Isolated States of America: 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 mobility in the US. Namely, county-to-county migration and commuting 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. These gaps remain 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, county-to-county social connectedness (as measured by the number of Facebook linkages) follows a similar pattern. 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 and in-commuting, suggesting the lack of mobility leads to slower labor market adjustment.

Keywords: Internal Migration, Commuting, Social Networks, Border Discontinuities
JEL Codes: J6, R1

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1 Introduction

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). Mobility is traditionally seen as both a chance 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). However, there is significant heterogeneity in local economic conditions across the country. Most counties are within 60 miles of another county with either significantly higher average wages, significantly lower average house prices, or both (Appendix Table A1). Although there might be other local characteristics that offset these raw spatial differences, it seems plausible that many individuals could encounter employment or housing "opportunities" through short distance mobility, either migration or commuting. Frictions that reduce or limit internal migration or commuting could lead to less dynamic local economies.

I document a previously undocumented aspect of US internal migration and commuting that has implications for labor market fluidity and dynamism. Using the Internal Revenue Service (IRS) county-to-county migration data, and Longitudinal Employer-Household Data (LEHD) Origin Destination Employment Statistics (LODES) data on county-to-county commute flows, I show that even conditional on distance, county-to-county migration and commute flows drop significantly when a state border lies 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. People are about twice as likely to commute to a different county in the same state than to an equally distant county in a different state. In other words, state borders reduce both long-term and temporary human mobility. In this paper, I document the extent of these empirical patterns, explore potential explanations for why this cross-border drop in mobility exists, and evaluate how this empirically evident mobility 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 utility or differences in moving costs. As I document, the gap in migration and commute rates associated with state borders does not appear to be driven by differences in local characteristics that could drive differences in utility. The cross-border mobility 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 market 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 and similar, such as counties in the same Metropolitan Area (MSA) or Commuting Zone (CZ) or even neighboring counties on state borders.

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 mobility gap. The fact that a similar discontinuity is present when examining county-to-county commute flows, suggests that the phenomenon 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, cross border migration and commute rates 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 over 60 percent less likely to move out of state than other individuals in the state that were born elsewhere.

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 and commuting associated with state borders falls substantially, suggesting that most of the discontinuity in mobility is empirically explained by social network strength or something correlated with the social network.

However, causality potentially runs in both directions: a lack of friends and acquaintances could reduce cross-border mobility, but a drop in migration/commuting 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 mobility 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). 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, simultaneously keeps people from moving or making social connections across state lines. A strong birth state identity could affect mobility, regardless of the presence of local ties to family and friends.

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 are not the main drivers of the drop in mobility precisely at state borders.

Analysis of Pew Research Center data on mobility (Pew Research Center, 2009) suggests that as much as 68 percent of people "identify" with their birth state, meaning birth state identity could play a significant role. 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 living outside their state of birth are no less likely to consider a move, while people with birth state identity currently reside in their birth state are significantly less likely to 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' family ties or ties to amenities in the area they currently live, suggesting birth state identity is a factor independent of other local ties.

I build on existing work exploring the role of local ties (Zabek, 2020), rootedness (Kosar et al., 2020), and migration costs (Desmet et al., 2018). 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. Spatial economic models also highlights the role of migration costs, but this is often an all-encompassing term meant to capture the fact that there are regional wage differences that are not equalized by migration (Desmet et al., 2018).

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 economic recovery from the Great Recession (Hershbein and Stuart, 2020), I show that counties at the state border, where this mobility friction is plausibly more binding, see slower recoveries in employment. Ten years after the initial 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 and in-commuting after the recession, leading to persistently worse labor market outcomes. This suggests that state borders 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 and economic mobility (Chetty et al., 2014) observed across the United States.

2 County-to-County Mobility Data

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. The annual IRS Statistics of Income (SOI) county-to-county migration flows data are 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 origin county population (in thousands) to measure the number of migrants per 1,000 people.

To capture county-to-county commute flows I use the LEHD Origin Destination Employment Statistics (LODES). These measures are constructed from LEHD microdata derived from unemployment insurance wage records. For over 90 percent of workers in the wage records, place of residence and place of employment are recorded, allowing the construction of publicly available county-to-county flows. I divide the number of workers by the county population to measure the number of commuters per 1,000 people

Because the IRS data do not provide migration flows for subpopulations, I supplement this data with migration microdata from the annual American Community Survey (ACS).[1] 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 and place of work differences across individual characteristics, like demographics, occupation, and place of birth. I use microdata from the 2012-2017 waves.[2]

I also exploit individual-level data from a 2008 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.

To understand the impact of state borders on social networks I use the Social Connect-

[1]The LODES provides flows for subgroups, but only by broad age, education, and industry categories.

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

edness Index (SCI) which maps county-to-county Facebook friendship networks 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 these 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 County-to-County Mobility: The Empirical Pattern

3.1 State Borders and County-to-County Migration and Commuting

Even in the raw IRS migration and LODES commuting 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 (commuters) 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.[3] Both within state and across state migration and commute 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 while commute rates are approximately twice as high for same-state county pairs.

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

$$Y_{od} = \sum_{b=15}^{59} \beta_b(\textit{Diff. State*b Miles Apart}) + \gamma_b(\textit{b Miles Apart}) + \varepsilon_{od} \tag{1}$$

[3] There 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 A4).

The outcomes of interest are the origin/destination specific number of migrants per 1,000 people at the origin and the origin/destination specific number of commuters per 1,000 people. The explanatory variables are the interactions between an indicator for whether the counties are in different states and a vector of one mile distance bin indicators. 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/commute rates for counties in the same state, while the β_b coefficients indicate how much lower the migration/commute 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 graphically, with the γ_b coefficients and the total effect for counties in different states ($\beta_b + \gamma_b$) plotted with 95 percent confidence intervals. These point estimates are provided in Appendix Figure A1 and match the means estimated in Figure 1 since migration and commuting levels in the omitted group is approximately zero. I use the final year IRS migration data are available, 2017, so there is only one observation per origin/destination pair. As I show in the appendix, the state-border discontinuity is similar for all years available in the data, since 1992 for migration and 2003 for commuting (see Appendix Figure A2).

This flexible parameterization does not impose strong assumptions on the way distance impacts mobility, but it also does not provide a concise estimate of how state borders reduce mobility. To distill the impact of state borders on migration and commute rates into a single parameter, I will estimate the ratio of 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. There is a similar 74 percent reduction in commuting.

3.2 Sensitivity of Pattern to Controls and Samples

Counties across the country differ on many dimensions, potentially explaining the cross-border differences in mobility. 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

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

The X_{od} vector includes differences in origin and destination labor markets (unemployment rates, employment to population ratios, average weekly wages, number of establishments, and industry shares); differences in the total 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 and throughout the paper, controlling for demographic, economic, and housing market differences between the origin and destination (the lighter plotted points) does not close the gap. State borders are still associated with a 67 percent reduction in migration rates and a 76 percent reduction in commuting.

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, I limit the rest of the analysis to origin counties that have at least one cross-border county within 60 miles (see the map in Figure A3).[4] As seen in the left panel of Figure 2, the distance gradient and state-border penalty is essentially unchanged. Conditional on distance, state borders reduce migration by 72 percent.

The patterns in migration and commuting are also similar if I limit the sample to include county pairs in the same commuting zone, and focus on commuting zones that cross state borders. By construction, these counties are close and economically connected. Even with a smaller sample and less precision there is still a significant reduction in migration associated with the state border (middle panel of Figure 2).[5] The impact of state borders is negative for commuting, but not precise.

The gap associated with state borders persist if I exclude county-to-county flows of zero (Appendix Figure A6). It is present across the Northeast, Midwest, and South (Appendix Figure A7), with some evidence in the West where counties are large, although the pattern is less clear.

3.3 Sensitivity to Measure of Distance

Comparing the direct distance between county population centroids might provide the wrong comparison. If cross-state road networks are more sparse, or if state borders correspond with natural features likes rivers (as is the case for at least one county in 41 states), travel across state lines might be more costly, even if equidistant. However, if I calculate the GPS travel time between each county pair and re-estimate equations (1) and (2), but measure distance in terms of minutes of travel, the role of state borders is similar, (right panel of Figure 2).[6]

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

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

[5]This pattern also holds for counties in the same MSA or neighboring counties on state borders (Appendix Figure A5).

[6]As seen in Appendix Figure A9, the state border penalty is similar for counties separated by land or by rivers.

state-border discontinuity in mobility or that can be ruled out as a important driving force. The second goal of this paper is to document to what extent this empirical pattern 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 that builds on the early work of Sjaastad (1962). In its simpliest 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

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

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

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

For state borders to influence migration rates, the model would suggest that either (1) local characteristics that contribute to utility differences or (2) moving costs between the origin and destination d change discontinuously at state borders.[7] 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). Newer

[7]Adding 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.

economic geography models incorporate moving costs (Desmet et al., 2018; Redding and Rossi-Hansberg, 2017), but these are often indirectly inferred from differences in population and migration rather than being derived from institutional or social features. 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. In the language of spatial economics, both exogenous (geographic features) and endogenous (economic and social features) amenities could evolve discontinuously across state borders (Redding and Rossi-Hansberg, 2017). Importantly, the utility components for migrants and commuters might be different. 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 potentially explain the mobility pattern. 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 a more conservative measure of 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 weekly wages, number of establishments); 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 3 and A10. As noted above, my analysis focuses on county pairs that are between 15 and 60 miles apart because there are few county pairs less than 15 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 polynominals become large as the distance falls below 15 miles.

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 eliminate the discontinuity in migration or commuting at the state border.

Another way to determine if the discontinuity is driven by differences in utility is to focus on county pairs that are "close" and economically 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 the middle panel of Figure 2, we see a similar decline in migration for counties in the same CZ and in Figure A5 the same is true for counties in the same MSA, or that border each other. These significantly smaller samples exhibit less precision, but nonetheless, state borders are associated with a 56 percent decline in migration for same-MSA counties.[8] People are at least twice as likely to move to a neighboring county in the same state then move to a neighboring county in a different state.[9] As seen in Appendix Figure A8, this pattern also holds for individual MSA, even 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 mobility across state borders does not appear to be driven by differential changes in location-specific utility, 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. For commuters, the costs are often different. Commuters can cross state-lines without incurring many of these adjustment costs associated with moving (such as updating registration), but still face some costs, such as state-level taxation. 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 migration adjustment costs.[10] However, I explore several potential cost channels that have been highlighted in the internal migration literature that could affect both migration and commuting.

[8] This number is 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.

[9] Among 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.

[10] One 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 A9 I plot estimates from a specification similar to equation (6), 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.

Occupational Licensing

Some states require licenses, certificates or education/training requirements for someone to perform certain tasks or occupations.[11] 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 either 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.

A comprehensive database of occupational licensing requirements across states and over time does not exist. Previous research exploring occupation licensing has had to rely on self-collected records state by state, for available occupations (Carollo, 2020). Furthermore, states sometimes license tasks rather than occupations, making it hard to map licenses to occupation codes. To explore the role of licensure, I exploit the relatively new licensing measures available in the CPS.[12] Starting in 2015, CPS respondents were asked three questions about professional licensing: (1) Do you have a currently active professional certification or a state or industry license? (2) Were any of your certifications or licenses issued by the federal, state, or local government? and (3) Is your certification or license required for your job? Following Kleiner and Soltas (2019), I indicate that an individuals' occupation is licensed by the government if they answer yes to the first and second question. I then collapse the CPS data to the state by year by 4-digit occupation code, to determine what share of workers in a given occupation and state report that they have a government issued license. As Kleiner and Soltas (2019) report, individual reports of licensure contain measurement error. Even in universally licensed occupations only about 65 percent of workers are flagged as having a government license. To improve the signal of these measures, I will consider a more restric-

[11] See Carollo (2020) and Kleiner and Soltas (2019) for a comprehensive treatment of the labor market and welfare impacts of occupational licenses.

[12] Results are similar if I instead use occupational licenses as captured by Johnson and Kleiner (2020) or the National Council of State Legislatures.

tive measure of occupational licensing (25 percent or more of the workers in the cell reported a government issued license) and a less restrictive measure (over 10 percent).[13]

To determine if occupational licenses produce the drop in migration and commuting at state borders I explore cross-state migration and commute rates by occupation licensure status in the ACS and estimate the following relationship

$$Y_{isot} = \beta \mathit{Licensed\ Occupation}_{isot} + \gamma_o + \delta_s + \phi_t + \varepsilon_{isot} \tag{5}$$

The outcomes of interest are a binary indicator that equals one if the individual moved out of state s in the past year and a binary indicator for if the worker commutes out of state s (i.e., their place of work is in a different state). The explanatory variable of interest is the indicator *Licensed Occupation*, which equals one if the individual in year t is in a occupation (o) where the share of workers in their state (s) that report having a license exceeds the pre-specified threshold (25 or 10 percent). For migration, the state of residence in the previous year is used to determine licensure status. For commuting, the current state of residence is used. I explore specifications that only control for occupation fixed effects; occupation, state, and year fixed effects (as in equation (5)), and occupation, state, and occupation by year effects. This last specification will compare workers in the same occupations in licensed and unlicensed states.

Results are reported in Table 1. Among the full population, being in a licensed occupation has no effect on moving out of state. Limiting the sample to those who move, to account for selection into moving, does not change the results. The coefficients are small, precise and positive, suggesting government issued licensing has no systematic effect on out-of-state migration. The pattern is similar for out-of-state commuting. Only one specification (including only occupation fixed effects) suggest a marginally significant 0.3 percentage point reduction in out-of-state commuting associated with occupational licensing.

[13]The CPS data does not explicitly separate federal, state, or local licenses. However, by including occupation by year fixed effects universal licensing practices will be absorbed, leaving state and local licensure.

I explore the impact of occupational licensing on migration and commuting further in Figure A11. First I restrict the sample to occupations that are licensed in at least one state, but not all states. I then plot each occupation's share that moved in the last year on the x-axis, and the share that moved out-of-state on the y-axis, separately for licensed stats and unlicensed states. Each occupation is weighted by the summed sampling weights for all of the workers in the cell. The linear relationship between these two migration shares for non-licensed occupations is plotted in blue with 95 percent confidence intervals. In general, occupations that have a higher migrant share have a higher out-of-state migrant share. I then overlay the plot for cells 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 if anything the linear relationship (in pink) for licensed occupations is steeper. Commute patterns are similar, although the slope for unlicensed occupations is significantly steeper. Overall, there is little evidence that occupational licensing leads to the drop in migration across state borders, but there is some evidence it could contribute to lower levels of cross-border commuting.

State Taxation

Taxation also varies across state lines, sometimes 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' locations are sensitive to these income tax differences. There is also heterogeneity across states in sales tax rates and corporate tax rates.

Differences in tax burden and state taxes could lead to discontinuous changes in migration and commuting across state borders. However, if the discontinuity is due to state level taxation, we would expect asymmetric behavior, with lower flows from low to high tax states and higher flows from high to low tax states. 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.

$$Y_{od} = \sum_{b=15}^{59} \beta_b(\textit{Higher*Diff. State*b Miles Apart}) + \theta_b(\textit{Lower*Diff. State*b Miles Apart}) \\ + \gamma_b(\textit{b Miles Apart}) + X'_{od}\Gamma + \phi_o + \delta_d + \varepsilon_{od} \quad (6)$$

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 mobility to counties in different states with a higher tax burden, while the θ_b represent the differential mobility to counties in a different state with a tax burden less than or equal to the origin. Both of these are relative to mobility between counties in the same state (where state taxes are the same).

In Figure 4 I show whether migration and commuting patterns differ for cross-state county pairs with high-to-low and low-to-high income, sales, and corporate tax burdens. Using tax burden estimates from the NBER TAXSIM I examine how the role of state borders differ for households that are married and filing jointly with two children and $75,000 of annual income in the left column. Conditional on distance, migration and commute rates to both higher and lower income tax destinations are lower than to counties in the same state. Furthermore, the patterns for high-to-low and low-to-high flows are not statistically distinguishable. The patterns are similar for states sales tax rates in the middle column. The point estimates for commuting to counties in lower sales tax states are consistently higher (e.g., the border penalty is smaller), but not statistically different. The border penalty is no different for migration or commuting to counties in states with higher or lower corporate tax rates (right column). There is no consistent evidence that differences in state taxation drive, or mediate, the drop in mobility associated with state borders.

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, the difference in tax burdens might vary across origin destination pairs or throughout the income distribution, meaning that for some subgroups a move would be associated with a smaller tax burden, while other groups could experience a tax increase. For this reason I also examine income tax burdens for various family types (single, married, with dependents) at multiple income levels to see if certain subpopulations' mobility patterns respond (Appendix A12, A14, A13). There are no systematic differences across any of the income levels or family types.

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.[14] I then calculate the percent change in total federal and state income tax burden between the original state and the other state in the commuting zone.[15] In Appendix Figure A15 I plot the share of migrants who move out-of-state by the change in the total tax burden in one percentage point bins. 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 lines is often higher when there is a large reduction in tax burden, but fewer households experience these large changes

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

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

so it is more disperse. 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. These can be thought of as negative costs or benefits associated with a move and could 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 (2005) 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. The potential impact of welfare policy on commuting will depend on whether applicants must establish residency. For example, medicaid recipients must reside in the state of application, where as state earned income tax credit (EITC) claimants only need to earn income and file taxes in the state.

Based on the existing work, I focus on two state transfer policies that affect low income households and vary across state lines: ACA medicaid expansions and earned income tax credit (EITC) state supplements.[16] I also examine the role of the effective state or national

[16]Since welfare reform in 1996, benefit levels and enrollment in traditional cash welfare, Temporary Aid for Needy Families (TANF), have been very low, and thus unlikely to drive the aggregate pattern. In Appendix

minimum wage, another policy that impacts the income of low-income households. For each of these policies I estimate a model similar to equation (6), but *Higher* and *Lower* now reference the benefit generosity in the destination state relative to the origin state. These estimates are plotted in Figure 5. Migration and commute rates to cross-border destinations with higher minimum wages, higher state EITCs, and medicaid expansions were not significantly different that 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 migration 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.[17][18]

Differential Costs Across Demographic Groups

Consistent with this evidence, cross-border mobility rates are similar across demographic groups that might face different adjustment costs or have different preferences. Using microdata from the 2012-2017 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 6). Among migrants, the share that cross state borders is fairly stable across most groups, between 15 and 22 percent.[19] There is an education gradient, with the share of migrants moving across state lines increasing with education.

Figure A16 I also explore differences by state-level TANF generosity and find no significant differences.

[17]Although it is not a state transfer program, state-to-state differences in per public public education spending could also drive differences in mobility. This likely captures state-level differences in both taxation and public spending. As seen in Appendix Figure A16 there is not asymmetric migration or commuting to out-of-state counties with higher or lower Pre-kindergarten through 12th Grade per pupil expenditures.

[18]In the LODES I can also examine census tract to census tract level commuting and see if county borders has a similar effect. Policy variation and costs such as taxes or registration requirements are generally controlled at the state level. However, I still observe a slight county border penalty in tract-to-tract commuting, suggesting something else is driving the pattern (Appendix Figure A18).

[19]The patterns are similar if I restrict the sample to migrants originally living in cross-state commuting zones (Appendix Figure A19).

Federal workers that move are also substantially more likely to move across state borders, at roughly 43 percent.[20] 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 additional adjustment costs when changing school districts, or state and local employees who are more likely to have state-specific pension benefits. The overall pattern is similar when examining the share of commuters that commute across state lines. For migration, 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. Out-of-state commute rates are also twice as high for workers residing outside their birth state, relative to those in their birth state.

I explore the role of birth state residence further in Table 2 by estimating

$$Y_{ipt} = \beta \, \textit{Originally in Birth State}_{ipt} + X_i'\Gamma + \delta_{pt} + \alpha_a + \gamma_o + \varepsilon_{ipt} \tag{7}$$

Where the outcome is whether or not individual i originially living in state and Public Use Micro Area (PUMA) p in year t moved. PUMAs are the smallest publically available measure of geography in the ACS. The explanatory variable of interest is the indicator *Orginially in Birth State*, which equals one if state-PUMA p was in the individual's state of birth. The PUMA by year fixed effects (δ_{pt}) make this a comparison of individuals who originally were living in the same local area at the same time, to see if the mobility of people in their birth state respond differently to local conditions than others living in the area. I will see how estimates differ when I include demographic controls (gender, race, marital status, number of children, and education), age fixed effects, and occupation fixed effects. Since place of work and commuting is measured contemporaneously in the ACS, I replace *Originally in Birth State* with *Currently in Birth State* when examining commuting.

Among people in the same local area, individuals born in that state are only 1.3 percent-

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

age 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 2). People in their birth state 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 but the state more generally. Residing in your birth state also affects cross-border commute rates. Workers living in their birth state are 1.7-1.9 percentage points (11-13 percent) less likely to commute out of state relative to workers living outside their birth state. Proximity to birth state appears to influence mobility across state borders, which could have large implications in aggregate, as approximately 52 percent of adults reside in their state of birth.

5 The Correlation Between Cross-Border Social Networks and Migration

Migrants and commuters are much less likely to cross state lines if they originally resided in their birth state (Figure 6 and Table 2). This potentially reflect local ties. In Figure 7 I explore this further by estimating equations (1) and (2) 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 8 I estimate equation (2) but control for the origin/destination Facebook friendship rate in addition to the other controls. The difference in migration rates between same-state and cross-border county pairs is compressed considerably, 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 gap in commute rates associated with state borders completely disappears, as well as the distance gradient, suggesting that after controlling for the strength of social connections, state borders have no additional impact on commute flows.

The fact that social network strength can empirically explain most of the state-border discontinuity in mobility 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, commuting, 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 mobility costs and low levels of migration and commuting. Alternatively, low levels of cross-border migration and commuting 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/mobility correlation. First, social network strength might fall at state borders, leading to large non-pecuniary, psychic costs and reduced mobility. For example, people might be less willing to move 20 miles away across the state border if 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, resulting in less mobility 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. If social networks are weaker across state borders, for any reason, mobility across state lines will become more costly, leading to lower migration and commute flows. Psychic costs related to social ties, however, would not explain why the social network across state borders was weaker to begin.

5.2 Information Frictions

Since social networks become more sparse across state lines, people might have less access to information about opportunities, differentially keeping 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 implies a similar causal direction as the non-pecuniary, psychic cost mechanism. Weaker social networks across state borders lead to less information about opportunities in markets across state lines, potentially reducing migration and commute flows. Without an exogenous source of information or change in the social network, we can not disentangle the non-pecuniary cost/social ties mechanism from the information friction mechanism.

