-state preference among public universities. In Appendix Figure A14 I test to see if cross-state migration is different in origin states where the share of public university enrollment that comes from within state is above or below the median. This does not appear to affect the drop in migration across state borders. Having a university with students enrolled from nearly all of the states (45) in the state also does not appear to explain the drop in cross-state migration, although the estimates are less precise here.

are 50 connected communities, the cluster borders approximate state borders, but there are obvious differences where one community spills across the state border. For example, New England is grouped as one cluster, Arizona and New Mexico are merged, and Northern Texas, Oklahoma, and parts of Kansas are combined into one Connected Community. There are similar cross-border aberrations when 25 or 75 Connected Communities are created.¹⁷ This would suggest that in some areas, social networks permeate state borders. If I treat Connected Communities as pseudo states, and re-estimate equation (2), we see a similar impact of pseudo borders on migration. Conditional on distance, migration rates across pseudo borders are about one third to one half as high as migration within the Connected Community, for various numbers of Connected Community Clusters (see Figure 13).

This provides an opportunity to test the relative explanatory power of state borders versus Connected Community pseudo borders. If the empirical migration pattern is driven by a drop in social network strength across state borders due to either non-monetary costs or information frictions, we would expect cross-border drop in migration to load onto the Connected Community pseudo borders rather than state borders. I modify equation (2) and include the full set of different state by distance interactions *and* different Connected Community (pseudo state) by distance interactions. As seen in Figure 14, most of the effect loads onto the physical state border, rather than the Connected Community borders. This would suggest that the drop in migration is less associated with the social network border than it is with the physical state border. As both non-monetary and information friction channels suggest the gap is driven by weaker social networks, these mechanisms are not likely to explain the impact of state borders on migration flows. Although non-pecuniary costs and information frictions undoubtedly influence migration decisions and flows, they do not appear to explain the drop in migration at state borders.

It is still possible behavioral biases like a home bias or a state identity exist. This would be consistent with the behavioral phenomenon of an endowment effect. Individuals are

¹⁷The Connected Communities include those in Alaska and Hawaii, which are not presented on the map.

“endowed” with an initial location (their birth state) which impacts their willingness to pay for a move. If this bias was present, two individuals with identical preferences would have different migration propensities if one was born in the origin and the other was not. This bias could on average lead to lower migration and weaker social networks across state borders. A preference for one’s own state and how this impacts migration is not captured in most surveys. As we saw in the ACS microdata, residing in your birth state is associated with only a slightly smaller probability of moving overall, but a substantially lower probability of moving out of state. However, this cannot solely be attributed to a birth state identity or home bias. Fortunately, in 2008, Pew Research Center conducted a survey on individual mobility (Pew Research Center, 2009). This survey asked over 2,000 people about their moving history, the places that they identify with and why, as well as presented hypothetical moving scenarios. As such, it is possible to observe how many people identify with their birth state and how this identity affects the stated and revealed preference over moving.

Unfortunately, individuals who have moved and who have not are asked slightly different questions. Individuals who have moved are asked, “You mentioned that you have lived in other places. When you think about the place you identify with the most—that is, the place in your heart you consider to be home—is it the place you live now, or is it some other place?” If the individual answered someplace else, or answered yes to the follow-up question, “Is there a place where you have lived that you identify with almost as much as where you live now?” They were asked to identify the place and the *state* of that place. Based on these measures I identify movers who exhibit a birth state preference.

Individuals who have never lived away from their local community were asked separate questions. Non-movers were asked to identify whether various factors were a “major reason”, “minor reason”, or not a reason they have not moved. In particular non-movers were asked about factors related to local, personal ties (i.e., family ties, connections to friends, or community involvement), local attributes or amenities (i.e., job or business opportunities, cost of living, the climate, a good place to raise children, recreation and outdoor activities,

medical or health reasons, or cultural activities), or identity and attachment to the geography (i.e., “no desire to live someplace else”, “I just feel I belong here”, or “I grew up here”). I then classify non-movers as exhibiting a birth state preference if they listed one of the identity factors as a “major reason” they have not moved. Overall, 59.2 percent of movers are classified as having a birth state preference and 81.4 percent of non-movers, leading to an overall average level of 68 percent.

Having a birth state identity is associated with differences in migration history and stated preferences (see Table 4. People with a birth preference are 35.3 percentage points less likely to have ever left their birth state (a 64 percent reduction at the mean), and 28.1 percentage points (80 percent) more likely to say that the place they would prefer to live is in their state of birth. The impact of a birth state identity is separate from personal local ties through friends and family. If we also control for whether an individual reports the reason for being where there are is due to family ties, connections to friends or community involvement the impact of birth state identity on ever leaving ones birth state falls to 23.1 percentage points but is still large and highly significant.

Birth state identity also reduces the people’s stated preferences about moving. Individuals with birth state identity are no less likely to report that they are willing to move, but are significantly less likely to report that they are willing to move if they currently reside in their birth state. Across specifications this corresponds birth state identity corresponds to a 13-14 percentage point (35-38 percent) drop in the likelihood of moving in the next five years. Given the large share of individuals that exhibit birth state identity and that reside in their birth state, this could explain a significant decline in migration across state borders.

6 Impact of State-Border Discontinuities on Local Labor Market Adjustment to Shocks

Birth state identity seem like a plausible mechanism that leads to an empirical reduction in migration at state borders. Whether the reduction in migration is due to birth state identity or some other factor, it is unclear if this empirical pattern has real impacts.

Migration flows are thought to be an important mechanism for labor markets to adjust to local shocks (Blanchard and Katz, 1992). Reduced mobility between neighboring counties on state borders might inhibit the rate at which labor markets adjust. In recent work, Hershbein and Stuart (2020) use event study methods to explore the employment dynamics of local labor markets after recessions in the US. They find that although employment starts to return to previous levels, negative effects persist for up to ten years.

Following their framework, I estimate a similar event study framework, but allow the dynamics of border and non-border counties to differ, as follow

$$\ln(Y_{ct}) = \sum_{\tau=2003}^{\tau=2017} \gamma_{\tau}(CZ\ shock* Year\ \tau) + \beta_{\tau}(Border* CZ\ shock* Year\ \tau) + \delta_c + \alpha_t + \varepsilon_{ct} \quad (6)$$

The outcome of interest is the natural log of total employment, population, the employment to population ratio, or migration flows (in or out) in county c in year t . This is regressed on a set of year fixed effect interacted with the size of the recession in the local labor market (commuting zone). This is measured as the change in commuting zone log employment between 2007 and 2009. Following Hershbein and Stuart (2020), 2005 is used as the omitted year.¹⁸ I also include a second set of interactions, that allow the effect to deviate for counties on the state border ($Border = 1$). The dynamic effects for non-border counties are represented by the γ_{τ} coefficients while the dynamic effects for border counties are represented by $\gamma_{\tau} + \beta_{\tau}$.

¹⁸Results are similar if I control for the 2005 outcome rather than the county fixed effect, as Hershbein and Stuart (2020) suggest (see Appendix Figure A15. Because the shock is constructed at the commuting zone rather than the county-level the mechanical relationship between the “treatment” and the outcome is broken.

County and year fixed effects are also included. Standard errors are corrected for clustering at the level the recession shock is measured, the commuting zone. Event study plots are presented in Figure 15.

For both border and non-border counties, recessions lead to a large, persistent decrease in employment and the employment to population ratio. However, in border counties both employment and the employment to population ratio are persistently lower and there is virtually no recovery up to ten years after the shock. These gaps are large, with employment and employment to population remaining 0.2-0.4 log points lower in border counties.¹⁹ A one percent drop in local employment is associated with 0.5 percent lower employment in 2017 in non-border counties, but an effect twice that size in border counties. In short, border counties still have not experienced an employment recovery 10 years after the start of the Great Recession. Consistent with the overall migration patterns documented here, this appears to be driven by differences in in-migration. In-migration to border counties is nearly 0.4 log points lower for the 6 years after the end of the recession. Out-migration from border counties is also lower, but significantly different. This pattern is consistent with prior work, showing that in-migration is more responsive to local economic shocks (Monras, 2018), and appears to be amplified in border counties.

Consistent with the drop in in-migration, total population also falls. Point estimates in border counties are marginally larger, but not significantly different. The impacts on employment would suggest that the employment propensity of in-migrants must be different in border and non-border counties. County border status does not appear to have differential impacts on average weekly wages.

Being a border county and experiencing less migration from neighboring counties leads to less labor market recovery after a recession, and more persistent negative impacts. Regardless of the mechanism behind the state-border discontinuity in migration, this empirical pattern has large and lasting impacts on labor market dynamism.

¹⁹Year-to-year effects are only significantly different between border and non-border counties in the later years, but outcomes from 2008 on are jointly significantly different.

7 Conclusion

I present new evidence that county-to-county migration in the US falls discontinuously across state borders. The drop in cross-state migration is large (a 60-70 percent reduction for close counties), persists when examining border counties or counties in the same labor market, and is not confined to particular demographic groups. Using the theoretical migration choice model to infer potential causes of this pattern, I find that differences in local characteristics which could differentially impact utility do not drive the difference. Occupational licensing and state income taxation do not appear to drive the gap, and other pecuniary adjustment costs are unlikely to be the sole driving force as county-to-county commuting follows a similar pattern.

Non-pecuniary costs and frictions play a potentially important role. Facebook friend networks exhibit a similar drop across state borders, and controlling for the Facebook network drastically mitigates the cross-state migration gap. This would suggest that the lack of social connections or the lack of information that might be transferred through social networks is associated with lower county-to-county migration.

This empirical pattern has real economic impacts. Border counties see lower in-migration after local economic shocks, and see persistently lower levels of employment and employment to population ratios. This sheds new light on how we should view and evaluate geographic differences in labor market dynamism. Future work is needed to better pinpoint (1) if the network effect is due to non-pecuniary costs or information frictions, (2) if other frictions, behavioral biases, or mechanisms drive the empirical pattern, and (3) if there are policy tools that can mitigate or offset the economic impact of this type of migration behavior.

References

- Bailey, M., Cao, R., Kuchler, T., Stroebel, J., and Wong, A. (2018). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives*, 32(3):259–280.
- Bartik, A. (2018). Moving costs and worker adjustment to changes in labor demand: Evidence from longitudinal census data. *Working Paper*.
- Blanchard, O. J. and Katz, L. F. (1992). Regional evolutions. *Brookings Papers on Economic Activity*, 1.
- Borjas, G. J. (1999). Immigration and welfare magnets. *Journal of Labor Economics*, 17:125–135.
- Diemer, A. (2020). Spatial diffusion of local economic shocks in social networks: Evidence from the us fracking boom. *Papers in Economic Geography and Spatial Economics*, No. 13, LSE Geography and Environment Discussion Paper Series.
- Gelbach, J. (2004). Migration, the life cycle, and state benefits: How low is the bottom? *Journal of Political Economy*, 112:1091–1130.
- Goodman, L. (2017). The effect of the affordable care act medicaid expansion on migration. *Journal of Policy Analysis and Management*, 36(1):211–238.
- Hershbein, B. and Stuart, B. (2020). Recessions and local labor market hysteresis. *working paper*.
- Johnson, J. E. and Kleiner, M. M. (2020). Is occupational licensing a barrier to interstate migration? *American Economic Journal: Economic Policy*, 12(3):347–373.
- Kaestner, R., Kaushal, N., and Ryzin, G. V. (2003). Migration consequences of welfare reform. *Journal of Urban Economics*, 53(3):357–376.

- Kaplan, G. and Schulhofer-Wohl, S. (2017). Understanding the long-run decline in interstate migration. *International Economic Review*, 58(1):57–94.
- Kleiner, M. M. and Soltas, E. J. (2019). A welfare analysis of occupational licensing in u.s. states. *NBER Working Paper No. 26383*.
- Kosar, G., Ransom, T., and van der Klaauw, W. (2020). Understanding migration aversion using elicited counterfactual choice probabilities. *Journal of Econometrics*, Forthcoming.
- Loughead, K. (2020). State individual income tax rates and brackets for 2020. *Tax Foundation, Fiscal Fact No. 693*.
- McCauley, J. (2019). The role of information in explaining the lack of welfare-induced migration. *Working Paper*, University of Bristol.
- McKinnish, T. (2007). Welfare-induced migration at state borders: New evidence from micro-data. *Journal of Public Economics*, 91(3-4):437–450.
- Molloy, R., Smith, C. L., Trezzi, R., and Wozniak, A. (2016). Understanding declining fluidity in the u.s. labor market. *Brookings Papers on Economic Activity*.
- Molloy, R., Smith, C. L., and Wozniak, A. (2011). Internal migration in the united states. *Journal of Economic Perspectives*, 25(2):1–42.
- Monras, J. (2018). Economic shocks and internal migration. *CEPR Discussion Paper No. DP12977*.
- Moretti, E. and Wilson, D. J. (2017). The effect of state taxes on the geographic location of top earners: Evidence from star scientists. *American Economic Review*, 107(7):1858–1903.
- Pew Research Center (2009). Mobility dataset. Pew Social Trends.
- Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy*, 90(6):1257–1278.

Rosen, S. (1979). Wage-based indexes of urban quality of life. In Straszheim, M. and Mieszkowski, P., editors, *Current Issues in Urban Economics*. Johns Hopkins University Press, Baltimore, MD.

Sjaastad, L. (1962). The costs and returns of human migration. *Journal of Political Economy*, 70(5):80–93.

Wilson, R. (2020). Moving to jobs: The role of information in migration decisions. *Journal of Labor Economics*, Forthcoming.

Zabek, M. (2020). Local ties in spatial equilibrium. *Working Paper*.

