Internal Migration in the United States 1960-2000: The Role of the State Border

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(Link to the Latest Version)

Abstract

Using a new migration data set, I document the U.S. internal migration between the periods 1960-2000. I find that the recent decline in migration is driven by lower migration across states, while within state migration has increased during the observed periods. Using a gravity framework, I estimate the effect of the state borders in the United States. I find that the border effect is strongly significant, and within state migration is 3.2 times higher than across state migration. Furthermore, the border effect has increased from 2.7 in 1960 to 3.6 in 2000. By using spatial and temporal variations, I find that the border effect is smaller in areas with similar social and economic characteristics, and the increase in the border effect can be attributed to the rising differences in house prices as states implement more restrictive land use regulations. I show that for high income destinations, the rise in regulations can explain all of the increase in the border effect.

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1 Introduction

High internal migration is one of the distinctive features of the United States (Greenwood 1997), with 1.5% of the population moving across states annually. During recent decades, however, researchers have found a universal decline in migration across multiple demographic and socioeconomic groups (Molloy et al. 2011). They also find that cyclical factors, such as recessive housing market and economic downturn, fail to explain the decrease.

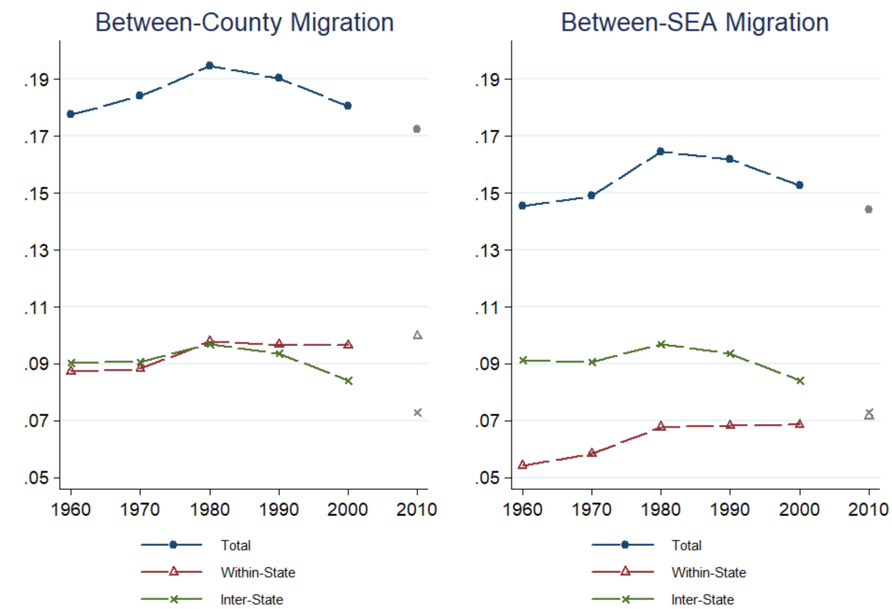
The dramatic slowdown in mobility is a puzzle and has triggered substantial research, but has yet to be adequately explained. One of the reasons this question remains unanswered is due to the limited availability of disaggregated migration data at the sub-state level prior to 1980, which has restricted researchers to observing cross-state moves or moves for recent decades only.[1] This trade-off between geography and period may lead to erroneous conclusions if, for example, the decline in migration is an extension of a previously existing trend.

I address this by using a newly constructed bilateral data of 5-year migration flows between State Economic Areas –a group of counties contained within states– starting from 1960 to 2000. The disaggregated data collected from the decennial Census Published Volumes allows for decomposing the declining trend in migration, and shows that this trend is absent in migration within states. By plotting the breakdown of the aggregate trend in migration, Figure 1 demonstrates the usefulness of sub-state migration data and provides the key motivation for my analysis of the border effect. Between-State Economic Area (SEA) moves on the right are a subset of between-county moves on the left, and for both graphs, the total migration rate is decomposed into movements within and across states.

There are three notable patterns to highlight from Figure 1. First, consistent with the literature, it is evident that total migration rate has declined since 1980. Using SEA data, the rate drops from 16.4% to 15.3%, indicating that 1.1% of the total population moved less over time. The extended migration data shows that the aggregate migration follows a hump-shaped trend, and was increasing prior to 1980. The breakdown of total migration into within- and cross-state moves demonstrates the second point that the recent decline is entirely driven by the fall in interstate migration. Compared

[1]Directly observed migration data between substate destination and origin pairs were not available prior to 1980, but researchers have inferred lifetime migration from state of birth and the current state of residence, or 5-year migration using households with 5-year-old (Rosenbloom and Sundstrom 2004) to extend data.