5.3 Birth State 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 can be viewed as a non-money migration cost, but is potentially distinct from the psychic cost of leaving social ties. The presence of home bias is consistent with less cross-state mobility from people in their birth state and more cross-state mobility 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). Importantly, the home bias mechanism would imply a different direction of causality relative to the other two mechanisms. A third factor (birth state identity) leads to both lower mobility and fewer friendship links across the state border. As such, it might be possible to separately test for these effects.

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. After pre-specifying a number of clusters, Connected Communities are constructed by grouping contiguous county into clusters where the social ties are stronger within the cluster than if a county was attached to a different, neighboring cluster. As seen in Figure 9, when there are 50 connected communities, the cluster borders approximate state borders, but there are obvious differences where communities spill across state borders. 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.[21] This would suggest that in some areas, social networks permeate state borders. If I treat Connected

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

Communities as pseudo states, and re-estimate equation (2), we see these pseudo borders have a similar impact on migration and commuting (Appendix Figure A20). Conditional on distance, migration rates across pseudo borders are about one third to one half as high as migration within the Connected Community.

This provides an opportunity to test the relative explanatory power of state borders versus Connected Community pseudo borders. If the empirical pattern in mobility is driven by a drop in social network strength across state borders due to either non-monetary costs or information frictions, we would expect the cross-border drop in migration and commuting to load onto the Connected Community pseudo borders rather than state borders. I modify equation (2) to include the full set of different state by distance interactions *and* different Connected Community (pseudo state) by distance interactions. As seen in Figure 10, most of the effect loads onto the physical state border, rather than the Connected Community borders.[22] This is true for any pre-specified number of communities, between 10 and 500 (Figure A22). This would suggest that the drop in mobility 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 and commute flows. Although non-pecuniary costs and information frictions undoubtedly influence migration decisions and flows, they do not appear to explain the drop in mobility at state borders.[23]

Theoretical Formulation. The empirical pattern is consistent with home bias or a birth state identity. This could be interpreted in the context of the behavioral phenomenon

[22] Although state borders are precisely measured, community borders are inherently measured with error. This might result in community borders carrying less predictive power. Using connected community assignments between 25 and 75 clusters, I calculate the fraction of scenarios where each county pair is assigned to the same cluster. I then weight each county pair observation by $(\mu - 0.5)^2$, where μ is the fraction of times (out of 51) the counties are in a different connected community. As such, county pairs that have more consistent connected community assignments receive more weight, while pairs where the assignment changes (plausibly because they are close to a social network "border") are down weighted. The results are similar (Appendix Figure A21).

[23] The pattern is similar when considering other well-defined, non-government borders, like time zones. Among the ten states split by time zone borders, county-to-county migration and commute flows between counties in the same state across time zone lines do not experience the same penalty, even though there are potential economic costs associated with these borders (Appendix Figure A23).

of endowment effects. Individuals are "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 over local characteristics 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 mobility and weaker social networks across state borders. The role of loss aversion and endowment effects in mobility decisions is not a new idea, but the existing discussion is limited to loss associated with the physical home (Genesove and Mayer, 2001; Morrison and Clark, 2016; Schkade and Kahneman, 1998).

Consider the following extension of the migration choice model in equation (3) above.

$$Move_{iod} = \begin{cases} 1 & \textit{if } u_{ids'} - u_{ios} \geq c_{iod} \\ 0 & \textit{else} \end{cases} \tag{8}$$

where u_{ios} represents the utility individual i achieves from characteristics in origin o in state s. Similarly, $u_{ids'}$ represents the utility for destination d in state s'. The utility of a given location is defined as follows

$$u_{ils} = u_i(X_l) + \mu(\hat{U}_i(s) - r_{ib}). \tag{9}$$

There are two components. The individual achieves utility from the local characteristics as before ($u_i(X_l)$), but there is also a gain-loss component relative to a reference point r_{ib}. The difference between the utility benefit of the location's state, $\hat{U}_i(s)$, and some reference point, r_{ib}. For the given setting, we will consider the reference point to be the utility benefit the individual experiences from being in their birth state, in other words $r_{ib} = \hat{U}_i(b)$. The piecewise function $\mu(x)$ is defined as follows

$$\mu(x) = \begin{cases} x & \textit{if } x \geq 0 \\ \lambda x & \textit{if } x < 0 \end{cases} \tag{10}$$

If the utility benefit of a given location is less than the utility benefit of the home state, the loss will be weighted by the parameter λ. If $\lambda > 1$ the individual exhibits loss aversion in the migration decision. If the individual exhibits a home bias, or birth state identity, we would expect $\hat{U}_i(s) < r_{ib}$ for all states other than the birth state, b. Consider an individual who exhibits a birth state identity and currently lives in origin o, a location in their birth state b. The utility they achieve at this location is

$$u_{iob} = u_i(X_o). \tag{11}$$

The destination utility the individual could achieve will differ, depending on if the destination is in or out of the birth state.

$$u_{ids} = \begin{cases} u_i(X_d) & \textit{if } s = b \\ u_i(X_d) + \lambda(\hat{U}_i(s) - r_{ib}) & \textit{if } s \neq b \end{cases} \tag{12}$$

As such, if there are two potential destinations, d and d', that have identical characteristics $(X_d = X_{d'})$ but d is in the birth state b and d' is in a different state s

$$c_{iod}* = u_i(X_d) - u_i(X_o) > u_i(X_{d'}) + \lambda(\hat{U}_i(s) - r_{ib}) - u_i(X_o) = c_{iod'}* \tag{13}$$

The cost threshold for moving to d (in the birth state) is higher than the threshold for moving to d' (in a different state). As such, a larger share of the population at o would be willing to move to d than d', even though the two destinations are identical on observables. Home bias or birth state identity can generate an endowment effect that produces theoretical results that match the empirical patterns. Consistent with the people in the ACS microdata being less likely to move if they currently reside in their birth state, the net loss aversion penalty will be smaller if the individual is currently living outside of their state, since the loss is incurred in both the origin and destination.

Empirical Evidence. A preference for ones 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 as family ties can also be at play. 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, asked about the places that they identify with and why, and presented hypothetical moving scenarios. As such, it is possible to observe how many people identify with their birth state and if this identity is associated with the stated and revealed preference over moving, independent of other more studied phenomena like personal ties (Zabek, 2020) and the draw of amenities (Kosar et al., 2020).

Unfortunately, individuals in the survey who had moved and who had not are asked slightly different questions. Individuals who had 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 had 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 region (i.e., "no desire to live someplace else", "I just feel I belong here", or "I grew up here"). I classify non-movers as exhibiting a birth state preference if they listed one of the three 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.

Using this data, I estimate the relationship between having a birth state identity and attitudes towards migration as follows

$$Y_{is} = \beta \mathit{Birth\ State\ Identity}_i + X_i'\Gamma + \delta_s + \varepsilon_i \tag{14}$$

The outcomes of interest are measures of migration for individual i in state s. *Birth State Identity* is defined as described above. I control for age and age squared, as well as fixed effects for gender, race, ethnicity, and education. Current state of residence fixed effects are also included. Estimates are weighted using the provided survey weights, and standard errors are corrected for clustering at the current state of residence level. I extend this equation in two ways. First, I include indicators for whether the individual reports familial ties or local amenities (e.g., labor market, schools, cultural amenities) as a major reason they live where they currently do to test for an independent relationship with state identity. Second, I interact the birth state identity measure, as well as the family and amenity ties measure, with an indicator that equals one if the individual currently resides in their birth state. As such, I can test if birth state identity impacts migration attitudes differently when someone currently lives in their birth state. This is estimated as

$$\begin{aligned} Y_{is} = \beta_1 \mathit{Birth\ State\ Identity}_i + \beta_2 \mathit{Birth\ State\ Identity}_i * \mathit{In\ Birth\ State}_i \\ + \beta_3 \mathit{Family\ Ties}_i + \beta_4 \mathit{Family\ Times}_i * \mathit{In\ Birth\ State}_i \\ + \beta_5 \mathit{Amenity\ Ties}_i + \beta_6 \mathit{Amenity\ Ties}_i * \mathit{In\ Birth\ State}_i \\ + \beta_7 \mathit{In\ Birth\ State}_i + X_i'\Gamma + \delta_s + \varepsilon_i. \end{aligned} \tag{15}$$

Having a birth state identity is associated with differences in migration history and stated preferences (Table 3). 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 other motivating factors. If we also control for whether an individual reports the reason for being where they are is due to family ties or local amenities the impact of birth state identity on ever leaving ones birth state is almost the same, at 32.8 percentage points, suggesting birth state identity has a separate effect from family ties or connection to local amenities.

Birth state identity also reduces people's stated preferences about moving. Overall, individuals with birth state identity are no less likely to report that they are likely to move, but individuals with birth state identity that currently reside in their birth state are 13.1 percentage points (35 percent) less likely to move. Even when controlling for having family ties or ties to local amenities in their current residence, being in your birth state with a birth state identity is still associated with a 12.3 percentage point reduction in the likelihood of moving. The pattern is similar when respondents were asked about moving to certain cities. Overall, having a birth state identity is not associated with a lower propensity to state they would move, but having a birth state identity and residing in your birth state is associated with a 8.4-9.0 percentage point reduction in being willing to move. 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. The tie to an initial state of residence could reflect a home bias that keeps people from moving across state borders, introducing a behavioral bias into the migration choice model.

This evidence on birth state identity and home bias is correlational and suggestive. However, I can corroborate this evidence with several other patterns. Comparing siblings in the Panel Study of Income Dynamics (PSID), to control for shared unobservables within a family, I find that when a family moves between children's births, the sibling who does not reside in their birth state at age 16 is more likely to move away from their 16-year-old state of residence as an adult, relative to their sibling still in their birth state (Appendix Table A2).[24] Using the ACS, I also explore state-level differences in cross-border migration. In the top panel of Figure 11 I plot the share of migrants that move out of state for each state. Out-of-state migration rates are highest in the Mountain West and Central states. In the bottom panel I plot the ratio of out of state migration for birth state and non-birth state residents. This ratio is highest in the Midwest and South East. More work is needed to explore the existence of birth state identity and the extent to which it causally restricts mobility.[25] Unfortunately, these are not topics that are measured in administrative data or large-scale surveys.

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

Regardless of whether the reduction in mobility 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) and reducing migration frictions in general (not border specific) can increase global productivity and welfare (Desmet et al., 2018). Reduced mobility between neighboring counties on state borders might inhibit the rate at which labor markets adjust. This could lead to long-run differences in local economic conditions across geography. In recent work, Hershbein and Stuart (2020) use event study methods to explore the employment dynamics

[24] The pattern still holds when controlling for whether or not the mother ever lived in the child's 16-year-old state while the child was an adult. If I also control for the share of the child's first 16 years they live in their birth state the coefficient on residing in your birth state at 16 is almost the same but imprecisely estimated. This might suggest that it is the state a child spends their formative years in that matters, not just the place they were born.

[25] One mechanism for "home bias" would be the in-state preference among public universities. In Appendix Figure A24 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.

of local labor markets after recessions in the US. Since treatment starts at the same time, this approach does not face many of the challenges highlighted for event studies with staggered treatment timing (Callaway and Sant'Anna, 2020; de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2020). Hershbein and Stuart (2020) 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

$$ln(Y_{ct}) = \sum_{\tau=2003}^{2017} \gamma_\tau(\mathit{CZ\ shock}*\mathit{Year}\ \tau)+\theta_\tau(\mathit{Border}*\mathit{Year}\ \tau)+\beta_\tau(\mathit{Border}*\mathit{CZ\ shock}*\mathit{Year}\ \tau)+\delta_c+\alpha_t+\varepsilon_{ct} \quad (16)$$

The outcome of interest is the natural log of total employment, population, the employment to population ratio, migration rates (in and out), and commute rates (in and out) in county c in year t. This is regressed on a set of year fixed effect interacted with *CZ shock*, the size of the recession in the local labor market (commuting zone), 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.[26] I also include two more sets of interactions. The border by year interact captures differential time trends between border and interior counties, while the border by year by size of the shock interactions allow the dynamic effect of the shock 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 of the shock for border counties are represented by $\gamma_\tau + \beta_\tau$. 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 12.

For both border and non-border counties, pre-recession trends are flat, and recessions lead to a large, persistent decrease in employment and the employment to population ratio.

[26]Results are similar if I control for the 2005 outcome rather than the county fixed effect, as suggested by Hershbein and Stuart (2020) (see Appendix Figure A25). 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.

However, in border counties both employment and the employment to population ratio are persistently lower and there is very little 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.[27] A ten percent drop in local employment during the great recession is associated with approximately 5 percent lower employment in 2017 in non-border counties, but an effect nearly twice that size (9.1 percent) in border counties. In short, border counties have experienced little to no employment recovery 10 years after the start of the Great Recession. Consistent with state borders influencing mobility, this appears to be driven by differences in in-migration and in-commuting. For a ten percent drop in employment during the recession, in-migration to border counties is nearly 4 percent lower for the first 6 years of recovery after the end of the recession. In-commuting to border counties is also around four percent lower, during the recovery through the end of the sample, in 2017. Out-migration and out-commuting from border counties is also lower, but not significantly different. This pattern is consistent with prior work, showing that in-migration is more responsive to local economic shocks (Monras, 2018), but appears to be amplified in border counties, where the border imposes an additional friction on mobility.[28]

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.[29]

[27]Year-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.

[28]Consistent with the drop in in-migration, total population also more in border counties, although the difference is not significant. 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.

[29]For reference, state border status leads to a similar decline in employment recovery as national border status, but unlike counties on the national border, the gap in employment and employment to population ratios does not close by 2017 (Appendix Figure A27). For completeness I also examine the employment response to positive local economics shocks in the form of fracking booms. In this setting employment in border counties appear to grow more slowly, but the difference is not significant. In-commuting to border counties is actually higher. (Appendix Figure A28).

7 Conclusion

I present new evidence that county-to-county mobility (both temporary, repeated commuting and discrete, long-term 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, and state welfare generosity do not appear to drive the gap. Other pecuniary adjustment costs are unlikely to be the sole driving force as county-to-county commuting, a form of temporary, repeated mobility, 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 mobility gap. I find suggestive evidence that this correlation is indicative of home bias, or birth state identity, which reduces people's willingness to move out of their home state. The data provide less evidence that a lack of social connections or information that might be transferred through social networks is associated with drop in mobility at state borders.

This empirical pattern has real economic impacts. Border counties see lower in-migration and in-commuting 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) the role of behavioral biases, like home bias or birth state identity, in reducing mobility across state borders, and (2) if there are policy tools that can mitigate or offset the economic impact of this type of migration behavior.

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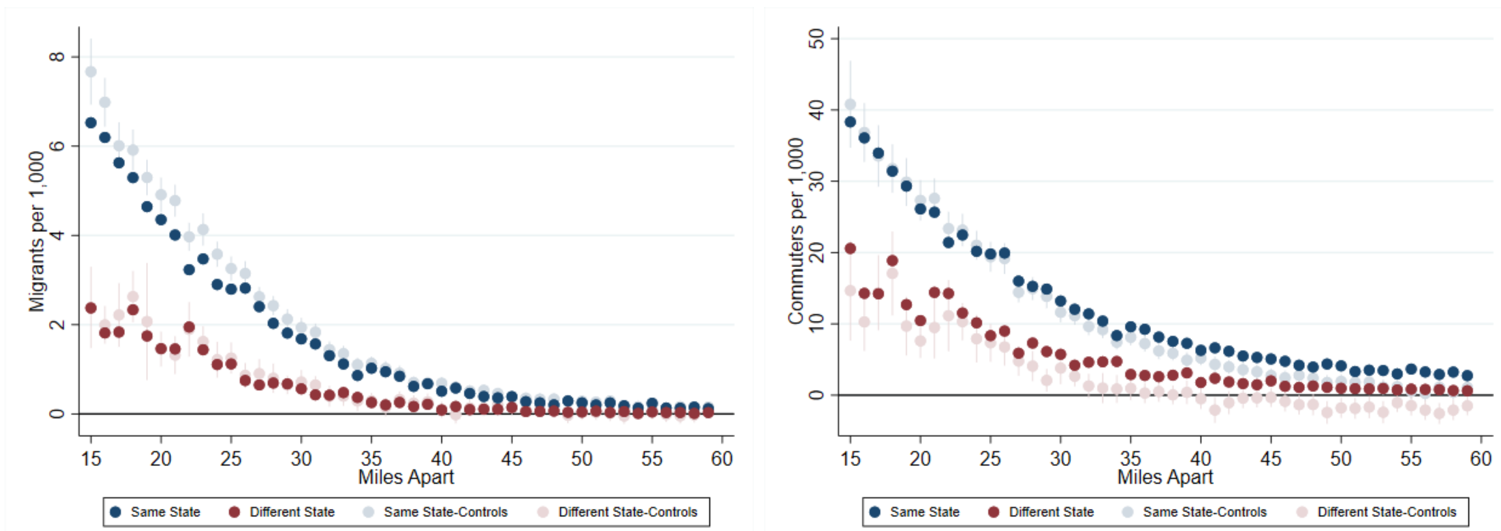
Tables and Figures

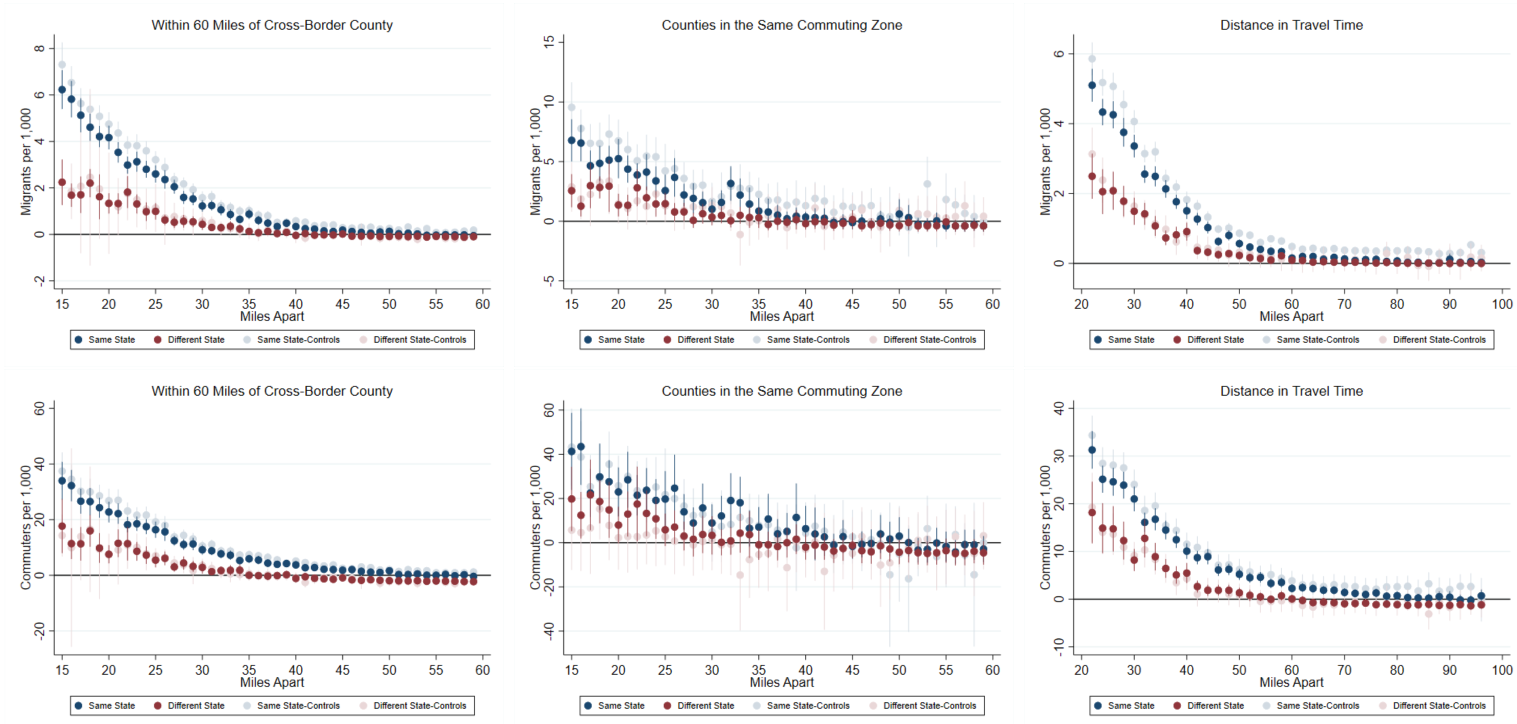
Figure 1: County-to-County Migration and Commute Rates by Distance for Same-State and Different-State County Pairs



Notes: Outcome in the left panel is number of migrants per one thousand people at the origin county using the IRS SOI county-to-county flows from 2017. Outcome in the right panel is the number of commuters per one thousand people at the origin county using the LODES origin-destination employment statistics aggregated to the county level from 2017. These measures are 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. "With Controls" plots coefficients 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, number of establishments), 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 and 2017 LODES.

