The Isolated States of America: Home State Bias and the Impact of State Borders on Mobility*

Riley Wilson

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Abstract

I document a new fact about mobility within the United States. County-to-county migration and commuting drop 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 an equally-distant county across state lines. Standard economic explanations, like differences in amenities or moving costs, have little explanatory power. Experimental evidence suggests many people experience "home state bias" and discount out-of-state moves, independent of whether social ties are present. This pattern has real economic costs, resulting in local labor markets that are less dynamic after negative economic shocks.

Keywords: Internal migration, commuting, social networks, home state bias, border discontinuities
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*Department of Economics, 2146 WVB, Brigham Young University, Provo UT, 84602. Phone: (801)422-0508. Email: riley_wilson@byu.edu. I gratefully acknowledge helpful comments from Dan Hamermesh, Nathaniel Hendren, Enrico Moretti, Lars Lefgren, Tyler Ransom, Abigail Wozniak, and participants at the Federal Reserve Board, IZA Junior/Senior Symposium, CESifo Labor Meetings, SOLE, SEA, PAA, the Utah/BYU Applied Economics Conference, the Utah Demography Summit, and the BYU brown bag. Adam Loudon and Thomas Barden provided excellent research assistance. This work has been generously supported by the W.E. Upjohn Institute's Early Career Research Grant No. 20-158-15. The online survey experiment RCT was registered as AEARCTR-0009590.

1 Introduction

The United States has traditionally been seen as a highly mobile country, with nearly one in five people changing their county of residence every five years. Even though internal migration has gradually declined over the past 40 years, the United States still exhibits higher internal mobility than most European countries (Molloy et al., 2011). Geographic mobility is often viewed as both a chance for individuals to find better job opportunities and a mechanism through which places adjust to local economic shocks, contributing to labor market fluidity and economic dynamism (Blanchard and Katz, 1992; Molloy et al., 2016). However, across the country there is still significant heterogeneity in real earnings (Diamond and Moretti, 2022), even in close proximity, suggesting that many people could encounter better economic "opportunities" through short distance mobility, either migration or commuting. Frictions that limit internal mobility could lead to less dynamic local economies.

I document a previously undocumented aspect of U.S. 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 county in the same state than to an equally distant county in a different state. People are about twice as likely to commute to a county in the same state as to an equally distant county in a different state. In other words, state borders reduce both long-term and temporary mobility. This pattern is consistent with evidence that most moves are local (Hendren et al., 2022) and that local ties limit migration (Zabek, 2020). However, it highlights that even when there are no legal restrictions or language barriers, political boundaries matter. In this paper, I do three things. First, I document the extent of these empirical patterns; second, I evaluate potential explanations for why this cross-border drop in mobility exists and provide compelling evidence of a new potential mechanism – "home state bias"; and third, I show that this mobility friction is economically costly, reducing the dynamism of local labor markets.

After documenting that this empirical fact is not simply a measurement issue, I consider various explanations, beginning with a focus on the canonical migration choice model (Sjaastad, 1962), which emphasizes differences in amenities 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 absolute or raw differences between the origin and destination in labor market characteristics, industry composition, demographic composition, natural amenities, political leaning, home values, or local test scores. It also is not explained by differences in state-level tax and transfer policy. Furthermore, this gap persists when I focus on counties that we would traditionally think of as being more interconnected, such as counties in the same metropolitan statistical area (MSA), commuting zone (CZ) or even neighboring counties on state borders.

Pecuniary moving costs, also do not explain the mobility gap. Because the discontinuity is present for both migration and commute flows, it is unlikely to be driven by pecuniary adjustment costs associated with moving across state lines (e.g., updating vehicle registration or driver's licenses). State occupational licenses do not explain the discontinuity.

In American Community Survey (ACS) microdata, the state border mobility penalty is similar across most demographic groups (i.e., age, race/ethnicity, gender, employment, or family structure), suggesting that 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 his or her birth state. The state border migration penalty is over twice as large for individuals originally living in their birth state relative to people living outside their birth state.

Building on this idea of local ties, I document a similar geographic discontinuity in Facebook friendship rates (Bailey et al., 2018) across state borders, consistent with origin ties and county-to-county connectedness playing a role. On average, people have twice as many Facebook friends in a same-state county 15 miles away as in a cross-border county 15 miles away. When I control for the Facebook network linkages between the origin and destination, the gap 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. This pattern is consistent with several augmentations of the simple migration model, including network strength, information frictions, or some third feature, like state-specific preferences or home bias affecting both mobility and social ties. As causality between mobility and social networks could run in multiple directions, I conduct an online experiment to identify the mechanisms that create the discontinuity in mobility at state borders.

In a stated-preference survey, I show respondents hypothetical opportunities that are approximately 100 miles away and would necessitate a move. For each individual, I independently randomize the amount of income associated with the opportunity, the presence of friends and family, and whether or not the destination is in the same state or a neighboring state. All other aspects of the opportunity are held constant. Individuals then report the percent chance that they would move for the opportunity, allowing me to independently identify the effects of social ties and moving to a different state. Having to move across state lines significantly reduces the reported propensity to move, but only for people currently living in their home state. Even when I present respondents with two scenarios that are identical in every way, but one is in their current state and one is in the neighboring state, individuals report significantly lower probabilities of moving across state lines. When asked what factors motivate this behavior, the most common response was feeling connected to their current state in ways they are not connected to a neighboring state. This behavior is consistent with a so-called "home state bias" Many people seem to identify with particular features of a state, and this familiarity is lost across state borders, thus leading to the cross-border drop in mobility. This can be modeled as an endowment effect and leads people to discount opportunities across state lines because they require leaving the "home state." The role of network strength or information frictions is less supported by the data. Using several other online surveys, I provide descriptive evidence that lends further support to the role of home state bias.

The concept of home bias affecting mobility is not new (Basu et al., 2022). However, it is often seen as a consequence of social networks (Borjas, 1992) or information frictions (Bryan et al., 2014). I provide evidence that some people exhibit a state-specific home bias that affects mobility across state borders, independent of social ties or information frictions. This work adds context to existing research exploring the role of local ties (Zabek, 2020), rootedness (Hendren et al., 2022; Kosar et al., 2020), and migration costs (Desmet et al., 2018; Ransom, 2022). Local ties tend to keep people near their birthplace, leading to muted migration responses to local economic shocks (Zabek, 2020). In the literature, "local ties" are used to capture the concept that people tend to live near their birthplace for unexplained reasons. This paper shows that people might use state boundaries to proxy for a set of features that they value, leading to a sense of home state identity and bias. As such, state borders and corresponding home state bias can help explain local ties and highlights the relative isolation of states. This work also sheds light on why the nonmoney costs of moving are large for individuals who self-identify as "rooted" to their location (Kosar et al., 2020), and why migration does not equalize regional wage differences (Desmet et al., 2018).

Finally, I show that this documented effect of state borders on mobility influences the dynamism of labor markets. Local labor markets that experienced worse economic shocks during the Great Recession saw persistent relative declines in employment and population (Hershbein and Stuart, 2020). Building on this analysis, I find that counties at the state border, where the state border mobility penalty is more binding, see bigger drops in employment after the shock and experience weaker recoveries in employment relative to other counties in the same local labor market. Ten years after the initial cyclical shock, employment measures in border counties have recovered approximately 34 percent less than other counties in the same state, consistent with muted mobility. Border counties also see significantly less in-migration and in-commuting during the recovery period, leading to persistently worse labor market outcomes. Proximity to state border leads to differences in local labor market dynamism and affects the ability of labor markets to adjust to local cyclical shocks. Short-run responses to mass layoffs show a similar pattern, suggesting that home state bias and the state border mobility penalty has real economic costs. Cross-state economies appear to be less connected than we might 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

The United States does not maintain a registry of residential histories. To document patterns of internal migration and related trends, I use several sources, which I briefly outline here, with full details 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 tax 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 commute flows. I divide the number of workers by the county population to measure the number of commuters per 1,000 people.

I use microdata from the 2012–2017 annual American Community Survey (ACS) to construct subgroup-specific migration and commute flows. The ACS surveys over one million households each year and collects information on household structure, demographics, employment, place of residency in the previous year, and more.[1]

I use the Social Connectedness Index (SCI) county-to-county Facebook friendship measures to look at state borders and social ties (Bailey et al., 2018). These data report the number of Facebook friends in each county pair from a snapshot of active Facebook users in 2016, scaled by an unobserved scalar multiple to maintain privacy. I supplement these data

[1] I do not use data from earlier years, because the smallest geographic measure, public use microdata area (PUMA) definitions, were updated in 2012.

with annual Surveillance, Epidemiology, and End Results (SEER) county population counts and state policy data from various sources.

3 The Empirical Pattern

3.1 State Borders and County-to-County Mobility

The relationship between distance and migration rates has long been documented (Schwartz, 1973). Average migration rates drop smoothly as the distance between origin and destination increases. However, it has not been documented that even in the raw IRS migration data, the magnitude of this pattern depends on whether the origin and destination counties are in the same state. In Figure 1, I plot the average number of migrants per 1,000 residents of the origin county, in 2017, in one-mile bins for all county pairs in the continental U.S., with population-weighted centroids 15–60 miles apart.[2] These average migration rates are plotted separately for county pairs in the same state, and county pairs separated by a state border. At the same distance, migration rates to same-state counties are approximately three times as high as migration rates to cross-state counties. The pattern is similar when looking at county-to-county commute rates. Conditional on distance, commute rates are approximately twice as high among same-state county pairs relative to cross-border pairs. State borders are associated with raw differences in both residential and employment mobility.[3] This is the first work examining how state borders affect human mobility. I will call this drop in mobility at state borders the state border mobility penalty or the state border penalty.

The first goal of this paper is to ensure that this pattern is not driven by measurement issues or potential mediating factors. This is best facilitated in a regression framework, rather than plotting means. Throughout the paper, I estimate versions of the following regression:

$$Y_{od} = \sum_{b=15}^{59} \beta_b(\textit{Diff. State*b Miles Apart}) + \gamma_b(\textit{b Miles Apart}) + \Gamma'|X_o - X_d| + \phi_o + \delta_d + \varepsilon_{od} \quad (1)$$

[2]I focus on these "close" county pairs because there is sufficient coverage of both within-state and cross-state pairs. There are 16 observations per origin county on average. No cross-border county pairs have population centroids less than six miles apart. I restrict to county pairs at least 15 miles apart to avoid comparisons with few observations. I also limit to counties less than 61 miles apart to avoid a compositional shift from typically sized counties to large states and counties in the West. The pattern is similar if I include county pairs that are closer or farther away (Figure A1). LODES commuting data is available at a finer geographic level, meaning I can also measure cross-border commuting at the census tract level. Using tract-to-tract flows, I estimate that same relationship, and find that even for census tracts just one miles apart, cross- state border commute flows are 45 percent lower (Figure A2).

[3]I use the data from 2017, so there is only one observation per origin/destination pair, but, as seen in Figure A3, the state-border discontinuity is similar for all years available in the data—since 1992 for migration and 2003 for commuting.

The outcomes of interest are the origin-to-destination specific number of migrants per 1,000 people at the origin and the origin-to-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 (distance between 60 and 61 miles) 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. This estimation can be adjusted to control for differences in local characteristics ($|X_o - X_d|$), as discussed below, or origin and destination fixed effects. When I do not include the origin and destination fixed effects or the controls the point estimates match the means estimated in Figure 1, since migration and commuting levels in the omitted group are approximately zero.

One benefit of this flexible parameterization is that it does not impose strong assumptions on the way distance impacts mobility, however 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 68 percent for county pairs between 15 and 60 miles apart. This gap is significant, with 95 percent confidence intervals of 63 and 73 percent. There is a similar 75 percent reduction in commute rates.

3.2 Robustness to Controls

Perhaps the most obvious explanation for the state border penalty is that counties differ on many dimensions, which could potentially explain the cross-border differences in mobility. To see how much of the state border penalty is explained by differences in local characteristics, I control for absolute differences in local characteristics and origin (ϕ_o) and destination (δ_d) fixed effects. The origin and destination fixed effects will control for observed and unobserved characteristics of the origin and destination. Following a gravity model framework (Schubert, 2022), controlling for absolute differences in local characteristics will capture how similar or dissimilar the origin and destination are, which might affect people's willingness to move. These controls include differences in labor markets (unemployment rates, employment-to-population ratios, average weekly wages, number of establishments, and industry shares); differences in the total population; differences in population density; differences in 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 the USDA natural amenity score; differences in the 2016 presidential Republican vote share; differences in the average home value; and differences in average math and reading standardized test scores from the Stanford Education Data Archive (SEDA) (Fahle et al., 2021). Just as differences in local characteristics might affect the net utility of migration, state-level policies might as well. I account for prominent state-level policies that have been highlighted in the internal migration literature by controlling for absolute differences in state-level policies. This includes state income tax burdens for various filing types (single, joint, household with children) and income levels ($10K, $25K, $50K, $75K, and $100k a year), state sales tax rates, state maximum corporate tax rates, state Earned Income Tax Credit (EITC) percentage of federal rate, state minimum wage, state Temporary aid for Needy Families (TANF) maximum benefit generosity, state-level K-12 per pupil spending, and whether or not the state has expanded Medicaid eligibility.[4] As seen in Figure 1 and throughout the paper, controlling for differences between the origin and destination (the lighter plotted points with confidence intervals) explains very little of the state border mobility penalty. State borders are still associated with a 58 percent reduction in migration rates and a 73 percent reduction in commuting.[5]

3.3 Robustness to Measurement

The state border mobility penalty is robust to measuring distance in travel time, rather than miles (Figure A4), suggesting this is not driven by borders that are harder to cross, such as river borders (Figure A5). It is unchanged when we limit the sample to counties within 60 miles of the state border to avoid compositional differences between same-state and cross-state pairs as some counties are far from state borders (Figures A6 and A7)[6]. It is virtually the same when I exclude county-to-county flows of zero (Appendix Figure A8),[7] If I instead estimate the gravity equation (Chaney, 2018), allowing differential effects for cross-state pairs, the state border penalty is similar, -0.53 log points for migrant flows and -1.45 log points for commuter flows (Table A2).

[4]A list of all of the local characteristics and policies I consider can be found in Appendix Table A1.

[5]This analysis imposes that controls enter with a particular functional form, because this might not perfectly capture the relationship, I explore including these controls differently in Appendix C.

[6]Throughout the rest of the analysis I will impose this restriction to avoid compositional changes, but the patterns are unchanged if we include all county pairs within 60 miles of each other.

[7]The IRS data are censored for privacy, so county-to-county flows below 20 are not provided. As such, these flows are treated as flows of zero.

3.4 Heterogeneity Across Place

The pattern persists when focusing on county pairs we *ex ante* expect to be similar and economically connected. In Figure 2 I plot the coefficients from equation (1) but limit the sample to county pairs in cross-state commuting zones (left panel) or neighboring counties on state borders (right panel).[8] In these considerably smaller samples, the mobility penalty is still significant.[9] Even in individual, well-known cross-state MSAs like New York City or Washington, D.C. state borders are associated with lower mobility (see Figure A11). The penalty is also present across census regions. When I estimate equation (1) by region we see similar patterns in the Northeast, Midwest, and South (Figure A12). The border penalty is not present in the West, but this is in part because counties are much larger and there are few county pairs in this distance range.

3.5 Heterogeneity Across People

The state border mobility penalty is also similar across different demographic groups. Using the 2012–2017 ACS microdata, I construct origin-to-destination migration and commute flows for different demographic groups. County is not universally available, so I instead map flows from origin Migration PUMAs (MIGPUMA) to destination MIGPUMA and use MIGPUMA population weighted centroids to construct distance, in miles.[10] I then estimate a version of equation (1) at the MIGPUMA level and include origin and destination fixed effects for each of the demographic groups.[11] To be succinct I plot the percent reduction in migration and commuting (e.g., ratio of area under the within-state and across-state curves) for origin/destination pairs between 15 and 60 miles in Figure 3, and provide the corresponding group-specific coefficient plots analogous to Figure 1 in Figures A13–A14. As in the IRS migration data, the state border gap in both migration and commuting is present and significant in the ACS full population. It is also incredibly similar across most demographic groups. The state border penalty is not significantly larger among parents

[8]When looking at neighboring counties, distance is restricted to 45 miles or less, as there are very few neighboring counties with population centroids more than 45 miles apart.

[9]The pattern is similar if limiting to counties in the same Metropolitan Statistical Area (MSA) or Designated Market Area (DMA), to capture television broadcast media markets (Figures A9 and A10).

[10]For privacy protection, the smallest geographic area released by the Census Bureau in public data is a Public Use Micro Area (PUMA). This is a pre-defined area that contains at least 100,000 (but less than 200,000) people. In urban areas this might be one county or a subset of a county. In rural areas this could contain multiple counties. PUMA do not cross state lines. When considering migration destinations, the Census Bureau reports the Migration PUMA (MIGPUMA). This is an aggregation of PUMAs such that entire counties are contained within the same MIGPUMA. As such, it is possible to map individuals in the ACS from an origina MIGPUMA to a destination MIGPUMA. The PUMA and MIGPUMA boundaries are fixed between 2012–2017.

[11]I do not include the controls for absolute differences, as these are not available at the MIGPUMA level.

with children (where school switching costs might be larger) or among state or local public employees (where state-specific pensions might impose large moving costs). The most stark difference is between people who were and were not living in their birth state one year ago.

People living in their birth state exhibit the largest state border penalty in migration and the second largest state border penalty in commuting (after state public employees). People not originally living in their birth state exhibit the smallest border penalty in both migration and commuting. This gap is significant. The border penalty is twice as large for individuals originally in their birth state than for individuals not in their birth state. I show this explicitly in Figure 4 by overlaying the distance bin coefficients for individuals originally in and not in their birth state. At a given distance, individuals in their birth state are just as likely to move or commute *within* state as someone not living in their birth state. However, the cross-border gap is significantly larger for people in their birth state, with migration rates only half as large for a given distance. The same pattern is also visible when looking at commuting but less stark. Consistent with other work (Coates and Mangum, 2021), living in one's 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. Consistent with this birth state pattern, as seen in Figure A13, the within state and cross-state distance gradients for immigrants and particularly for Hispanic immigrants, are not significantly different, suggesting little to no state border mobility gap for immigrants. This is consistent with immigrants having fewer local ties and with Cadena and Kovak (2016), who show that Hispanic immigrants are more mobile.

4 Canonical Economic Explanations

There are theoretical reasons the state border mobility penalty might arise. In its simplest form, the canonical model of migration choice (Sjaastad, 1962) presents the decision to migrate as a comparison between the utility gain and the cost associated with moving from origin o to destination d, as follows:

$$Move_{iod} = \begin{cases} 1 & if\ u_i(X_d) - u_i(X_o) \geq c_{iod} \\ 0 & else \end{cases} \tag{2}$$

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

$$c_{iod} < c^*_{iod} = u_i(X_d) - u_i(X_o). \tag{3}$$

Discrete changes at state borders in local amenities or characterstics (X_d and X_o) that contribute to utility or moving costs that arise when crossing borders could result in discrete changes in migration propensities and migration rates.[12] For example, if the prevalence of jobs changes discretely at the border, or if states have different income tax levels, this could affect the differences in place-specific utility. From equation (2) it is clear that in addition to differences in local amenities, discontinuities in the cost of moving at state borders would also affect migration propensities. Moving costs are large for many individuals (Bartik, 2018; Kosar et al., 2020), and this could drive the state border penalty if individuals face additional costs when moving across state lines.

4.1 Differences in Local Characteristics and Amenities

Differences in local characteristics and amenities are unlike to be driving the state border penalty. As seen previously in Figure 1, the state border mobility penalty changes very little when I include origin and destination county fixed effects and control for all of the absolute differences in characteristics, amenities, and policies between the origin and destination.

The state border mobility penalty is robust to accounting for differences in amenities and state policy in various ways. For succinctness, these are included as additional analyses in Appendix C. Plots analogous to Figure 1, but for each of the absolute differences, show that local characteristics do not tend to become more dissimilar as we approach the state border and there are not discrete changes in local characteristics at state borders. Controlling for raw differences in origin and destination characteristics instead of including absolute differences does not affect the state border penalty. I separately explore various state-level tax and transfer policies in detail in Appendix C, and show they do not explain the state border penalty which exists in equilibrium. At first, this might appear to conflict with previous evidence that the mobility of some groups is responsive to differences in state taxation (Moretti and Wilson, 2017) or transfer generosity (Borjas, 1999; Gelbach, 2004; Goodman, 2017; Kaestner et al., 2003; McCauley, 2019; McKinnish, 2005, 2007). These papers exploit changes in policy (either the introduction or increased generosity) to identify the effect of the policy on migration. In a spatial equilibrium framework (Roback, 1982; Rosen, 1979), this moves the market equilibrium, so we would expect mobility to equilibrate utility across place after a change in local amenities (like tax rates) that people value. It is therefore possible that changes in local characteristics, taxes, or transfer policy affect mobility, but

[12] Adding multiple potential destination turns the decision into a multinomial decision in which 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, consistent with Borusyak et al. (2022).

does not explain the state border mobility penalty which is observed in the cross-section, when markets are plausibly in –or approaching– equilibrium.[13]

4.2 Pecuniary Moving Costs

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, cross-state moves could impose additional pecuniary costs. For example, you are required to renew your license and car registration when you move to another state, but not if you move to a different county in the same state. The costs faced when considering residential moves (migration) and employment moves (commuting) often differ. Commuters can cross state lines without incurring adjustment costs associated with moving (such as updating registration), but they still face some costs, such as state-level taxation. Because the pattern for migration and commuting is similar, the impact of state borders is likely not solely driven by pecuniary adjustment costs.[14]

Another pecuniary moving cost that applies specifically to cross-state moves is state-level occupational regulation. Some states require licenses, certificates, or education/training requirements for someone to perform certain tasks or occupations.[15] Using measures of occupational licensing available in the Current Population Survey (CPS) I identify whether individuals in the ACS microdata are in occupations that are either licensed or unlicensed by their state. I then estimate a version of equation (1) at the MIGPUMA level, separately for individuals in licensed and unlicensed occupations, but find no differences in the state border penalty for individuals in licensed and unlicensed occupations.[16]

4.3 Non-pecuniary Costs

Less cross-border mobility of individuals in their birth state highlights the potential role of local ties. If county-to-county connections are stronger within state than across states, individuals might face an additional non-pecuniary cost of forgoing local ties when crossing state lines. There is evidence that local ties keep people from leaving labor markets (Zabek,

[13]Previous work also finds that some absolute differences in local characteristics influence migration flows Schubert (2022). I too estimate that some measures have a significant effect on migration flows, but they do not explain the effect of state borders.

[14]As seen in Appendix Figure A5, the mobility gap is not significantly different for river- and non-river borders, which could differentially affect commuters. The pattern is also not driven by the costs associated with crossing time zones. Figure A15 shows that the pattern is similar for county pairs in the same time zone or that cross time zones.

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

[16]See Appendix C for more details.

2020). Measureable social ties are in fact weaker across state lines than within state. In Figure 5, I estimate equation (1) with the scaled number of Facebook friends between each county pair divided by the origin population as the outcome. This measure is known as the SCI and is constructed from a snapshot of active Facebook users in 2016. Like migration and commuting, there is a distance gradient in the number of Facebook friends, but once again, conditional on distance, friendship rates are significantly lower for cross-border county pairs than for counties in the same state. Including origin and destination fixed effects and origin/destination controls do not significantly affect the pattern.

Furthermore, controlling for the origin/destination Facebook friendship rate in addition to the other controls in equation (1) considerably compresses the gap in migration associated with state borders (bottom panel of Figure 5). 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. 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 significant 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.

However, it must be acknowledged that causality between mobility and social networks could run in either (or both) directions. Weaker social networks across state borders could impose large psychic costs associated with leaving friends and family or information frictions, leading to low levels of mobility. 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. To see if state borders or social network borders have more explanatory power I estimate a horse race regression. Following Bailey et al. (2018), I use the SCI to construct contiguous county groups ("Connected Communities") where the social ties are stronger within the cluster than if a county was attached to a different, neighboring cluster. If I look only at border of these Connected Community, they predict similar drops in mobility (Figure A17), consistent with Figure 5. However, these borders often align with state borders (Figure 6), with some deviations where social networks spill across state borders.[17] I exploit these deviations by estimating equation (1) but also including a vector of distance bins interacted with indicators that equal one if the origin and destination are in different Connected Communities. If the drop in mobility is actually driven by a drop in social network strength we would expect the Connected Community pseudo borders to be more explanatory than the state borders. Empirically this is not the case. Most of the

[17]This map includes 50 connected communities. The map looks similar if more or fewer connected communities are created. See Appendix B for more information.

effect loads onto the physical state border, rather than the Connected Community borders (Figure 6). Only 5-7 percent of the state border mobility gap can be explained by Connected Community borders, suggesting that although highly intertwined, social network ties are not the causal mechanism that is simply proxied by state borders and that other mechanisms are at play.[18]

5 Home State Bias and the State Border Mobility Penalty

Conditional on distance, there is a discrete, significant decline in human mobility and social ties across state lines, even when accounting for potential differences in amenities and state policy. These effects are most pronounced for people living in their birth state. As both mobility and social ties are affected, there are several plausible mechanisms.

5.1 Network Strength

Existing work suggests that the non-pecuniary, psychic 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). If this mechanism is present, people might be less willing to move 20 miles away across the state border if they have fewer family or friends there. However, network strength would imply a direction of causality. The drop in mobility across state lines is caused by fewer social connections across state lines. This does not explain why the social network was weaker across state borders to begin with and is not supported by the horse race evidence above.

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 internalizing returns and conditions in counties outside of their home state. These frictions could keep people from following the behavior in equation (2) because there is uncertainty surrounding outcomes. 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). This follows Kaplan and Schulhofer-Wohl's (2017) argument that improved access to information over the last 40 years has allowed people to avoid moves that result in low-quality matches. The information

[18]Since Facebook might not capture all social connections, I estimate several versions of this horse race re-weighting to account for measurement error in Connected Community borders, (Figure A18) and varying the number of Connected Communities (Figure A19). Please see Appendix B for more details.

friction mechanism implies that weaker social networks across state borders lead to less information about opportunities in markets across state lines, potentially reducing mobility flows. However, as with the network strength mechanism, this does not explain why the social network was weaker across state borders to begin with and is not supported by the horse race evidence above.

5.3 State Identity and Home Bias

Alternatively, something else could be simultaneously affecting some people's cross-state mobility and cross-state social ties. People could exhibit state-specific preferences. For example, people might hold a state identity that creates a "home bias," making it systematically more costly to move away from their home state which in turn could result in more condensed or isolated social networks. This home bias could arise if people feel a sense of identity, familiarity, or connectedness with their state. Evidence from East and West German suggest geographic identity matters (Heise and Porzio, 2019) and there is a well documented equity home bias, showing that investors over-invest in domestic assets, relative to world markets. This seems to be driven by a behavioral bias (Strong and Xu, 2003).

State identity could introduce another non-pecuniary, psychic moving cost, potentially distinct from the cost of leaving social ties, leading to a home bias. A home state bias would enter the migration decision like an endowment. Individuals are "endowed" with a home location (for example, their birth state), which affects the total cost of moving. For an individual born in state S, the migration decision would be as follows,

$$Move_{iod} = \begin{cases} 1 & \text{\textit{if}}\ u_i(X_d) - u_i(X_o) \geq c_{iod} + \tilde{c}_i(o,d) \\ 0 & \text{\textit{else}} \end{cases} \tag{4}$$

where $\tilde{c}_i(o,d)$ is an individual specific nonlinear cost function, as follows:

$$\tilde{c}_i(o,d) = \begin{cases} \phi > 0 & \text{\textit{if}}\ o \in S\ \text{\textit{and}}\ d \notin S \\ 0 & \text{\textit{else}} \end{cases} \tag{5}$$

The additional cost, ϕ, is only incurred if o is in the individual's initially endowed state S and d is not in S. If the individual is considering a move within state or is already outside state S, this additional cost is zero. For two potential destinations, d and d', that have identical characteristics ($X_d = X_{d'}$), but d is in the birth state S and d' is in a different state,

$$c_{iod}* = u_i(X_d) - u_i(X_o) > u_i(X_{d'}) - u_i(X_o) - \phi = c_{iod'}* \tag{6}$$

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, individuals with these preferences are more willing to move to d than to d', even though the two destinations are identical on observables. Note, however, that if the origin is not in the state of birth, the propensity to move to the two locations is identical. The home identity need not be linked to the state of birth, although this is often where people spend their formative years.

Although this is a potential explanation for migration, does it extend to commuting, or the drop in trade at state borders (Coughlin and Novy, 2012)? In both of these cases the agent can still reside in the home location. If home bias imposes a sufficiently large cost, agents that exhibit home bias will not consider out-of-state options as viable alternatives. As such, a home bias could affect the probability that an individual (or firm) includes the potential destination in their choice set of places to move to, commute to, or trade with. For example, someone might not even consider commuting to a job in the neighboring state because it seems foreign and unfamiliar. They might limit their search or ignore out-of-state job postings in a way that excludes them from the choice set. This is consistent with equation (6) where ϕ is large and could help explain the parallel results in commuting and trade.

Home state bias would yield the ACS empirical pattern of lower cross-state mobility from people in their birth state and more cross-state mobility from people outside of their birth state. These mobility patterns could then explain the drop in friendship links across state lines. This mechanism would also imply a different direction of causality relative to network strength or information frictions as a third factor (state identity or home state bias) leads to both lower mobility and fewer friendship links across the state border. As such, it might be possible to test for home state bias separately from psychic costs or information frictions.

5.4 Experimental Evidence of Home State Bias

To better understand the mechanisms driving the drop in mobility at state borders I conducted an online experiment. In a stated-preferences framework, I elicit respondents' probability of moving in a hypothetical scenario, where I experimentally vary certain conditions, while holding all others constant. Similar to Kosar et al. (2020), this allows me to estimate the impact of certain attributes on the decision to move. In this framework I can separately estimate the effect of state borders and family and friend social ties and determine what mechanisms discussed above are most consistent with the drop in mobility at state borders. I outline the experiment here, with complete details in Appendix B.

5.4.1 Experimental Set-up

In the survey, respondents were presented with a hypothetical opportunity, as follows

We will next describe a set of circumstances and would like you to think of how these circumstances would affect your moving plans over the next two years.

Suppose that you (and your household) were offered the following opportunity to move over the next two years, and you had to decide whether to take the offer or continue living at your current location. The offer to move is contingent on your staying there for at least 3 years. If you own your home, assume that, if you were to move, you would be able to sell your current primary residence today and pay off your outstanding mortgage (if you have one).

–New Page–

Suppose you are offered an opportunity with the following characteristics:

- *Your household income increases by [10%/20%/50%]*
- *This opportunity is about 100 miles away, but [in the neighboring state/still in {current state}]. Because of the distance, commuting does not make sense so you must move.*
- *[None of your family and current friends live nearby.]*

Imagine you could have an exact copy of your current house and you would earn your income in a similar way as it is earned now. Suppose that the locations are otherwise identical in all other aspects to your current location, including the cost of housing.

What is the percent chance you would choose to move to this neighborhood?[19]

For each respondent, the three characteristics in brackets are independently randomized. With equal probabilities individuals observe either a 10%, 20%, or 50% increase in household income. With equal probability individuals observe a move either in a neighboring state or in the same state as they reported as their current state of residence. Finally, with equal probability individuals either observe that none of their family or friends live nearby or they do not observe anything at all about family or friends (i.e., only two of the bullet points are shown).[20] Importantly, all individuals observe a move that is about 100 miles away and are told to assume all other aspects of the location are identical. This maps back to the preceding county-to-county flow analysis conditional on distance and shuts down other potential sources of variation, allowing me to focus on changes in income, proximity to social ties, and the role of the state border.[21]

[19]Much of this language is adopted from Kosar et al. (2020).