Tables and Figures

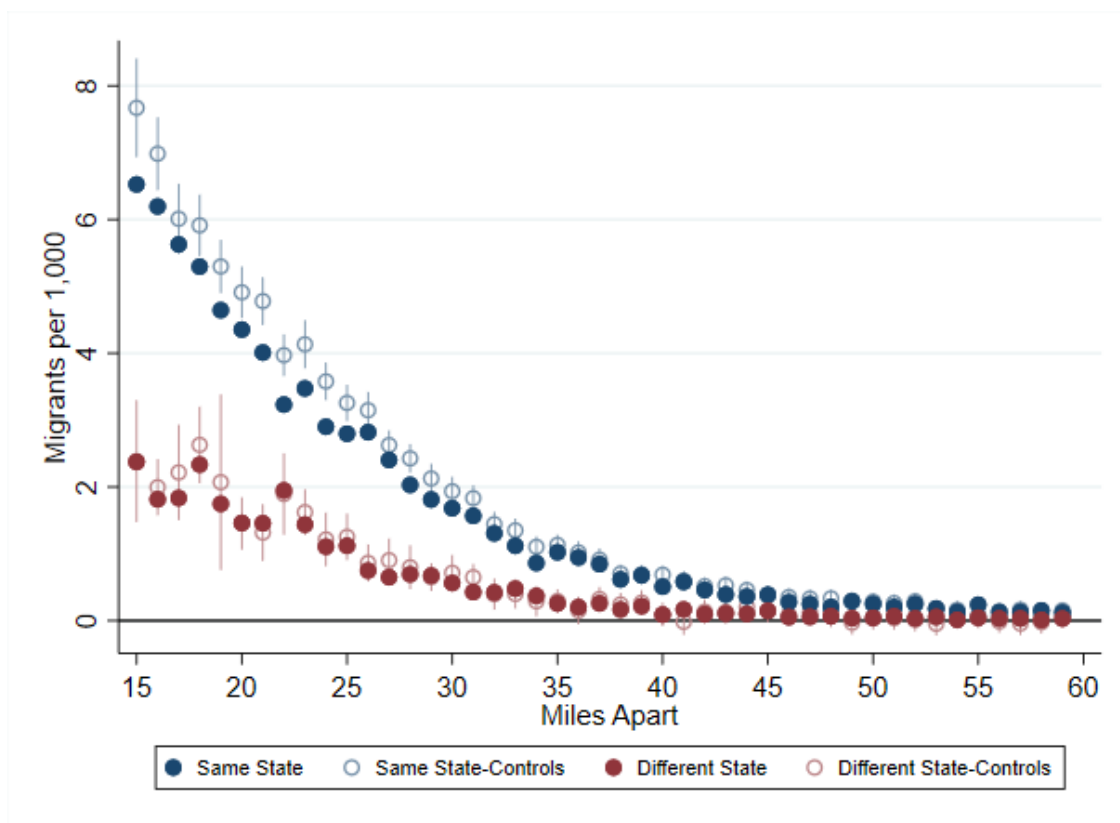


Figure 1: County-to-County Migration Rates by Distance and for Same-State and Different-State Counties

Notes: Outcome is number of migrants per one thousand people at the origin county using the IRS SOI county-to-county flows from 2017. This is then averaged into 1-mile bins for county pairs in the same state and county pairs in different states. Distance is the distance between the population weighted county centroids. The "with Controls" plots coefficients for one-mile bins from equation (2), accounting for origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment to population ratio, average weekly wages), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20-34, 35-49, 50-64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, and differences in the county housing price index, converted to dollars using the median house value from 2000. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI.

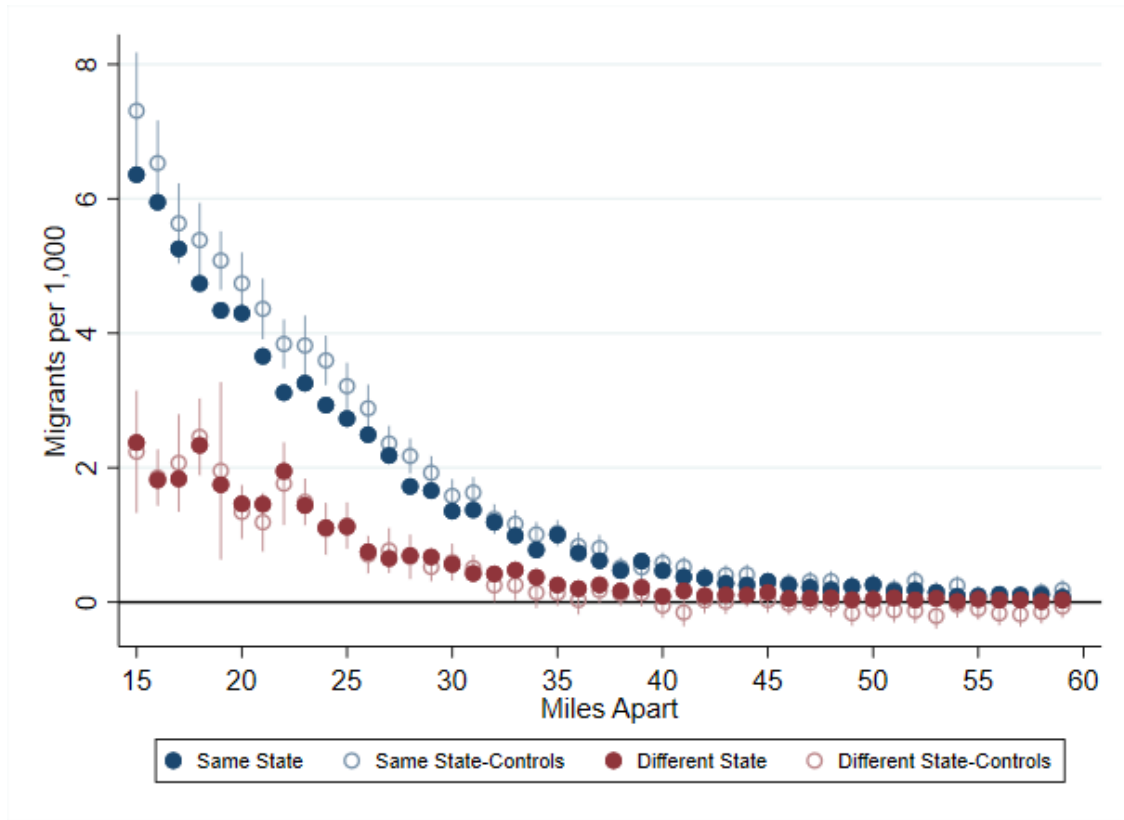


Figure 2: County-to-County Migration Rates by Distance and for Same-State and Different-State Counties, Counties Within 60 Miles of State Border

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Outcome is number of migrants per one thousand people at the origin county using the IRS SOI county-to-county flows from 2017. This is then averaged into 1-mile bins for county pairs in the same state and county pairs in different states. Distance is the distance between the population weighted county centroids. The "with Controls" plots coefficients for one-mile bins from equation (2), accounting for origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment to population ratio, average weekly wages), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20-34, 35-49, 50-64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, and differences in the county housing price index, converted to dollars using the median house value from 2000. 95-percent confidence intervals are provided.

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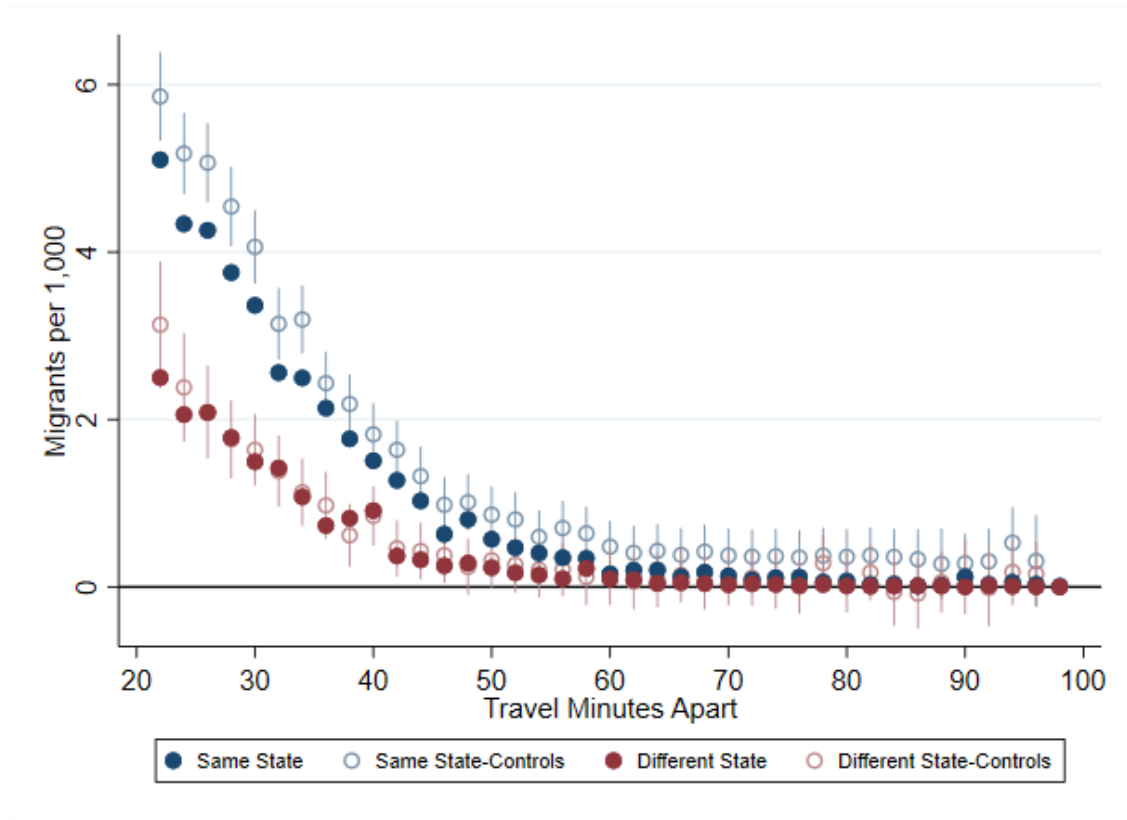


Figure 3: County-to-County Migration Rates by Travel Time and for Same-State and Different-State Counties

Notes: Outcome is number of migrants per one thousand people at the origin county using the IRS SOI county-to-county flows from 2017. This is then averaged into 2-minute travel time bins for county pairs in the same state and county pairs in different states. Travel Time is calculated as the average time to travel from one county population centroid to the other. The "with Controls" plots coefficients for one-mile bins from equation (2), accounting for origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment to population ratio, average weekly wages), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20-34, 35-49, 50-64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, and differences in the county housing price index, converted to dollars using the median house value from 2000. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI.

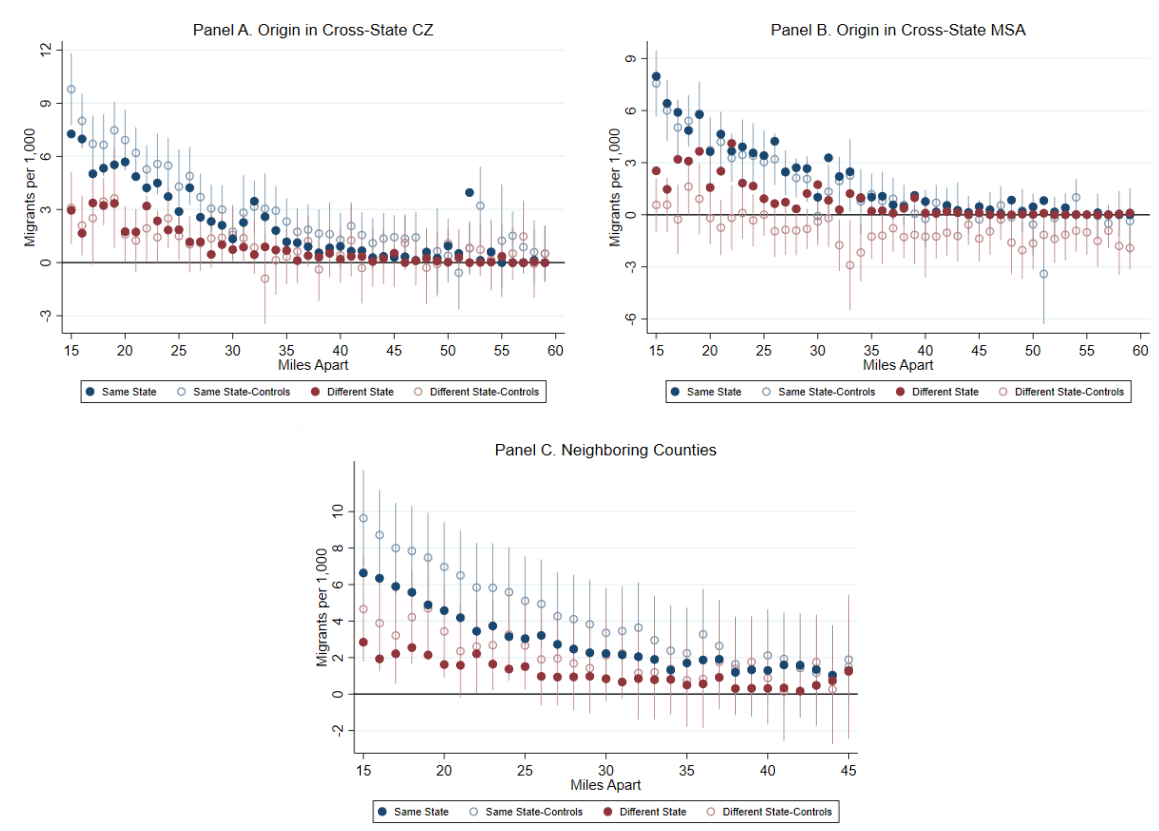


Figure 4: County-to-County Migration Rates by Distance for Connected and Close Counties

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Each panel plots the coefficients from equations (1) and (2) for a different subset of counties. In Panel A, only counties in a cross-state CZ are included. In Panel B, only counties in a cross-state MSA are included. In Panel C, only contiguous counties are included. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI.