Figure 1 – Internal Migration Rates



Note: Author's calculation based on the 5-year migration data from the decennial Censuses and American Community Survey (ACS). Migrants are in shares of the total population above 5 years old. Data point in 2010 is an approximation of the 5-year migration rate, using the average annual migration rates from the ACS 2006-2011. The county migration data is only available at the aggregate level before 1980.

to 1980, migration rate across states falls by 1.3% from 9.7% to 8.4%, whereas migration within states has increased by 0.1% from 6.8% to 6.9%. Thus, follows the third point, that within-state migration and cross-state migration are progressively moving in opposite directions as more migrants move within states and increasingly less across states over time.[2]

These patterns suggest an increasing preference for moves within state borders, and this study contributes to the literature by providing answers to the questions: (1) how large is the state border effect for the U.S. internal migration? (2) how does the border effect vary across time? and (3) why did the border effect increase?

First, as intranational migrants are not subject to formal or informal border barriers, such as visa policies or language differences, and the states in the U.S. are highly integrated, the reason

[2]Molloy, et al. (2013) use the Current Population Survey (CPS) annual migration data and finds decline in migration between 1980-2010 for all geographical levels, across state, within state, and also within county. Intra-county drops from 14% to 10%, and intra-state drops from 3.5% to 2%. There may be few possible reasons why my findings are different. The same authors do state in their 2011 paper that the CPS overstates migration decline compared to other data sources. The CPS is a much smaller sample compared to the decennial Census and observes migration in the previous year. As annual migration picks up more temporal moves, it may be that there is less repeat migration.

for the presence of the border effect at the state line is not apparent. In order to measure the significance of this "home state bias" in migration, I use the gravity framework. For estimation, I employ the Poisson Pseudo-maximum Likelihood (PPML) estimator following Silva and Tenreyro (2006), which performs well in the presence of heteroskedastic error terms and a large number of zero flows in the dependent variable. This is the first paper, to my knowledge, to present a measure of the state border effect for the U.S. domestic migration starting from 1960, which is made possible due to the newly collected data that includes within-state migration flows. I find that a significant border effect exists for domestic migration and it is robust across different specifications. The size of the border effect implies that within state migration is 3.2 times higher than migration across states.

To answer the second question, I use the panel structure of the data and estimate state border effects over 5 decades. Given the lower direct and indirect costs of moving due to improved transporation and technology, the border effect is expected to have fallen over time. On the contrary, I show that consistent with the patterns in Figure 1, the state border effect has grown larger over time. The state border effect not only persists throughout the 1960-2000 period, but the effect of the border increases from 2.7 in 1960 to 3.6 in 2000.

Third, to explain the border effect, I evaluate how the border effect changes as destination and origin areas differ across various socioeconomic characteristics. I find that the dissimilarities between pairs contribute to increasing the border 'barrier', hindering migrants from moving across states. For example, between destination and origin areas that have the same median family income, the border effect falls by 37% from 3.2 to 2. Over time, I find that for a given pair of SEAs, the border effect grows larger as the dissimilarities increase. In particular, I show that the increase in the border effect rises with the house price differences over time.

The change of regulatory climate toward constraining housing supply has caused a surge in house price dispersion in the last few decades (Glaeser et al. 2005). I use the land use regulation data constructed by Ganong and Shoag (2017), who show that the land use regulations reduce net migration and regional income convergence. This study tests the effect of land use regulations on the state borders, providing empirical support for the link between regulations and migration. Specifically, I find that the regulations negatively affect the in-migration to states. I show that the states with restrictive land uses have higher border effects, and particularly for high income destinations, the border trend is completely explained by the rise in regulations. Thus, there are increasingly less migrants moving across states to high income areas in land use restricted states as limited housing supply reduces the housing affordability in the area.

A comparison of two areas from the data, LA/Orange County in California and Dallas County in Texas illustrates this idea well. Between 1960 and 2000, the total 5-year migration inflow to LA/Orange County dropped by almost 30% from 1,044,545 to 756,845 as its median house value increased by 1400% from $15,900 to $239,650. During the same period, the influx of migrants to Dallas County more than doubled from 164,134 to 312,593 while its median house values increased only by half as much from $11,200 to $92,700. California is one of the most highly land use regulated states, while Texas has the lowest regulations.