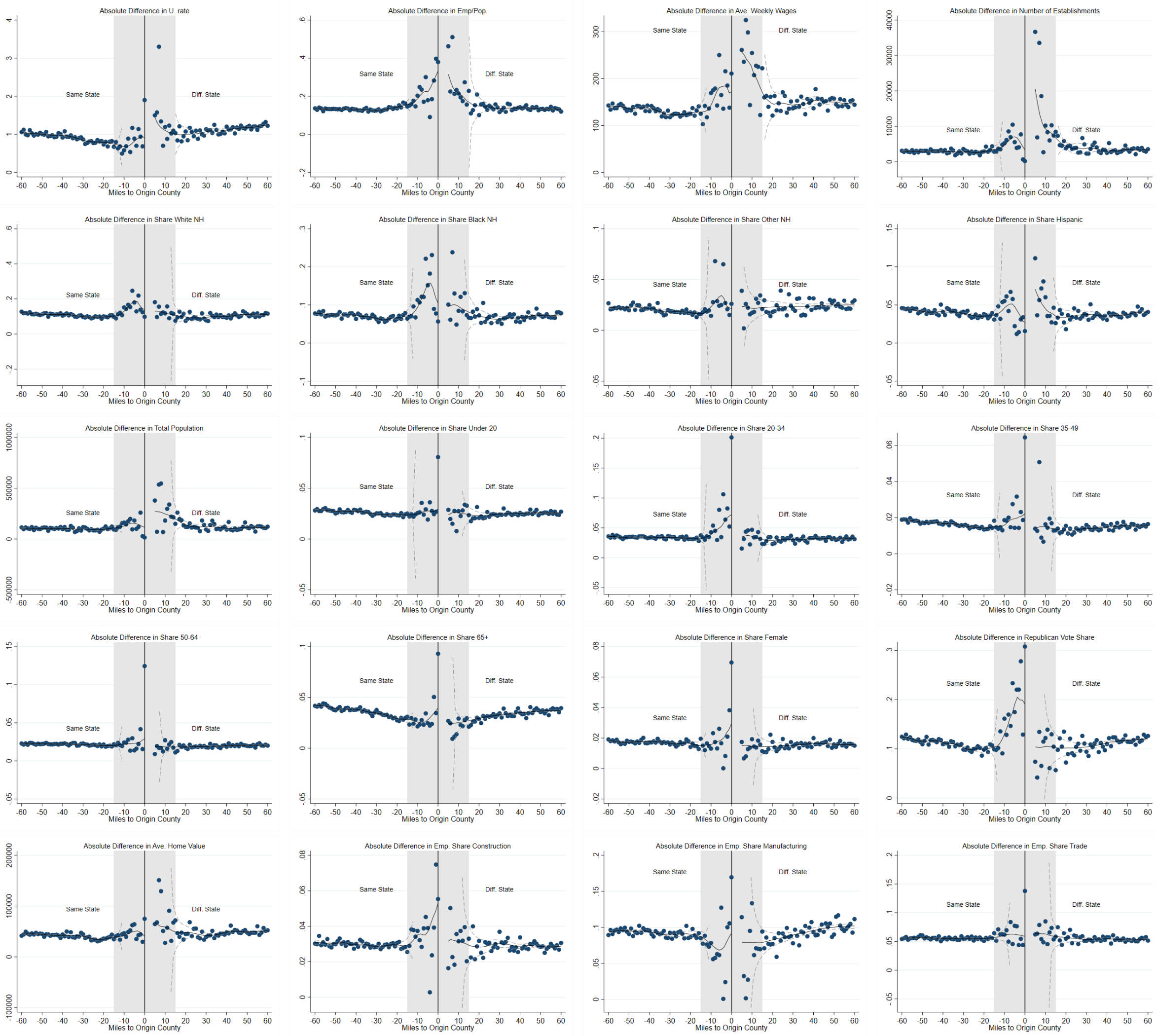
Figure 2: Sensitivity of Migration and Commuting Across State Borders



Notes: Coefficients from equation (1) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel restricts the sample to only include counties within 60 miles of a county in a different state. The middle panel restricts the sample to counties in commuting zones that cross state borders and only include county pairs that are in the same commuting zone. In the first two panels, distance is the number of miles between the population weighted county centroids. The right panel only includes counties within 60 miles of a county in a different state, but distance is the number of minutes of travel time between the population weighted county centroids. "With Controls" plots coefficients 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, number of establishments), 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 and 2017 LODES.

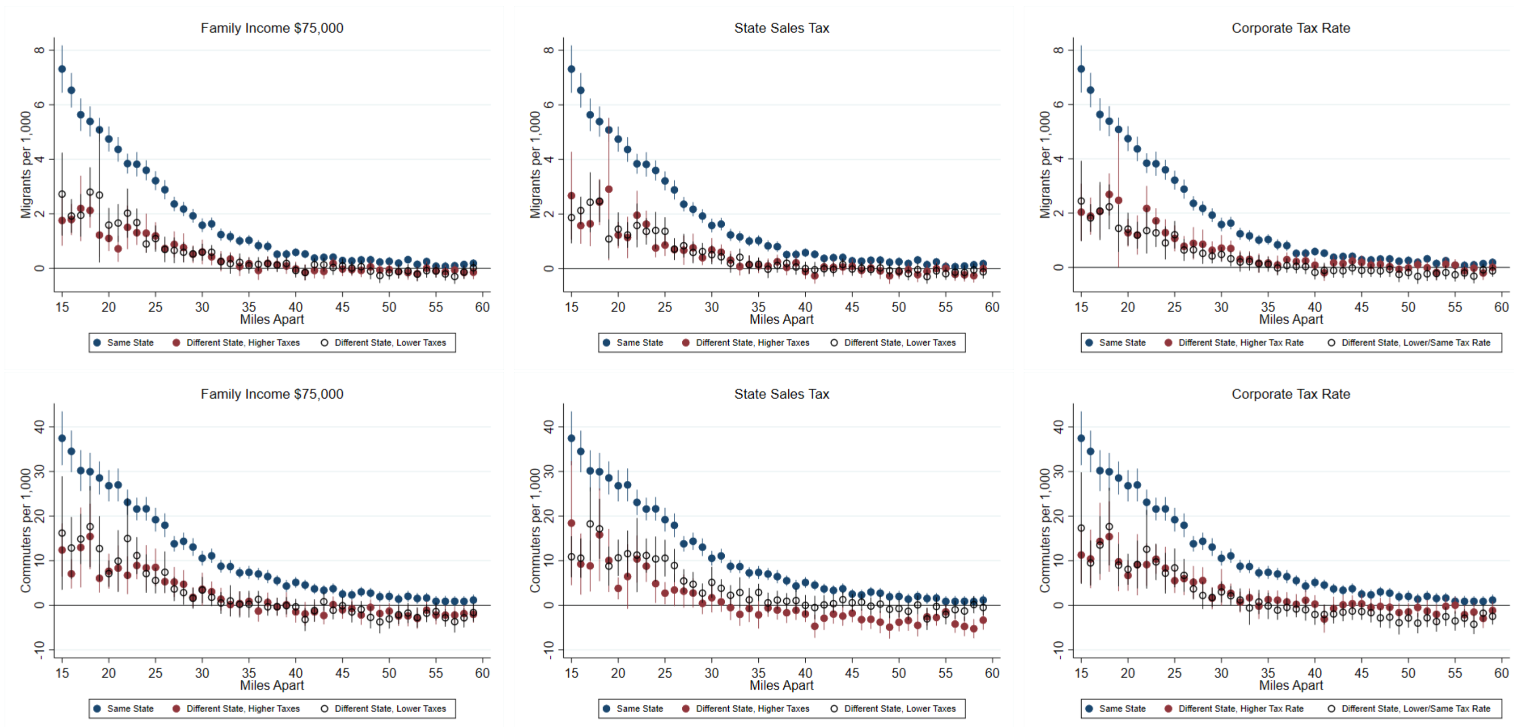
Figure 3: Role of Differences in Utility: Changes in Local Characteristics at State Border



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 QCEW 2017, SEER 2017 data, NCSL 2016 vote data, and FHFA HPI 2017 data.

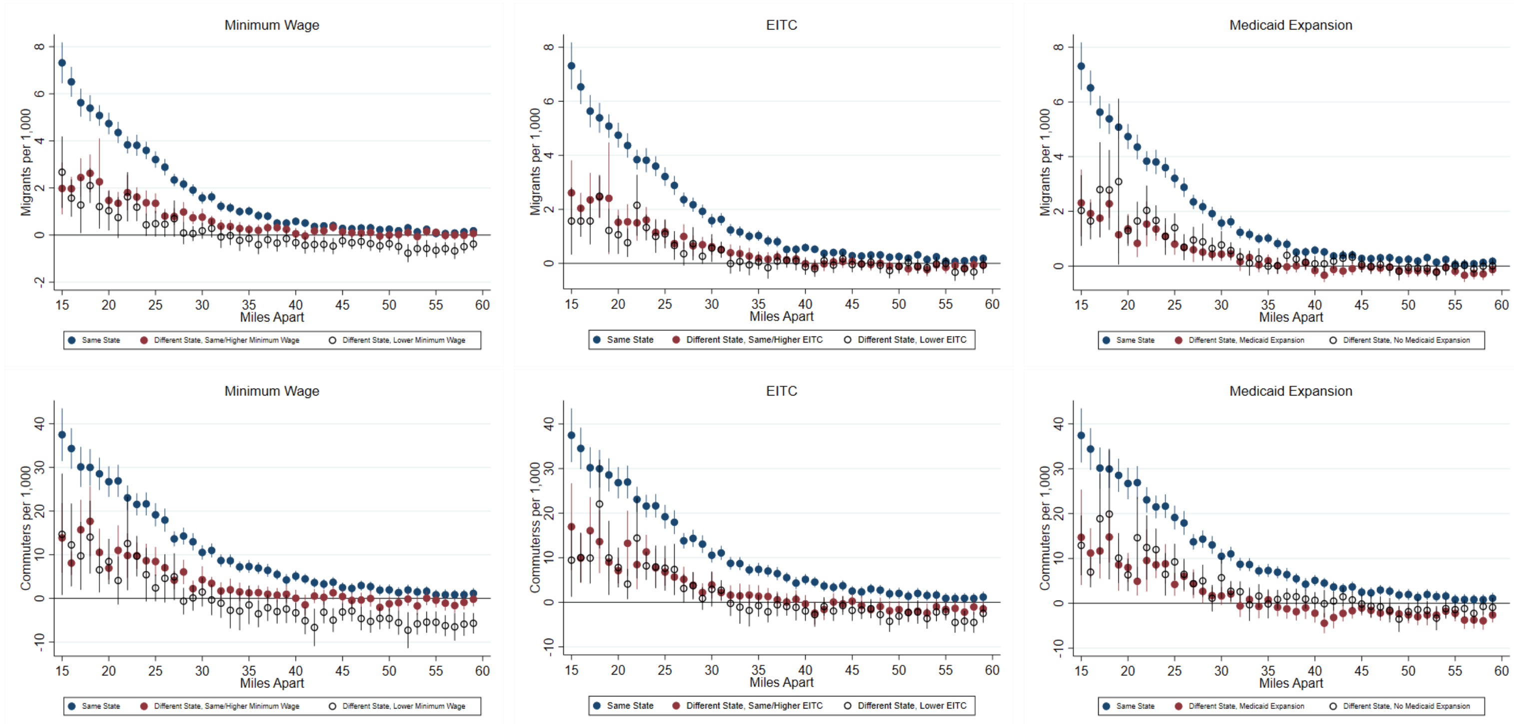
Figure 4: Role of State Taxation: Migration and Commuting Across State Borders



Notes: Coefficients from equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel plots differences by state+federal income tax burdens for a married household with two dependents with $75,000 annual income. The middle panel plots differences by state sales tax rates. The right panel plots differences by the maximum state corporate tax rate. Controls include 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, number of establishments), 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 and 2017 LODES.

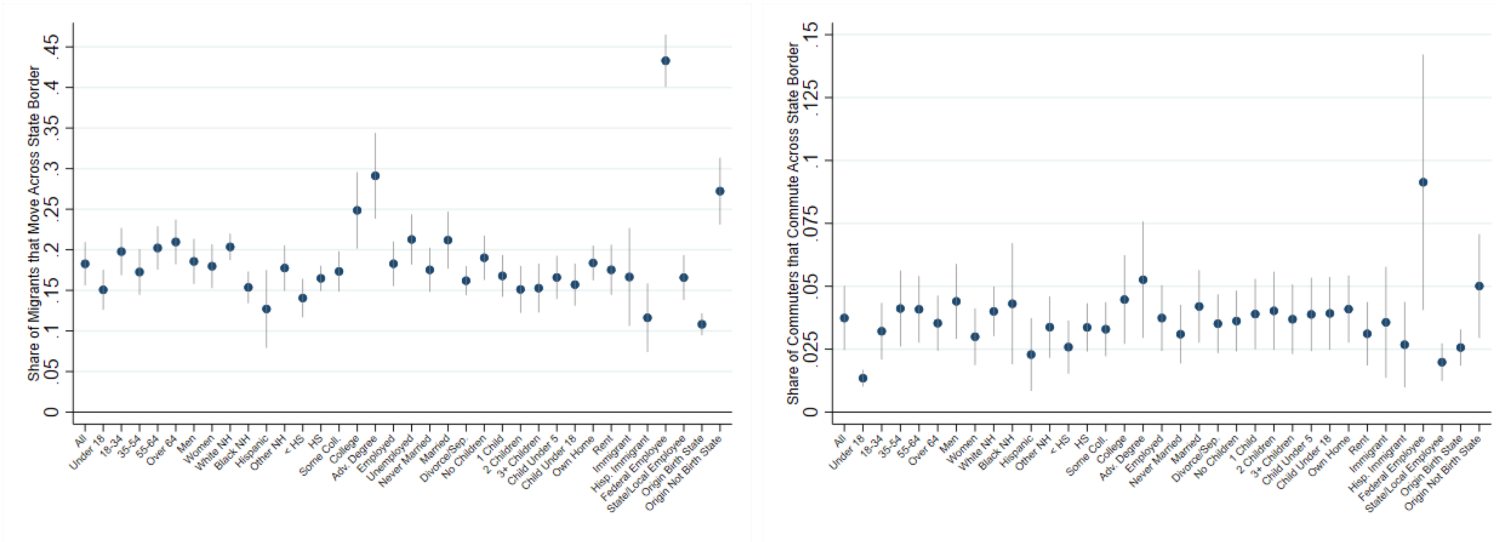
Figure 5: Role of State Benefits and Welfare: Migration and Commuting Across State Borders



Notes: Coefficients from equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel plots differences by the prevailing minimum wage. The middle panel plots differences by generosity of the state EITC. The right panel plots differences by whether or not the state expanded medicaid after the Affordable Care Act. Controls include 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, number of establishments), 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 and 2017 LODES.

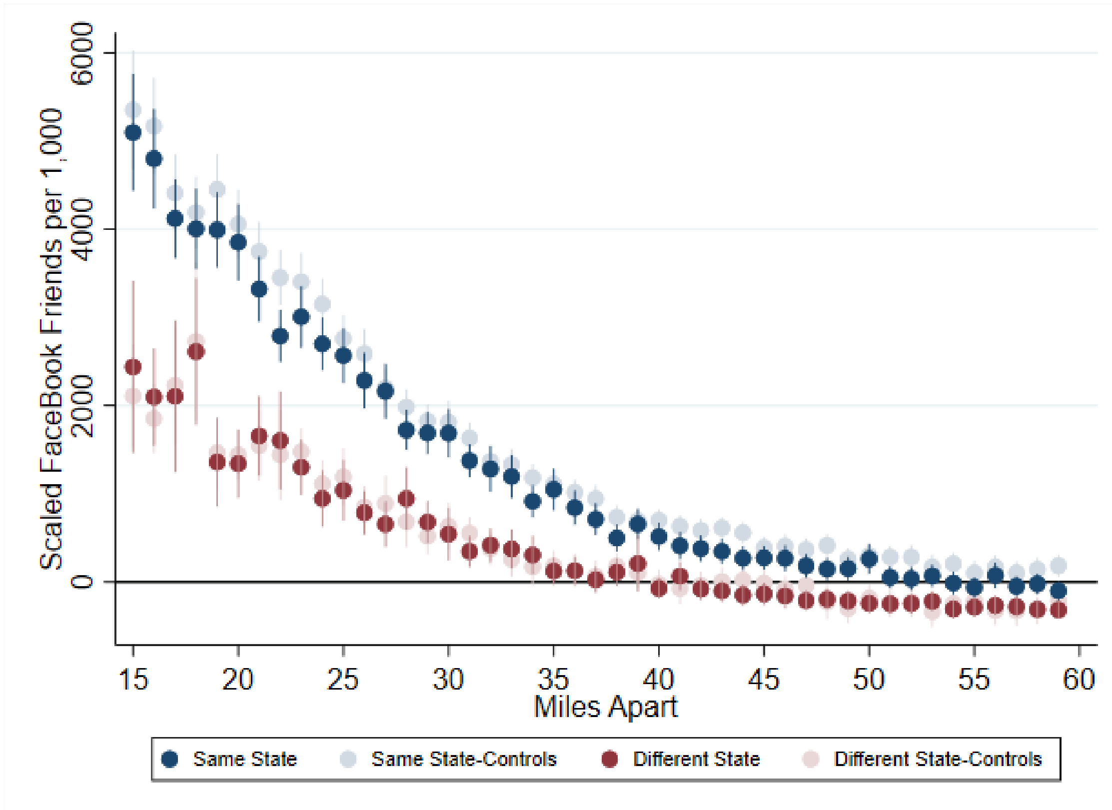
Figure 6: Role of Demographics: Cross-State Migration and Commuting Across Demographic Groups in the ACS



Notes: Each point represents the share of migrants that move across state borders within the last year using the 2012-2017 ACS (left) or the share of commuters who travel across state lines when they commute using the 2012-2017 ACS (right).

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

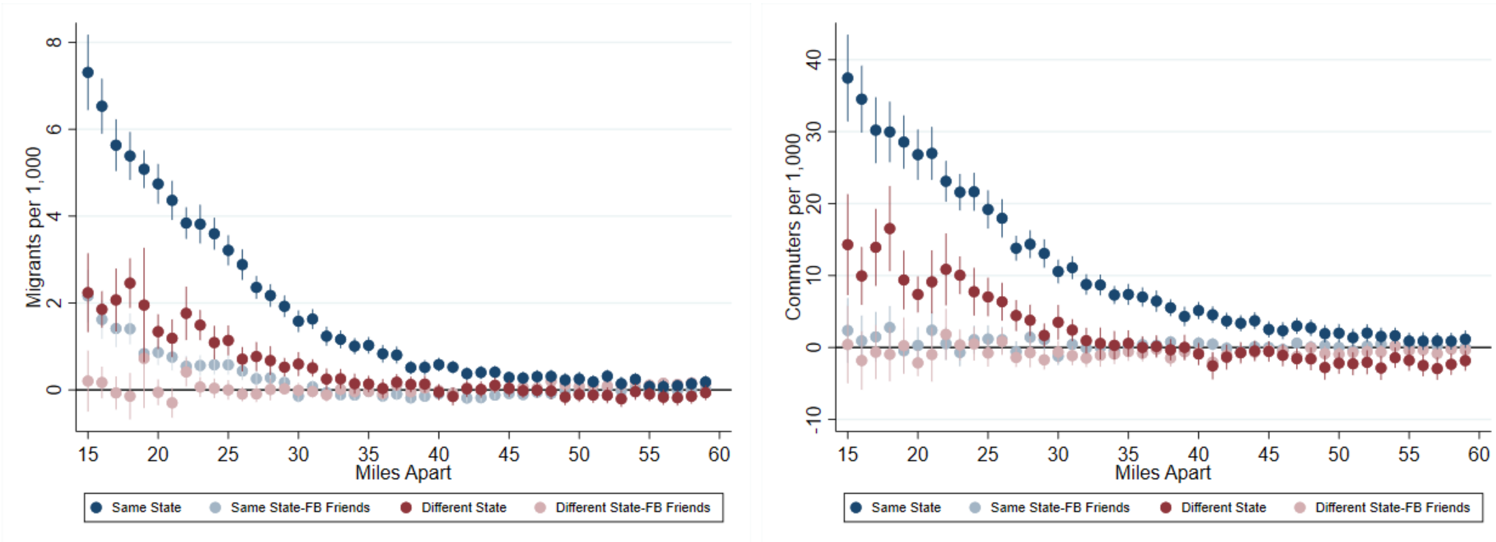
Figure 7: Impact of State Borders on County-to-County Facebook Friendship Rates



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. The number of Facebook friends is scaled by an unknown constant, for privacy. 95-percent confidence intervals are included.

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

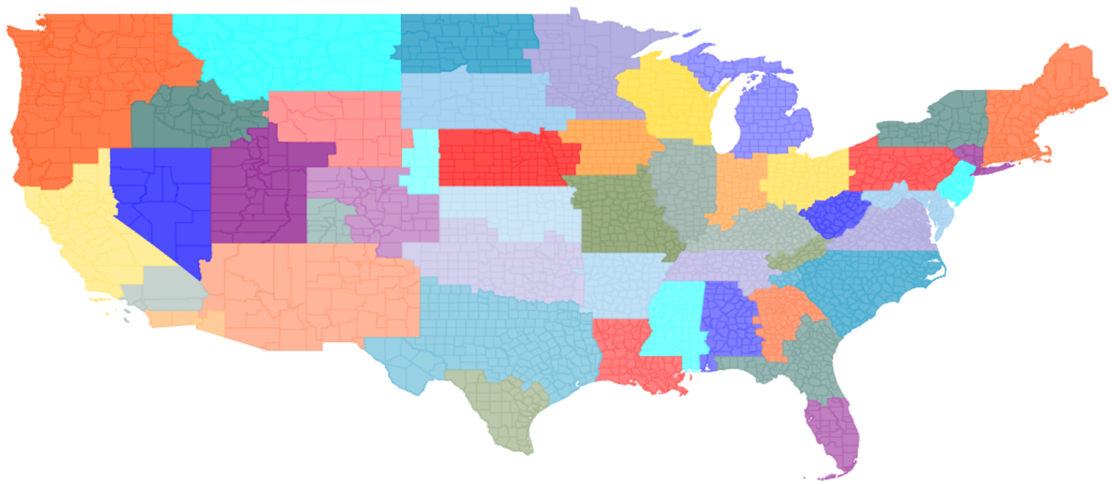
Figure 8: Mediating Role of Facebook network on Migration and Commuting Across State Borders



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

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

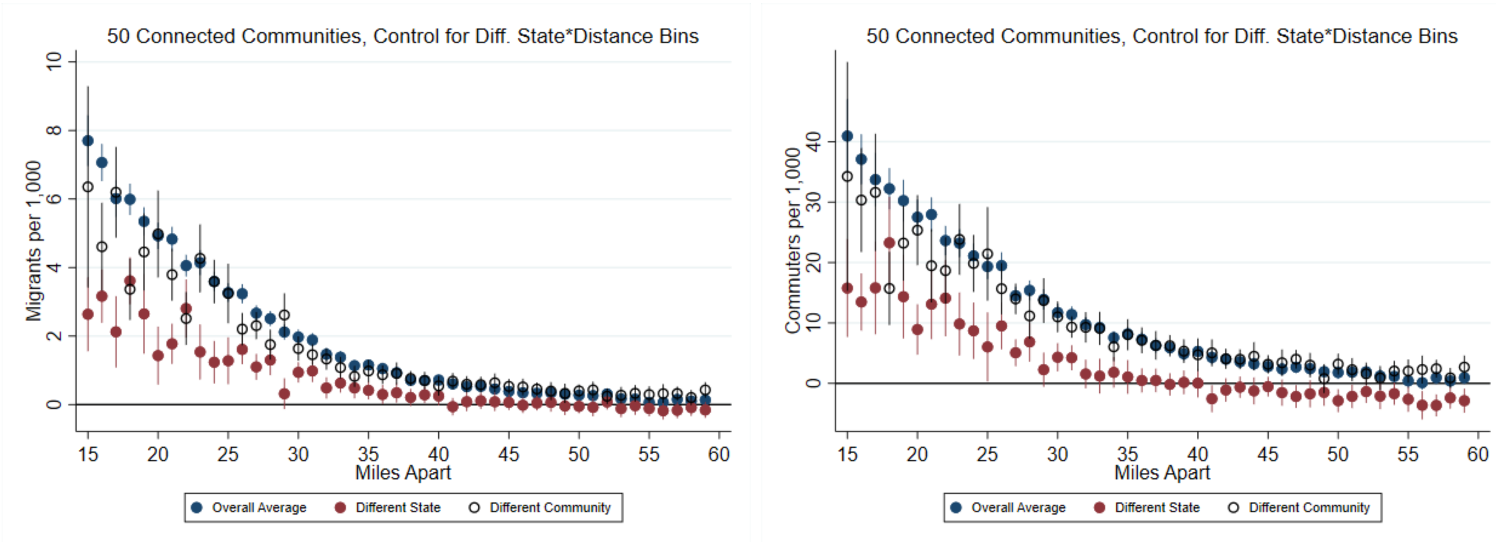
Figure 9: Connected Community Clusters Based on Facebook Friendship Links, 50 Communities