[20]When looking at proximity to social ties I omit the statement rather than provide a statement like, "some of your family and current friends live nearby." This is to avoid creating scenarios where not only the individual, but their extended family and friends also are moving.

[21]The county-to-county analysis focuses on county pairs within 60 miles of each other. For the survey I set the distance to "about 100 miles" so that the hypothetical scenario is consistent with reality. By excluding respondents from the West, Texas, and Rhode Island, each respondent resides in a place where you can move 100 miles and still have options within the state but also have options in the neighboring state.

With this experimental manipulation, I can estimate how each of these factors affect the reported percent chance of moving as follows

$$\begin{aligned} \textit{Percent Move}_i = \beta_1 \textit{Different State}_i + \beta_2 \textit{No Family/Friends Nearby}_i \\ + \beta_3 \textit{Increase in Income}_i + \varepsilon_i \end{aligned} \quad (7)$$

The coefficient β_1 will provide an estimate of how the destination being across state lines affects the average reported percent chance of moving. Because the presence of family and friends are randomized separately I can isolate any effect of the state border separate from social ties. Because respondents are asked to hold all other aspects identical, β_1 is capturing the effect of the state border. Robust standard errors are estimated.

If this is truly a home state bias, we would only expect the cross-state border treatment to affect people living in their home state (see equations (4)-(6)). To test this mechanism, I also estimate the following specification to allow the effects to differ if people currently reside in their home state

$$\begin{aligned} \textit{Percent Move}_i = \beta_1 \textit{Different State}_i + \beta_2 \textit{No Family/Friends Nearby}_i + \beta_3 \textit{Increase in Income}_i \\ + \beta_4 \textit{Different State} * \textit{In Home State}_i + \beta_5 \textit{In Home State}_i + \varepsilon_i \end{aligned} \quad (8)$$

The coefficient β_4 represents the gap in reported migration probabilities associated with an out of state move among people currently living in their home state. The coefficient β_1 will represent the difference for people living outside of their home state. I measure home state in two ways. First, building on the ACS evidence I see if people reside in their state of birth. Sixty three percent of the survey sample live in their birth state. Second, at the end of the survey I ask individuals what state they would call their home state and why. Eighty percent of the survey sample reside in their home state. When asked why this is their home state, nearly 48 percent of the sample referenced being born there or living there all of their life.

After the first hypothetical setting, I present each respondent with a scenario identical to the first, except the respondent observes the opposite destination treatment. For example, if the respondent was initially randomized into the neighboring state treatment, they now observe an opportunity with all of the same characteristics except it is in the individual's current state of residence. With both of these experimental scenarios I can look within person at how the state border affects the propensity to move when everything else is theoretically held constant. On the individual panel, with two observations per respondent I estimate

$$\textit{Percent Move}_i = \beta_1 \textit{Different State}_i + \gamma_i + \varepsilon_i \quad (9)$$

The coefficient β_1 indicates how much lower the propensity to move is in the scenario that is across state lines. Individual fixed effects are included to make this a within person comparison and standard errors are corrected for clustering at the individual level. Because the size of the income increase and the presence of family/friends is unchanged within person, these treatments are colinear with the individual fixed effects. I can also explore how much of this gap is driven by people living in their home state by estimating the following

$$Percent\ Move_i = \beta_1 Different\ State_i + \beta_2 Different\ State * In\ Home\ State_i + \gamma_i + \varepsilon_i \quad (10)$$

The β_2 coefficient allows the size of the border penalty to vary for people currently residing in their home state. Once again, I use either the state of birth or the self-reported home state as the individual's home state.

After observing each individual's decision in both scenarios I then ask why they were less (or more) likely to move when the opportunity was just as far away but in the neighboring state. Individuals are then provided with a list of potential reasons and asked to rank if they are "not relevant", "somewhat relevant", or "highly relevant." These include many of the potential mechanisms explored in Section 4, including differences in job opportunities, differences in racial/ethnic composition, differences in cost of living, differences in occupational requirements, differences in state taxes, and the need to update car and driver's license registration. I then also provide reasons that align with having a home state bias, such as differences in state culture, being a fan of your state's sports teams, not being familiar with living conditions and laws in the neighboring state, and feeling like you connect more with your current state than the neighboring state. Because I experimentally varied the presence of family and friends the psychic cost of leaving friends and family is constant across the two scenarios. From these questions, I can determine if the drop in migration propensities across state lines is consistent with home bias motivations.

5.4.2 Experimental Results

I collected responses from 1,808 participants of Prolific's online professional survey panel. The survey sample is more white, younger, and more educated than the general population, but characteristics are balanced between the neighboring state and the same state treatment group (Table A4). Virtually all participants passed the attention check.

Results from the initial experimental scenario are provided in Table 1. For the full sample, the out-of-state scenario is associated with an insignificant, one percentage point increase. However, once we allow for heterogeneity for people living in their home state we observe stark differences. Individuals living in their birth state reported being 9.4 percentage points less likely to move on average if the scenario included a move to the neighboring state.[22] There is a similar 8 percentage point drop if I instead look at individuals living in their reported home state. This represents a 15 to 18 percent decrease in the reported probabilities. Individuals currently living in their home state (as captured by their birth state or reported home state) are significantly less likely to consider moves to a neighboring state. For individuals living outside their home state, the cross-state scenario is actually associated with an increased reported probability of moving. This is consistent with patterns in the ACS, where many of the cross-state moves took people back to their birth state.[23]

Once again, because I experimentally vary whether or not there are family and friends nearby, this state border effect is independent of moving away from social ties.[24] Because income is also experimentally varied, I can determine an individual's willingness to pay to avoid an out-of-state move. For each one percent increase in household income, the average reported probability of moving increases by 0.5 percentage points. This would suggest that, on average, individuals living in their home state would be willing to pay 16 to 19 percent of their income to avoid moving across state lines.

In columns (4)-(6) of Table 1 I report the results from the within person panel. In the full sample, individuals report moving probabilities that are a significant 1.5 percentage points lower if the opportunity is in the neighboring state but everything else is the same. The effects are larger if the individual is living in their birth state (although not significantly different). Most of the effect loads onto individuals living in their home state. They report moving probabilities that are a significant 2.9 percentage points lower. Even holding all else equal, the same person reports being less likely to move across state borders suggesting there is an extra cost to moving across state lines.[25]

I next look at the respondents' comments on why state borders matter. In Figure 7 I document stark differences in the reasons people give for their migration decisions. First, I look at differences in what reasons are relevant between people in their home state and out of their home state. Whether I use birth state or reported home state the patterns are similar. People in their home state are 25 percentage points more likely to say that they connect more to their current state than the neighboring state, and that this is relevant to

[22]Although the total effect $\beta_1 + \beta_4$ is not significantly different from zero, the total effect for people in their birth state ($\beta_4 + \beta_5$) is significantly different from zero, consistent with them being less likely to consider a out-of-state move.

[23]Following the existing literature (Kosar et al., 2020), I also provide estimates using the log odds ratio as the transformed outcome. This will guarantee that the model is not predicting probabilities less than zero or greater than one. In these specifications I replace reported probabilities of 0 with 0.001 and reported probabilities of 1 with 0.999. I provide both OLS and least absolute deviation (LAD) estimates in Table A5.

[24]The state border point estimates are larger if the individual is also primed that there are no family and friends nearby.

[25]I provide analogous estimates of equation (10) using the log odds ratio in Table A6.

their moving decisions. The next closest is being a fan of state sports (also related to home state bias) and then feeling more familiar with conditions and laws in their current state. None of the other reasons related to differences in local characteristics or policy come close in magnitude or significance. These patterns suggest that people might use state boundaries to proxy for a set of features that they value, leading to a sense of identity and connectedness. As such, it might not be the literal state that matters, but the combination of features that people associate with the state.

In Figure A20 I also show differences in the relevant reasons depending on whether the individual reported a lower percent chance of moving across state lines. The pattern is similar here, with a connection to the current state being the largest difference (33 percentage points), but some other differences are also large and significant, such as familiarity and adjustment costs (the need to update car registration or driver's licenses). Although it is clear that many factors enter the decision to move, and particularly to move across state lines, a sense of connection to one's current state is particularly relevant, suggesting home state bias has a substantive impact on mobility flows.

The presence of home state bias is supported in observational settings as well. In a 2013 Gallup poll, individuals rated their own state of residence (Table A7). Consistent with state identity driving the drop in mobility, the drop in both migration and commuting across state lines is larger when more people think their state is "the best" (Table A8). Ticket sales data suggest profession and college sports team fan bases tend to follow state lines (Figure A21 and Table A9), which we would expect if people exhibited home state bias. Using data from a 2008 Pew Research Center survey on state identity, I estimate patterns similar and find that people with a birth state identity are significantly less likely to consider a move *but only* if they currently reside in their birth state (Figure A10).[26]

6 Impact of State Border Penalty on Labor Market Dynamism

The state border penalty has the potential to affect labor market mobility and impose real economic costs. Mobility is an important mechanism for labor markets to adjust to local shocks (Blanchard and Katz, 1992); reducing migration frictions in general (not just border specific frictions) can increase global productivity and welfare (Desmet et al., 2018). Depressed mobility across state borders might slow the rate at which labor markets adjust. This could lead to long-run differences in local economic conditions across geography. I follow existing methods (Hershbein and Stuart, 2020) and focus on negative shocks associated with

[26]See Appendix B for details.

the Great Recession, as the persistent of the Great Recession is of general interest.[27]

Historically, researchers have used panel vector autoregressive (VAR) models to estimate the dynamics of local labor market recoveries to shocks (Blanchard and Katz, 1992; Dao et al., 2017). However, recent work has found that without infeasibly long time series, these VAR estimation strategies will exhibit significant finite sample bias and can even yield opposing results at different levels of geography (Hershbein and Stuart, 2020). Hershbein and Stuart (2020) use an alternative event study approach to explore the employment dynamics of local labor markets after recessions in the U.S.[28] They find that local labor markets that experienced larger employment declines during the 2007–2009 recession see persistently lower levels of relative employment up to 10 years later.

Building on their framework, I provide suggestive evidence of how proximity to state border affects mobility and local labor market dynamism. As seen in Figure 1, most moves and commutes are local. At the county-level approximately 85 percent of migrants moved less than 60 miles, while approximately 60 percent of cross-county commuters travel less than 60 miles. Combined with the state border penalty, this suggests that mobility flows to border areas will be lower in equilibrium. Empirically this is true. Despite looking similar on other dimensions, both in- and out-migration is 4-5 percent lower and commute flows are 5-13 percent lower in border counties than in nonborder counties in the same state (see Table 2). This raises the possibility that labor markets in border counties are less dynamic and more isolated. After a negative labor market shock, we would expect a decrease in inflows (both migration and commuting) and an increase in outflows. However, because of the state border penalty, the inflows might be more responsive (i.e., fewer move-ins) while the outflows might be less responsive (i.e., fewer move-outs) in border counties. This stickiness in population means that some other margin must adjust, and could lead to bigger labor market responses and more persistent shocks. I test to see if employment rates are more volatile and recover more slowly in border counties relative to nonborder counties in the same state that experienced a similarly size shock during the 2007–2009 recession.

Following Hershbein and Stuart (2020), I calculate the change in log employment at the commuting zone level between 2007 and 2009 to measure the relative severity of the 2007–2009 recession for different local labor markets and call this the $CZshock$. I then assign counties to commuting zones, so a border county and nonborder county will be assigned the same measure of severity if they are in the same commuting zone. This measure allows me to

[27] Positive shocks could yield different responses. Unfortunately during this time period, there are not many positive shocks that hit border and non-border counties equally.

[28] 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).

compare counties that experienced a similarly severe shock. Almost by construction, border counties and nonborder counties in the same commuting zone will adjust similarly during the recession, but what happens right after the recession shock will highlight if border counties (which experience more population stickiness) experience more volatility.

I estimate an augmented version of the Hershbein and Stuart (2020) model, allowing the dynamics of border and nonborder counties to differ, as follows:

$$ln(Y_{ct}) - ln(Y_{c2005}) = \sum_{\tau=2003}^{2017} \gamma_\tau(CZ\ shock * Year\ \tau) + \theta_\tau(Border * Year\ \tau) + \beta_\tau(Border * CZshock * Year\ \tau) + \alpha_{st} + \varepsilon_{ct} \tag{11}$$

Y_{c2005} is the measure observed in 2005, so the outcome is the within county log change in Y_{ct} relative to the measure two years before the beginning of the national recession. The outcomes of interest are the natural log of the employment-to-population ratio, total wage income, 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 effects interacted with *CZ shock*, which is measured as the change in commuting zone log employment between 2007 and 2009. Counties in the same commuting zone experience the same treatment. Following Hershbein and Stuart (2020), 2005 is used as the omitted year. I also include two more sets of interactions. The border-by-year interactions capture differential time trends between border and nonborder 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. The dynamic effects for nonborder counties are represented by the γ_τ coefficients, while the dynamic effects of the shock for border counties are represented by $\gamma_\tau + \beta_\tau$. State by year fixed effects are also included allowing me to compare counties in the same state.[29] Standard errors are corrected for clustering at the level at which the recession shock is measured, the commuting zone. Event study plots are presented in Figure 8.

This specification uses border status to proxy for the severity of the state border penalty on gross mobility flows. However, one concern is that being a border county is correlated with other characteristics that affect the severity of or recovery to cyclical shocks. As seen in Table 2, the size of the commuting zone shock is not statistically different between border and nonborder counties in the same state.[30] Not only is the magnitude of treatment similar, but other observables are as well. The industrial and population composition of border

[29]Following Hershbein and Stuart (2020) I examine relative deviations in the county outcome rather than include county fixed effects, although the patterns are similar if I instead examine the undifferenced log outcome with county fixed effects.

[30]Furthermore, since both border and nonborder counties in the same state can be in the same commuting zone, I can augment equation (11) to include commuting zone by year effects to directly compare border and nonborder counties in the same commuting zone that experienced the exact same shock. In this specification there is still a differential recovery, but the estimates are much less precise.

counties and interior counties are similar, with few statistical differences when comparing counties in the same state and year (as is the case with state by year fixed effects). Evidence from observables supports the assumption that the direct effect of the recession would be similar for border and nonborder counties. The most significant statistical differences show up in the age distribution (although they are small in magnitude). For this reason, I will control for county-level age shares in equation (11) throughout.[31]

By estimating the event study in equation (11), I can also verify that the pre-trends are consistent with the parallel trends assumption. From Figure 8 we see that pre-trends are flat, providing further evidence that nonborder counties provide a reasonable counterfactual for border counties in the same state. Even if I cannot fully attribute the effects of being a border county to the state border penalty, by looking at migration outcomes in the same specification I can verify that the mobility mechanism is present and that patterns are consistent with what we would theoretically expect if the state border penalty was at play.

As seen in Figure 8, for both border and nonborder counties, experiencing a larger commuting zone-level decline in employment during the recession led to a large, persistent decrease in the employment-to-population ratio and total wage income. However, in border counties, the employment-to-population ratio and total wage income see more negative adjustment in the wake of the shock. This is what we would expect if border counties were more isolated. Employment and wage income also stay persistently lower in border counties, consistent with less adjustment through mobility flows.[32] There is very little relative recovery up to 10 years after the shock.[33] Year-to-year effects are only significantly different between border and nonborder counties in the later years, but effects from 2010 to 2017 are jointly significant. To understand the magnitude of these effects, the average drop in the level of commuting zone employment would imply employment-to-population ratios that are twice as low (3.3 percent) in border counties than in nonborder counties (1.8 percent) in 2017.[34] At the median level of total wage income, the point estimates suggest the average drop in commuting zone employment during the great recession led to total wage income that was \$6.3 million lower in border counties 10 years later, with a total additional wage loss of \$28.2 million during the 2010–2017 recovery. These gaps are large. Even 10 years later,

[31]One concern is that counties on the state border are less likely to be at the center of the labor market. However, I find that estimates are similar if I exclude non-border counties that are not on commuting zone borders or if I control for counties' commuting zone employment concentration, interacted with year.

[32]As seen in Figure A22, the economic shock does not have a differential effect on average weekly wages in border counties. This is consistent with the persistent drop in employment and the drop in migration inflows having offsetting effects on equilibrium wages.

[33]By construction, equation (11) estimates the amount of recovery relative to places that experienced less-severe recessions. This pattern does not imply that there was no recovery, but that border counties recovered more slowly than nonborder counties that experienced a similarly sized shock.

[34]Commuting zone-level employment fell by 4.4 percent on average between 2007 and 2009.

the employment recovery in border counties lags by 34 percent and the total wage income recovery lags by 54 percent relative to the recovery in nonborder counties in the same state which experienced the same-sized cyclical shock.

In short, border counties have experienced less employment recovery 10 years after the start of the Great Recession. Consistent with the state border mobility penalty as a mechanism, we observe drops in in-migration and in-commuting. For each 10 percent drop in employment during the recession, in-migration to border counties is nearly 4 percent lower than in nonborder counties for the first 6 years of recovery after the end of the recession.[35] In-commuting to border counties is also around 4 percent lower during the recovery through the end of the sample in 2017. Out-migration and out-commuting from border counties is also lower during the recovery, but not significantly different. Consistent with most moves being local, and state borders reducing mobility flows in border counties, there is less inflows to border counties in the wake of a negative, local economic shock. This gap in mobility appears starting after the recession, implying that border counties in hard-hit labor markets see less of an adjustment mobility response than elsewhere. These patterns are unlikely to be driven by some other unobserved factor of border counties, as that factor would have to only come into play in the wake of an economic shock and to specifically reduce mobility in-flows to the border county. Consistent with the drop in in-migration, total population also falls more in border counties, although the difference is not significant. With more isolated populations, we might expect adjustment on the wage margin. However, consistent with sticky wages, county border status does not appear to have differential impacts on average weekly wages. Instead the shock in border counties is absorbed by larger drops in employment and more firm closure. Higher levels of job destruction and firm closure can also help explain why the shock is more persistent (Figure A22).

One concern with the previous analysis is that cyclical shocks might be more persistent in border counties for other, unobserved reasons. However, the pattern is consistent when examining short-term responses to employment loss due to mass layoffs, which are plausibly more exogenous. Using Bureau of Labor Statistics county-level mass layoff counts from 1996 to 2012, I estimate the relationship between the number of mass layoffs (as a percent of total employment) in a county and log employment, log in-migration rates, and log out-migration rates, controlling for county and state-by-year fixed effects, to compare counties in the same state. I then examine how this pattern varies depending on if the county is a border county or not. When one percent of the workforce experiences a mass layoff, total annual employment

[35]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.

falls by 0.5 percent (Table 3). This relationship is similar in border counties. As expected, an increase in mass layoffs is associated with a reduction in in-migration rates (0.4 percent) and an increase in out-migration (0.4 percent). However, the pattern differs in border and nonborder counties in the same state. When one percent of the workforce experiences a mass layoff, in-migration drops 0.2 percent in nonborder counties and 0.7 percent in border counties. Out-migration increases by 0.5 percent in nonborder counties, but only by 0.2 percent in border counties. Consistent with the state border penalty and home state bias, this results in populations that are more similar before and after the shock in border counties than in nonborder counties.

Furthermore, using the ACS microdata, I can explore individual responses to mass layoffs depending on whether or not the individual is living in their state of birth. If the difference in local labor market effects are truly driven by home state bias and the state border penalty, we would expect less out-migration from people in their birth state. When focusing on border areas, the out-migration response to mass layoffs is completely driven by people who were not in their birth state, with people in their birth state less likely to move out of the state and less likely to move out of the local area overall.[36] This results in dis-employment effects that are three times as large for people in their birth state.

This short-term analysis exploiting more plausibly exogenous local shocks provide consistent evidence that populations are more stable in border counties after economic shocks, which could result in more persistent shocks in the long run. This stickiness appears to be driven by people in their birth state, consistent with home state bias having real economic consequences. During mass layoffs and cyclical downturns, border counties, where the state border mobility penalty is arguably the most binding, experience less adjustive mobility, slower labor market recovery, and more persistent negative impacts. Although not definitive, this does provides compelling evidence that the drop in mobility across state borders has large and lasting impacts on labor market dynamism and should be explored further.

7 Conclusion

I present new evidence that both residential and employment county-to-county mobility in the U.S. 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. Traditional economic explanations, such as differences in amenities or state policies which

[36]In non border MIGPUMAs, people in their birth state are still less likely to move out of sate in response to a mass layoff, but because most moves are local and they are not at the border, the drop in the probability of moving out of the local area does not fall as much.

could affect utility or costs do not drive the difference.

Instead, I find evidence that a novel, psychological mechanism exists and leads some people to discount opportunities across state lines. I call this mechanism home state bias. In an experimental setting, people currently in their home state report being significantly less likely to consider a move out of state. This penalty is large. People in their home state would be willing to pay 16 to 19 percent of income to avoid moving across state lines. People in their home state are significantly more likely to report feeling connected to their home state than the neighboring state and report that this is relevant to their migration decisions. This is further supported by other descriptive and quasi-experimental evidence, suggesting that state borders significantly affect people's mobility decisions because it would require them to leave the place that they identify with.[37]

This is surprising given the history and nature of US state borders. Starting with the original European colonies and continuing through US territorial expansion there has been a history of borders being determined by a higher, distant power (Stein, 2008). Prior to national independence, English monarchs would resolve colonial border disputes by dictating new borders in degrees of latitude and longitude, often in ways that diverged from both interested parties' proposals but mollified broader geopolitical interests. After independence, Congress defined borders (once again, often in ways that diverged from both interested parties' proposals) with an overarching goals of making states equal and maintaining balance between free and slave states (Stein, 2008). Although some state borders were placed to preserve local interests,[38] the guiding principle of equality was often literal, breaking territories into as nearly equally sized states as possible, even if that required angling borders away from natural geographic boundaries. This led to many border segments that are unnatural, or simply, lines on a map.[39]

So why do some people exhibit home state bias? On some dimensions this is still an open question. As noted in the survey experiment, many people feel connected to the place they were born or grew up. They are more familiar with conditions there. People might use state boundaries to proxy for a set of features that they value, leading to a sense of identity and connectedness. The experiment suggests that many people experience large non-pecuniary costs when moving across state borders, resulting in the state border mobility penalty. Over time this population stickiness leads to states developing unique identities and

[37]These patterns add context to cross-border empirical strategies. On the one hand, counties across state lines are observably quite similar, and reduced cross-border mobility mitigates concerns about "treatment" contamination. On the other hand, the existence of the state border discontinuity in migration and home state bias would suggest people across state borders are different.

[38]For example, Louisiana's borders were drawn to encompass the French settlements of the Louisiana Purchase and provide former-French settlers a sense of autonomy.

[39]See Stein (2008) for an insightful discussion of how all of the US state borders were determined.

cultures, reinforcing perceptions of local conditions and familiarity and reducing cross-border mobility, even if the state border is not very far away.

The drop in mobility at state borders has real economic impacts. After local economic shocks, border counties see lower in-migration and in-commuting and persistently lower employment levels and total wage income than other counties in the same state. This friction is costly, even 10 years out, employment rates in border counties only exhibit half of the recovery as nonborder counties. On average, border counties lose an additional $28.2 million in wage earnings during the eight year recovery period, relative to nonborder counties. This sheds new light on how we should view and evaluate geographic differences in labor market dynamism. Future work is needed to fully document the economic implications of home state bias and determine whether there are policy tools that can mitigate or offset the economic impact of this feature of human mobility.

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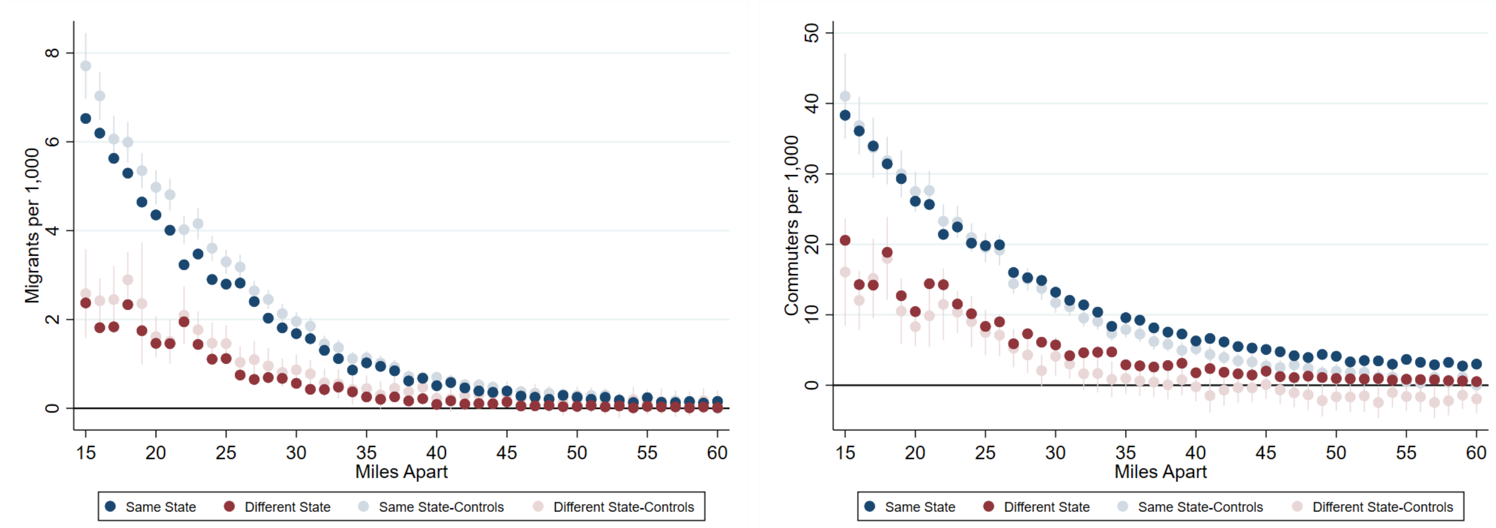
Tables and Figures

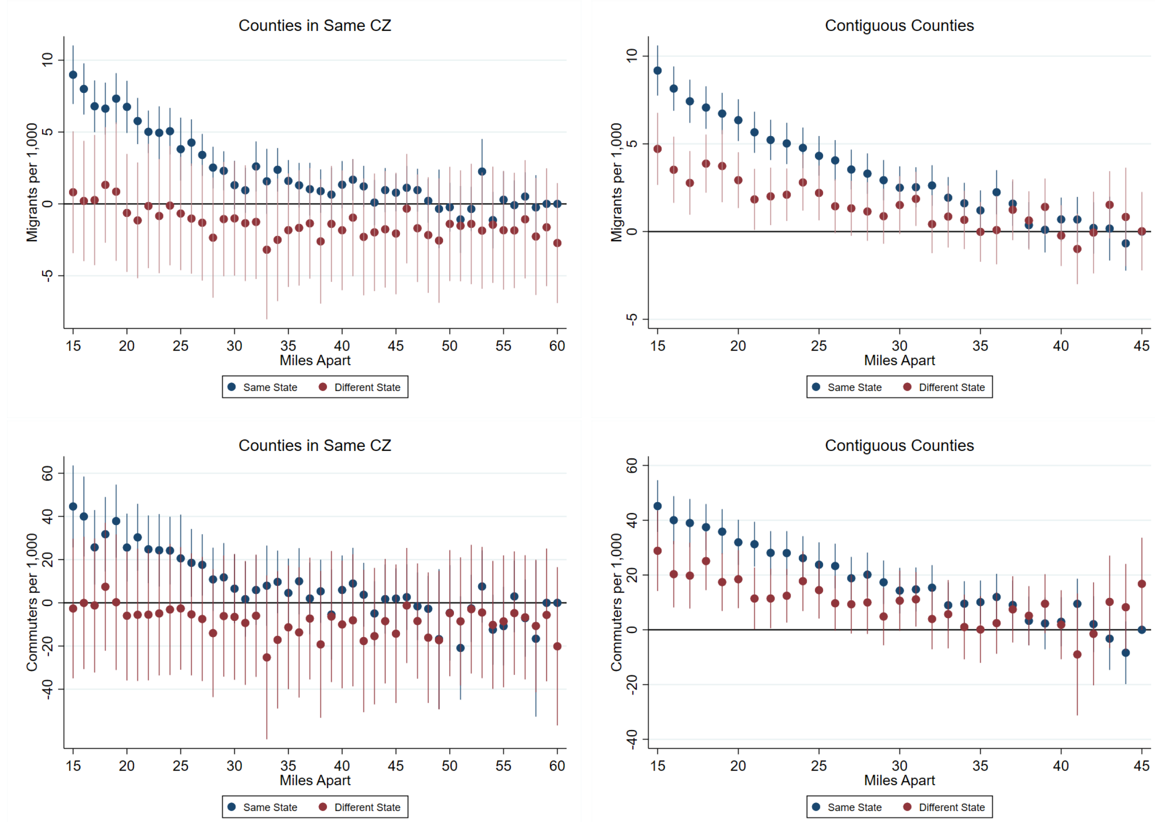
Figure 1: County-to-County Migration and Commute Rates by Distance for Same-State and Different-State County Pairs



NOTE: Outcome in the left panel is number of migrants per 1,000 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 1,000 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 one-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. "–Controls" plots coefficients from equation (1), accounting for origin fixed effects and destination fixed effects as well as absolute 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 of natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others), differences in demographics (total population, population density, 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, differences in the county housing price index converted to dollars using the median house value from 2000, differences in average third- through eighth-grade math and reading language arts test scores, and differences in policy (income tax burden, corporate tax rates, sales tax rates, Medicaid expansion, state Earned Income Tax Credit percent, minimum wage, TANF generosity, and K-12 per pupil spending). Ninety-five-percent confidence intervals are provided.

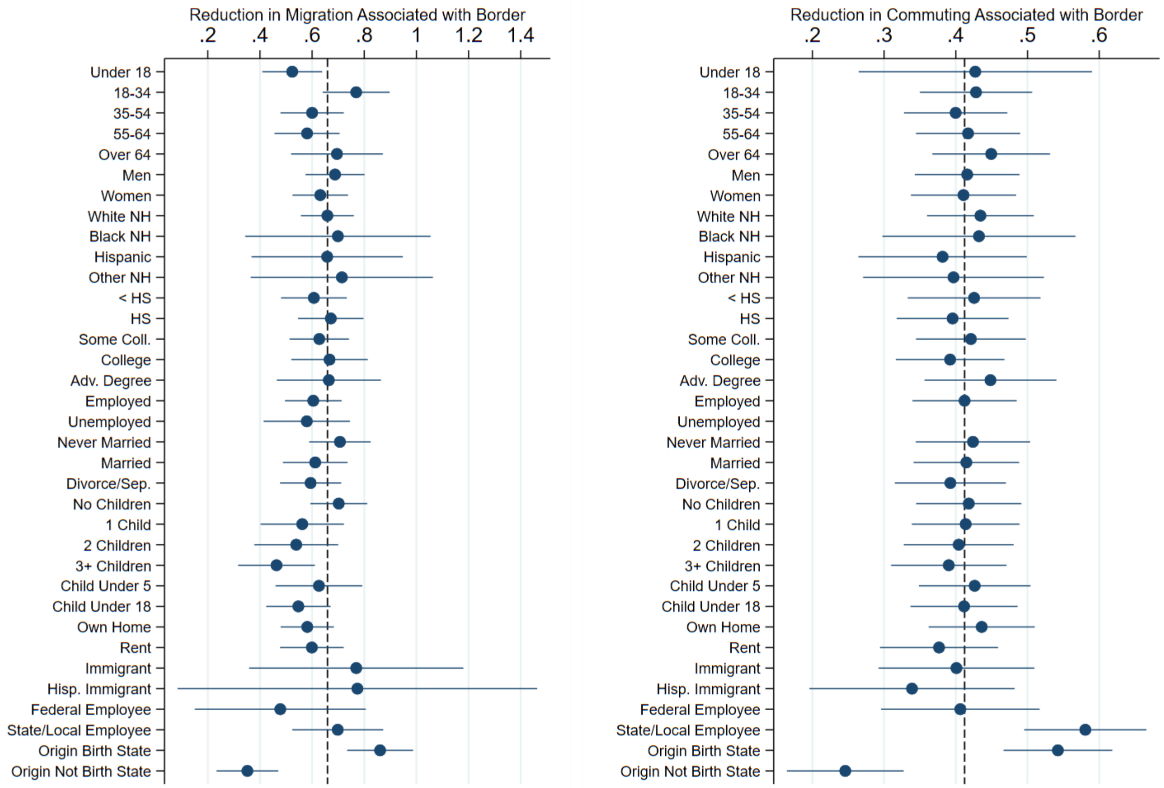
SOURCE: Author's own calculations using the 2017 IRS SOI and 2017 LODES.