This paper builds on the "border puzzle" in the trade literature and the internal migration literature. Researchers find that there are significant barriers to trade at intranational borders (Agnosteva et al. 2014), and explain this in part by information networks or wholesaling activity (Combes et al. 2005; Millimet and Osang 2007; Hillberry and Hummels 2003). This paper is the first to provide a measure of the state border effect for the U.S. internal migration, and to evaluate how socioeconomic differences affect the border effect. There is also a growing body of research on documenting and explaining the decline of internal migration in the United States (Molloy et al. 2011), through labor market changes (Kaplan and Schulhofer-Wohl 2017; Molloy et al. 2017), demographic shifts (Rhee and Karahan 2015), or state regulation changes (Johnson and Kleiner 2015; Ganong and Shoag 2017). I contribute to this literature by constructing a novel data set of bilateral migration flows. I show that the border effect has increased over time, and this increase is correlated with large differences in housing prices, as state governments increasingly implement land use regulations.

2 Related Literature

This paper is broadly related to two strands of literature. First, it is related to the trade literature on the "border puzzle" and especially on domestic borders. Since the seminal finding of McCallum

(1995)'s border effect between Canada and the United States, researchers have continued to find significant border effects in trade flows despite increasingly integrated global economy. Studies show that the estimated effects of trade frictions at the border can be explained in part by the tariffs and trade barriers, currency, home bias in preferences, historical colony experiences, regional trade agreements, as well as technical issues in estimating gravity model specifications (Anderson and van Wincoop 2003; Bergstrand et al. 2015; Helpman et al. 2008; Silva and Tenreyro 2006).

However, significant home bias is also found for domestic trade flows across subnational borders, which are not subject to the aforementioned trade barriers and have more comparable distance measures.[3] Wolf (2000) finds that the U.S. trade flows within states are three times higher than across states, even in the absence of formal and informal trade barriers. Researchers have shown that the presence of domestic border effects can be explained in part through factors such as information networks or wholesaling activity (Combes et al. 2005; Hillberry and Hummels 2003; Millimet and Osang 2007). This study uses the same methods to measure the state border effect for internal migration flows.

Second, it is related to literature examining the aggregate trend and the determinants of internal migration in the United States.[4] The decline of the U.S. migration from 1980, using multiple sources of migration data, is well-documented in Molloy et al. (2011). My data extends the 5-year migration flows at sub-state levels of geography and confirms the decrease in migration. Migration is determined by a combination of multiple factors, including but not limited to, demographic characteristics, job opportunities, amenities, family reasons, government policies, and natural disasters. This paper is closely related to literature that studies the drivers of the recent decline in mobility, and researchers are able to explain the trend in part through channels such as changes in labor market (Kaplan and Schulhofer 2017; Molloy et al. 2016) or demographic shifts (Karahan and Rhee 2014). Most of the research focus on the decline post-1990 as better data is available, and the decrease is more pronounced, but my data extends the period of observation, making it possible to document and observe earlier trends.

State regulations and interstate agreements are also possible explanations for migration slow-

[3]See Agnosteva et al. (2014) for literature on intranational border barrier for trade.

[4]For the history of internal migration in the U.S. and the overview of literature, see Greenwood 1997; Molloy et al. 2011.

down, as state policies such as occupational licenses, land use regulations, or other interstate compacts can have direct implications for mobility.[5] This study explains the state border trend through the relationship between land use regulations, housing supply, and migration (Glaeser et al. 2005; Glaeser and Ward 2009; Quigley and Raphael 2005;Ganong and Shoag 2017). Ganong and Shoag (2017) build a panel measure of land use regulations at the state level between 1940-2010, and explain the lower income convergence after 1980 through skill sorting driven by lower net migration in high income places with strict land use regulations. Their idea is that for land use restricted states with high income, limited housing supply increases the house prices, making it less affordable for low-skilled workers in particular.

Research that lie at the intersection of the two strands of the literature are most closely related to this study. Kone et al. (2016) uses the same empirical strategy as this paper and measures the border effect at the state line for different subgroups of populations in India. They also suggest that state level policies contribute to the state border and provide some preliminary evidence. Their data is more recent but more disaggregated, and offer a good comparative measure for this study. Ganong and Shoag (2017) is also closely related to this paper. My results complement their findings and support the claim that land use regulations negatively affect migration.