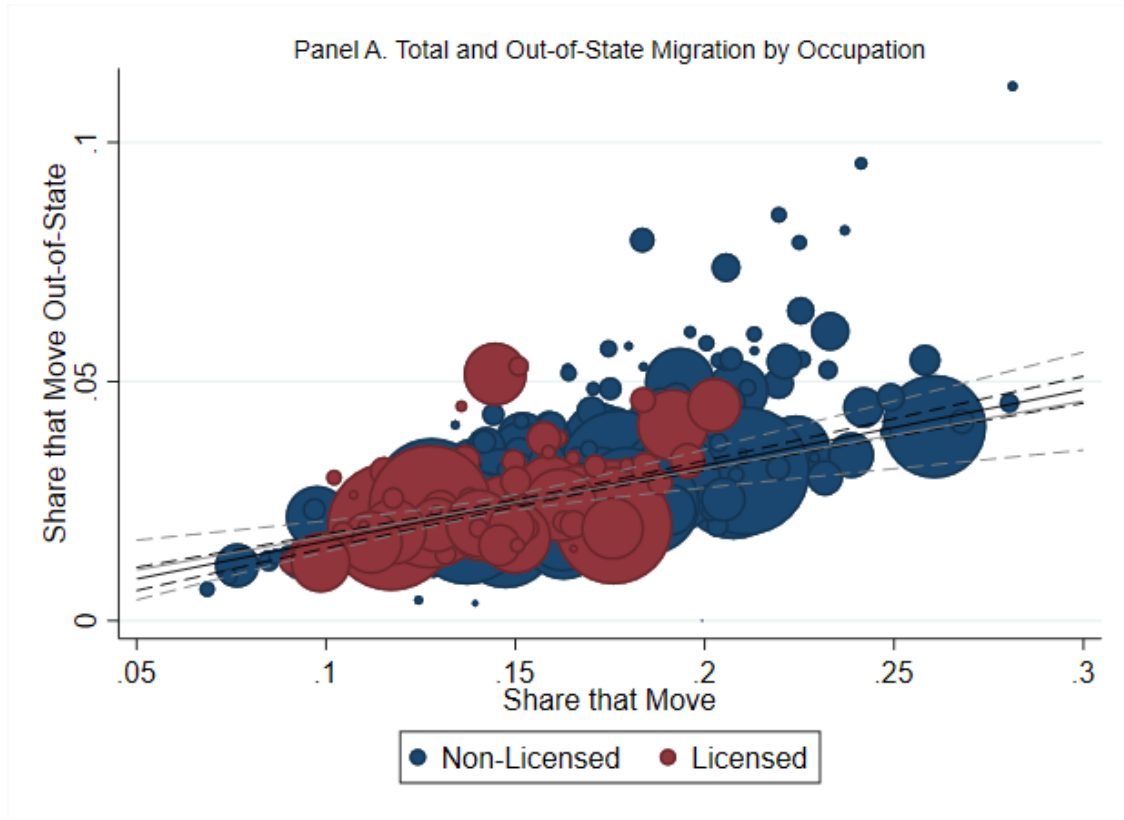


Figure 5: Role of Pecuniary Costs: Cross-state Migration by Occupation by Occupational Licensing

Notes: Each point represents the migration rates by occupational code using the 2012-2017 ACS. The size of the point is scaled to represent the population weighted number of people in the occupation. The black linear prediction is for non-licensed occupations. The gray linear prediction is for licensed occupations. Linear predictions include 95-percent confidence intervals.

Source: Author's own calculations using the 2012-2017 ACS.

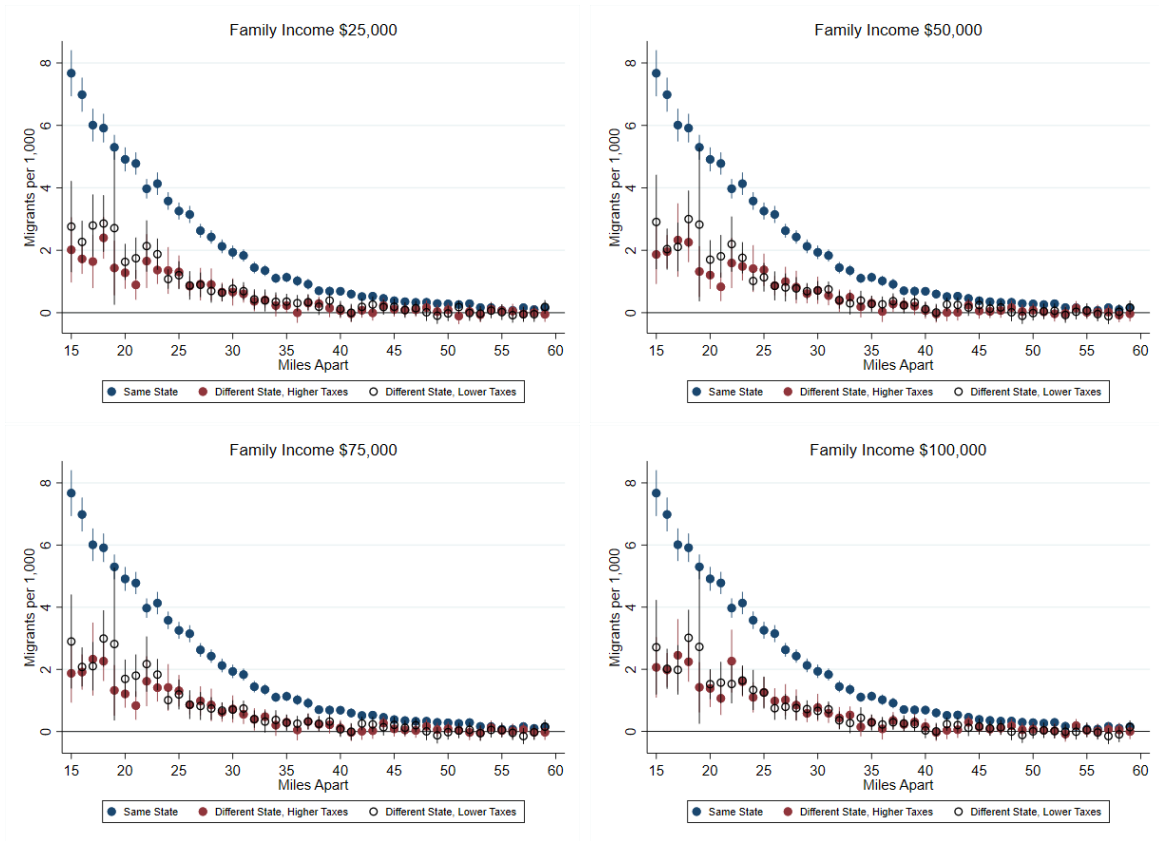


Figure 6: Role of Pecuniary Costs: Differences in State Income Tax Burden by Income Level

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Each panel plots the coefficients from equation (5) with and without controls, where *Higher* is having a higher state income tax burden. For each income level, the state income tax burden is calculated for a married household filing jointly with 2 children using Taxsim. Cross-border county pairs classified as having a state income tax burden that is less than or equal to the tax burden in the origin state or greater than in the origin state. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI.

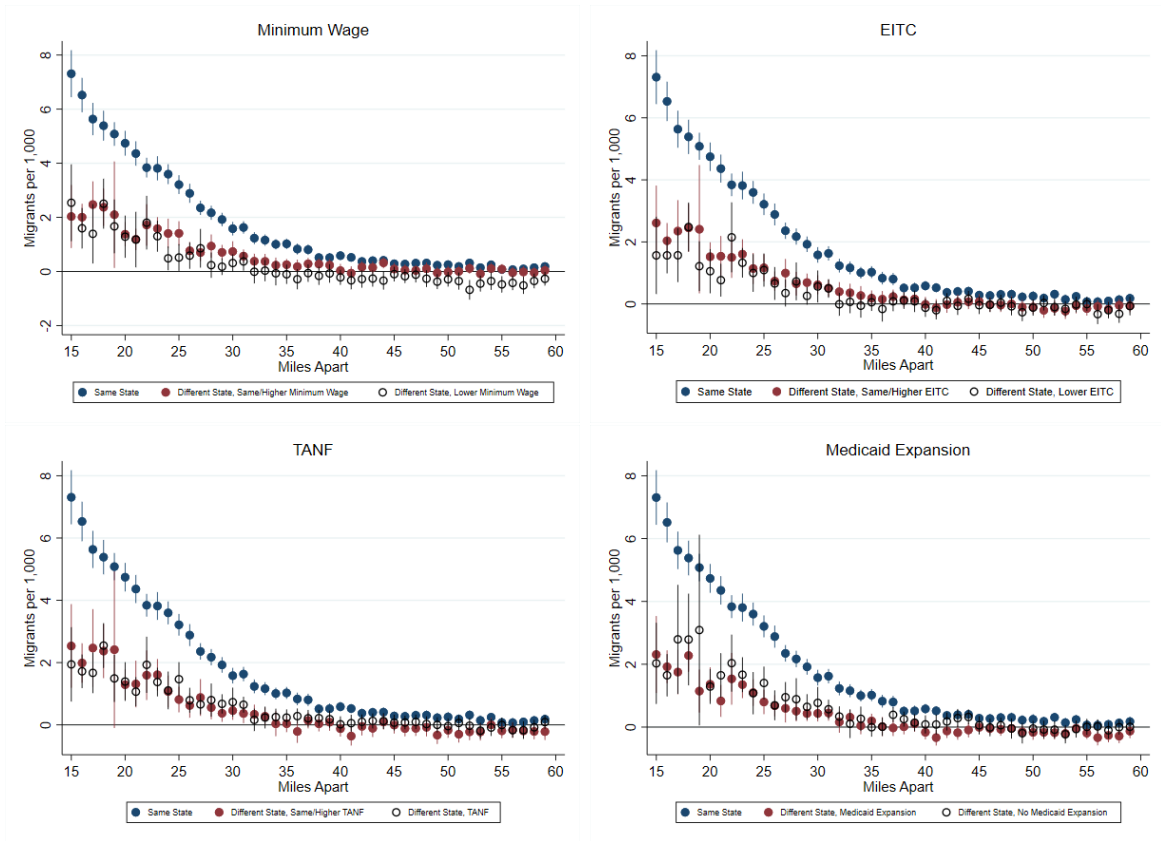


Figure 7: Role of Pecuniary Costs: Differences in State Transfer Policy and “Welfare Migration”

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Each panel plots the coefficients from equation (5) with and without controls, where *Higher* is having a more generous state policy specified. Cross-border county pairs classified as having a state benefit that is less than or equal to the benefit in the origin state or greater than in the origin state. 95-percent confidence intervals are provided.

Source: Author’s own calculations using the 2017 IRS SOL.

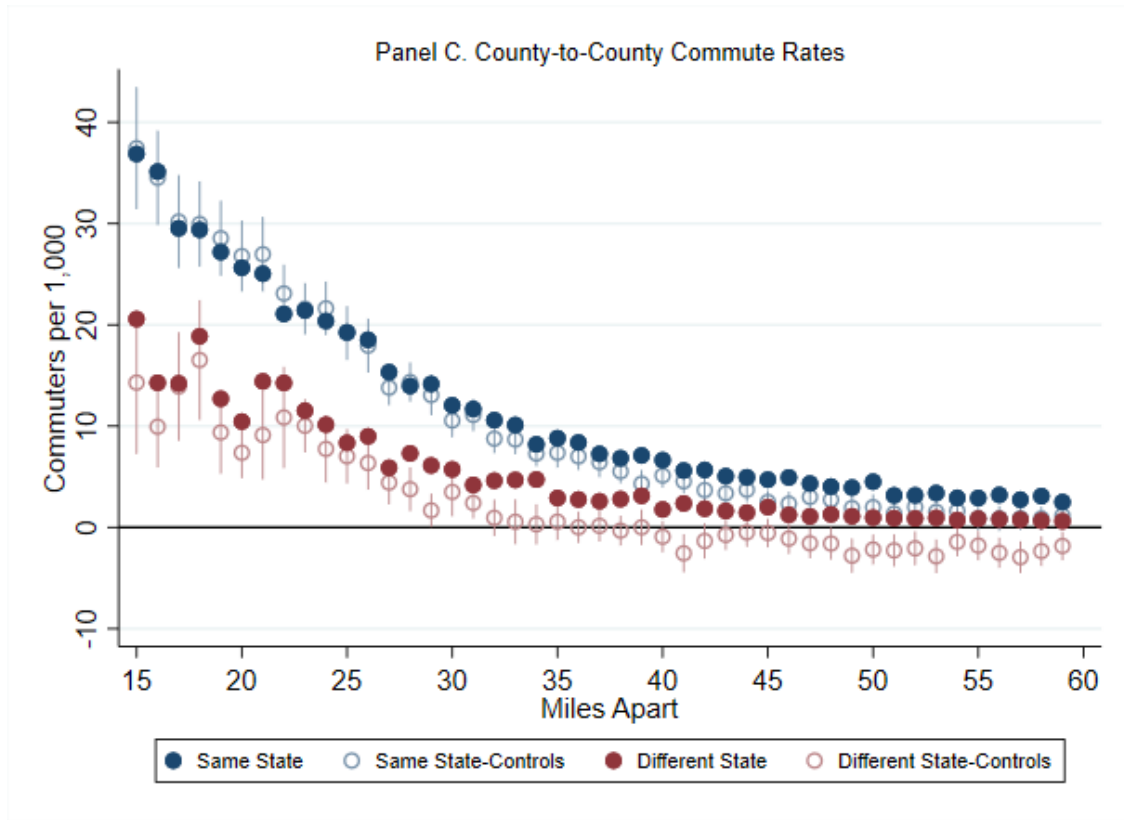


Figure 8: Role of Pecuniary Costs: Impact of State Borders on County-to-County Commute Flows

Notes: Point estimates from equation (1) and (2) are plotted, where the outcome is the number of commuters per 1,000 people at the origin, from the 2017 LODES. 95-percent confidence intervals are included.

Source: Author's own calculations using the 2017 LODES.