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

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

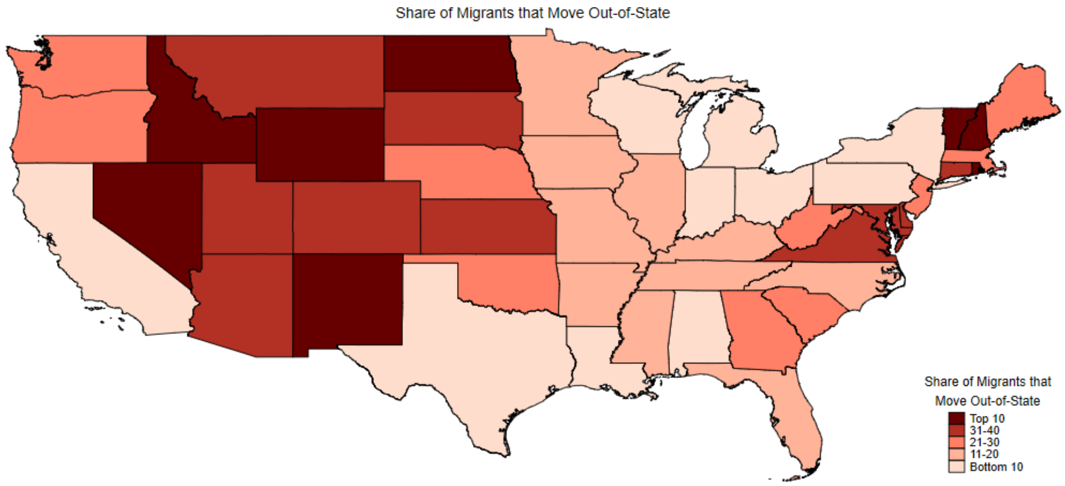
Figure 10: Horserace Regression: Relative Importance of Physical State Borders versus Pseudo Connected Community Borders

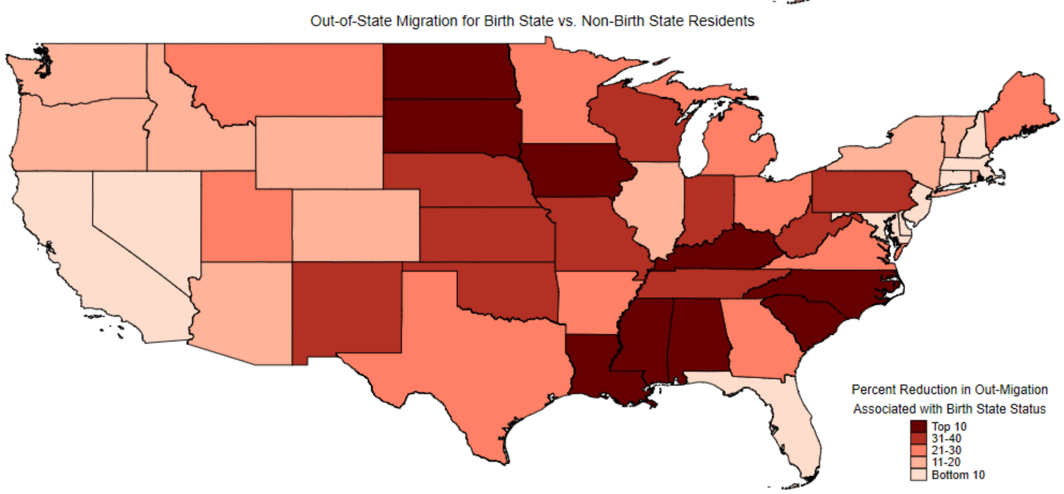


Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. The outcomes are migration rates (left) and commuting rates (right). Each panel plots the coefficients from equation (2) but includes the full set of state border by distance interactions and the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

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

Figure 11: Impact of State Border on Out-of-State Migration by State





Notes: On the top the share of migrants that move out of state is plotted for each state. On the bottom the ratio of the share of migrants that move out of state for birth state and non-birth state residents is plotted for each state.

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

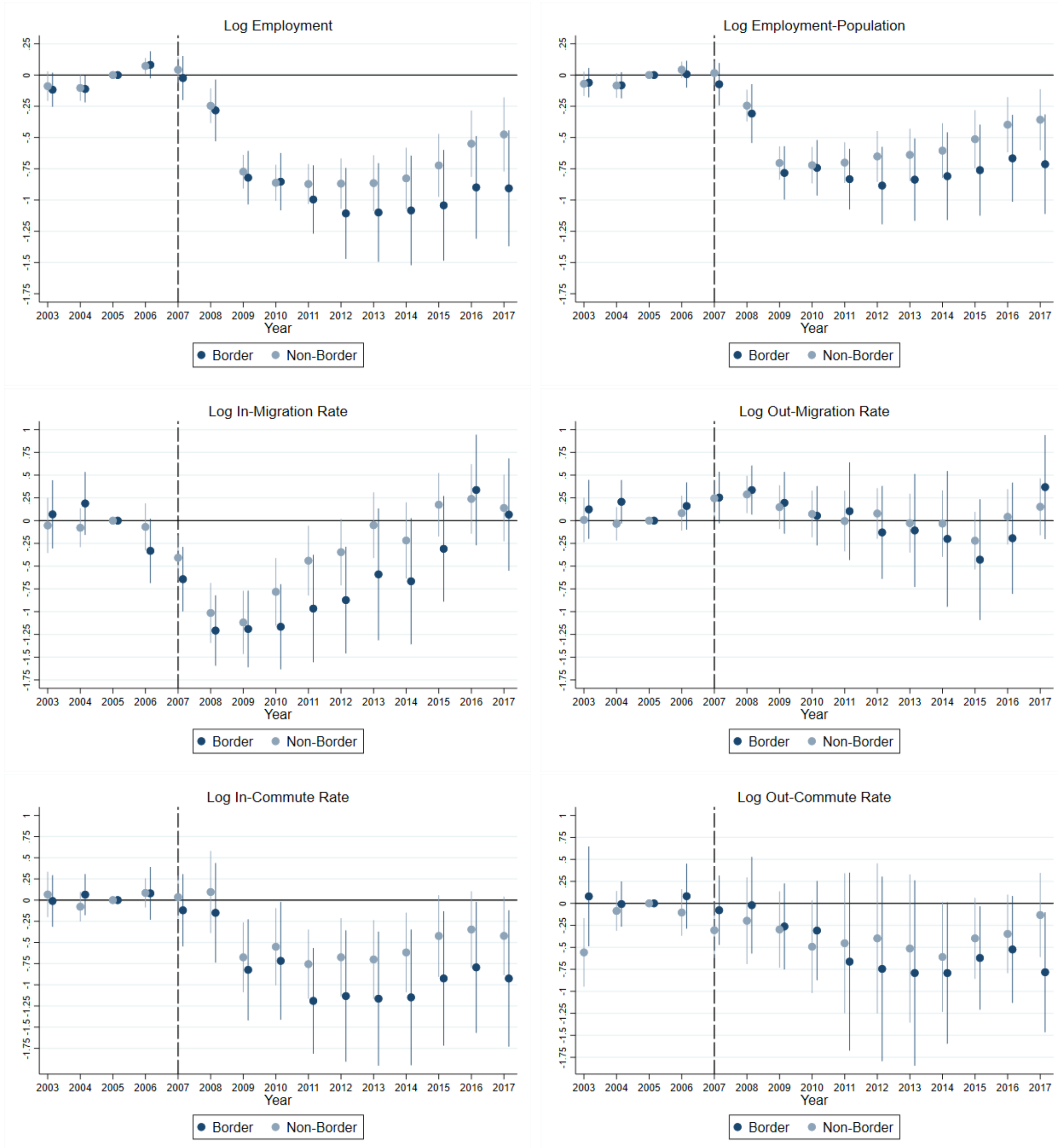


Figure 12: Impact of State Borders on Labor Market Recovery After the Great Recession

Notes: Event study coefficients from the equation (16) 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, and 2003-2017 LODES.

Table 1: Impact of State Occupational Licenses on Cross-State Migration, ACS Microdata

	Sample: All Individuals Move Out of State in Last Year			Sample: All Movers Move Out of State in Last Year			All Commuters Commute Out of State		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	More Restrictive Measure of Occupational Licensing								
Licensed Occupation	0.001	0.001	0.001	0.004	0.003	0.003	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.013)	(0.012)	(0.013)	(0.003)	(0.001)	(0.001)
Occupation F.E.	X	X	X	X	X	X	X	X	X
State and Year F.E.		X	X		X	X		X	X
Occupation by Year F.E.			X			X			X
Dependent Mean	0.023	0.023	0.023	0.169	0.169	0.169	0.039	0.039	0.039
Observations	9,493,532	9,493,532	9,493,532	1,271,370	1,271,370	1,271,370	4,300,760	4,300,760	4,300,760
	Less Restrictive Measure of Occupational Licensing								
Licensed Occupation	0.001	0.001	0.001	0.000	0.001	0.001	-0.003*	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.010)	(0.010)	(0.010)	(0.002)	(0.001)	(0.001)
Occupation F.E.	X	X	X	X	X	X	X	X	X
State and Year F.E.		X	X		X	X		X	X
Occupation by Year F.E.			X			X			X
Dependent Mean	0.023	0.023	0.023	0.169	0.169	0.169	0.039	0.039	0.039
Observations	9,493,532	9,493,532	9,493,532	1,271,370	1,271,370	1,271,370	4,300,760	4,300,760	4,300,760

Notes: Sample restricted to adult respondents to the 2015-2017 ACS. State occupational licensing measures constructed from the Current Population Survey(CPS) questions on job certification. From 2015, CPS respondents have been asked if they have a professional certificate or license; if the license was issued by the federal, state or local government; and if the government issued license is required for their job. I then construct the share of adults in state-by-year-by-4-digit occupation bins that report having a government issued license. As (Kleiner and Soltas, 2019) report, occupational licensing in the CPS is measured with error. Even universal licensed occupations have licensure rates below 100 percent. To indicate the presence of a license, I indicate whether the fraction of adults in the state, year, occupation bin that report a government license is over a given threshold. In the top panel the threshold is 25 percent. In the bottom panel the threshold is 10 percent. For migration outcomes, fixed effects for state of residence one year ago are included in columns (2) and (4). For commuting, fixed effects for the current state of residence are included in column (6). Standard errors corrected for clustering at the state level (state of residence in previous year for migration, current state for commuting). $p<.1$ *, $p<.05$ **, $p<.01$ ***.

Table 2: Relationship Between Birth State Residence and Migration

			Among Movers				Among Commuters	
	Move at All		Move Out of PUMA, Stay in State		Move Out of State		Commute Out of State	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Originally in Birth State	-0.013***	-0.035***	0.048***	0.052***	-0.152***	-0.157***		
	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.003)		
Currently in Birth State							-0.019***	-0.017***
							(0.002)	(0.001)
Demographic Controls		X		X		X		X
Dependent Mean, Not Birth State	0.15	0.15	0.16	0.16	0.24	0.24	0.05	0.05
Observations	18,871,967	18,871,967	2,537,353	2,537,352	2,537,353	2,537,352	8,426,384	8,426,383

Notes: Sample restricted to adult respondents to the 2012-2017 ACS. Estimates obtained by regressing equation (7). For migration outcomes, PUMA by state of residence one year ago fixed effects are included in columns. For commuting, PUMA by current state of residence fixed effects are included. Standard errors corrected for clustering at the state-by-PUMA level (previous year's state for migration, current year's state for commuting). p<.1 *, p<.05 **, p<.01 ***.

Table 3: Relationship Between Birth State Identity and Migration, Pew Mobility Survey

	Ever Left Birth State		Birth State Preferred		Likely Move in Next 5 Years		Would Move to One of MSA Provided	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Birth State Identity	-0.353***	-0.328***	0.281***	0.268***	-0.019	-0.011	0.043	0.045
	(0.021)	(0.022)	(0.027)	(0.026)	(0.037)	(0.038)	(0.027)	(0.027)
Birth State Identity*In Birth State					-0.131**	-0.123**	-0.084**	-0.090**
					(0.055)	(0.057)	(0.041)	(0.041)
Family Ties		-0.143***		0.072***		-0.073**		-0.024
		(0.025)		(0.021)		(0.035)		(0.028)
Family Ties*In Birth State						-0.001		0.037
						(0.046)		(0.035)
Amenity Ties		0.019		-0.005		0.063		0.075*
		(0.028)		(0.025)		(0.043)		(0.038)
Amenity Ties*In Birth State						-0.112**		-0.063
						(0.055)		(0.046)
In Birth State					0.019	0.118*	0.008	0.045
					(0.055)	(0.063)	(0.031)	(0.055)
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. p<.1 *, p<.05 **, p<.01 ***.

Appendix Tables and Figures

Table A1: 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

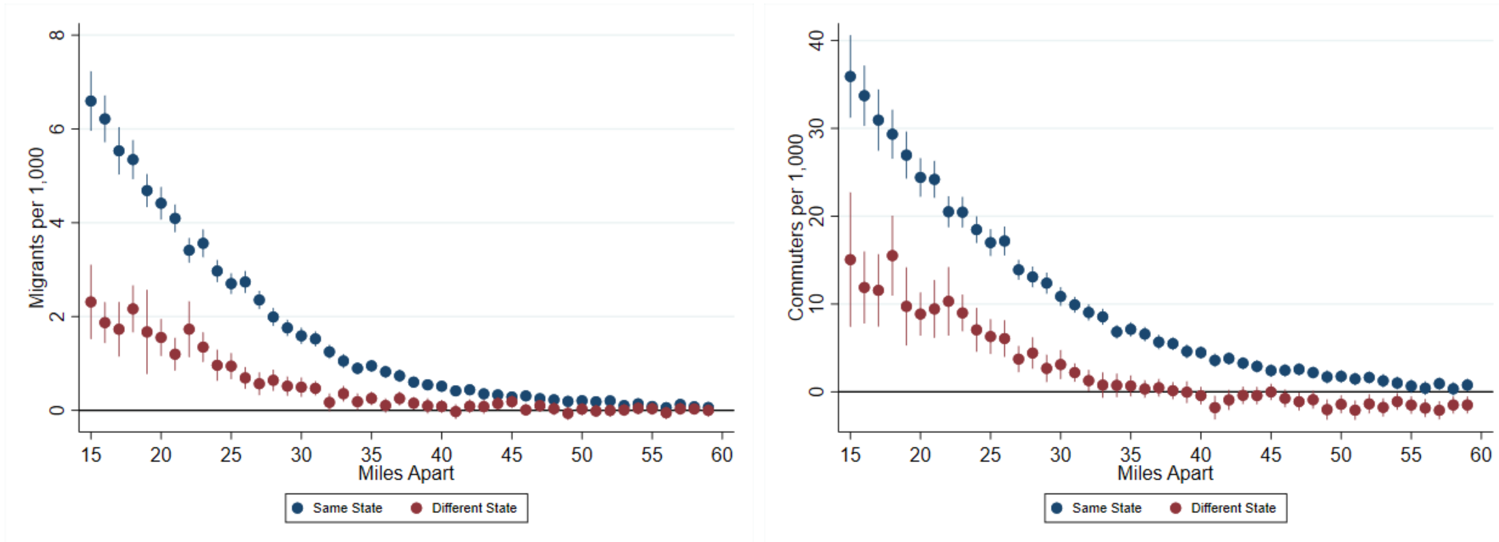
Notes: Shares reported based on 2017 measures. Unemployment data obtained from the BLS LAUS, Average Weekly Wages obtained from the QCEW, Average House Price obtained by combining FHFA county house price indices, with home values from the 2000 Census to estimate 2017 average house prices. Distance is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

Table A2: Propensity to Move Out-of-State if Living in Birth State at 16, PSID Sibling Comparison

	Moved from State Lived in at 16-Years-Old							
	Between Ages 18-30				Between Ages 18-40			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In Birth State at 16	-0.067	-0.096**	-0.104**	-0.094	-0.131**	-0.146**	-0.150**	-0.127
	(0.042)	(0.046)	(0.045)	(0.078)	(0.056)	(0.067)	(0.068)	(0.110)
Mother Present in 16-Year-Old State During Time Period			-0.303***	-0.304***			-0.304***	-0.304***
			(0.069)	(0.069)			(0.114)	(0.114)
Share of First 16 Years in Birth State				-0.016				-0.043
				(0.096)				(0.133)
Birth State and Cohort F.E.		X	X	X		X	X	X
Mother F.E.	X	X	X	X	X	X	X	X
	Birth Cohorts 1968-1989				Birth Cohorts 1968-1979			
Dependent Mean	0.216	0.216	0.222	0.222	0.240	0.240	0.246	0.246
Observations	5,205	5,205	4,768	4,768	3,258	3,258	3,003	3,003

Notes: Sample restricted to children of the PSID that were born in 1968 or later, so that state of residence at birth can be established. Outcome variables are indicators for whether the individual has moved from the state they lived in at 16 by the specified ages. Only moves in adulthood are included. *In Birth State at 16* indicates if the child is living in their state of birth at age 16. In 1999 the PSID moved to a biannual survey. As such, outcomes at specific ages are not observed for cohorts born later. For this reason, I update variables to go through the specified age plus one for cohorts that are not surveyed when they reach the specified age (e.g., 16, 30, or 40). Samples are restricted to include birth cohorts that reach the maximum age specified in the outcome by 2019, the last available year in the data. Mother fixed effects are included to make this a within sibling comparison. Birth cohort fixed effects control for fixed differences in the propensity of moving by birth year, while birth state fixed effects control for fixed differences in the propensity of moving across birth states. Standard errors corrected for clustering at the mother id level. $p<.1$ *, $p<.05$ **, $p<.01$ ***.

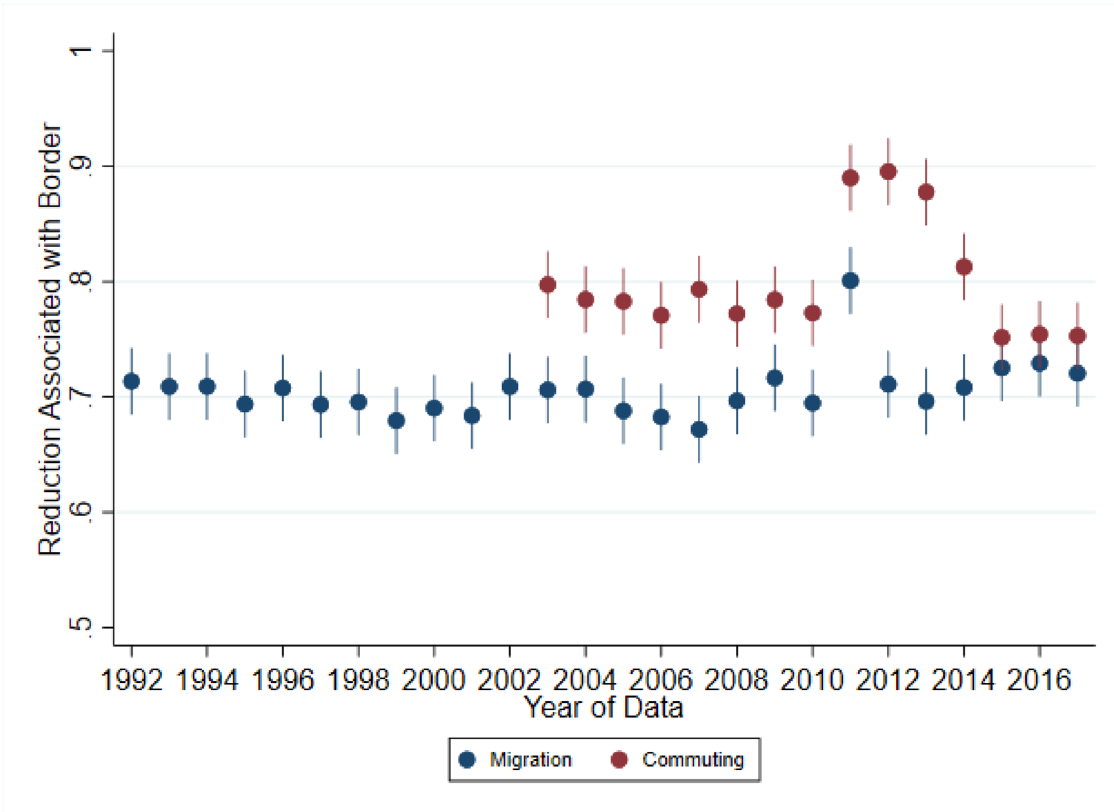
Figure A1: County-to-County Migration and Commute Rates by Distance for Same-State and Different-State County Pairs, Regression Estimates



Notes: Outcome in the left panel is number of migrants per one thousand people at the origin county using the IRS SOI county-to-county flows from 2017. Outcome in the right panel is the number of commuters per one thousand people at the origin county using the LODES origin-destination employment statistics aggregated to the county level from 2017. Point estimates from equation (1) are plotted with 95 percent confidence intervals.

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

Figure A2: Relationship Over Time: Impact of State Borders on County-to-County Migration and Commuting from 1992 to 2017



Notes: The reduction in migration (blue) and commuting (red) associated with state borders for each year from 1992-2017 are plotted with 95 percent confidence intervals. Average migration rates for same-state and cross-state county pairs in the 20 mile bin are plotted for 1992-2017. These estimates are obtained regressing equation (2) for each year from 1992 to 2017 separately, then estimating the ratio of area under the curve for same-state and cross-state county pairs between 15 and 60 miles apart. 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, LODES data from 2003-2017.