Figure 2: Impact of State Borders on Migration and Commuting in Close, Connected Regions



NOTE: Coefficients from equation (1) are plotted. Migration is plotted in the top panel, commuting in the bottom. The left panel restricts the sample to include only counties in commuting zones (CZ) that cross state borders and to include only county pairs that are in the same CZ. The right panel includes only counties that are on state borders and are contiguous. Estimation controls for origin and destination fixed effects and absolute differences in origin destination characteristics and policy (see notes to Figure 1). Ninety-five-percent confidence intervals are provided.

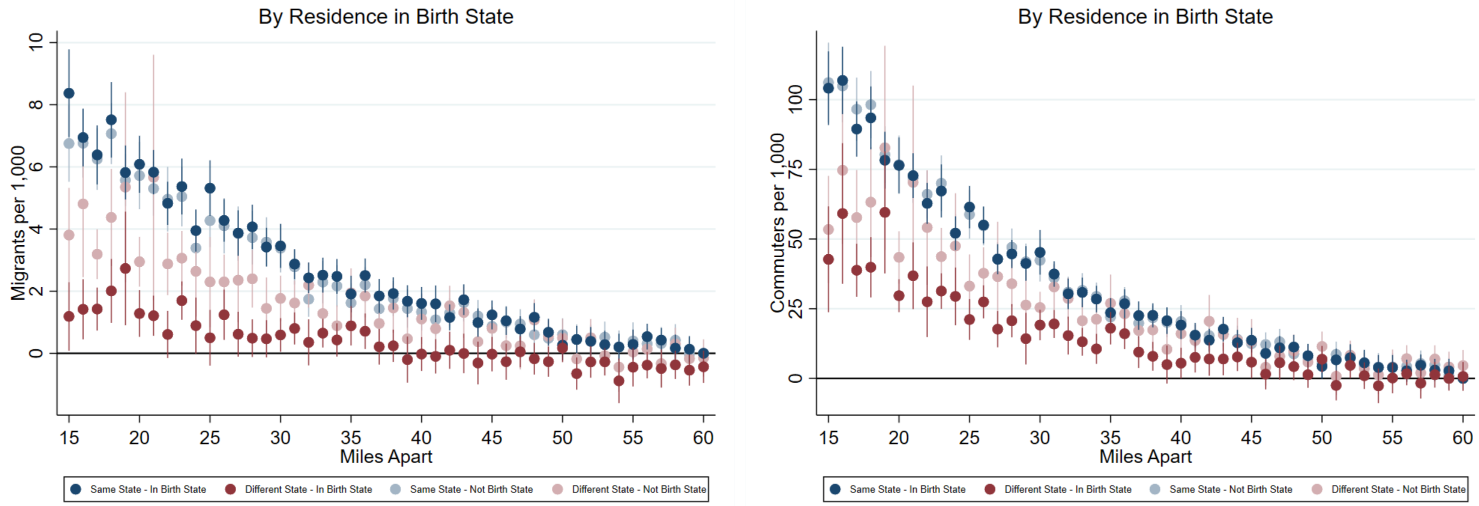
Figure 3: Heterogeneity by Demographics: Size of the State Border Penalty across Demographic Groups in the ACS



NOTE: These estimates are obtained by regressing equation (1) for MIGPUMA to MIGPUMA flows for each given demographic group from the 2012–2017 ACS. I then estimate the ratio of area under the curve for same-state and cross-state county pairs between 15 and 60 miles apart. The dotted line is the reduction in mobility for the full ACS sample. The full plots corresponding to Figure 1 for each group are provided in Appendix Figures A13-A14. The reduction in migration associated with state borders for each demographic group are plotted in the left panel with 95 percent confidence intervals. The reduction in commuting associated with state borders for each demographic group are plotted in the right panel with 95 percent confidence intervals.

SOURCE: Author's own calculations using the 2012–2017 ACS.

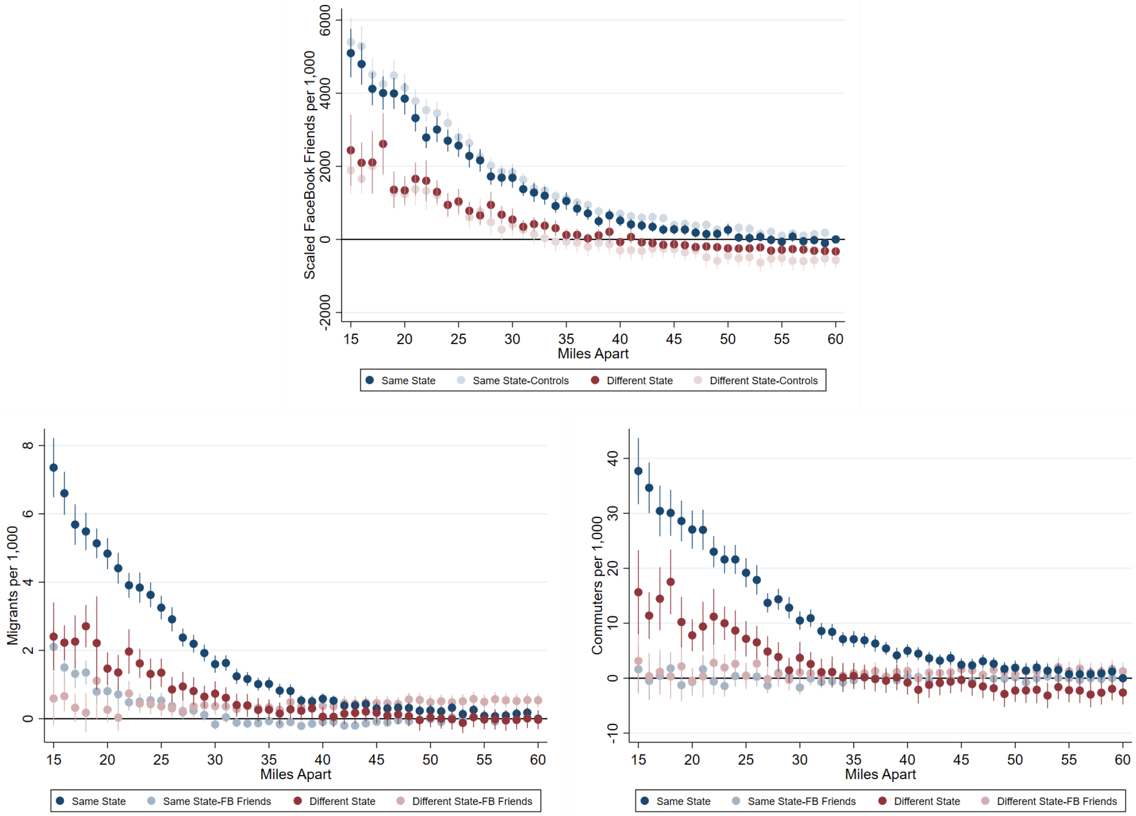
Figure 4: Heterogeneity by Birth State Residence: Impact of State Borders on Migration and Commuting



NOTE: Outcome in the left panel is number of migrants per 1,000 people at the origin MIGPUMA using flows constructed from the 2012–2017 ACS. Outcome in the right panel is the number of commuters per 1,000 people at the origin MIGPUMA. These estimates are obtained by separately regressing equation (1) for MIGPUMA to MIGPUMA flows for individuals who were living in their birth state the previous year and for individuals not living in their birth state in the previous year. Distance is the distance between the population-weighted MIGPUMA centroids. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2012–2017 ACS.

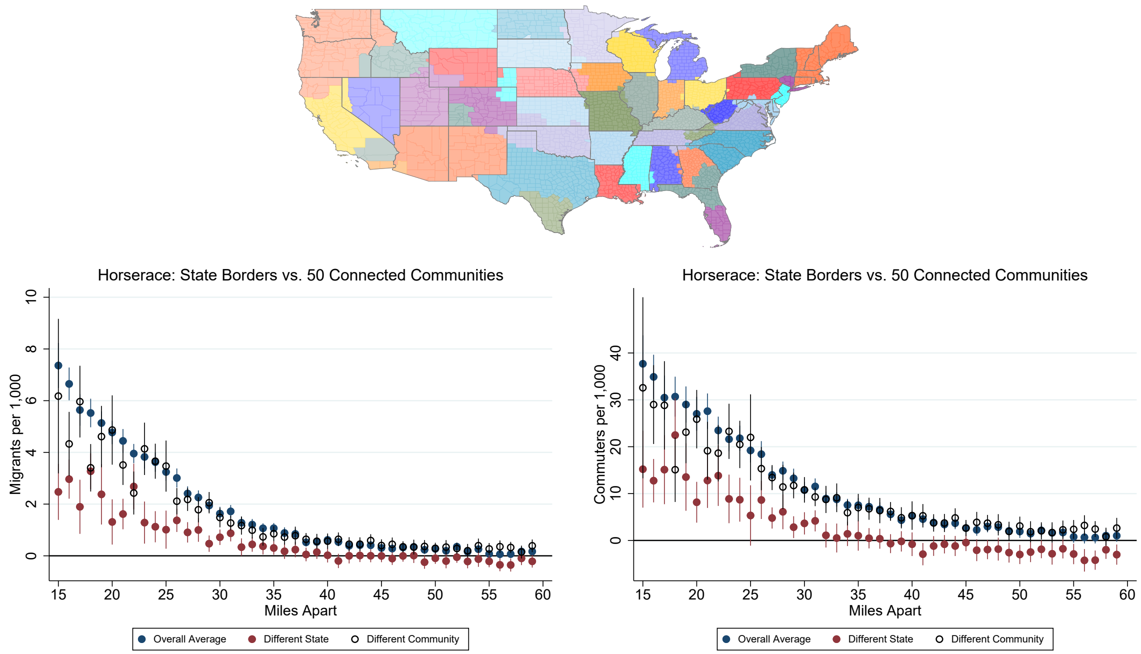
Figure 5: Impact of State Borders on County-to-County Facebook Friendship Rates and Mediating Role of Facebook Network on Cross-Border Mobility



NOTE: In the top panel, coefficients from equation (1) with and without controls are plotted where the outcome is the number of Facebook friends between residents of the origin and destination counties per 1,000 people in the origin county in 2000 using the SCI. The number of Facebook friends is scaled by an unknown constant, for privacy. "–Controls" plots coefficients from equation (1), accounting for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). In the bottom panel, the coefficients from equation (1) are plotted, where the outcome is the migration rate and commuting rate and the county-to-county Facebook friendship rate is controlled for in addition to the other controls. Ninety-five-percent confidence intervals are included.

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

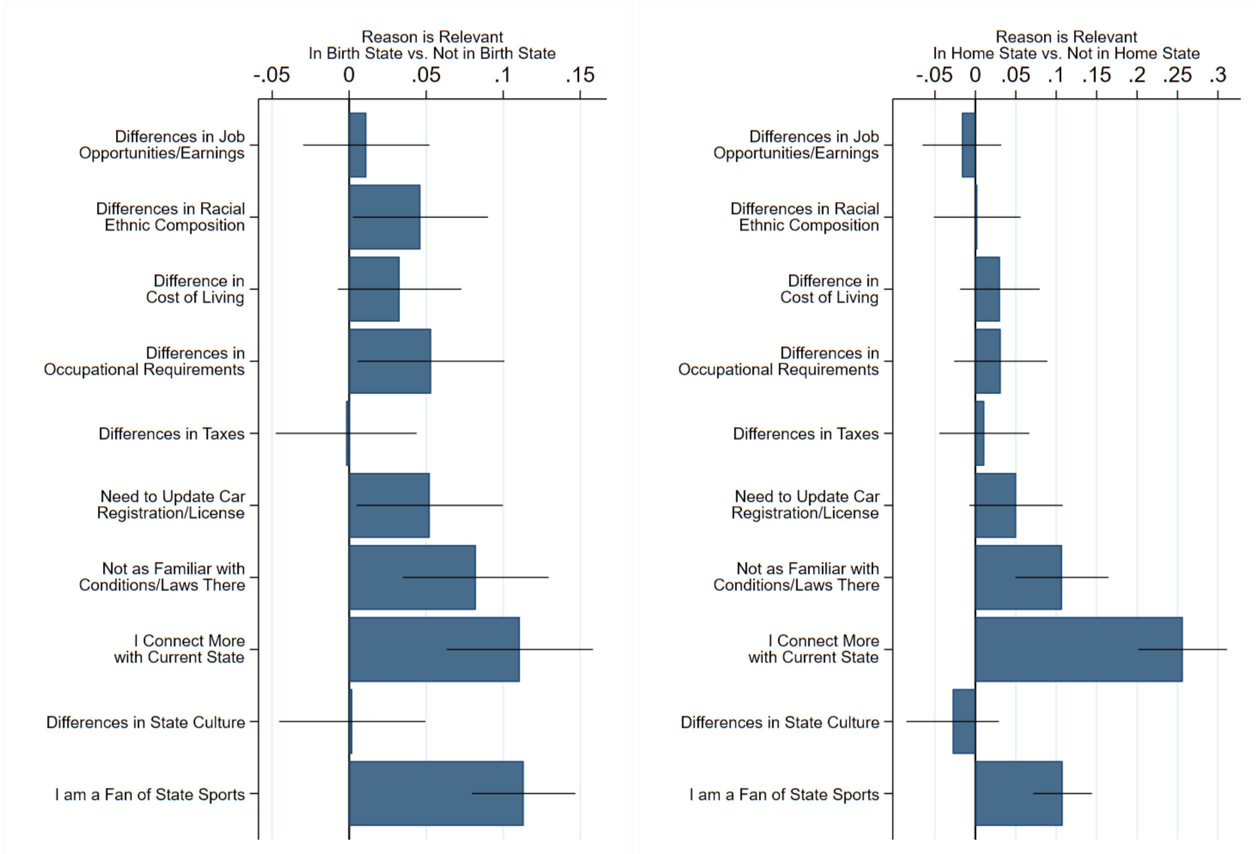
Figure 6: Horse Race Regression: Relative Importance of Physical State Borders versus Pseudo Connected Community Borders



NOTE: 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 (1) but includes the full set of state-border-by-distance interactions and the connected-community-border-by-distance interactions. Estimates control for origin and destination fixed effect and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five-percent confidence intervals are provided.

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

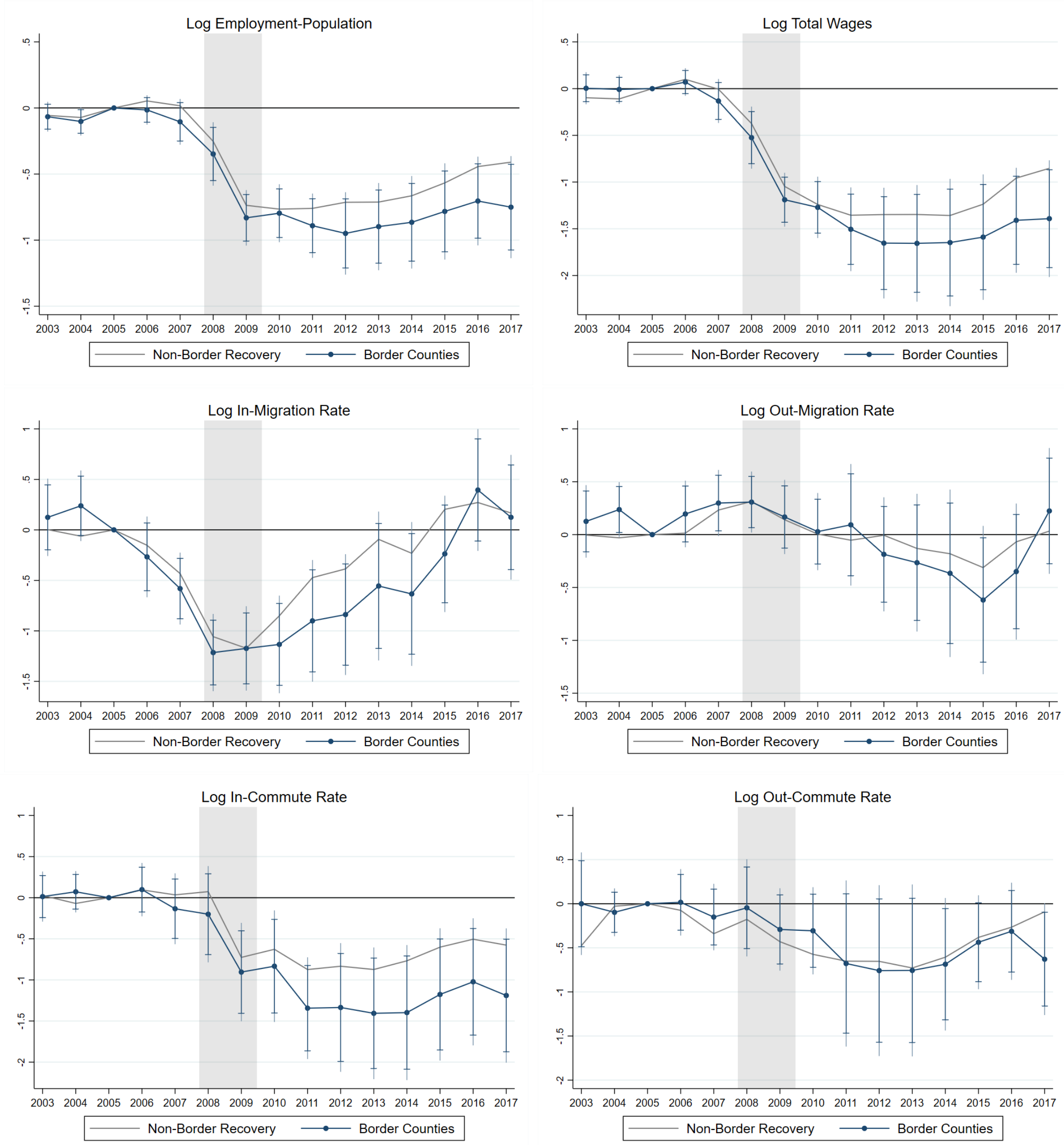
Figure 7: Experimental Evidence: Reasons that Influence Decision to Move Across State Borders



NOTE: Sample consists of 1,806 Prolific survey respondents whose location in the Prolific database was in the continental United States, but not the large Western states, Texas, or Rhode Island. These states are excluded as there are some places in the state where there is not either a viable option in state or out of state 100 miles away. The left panel plots the difference in the share of respondents who report that the reason is "somewhat relevant" or "highly relevant" between individuals living in their birth state and individuals not living in their birth state. The right panel plots the difference in the share of respondents who report that the reason is "somewhat relevant" or "highly relevant" between individuals living in their home state and individuals not living in their home state. 95-percent confidence intervals with robust standard errors are provided.

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

Figure 8: Impact of State Borders on Labor Market Recovery After the Great Recession



NOTE: Event study coefficients from equation (11) are plotted with 90 and 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. The outcome is the within county deviation relative to the 2005 level. State-by-year fixed effects as well as an indicator for being a border county interacted with year fixed effects, are included. Annual, county-level age share controls are also 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: Experimental Impact of State Borders on Migration Propensity

	Percent Chance Would Move					
	Initial Experiment			With-in Person		
	(1)	(2)	(3)	(4)	(5)	(6)
Different State	0.999	6.991***	7.212**	-1.519***	-0.793	0.813
	(1.557)	(2.567)	(3.553)	(0.385)	(0.655)	(0.947)
Different State*In Birth State		-9.432***			-1.156	
		(3.229)			(0.808)	
Different State*In Home State			-7.968**			-2.911***
			(3.956)			(1.035)
In Birth State		1.309				
		(2.292)				
In Home State			-2.883			
			(2.911)			
Increase in Income (%)	0.511***	0.514***	0.513***			
	(0.045)	(0.045)	(0.045)			
No Family/Friends Nearby	-3.501**	-3.307**	-3.249**			
	(1.557)	(1.555)	(1.554)			
Control Mean	52.00	52.00	52.00	50.36	50.36	50.36
Observations	1,806	1,806	1,806	3,612	3,612	3,612

NOTE: Sample consists of 1,806 Prolific survey respondents whose location in the Prolific database was in the continental United States, but not the large Western states, Texas, or Rhode Island. These states are excluded as there are some places in the state where there is not either a viable option in state or out of state 100 miles away. The change in income, location of destination relative to the state border, and absence of family and friends are randomized independently. "Different State" indicates the individual saw a scenario where the destination was just as far away, but in the neighboring state. In columns (1)-(3) I only include observations from the first hypothetical move scenario to avoid any priming individuals might receive from the two sequential scenarios. Columns (4)-(6) include two observations per person, where the only difference in the scenarios was one had the destination in the same state, the other had the destination in the neighboring state. Individual level fixed effects are included in columns (4)-(6). Because the increase in income and presence of family are not varied within person they are colinear with the individual-level fixed effects in columns (4)-(6). Robust standard errors are provided for columns (1)-(3) while individual-level clustered standard errors are provided for columns (4)-(6). $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Table 2: Summary Statistics for Border and Nonborder Counties

	Pre-2007			Post-2007		
	Interior Counties	Border Counties	Difference, Controlling for State-by-Year Effects	Interior Counties	Border Counties	Difference, Controlling for State-by-Year Effects
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_{09-07} Log CZ Emp. (Shock)	0.04	0.05	0.001	0.04	0.05	0.001
In-Migration Rate	5.13	4.82	-0.266***	4.93	4.62	-0.225***
Out-Migration Rate	4.94	4.71	-0.167***	4.85	4.61	-0.179**
In-Commute Rate	14.67	13.13	-1.741***	16.50	15.06	-1.523***
Out-Commute Rate	19.30	18.11	-1.049***	23.74	22.42	-0.886***
Total Employment (1,000s)	41.88	39.95	-3.309	42.97	40.49	-3.589
Number of Establishments	2647.05	2511.12	-199.423	2854.11	2670.35	-202.332
Total Wages (Millions)	1671.15	1674.67	-80.994	2089.35	2044.36	-124.003
Average Weekly Wages	564.23	568.42	-4.049	694.82	698.88	-3.235
Share Emp. Natural Resources	0.04	0.04	0.002	0.04	0.04	0.001
Share Emp. Construction	0.05	0.05	-0.002	0.04	0.04	-0.001
Share Emp. Manufacturing	0.13	0.13	0.000	0.11	0.11	-0.002
Share Emp. Trade	0.19	0.19	-0.001	0.19	0.19	-0.001
Share Emp. Information	0.01	0.01	-0.001*	0.01	0.01	-0.001*
Share Emp. Finance	0.04	0.04	-0.001	0.04	0.04	-0.000
Share Emp Professional	0.06	0.06	-0.002	0.06	0.06	-0.002
Share Emp. Education/Health	0.11	0.11	-0.001	0.12	0.12	-0.002
Share Emp. Hospitality	0.09	0.09	0.004	0.09	0.10	0.003
Share Emp. Other	0.03	0.03	0.000	0.02	0.02	0.000
Share Emp. Public	0.21	0.21	0.005	0.21	0.21	0.005
Total Population (1,000s)	94.72	93.92	-2.206	101.73	98.46	-4.051
Population/Square Mile	29.13	50.61	17.105	31.13	52.66	17.235
Share Female	0.50	0.50	0.000	0.50	0.50	-0.000
Share NH White	0.80	0.82	0.003	0.78	0.80	0.003
Share NH Black	0.09	0.09	-0.002	0.10	0.09	-0.002
Share NH Other	0.03	0.03	0.002	0.03	0.03	0.002
Share Hispanic	0.08	0.06	-0.003	0.10	0.08	-0.002
Share Under 20	0.27	0.27	-0.001	0.26	0.25	-0.001
Share 20-34	0.18	0.17	-0.004***	0.18	0.18	-0.003**
Share 35-49	0.21	0.21	-0.001	0.19	0.19	-0.001
Share 50-64	0.19	0.19	0.002**	0.21	0.21	0.002
Share 65+	0.15	0.15	0.004**	0.17	0.17	0.004**
CZ Emp. Share/CZ Pop. Share	0.87	0.87	-0.006	0.87	0.87	-0.006

NOTE: Observation at the county by year level. State-by-year fixed effects are included in columns (3) and (6) to compare characteristics between counties in the same state and year. Differences in population density are driven by New York City. Means are similar if New York is excluded. The commuting zone employment share divided by the commuting zone population share captures the relative centrality of the county in the commuting zone network. A number greater than one would indicate that the county contains relatively more of the commuting zone's employment than the commuting zone's population. Standard errors corrected for clustering at the commuting zone level. $p < 0.1 =$ *; $p < 0.05 =$ **; $p < 0.01 =$ ***.

Table 3: Employment and Mobility Response to Mass Layoffs

	County-level Outcomes						Individual-level Outcomes in Border MIGPUMA		
	Log Employment		Log In-Migration Rate		Log Out-Migration Rate		Move State	Move MIGPUMA	Employed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mass Layoffs (% Employment)	-0.005***	-0.005***	-0.004***	-0.002**	0.004***	0.005***	0.007***	0.005***	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mass Layoffs (% Employment)*Border County		0.001		-0.005***		-0.003***			
		(0.001)		(0.001)		(0.001)			
Mass Layoffs (% Employment)*In Birth State							-0.010***	-0.007***	-0.004*
							(0.001)	(0.001)	(0.002)
Dependent Mean	9.63	9.63	1.54	1.54	1.52	1.52	0.03	0.06	0.70
Observations	37,075	37,075	37,075	37,075	37,075	37,075	5,999,850	5,999,850	5,999,850

NOTE: In columns (1)-(6) observation at the county by year level between 1996 and 2012. State-by-year and county fixed effects are included. Standard errors corrected for clustering at the commuting zone level. In columns (7)-(9) observation at the individual level, for individuals 18-65 in the 2005-2011 ACS. Only individuals living in border MIGPUMAs. MIGPUMA and year fixed effects are included. Standard errors corrected for clustering at the MIGPUMA level. $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

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Appendix A. Additional Tables and Figures

Table A1: Local Characteristic and Policy Control Measures

Measure	Source	Description
	Characteristic/Amenity	
Unemployment Rate	BLS LAUS	Annual, not seasonaly adjusted
Employment-to-population Ratio	QCEW and SEER	
Average Weekly Wages	QCEW	
Industry employment shares	QCEW	Natural Resources, Construction, Manufacturing, Trade, Information, Finance, Professional, Education/Health, Hospitality, Public Admin, Other
Number of Establishments	Census SUSB	
Total Population	SEER	
Population Density	Census Shapefile and SEER	People per square KM
Share Female	SEER	
Race Shares	SEER	White NH, Black NH, Other NH, Hispanic
Age Shares	SEER	Under 20, 20-34, 35-49, 50-64, Over 64
Average January Temperature	USDA	
Average January Sunshine	USDA	
Average July Temperature	USDA	
Average July Humidity	USDA	
Natural Amenities Scale	USDA	
2016 Presidential Republican Vote Share	MIT Election Lab	
Average Home Value	FHFA	Housing Price Index converted to dollars using 2000 Median House Value
Average Math Scores	SEDA	3rd–8th Grade Averaged over 2008–2018
Average English Scores	SEDA	3rd–8th Grade Averaged over 2008–2018
	State Policy	
State+Federal Income Tax Burden	NBER TAXSIM	Single, Joint (no dependents), Joint (two dependents) at income levels \$10K, \$25K, \$50K, \$75K, \$100K
State Sales Tax Rate	Tax Foundation	
State Corporate Tax Rate	Tax Foundation	Maximum tax rate
Minimum Wage	DOL	if not state minimum wage, federal is applied
State EITC supplement	NBER	percentage of federal EITC
State TANF generosity	CRS	Maximum monthly benefit for single-parent family with two children
State Medicaid Expansion	Kaiser Family Foundation	Indicator for expanded by 2017
K-12 per pupil spending	NCSES	

NOTE: Details for each data source found in the data appendix (Appendix D).

Table A2: Gravity Equation Specification: Impact of State Borders on Mobility Flows

	Log Migrant Flow			Log Commuter Flow		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Origin Population	0.417***	0.446***		0.445***	0.461***	
	(0.011)	(0.009)		(0.011)	(0.010)	
Log Destination Population	0.374***	0.403***		0.823***	0.837***	
	(0.009)	(0.008)		(0.009)	(0.008)	
Log Distance	-0.053***	-0.053***	-0.075***	-0.075***	-0.070***	-0.073***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Different State		-0.748***	-0.560***		-1.309***	-1.460***
		(0.026)	(0.074)		(0.020)	(0.061)
FE and Controls			X			X
Dependent Mean	4.97	4.97	5.06	4.21	4.21	4.73
Observations	14,829	14,829	12,664	49,003	49,003	33,603

NOTE: Observation at the origin/destination county pair level, using the IRS SOI 2017 data. *Diff. State* is an indicator for whether the counties are in different states. Following the standard gravity equation, the natural log of the mobility flow is regressed on the natural log of the origin population, the destination population, and distance. I then include an indicator for being in a different state. In column (3) and (6) origin county fixed effects, destination county fixed effects, and controls for absolute differences in local characteristics and state policy are included (see notes to Figure 1 for the list of controls). The log population measures are absorbed once the origin and destination fixed effects are included. Standard errors corrected for clustering at the origin county level. $p < 0.1 = *$; $p < 0.05 = **$; $p < 0.01 = ***$.

Table A3: 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	0.003	0.004	0.004	0.002	0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.014)	(0.013)	(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	0.022	0.022	0.022	0.174	0.174	0.174	0.039	0.039	0.039
Observations	9,374,027	9,374,027	9,374,027	1,206,355	1,206,355	1,206,355	4,271,549	4,271,549	4,271,549
	Less Restrictive Measure of Occupational Licensing								
Licensed Occupation	0.001	0.001	0.001	-0.000	0.002	0.002	-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	0.022	0.022	0.022	0.174	0.174	0.174	0.039	0.039	0.039
Observations	9,374,027	9,374,027	9,374,027	1,206,355	1,206,355	1,206,355	4,271,549	4,271,549	4,271,549

NOTE: 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 on, 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-four-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, state fixed effects are for the state of residence one year ago. For commuting outcomes, state fixed effects are for the current state of residence. All specifications control for distance to the border. Standard errors corrected for clustering at the state level (state of residence in previous year for migration, current state for commuting). $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Table A4: Experimental Survey Summary Statistics

	Same State (1)	Neighboring State (2)	P-value (3)
Male	0.50	0.50	0.93
White	0.80	0.81	0.37
Black	0.06	0.08	0.09
Asian	0.07	0.04	0.02
Other	0.07	0.06	0.35
Race Missing	0.01	0.01	0.76
Age	37.42	37.96	0.38
Less HS	0.01	0.01	0.83
HS	0.13	0.14	0.68
Some College	0.32	0.32	0.80
College	0.40	0.38	0.38
Advanced Degree	0.14	0.15	0.55
Employed	0.71	0.72	0.92
Unemployed	0.09	0.12	0.12
Not in LF	0.18	0.16	0.21
HH Income ($1,000s)	69.18	67.43	0.39
In Birth State	0.62	0.64	0.36
In Home State	0.81	0.79	0.20
Pass Attention Check	1.00	1.00	1.00
Minutes Taken	5.27	6.45	0.33
Change in Income Level (%)	26.56	26.71	0.85
No Family/Friends Nearby	0.50	0.50	1.00
Observations	904	904	

NOTE: Sample consists of 1,808 Prolific survey respondents whose location in the Prolific database was in the continental United States, but not the large Western states, Texas, or Rhode Island. These states are excluded as there are some places in the state where there is not either a viable option in state or out of state 100 miles away. Two of the respondents did not complete the survey and could not be included in the analysis sample. The change in income, location of destination relative to the state border, and absence of family and friends are randomized independently. “Different State” indicates the individual saw a scenario where the destination was just as far away, but in the neighboring state.