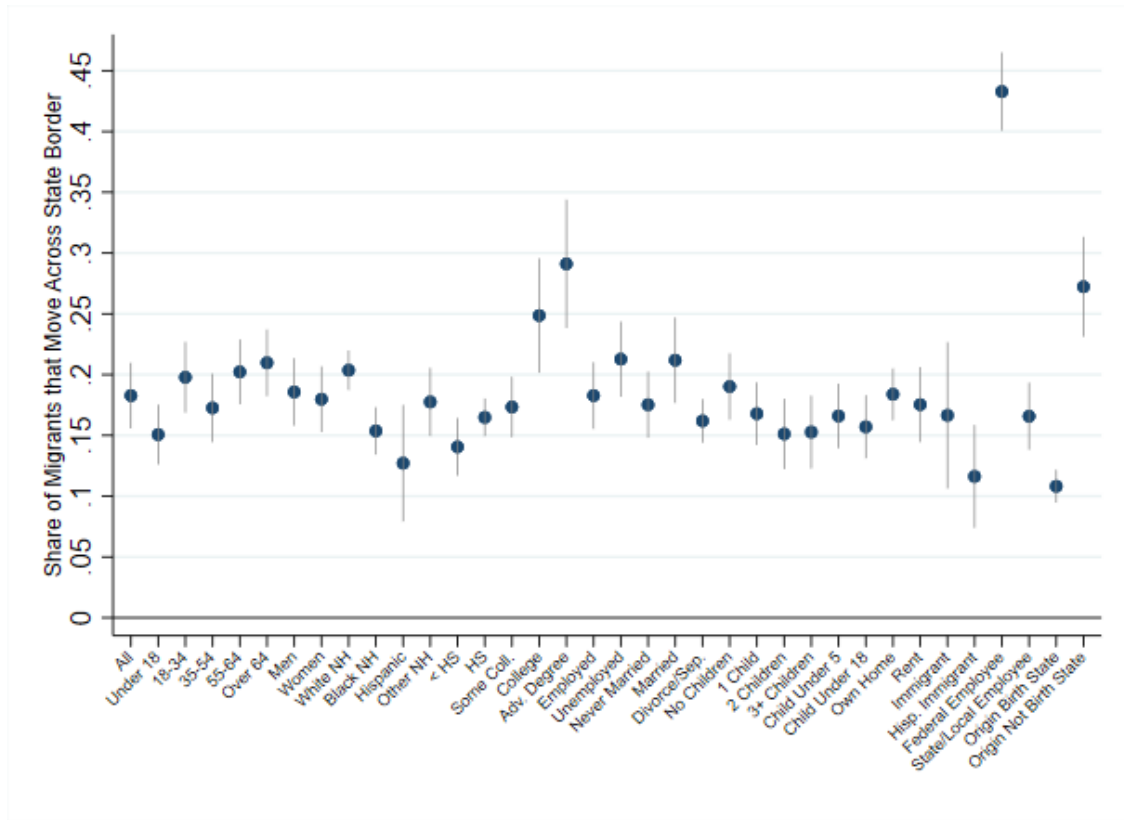


Figure 9: Role of Pecuniary Costs: Cross-State Migration Across Demographic Groups

Notes: Each point represents the share of migrants that move across state borders within the last year using the 2012-2017 ACS.

Source: Author's own calculations using the 2012-2017 ACS.

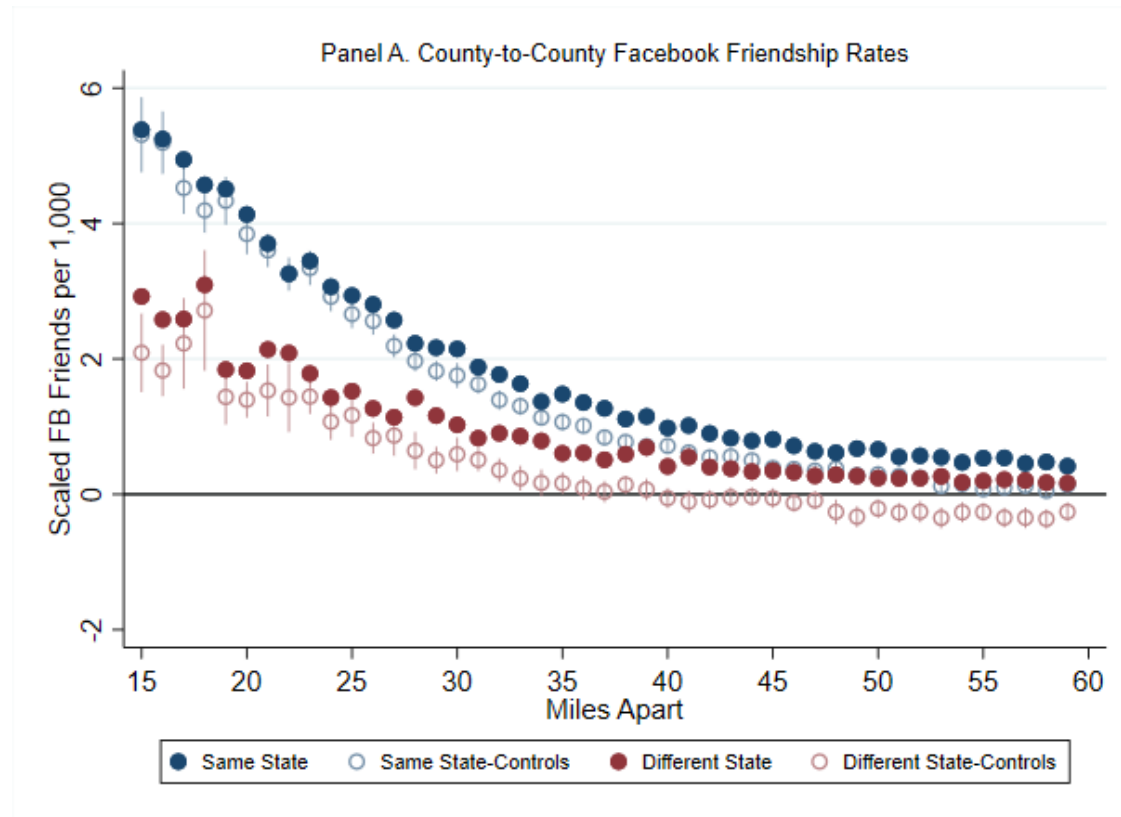


Figure 10: Role of Non-Pecuniary Costs: Impact of State Borders on County-to-County Facebook Friendship Rates

Notes: Coefficients from equations (1) and (2) are plotted where the outcome is the number of Facebook Friends of residents in the destination county per person in the origin county in 2000 using the SCI. 95-percent confidence intervals are included.

Source: Author's own calculations using the 2016 SCI and 2017 IRS SOI.

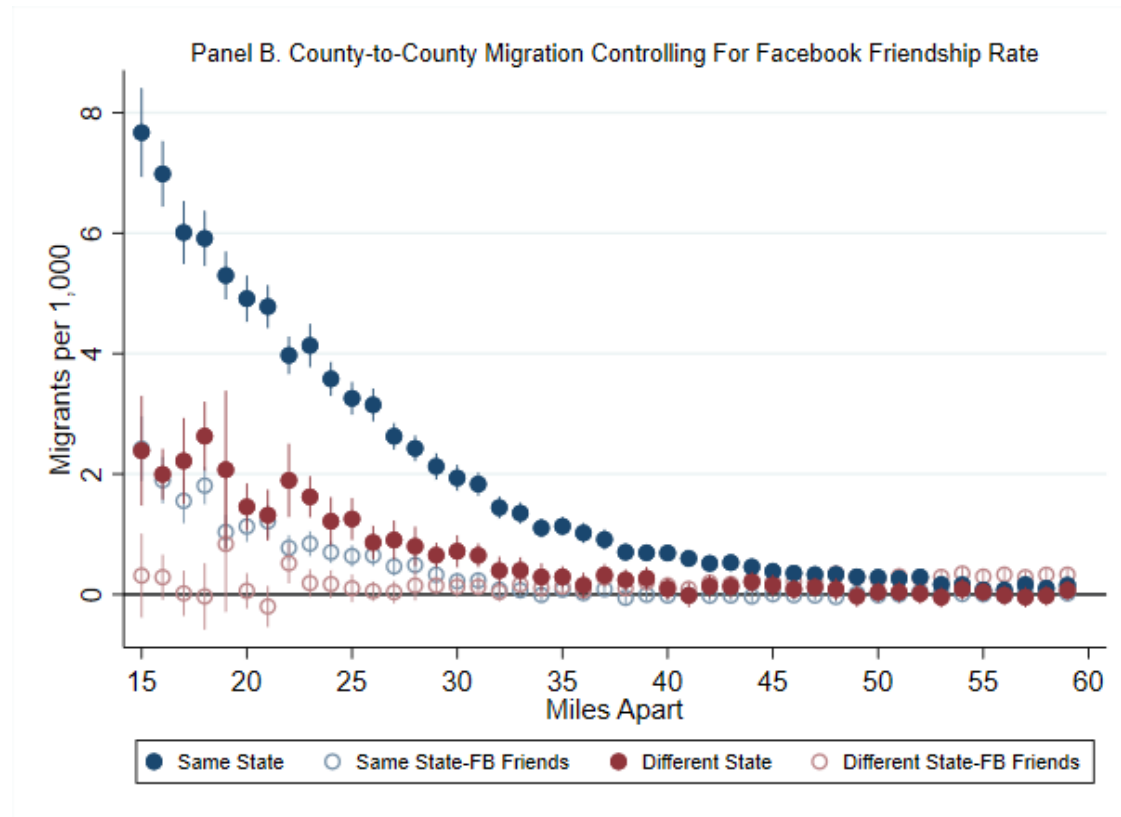


Figure 11: Role of Non-Pecuniary Costs: Mediating Role of Facebook network on Migration Rates

Notes: Coefficients from equation (2) where the outcome is the migration rate and when we also control for the county-to-county Facebook friendship rate are plotted. 95-percent confidence intervals are included.

Source: Author's own calculations using the 2016 SCI and 2017 IRS SOI.

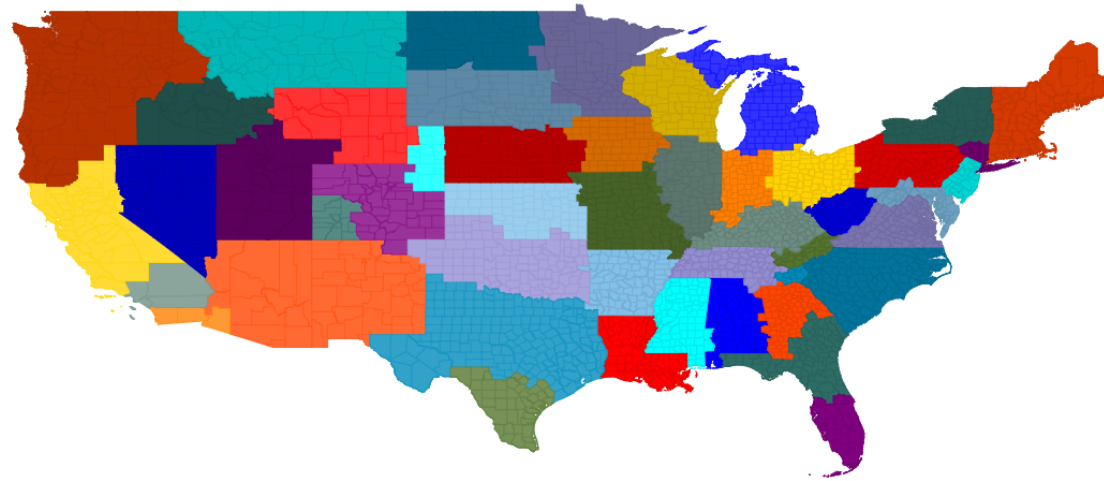


Figure 12: Connected Community Clusters Based on Facebook Friendship Links, 50 Communities

Notes: Connected Community boundaries plotted when there are 50 connected community clusters. These clusters capture contiguous counties cover then entire country.

Source: Author's own calculations using the 2016 SCI.

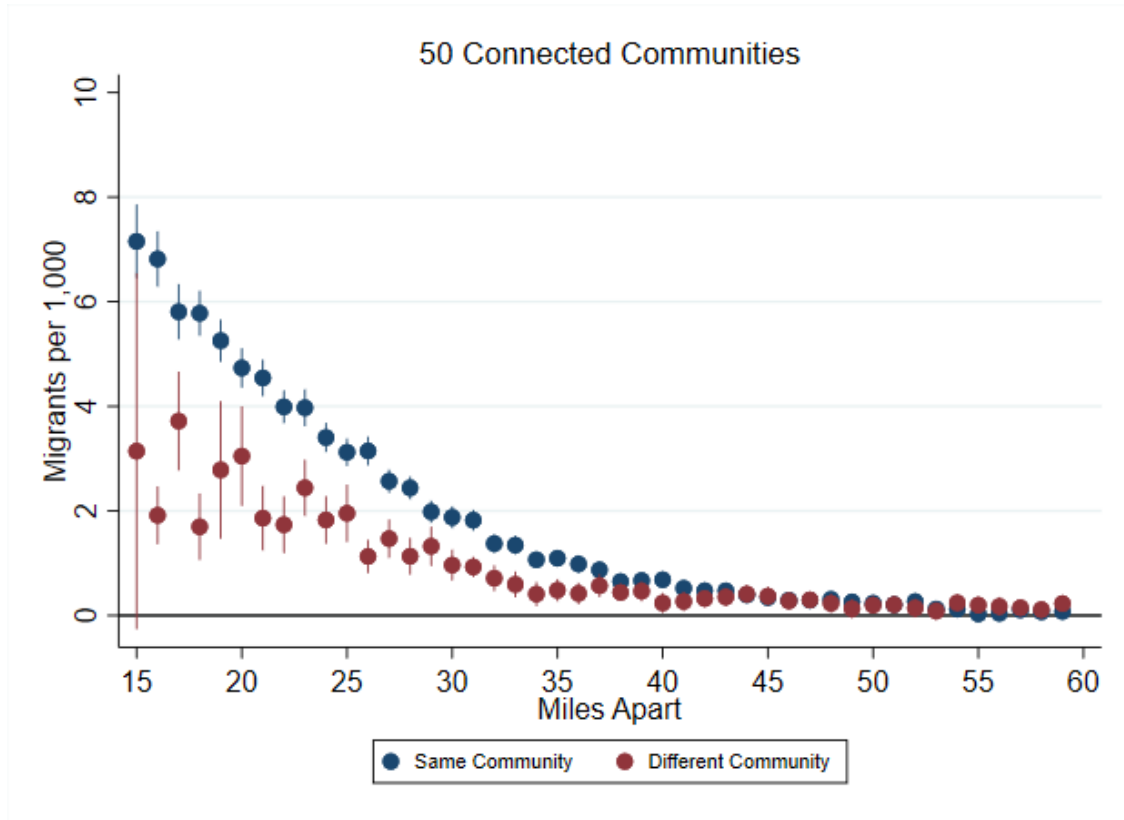


Figure 13: County-to-County Migration Rates by Distance and for Same-Connected Community and Different-Connected Community Counties

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. The coefficients from equation (2) are plotted, but rather than using the physical state borders, the Connected Community pseudo borders are used. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI and 2016 SCI.