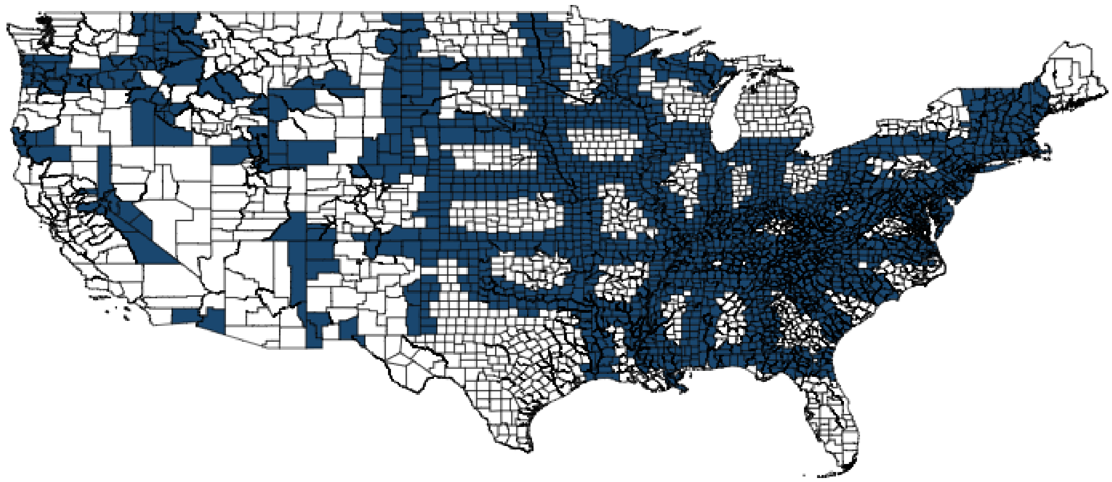
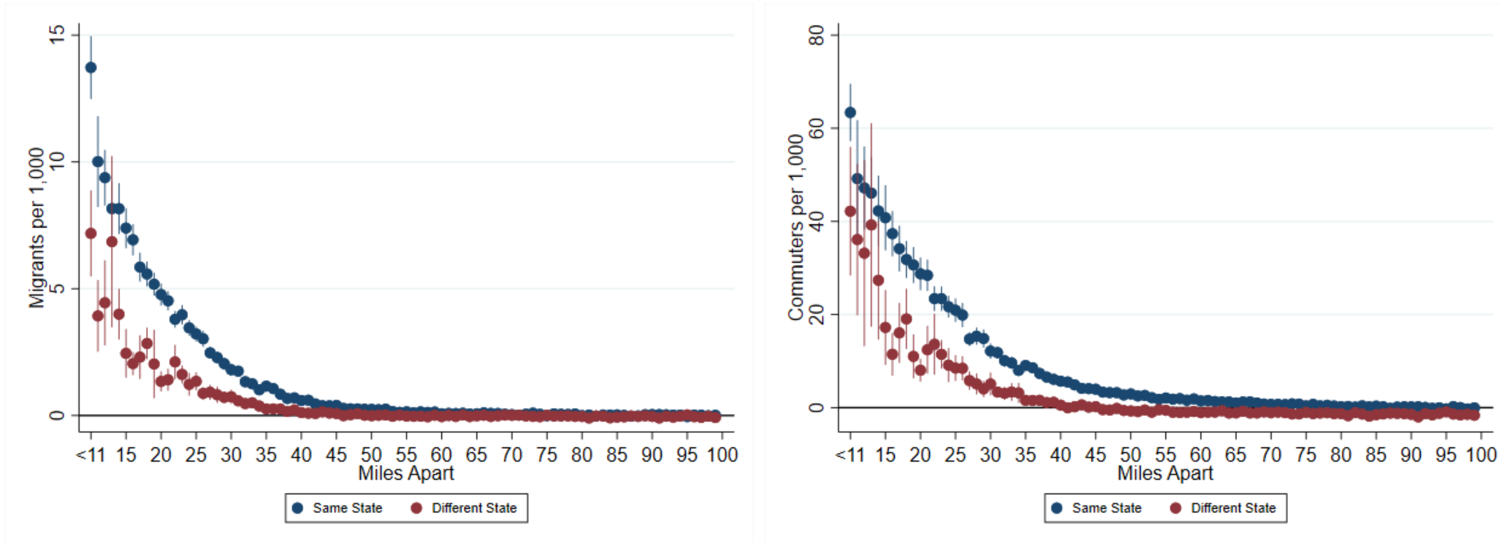


Figure A3: Counties within 60 Miles of a County in a Different State

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.

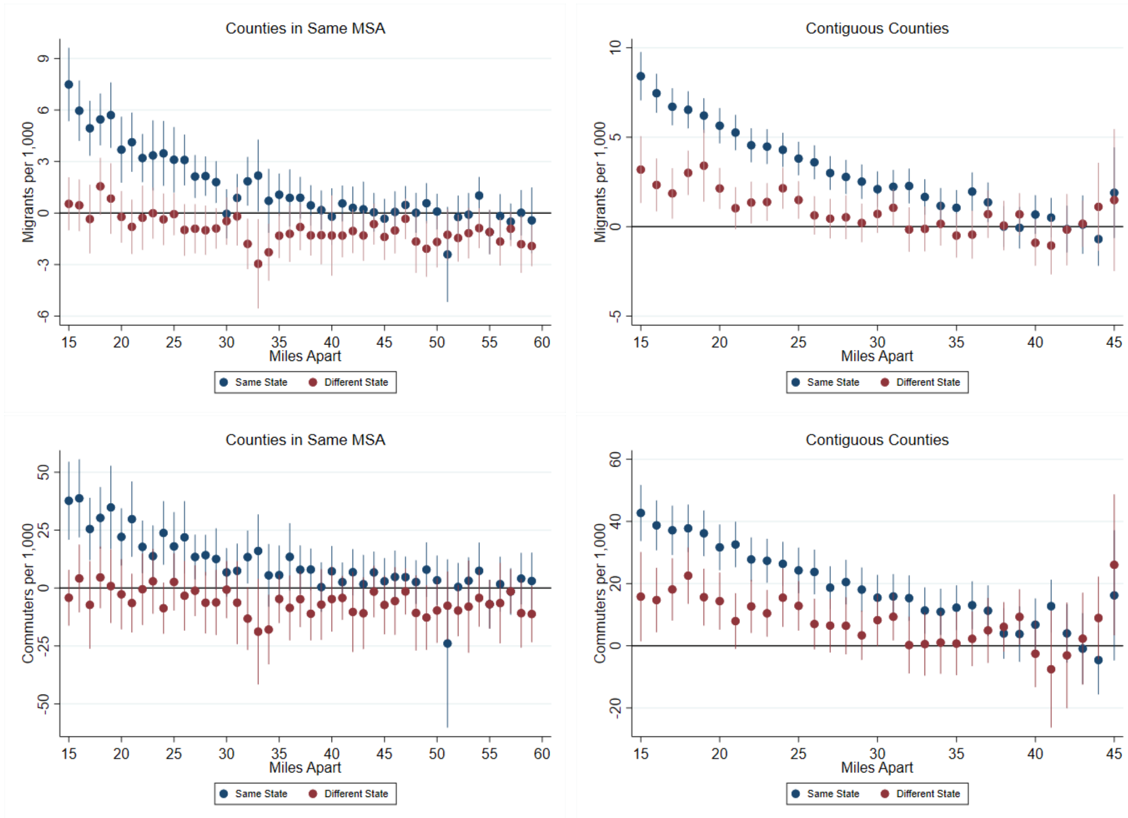
Figure A4: County-to-County Migration and Commute Rates by Distance and for Same-State and Different-State Counties, Including Closer and Farther Distance Bins



Notes: Outcome in the left panel is number of migrants per one thousand people at the origin county using the IRS SOI county-to-county flows from 2017. Outcome in the right panel is the number of commuters per one thousand people at the origin county using the LODES origin-destination employment statistics aggregated to the county level from 2017. Point estimates are obtained by estimating an equation similar to equation (2), but more distance bins are added. The <11 bin includes all pairs less than 11 miles apart. 95-percent confidence intervals are provided.

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

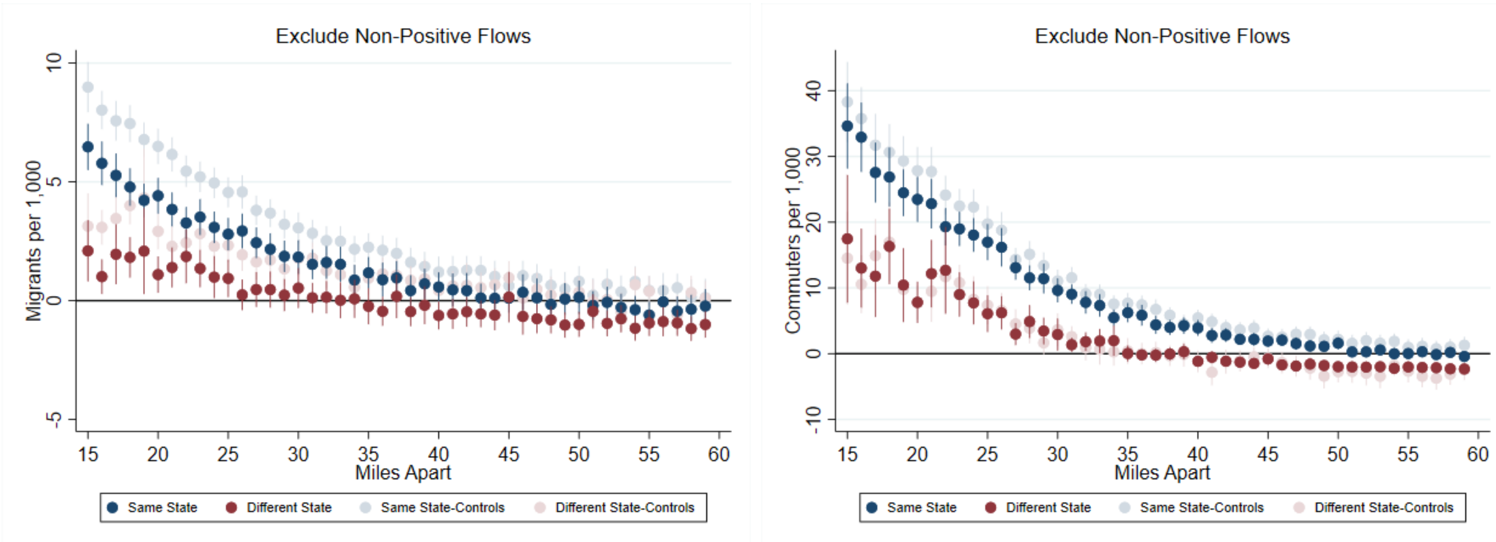
Figure A5: Impact of State Borders on Migration and Commuting in Close, Connected Regions



Notes: Coefficients from equation (2) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel restricts the sample to only include counties in MSAs that cross state borders and only include county pairs that are in the same MSA. The right panel only includes counties that are on state borders and are contiguous. Estimation controls 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, number of establishments), 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 and 2017 LODES.

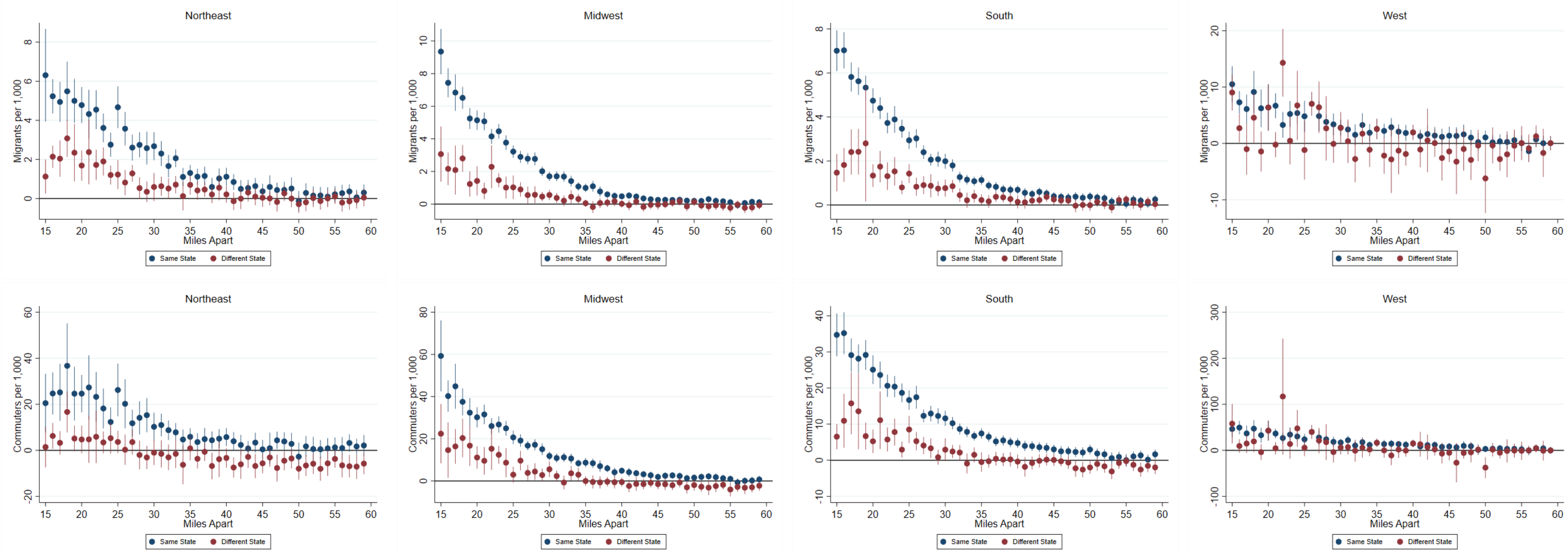
Figure A6: Impact of State Borders on Migration and Commute, Excluding County-to-County Flows of Zero



Notes: Outcome in the left panel is number of migrants per one thousand people at the origin county using the IRS SOI county-to-county flows from 2017. Outcome in the right panel is the number of commuters per one thousand people at the origin county using the LODES origin-destination employment statistics aggregated to the county level from 2017. Point estimates from equations (1) and (2) are plotted with 95 percent confidence intervals. Sample restricted to exclude county-to-county observations where the migration/commute rate is zero. Some of these zero flows are artificially suppressed, for data privacy.

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

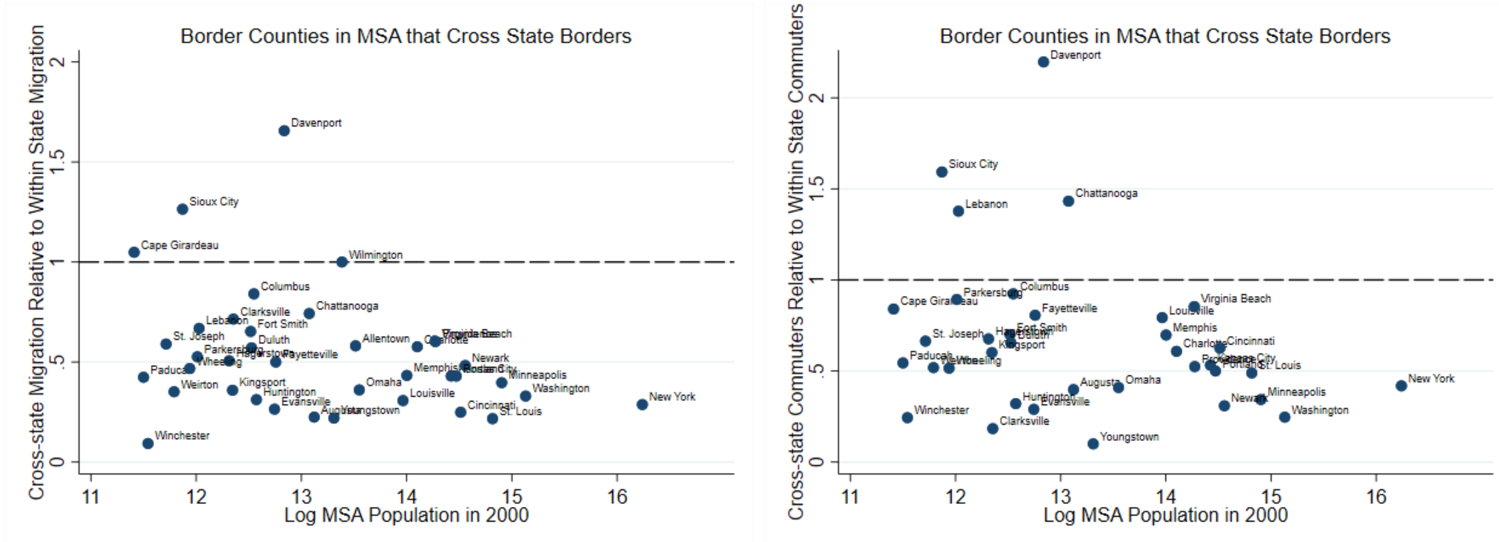
Figure A7: Impact of State Borders on Migration and Commuting in Close, by Census Region



Notes: Coefficients are plotted from equation (2), estimated separately by origin county census region. Migration is plotted in the top panel, commuting in the bottom. Estimation controls 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, number of establishments), 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 and 2017 LODES.

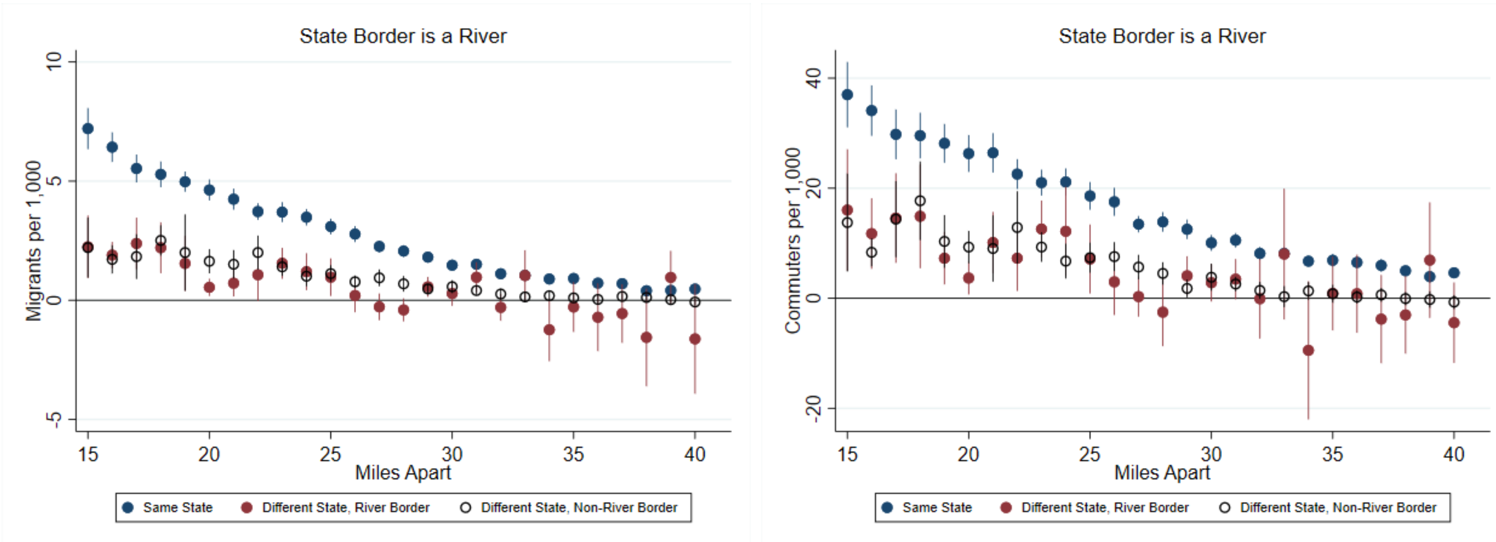
Figure A8: Impact of State Borders on Migration and Commute Estimated by MSA



Notes: The ratio of cross-border migration/ commuting relative to within state migration/commuting 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 and 2017 LODES.

Figure A9: Impact of State Borders, 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 (6) 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 and 2017 LODES.