Table A5: Alternative Estimation of Experimental Impact of State Borders on Migration Propensity

	Log Odds Ratio					
	OLS Estimates			LAD Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Different State	0.037	0.668**	0.622	0.000	0.281*	0.354
	(0.165)	(0.280)	(0.389)	(0.098)	(0.162)	(0.266)
Different State*In Birth State		-0.995***			-0.405*	
		(0.346)			(0.214)	
Different State*In Home State			-0.754*			-0.354
			(0.430)			(0.300)
In Birth State		0.199			0.000	
		(0.247)			(0.164)	
In Home State			-0.401			-0.092
			(0.314)			(0.246)
Increase in Income (%)	0.047***	0.047***	0.047***	0.028***	0.032***	0.031***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
No Family/Friends Nearby	-0.382**	-0.363**	-0.356**	-0.251**	-0.205**	-0.092
	(0.165)	(0.165)	(0.165)	(0.099)	(0.099)	(0.120)
Control Mean Probability	52.00	52.00	52.00	52.00	52.00	52.00
Observations	1,806	1,806	1,806	1,806	1,806	1,806

NOTE: Sample consists of 1,806 Prolific survey respondents whose location in the Prolific database was in the continental United States, but not the large Western states, Texas, or Rhode Island. These states are excluded as there are some places in the state where there is not either a viable option in state or out of state 100 miles away. The change in income, location of destination relative to the state border, and absence of family and friends are randomized independently. "Different State" indicates the individual saw a scenario where the destination was just as far away, but in the neighboring state. The Log Odds Ratio is $ln(prob.\ move_i/(1-prob.\ move_i))$ where the probability of moving is set equal to 0.001 if it is reported as 0 and 0.999 percent if it is reported as 1 (Kosar et al., 2020). Least Absolute Deviation (LAD) estimates are included to address potential measurement error in reported probabilities (Kosar et al., 2020). Robust standard errors are provided. $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Table A6: Alternative Estimation of Experimental Impact of State Borders on Migration Propensity, Within Person Design

	Log Odds Ratio		
	OLS Estimates		
	(1)	(2)	(3)
Different State	-0.143***	-0.059	0.192*
	(0.045)	(0.078)	(0.108)
Different State*In Birth State		-0.134	
		(0.095)	
Different State*In Home State			-0.418***
			(0.119)
Control Mean Probability	50.36	50.36	50.36
Observations	3,612	3,612	3,612

NOTE: Sample consists of 1,806 Prolific survey respondents whose location in the Prolific database was in the continental United States, but not the large Western states, Texas, or Rhode Island. These states are excluded as there are some places in the state where there is not either a viable option in state or out of state 100 miles away. The change in income, location of destination relative to the state border, and absence of family and friends are randomized independently. "Different State" indicates the individual saw a scenario where the destination was just as far away, but in the neighboring state. The Log Odds Ratio is $ln(prob.\ move_i/(1 - prob.\ move_i))$ where the probability of moving is set equal to 0.001 if it is reported as 0 and 0.999 percent if it is reported as 1 (Kosar et al., 2020). Least Absolute Deviation (LAD) estimates with fixed effects are only consistent as the number of observations per individual goes to infinity (Kato et al., 2012). Because there are only two observations LAD estimates are not provided. Clustered standard errors are provided. $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Table A7: Share of Gallup Respondents Who Feel Their State Is the Best Possible State to Live In

State	Share of Respondents Who Feel Their State is the Best Possible State to Live In
TEXAS	0.28
ALASKA	0.27
HAWAII	0.25
MONTANA	0.24
NORTH DAKOTA	0.21
WYOMING	0.21
COLORADO	0.18
UTAH	0.15
WASHINGTON	0.14
VERMONT	0.14
IOWA	0.13
MINNESOTA	0.13
CALIFORNIA	0.13
SOUTH DAKOTA	0.13
NEW HAMPSHIRE	0.13
OREGON	0.13
FLORIDA	0.11
WEST VIRGINIA	0.11
IDAHO	0.11
ARIZONA	0.10
SOUTH CAROLINA	0.10
TENNESSEE	0.10
MAINE	0.10
NEBRASKA	0.10
ALABAMA	0.10
NEW YORK	0.09
GEORGIA	0.09
NEVADA	0.09
WISCONSIN	0.08
KENTUCKY	0.08
ARKANSAS	0.08
VIRGINIA	0.07
MISSISSIPPI	0.07
OKLAHOMA	0.07
MASSACHUSETTS	0.07
DELAWARE	0.07
LOUISIANA	0.07
PENNSYLVANIA	0.06
INDIANA	0.06
NORTH CAROLINA	0.06
NEW JERSEY	0.06
MICHIGAN	0.05
NEW MEXICO	0.05
MARYLAND	0.05
KANSAS	0.05
MISSOURI	0.04
OHIO	0.04
CONNECTICUT	0.03
RHODE ISLAND	0.03
ILLINOIS	0.03

NOTE: Estimates constructed by Gallup, based on a 2013 survey of nearly 600 respondents from each state. Obtained from Gallup at `https://news.gallup.com/poll/168653/montanans-alaskans-say-states\-among-top-places-live.aspx?version=print`.

Table A8: Heterogeneous Impact of State Border on Mobility by Strength of State Identity, Gallup Survey

	Migrants per 1,000		Commuters per 1,000	
	(1)	(2)	(3)	(4)
Diff. State	-0.695***	0.047	-5.645***	-3.205***
	(0.033)	(0.135)	(0.252)	(0.822)
Diff. State*Share Feel State is the Best		-9.757***		-32.159***
		(0.135)		(0.822)
Dependent Mean	1.00	1.00	8.08	8.09
Observations	24,704	24,676	24,704	24,676

NOTE: Observation at the origin/destination county pair level, using the IRS SOI 2017 data. *Diff. State* is an indicator for whether the counties are in different states. *Share Feel State is "the Best"* is obtained from a 2013 Gallup survey on own-state preferences and measured at the state level. All regressions include one-mile-distance bin fixed effects as well as origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Distance is the distance between the population-weighted county centroids. Standard errors are corrected for clustering at the origin county level. $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Table A9: How Predictive are State Borders of Sports Team Fan Borders Among Neighboring Counties?

	NFL Team Border (1)	MLB Team Border (2)	NBA Team Border (3)	NCAA Basketball Team Border (4)
State Border Between Counties	0.119***	0.160***	0.177***	0.412***
	(0.018)	(0.017)	(0.017)	(0.020)
Local Controls	X	X	X	X
Dependent Mean	0.212	0.120	0.302	0.358
Observations	11,910	11,910	11,910	11,910

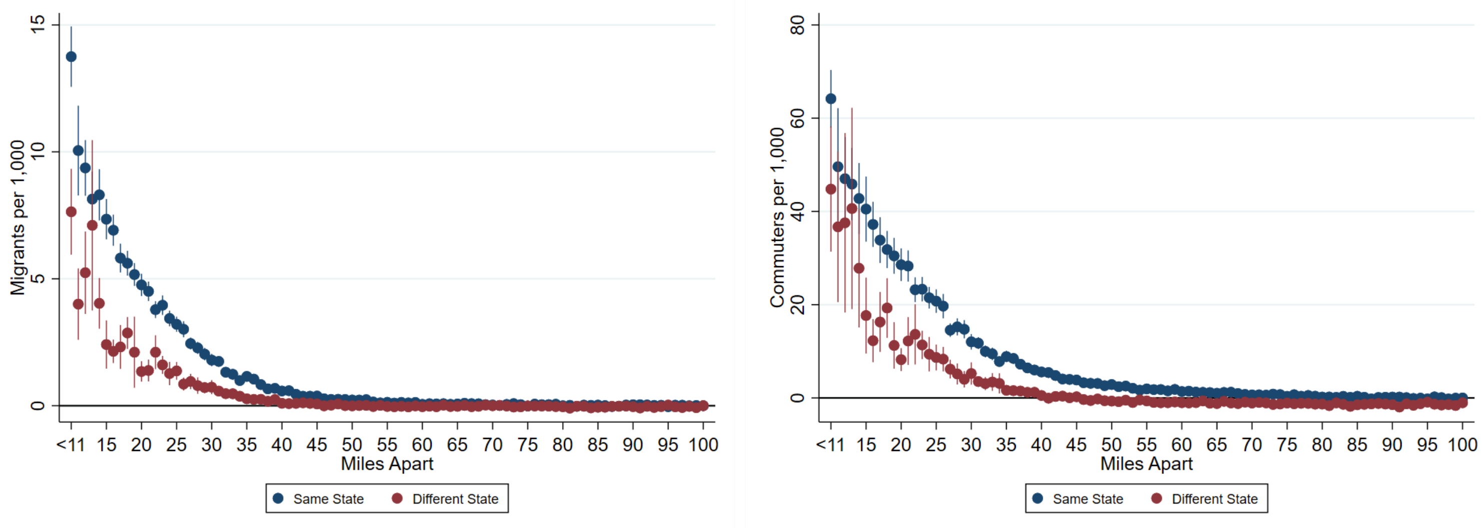
NOTE: Sample restricted to neighboring counties, with one observation for each county (origin) and each bordering county (destination). Outcome of interest is whether or not there is a sport team fan border between the two counties. State border is an indicator that equals one if there is a state border between the two counties. Controls for the differences in local characteristics between origin and destination, as in equation (1), are also included. Fixed effects for origin and destination county are included and absolute differences in origin destination characteristics (see notes to Figure 1). Standard errors corrected for clustering at the origin county level. Estimates are similar if only one observation per border pair is included, or if controls are excluded. $p < 0.1$ = *; $p < 0.05$ = **; $p < 0.01$ = ***.

Table A10: 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*
		(0.029)		(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

NOTE: Sample restricted to U.S.-born survey respondents from the 2008 Pew Research Center Mobility Survey. Regression controls for sex, education level, race, ethnicity, age and age squared, as well as current state of residence fixed effects. Observations are weighted using the Pew Research Center survey weights. Standard errors corrected for clustering at the current state of residence level. p < 0.1 = *; p < 0.05 = **; p < 0.01 = ***.

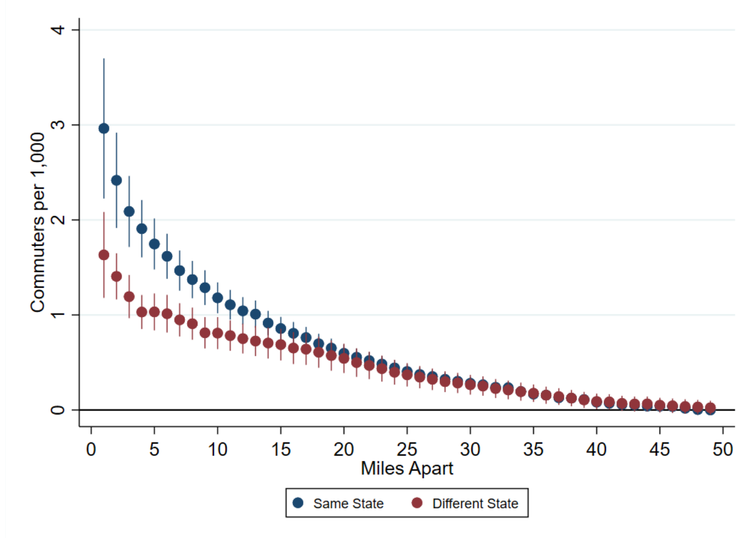
Figure A1: Including Closer and Farther Distance Bins: County-to-County Migration and Commute Rates by Distance and for Same-State and Different-State Counties



NOTE: Outcome in the left panel is number of migrants per 1,000 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 1,000 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 (1), but more distance bins are added. Estimates control for origin and destination fixed effects as well as absolute differences in origin destination characteristics (see notes to Figure 1). The "<11 bin" includes all pairs less than 11 miles apart. Ninety-five-percent confidence intervals are provided.

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

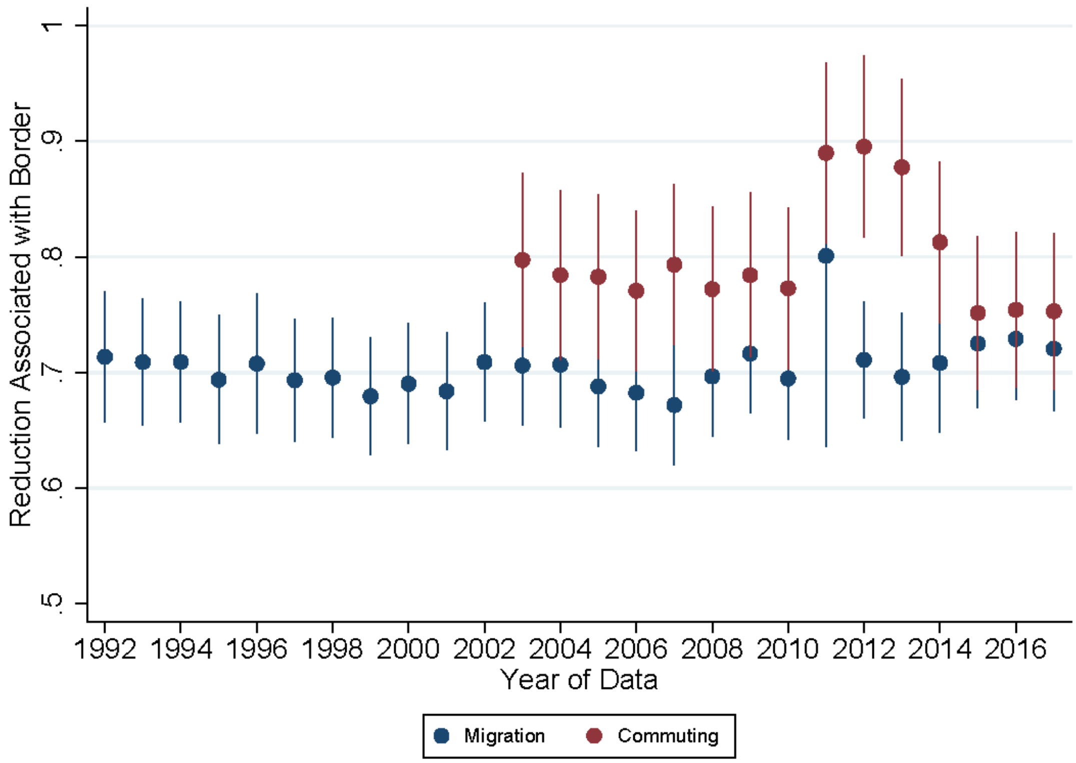
Figure A2: Tract-to-Tract Commute Rates for Very Close Distances for Same-State and Different-State Census Tracts



NOTE: Outcome is the number of commuters per 1,000 people at the origin tract using the LODES origin-destination employment statistics aggregated to the census tract level from 2017. Point estimates are obtained by estimating an equation similar to equation (1), with individual mile distance bins between 0 and 49 miles, the 50 to 51 mile bin is the omitted reference bin. Estimates control for origin and destination tract fixed effects. Ninety-five-percent confidence intervals are provided.

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

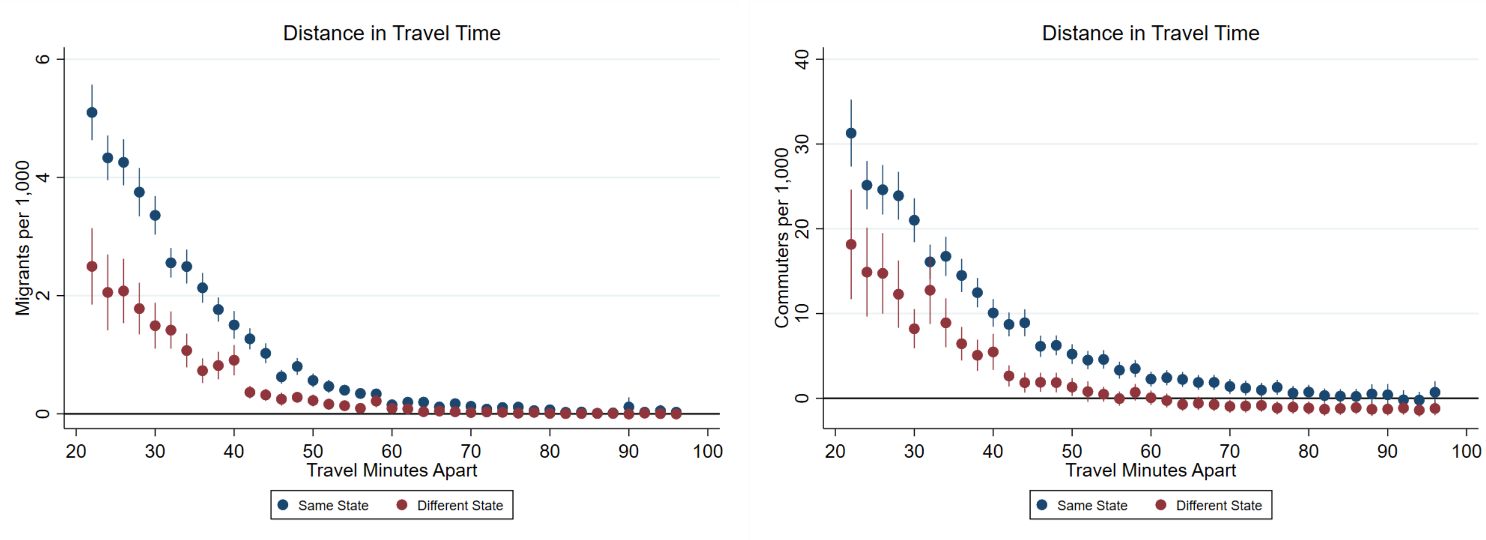
Figure A3: Relationship over Time: Impact of State Borders on County-to-County Migration and Commuting from 1992 to 2017



NOTE: The reduction in migration (blue) and commuting (red) associated with state borders for each year from 1992 to 2017 are plotted with 95 percent confidence intervals. These estimates are obtained by regressing equation (1) (without the absolute difference controls) 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 was increased to 20.

SOURCE: Author's own calculations using the IRS county-to-county flows from 1992 to 2017, LODES data from 2003 to 2017.

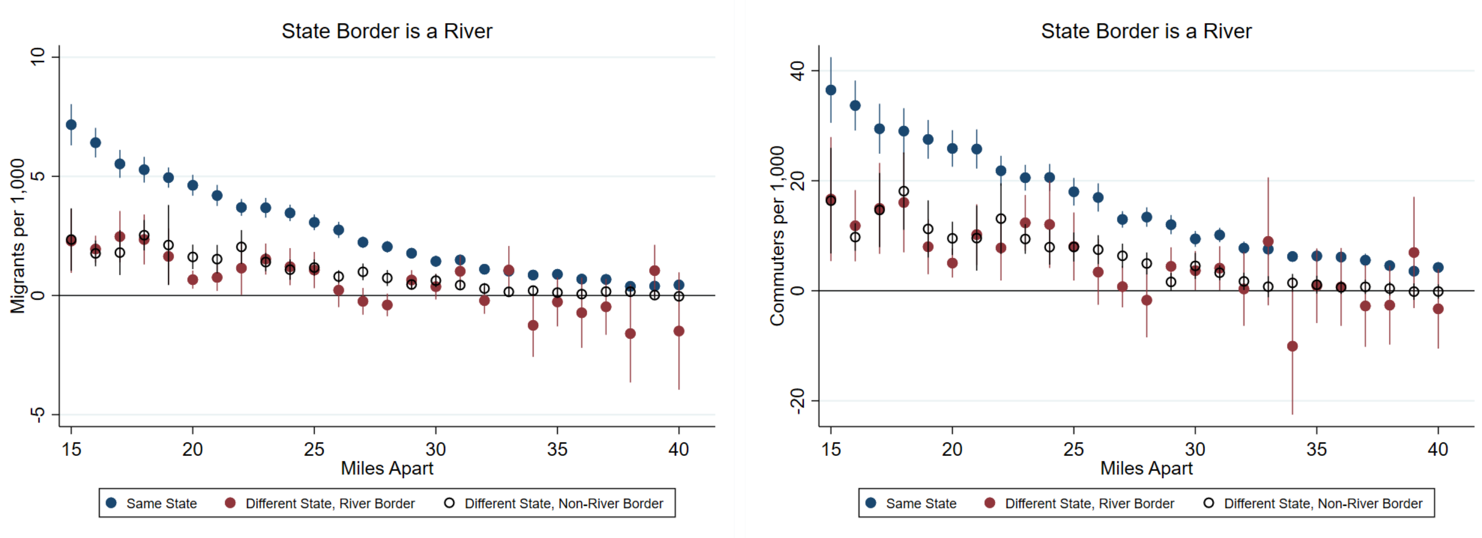
Figure A4: Measuring Distance in Travel Time



NOTE: Coefficients from equation (1) are plotted. Only counties within 60 miles of a county in a different state are included, but distance is the number of minutes of travel time between the population-weighted county centroids. The right panel restricts the sample to only include counties within 60 miles of a county in a different state. "–Controls" plots coefficients from equation (1), accounting for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five-percent confidence intervals are provided.

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

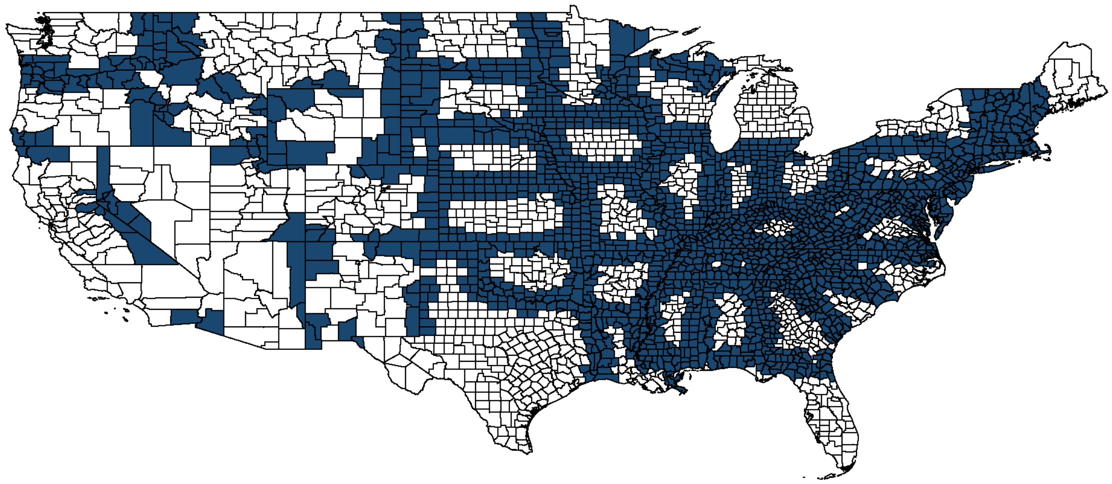
Figure A5: Impact of State Borders, States Separated by Rivers vs. Arbitrary Borders



NOTE: Sample restricted to counties that are less than 60 miles from another county in a different state. Coefficients from equation (20), where the characteristic is the presence of a river border between states. Estimation includes controls for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five-percent confidence intervals are provided.

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

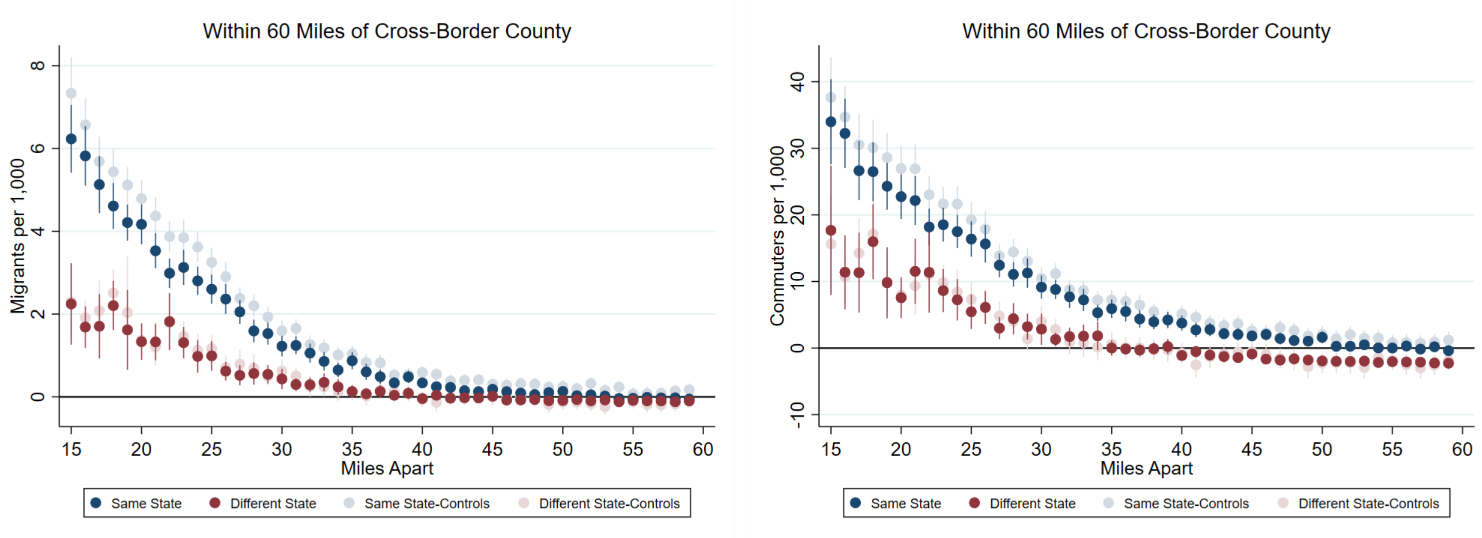
Figure A6: Counties within 60 Miles of a County in a Different State



NOTE: 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.

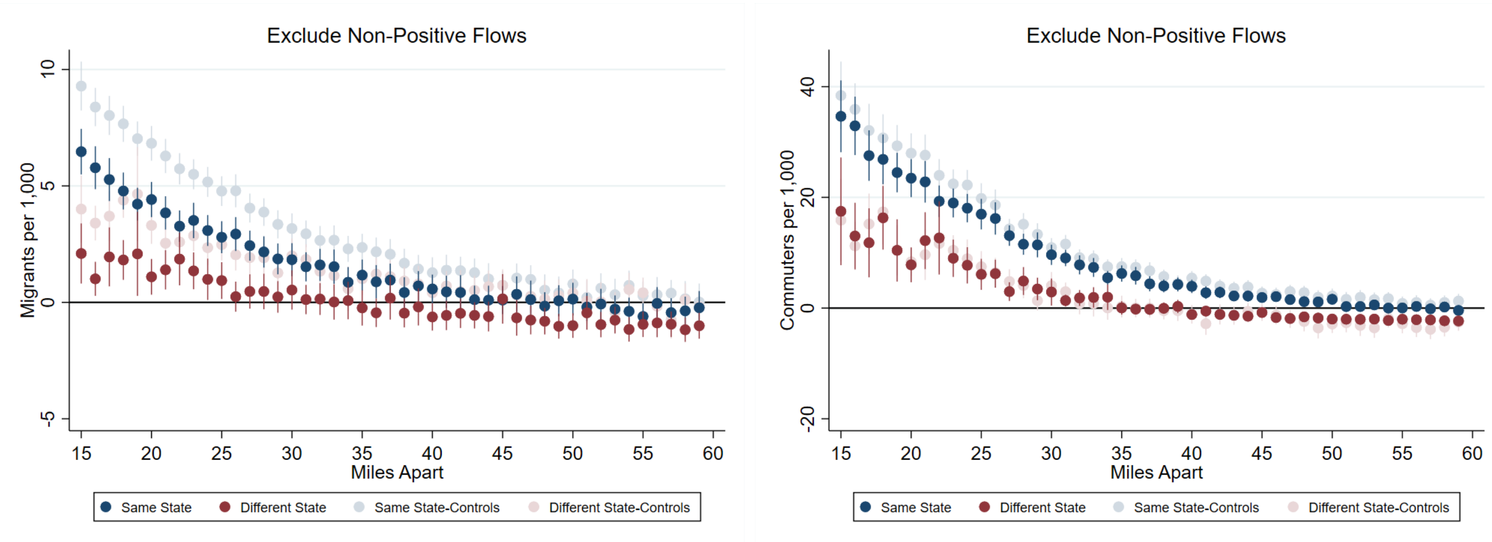
Figure A7: Robustness to Sample Composition, Counties within 60 Miles of Border



NOTE: Coefficients from equation (1) are plotted. The he sample is restricted to only include counties within 60 miles of a county in a different state. "–Controls" plots coefficients from equation (1), accounting for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five-percent confidence intervals are provided.

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

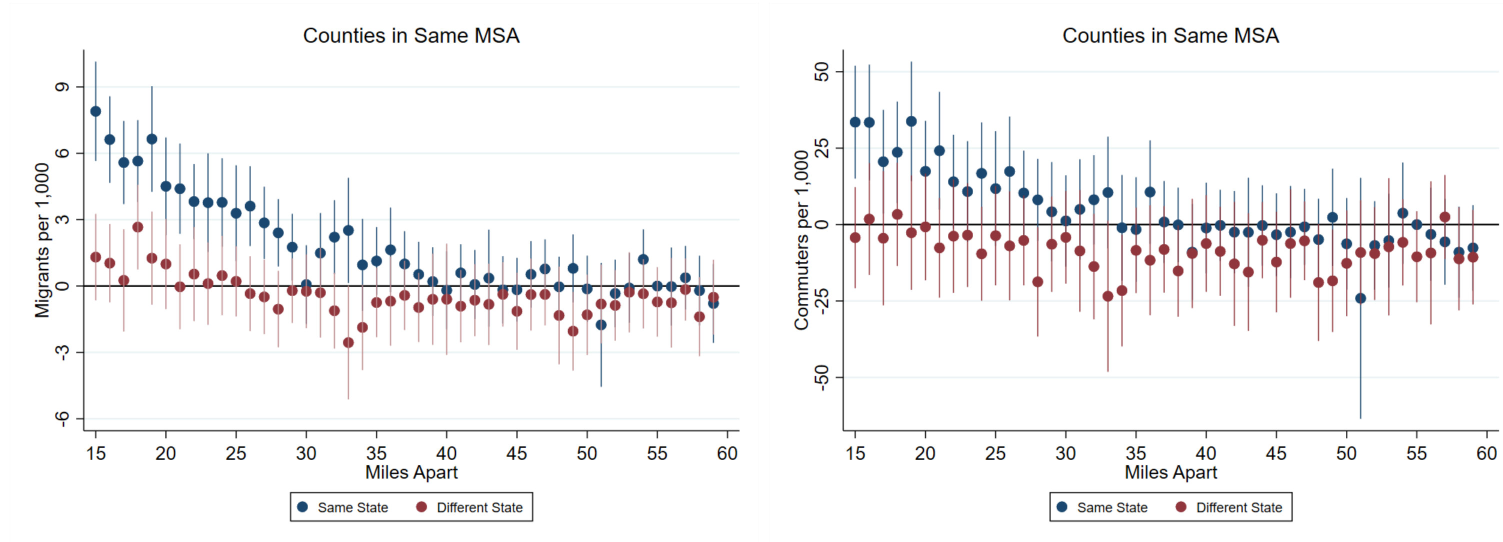
Figure A8: Excluding County-to-County Flows of Zero: Impact of State Borders on Migration and Commute



NOTE: Outcome in the left panel is number of migrants per 1,000 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 1,000 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. Sample restricted to exclude county-to-county observations where the migration/commute rate is zero. For data privacy, small county-to-county flows are suppressed, so some of these zero flows are suppressed flows. Estimation control for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1).