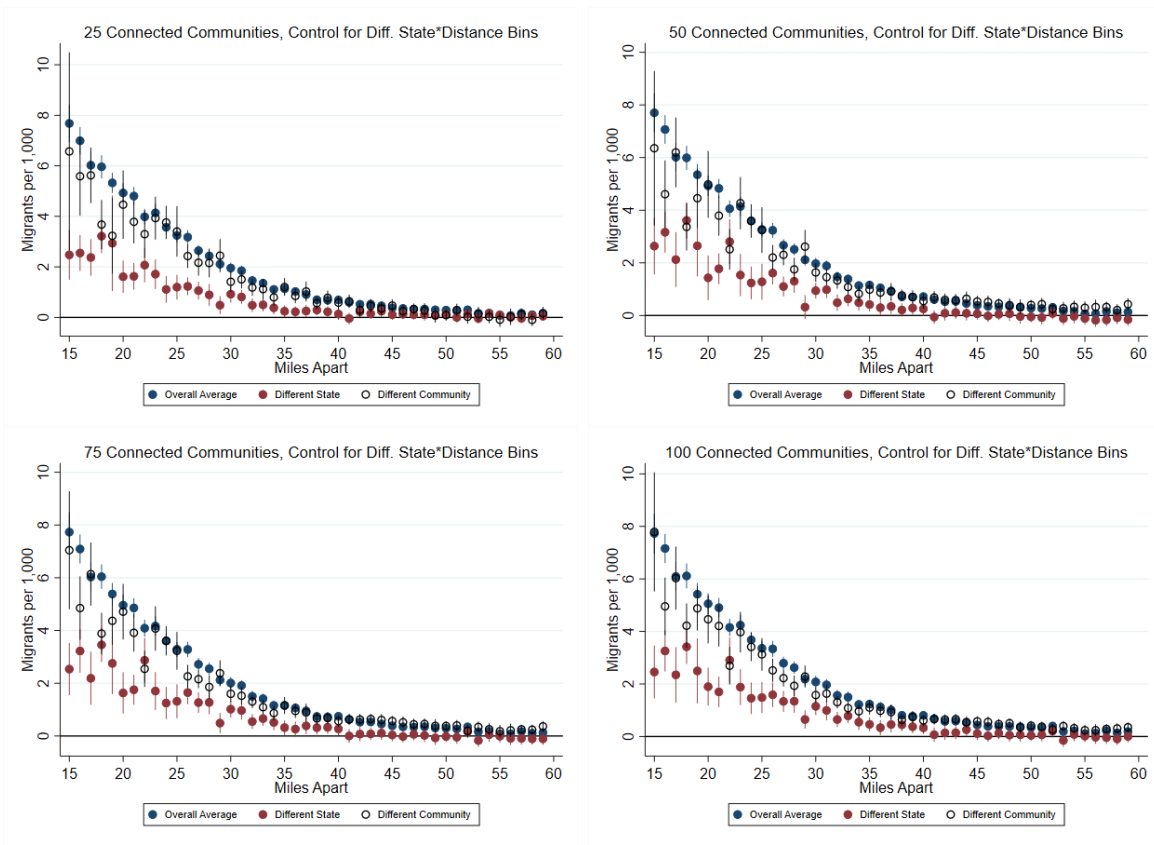


Figure 14: Horseshoe Regression: Relative Importance of Physical State Borders versus Pseudo Connected Community Borders

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Each panel plots the coefficients from equation (2) but includes the full set of state border by distance interactions and the pseudo community border by distance interactions. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI and 2016 SCI.



Figure 15: Impact of State Borders on Labor Market Recovery After the Great Recession

Notes: Event study coefficients from the equation (6) are plotted with 95 percent confidence intervals, and represent the percent change in outcomes relative to 2005, for each percentage point increase in commuting zone employment reduction between 2007 and 2009. Observation at the county by year level. County, state-by-year fixed effects, as well as an indicator for being a border county interacted with year fixed effects are included. Standard errors corrected for clustering at the commuting zone level.

Source: Author's own calculations using the 2000-2017 QCEW and 2000-2017 IRS SOI.

Table 1: Share of Counties with Labor Market or Housing Conditions Nearby

	Distance Between Origin and Destination					
	In Different Commuting Zone					
	<30 Miles (1)	<60 Miles (2)	<90 Miles (3)	<30 Miles (4)	<60 Miles (5)	<90 Miles (6)
	Exists County with Unemployment Rate...					
10 Percent Lower	0.54	0.81	0.90	0.30	0.73	0.87
20 Percent Lower	0.31	0.63	0.77	0.17	0.55	0.73
30 Percent Lower	0.13	0.39	0.53	0.07	0.34	0.51
	Exists County with Average Weekly Wages...					
10 Percent Higher	0.53	0.83	0.91	0.28	0.74	0.88
20 Percent Higher	0.36	0.70	0.83	0.16	0.60	0.79
30 Percent Higher	0.22	0.56	0.74	0.09	0.45	0.69
	Exists County with Average House Price...					
10 Percent Lower	0.60	0.85	0.93	0.39	0.80	0.91
20 Percent Lower	0.48	0.75	0.84	0.31	0.69	0.82
30 Percent Lower	0.36	0.60	0.71	0.24	0.56	0.69
	Both Wages and Housing...					
10 Percent Difference	0.25	0.48	0.61	0.13	0.41	0.58
20 Percent Difference	0.12	0.28	0.37	0.06	0.24	0.35
30 Percent Difference	0.05	0.17	0.24	0.03	0.14	0.22

Notes: Shares reported based on 2017 measures. Unemployment data obtained from the BLS LAUS, Average Weekly Wages obtained from the QCEW, Average House Price obtained by combining FHFA county house price indices, with home values from the 2000 Census to estimate 2017 average house prices. Distance is the distance between county population centroids. Author's own calculations.

Table 2: Impact of State Occupational Licenses on Cross-State Migration, ACS Microdata

	Outcome: Move Out of State in Last Year					
	Include Occupation F.E.			Include Occupation, State, and Year F.E.		
	NCSL Licenses (1)	State Policy Index (2)	Both (3)	NCSL Licenses (4)	State Policy Index (5)	Both (6)
	Sample: All Individuals					
State Licensed	0.000 (0.005)	-0.001 (0.005)	0.000 (0.003)	-0.002 (0.004)	0.001 (0.004)	-0.000 (0.003)
Dependent Mean	0.020	0.022	0.021	0.020	0.022	0.021
Observations	1,099,506	647,543	1,477,050	1,099,506	647,543	1,477,050
	Sample: Those that Moved at All					
State Licensed	-0.009 (0.030)	0.001 (0.028)	-0.002 (0.018)	-0.015 (0.027)	0.010 (0.023)	0.000 (0.017)
Dependent Mean	0.155	0.159	0.161	0.155	0.159	0.161
Observations	143,103	90,852	195,416	143,103	90,852	195,416

Notes: Sample restricted to adult respondents to the 2012-2017 ACS. State occupational licensing measures recorded from the State Policy Index and the National Conference of State Legislatures.

Table 3: Relationship Between Birth State Residence and Migration

	Move at All		Among Movers			
	(1)	(2)	(3)	(4)	(5)	(6)
Originally in Birth State	-0.013*** (0.002)	-0.035*** (0.001)	0.048*** (0.002)	0.052*** (0.002)	-0.152*** (0.004)	-0.157*** (0.003)
Demographic Controls		X		X		X
Dependent Mean, Non-Origin Born	0.15	0.15	0.16	0.16	0.24	0.24
Observations	18,871,967	18,871,967	2,537,353	2,537,352	2,537,353	2,537,352

Notes: Sample restricted to adult respondents to the 2012-2017 ACS. Standard errors corrected for clustering at the state-PUMA level. State-puma by year, age, and occupation fixed effects are included.

Table 4: Relationship Between Birth State Identity and Migration, Pew Mobility Survey

	Ever Left Birth State (1)	Birth State Preferred (2)	Birth State Preferred (3)	Birth State Preferred (4)	Likely Move in Next 5 Years (5)	Likely Move in Next 5 Years (6)	Would Move to One of MSA Provided (7)	Would Move to One of MSA Provided (8)
Birth State Identity	-0.353*** (0.021)	-0.231*** (0.024)	0.281*** (0.027)	0.281*** (0.027)	-0.019 (0.037)	0.012 (0.039)	0.043 (0.027)	0.064** (0.027)
Birth State Identity*In Birth State					-0.131** (0.055)	-0.140** (0.056)	-0.084** (0.041)	-0.113*** (0.040)
Personal Ties		-0.463*** (0.031)		0.001 (0.027)		-0.215*** (0.050)		-0.142*** (0.038)
Personal Ties*In Birth State						0.119** (0.057)		0.177*** (0.052)
In Birth State					0.019 (0.055)	0.028 (0.060)	0.008 (0.031)	-0.012 (0.031)
Dependent Mean	0.555	0.555	0.351	0.351	0.370	0.370	0.781	0.781
Observations	1,948	1,948	1,949	1,949	1,948	1,948	1,948	1,948

Notes: Sample restricted to US born survey respondents from the 2008 Pew Research Center Mobility Survey. Observations are weighted using the Pew Research Center survey weights. Standard errors corrected for clustering at the current state of residence level.

Appendix Tables and Figures

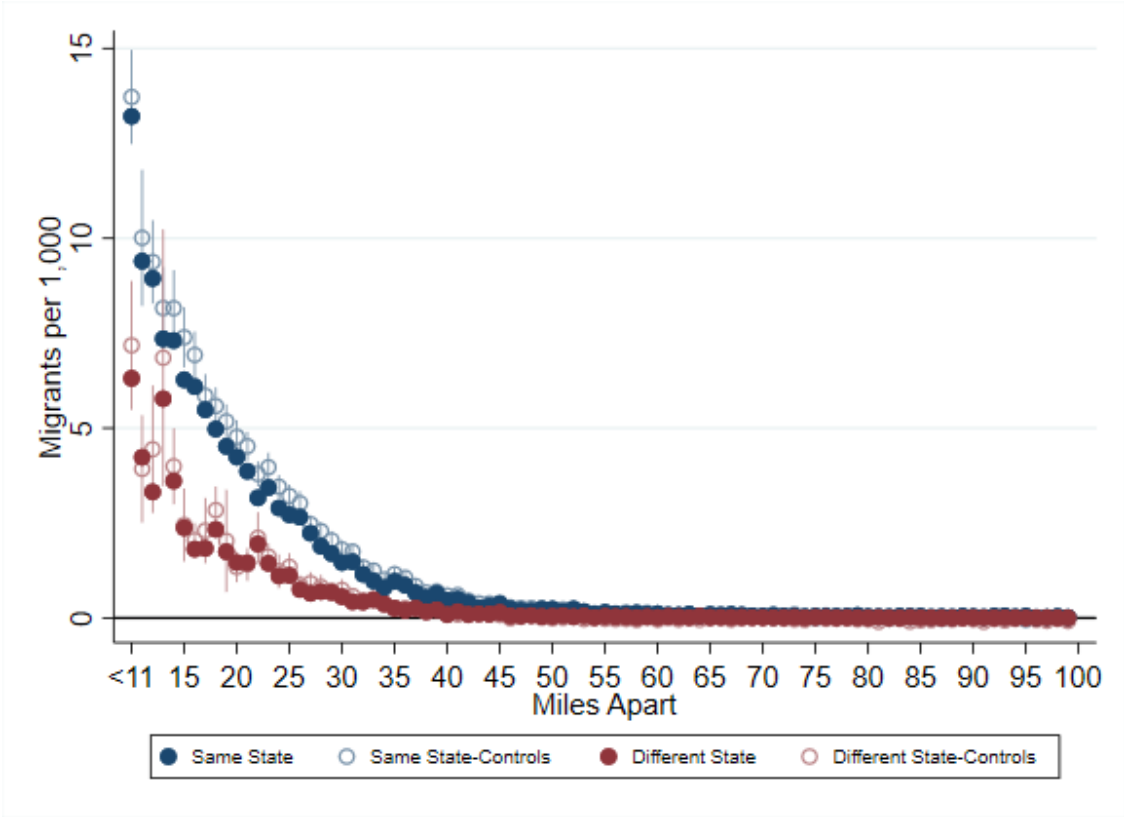


Figure A1: County-to-County Migration Rates by Distance and for Same-State and Different-State Counties, Including Closer and Farther Distance Bins

Notes: Outcome is number of migrants per one thousand people at the origin county using the IRS SOI county-to-county flows from 2017. This is then averaged into 1-mile bins for county pairs in the same state and county pairs in different states. Distance is the distance between the population weighted county centroids. The "with Controls" plots coefficients for one-mile bins from equation (2), accounting for origin fixed effects, destination fixed effects, and differences between the origin and destination county in labor market measures (the unemployment rate, employment to population ratio, average weekly wages), differences in industry shares (share in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, share female, non-Hispanic White, non-Hispanic Black, non-Hispanic other, Hispanic, under 20, 20-34, 35-49, 50-64, and 65 and older) differences in natural amenities (the January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale), the 2016 presidential Republican vote share, and differences in the county housing price index, converted to dollars using the median house value from 2000. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI.