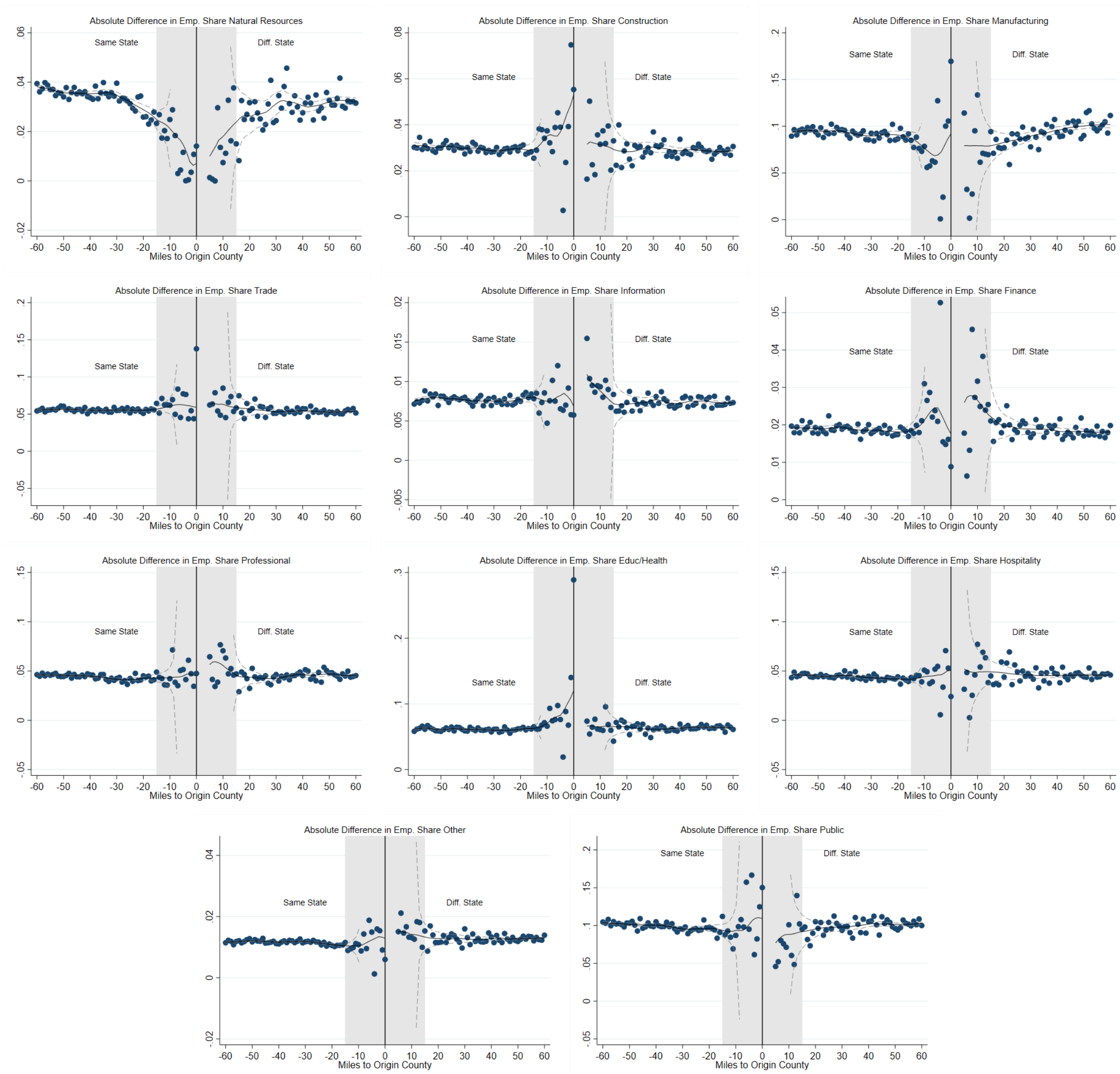
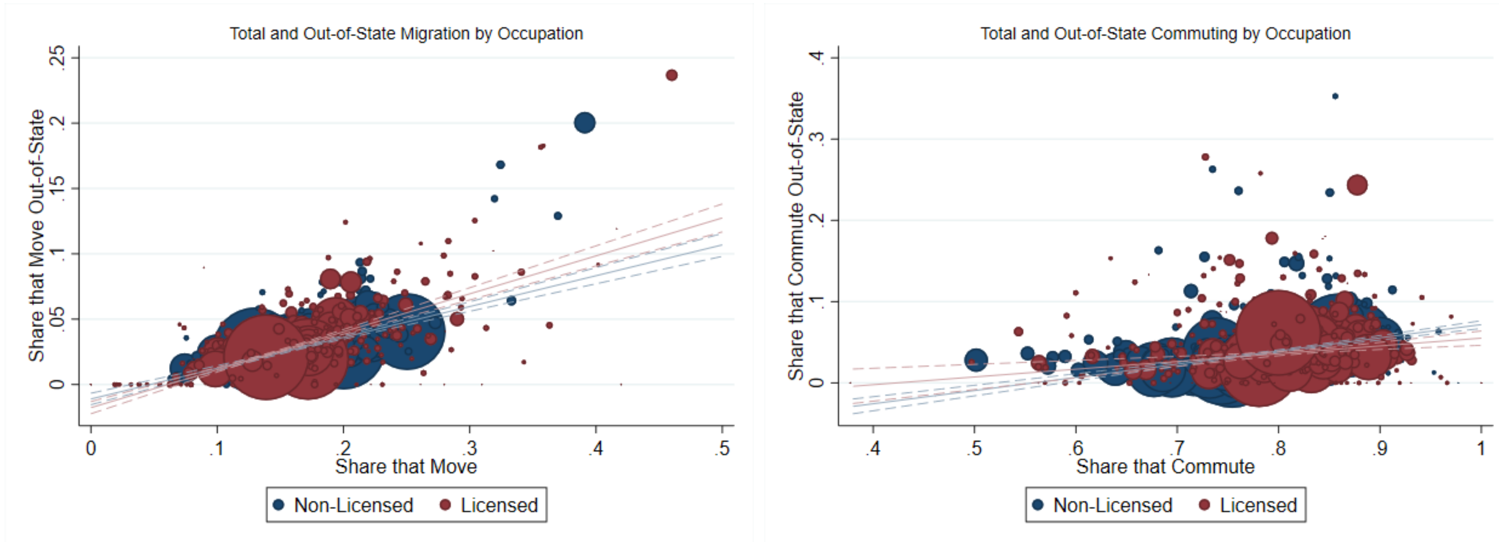


Figure A10: Role of Differences in Utility: Changes in Local Industry Composition at State Border

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.

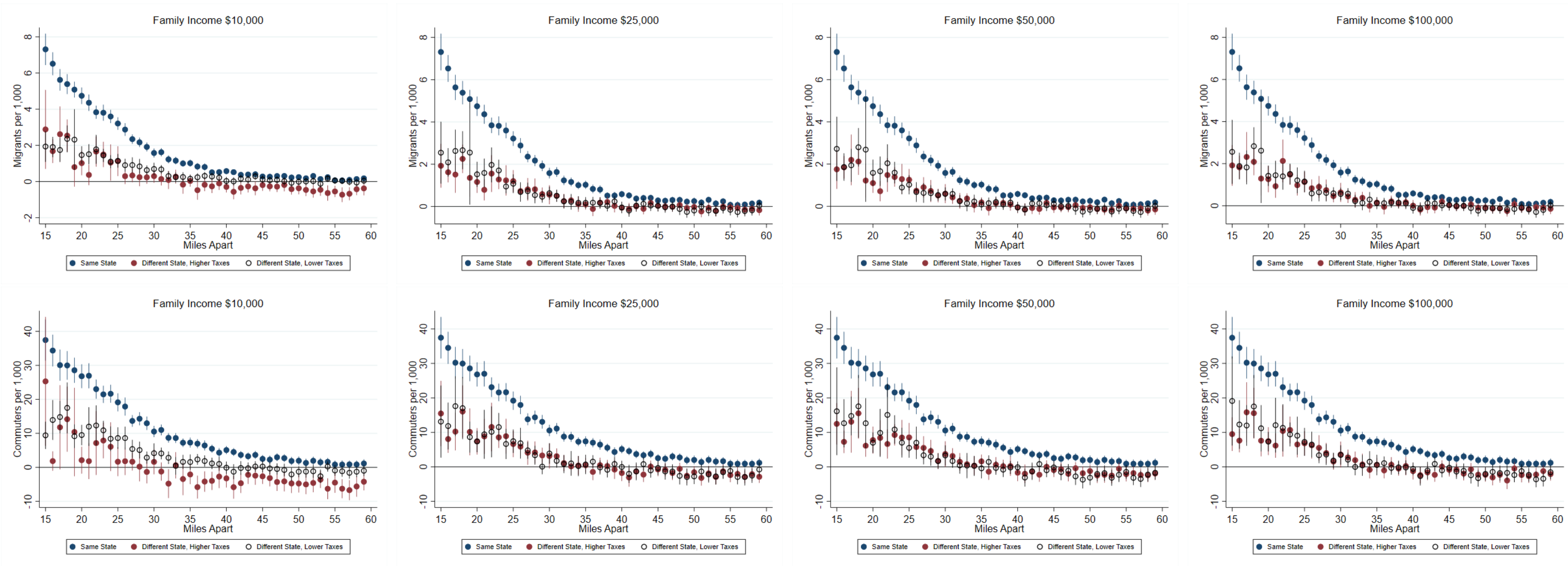
Figure A11: Occupation-Level Cross-state Migration and Commuting by Occupational Licensing



Notes: Each point represents the migration/commuting rates by occupational code and governmental licensure status using the 2015-2017 ACS. For each occupation that are two points, one for workers in licensed states and time periods, one for workers in non-licensed states and time periods. Sample restricted to occupations that are licensed in some states but not all. The size of the point is scaled to represent the population weighted number of people in the occupation. The blue linear prediction is for non-licensed occupations. The pink linear prediction is for licensed occupations. Linear predictions include 95-percent confidence intervals.

Source: Author's own calculations using the 2015-2017 ACS.

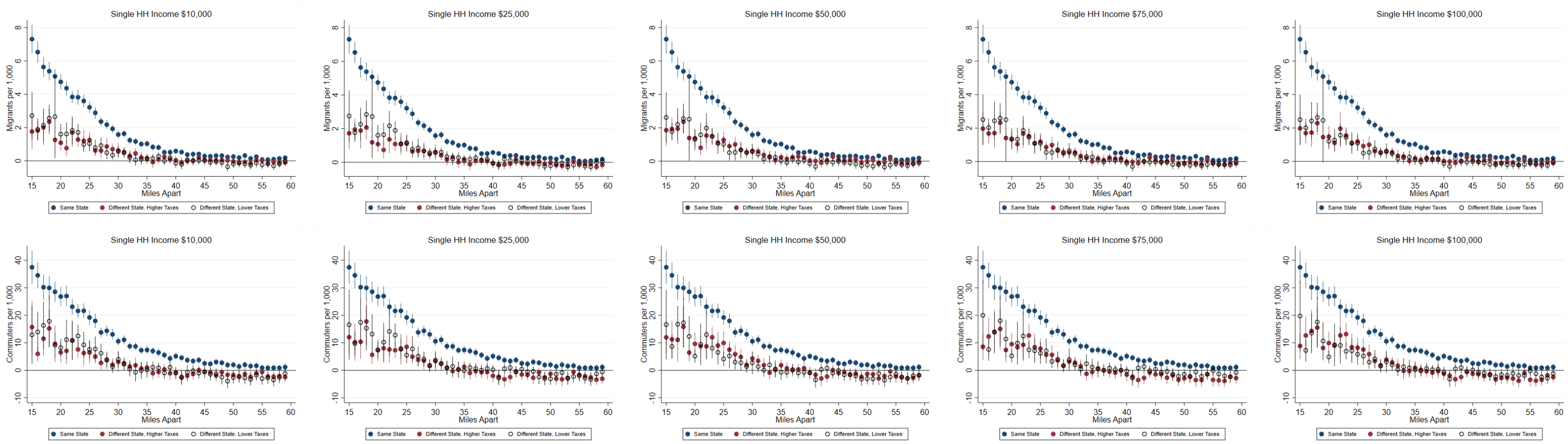
Figure A12: Role of State Income Taxation: Migration and Commuting Across State Borders, Married, Filing Jointly with Two Dependents



Notes: Coefficients from equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The point estimates represent differences by state+federal income tax burdens for a married household with two dependents with various levels of annual income. 95-percent confidence intervals are provided.

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

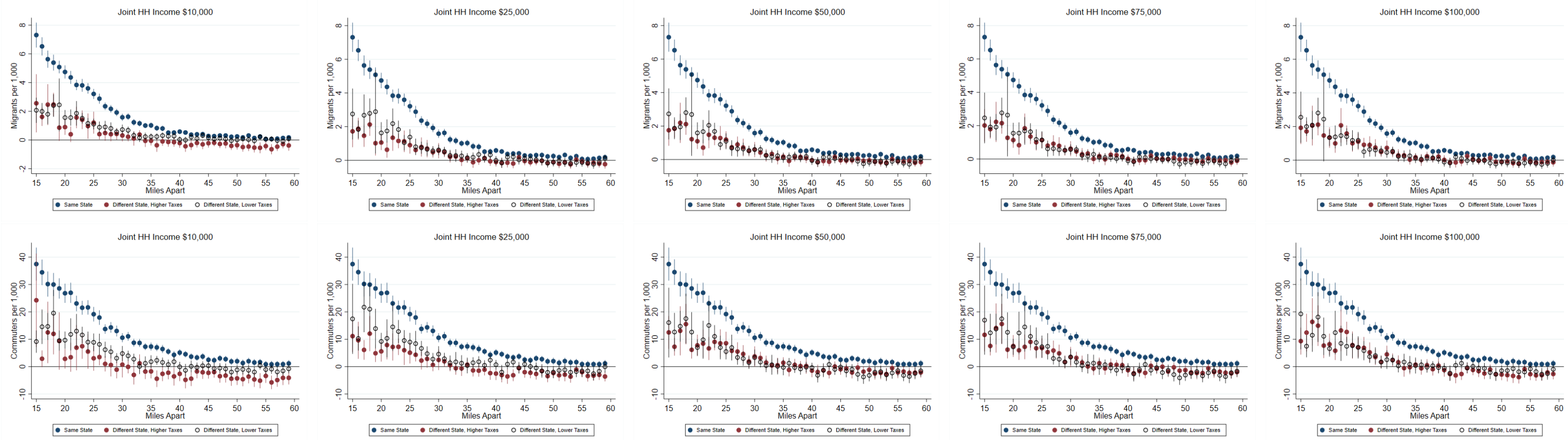
Figure A13: Role of State Income Taxation: Migration and Commuting Across State Borders, for a Single Individual



Notes: Coefficients from equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The point estimates represent differences by state+federal income tax burdens for a single individual with various levels of annual income. 95-percent confidence intervals are provided.

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

Figure A14: Role of State Income Taxation: Migration and Commuting Across State Borders, for a Joint Filers with no Dependents



Notes: Coefficients from equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The point estimates represent differences by state+federal income tax burdens for a married, joint household with no children with various levels of annual income. 95-percent confidence intervals are provided.

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

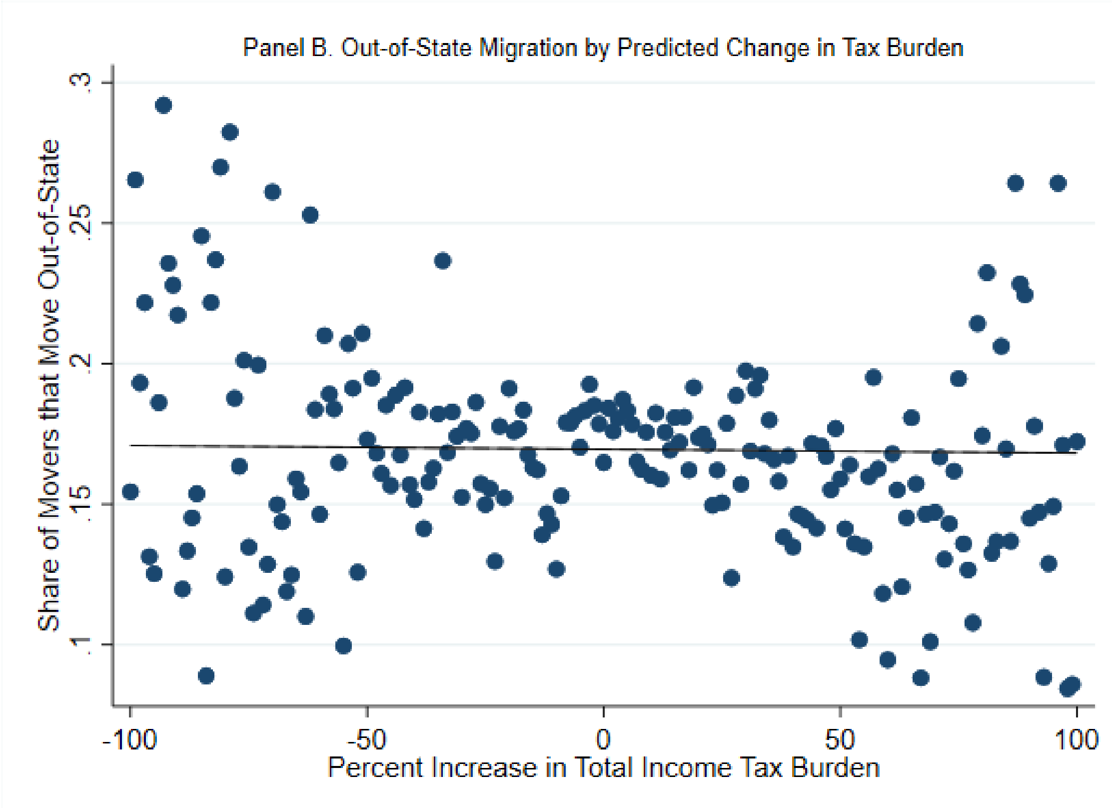
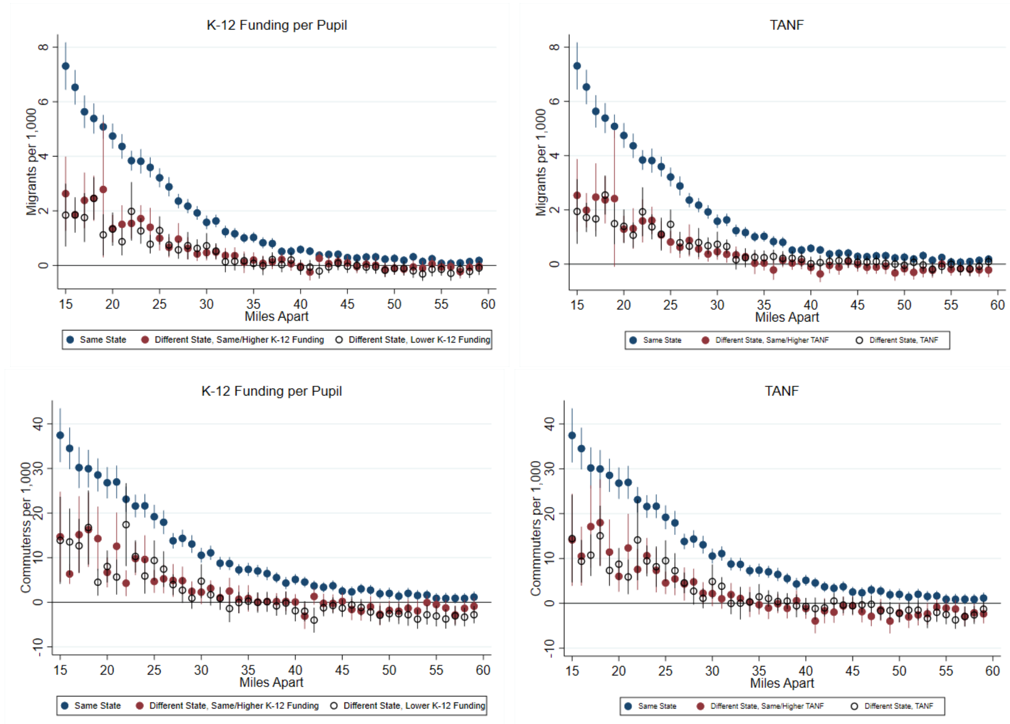


Figure A15: Share of Households that Move Out-of-State by Expected Percent Increase in Tax Burden

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.

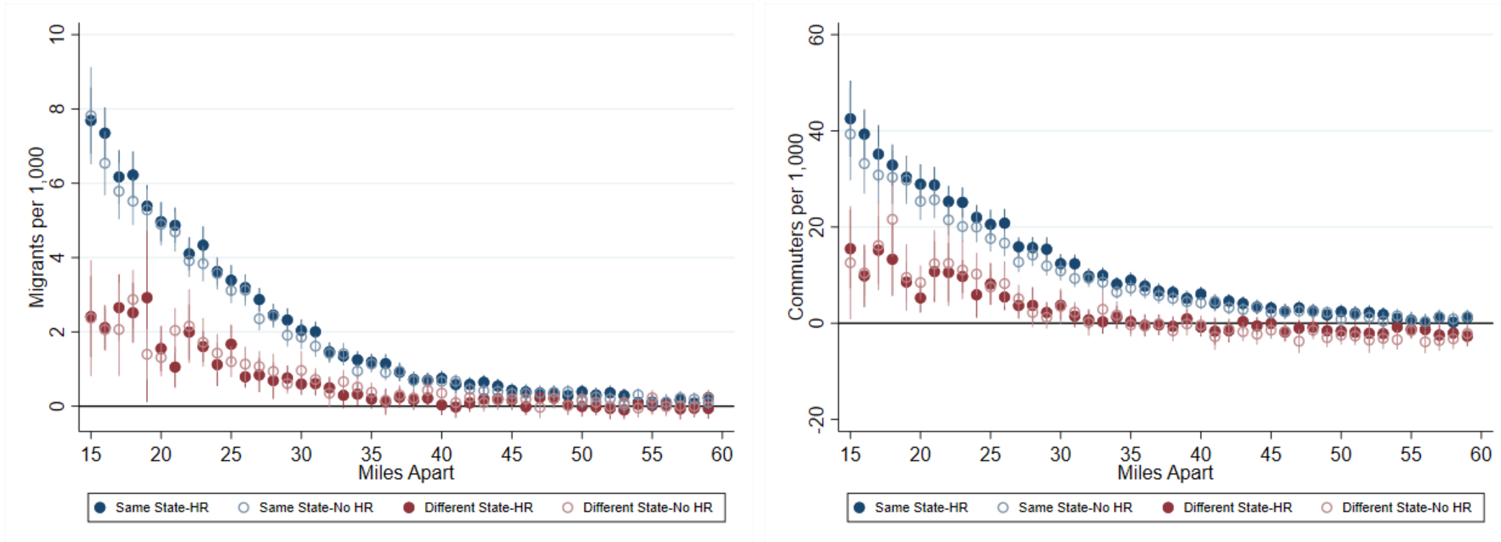
Figure A16: Impact of State Borders on Migration and Commuting by Pre-K-12 Per Pupil Spending and TANF Generosity



Notes: Coefficients from equation (6) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel plots differences by Pre-K-12 per pupil public school spending. The right panel plots differences by the TANF benefit rate. Controls include 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, number of establishments), 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 IRS county-to-county flows from 2017.

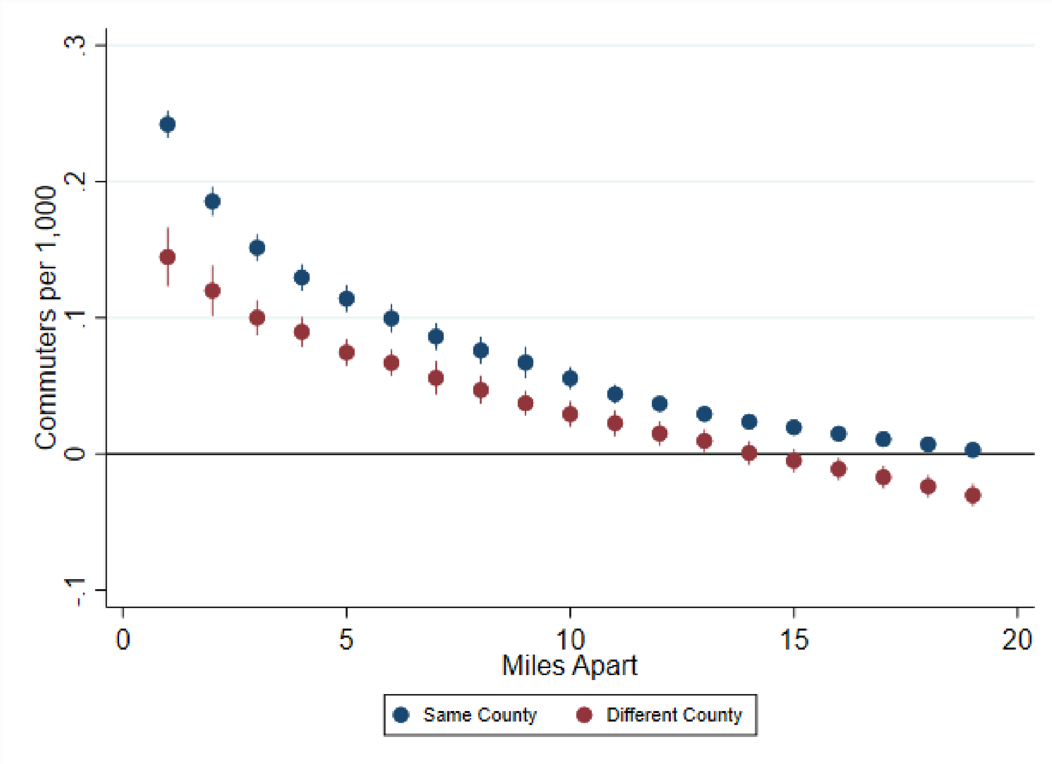
Figure A17: Impact of State Borders on Migration and Commuting by County Home Rule Regulation



Notes: Coefficients from equation (6) are plotted. Migration is plotted on the left, commuting on the right. Differences by the presence of Home Rule laws (as reported by Shoag et al., 2019). Controls include 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, number of establishments), 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 IRS county-to-county flows from 2017.