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

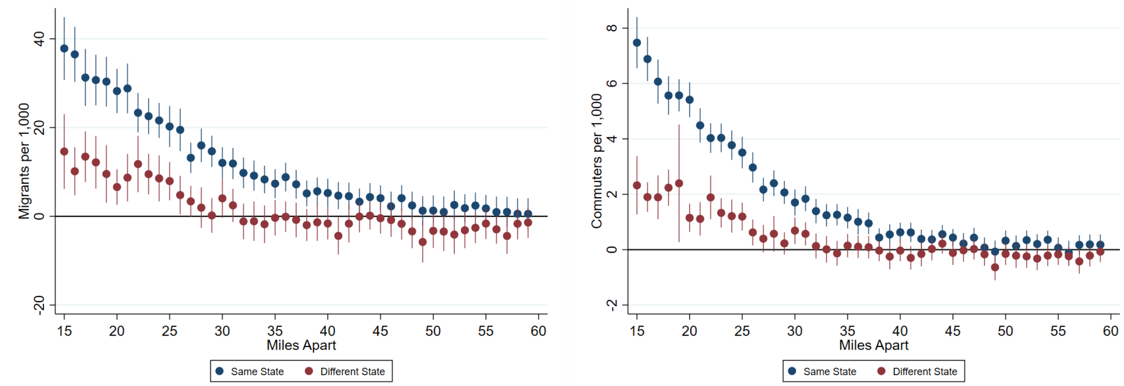
Figure A9: Impact of State Borders on Migration and Commuting in Cross-Border MSA



NOTE: Coefficients from equation (1) are plotted. Migration is plotted in the left panel, commuting in the right. The sample only counties in MSAs that cross state borders and includes only county pairs that are in the same MSA. Estimation controls for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five-percent confidence intervals are provided.

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

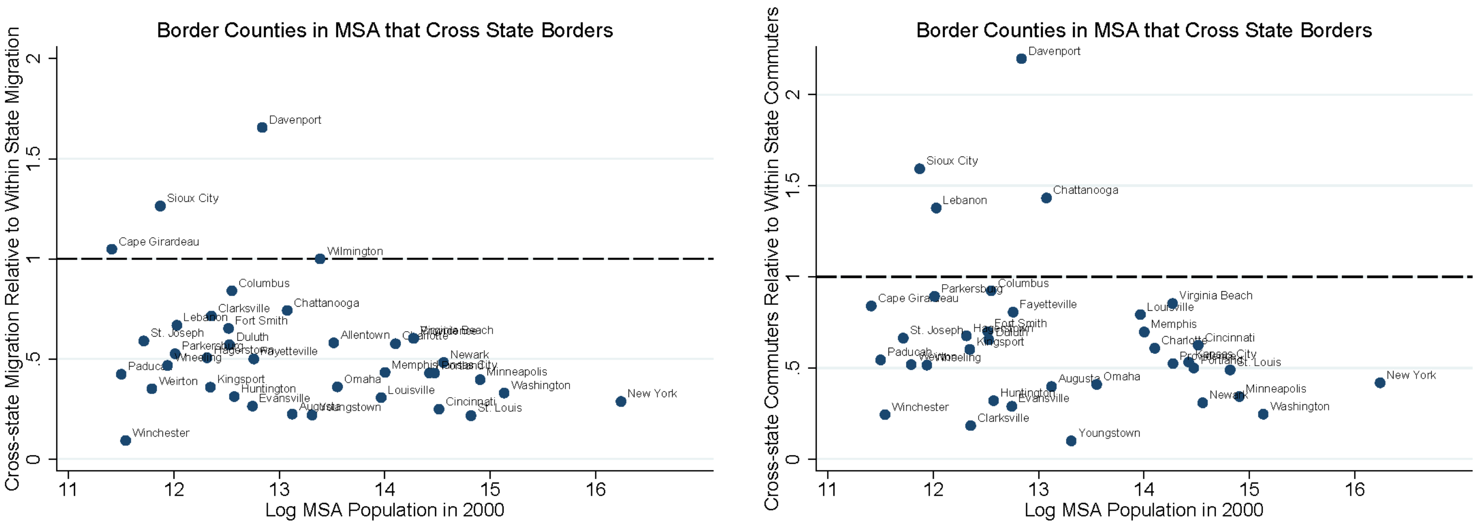
Figure A10: Impact of State Borders on Migration and Commuting in Cross-Border Designated Market Areas



NOTE: Coefficients from equation (1) are plotted. Migration is plotted in the left panel, commuting in the right. The sample is restricted to include only counties in Designated Market Areas (DMAs) that cross state borders and to include only county pairs that are in the same DMA. A DMA is meant to capture similar media markets. Estimation controls for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five-percent confidence intervals are provided.

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

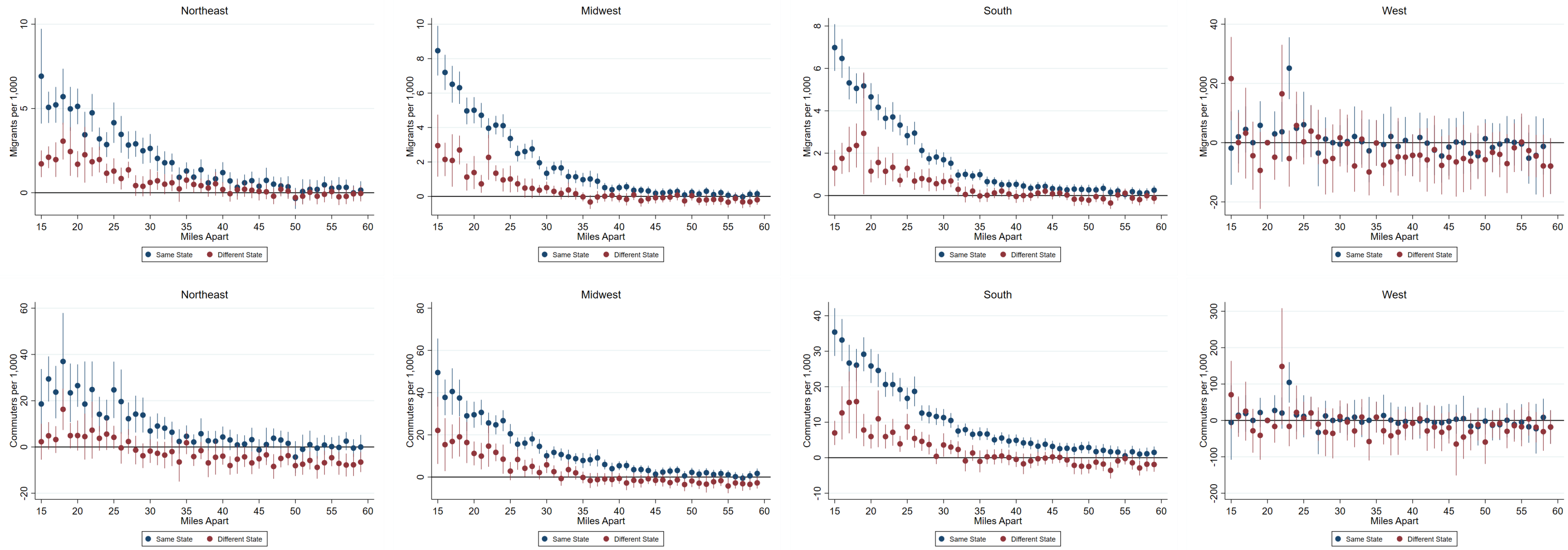
Figure A11: MSA Specific Estimates: Impact of State Borders on Migration and Commute



NOTE: 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.

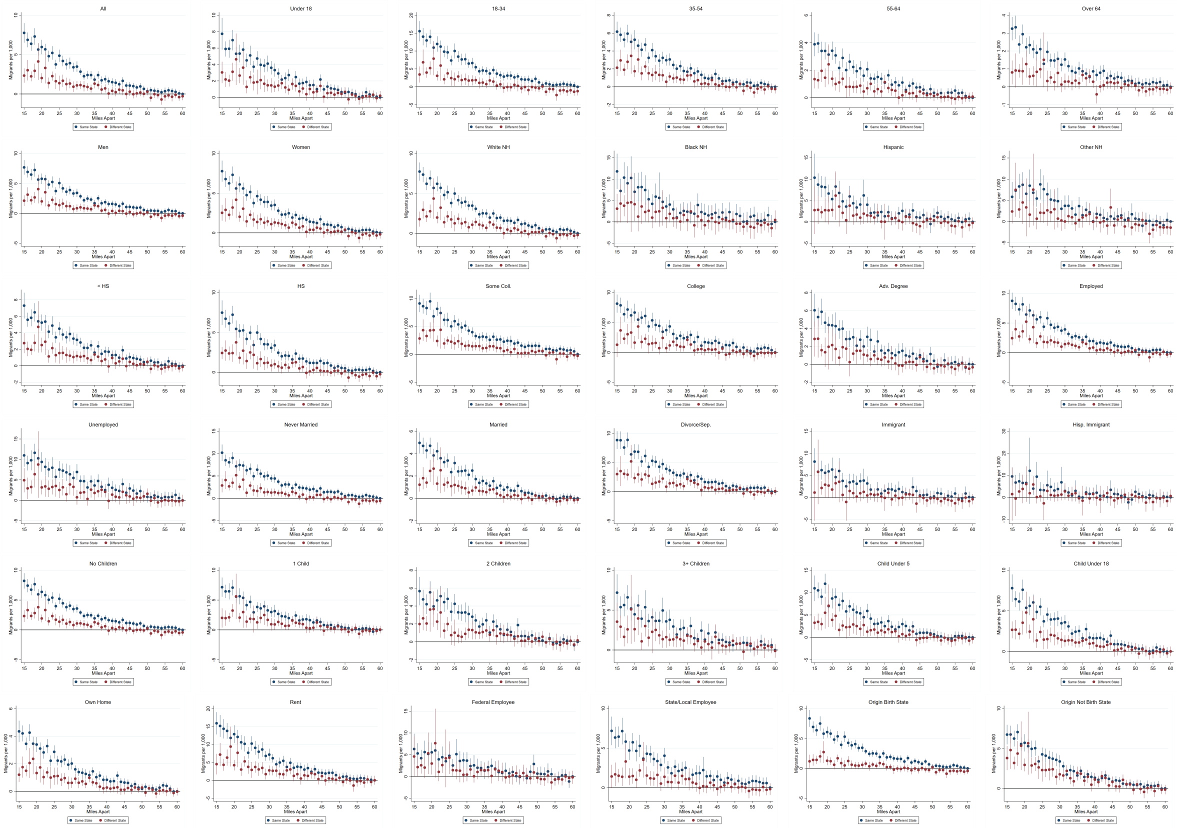
Figure A12: Census Region Heterogeneity: Impact of State Borders on Migration and Commuting



NOTE: Coefficients are plotted from equation (1), estimated separately by origin-county census region. Migration is plotted in the top panel, commuting in the bottom. Estimation controls for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Counties in the West are generally larger, and fewer of them meet the criteria of being within 60 miles of another county in a different state, leading to smaller samples. Ninety-five-percent confidence intervals are provided.

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

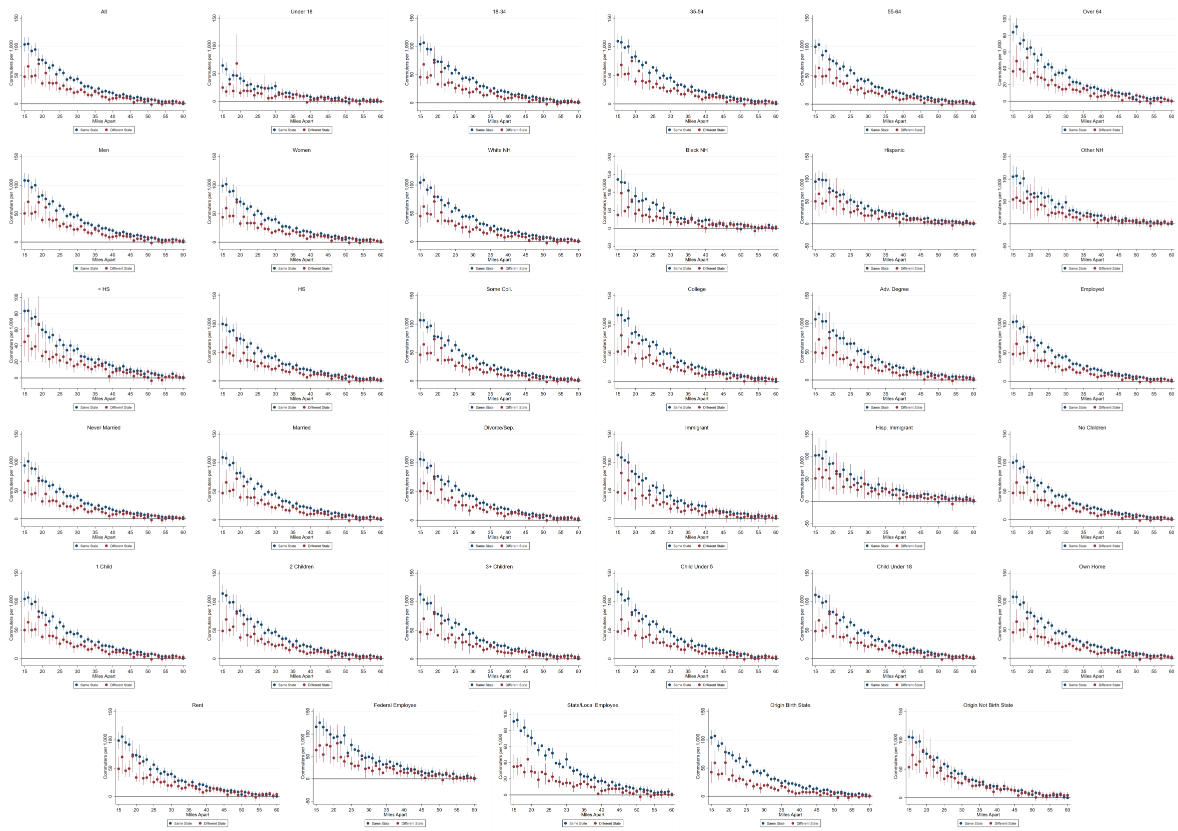
Figure A13: Heterogeneity by Demographics: Impact of State Borders on Migration by Demographic Groups in the ACS



NOTE: These estimates are obtained by separately regressing equation (1), without the absolute difference controls, for MIGPUMA to MIGPUMA flows for individuals in each demographic group. Distance is the distance between the population-weighted MIGPUMA centroids. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2012–2017 ACS.

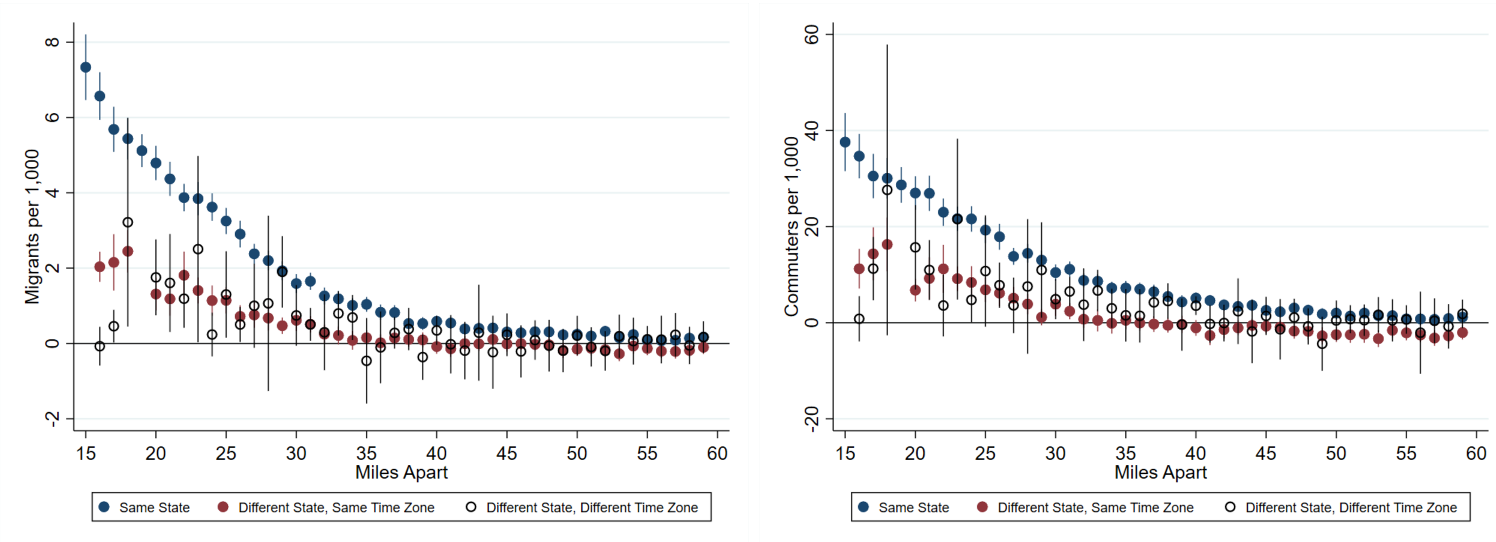
Figure A14: Heterogeneity by Demographics: Impact of State Borders on Commuting by Demographic Groups in the ACS



NOTE: These estimates are obtained by separately regressing equation (1), without the absolute difference controls, for MIGPUMA to MIGPUMA flows for individuals in each demographic group. Distance is the distance between the population-weighted MIGPUMA centroids. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2012–2017 ACS.

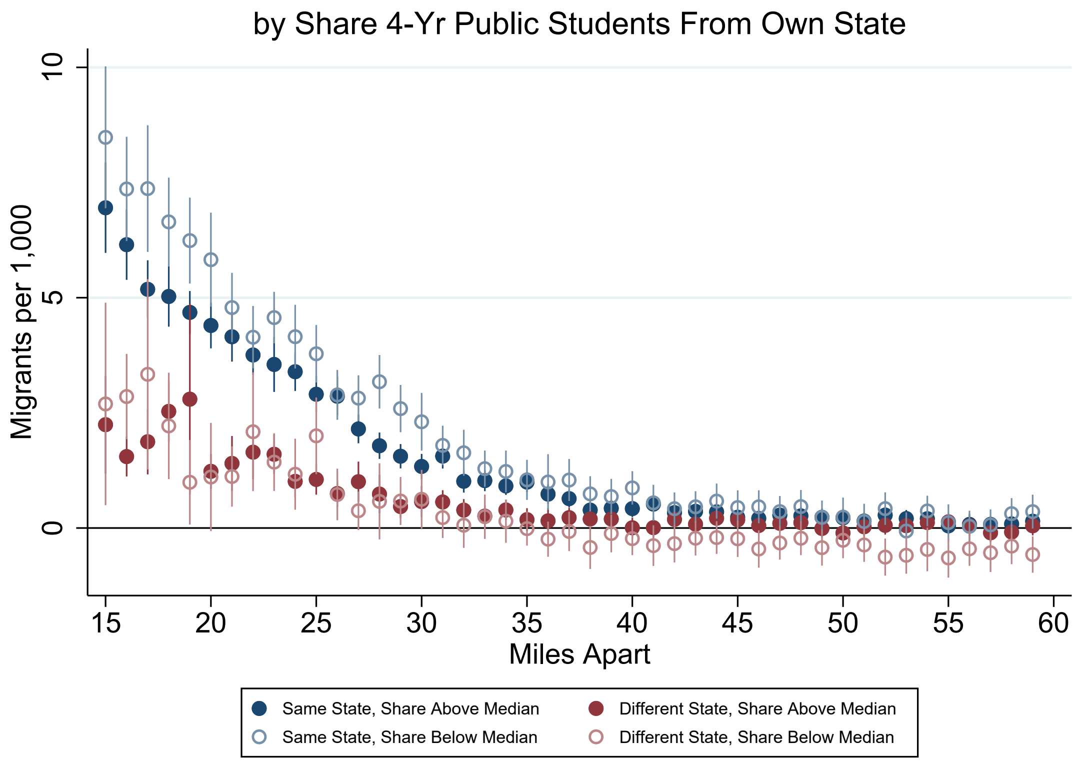
Figure A15: Role of Time Zone: Migration and Commuting across State Borders



NOTE: Coefficients from equation (20) are plotted, where the "higher" indicator measures if the counties are in the same time zone. Migration is plotted in the left panel, commuting in the right. There is no coefficient for county pairs in different states in different time zones at 15 or 19 miles because there are no county pairs in these bins. Controls include origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five-percent confidence intervals are provided.

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

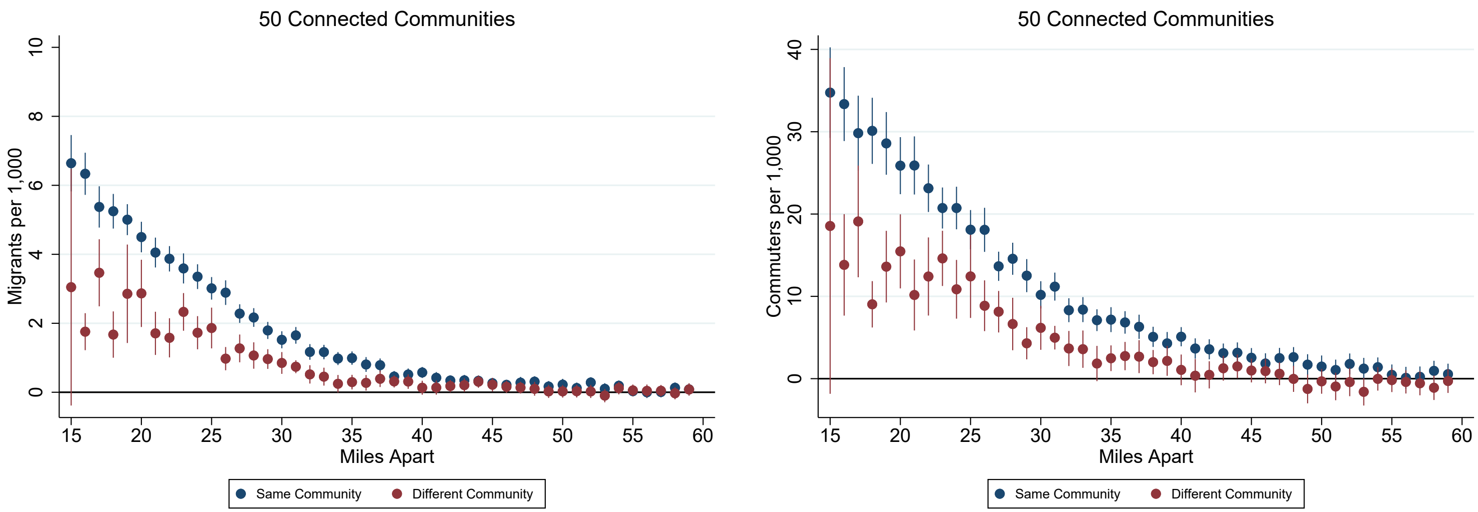
Figure A16: Identity from State Colleges: Migration by Interstate Connectivity of State Colleges



NOTE: Sample restricted to counties that are less than 60 miles from another county in a different state. Coefficients from equation (1), in which 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. Estimates control for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five percent confidence intervals are provided.

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

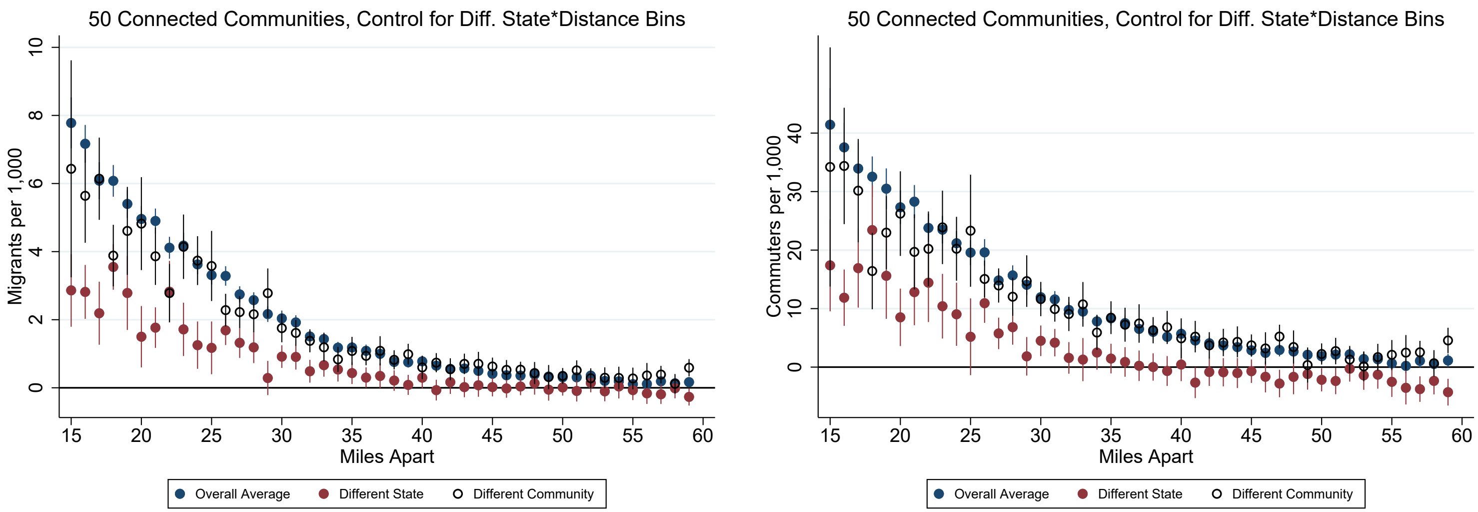
Figure A17: Impact of Pseudo Connected Community Borders on Migration and Commuting



NOTE: 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 (1) but includes the full set of connected-community-border-by-distance interactions rather than state-border-by-distance interactions. Estimates control for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five percent confidence intervals are provided.

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

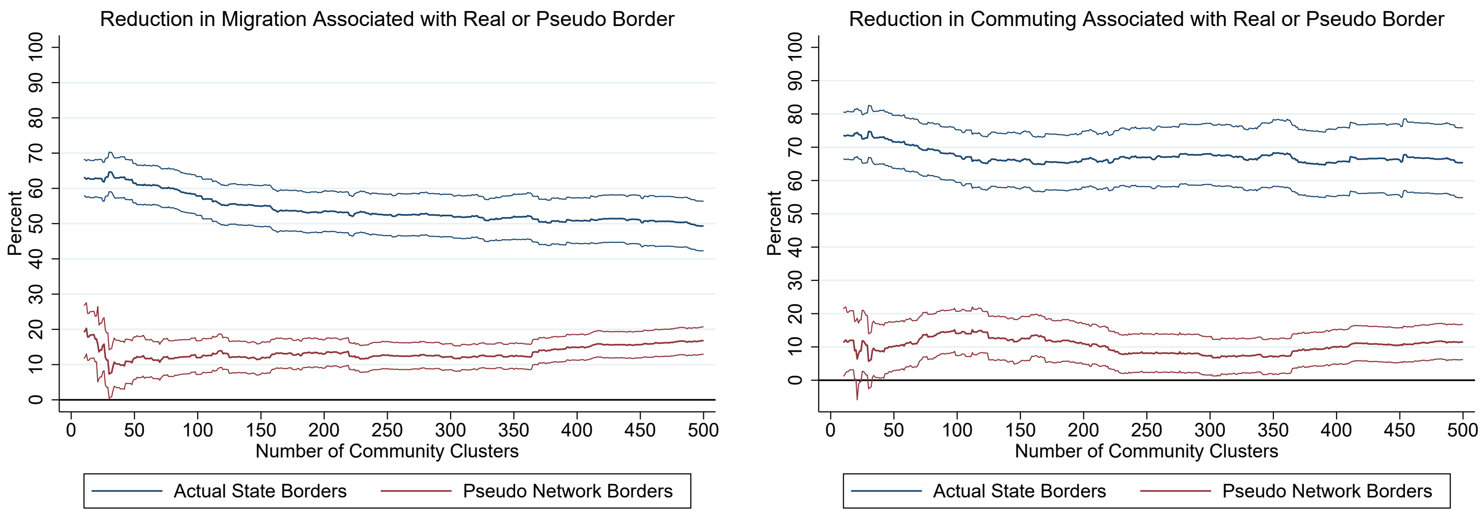
Figure A18: Horse Race Regression: Relative Importance of Physical State Borders versus Pseudo Connected Community Borders, Weighted by Connected Community Border Persistence



NOTE: 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 (1) but includes the full set of state-border-by-distance interactions and the connected-community-border-by-distance interactions. Estimates control for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Observations are weighted with the following weights $(\mu - 0.5)^2$, in which 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. Ninety-five percent confidence intervals are provided.

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

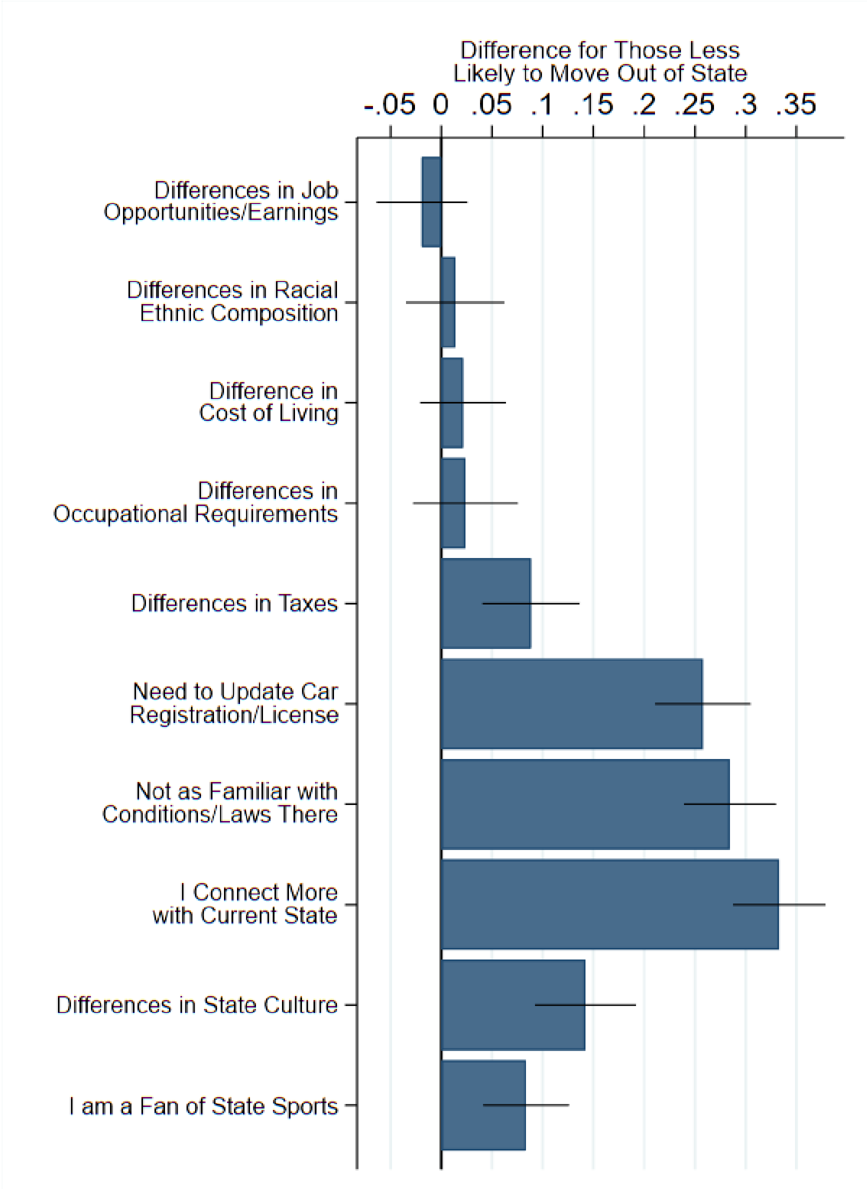
Figure A19: Horse Race Regression: Relative Importance of Physical State Borders versus Pseudo Connected Community Borders for Various Pre-specified Numbers of Connected Communities



NOTE: 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 associated with physical state borders or pseudo connected community borders from equation (1) 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. Estimates control for origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five percent confidence intervals are provided.