3 Data and Empirical Framework

3.1 Data

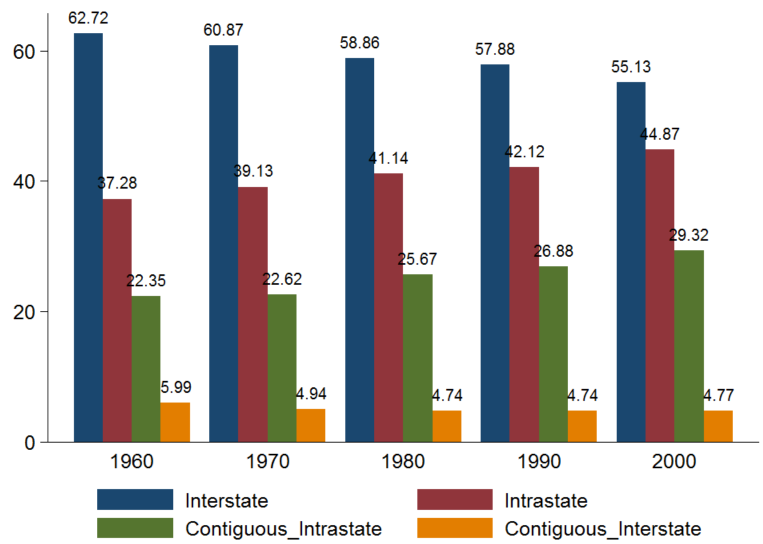
The data consists of bilateral migration flows, destination and origin characteristics, and the bilateral controls that include distance, contiguity, the dissimilarity measures of socioeconomic variables, and the land use regulation measure.

All of the variables are defined at the State Economic Area (SEA) level, except the land use regulation data which is only available at the state level. The SEAs were defined by the Census Bureau in 1950 as single counties or groups of contiguous counties within the same state that had similar characteristics. The 1960 set of SEAs that are used in this study were revised to reflect

[5]Studies on the impact of occupational licensing on migration has been limited due to lack of a comprehensive data, and existing works show mixed results for select occupation groups (DePasquale and Stange 2016; Johnson and Kleiner 2015). Feng (2014) finds that interstate banking deregulation frees capital flows, reducing labor mobility as wage differences decline. This leads to a decline in interstate migration during 1990-2005.

minor changes and also include Alaska and Hawaii. The size and the number of SEAs per state vary widely, between 1 and 31 per state. For empirical analysis, the time-invariant differences of SEAs will be controlled by the destination and origin fixed effects. There are 509 SEAs in total that cover the entire U.S. They constitute 258,572 pairs of destination and origin SEAs in total for each census year, out of which 6,666 (2.58%) are the pairs of within state moves and 2,794 (1.08%) pairs are contiguous SEAs. Figure 2 shows the migrants for each category in shares of total inter-SEA migrants over time. The contiguous intrastate moves alone comprises 20% to 30% of the total migration, and on average, more than 80% of all intrastate moves. Thus, contiguity is a strong indicator of high migration, and the baseline estimates are also reported for the contiguous sample.

Figure 2 – Share of Migrants by Category



The migration data is collected from the Decennial Published Census Volumes for every decade between 1960 and 2000. Starting from 1940, the Decennial Census includes the question on the respondent's migrant status and the previous residence five years ago. The decennial census publishes SEA-to-SEA bilateral 5-year migration flows for 1960 and 1970, and county-to-county bilateral 5-year migration flows from 1980 to 2000.[6] By combining the two datasets at the SEA level, a 509-by-508 matrix of migration flows for five periods is constructed. The 5-year migration flows between SEAs published by the Census has some limitations. Repeated migration, within-SEA moves, or

[6]The data starts from 1940, but in the 1950 decennial census, only annual migration flows are available. Thus, data between 1960 and 2000 is used in this study.

any migration outside the five-year period will not be counted. Despite the shortcomings of the data, the Census bilateral migration flow data best serves the purpose of this study as it covers the entire United States and is representative of the whole population above 5 years old for the longest period of time.[7]

For destination and origin characteristics, county level data on population, median family income, unemployment rate, education, number of manufacturing plants, urbanization, median rent and house values, percentage of blacks, and the vote shares for the Republican Party are collected and aggregated at the SEA level for use.[8] As most of the variables are collected in the census year, lagged variables are used for the possibility of reverse causality.

The data also include dyadic variables that are fixed over time, such as distances and contiguity, and time-varying bilateral variables that proxy for how alike the SEAs are. The bilateral distances of SEAs are calculated by averaging the distances between all the possible combinations of the county pairs in two SEAs. The contiguity variable also uses the contiguity of the consisting counties, and takes the value of one if a pair of SEAs have counties that are adjacent to each other.[9] As explained in previous section, the dissimilarity measures are Euclidian distances of destination and origin on socioeconomic variables. The cross-sectional summary statistics of all variables are included in Table 1.