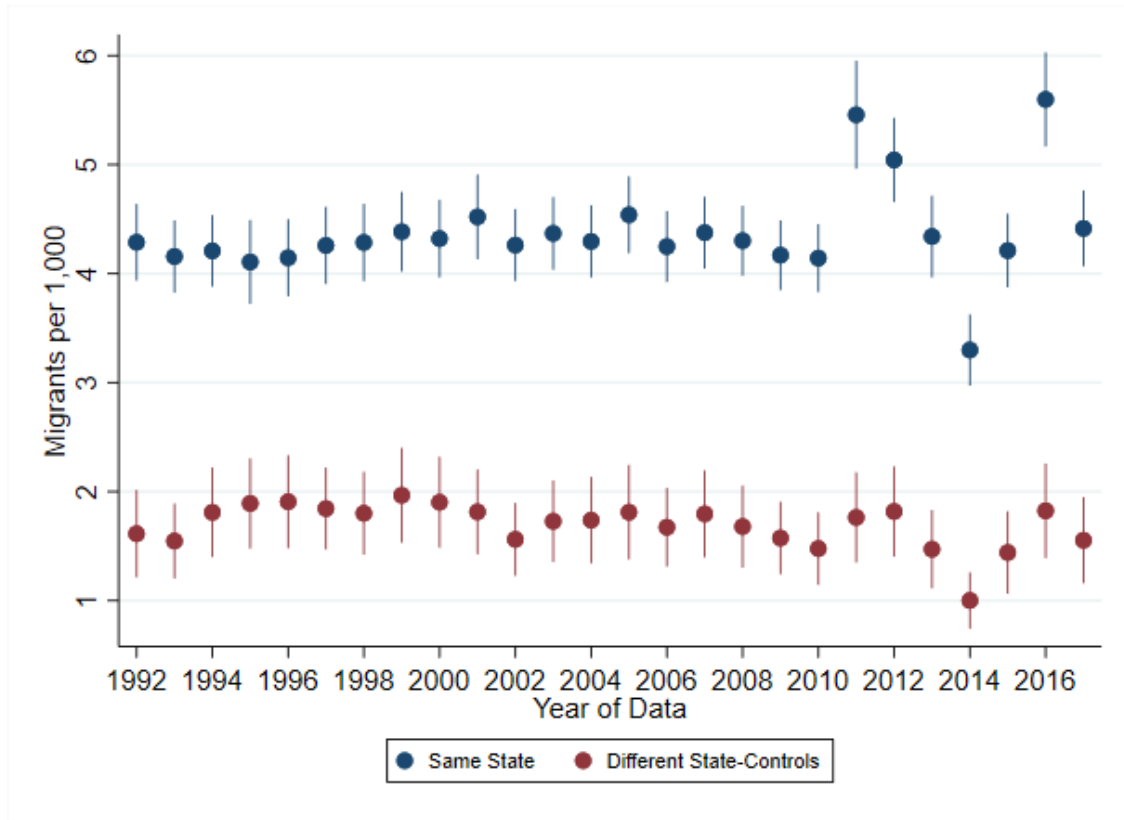


Figure A2: Impact of State Borders on County-to-County Migration from 1992 to 2017

Notes: Average migration rates for same-state and cross-state county pairs in the 20 mile bin are plotted for 1992-2017. Also estimates for the 20 mile bin are obtained by regressing equation (2) for each year from 1992 to 2017 separately are plotted. 95-percent confidence intervals are provided. IRS migration data measures changed significantly in 2011 and 2013. In 2011, the IRS extended the data collection period from September to the end of the year, which includes more complicated returns. They also used the information of other household members to identify links over time. Prior to 2013, county-to-county flows below 10 tax units (households) was suppressed. In 2013 that limit increased to 20.

Source: Author's own calculations using the IRS county-to-county flows from 1992 to 2017.

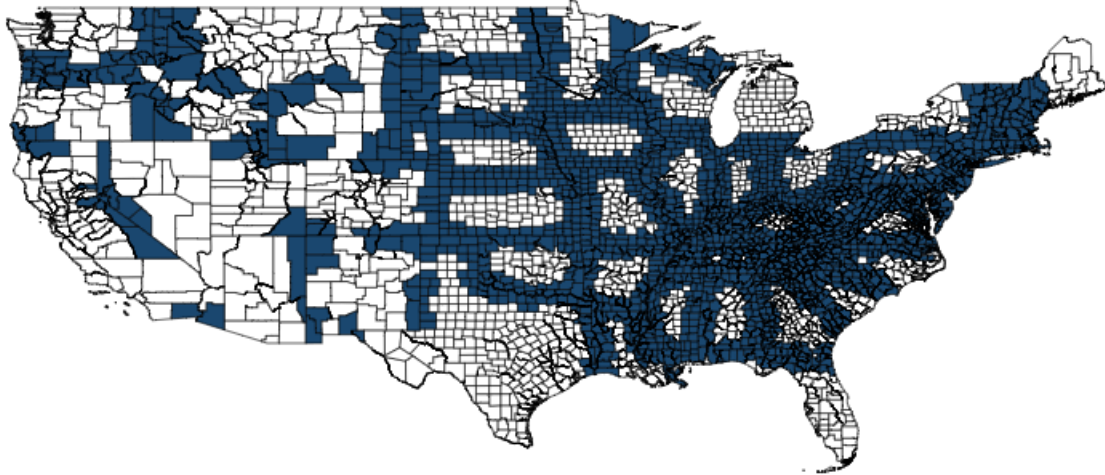


Figure A3: Counties within 60 Miles of a County in a Different State

Notes: Counties with a population centroid less than 60 miles from the population centroid of another county in a different state are indicated.

Source: Author's own calculations.

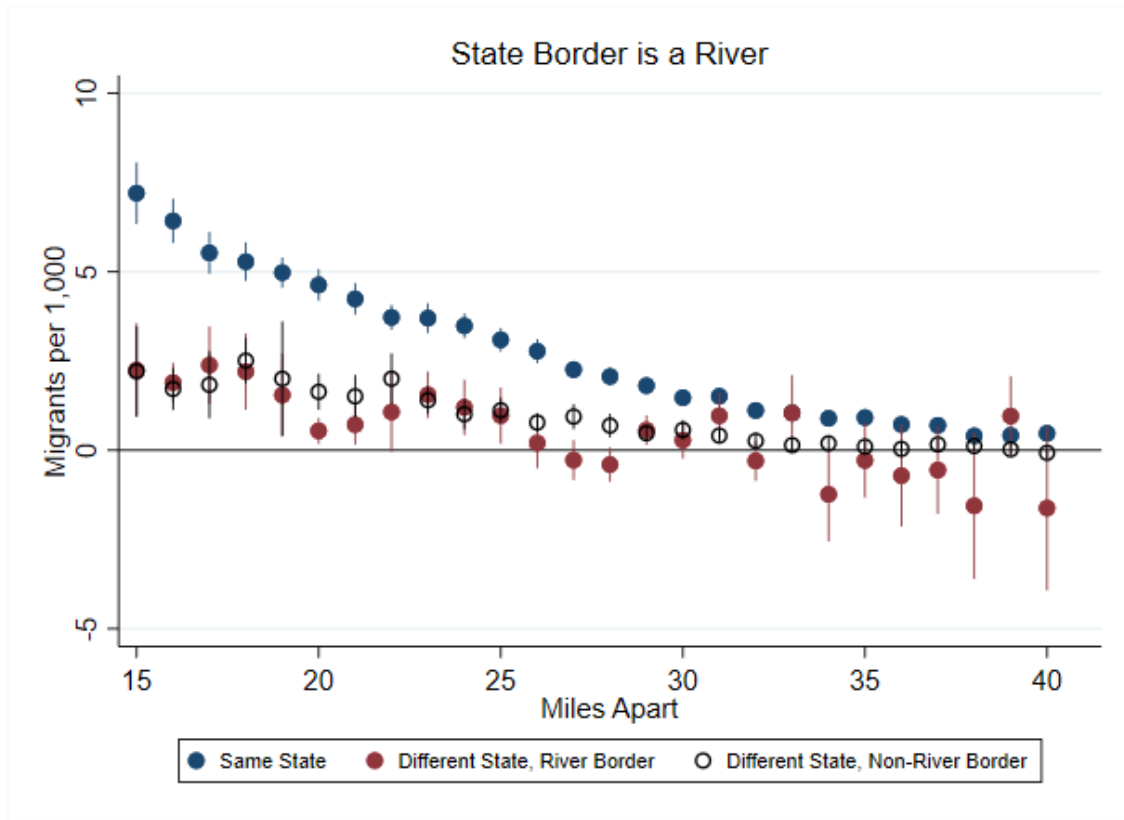


Figure A4: Role of Pecuniary Costs: States Separated by Rivers vs. Arbitrary Borders

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Coefficients from equation (2) where the characteristic is the presence of a river border between states. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI.

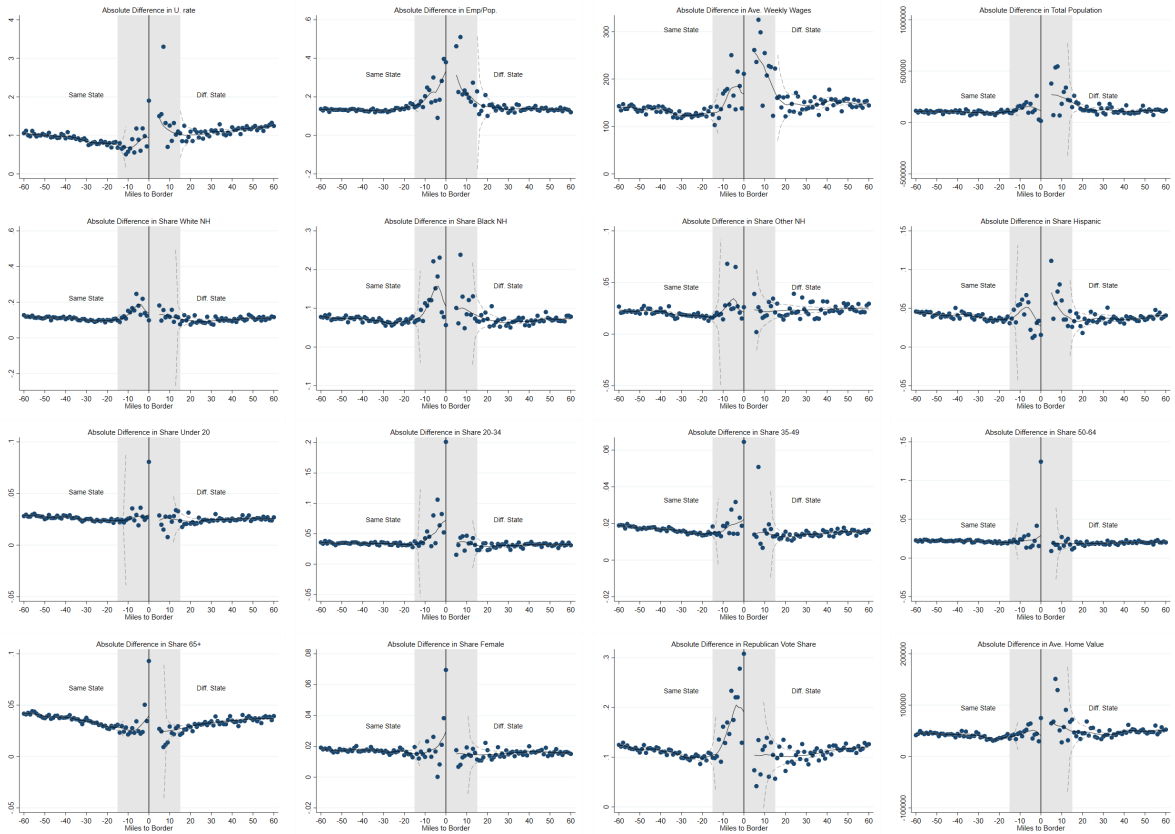


Figure A5: Role of Differences in Utility: Changes in Local Characteristics at State Border

Notes: Average difference in characteristics in one mile bins for county pairs in the same state and different states are plotted with local linear polynomial regressions and 95-percent confidence intervals. There are few county pairs within 15 miles of each other, and these are excluded from my main analysis. These pairs are shaded in gray for reference.

Source: Author's own calculations using the SEER 2017 data, NCSL 2016 vote data, and FHFA HPI 2017 data.