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

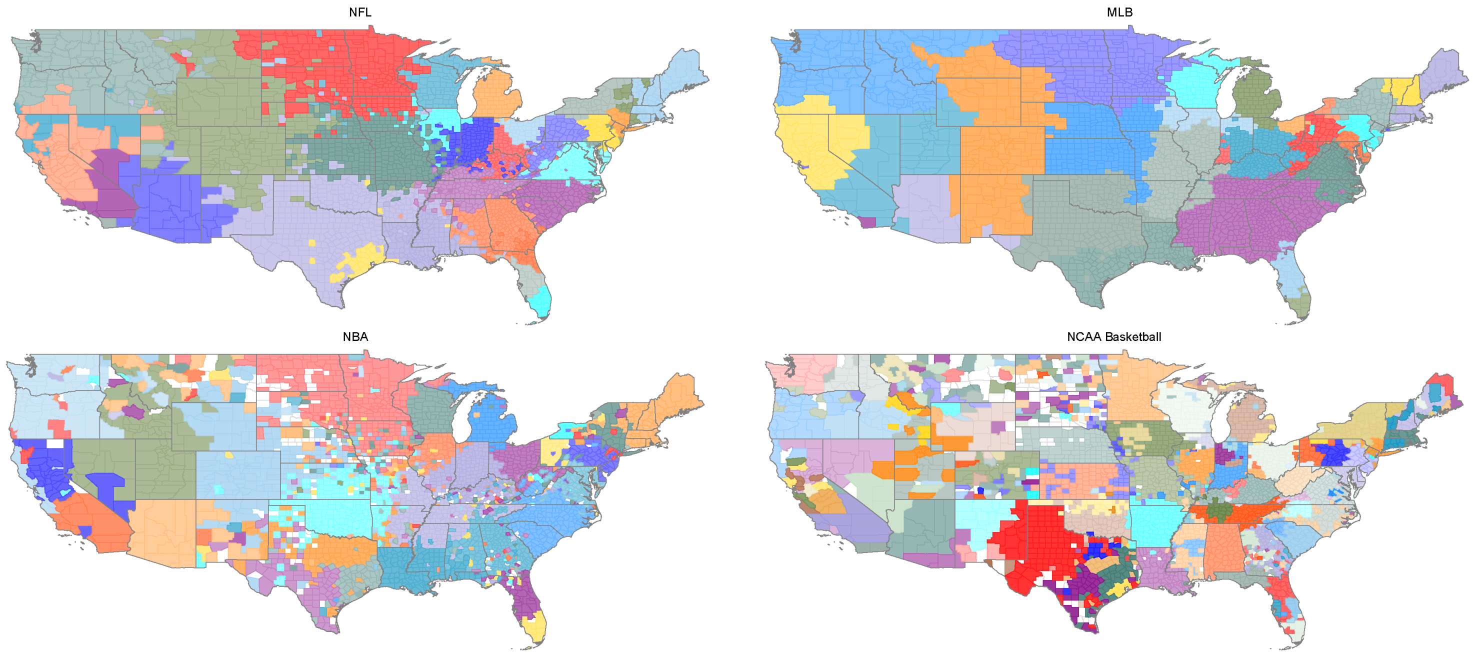
Figure A20: Experimental Evidence: Reasons that Influence Decision to Move Across State Borders, People Who Were Less-Likely to Move



NOTE: Sample consists of 1,806 Prolific survey respondents whose location in the Prolific database was reported as in the United States, but excluding the large Western states, Texas, and Rhode Island. These states are excluded as there are some places in the state where there is not either a viable option in state or out of state 100 miles away. This plots the difference in the share of respondents who report that the reason is "somewhat relevant" or "highly relevant" between individuals who were less likely to move to the neighboring state and individuals who were more likely to move to the neighboring state. 95-percent confidence intervals with robust standard errors are provided.

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

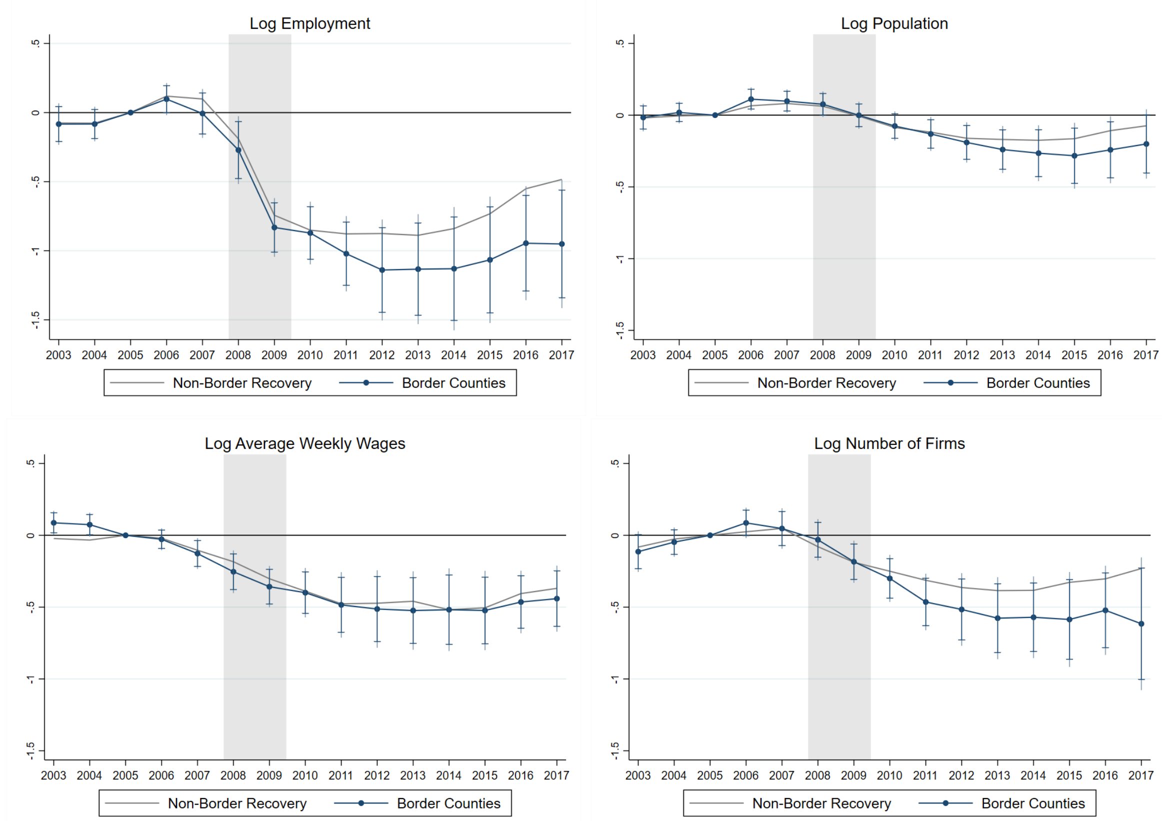
Figure A21: Professional and College Sport Ticket Sales Fandom Maps



NOTE: National Football League (NFL), Major League Baseball (MLB), National Basketball Association (NBA), and National Collegiate Athletic Association (NCAA) basketball fan location maps, as estimated by county level SeatGeek (NFL and MLB) and Vivid Seats (NBA and NCAA) ticket purchase data. White indicates there was not sufficient ticket purchase data to determine a primary team following. State borders are provided in gray.

SOURCE: Author's own calculations using SeatGeek NFL and MLB fandom maps and Vivid Seats NBA and NCAA fandom maps.

Figure A22: Impact of State Borders on Employment, Population, Wages, and Firms after the Great Recession



NOTE: Event study coefficients from equation (11) 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. The outcome is the within county deviation relative to the 2005 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, and 2003–2017 LODES.

For Online Publication

Appendix B. Additional Analysis Details

1.1 State Border versus Social Network Border Horse Race

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 in which 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 prespecifying a number of clusters, Connected Communities are constructed by grouping contiguous counties into clusters in which the social ties are stronger within the cluster than if a county was attached to a different, neighboring cluster. As seen in Figure 6, 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.[40] This would suggest that in some areas, strong social ties permeate state borders. If I treat Connected Communities as pseudo states and reestimate equation (1), but use Connected Community borders, we see that these pseudo borders have the same directional impact on migration and commuting (Appendix Figure A17). 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 psychic costs of leaving relations or information frictions, we would expect the cross-border drop in migration and commuting to load onto the Connected Community pseudo borders rather than the state borders. I modify equation (1) to include the full set of different state-by-distance interactions *and* different Connected-Community-by-distance interactions to test the explanatory power of the two in a horse race regression. As seen in Figure 6, most of the effect loads onto the physical state border, rather than the Connected Community borders. This pattern persists when accounting for the fact that Connected Community borders are potentially measured with error,[41] or using anywhere between 10 and 500 prespecified communities (Figure A19). 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 psychic costs of leaving relations and information friction channels suggest that 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 network strength and information frictions undoubtedly influence migration decisions and flows, they do not appear to explain the drop in mobility at state borders.

1.2 Online Experiment

I rely on an online survey experiment to establish the presence of home state bias. In this section I outline the survey in detail. This survey was approved by the BYU IRB (IRB#: IRB2022-243) and was pre-registered through the AEA RCT registry (AEARCTR-0009590).

[40] Fifty Connected Communities include one each in Alaska and Hawaii, which are not presented on the map.

[41] 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 in which 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) that 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 A18).

Using the Prolific professional survey respondent panel, I collected survey responses from 1,808 US respondents over the age of 18 who are told they are participating in a survey about moving decisions. The survey contained four main components. First, each respondent was asked a series of demographic questions including, their current state of residence, current zip code of residence, birth state, education level, employment status, household income (in $10,000 bins), if they have family that live near by, if they still have family that live in their birth state, the number of times they moved before their 18th birthday, the number of times they moved states before their 18th birthday, and their state of residence at age 18. I then ask an attention check question. In the full sample there were only eight people (0.44 percent) who answered the attention check in correctly.

I next provide each individual with a hypothetical scenario and ask them to provide the percent chance that they would move to the hypothetical opportunity. First, everyone sees the following screen:

> We will next describe a set of circumstances and would like you to think of how these circumstances would affect your moving plans over the next two years.
>
> Suppose that you (and your household) were offered the following opportunity to move over the next two years, and you had to decide whether to take the offer or continue living at your current location. The offer to move is contingent on your staying there for at least 3 years. If you own your home, assume that, if you were to move, you would be able to sell your current primary residence today and pay off your outstanding mortgage (if you have one).

This language is taken almost directly from a similar stated preference migration experiment by (Kosar et al., 2020). The next screen presents the hypothetical scenario where three things (listed in italics in brackets) are independently randomized as seen below

> Suppose you are offered an opportunity the the following characteristics:
>
> - Your household income increases by *[10%/20%/50%]*
> - This opportunity is about 100 miles away, but *[in the neighboring state/still in {current state}]*. Because of the distance, commuting does not make sense so you must move.
> - *[None of your family and current friends live nearby.]*
>
> Imagine you could have an exact copy of your current house and you would earn your income in a similar way as it is earned now. Suppose that the locations are otherwise identical in all other aspects to your current location, including the cost of housing.
>
> What is the percent chance you would choose to move to this neighborhood?[42]

Individuals will see different levels of income increases associated with the move (all with equal probability). They will also see that the destination is either in the current state they live in or in "the neighboring state" with equal probability. And with equal probability they will either observe the last bullet point making it explicit that there will be no family or current friends nearby or they will see nothing at all (only the first two bullet points). When looking at the proximity to family I randomize the salience of their presence rather than stating something like "some of your family and current friends live nearby" to avoid creating scenarios that are inconsistent with reality. If the individual does not have family and friends 100 miles away in the neighboring state then this hypothetical scenario is not consistent with reality. By randomizing these three components independently I can verify that the state border has a separate effect from the presence of social ties and I can compare the effects of these treatments to the effects of income to estimate people's willingness to pay to avoid leaving their state.

It is worth noting several aspects of this question. Individuals are asked to hold all else constant. They are explicitly told that they will have an exact copy of their current house and that they would earn their income in a similar way as it is earned now, to hold employment and job characteristics constant. They are also told that the locations are otherwise identical in all other aspects to the current location, including the cost of housing. In this experiment I am also to isolate the location relative to the state border from other factors that might differ in the previous county-to-county analysis.

[42] Much of this language is adopted from Kosar et al. (2020).

One aspect that is not varied is the distance of the destination, all opportunities are about 100 miles away. This maps back to the county-to-county analysis which looks at within state and cross-state migration, conditional on distance. The 100 mile distance was picked intentionally to make the hypothetical scenarios consistent with the real world so that there are real places both within the state and in a neighboring state that is approximately 100 miles away. Even the 100 mile distance creates scenarios that are not realistic in some states. For example, there are places in Central Texas where 100 miles away only leaves opportunities in the same state. Similarly, in Rhode Island it is not possible to be 100 miles away and still in Rhode Island. For this reason, I exclude Alaska, Hawaii, the Western states (Washington, Oregon, California, Idaho, Nevada, Arizona, Utah, Montana, Wyoming, Colorado, New Mexico), Texas, and Rhode Island.[43] Using the individual's reported zip code of residence I can also verify that I did not present scenarios inconsistent with reality. All but 20 respondents provided a zip code that matched to a database of US zip codes. Of those with a viable zip code, only 35 live in a zip code where the population centroid is less than 100 miles to all parts of the state border and only 7 live in a zip code where the population centroid is more than 100 miles to all parts of the state border. For many of these exceptions, the border is still close. For example, for 14 of the 35 respondents who live in zip codes where the population centroid is less than 100 miles to all parts of the state border, they are at least 85 miles away, suggestion the "about 100 miles" is still accurate.

The third component of the survey replicates the hypothetical scenario presented above with one distinct difference. The scenario is presented as the exact same except the "in the neighboring state/still in current state" treatment is reversed. As such, each individual observes two experimental settings where everything is identical except for whether or not the move is within state or across state lines. This allows me to look at within person differences associated with the state border holding everything else constant.

Finally, the last portion of the survey tries to understand mechanisms and motivations. Using the responses from the two hypothetical opportunities I next ask, "You said you were [less/more] likely to consider a move that is just as far away, but in the neighboring state. How relevant are each of the following reasons to that decision?" They are they presented with the following list of reasons where they can indicate "Not relevant", "Somewhat relevant", or "Highly relevant":

- Differences in state taxes
- Differences in the cost of living
- Differences in occupation requirements for your job (licensing, pensions, etc.)
- Differences in job opportunities and earning potential
- Differences in racial/ethnic composition of the population
- I would have to update things like car registration or driver's license
- I am not as familiar with living conditions or laws in neighboring states
- I connect with {current state} more than I do with neighboring states
- Differences in state culture
- I am a fan of {current state}'s sports teams (ex: NFL, NBA, MLB, or college sports)

These reasons are listed in random order for each individual. These reasons are meant to identify some of the most compelling potential reasons for a state border discontinuity in mobility. It includes differences in local characteristics (job opportunities, earnings, racial composition, cost of living), adjustment costs (updating car registration), and other cost differences (taxes, occupation requirements). It also includes information frictions (not as familiar with conditions/laws). It then includes three questions related to home state tie or bias, "I connect with my current state more than others", "Differences in state culture", and "I

[43] This selection criteria is presented to Prolific, who then solicited survey respondents based on their state of residence listed in their database. This information is not updated instantaneously. As such, there are 17 respondents who report their current state of residence is in one of the states listed above. I do not exclude these individuals from the baseline analysis, but results are robust to their exclusion.

am a fan of my state's sports teams". From this, I can see what reasons people cite as the most relevant to their decision to move across state lines.[44]

I then ask individuals which state they would call their home state, and allow them to explain why. In the sample 73 percent of respondents list their home state as their state of birth. When asked why they consider that state their home state there is a myriad of reasons, but the most common reason is related to be being born or raised in there (about 48 percent). With this four components I am able to estimate how state borders affect decisions to move, explore how this might vary for people depending on whether or not they are living in their home state, and see what reasons they believe are relevant to their stated decisions.

With this experimental manipulation, I estimate how each of these factors affect the reported percent chance of moving as follows

$$\begin{aligned} \textit{Percent Move}_i = \beta_1 \textit{Different State}_i + \beta_2 \textit{No Family/Friends Nearby}_i \\ + \beta_3 \textit{Increase in Income}_i + \varepsilon_i \end{aligned} \tag{12}$$

The coefficient β_1 will provide an estimate of how the destination being across state lines affects the average reported percent chance of moving. Because the presence of family and friends are randomized separately I can isolate any effect of the state border separate from social ties. Because respondents are asked to hold all other aspects identical, β_1 is capturing the effect of the state border. Robust standard errors will be estimated.

If this is truly a home state bias, we would expect the cross-state border treatment to be concentrated among people living in their home state (see equations (4)-(6)). As such, I will also estimate the following specification to allow the effects to differ if people currently reside in their home state

$$\begin{aligned} \textit{Percent Move}_i = \beta_1 \textit{Different State}_i + \beta_2 \textit{No Family/Friends Nearby}_i \\ + \beta_3 \textit{Increase in Income}_i + \beta_4 \textit{Different State} * \textit{In Home State}_i + \beta_5 \textit{In Home State}_i + \varepsilon_i \end{aligned} \tag{13}$$

The coefficient β_4 will represent the gap in reported migration probabilities associated with an out of state move among people currently living in their home state. The coefficient β_1 will represent the difference for people living outside of their home state. I will measure home state in two ways. First, building on the evidence in the ACS I will see if people reside in their state of birth. Sixty three percent of the survey sample live in their birth state. Second, at the end of the survey I ask individuals what state they would call their home state and why. Eighty percent of the survey sample reside in their home state. When asked why this is their home state, nearly 48 percent of the sample said something about being born there or living there all of their life.

With both of experimental scenarios I can look within person at how the state border affects the propensity to move when everything else is theoretically held constant. On the individual panel, with two observations per respondent I estimate

$$\textit{Percent Move}_i = \beta_1 \textit{Different State}_i + \gamma_i + \varepsilon_i \tag{14}$$

The coefficient β_1 indicates how much lower the propensity to move is in the scenario that is across state lines. Individual fixed effects are included to make this a within person comparison and standard errors are corrected for clustering at the individual level. Because the size of the income increase and the presence of family/friends is unchanged within person, these treatments are colinear with the individual fixed effects. I can also explore how much of this gap is driven by people living in their home state by estimating the following

$$\textit{Percent Move}_i = \beta_1 \textit{Different State}_i + \beta_2 \textit{Different State} * \textit{In Home State}_i + \gamma_i + \varepsilon_i \tag{15}$$

The β_2 coefficient allows the size of the border penalty to vary for people currently residing in their home state. As above, I will use either the state of birth or the self-reported home state as the individual's home

[44] Notice, I do not ask about proximity to family or friends. That is because in the set up I have held that fixed.

state.

When examining reasons for being less/more likely to move across state lines I collapse the relevant measure into a binary that equals one if the individual listed that the reason was "Somewhat relevant" or "Highly relevant". I then look at differences based on whether or not the individual is living in their home state. I estimate two specifications using birth state and self-reported home state to measure home state. I then estimate the bi-variate regression looking at if they report that the reason is relevant on being in their home state, with robust standard errors. I also look at individuals who reported that they were less likely to move when the destination was in a different state (27 percent) relative to those who were equally likely (59 percent) and those who were more likely to move to a different state (14 percent).

As seen in Appendix Table A4, the different state and same state treatment samples are balanced across observable dimensions and similar to the general population. The sample is 50 percent male, 80 percent White, 6-8 percent Black, 4-7 percent Asian, and 6-7 percent Other race. The sample population is more White than the general population and Black and Hispanic minorities are less represented. The sample is young, with an average age about about 37.5, and is also more educated than the general population. In the sample 63 percent of individuals are in their birth state and 80 percent are in their home state. It took respondents about 6 minutes on average to complete the survey (the median was about 4 minutes).[45]

1.3 Empirical Evidence Supporting The Home State Bias Mechanism

1.3.1 Gallup Poll State Preference

If the drop in mobility at state borders is driven by a state identity, we would expect the drop to be larger in places with a stronger state identity. In a 2013 Gallup poll, approximately 600 adults from each state were asked whether or not they would describe the state where they live as "the best," "one of the best," or "the worst" state to live in.[46] The share of residents who felt their state was "the best" varied across states. For example, 28 percent of Texas residents felt that Texas was "the best" state to live in, while only 3 percent of Rhode Island residents felt their state was "the best" (see Appendix Table A7 for a full list). Since this measure is fixed across origin county, it is directly absorbed in origin county fixed effects. However, I can estimate how this measure interacts with the impact of state borders on county-to-county migration and commute flows by modifying equation (1) as follows:

$$Y_{od} = \beta_1 \textit{Diff. State} + \beta_2 \textit{Diff. State*Share Feel State is “the Best”}_s + \sum_{b=15}^{59} \gamma_b (\textit{b Miles Apart}) + X_{od}\Gamma + \phi_o + \delta_d + \varepsilon_{od} \quad (16)$$

In this regression, I still flexibly control for distance, but only the average effect of being in a different state for counties 15 to 60 miles apart is estimated. This parametric restriction allows for more precision than mile-by-mile estimates. I then interact state borders with the share of residents who felt their state was "the best" to test whether the state border has more or less predictive power in states that appear to have a stronger state identity.

Consistent with the border penalty in Figure 1, being across a state border is associated with 0.6 fewer migrants and 5.3 fewer commuters per 1,000 residents (columns 1 and 3 of Table A8). When we interact this with state identity, we see that the state border is not associated with any change in migration for counties in states with no state identity (e.g., 0 percent of respondents think their state is "the best"). However, a 10 percentage point increase in the number of respondents who think their state is "the best" is associated with

[45]Survey respondents were paid for participation. Initial estimates suggested that it would take at least 10 minutes to complete so individuals were offered $2 to complete it ($12/hour in expectation). In a small pilot sample of 60 completion times were much quicker (around 4 minute median time) so for the rest of the sample they were told the survey would take about 5 minutes and were offered $1 (still $12/hour in expectation).

[46]Survey results were released here: `https://news.gallup.com/poll/168653/montanans-alaskans-say-states-among-top-places-live.aspx`.

0.9 fewer migrants per 1,000 residents to cross-border counties. For commuting, the direct effect of state borders is smaller when interacting with state identity but is still significant, and the strength of the origin state identity leads to significant reductions in commuters across state borders. This descriptive evidence is consistent with state identity contributing to the drop in mobility at state borders.

1.3.2 The Location of Profession and College Sports' Fans

State preference and home bias might show up in other behavior as well. Using SeatGeek and Vivid Seats ticket sales data I create a county level mapping of the most popular team by sport for NFL, MLB, NBA, and college basketball. Profession and college sports team fan bases also tend to follow state lines (Appendix Figure A21). In fact, being separated by state border is highly predictive of being fans of different sports teams. Among neighboring counties, I estimate the following regression

$$\textit{Different Team}_{od} = \beta_1 \textit{State Border Between Counties}_{od} + \delta_o + \gamma_d + \varepsilon_{od} \tag{17}$$

Among neighboring counties, I test to see if being separated by a state border is predictive of rooting for a different professional team. I include origin county and destination county fixed effects to control for fixed characteristics of the two locations. Standard errors are corrected for clustering at the origin county level. This specification allows me to test if there is a difference in which team counties root for if they are in the same state versus if they are across the state border. Separation by a state border is highly predictive of separation by a team fan border for the NFL, MLB, NBA, and particularly NCAA college basketball, where teams are more closely tied to states (e.g., University of Michigan, the Ohio State) (Appendix Table A9). People are more likely to root for the same team as others within their state than to root for the team that people across state lines are rooting for. This pattern is consistent with a home state bias that makes people feel more unified and connected to things associated with their state.[47]

1.3.3 Pew Research Poll State Identity

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, the 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 whether this identity is associated with the stated and revealed preference about moving, independent of other more studied phenomena like personal ties (Zabek, 2020) and the draw of amenities (Kosar et al., 2020).

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 "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 identity or say they identify with their birth state.

Individuals who had never lived away from their local community were asked separate questions. Nonmovers were asked to identify whether various factors were a "major reason," "minor reason," or not a reason they have not moved. In particular, nonmovers 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 nonmovers as

[47] Alternative measures using Facebook data and looking at college football show an even stronger tie between state and sports fan borders (https://www.nytimes.com/interactive/2014/10/03/upshot/ncaa-football-map.html).

exhibiting a birth state identity if they listed one of the three identity factors as a "major reason" they have not moved. Overall, 59.2 percent of movers and 81.4 percent of nonmovers are classified as having a birth state identity, for an overall average of 68 percent.

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

$$Y_{is} = \beta \textit{Birth State Identity}_i + X_i\Gamma + \delta_s + \varepsilon_i \tag{18}$$

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 for 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 that person lives where he or she currently does, to verify that state identity has an independent effect and is not simply colinear with familial or amenity ties. Second, I interact the birth-state identity measure, as well as the family and amenity ties measure, with an indicator that equals 1 if the individual currently resides in his or her birth state. Consistent with the endowment-effect model, I can test if birth-state identity impacts migration attitudes differently when someone currently lives in his or her birth state. This is estimated as

$$\begin{aligned} Y_{is} = \beta_1 \textit{Birth State Identity}_i &+ \beta_2 \textit{Birth State Identity}_i * \textit{In Birth State}_i \\ &+ \beta_3 \textit{Family Ties}_i + \beta_4 \textit{Family Times}_i * \textit{In Birth State}_i \\ &+ \beta_5 \textit{Amenity Ties}_i + \beta_6 \textit{Amenity Ties}_i * \textit{In Birth State}_i \\ &+ \beta_7 \textit{In Birth State}_i + X_i\Gamma + \delta_s + \varepsilon_i. \end{aligned} \tag{19}$$

Having a birth-state identity is associated with differences in migration history and stated preferences (Table A10). People with a birth preference are 35.3 percentage points less likely to ever have 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. If I control for whether an individual reports that the reason for being where they are is due to family ties or local amenities, the impact of birth-state identity on ever leaving one's birth state is almost the same, at 32.8 percentage points, suggesting the effect of birth-state identity is not simply colinearity.

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 one's 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 that they would move, but having a birth-state identity and residing in one's birth state is associated with an 8.4–9.0 percentage point reduction in being willing to move. This is consistent with a home bias that makes out-of-state moves away from the home state more costly, relative to other moves. 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, by imposing additional costs on cross-border moves in the migration choice model.

For Online Publication

Appendix C. Robustness to Local Characteristics and Policies

1.1 Controlling for Differences in Local Characteristics

Discrete changes in local amenities at state borders could result in discrete differences in aggregate migration propensities. Both exogenous (geographic features) and endogenous (economic and social features) amenities could matter (Redding and Rossi-Hansberg, 2017). Unless borders are determined by geographic features (such as a river) it is unlikely that geographic amenities such as rainfall or winter temperatures will change discretely at state borders. As seen in Figure A5, the use of rivers as borders does not explain the state border penalty, but because of both selection and policy, economic and social features might discretely change at state borders. Differences in local characteristics between an origin and destination could impose either bidirectional mobility costs or asymmetric directional effects. For instance, differences in the industry composition between counties A and B could make it more costly for individuals to adjust from A to B and from B to A (suggesting absolute differences matter), while differences in real home prices between A and B could affect migration asymmetrically (suggesting raw differences matter).

In Figures C1 and C2 I document the extent to which local characteristics diverge as we approach the state border. To do this I estimate equation (1) with origin and destination fixed effects, where the outcome is the absolute difference in a given characteristic between the origin and destination county. This will capture how dis-similar places get as we approach the state border. For each county pair there are two observations, so by construction, raw differences between the origin and destination by distance will be mean zero. I examine absolute origin/destination differences in measures that are frequently used as controls (or outcomes) in many labor market and demographic studies. I examine labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments); industry shares (shares in natural resources and mining, construction, manufacturing, trade, information, finance, professional, education and health, hospitality, public sector, and all others); demographics (total population, population density, 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 (January average temperature, January average sunlight, July average temperature, July average humidity, and the USDA natural amenities scale); the 2016 presidential Republican vote share; the county housing price index, converted to dollars using the median house value from 2000; and the county average standardized math and reading/language arts test score for third through eighth grade (averaged over 2008–2017), obtained from SEDA (Fahle et al., 2021).[48] Unlike migration and commute rates, the within-state and cross-state point estimates are overlapping and not statistically distinguishable. At a given distance, the average absolute difference in characteristics is no different between counties in the same state and counties across state lines, suggesting that local amenities do no discretely change at the state border. There are a few exceptions. As seen in Figure C1 there is a significant gap between unemployment rates, average math test scores, and average reading test scores between same-state and cross-state county pairs suggesting these measures do not converge as we approach the state border. Unlike mobility, these gaps are more or less constant as distance increases. As seen in Figures 1, C3, and C4 controlling for observable absolute and raw differences in these characteristics does not eliminate the discontinuity in migration or commuting at the state border.

I explore this further in Figure C5. If I estimate equation (1) with origin and destination fixed effects where the outcome is the residualized migration rate (commute rate) accounting for these absolute differences the pattern is virtually unchanged, suggesting the gap is not explained by absolute differences in local characteristics. Furthermore, if I use these absolute differences and one-mile distance bins to predict origin/destination migration rates (commute rates), and then estimate equation (1) with origin and destination fixed effects, where the outcome is the predicted migration rate (commute rate) there is no mobility gap associated with the state border (also Figure C5). The state border mobility gap is not explained by theoretical, discrete changes in local characteristic at state borders.

One might be inclined to control for raw differences between the origin and destination if we think there

[48] These are the same measures controlled for in Figure 1 and throughout the paper.

is asymmetry (e.g., people move towards lower unemployment areas and away from higher unemployment areas). However, since there are two observations for each county pair (one where the county is the origin, one where it is the destination) in the sample, there will be symmetry in the matrix of origin/destination variables and the origin and destination fixed effects fully span the origin/destination differences, making them collinear. In Figure C3 I show that the pattern is virtually identical when I control for raw differences in origin and destination characteristics instead of including absolute differences and origin and destination fixed effects. In Figure C4 I show how each absolute and raw difference affects the gap in mobility associated with the state border independently.