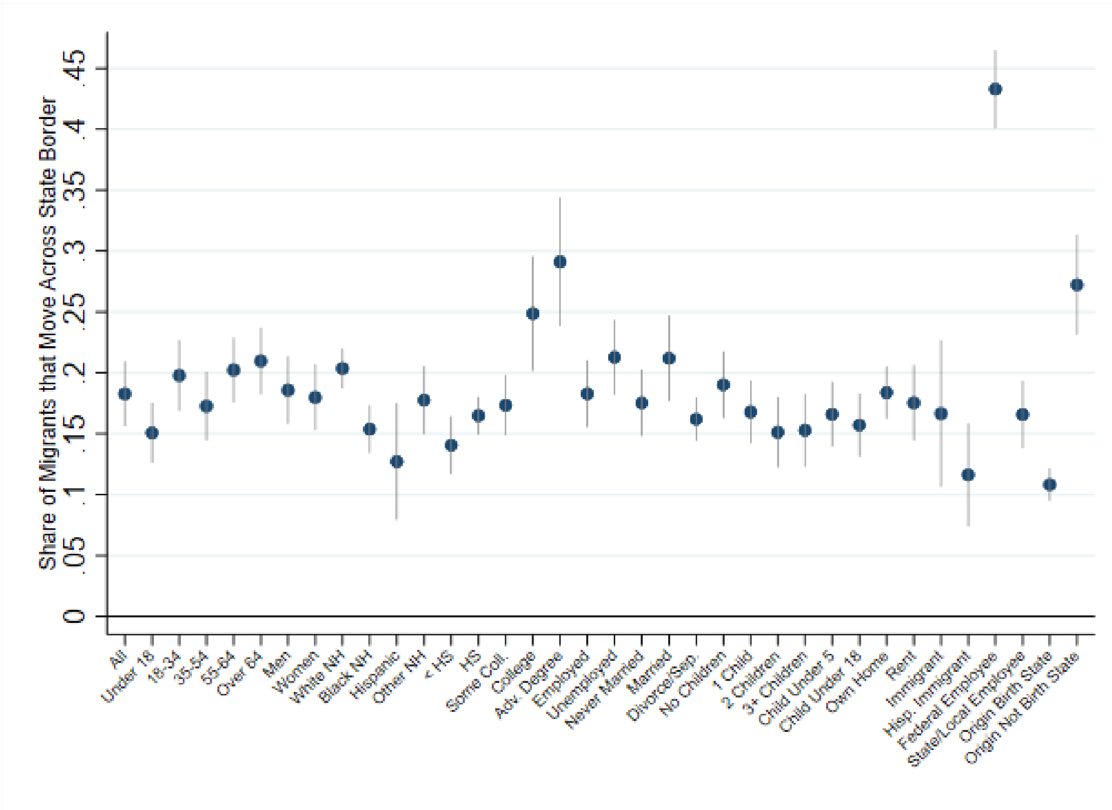
Figure A18: Census Tract-to-Tract Commute Rates by Distance for Same-County and Different-County Tract Pairs



Notes: Outcome is the number of commuters per one thousand people at the origin tract using the LODES origin-destination employment statistics aggregated to the tract level from 2017. Distance is the distance between the population weighted tract centroids. 95-percent confidence intervals are provided.

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

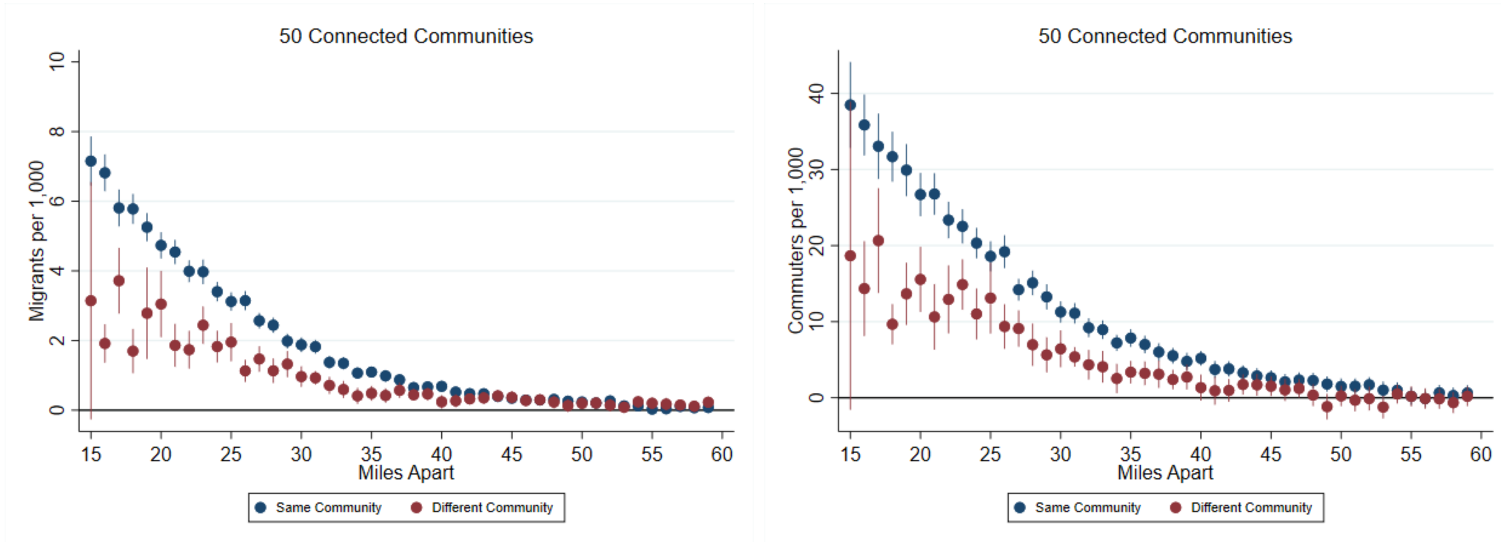
Figure A19: Role of Demographics: Cross-State Migration Across Demographic Groups in the ACS, All Individuals



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

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

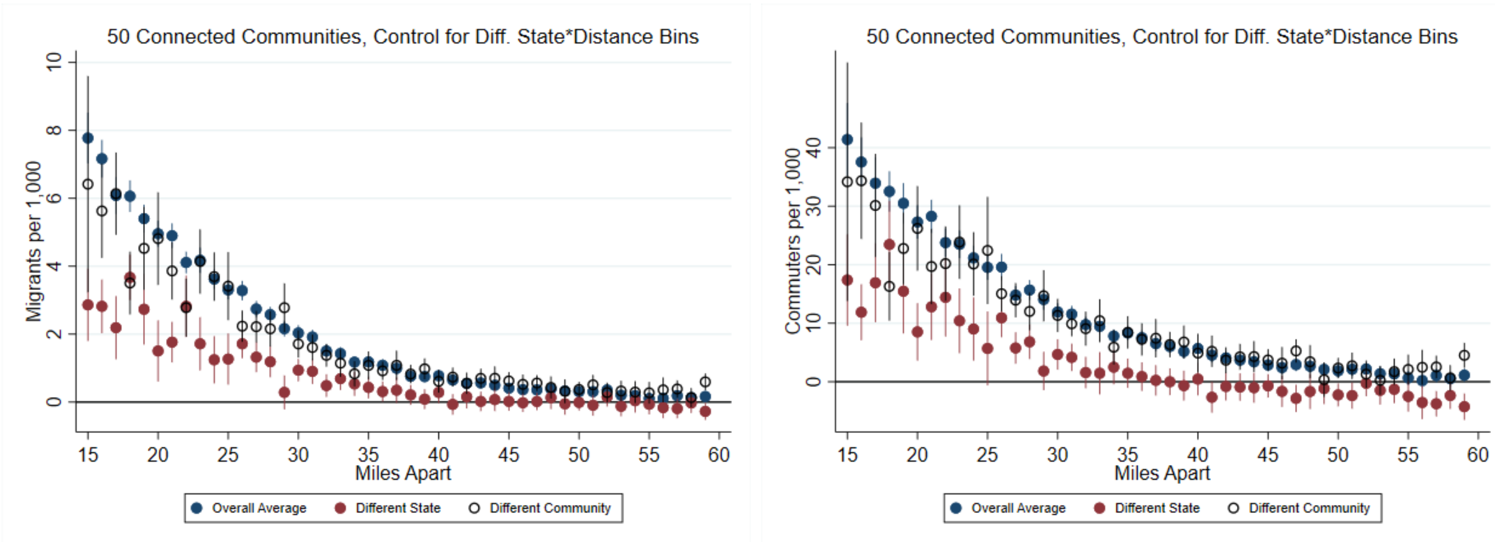
Figure A20: Impact of Pseudo Connected Community Borders on Migration and Commuting



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

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

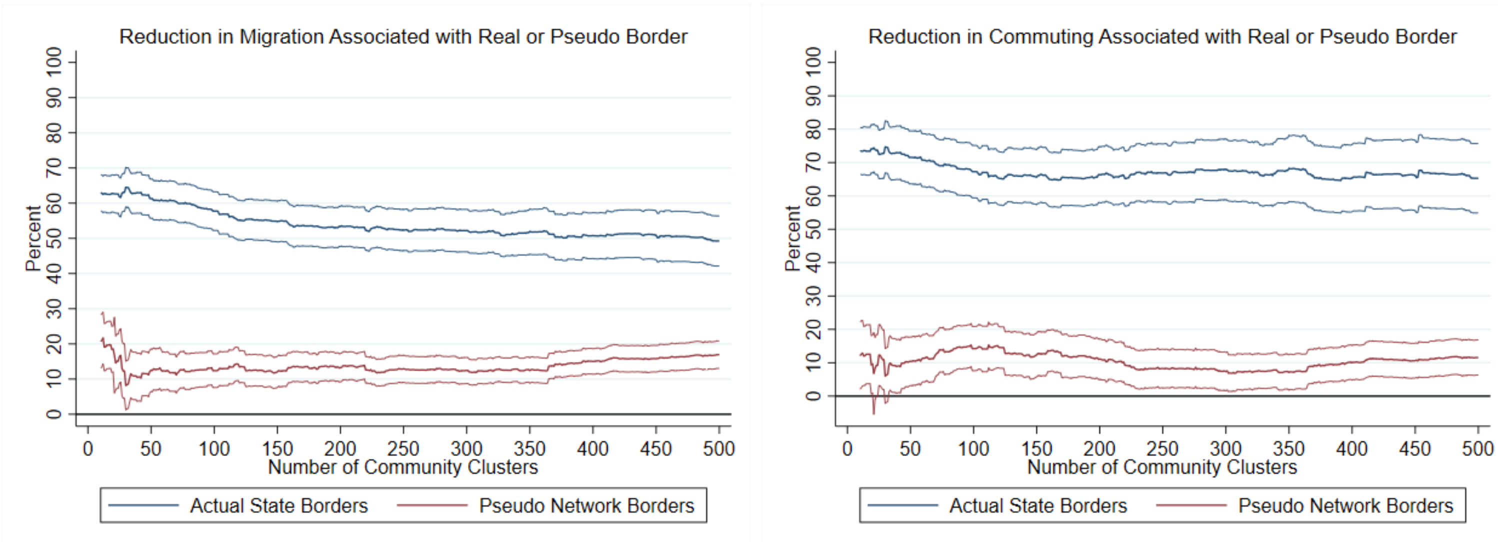
Figure A21: Horserace Regression: Relative Importance of Physical State Borders versus Pseudo Connected Community Borders, Weighted by Connected Community Border Persistence



Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. The outcomes are migration rates (left) and commuting rates (right). Each panel plots the coefficients from equation (2) but includes the full set of state border by distance interactions and the connected community border by distance interactions. Observations are weighted with the following weights $(\mu - 0.5)^2$, where μ is the fraction of times (out of 51) the counties are in a different connected community when all pre-specified cluster numbers from 25 to 75 are included. The weights subtract 0.5 and are squared so that the more county pairs have the same assignment, the higher the weight. This captures greater confidence in the connected community assignment. 95-percent confidence intervals are provided.

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

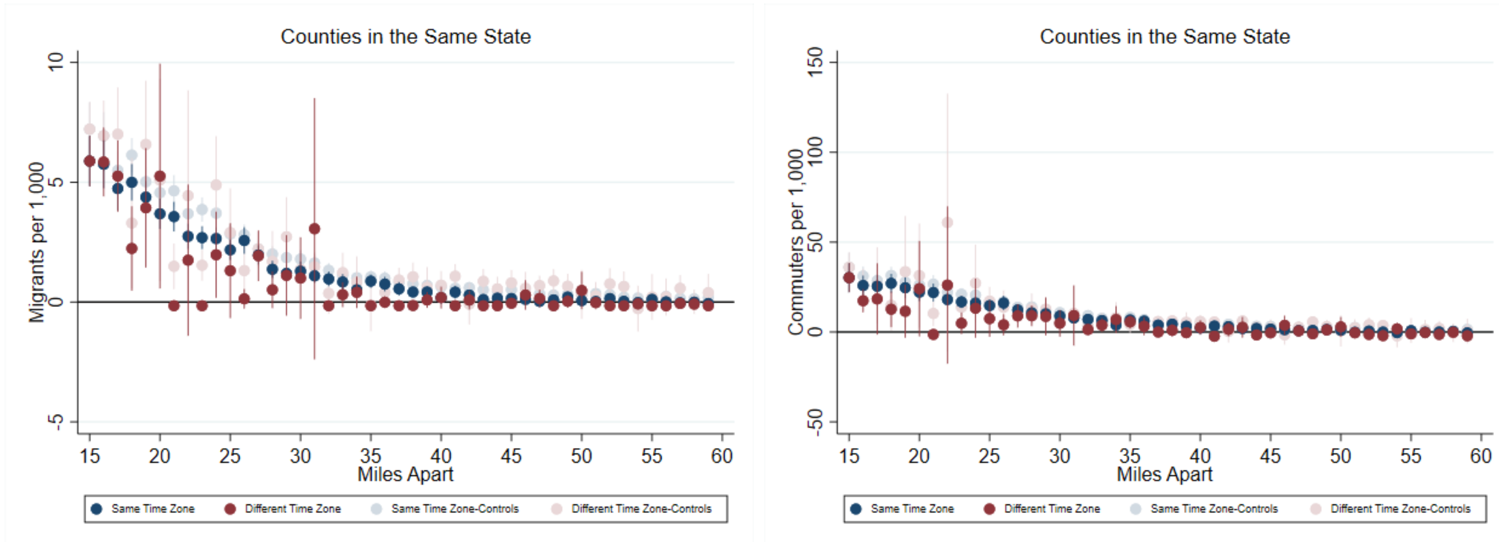
Figure A22: Horserace Regression: Relative Importance of Physical State Borders versus Pseudo Connected Community Borders for Various Pre-Specified Numbers of Connected Communities



Notes: Sample restricted to counties that are less than 60 miles from another county in a different state. The outcomes are migration rates (left) and commuting rates (right). Each point is a measure of the gap in migration due to physical state borders or pseudo connected community borders from equation (2) but includes the full set of state border by distance interactions and the connected community border by distance interactions, where the pre-specified number of connected communities is varied between 10 and 500. 95-percent confidence intervals are provided.

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

Figure A23: County-to-County Migration and Commute Rates by Distance Across Time Zone Borders Among Counties in the Same State



Notes: Outcome in the left panel is number of migrants per one thousand people at the origin county using the IRS SOI county-to-county flows from 2017. Outcome in the right panel is the number of commuters per one thousand people at the origin county using the LODES origin-destination employment statistics aggregated to the county level from 2017. Only counties in the same state, in states that span multiple time zones, are included. Distance is the distance between the population weighted county centroids. "With Controls" plots coefficients 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, number of establishments), 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 and 2017 LODES.

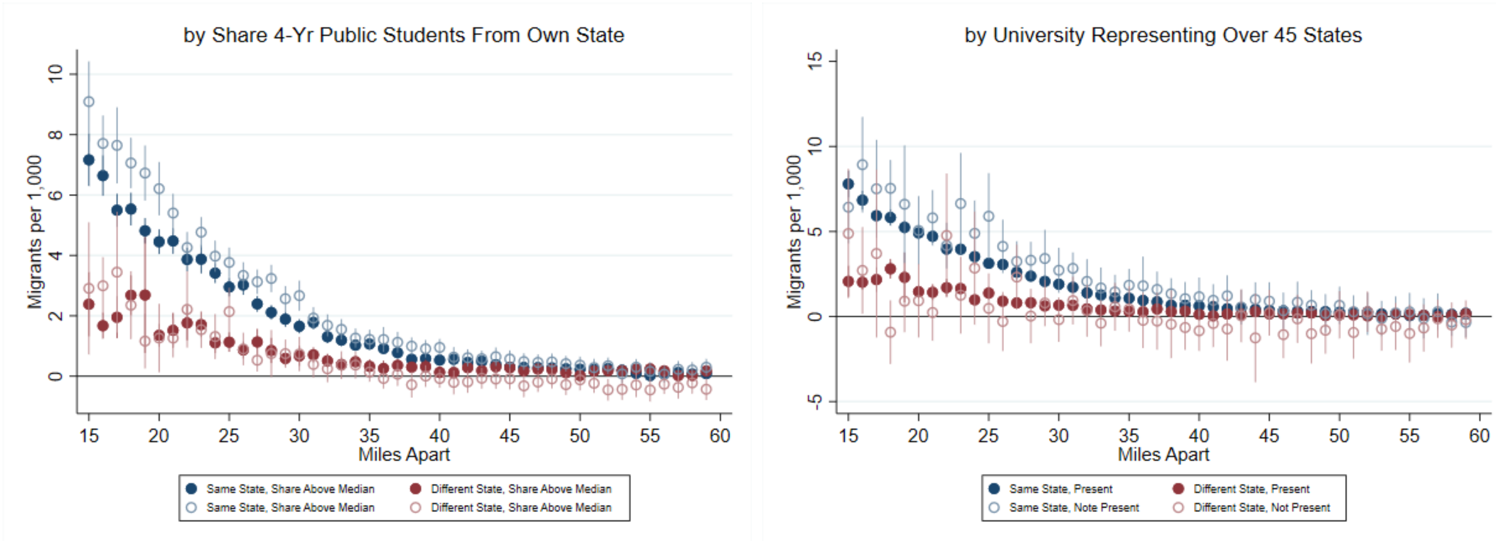


Figure A24: Identity from State Colleges: Migration by Interstate Connectivity of State Colleges

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.

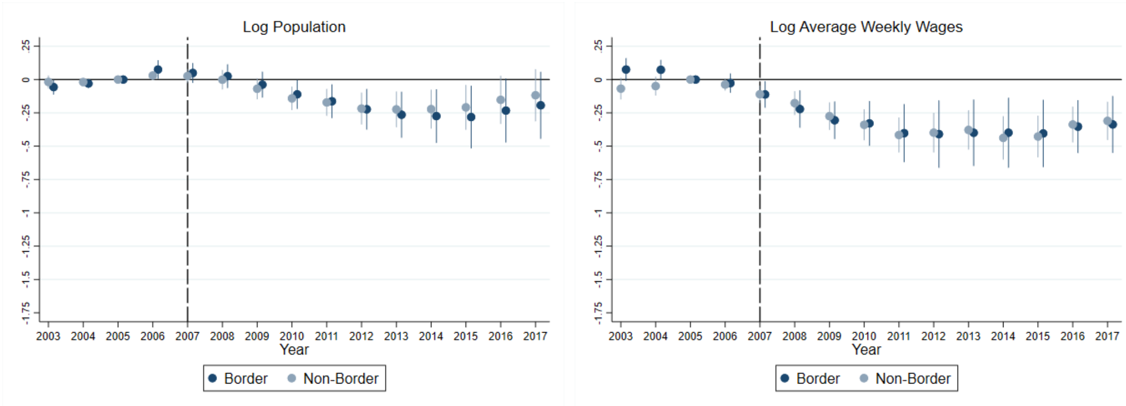
Source: Author's own calculations using the 2017 IRS SOI.

Figure A25: Impact of State Borders on Labor Market Recovery After the Great Recession, Lagged Outcome Control

Notes: These estimates are similar to those in Figure 12, 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.

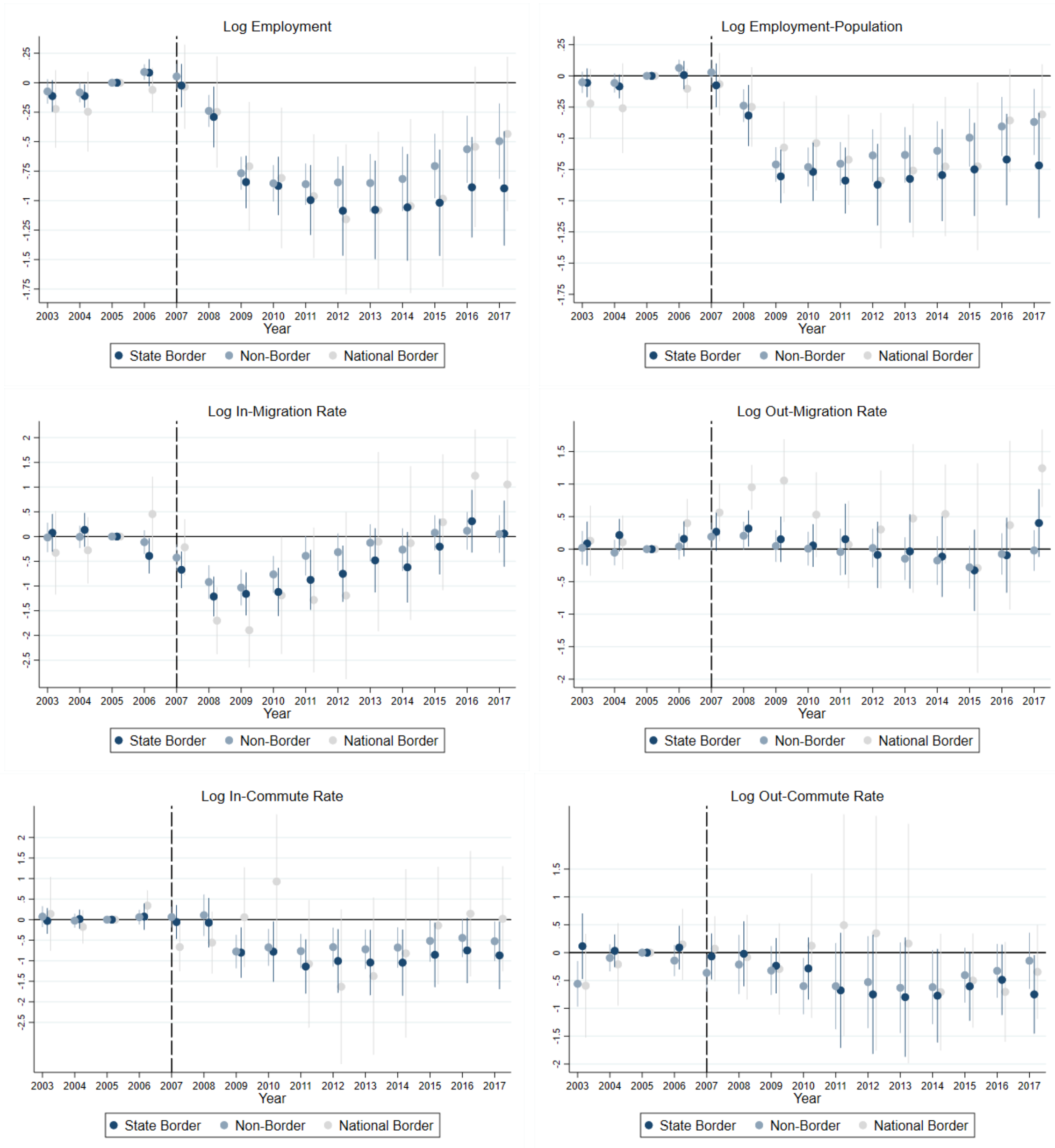
Figure A26: Impact of State Borders on Population and Wages After the Great Recession



Notes: Event study coefficients from the equation (16) 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, and 2003-2017 LODES.