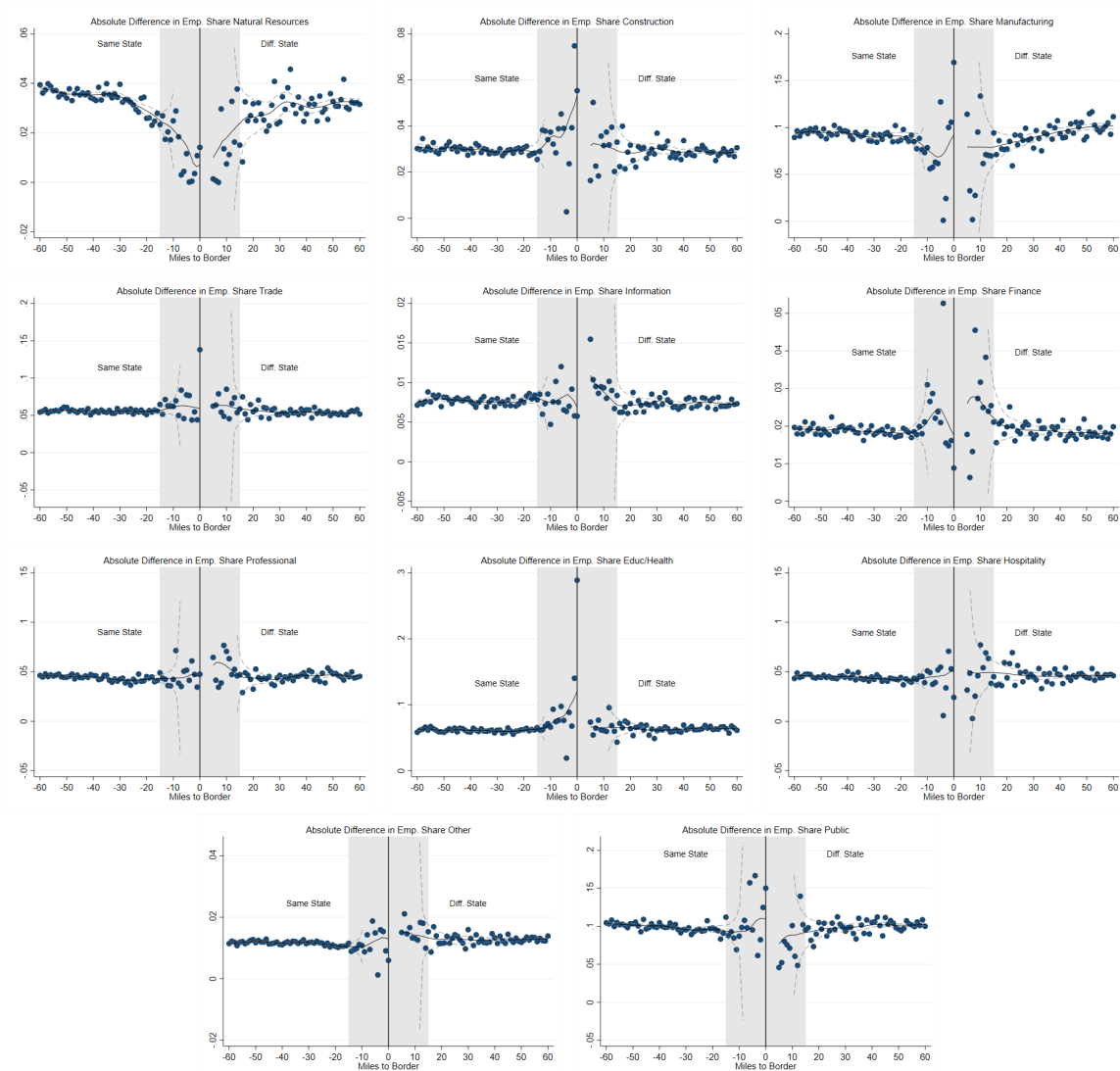


Figure A6: Role of Differences in Utility: Changes in Local Industry Composition at State Border

Notes: Average difference in characteristics in one mile bins for county pairs in the same state and different states are plotted with local linear polynomial regressions and 95-percent confidence intervals. There are few county pairs within 15 miles of each other, and these are excluded from my main analysis. These pairs are shaded in gray for reference.

Source: Author's own calculations using the QCEW 2017 data.

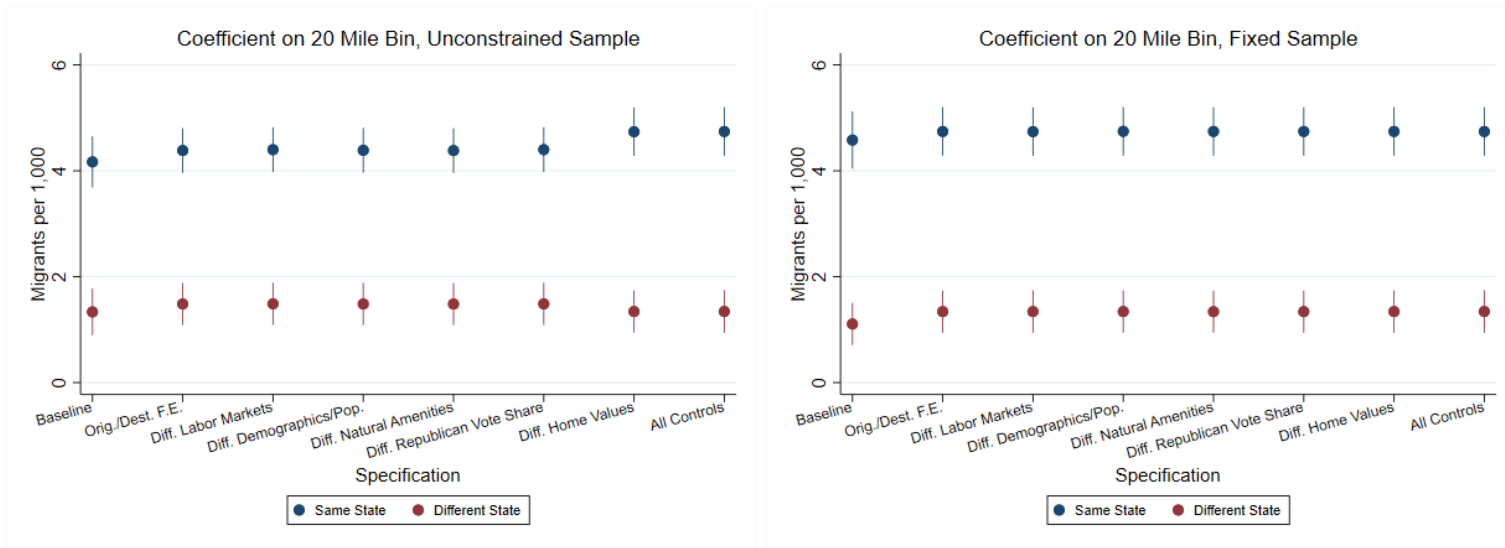


Figure A7: Estimate Sensitivity to Each Separate Group of Controls

Notes: Point estimates for the 20 mile bin are obtained by regressing equation (2) including each group of controls separately are plotted. 95-percent confidence intervals are provided. The panel on the left does not constrain the sample to be the same across all specifications. The panel on the right constrains the sample to be the same, requiring non-missing controls across all types of controls.

Source: Author's own calculations using the IRS county-to-county flows from 2017.

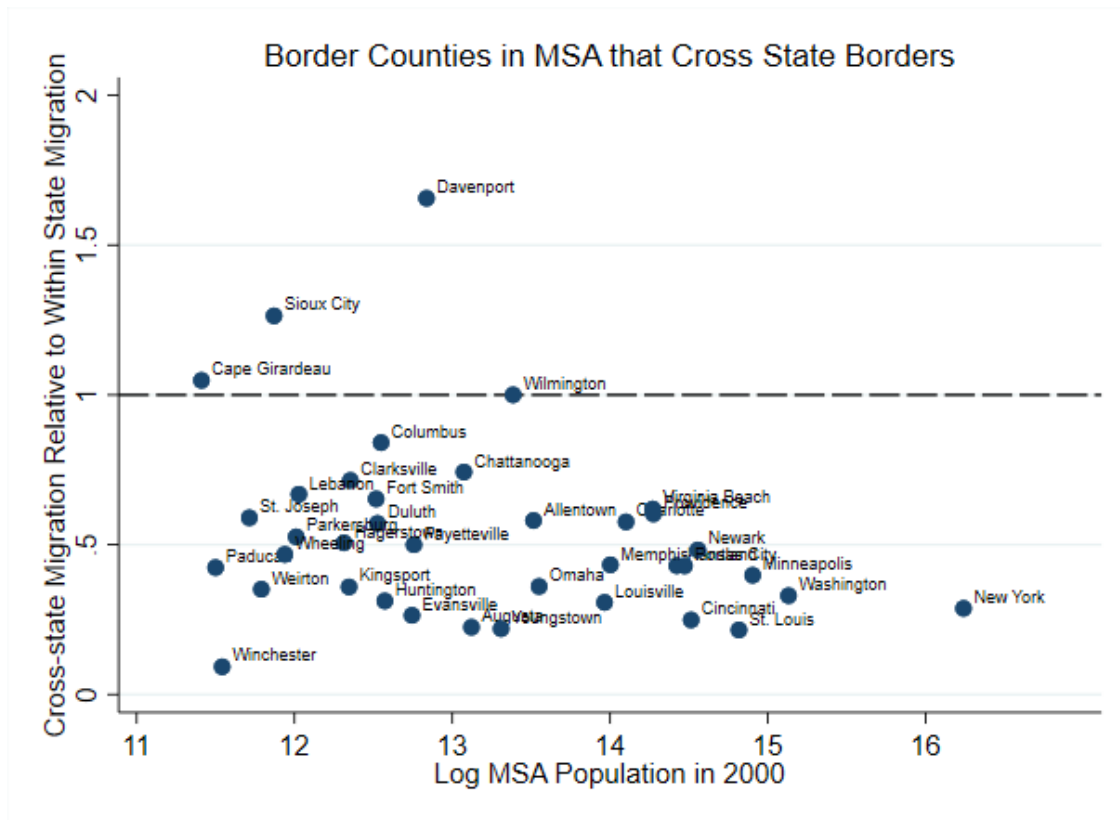


Figure A8: Impact of State Borders on County-to-County Migration by Specific MSA

Notes: The ratio of cross-border migration relative to within state migration for county pairs in the same MSA is plotted for each MSA that crosses state borders and has more than one county in each state.

Source: Author's own calculations using the 2017 IRS SOI.

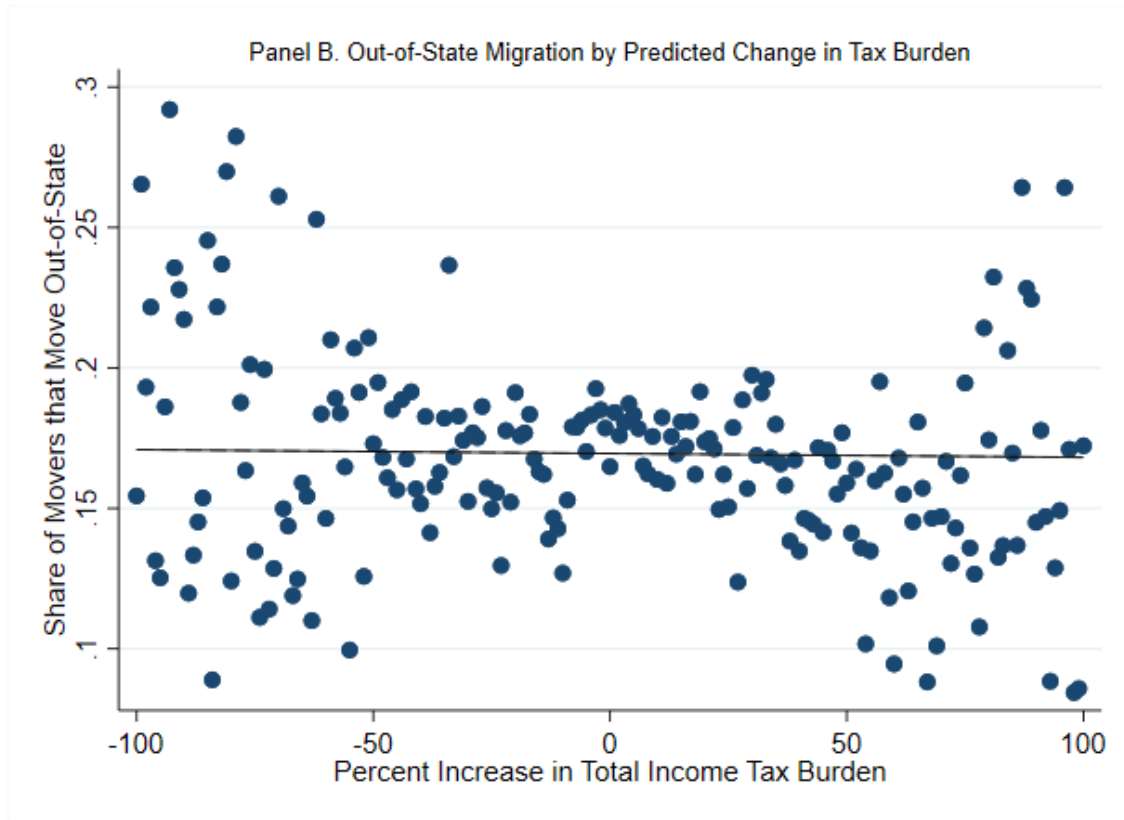


Figure A9: Share of Households that Move Out-of-State by Expected Percent Increase in Tax Burden

Notes: Sample is limited to families originally living in a commuting zone that crosses a state border. Each point represents the share of migrants that moved across state borders, by the difference in the average total income tax burden associated with moving between the origin state and the other state(s) in the commuting zone. The black line indicates the linear relationship.

Source: Author's own calculations using the 2012-2017 ACS Microdata.

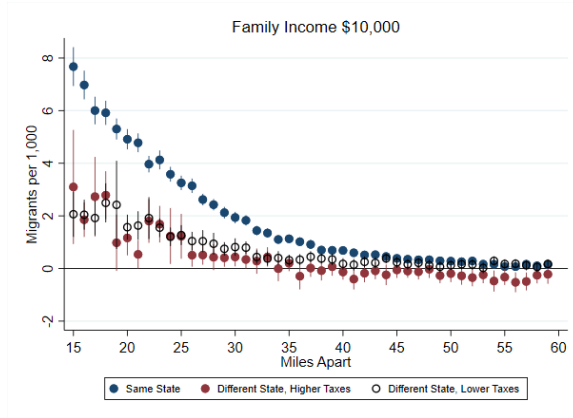


Figure A10: Role of Pecuniary Costs: Differences in State Income Tax Burden for Joint Households with 2 Children, \$10,000 Income

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Each panel plots the coefficients from equation (5) with and without controls, where *Higher* is having a higher state income tax burden. For each income level, the state income tax burden is calculated for a married household filing jointly with 2 children using Taxsim. Cross-border county pairs classified as having a state income tax burden that is less than or equal to the tax burden in the origin state or greater than in the origin state. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI.