1.2 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 0.0 and 13.3 percent (Loughead, 2020), and there are also differences in sales tax and corporate tax rates across states. Moretti and Wilson (2017) find that high performing scientists' locations are sensitive to state tax differences, suggesting that differences in state taxation could explain the pattern around state borders.

As noted above, differences in state taxes could affect flows asymmetrically. The drop in mobility at state borders could be masking heterogeneity between low-tax to high-tax pairs and high-tax to low-tax pairs. Perhaps cross-state flows are only lower when considering county pairs where the tax burden is higher in the destination than it is in the origin and there is no border penalty when considering flows from high tax origins to lower tax destinations. By estimating the following equation I can exploit this asymmetric treatment and determine if the border penalty is explained by differences in state tax policy.

$$Y_{od} = \sum_{b=15}^{59} \beta_b(\textit{Higher*Diff. State*b Miles Apart}) + \theta_b(\textit{Lower*Diff. State*b Miles Apart}) \\ + \gamma_b(\textit{b Miles Apart}) + X_{od}\Gamma + \phi_o + \delta_d + \varepsilon_{od} \quad (20)$$

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 county is less than or equal to the burden at the origin. The β_b represents the mobility border penalty between counties where the destination's tax burden is higher, while the θ_b represents the mobility border penalty between counties where the destination's tax burden is less than or equal to the origin county. Both of these are relative to mobility between counties in the same state (where state taxes are by definition the same), so there are three mutually exclusive groups. If the state border penalty is driven by differences in state tax policy, we would expect the θ_b to be close to zero and insignificant and the β_b to be large, negative and significant.

In Figure C6, 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 differs 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. The patterns for high-to-low and low-to-high flows are not statistically distinguishable. The patterns are similar for states' sales tax rates, shown in the middle column. The border penalty is smaller for commuting to counties in lower-sales-tax states, 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).

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, since the difference in tax burdens varies across origin destination pairs and throughout the income distribution, some subgroups would face smaller tax burdens, while other groups would experience a tax increase. Across various family types and multiple income levels there are no systematic differences in the mobility gap between low-to-high and high-to-low tax county pairs (Figures C7, C9, C8). An examination of household-specific tax burdens in the ACS microdata also suggest state taxes do not explain the gap in mobility across state lines (see Figure C10 and Appendix B for details). The state border penalty also persists across state pairs with state tax reciprocity agreements (Figure C11).[49] Although some groups, like star scientists (Moretti and Wilson, 2017), might be sensitive to tax burden differences, There is no consistent evidence that differences in state taxation drive, or mediate, the aggregate drop in mobility associated with state borders.

1.2.1 Household-Specific State Income Tax Burdens on Migration Behavior

I can also exploit household-specific tax burdens associated with a potential move for family units in the 2012–2017 ACS microdata. I use TAXSIM to calculate their household-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.[50] I then calculate the percentage change in total federal and state income tax burden between the original state and the other state in the commuting zone.[51] In Appendix Figure C10, 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. Instead, there is no significant relationship between the change in tax burden and the out-of-state migration share.

1.3 State Transfer Policy and "Welfare Migration"

State transfer programs also differ, leading to discontinuities in potential low-income benefits at state lines. There is a long, mixed literature exploring interstate migration responses to state transfer policy , or "welfare migration" (Borjas, 1999; Gelbach, 2004; Goodman, 2017; Kaestner et al., 2003; McCauley, 2019; McKinnish, 2005, 2007). Like taxes, the drop in mobility at state borders could theoretically be driven by county pairs where benefit generosity is lower in the destination than in the origin, leading to asymmetric mobility effects. To see if transfer policy is causing the border penalty I re-estimate equation (20) exploiting transfer policy asymmetry.

Based on the existing work, I focus on several state policies that affect low-income households and vary across state lines: ACA medicaid expansions and Earned Income Tax Credit (EITC) state supplements, and the effective state or national minimum wage. For each of these policies, I estimate a model similar to equation (20), but $Higher$ and $Lower$ now reference the benefit generosity in the destination state relative to the origin state. These estimates are plotted in Figure C12. For all three policies, cross-border migration was significantly lower than within-state migration but, the flows between low-to-high and high-to-low benefit states are not significantly different, suggesting the discontinuity in migration across state borders is not driven by differences in state transfer policy. This is also true of Temporary Aid for Needy Families (TANF) spending and state-to-state differences in per-pupil public education spending (Figure C13).

[49]Even if tax rates are the same, filing state taxes across multiple states could impose another burden, potentially reducing mobility. Some states have state tax reciprocity agreements. For example, residents of Maryland who work in Virginia or D.C. will have Maryland state taxes withheld and thus only need to file taxes in Maryland (see data Appendix for a full list of tax reciprocity agreements). As seen in Figure C11, the affect of state borders on migration and commuting is similar regardless of whether the origin and destination states have tax reciprocity agreements.

[50]For commuting zones with multiple states, I compare the tax burden in the origin state to the average tax burden in the other states. The pattern is similar if I instead compare the maximum or minimum tax burden in the other states.

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

1.4 Total Effect of State Policy

It is possible that isolated tax and transfer policy differences have a minor impact on cross border migration, but collectively explain the phenomenon. In Figure C14 I explore this in two ways. In the top panel, I control for the absolute difference in all of the tax and transfer policies considered in the previous two sections in addition to the baseline set of absolute difference controls. This has virtually no effect on the cross-state mobility gap. In the bottom panel, I take all of these same policies, identify origin-destination pairs where we would predict the flow to be lower along each of these dimensions (i.e., destination has higher taxes or lower benefits than the origin) and include all of these *Lower* interactions, as well as the direct effect of being a different state. As such, the direct effect of being in a different state will capture the flows with the most favorable policy conditions. If anything the residual effect of state borders, which captures flows for pairs with the least policy obstacles, grows larger. The effect of state borders on mobility does not appear to be driven by differences in state policy.

1.5 Occupational Licensing

Another pecuniary moving cost that applies specifically to cross-state moves is differences in state occupational regulation. Some states require licenses, certificates, or education/training requirements for someone to perform certain tasks or occupations.[52] In many cases, these requirements do not include state reciprocity. Johnson and Kleiner (2020) show that among 22 universally licensed occupations, 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 time trends in interstate migration.

There is no comprehensive database of annual, state-level occupational licensing requirements. Previous research has had to rely on self-collected records state-by-state for available occupations (Carollo, 2020). Furthermore, states often 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 Current Population Survey (CPS).[53] 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 individual's occupation is licensed by the government if he or she answers yes to the first and second questions. I collapse the CPS data to the state-by-year-by-four-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 restrictive measure of occupational licensing, where 25 percent or more of the workers in the cell reported a government-issued license.[54]

Using the occupation mapping from the CPS, I identify whether individuals in the ACS microdata are in occupations that are either licensed or unlicensed by their state. Then, following the method outlined in section 3.5, I estimate a version of equation (1) at the MIGPUMA level separately for individuals in licensed and unlicensed occupations. These coefficients are plotted in Figure C15. For both migration and commuting there are no discernable differences in the state border penalty between people in licensed and unlicensed occupations. As noted above, although changes in occupational licensure might affect cross-state flows, cross-sectional differences in licensure do not explain the state border mobility penalty.[55] Regressions comparing out-of-state migration and commuting between individuals in the same occupation, but in licensed

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

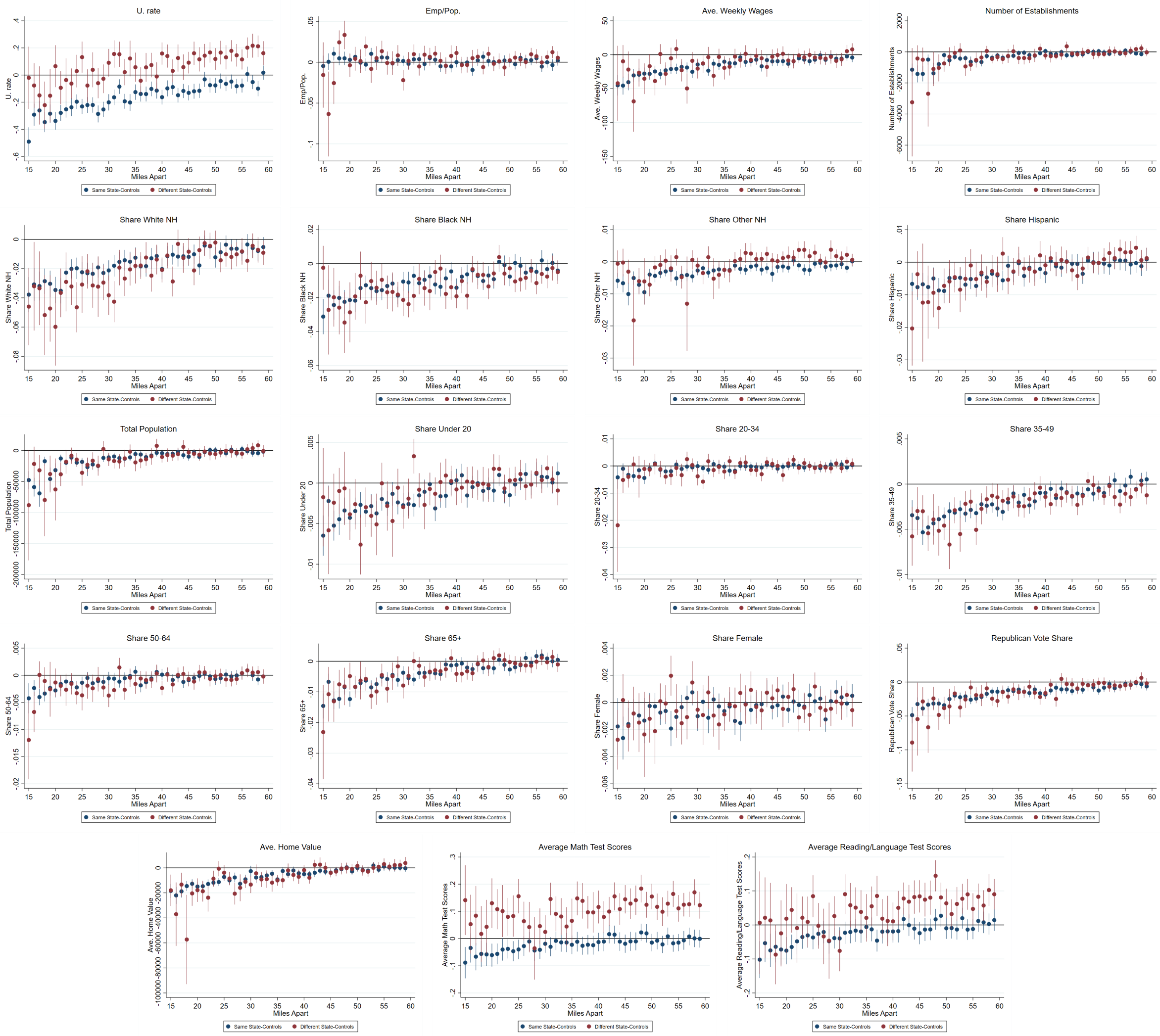
[53] Results are similar if I instead use occupational licenses as captured by Johnson and Kleiner (2020) or the National Council of State Legislatures.

[54] I also consider a less restrictive measure where at least 10 percent of workers report a government-issued license and find similar patterns.

[55] This result differs from the result in Johnson and Kleiner (2020), since they are only focusing on individuals who move over 50 miles.

or unlicensed states also do not provide any evidence that occupational licensing drives the state border mobility penalty (Table A3).

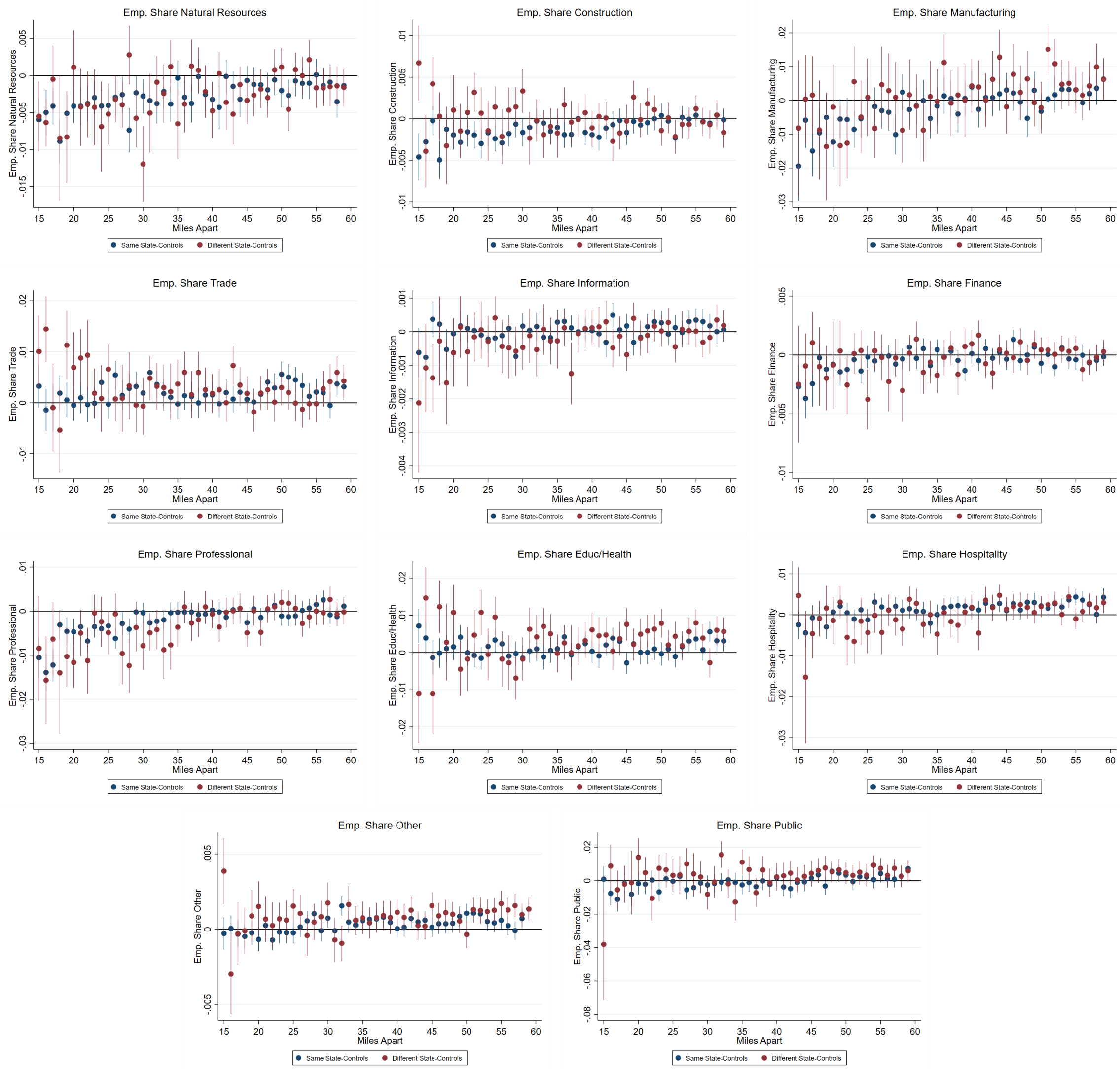
Figure C1: Role of Differences in Utility: Impact of State Borders on Local Characteristics



NOTE: Coefficients from equation (1) are plotted where the outcome is the absolute difference in the specified characteristic between the origin and destination. Estimation controls for origin and destination fixed effects. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the QCEW 2017, SEER 2017 data, NCSL 2016 vote data, FHFA HPI 2017 data, and SEDA 2008–2017 test score data.

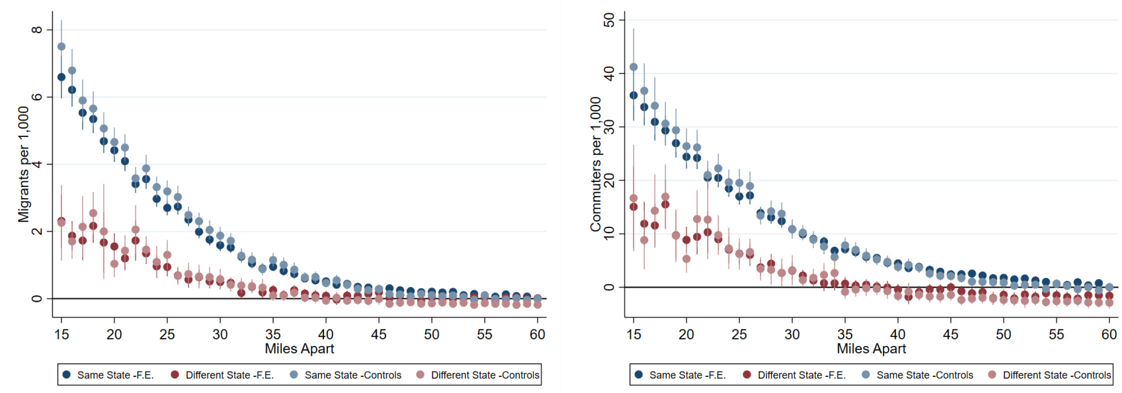
Figure C2: Role of Differences in Utility: Impact of State Borders on Local Industry Composition



NOTE: Coefficients from equation (1) are plotted where the outcome is the absolute difference in the specified industry share between the origin and destination. Estimation controls for origin and destination fixed effects. Ninety-five-percent confidence intervals are provided.

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

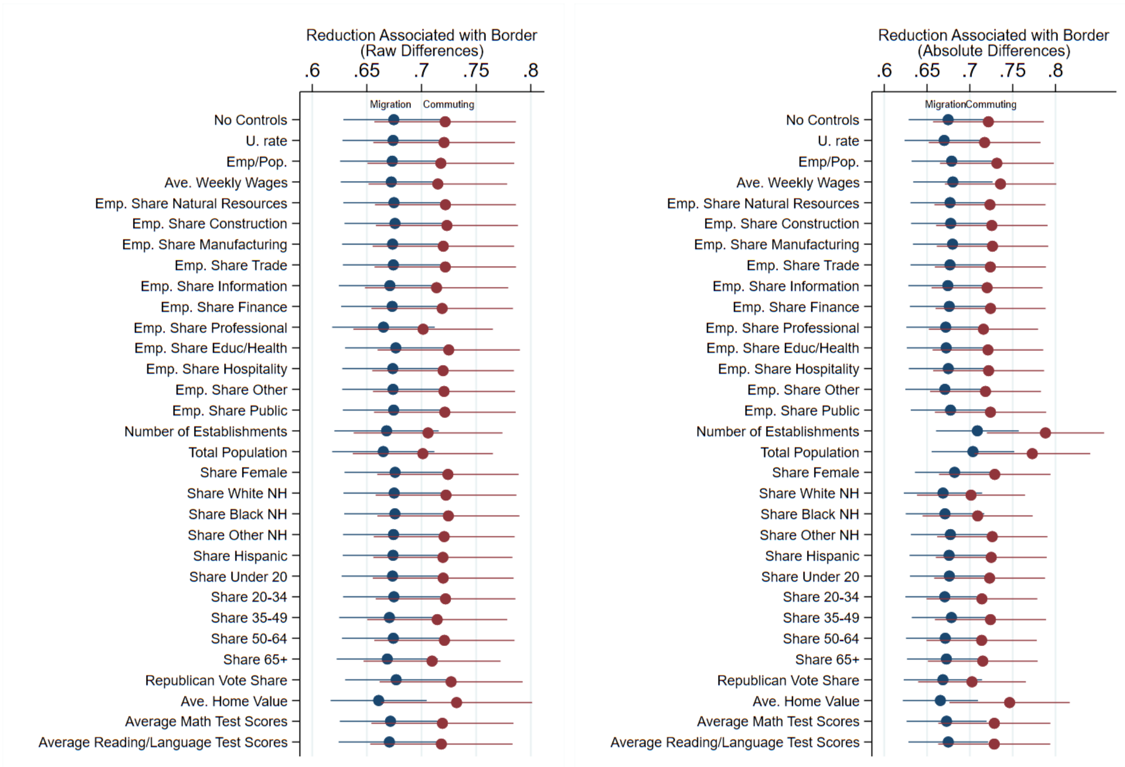
Figure C3: County-to-County Migration and Commute Rates by Distance for Same-State and Different-State County Pairs, Controlling for Raw Origin/Destination Differences



NOTE: The reduction in migration (blue) and commuting (red) associated with state borders when controlling for raw differences in origin/destination characteristics separately. Controls include, 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 of 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, differences in the county housing price index converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. 95 percent confidence intervals, based on county or origin clustering, are provided.

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

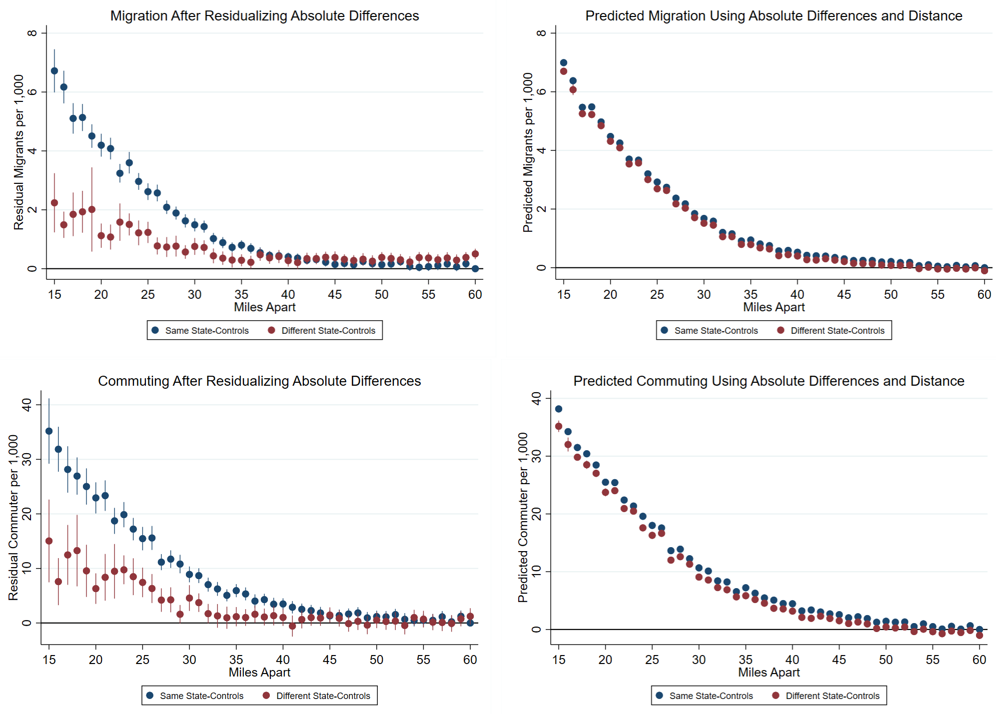
Figure C4: County-to-County Migration and Commute Rates by Distance for Same-State and Different-State County Pairs, Controlling for Each Origin/Destination Difference Separately



NOTE: The reduction in migration (blue) and commuting (red) associated with state borders when controlling for each difference in origin/destination characteristics separately. The panel on the left includes raw differences between the origin and destination. The panel on the right includes absolute differences. Controls include, 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 of 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, differences in the county housing price index converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. 95 percent confidence intervals, based on county or origin clustering, are provided.

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

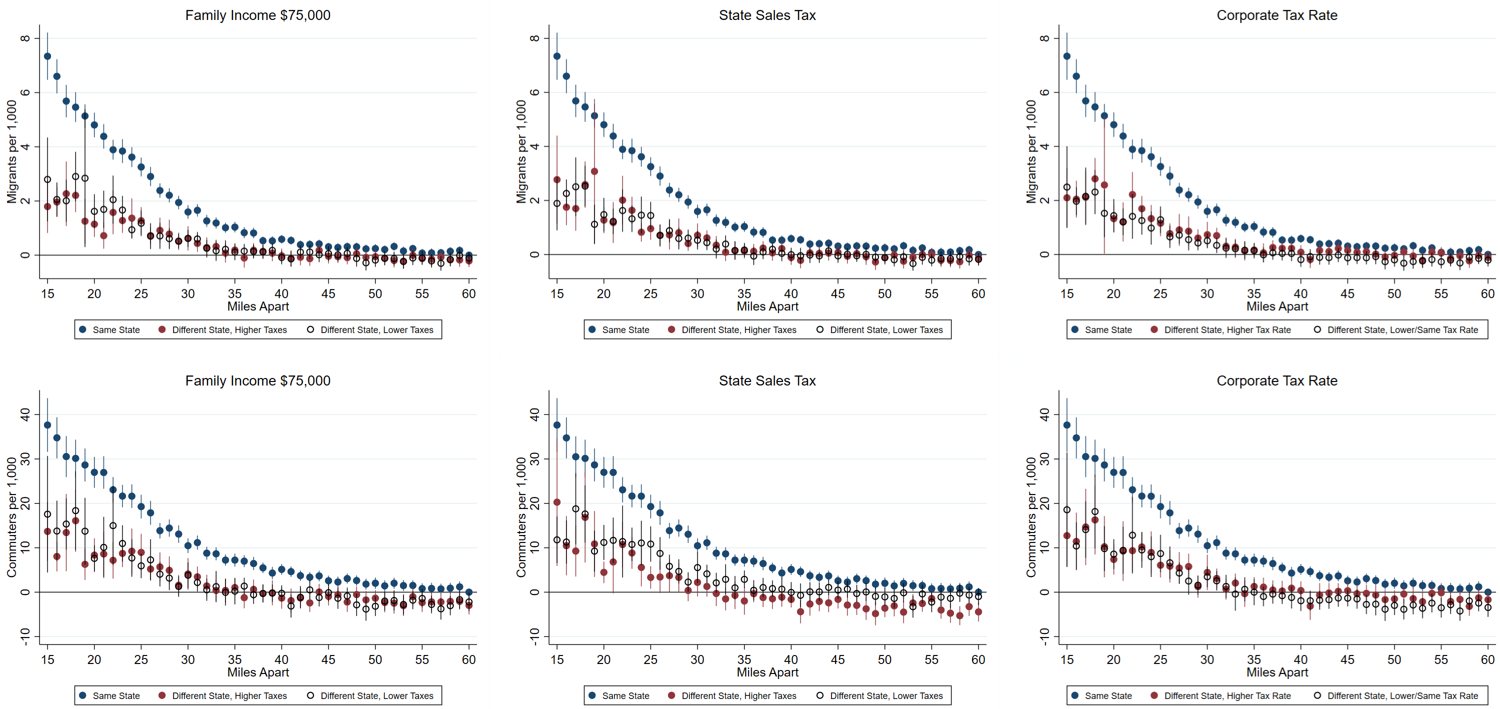
Figure C5: Role of Differences in Local Characteristics: Impact of State Borders on Migration and Commuting Accounting for Absolute Differences



NOTE: In the left panels, coefficients from equation (1) are plotted where the outcome is the residual of migrants per 1,000 (top) or commuters per 1,000 (bottom) after controlling for absolute differences in labor market measures (the unemployment rate, employment-to-population ratio, average weekly wages, number of establishments), differences in industry shares (share of 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, differences in the county housing price index converted to dollars using the median house value from 2000, and differences in average third- through eighth-grade math and reading language arts test scores. Partialing-out absolute differences does not substantively change the role of state borders. In the right panels, coefficients from equation (1) are plotted where the outcome is the predicted number of migrants per 1,000 (top) or commuters per 1,000 (bottom) using the same absolute differences and one mile distance bins to predict. Migration and Commuting predictions based on absolute differences and distance do not yield differences for same-state and cross-state pairs. Estimation controls for origin and destination fixed effects. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2017 IRS SOI, 2017 LODES, QCEW 2017, SEER 2017 data, NCSL 2016 vote data, FHFA HPI 2017 data, and SEDA 2008–2017 test score data.

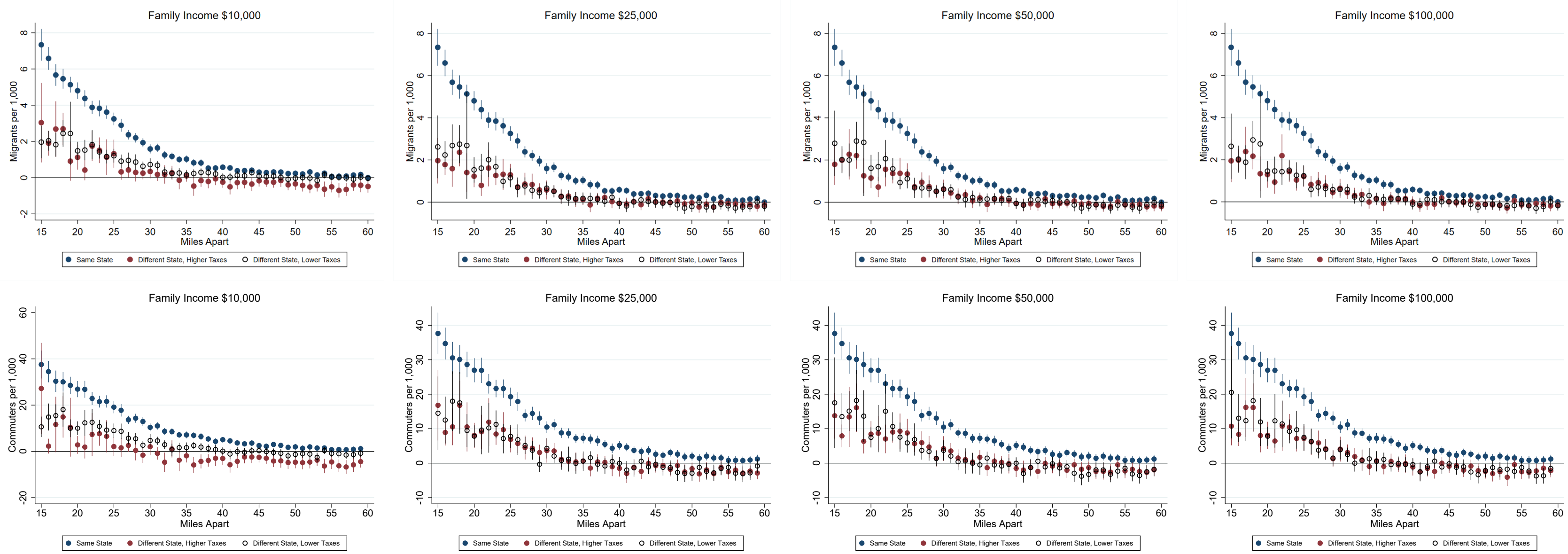
Figure C6: Role of State Taxation: Migration and Commuting across State Borders



NOTE: Coefficients from equation (20) 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 and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five-percent confidence intervals are provided.