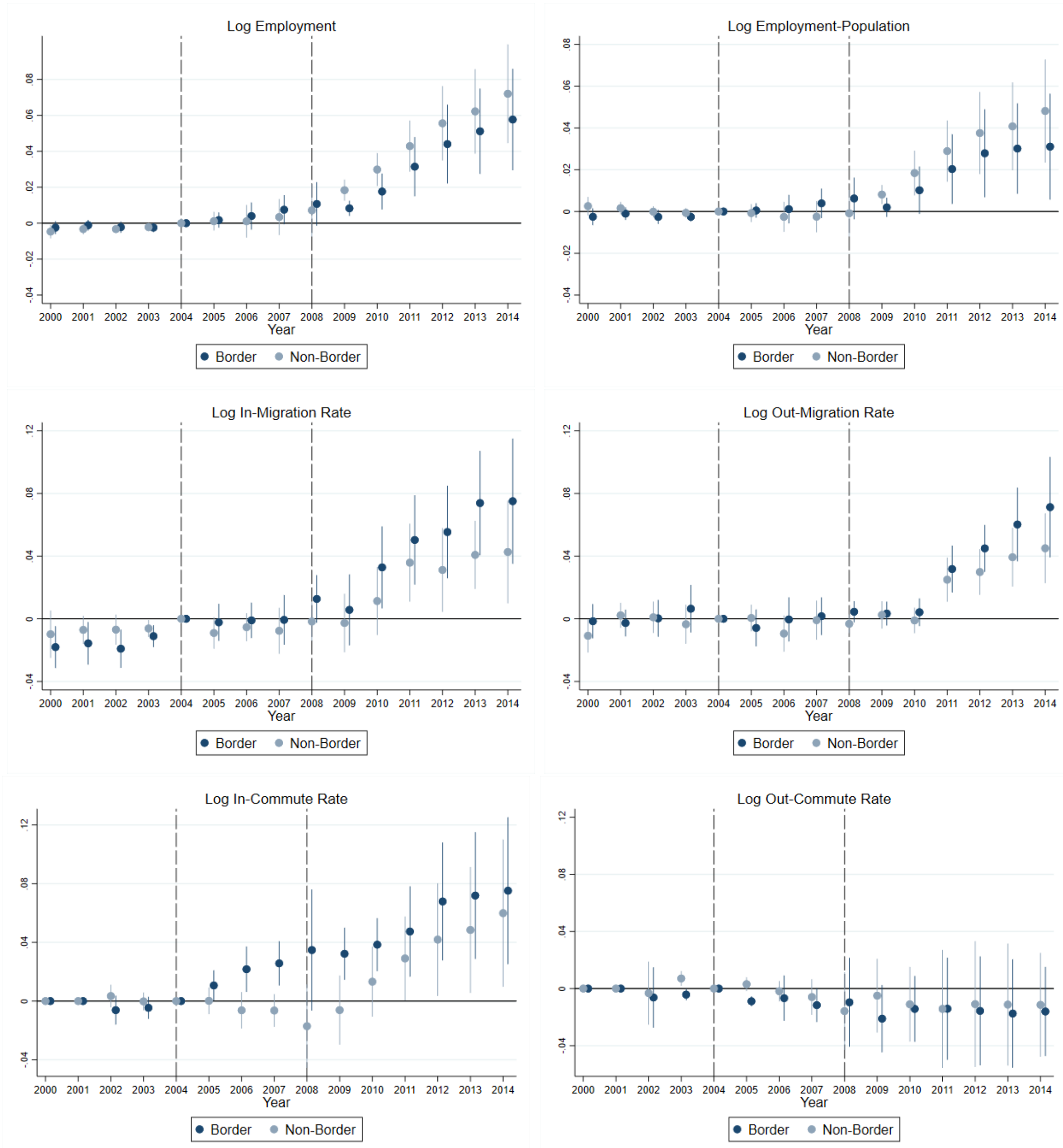
Figure A27: Impact of State Borders on Labor Market Recovery After the Great Recession, Relative to Counties on the National Border



Notes: Event study coefficients from the equation (16) 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. However, counties on the national border (bordering Canada or Mexico) are also allowed to have separate effects. 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, and 2003-2017 LODES.

Figure A28: Impact of State Borders on Labor Market Impacts of Fracking



Notes: Event study coefficients from estimation similar to equation (16) are plotted with 95 percent confidence intervals, but rather than the change in employment from 2007-2009, the total simulated oil and gas reserves (take from Wilson, (2020)) are used. 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, and 2003-2017 LODES.

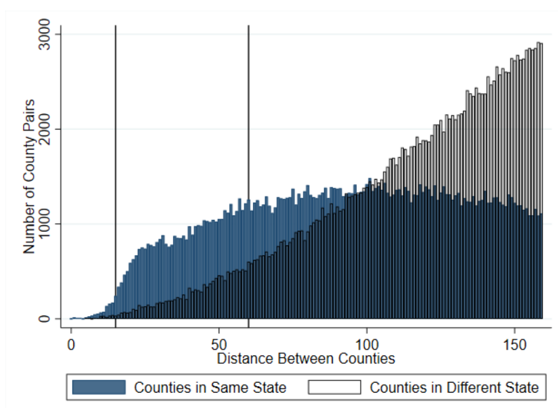
For Online Publication: Appendix B. Data Appendix

Census Bureau County Geography Files

Sources: https://www.census.gov/geographies/reference-files/2000/geo/2000-centers-population.html
https://www.census.gov/geographies/reference-files/2010/geo/county-adjacency.html

To construct the analysis sample, I first use the 2000 county population centroid file, provided by the Census Bureau. From this file, I preserve the county FIPS code and the county population centroid latitude and longitude coordinates. I then expand this data set to pairwise match each county with every other county in the United States. I then calculate the geodic distance between each county pair, and restrict the sample accordingly. For most of the analysis, I focus on county pairs that are between 15 and 60 miles apart, although in Appendix Figure A4 I extend the sample to include county pairs between 0 and 100 miles apart. The main reason I restrict the sample by distance is for interpretability. As seen in Appendix Figure B1, there are very few cross state county pairs less than 15 miles apart. Similarly, as distance increases the number of county pairs that are in the same state also begins to fall, and the composition of same state pairs shifts towards larger, Western states. To disentangle state border effects from compositional effects I restrict the sample to include a common support of both within state and across border county pairs, between 15 and 60 miles apart. I then connect this data to the county adjacency file, provided by the Census Bureau. This file contains a list of all counties that border the focal county, allowing me to also identify neighboring counties. I then merge this data to various data sources to capture migration, commuting, and other local characteristics. Below I describe each of the key datasets used in my analysis, as well as important characteristics of data construction.

Figure B1: Number of County Pairs by Distance



Notes: The number of within state and across state county pair bins are plotted in one mile distance bins.

Source: Author's own calculations using the 2000-2017 IRS SOI, and 2003-2017 LODES.

Internal Revenue Service Statistics of Income County Flows

Source: https://www.irs.gov/statistics/soi-tax-stats-migration-data

The Internal Revenue Service (IRS) Statistics of Income (SOI) division uses annual, household-level Tax Form 1040 filings to construct annual counts of county-to-county flows of individuals and households. These files provide the number of tax returns (to proxy for households) and exemptions (to proxy for individuals) that were filed in one county in year $t-1$ and in another county in year t. Most filing occurs between February and April, so annual migration flows capture moves from approximately March or April from one year to the next. For privacy purposes, the IRS suppresses county pairs that have fewer than twenty returns move in each year. The suppression threshold increased from 10 to 20 returns in the 2013 data release. I record county pairs that are not observed, but potentially have small, positive flows, as zeroes. This potentially introduces measurement error. Because I am focusing on relatively close county pairs (less than 60 miles apart) suppression is less of a concern than it would be for more distant county pairs. As seen in Appendix Figure A6, the patterns are unchanged if I limit the sample to only include non-suppressed migration flows.

In 2011, the IRS made several changes. First, they extended the tax data collection period from September to December. As such, households that requested extensions, and tend to be higher income, were more represented (Pierce, 2015). Second, the IRS also expanded the way that matches were identified to consider all heads, spouses, and dependents. Using both the new method and old method, the IRS calculated state-level net migration rates to determine how much the series was affected. They find that 44 of the states (plus DC) differed by less than 5 percent and only Wyoming varied by more than 10 percent. Throughout the analysis I focus on the cross-section in 2017, so estimates are not impacted by these methodological changes over time. However, these changes might help explain the variation in Figure A2 which plots the migration estimates back to 1992.

Some moves are not captured in the IRS data. Households with low income (between $12,000-28,000 depending on age and filing status) are not required to file a Form 1040. However, many of these households will file in order to receive transfer benefits administered through the tax system, like the EITC and Child Tax Credit. The IRS tax data also will not capture successive moves within a year.

American Community Survey Microdata

Source: https://usa.ipums.org/usa/

The IRS county to county flows only provide aggregate flows, and do not provide flows for subpopulations (e.g., gender, marital status, education). To explore heterogeneous out-of-state migration I also exploit the 2012-2017 American Community Survey Microdata obtained from IPUMS (Ruggles et al., 2019). The ACS is an annual Census Bureau survey of approximately one percent of households each year. In addition to collecting information about household structure, demographics (age, race/ethnicity, gender, marital status), education, and employment, it asks individuals where they lived in the previous year, making it possible to explore one-year migration patterns. The smallest geographic unit in the ACS is the Public Use Micro Area (PUMA). PUMAs are geographic areas defined by population that are large enough to preserve privacy. Migration geographic data is only available at the Migration PUMA (MIGPUMA), which is an aggregation of PUMAs to the county-level or higher, depending on population size.[30] Because MIGPUMA are often much larger than counties, the ACS data is not fit to estimate the same county-to-county flow by distance equations used with the IRS data. Instead, I focus on the probability of moving out of state, conditional on moving at all, regardless of distance to the border. In the Appendix I also examine the unconditional probability of moving out of state. I have also estimated ACS results focusing on individuals living in cross-state commuting zones (to isolate people plausibly close to the border) and find a similar pattern of results.

LEHD Origin Destination Employment Statistics Commute Data

Source: https://lehd.ces.census.gov/data/

The LEHD Origin Destination Employment Statistics (LODES) links workers' place of residence to their place of work, at the Census block pair level. As such, it is possible to construct measures of commuting. Using Census block to county crosswalks, I aggregate worker residence and work counts to the county level, to construct county-to-county commute flows. This data is available since 2002 on, but for consistency I focus on the data from 2017. The LODES does provide some subpopulation counts, but only for broad age (under 30, 30-54, over 54), monthly earnings (under $1,250, $1,250-3,333, over $3,333), and industry (goods, trade/transportation, other) groups. Place of residence is missing for about 10 percent of the LEHD worker sample, and imputed using categorical models based on sex, age, race, income, and county of work. For privacy, some noise is introduced at the Census block level, which likely remains at the county level, although to a lesser extent.

[30] Only in several New England states are MIGPUMA smaller than the county-level.

Social Connectedness Index from Facebook Data

Source: https://data.humdata.org/dataset/social-connectedness-index?

To capture county-to-county social ties I use the Social Connectedness Index (SCI), constructed by Bailey et al. (2018). This measure is derived from Facebook microdata and counts the number of friendship links between each county and every other county in the US from a snapshot of active Facebook users in 2016. An active users is "a registered Facebook user who logged in and visited Facebook through our website or a mobile device, or used our Messenger application... in the last 30 days" (Bailey et al., 2018). As such, I observe a static measure of each county's social network, as captured by Facebook users. At the time there were 236 million active Facebook users in the US and Canada (Bailey et al., 2018). I multiply the SCI by 400, so that the smallest reported value is 1. This number is a scalar multiple of the actual county-to-county number of friends, which is multiplied by a constant to preserve privacy. This measure has been shown to correlated with other proxies of social networks (Bailey et al., 2018). I originally obtained through an individual data use agreement, but the authors have since made versions of the data publicly available at the link provided above.

Pew Social Trends – October 2008 Survey

Source: https://www.pewresearch.org/social-trends/dataset/mobility/

The October 2008 Pew Social Trends was a survey of 2,260 adults living in the continental US, conducted by Princeton Survey Research International. It was conducted between October 3-19, 2008. During the 20 minute survey, respondents were asked questions concerning place of residence, moving histories, what places they identify with, why they identify with those places, and whether they would consider moves in the future. I make use of several questions in particular. Question 17 asks what state individuals were born in. Question 9 asks, "Have you lived in or near your local community your entire life, aside from the time you may have spent away in school or college, or have you lived in other places?" With these two questions I am able to identify individuals who have never left their birth state.

Unfortunately, individuals who have ever moved or never moved are sometimes asked slightly different questions. Non-movers are asked Question 15, "For each of the following, tell me if this was a major reason, a minor reason, or not a reason you have lived there all your life." They are then presented with various reason, including job or business opportunities; cost of living; family ties; no desire to live someplace else; the climate; connections to friends; community involvement; I just feel I belong here; a good place to raise children; recreational and outdoor activities; medical and health reasons; cultural activities; or I grew up here. I split these reasons into three groups: personal/social ties (family ties, connections to friends, and community involvement); amenity ties (job or business opportunities, cost of living, the climate, a good place to raise children, recreational and outdoor activities, medical and health reasons, and cultural activities); and place-based identity (no desire to live someplace else, I just feel I belong here, and I grew up here). The place-based identity features tie an individual to an area, but not necessarily because of local amenities or social connections in the area. I measure birth state identity among the non-movers as anyone who reported a place-based identity reason as a major reason for living here all of their life.

Movers are asked Question 20, "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?" In a follow up question, they are asked where that place is and which state it is in. Combining this information, I can identify movers who exhibit a birth state identity. Movers are also asked a question, similar to Question 15 for non-movers, but the options are different: job or business opportunities; cost of living; family ties; education or schooling; the climate; a good place to raise children; recreational and outdoor activities; medical and health reasons; cultural activities; or retirement. As such, I can only compare birth state identity to family ties and amenity ties in Table 3.

All participants are asked in Question 38 which state they would prefer to live in, including their current state of residence. From this, I can calculate whether participants would prefer to live in their birth state. All participants are also asked in Question 8 how likely they are to move in the next five years. The sample is then randomly split into three groups, and each is asked the following, "As I read through the following places, just tell me your first reaction—Would you want to live in this city or its surrounding metropolitan area or NOT want to live there?" They are then given a list of 10 large metropolitan areas spread throughout the country. Because only one third of the sample is asked each of these questions, there is not enough power to examine these separately. Instead, I create a binary outcome that equals one if the individual said that they were willing to move to any of the cities. From this outcome I estimate if birth state identity is associated with a change in the probability of saying they would move to a randomized list of large MSA.

Because birth state identity depends on observing the individual's state of birth, foreign born survey participants are excluded from the analysis, leading to a sample of 1,949 individuals. All regression estimates are weighted using the nationally representative survey weights provided by Pew.

National Cancer Institute Surveillance, Epidemiology, and End Results Program

Source: https://seer.cancer.gov/popdata/download.html

I obtain annual, county-level population estimates from Surveillance, Epidemiology, and End Results Program (SEER). The US Census Bureau provides annual single-year age population estimates at the county-level to the National Cancer Institute. These estimates are available by gender and race by origin (Hispanic vs. Non-Hispanic). This population data is used in the denominator to create migration rates, commute rates, and employment and population ratios. To construct these rates I use the full population in the denominator. I also construct race shares, under 20, 20-34, 35-49, 50-64, and over 64 age shares, and gender shares. These are then merged to both the origin and destination counties of each county pair.

Local Area Unemployment Statistics

Source: https://download.bls.gov/pub/time.series/la/la.data.64.County

I obtain county-level labor force, employment, and unemployment levels which we use to construct unemployment rates from the BLS Local Area Unemployment Statistics. These measures are then merged to the origin county and then again to the destination county to observe differences between origin and destination counties.

Quarterly Census of Employment and Wages

Source: https://www.bls.gov/cew/downloadable-data-files.htm

I obtain county-level annual measures of employment and wage earnings by industry from the BLS Quarterly Census of Employment and Wages. I also construct employment industry shares for ten broad industries (natural resources, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, and other). These measures are then merged to both the origin and destination counties in each county pair. During this period, Shannon County South Dakota was changed to Oglala County. To facilitate the merge, the fips code for Shannon County South Dakota (46113) is changed to the time consistent Oglala County fips code (46102).

Federal Housing Finance Agency House Price Index

Source: https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#qexe

I obtain a county-level house price index from the Federal Housing Finance Agency. This is a developmental index, that is not seasonally adjusted. This measure indicates how much house prices changed within an area, but because they are normalized it does not facilitate a cross-county comparison. To create a comparable series, I collect county-level median house prices from the 2000 Decennial Census, and then use the price index to pull county-level prices forward and backward in time. This measure is then merged to both the origin and destination county in each county pair.

2017 SUSB Annual Data Tables by Establishment Industry

Source: https://www.census.gov/data/tables/2017/econ/susb/2017-susb-annual.html

I use the 2017 Statistics of US Businesses annual table to estimate the number of establishments at the county level. This measured is used to estimate strategic firm location behavior with respect to state borders.

I then merge these measures to both the origin and destination counties in each county pair. Number of firms can also be captured in the QCEW and provide a similar pattern.

County Partisanship and 2016 Presidential Vote Share

Source: https://electionlab.mit.edu/data#data

I collect county voting patterns from 2000 to 2016 from the MIT Election Lab. We observe the vote share for each party in each presidential election. We keep the Republican vote share in the 2016 election. I then merge these measures to both the origin and destination counties in each county pair.

State Income Tax Burden

Source: http://users.nber.org/ taxsim/state-tax-rates/

Using state tax levels for representative taxpayers, calculated by NBER TAXSIM, I construct income tax burdens. Some states do not have state income taxes, as such, I calculate the total federal plus state income tax burden to calculate percent differences in income tax burden. Tax levels are calculated for taxpayers with either \$10,000, \$25,000, \$50,000, \$75,000, or \$100,000. Four different family types are considered, single, single/elderly, joint (no dependents) and joint with two dependents. We plot results for single, joint (no dependents), and joint (two dependents) at all of the income levels.

State Minimum Wages

Source: https://www.dol.gov/agencies/whd/state/minimum-wage/history

State minimum wages for 2017 are obtained from the US Department of Labor. Some state minimum wages are not universal, but rather apply to certain firm sizes. I keep the most universal minimum wage for each state and merge this to both the origin and destination counties. For states without a state specific statute, the federal minimum wage is used.

State EITC Supplement Rate

Source: https://users.nber.org/ taxsim/state-eitc.html

I collect state EITC supplement rates from the NBER for the year 2017. For most states, these rates are percentage supplements to the federal EITC rate. There are several exceptions. The California rate only applies to the phase-in region (until about \$22,300 for households with children in 2017). The rate is Wisconsin depends on the number of qualifying depends, for Wisconsin I keep the lowest rate of 4 percent. I include both refundable and non-refundable credits.

State TANF Benefit Levels

Source: https://fas.org/sgp/crs/misc/RL32760.pdf

State Temporary Aid for Needy Families (TANF) maximum monthly benefit levels for a single-parent family with two children are collected from Congressional Research Services, from March 2018. TANF is distributed to states through a block grant, and states have flexibility over how these funds are used.

State by State Medicaid Expansion

Source: https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/

As part of the Affordable Care Act, states were allowed to expand Medicaid to include low-income adults up to 138% of the federal poverty level. I collect records of states that had expanded Medicaid by December, 2017 from the Kaiser Family Foundation.

Pre-K Through 12 Public School Expenditures per Pupil

Source: https://ncses.nsf.gov/indicators/states/indicator/public-school-per-pupil-expenditures/table

I obtain county-level annual Pre-kindergarten through 12th grade public school spending per pupil from the National Science Board, with statistics originally produced by the US Department of Education, National Center for Education Statistics. The measure captures local, state, and federal spending on elementary and secondary education, divided by pre-kindergarten through 12th grade public school enrollment. I then merge this measure to both the origin and destination counties in each county pair.

State Sales Tax Rates

Source: https://taxfoundation.org/state-and-local-sales-tax-rates-in-2017/

I obtain state sales tax rates from the Tax Foundation for the year 2017. Average and maximum local sales tax rates are also provided, but there is no indication of what counties these measures apply to. Some states do not have sales tax. These measures are merged to both the origin and destination counties in each county pair.

State Corporate Income Tax Rates

Source: https://taxfoundation.org/state-corporate-income-tax-rates-brackets-2017/

I obtain state corporate income tax rates from the Tax Foundation for the year 2017. Some states have a single corporate income tax rates, others have a progressive schedule of rates ranging from 0 to 12 percent. For each state I keep the maximum corporate income tax rate. This is then merged to both the origin and destination county to determine if migration and commuting patterns differ when the potential destination has higher or lower corporate tax rates.

Shoag, Tuttle, and Veuger (2019) Home Rule

Source: Obtained from the authors

I obtain measures of “home rule” or within state county-powers from (Shoag et al., 2019). This measure captures the amount of county autonomy which might be related to state identity or individuality.