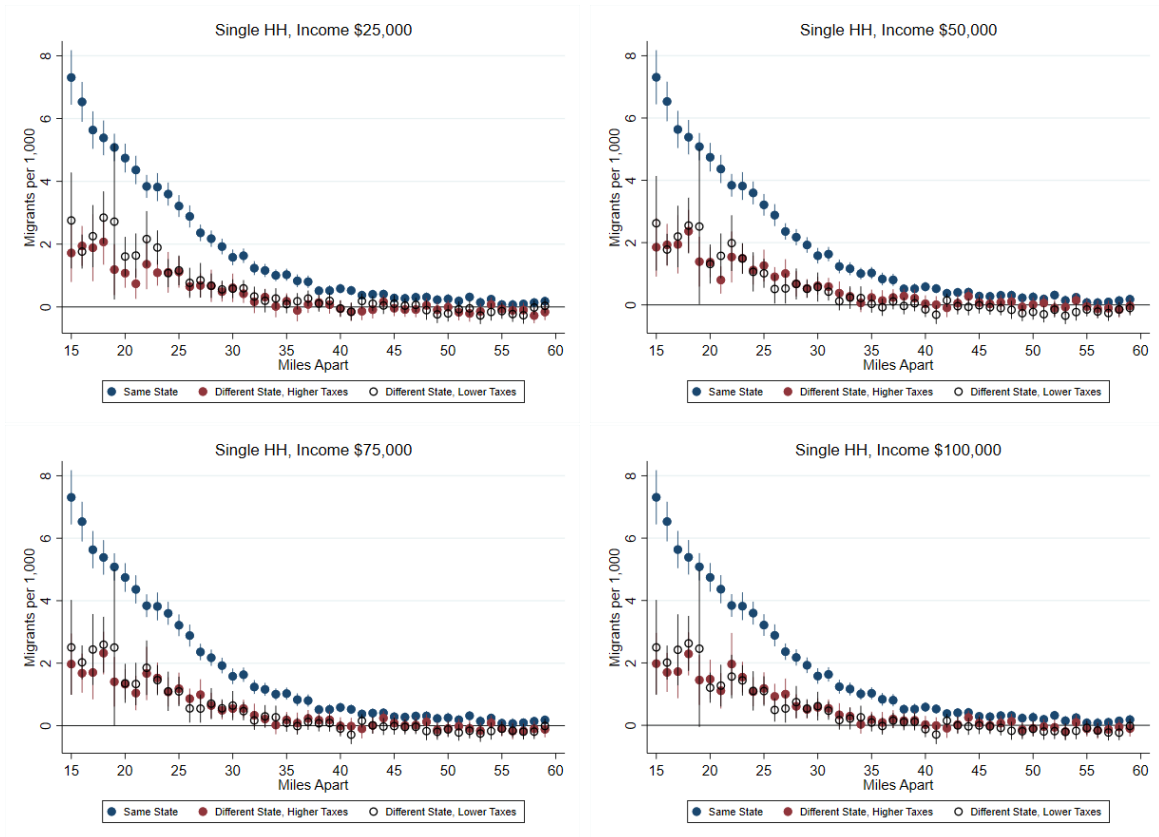


Figure A11: Role of Pecuniary Costs: Differences in State Income Tax Burden by Income Level for Single Households

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Each panel plots the coefficients from equation (5) with and without controls, where *Higher* is having a higher state income tax burden. For each income level, the state income tax burden is calculated for a single householder using Taxsim. Cross-border county pairs classified as having a state income tax burden that is less than or equal to the tax burden in the origin state or greater than in the origin state. 95-percent confidence intervals are provided.

Source: Author’s own calculations using the 2017 IRS SOI.

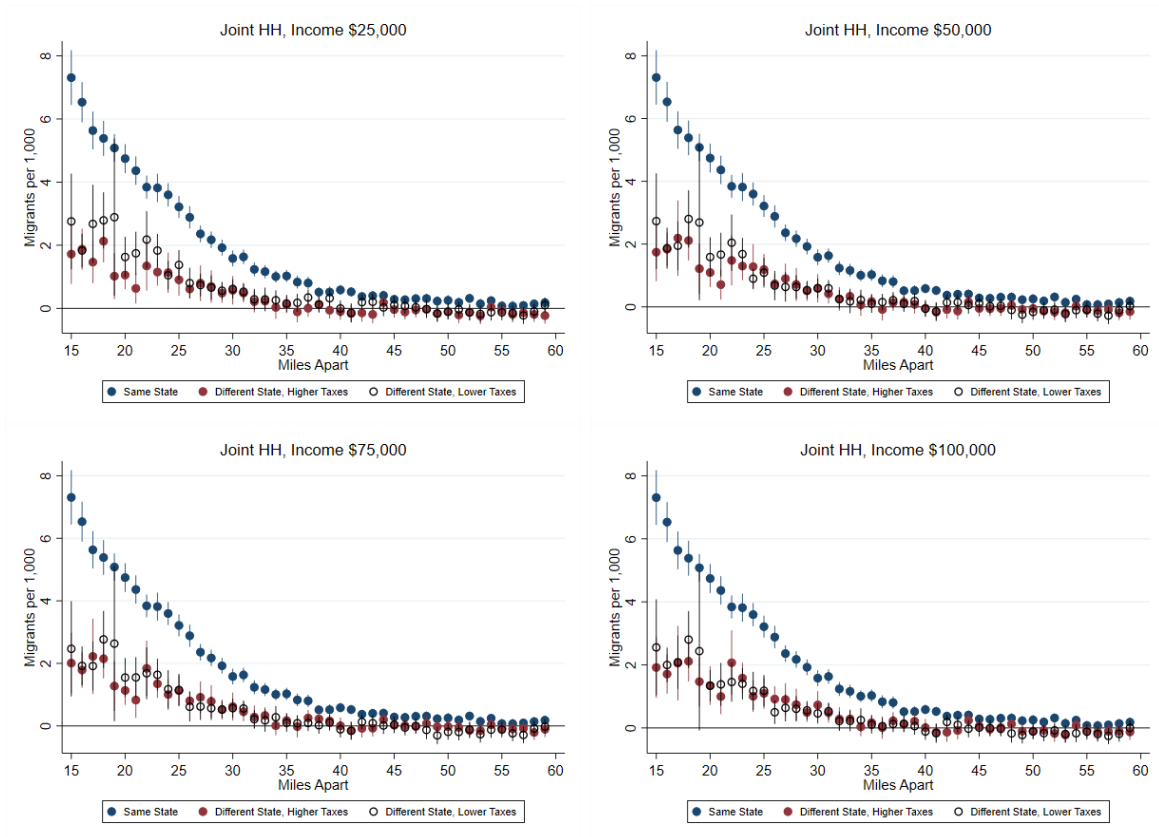


Figure A12: Role of Pecuniary Costs: Differences in State Income Tax Burden by Income Level for joint Households

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Each panel plots the coefficients from equation (5) with and without controls, where *Higher* is having a higher state income tax burden. For each income level, the state income tax burden is calculated for a married household filing jointly without children using Taxsim. Cross-border county pairs classified as having a state income tax burden that is less than or equal to the tax burden in the origin state or greater than in the origin state. 95-percent confidence intervals are provided.

Source: Author’s own calculations using the 2017 IRS SOI.

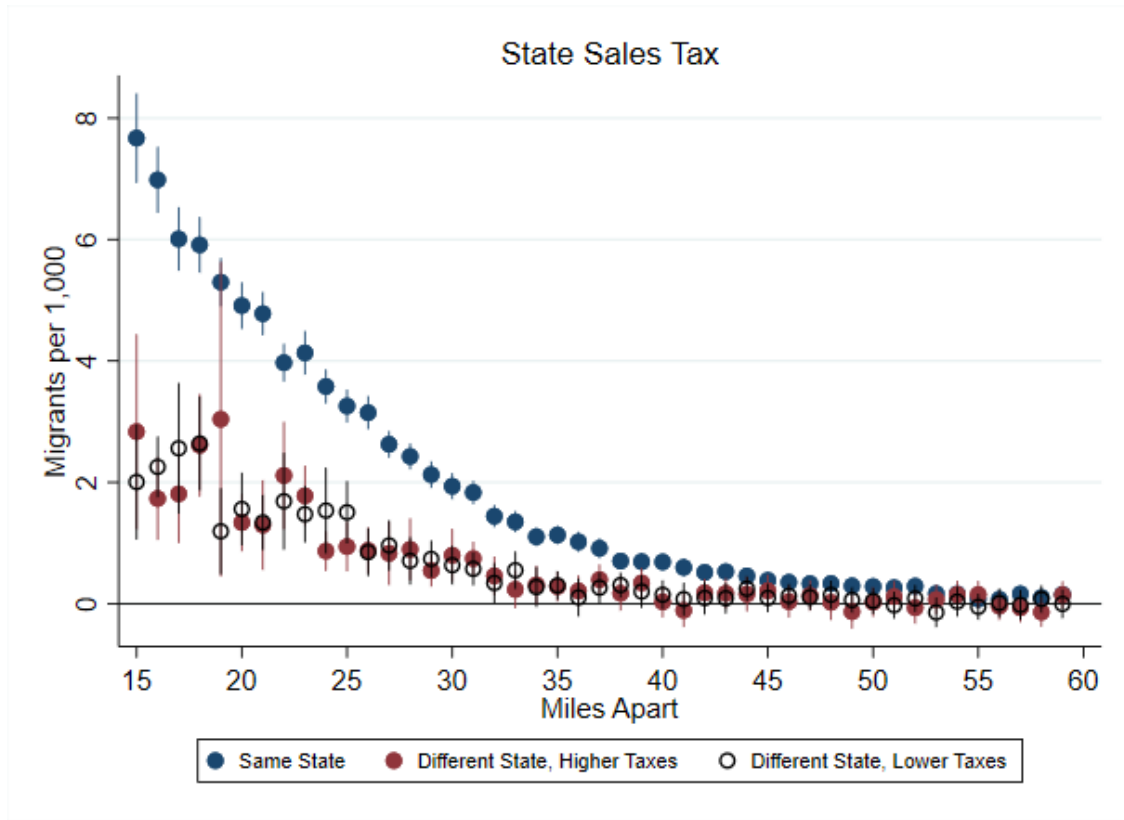


Figure A13: Role of Pecuniary Costs: Differences in State Sales Tax Burden

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Each panel plots the coefficients from equations (1) and (2) where the characteristic is the state income tax burden. For each income level, the state income tax burden is calculated for a married household filing jointly using Taxsim. Cross-border county pairs classified as having a state income tax burden that is less than or equal to the tax burden in the origin state or greater than in the origin state. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI.

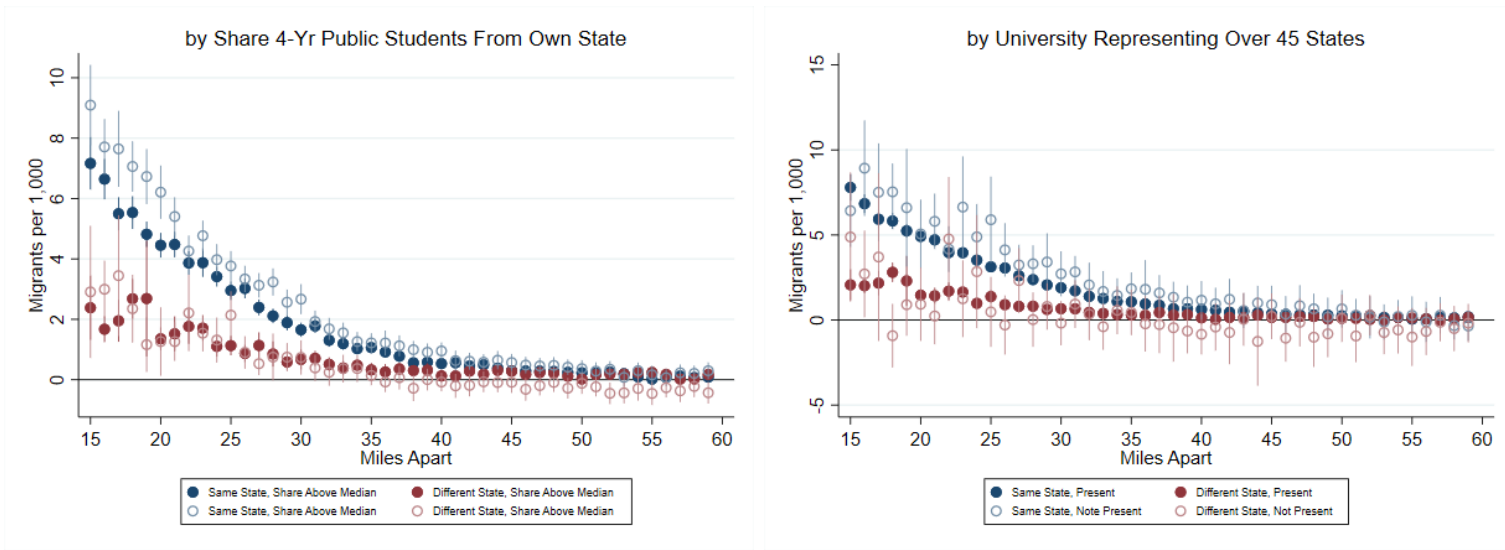


Figure A14: Identity from State Colleges: Migration by Interstate Connectivity of State Colleges

Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. Coefficients from equation (2) where the characteristic is whether public four year institutions have an above or below median share of own state students (in the left Panel) and whether there is a university in the state with students from 45 or more states. 95-percent confidence intervals are provided.

Source: Author's own calculations using the 2017 IRS SOI.



Figure A15: Impact of State Borders on Labor Market Recovery After the Great Recession, Lagged Outcome Control

Notes: These estimates are similar to those in Figure 15, but rather than including county fixed effects, I control for the county-level outcome from 2005, as suggested by (Hershbein and Stuart, 2020). Event study coefficients are plotted with 95 percent confidence intervals, and represent the percent change in outcomes relative to 2005, for each percentage point increase in commuting zone employment reduction between 2007 and 2009. Observation at the county by year level. State-by-year fixed effects, as well as an indicator for being a border county interacted with year fixed effects are included. Standard errors corrected for clustering at the commuting zone level.

Source: Author's own calculations using the 2000-2017 QCEW and 2000-2017 IRS SOI.