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

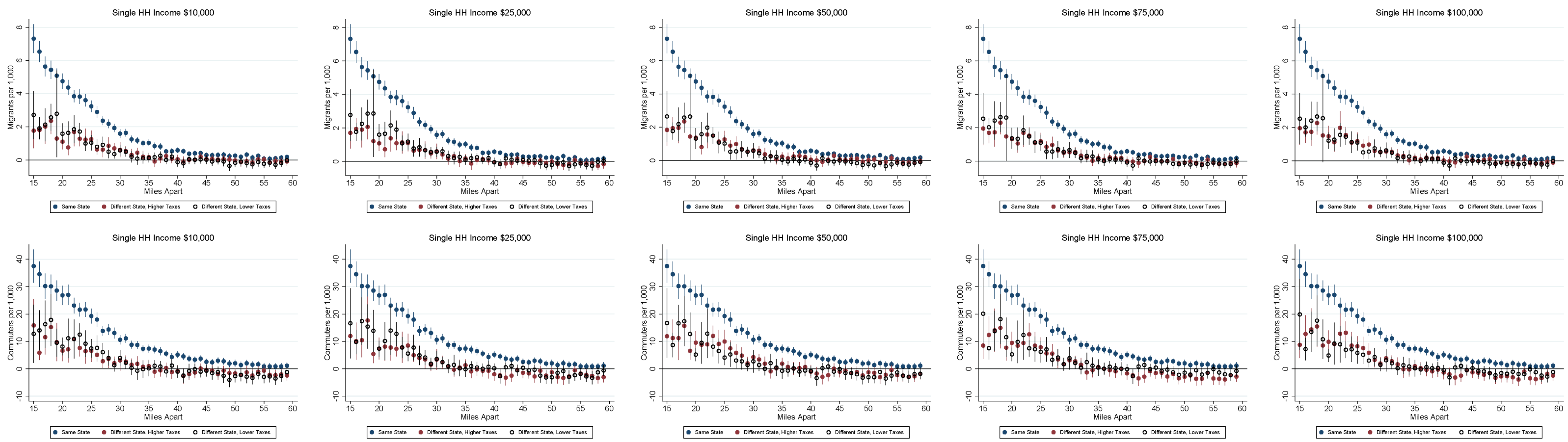
Figure C7: Role of State Income Taxation: Migration and Commuting across State Borders, Married, Filing Jointly with Two Dependents



NOTE: Coefficients from equation (20) 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. The same controls are included as listed in the notes for Figure 1. Ninety-five percent confidence intervals are provided.

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

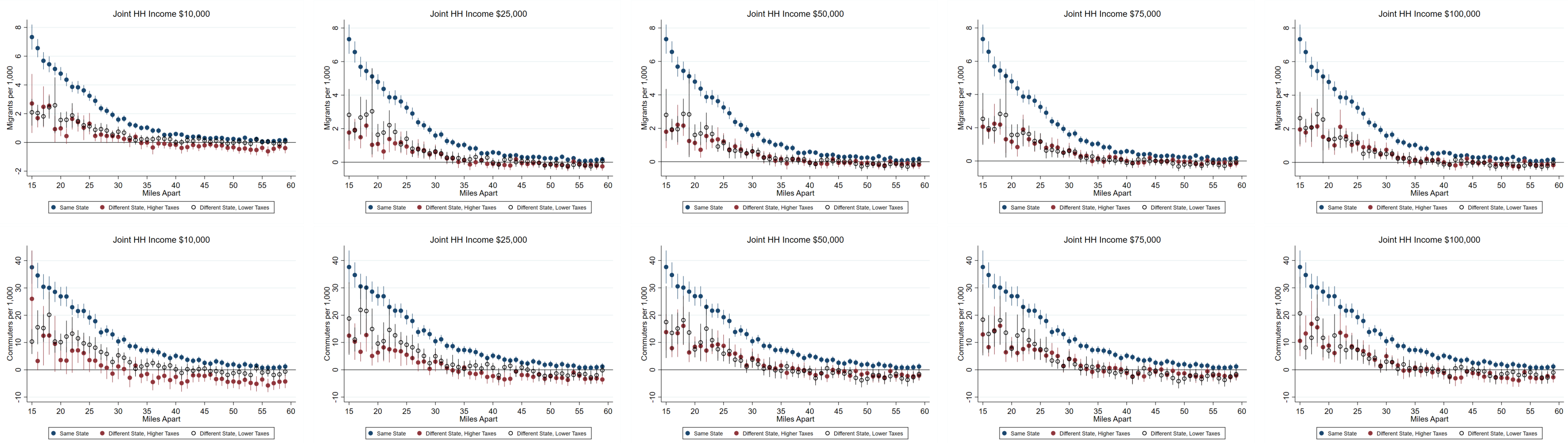
Figure C8: Role of State Income Taxation: Migration and Commuting across State Borders, for a Single Individual



NOTE: Coefficients from equation (20) 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. The same controls are included as listed in the notes for Figure 1. Ninety-five percent confidence intervals are provided.

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

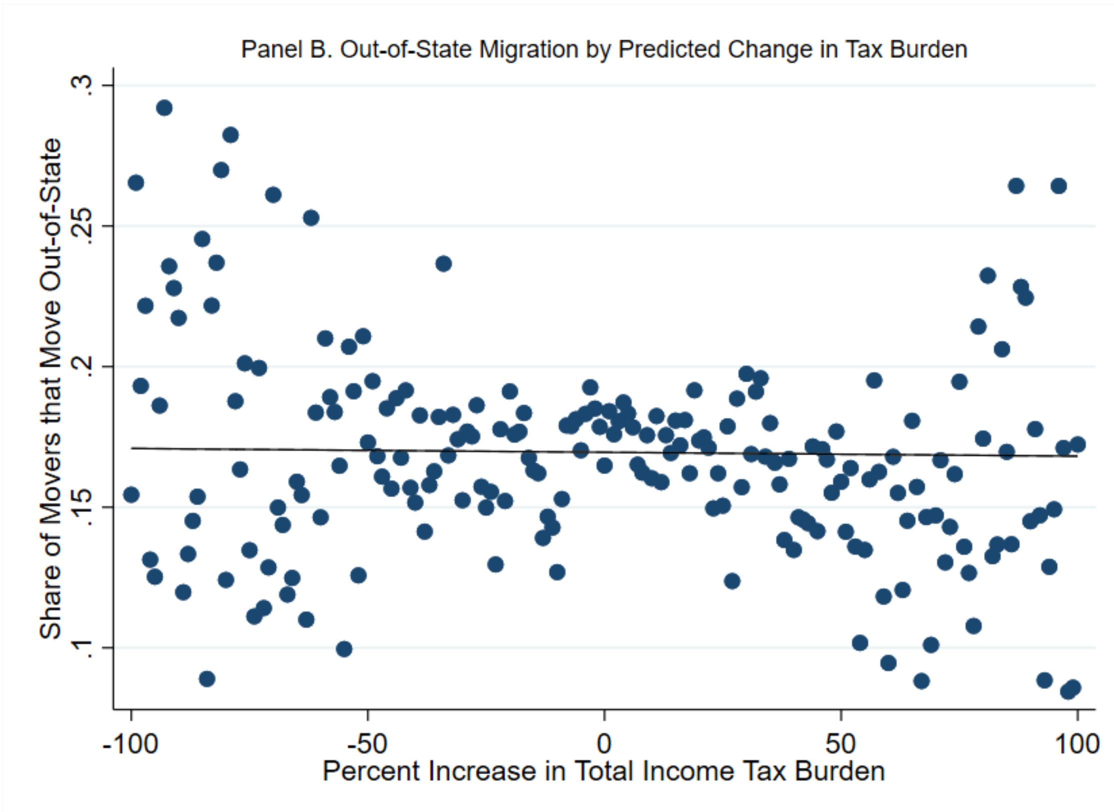
Figure C9: Role of State Income Taxation: Migration and Commuting across State Borders, for a Joint Filer with no Dependents



NOTE: Coefficients from equation (20) 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. The same controls are included as listed in the notes for Figure 1. Ninety-five percent confidence intervals are provided.

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

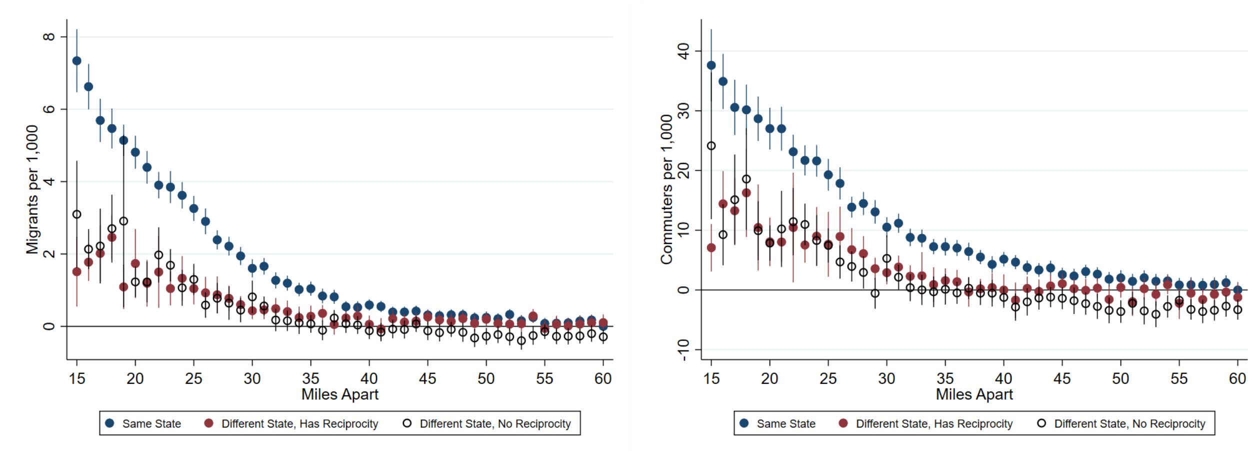
Figure C10: Share of Households That Move Out-of-State by Expected Percent Increase in Tax Burden



NOTE: 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. If there are more than two states in a commuting zone, the average total income tax burden is used. Results are similar if instead the maximum or minimum total income tax burden is used. The black line indicates the linear relationship.

SOURCE: Author's own calculations using the 2012–2017 ACS Microdata.

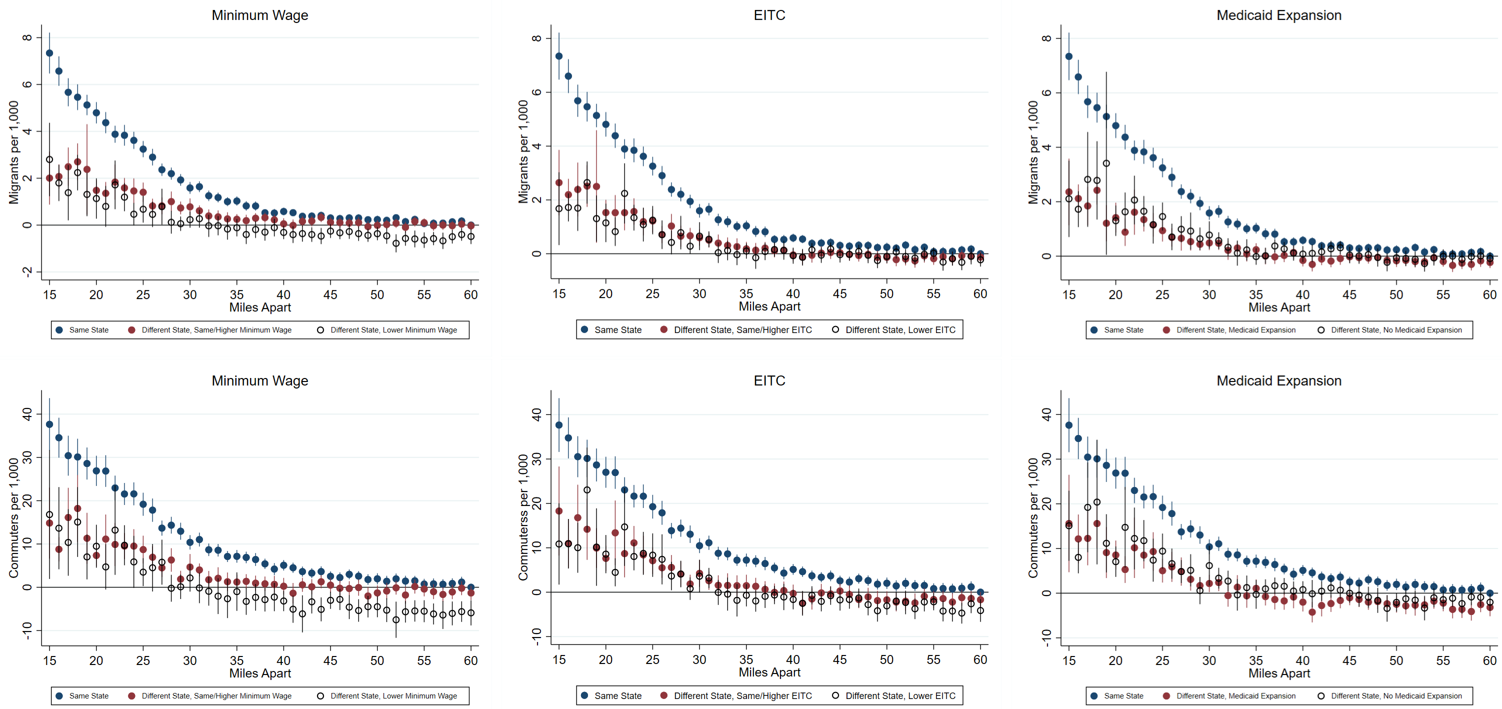
Figure C11: Role of State Income Taxation Reciprocity Agreements



NOTE: Coefficients from equation (20) are plotted, where the high/low difference is whether the origin and destination state have a tax reciprocity agreement. Migration is plotted in the left panel, commuting in the right. The same controls are included as listed in the notes for Figure 1. Ninety-five-percent confidence intervals are provided.

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

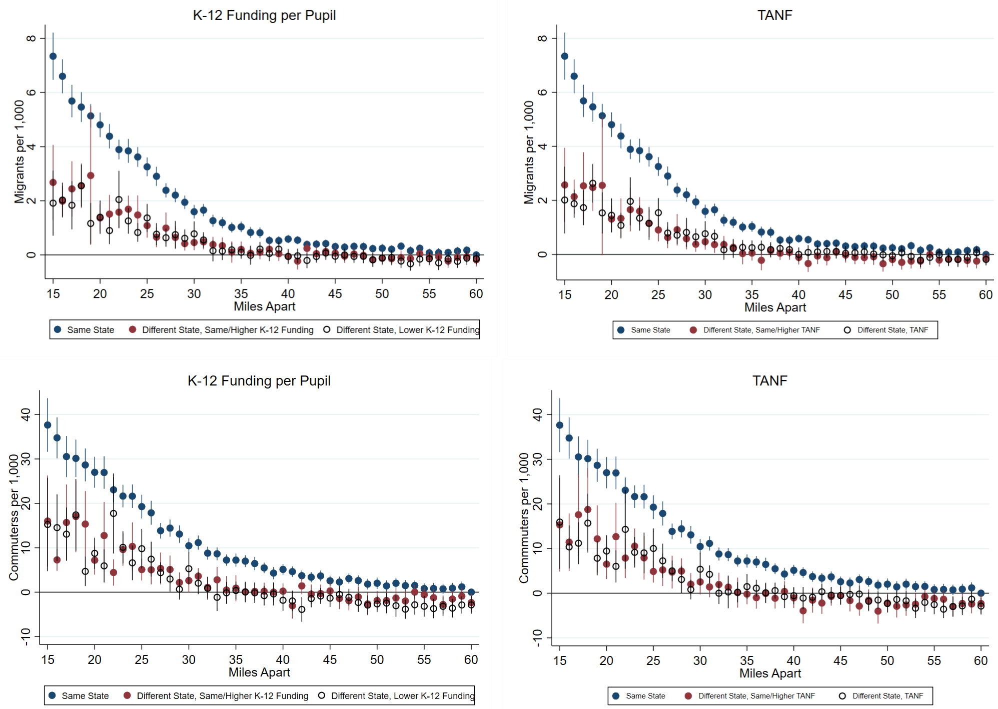
Figure C12: Role of State Benefits and Welfare: Migration and Commuting across State Borders



NOTE: Coefficients from equation (20) 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 the state expanded Medicaid after the Affordable Care Act. Controls include origin and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five-percent confidence intervals are provided.

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

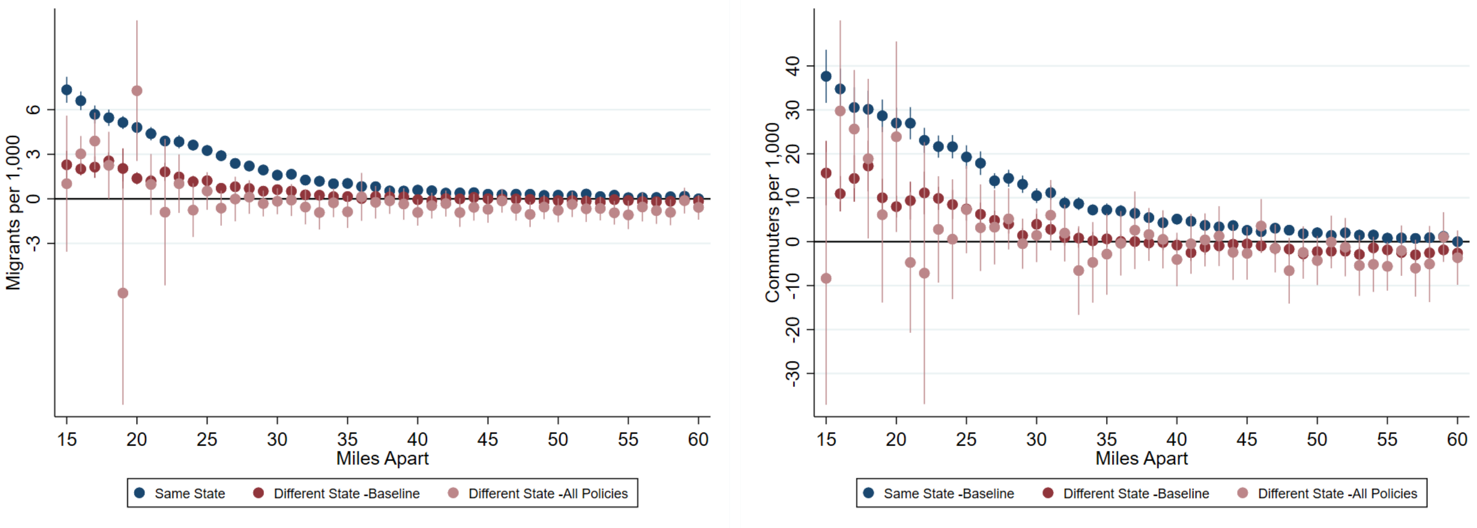
Figure C13: Impact of State Borders on Migration and Commuting by Pre-K–12 Per Pupil Spending and TANF Generosity



NOTE: Coefficients from equation (20) 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 and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five percent confidence intervals are provided.

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

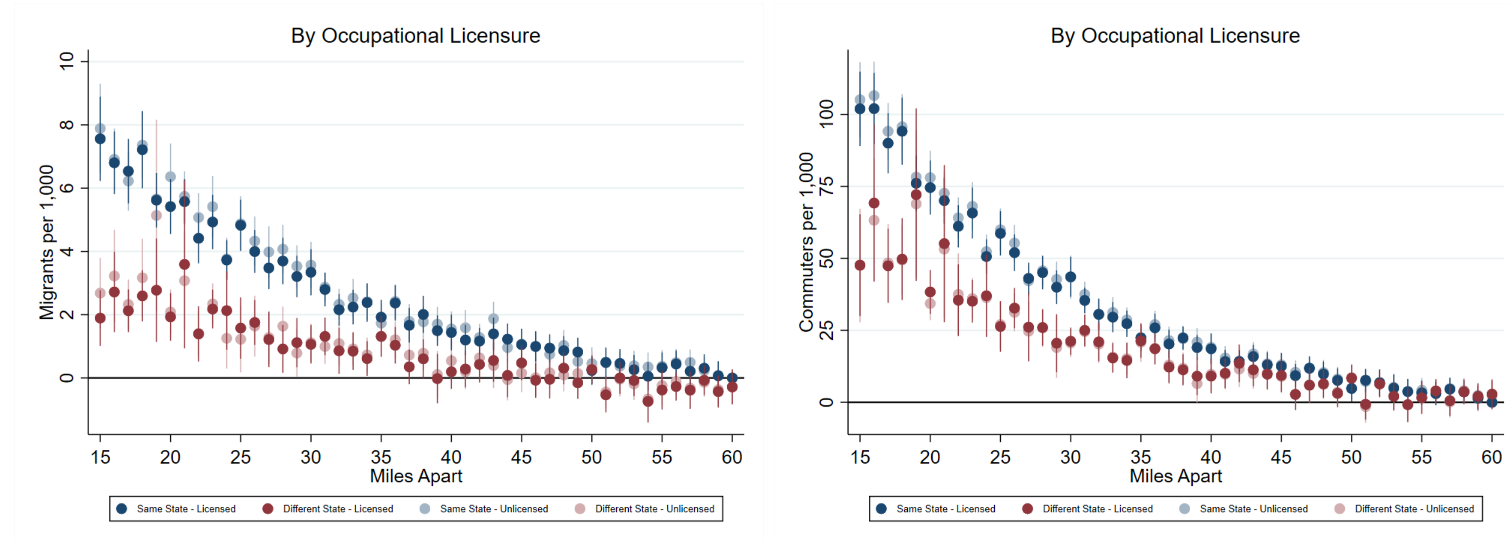
Figure C14: Accounting for All Tax and Transfer Policies Simultaneously: Impact of State Borders on Migration and Commuting



NOTE: In the top panel, I estimate equation (1) but also control for absolute differences in all of the state policies (tax and transfer) explored. Migration is plotted on the left, commuting on the right. In the bottom panel, coefficients from equation (20) are plotted. Migration is plotted on the left, commuting on the right. For each of the tax and transfer policies previously discussed in the paper, and indicator is created that indicates if the measure is less favorable in the destination relative to the origin. For example, if taxes in the destination are higher than in the origin, or if the minimum wage in the destination is lower than in the origin. These indicators are then interacted with the different state indicator and one mile bin measures. As such, the different state by mile bin interactions capture the average migration and commute flow for places where moving is the most favorable (e.i., they would encounter lower taxes and more generous transfers). Controls include origin fixed effects and destination fixed effects and absolute differences in origin destination characteristics (see notes to Figure 1). Ninety-five percent confidence intervals are provided. If I instead control for absolute differences in all of the policies (in addition to all of our other controls) the estimates are not substantially different from those in Figure 1.

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

Figure C15: Role of Occupational Licensing: Impact of State Borders on Migration and Commuting by Occupational Licensure



NOTE: Outcome in the left panel is number of migrants per 1,000 people at the origin MIGPUMA using flows constructed from the 2012–2017 ACS. Outcome in the right panel is the number of commuters per 1,000 people at the origin MIGPUMA. These estimates are obtained by separately regressing equation (1) for MIGPUMA to MIGPUMA flows for individuals who were in licensed occupations and for individuals not in licensed occupations using the 25 percent reporting cutoff. Distance is the distance between the population-weighted MIGPUMA centroids. Ninety-five-percent confidence intervals are provided.

SOURCE: Author's own calculations using the 2012–2017 ACS.

For Online Publication

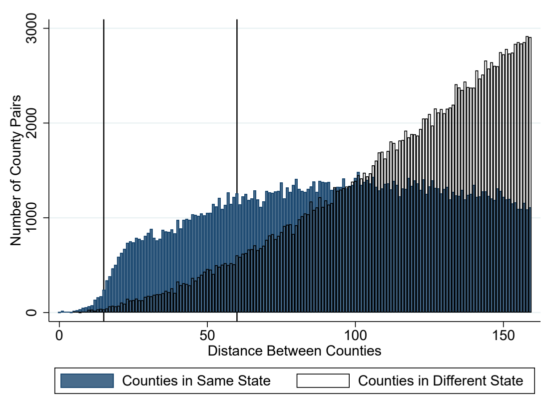
2 Appendix D. Data Appendix

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. This is the county centroid, weighted by the distribution of the population across the county. I then expand this data set to pairwise match each county with every other county in the United States. I then calculate the geodesic distance between the population centroids of 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 A1 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 D1, 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 with various data sources to capture migration, commuting, and other local characteristics. In Table A4 I also calculate distance between county population-weighted centroids based on travel time. To do this, I used the Stata command, georoute, which uses HERE API to calculate the travel time by car from the origin county's population centroid to the destination county's population centroid. This captures the travel time at the time the request was submitted to HERE which was in the evening (5-10pm) on Saturday January 9, 2021. Below, I describe each of the key data sets used in my analysis, as well as important characteristics of data construction.

Figure D1: Number of County Pairs by Distance



NOTE: 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 20 returns whose filers have moved in previous year. The suppression threshold increased from 10 to 20 returns in the 2013 data release. I record county pairs that are not observed, but that 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 A8, the patterns are unchanged if I limit the sample to only include nonsuppressed migration flows.

In 2011, the IRS made several changes. First, it extended the tax data collection period from September to December. As such, households that requested extensions, which tend to be higher income, were more heavily 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 the 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 the District of Columbia) 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 A3, which plots the migration estimates back to 1992.

Some moves are not captured in the IRS data. Households with low income (between $12,000 and $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 the 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 1 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. For privacy protection, the smallest geographic area released by the Census Bureau in public data is a Public Use Micro Area (PUMA). This is a pre-defined polygon that contains at least 100,000 (but less than 200,000) people. In urban areas this might be one county or a subset of a county. In rural areas this could contain multiple counties. PUMA do not cross state lines. When considering migration destinations, the Census Bureau reports the Migration PUMA (MIGPUMA). This is an aggregation of PUMAs such that entire counties are contained within the same MIGPUMA. As such, it is possible to map individuals in the ACS from an origina MIGPUMA to a destination MIGPUMA. The PUMA and MIGPUMA boundaries are fixed between 2012–2017. PUMAs are geographic areas defined by population that is large enough to preserve privacy. Migration geographic data are only available at the Migration PUMA (MIGPUMA), which is an aggregation of PUMAs to the county level or higher, depending on population size.[56] Using the ACS I construct MIGPUMA-to-MIGPUMA flows for various demographic groups, analogous to the IRS SOI and LODES county-to-county flows. As with the IRS SOI, I calculate distance as the geodesic distance between the population centroids of each county pair.

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

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. These data are available from 2002 on, but for consistency I focus on the data from 2017. The LODES does provide some subpopulation counts, but only for broad ranges involving 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 is 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.

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 United States from a snapshot of active Facebook users in 2016. An active user 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 U.S. 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 be correlated with other proxies of social networks (Bailey et al., 2018). I originally obtained it 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 United States, conducted by Princeton Survey Research International between October 3 and 19, 2008. During the 20-minute survey, respondents were asked questions concerning place of residence, moving histories, what places they identified with, why they identified 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 are sometimes asked slightly different questions from those who have never moved. Nonmovers 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 reasons, 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: 1) personal/social ties (family ties, connections to friends, and community involvement); 2) 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 nonmovers as anyone who reported a place-based identity reason as a major reason for living here all his or her 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 nonmovers, 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 A10.

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?" Participants 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 1 if the individual said that they were willing to move to any of the cities. From this outcome, I estimate whether birth-state identity is associated with a change in the probability of participants saying they would move to a randomized list of large MSAs.

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.

Gallup Survey on Residents' Views on Own State

Source: https://news.gallup.com/poll/168653/montanans-alaskans-say-states-among-top-places-live.aspx?version=print

Between June and December 2013, Gallup conducted a survey of more than 600 residents each for every state. They specifically asked residents whether they view their state as "the best possible state to live in." Surveys were conducted by phone, and the sample is reweighted for sampling error, nonresponse, and to match state demographics. I only observe Gallup's state-level estimates of the share of residents that feel their state is the "best possible state to live in," the "best or one of the best possible states to live in," or the "worst possible state to live in."

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 the Surveillance, Epidemiology, and End Results Program (SEER). The U.S. 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 by race by origin (Hispanic vs. Non-Hispanic). These population data are 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; gender shares; and age shares for under 20, 20–34, 35–49, 50–64, and over 64. 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 10 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, 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 U.S. Businesses annual table to estimate the number of establishments at the county level. This measure 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. The number of firms can also be captured in the QCEW and provides 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 income of either \$10,000, \$25,000, \$50,000, \$75,000, or \$100,000. Four different family types are considered: 1) single, 2) single/elderly, 3) joint (no dependents), and 4) joint with two dependents. We plot results for single, joint (no dependents), and joint (two dependents) at all of the income levels.

State Income Tax Reciprocity Agreements

Source: https://tax.thomsonreuters.com/blog/state-by-state-reciprocity-agreements/

As upheld by the U.S. Supreme Court in *Comptroller of the Treasury of Maryland v. Wynne* on May 15, 2015, states are not allowed to "double" tax income earned out of state. To avoid paying taxes in both your state of work and state of residence, workers must typically file tax returns in both states, with a tax credit in your state of residence for personal income tax paid in another jurisdiction. Filing taxes in both states could impose an additional hassle cost associated with cross-border commuting. Some states include tax-filing reciprocity agreements, so that workers only pay taxes based on their state of residence rather than on their state of employment. This list was provided by Thomson Reuters, but similar lists can be found elsewhere. New Jersey used to have a reciprocity agreement with Pennsylvania, but that was discontinued in December 2016, meaning Pennsylvania residents working in New Jersey would have to file taxes in both states to receive the credit.

State	States with a Reciprocity Agreement
Arizona	California, Indiana, Oregon, Virginia
Illinois	Iowa, Kentucky, Michigan, Wisconsin
Indiana	Kentucky, Michigan, Ohio, Pennsylvania, Wisconsin
Iowa	Illinois
Kentucky	Illinois, Indiana, Michigan, Ohio, Virginia, West Virginia, Wisconsin
Maryland	Pennsylvania, Virginia, Washington, D.C., West Virginia
Michigan	Illinois, Indiana, Kentucky, Minnesota, Ohio, Wisconsin
Minnesota	Michigan, North Dakota
Montana	North Dakota
North Dakota	Minnesota, Montana
Ohio	Indiana, Kentucky, Michigan, Pennsylvania, West Virginia
Pennsylvania	Indiana, Maryland, New Jersey, Ohio, Virginia, West Virginia
Virginia	Kentucky, Maryland, Pennsylvania, Washington, D.C., West Virginia
Washington, D.C.	Maryland, Virginia
West Virginia	Kentucky, Maryland, Ohio, Pennsylvania, Virginia
Wisconsin	Illinois, Indiana, Kentucky, Michigan

State Minimum Wages

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

State minimum wages for 2017 are obtained from the U.S. 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.

Stanford Education Data Archive County-level Test Scores Version 4.1

Source:https://edopportunity.org/get-the-data/seda-archive-downloads/

County-level, standardized math and reading language arts (RLA) test scores are obtained through the Stanford Education Data Archive (Fahle et al., 2021). These estimates provide measures of standardized test achievement for students from 3rd to 8th grade between 2008 and 2018. I use the county-level pooled by subject Bayesian Estimation estimates which average across all cohorts and years. These test scores are derived from each state's mandatory testing and are obtained through ED*Facts* at the U.S. Department of Education. These scores are then mapped into a common scored exam, the National Assessment of Educational Progress (NAEP) using Heteroskedasticity Ordered Probit models. The pooled mean estimates are obtained through hierarchical linear modeling. I include the residual shrinking Empirical Bayes estimates.

SeatGeek Professional Sports Fandom Maps

Source: https://seatgeek.com/tba/articles/where-do-mlb-fans-live-mapping-baseball-fandom-across-the-u-s/

https://seatgeek.com/tba/articles/where-do-nfl-fans-live-mapping-football-fandom-across-the-u-s/

SeatGeek collects information on the location of individuals who buy tickets to NFL and MLB games. They then aggregate up the ticket sales at the count level to determine which team has the most seats purchased for each county. No other additional information is provided on how these measures are created.

Vivid Seats NBA and NCAA Basketball Fandom Map

Source: https://www.inc.com/nick-devlin/nba-fan-map-vivid-seats-marketing-strategy.html
https://www.vividseats.com/blog/most-popular-college-basketball-teams-map

Vivid Seats collects information on the location of individuals who buy tickets to NBA games and NCAA basketball games. They then aggregate up the ticket sales at the county level to determine which team has the most seats purchased for each county. No other additional information is provided on how these measures are created.