The land use regulations data is from Ganong and Shoag (2017). The authors use the state level counts of state supreme and appellate court cases with string "land use" as a proxy for the strictness of the regulations. The measure is constructed as a rank of per capita cases for each state every year between 1940-2011, and takes a value between [0,1].

[7] The three main sources for U.S. migration data are the Current Population Survey (CPS), Internal Revenue Service (IRS), and the decennial census (hereafter, the Census). Both the CPS and the IRS data provides annual migration data. The CPS data is at individual level and starts from 1947 but the sample is much smaller and the previous residence is only available at the state after 1985. The IRS data is more disaggregated county-to-county annual migration data, but it starts from 1978 and only includes tax-payers. The Census microdata also provides individual level migration but geographical information lower than SEA, Countygroup or PUMA is suppressed for different years, making it difficult to build data at a consistent level over time.

[8] ICPSR 2896. http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/2896

[9] County bilateral distance data is from NBER County Distance Database (http://www.nber.org/data/county-distance-database.html). County contiguity data is from the Census County Adjacency File (https://www.census.gov/geo/reference/county-adjacency.html).

Table 1 – Summary Statistics

Census Year	1960		1970		1980		1990		2000	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Migrants	88.12	612.55	102.12	716.79	133.76	989.79	144.22	1,183.33	154.97	1,210.44
Population	297,092.40	588,421.10	352,260.70	706,423.60	399,007.80	800,024.50	444,792.30	806,004.40	488,246.50	880,601.20
Median Family Income	2,630.87	769.07	4,836.54	1,284.36	8,418.01	1,865.14	15,596.00	3,013.74	31,542.93	7,094.46
Median Rent	35.90	9.05	58.58	15.44	90.40	22.84	210.41	40.95	367.71	104.05
Median House Value	5,809.86	2,200.90	9,324.81	3,083.54	13,604.60	4,695.81	40,446.39	14,589.73	67,058.61	40,295.26
High School Graduates (%)	30.69	10.10	37.82	9.77	48.44	10.95	62.87	10.42	72.53	8.50
Unemployed (%)	4.27	1.96	5.32	1.88	4.59	1.68	6.93	2.50	6.62	2.18
Urbanization (%)	44.67	26.09	48.78	26.82	51.75	27.35	53.18	27.57	53.82	28.01
Black (%)	9.85	14.18	9.60	13.43	9.37	12.51	9.43	12.42	9.75	12.53
Republican Votes (%)	55.36	12.60	43.53	12.49	47.92	8.06	55.16	8.35	43.32	8.56
Land Use Regulations (raw)	0.72	1.07	1.67	2.43	3.49	3.96	7.35	8.62	10.60	14.32
Land Use Regulations (centile)	0.22	0.18	0.33	0.23	0.52	0.24	0.71	0.20	0.73	0.19

[a] All variables are at the SEA level, except migrants and the land use regulations, which are at the SEA-pair and the state level. Migrants are defined for the previous 5 years to the census year. The control variables and the land use regulations are lagged, and the periods nearest to the census year are used.

3.2 Descriptive Facts

3.2.1 Push and Pull Factors of Migration

Before discussing the state border effects for migration, this section examines the economic factors at origin and destination that attract migrants during the period from 1960 to 2000. For the main analysis, all of the time-varying observables and unobservables at destination and origin will be absorbed by the fixed effects.

Following the traditional gravity equation, the OLS estimates are reported in Table 2. All specifications include the bilateral controls of distance and contiguity to account for the cost of migration between each pair. As destination, origin, and year fixed effects capture all of the time-invariant destination and origin factors that may affect migration, such as climate or areas size, and any decade-specific migration shocks, the identification comes from variation in the control variables over time. To prevent possible endogeneity and reverse causality issues, the control variables are lagged and the values of previous decades are used for each census year instead.

The first column shows the OLS outputs from specification without any push or pull factors, and then each factor is added one by one in the following columns. The estimates for distance and contiguity are very stable and strongly significant across regressions, and the migration flows are decreasing in distance and non-contiguity of the pairs. Consistent with the findings from previous works, the coefficients for population at both destination and origin are positive and significant. The SEAs with growing populations both send and receive more migrants. Similar to population, median family income, education, and median house value also have positive coefficients for both destination and origin. The three variables are highly correlated (0.83-0.96) and this affects the outcomes as areas with high house values also have high family income and larger shares of educated populations. The growing income at destinations attract migrants, whereas the rising house values at origin causes out-migration. Areas with increasing shares of educated populations also have positive coefficients, as educated populations are more likely to migrate. When all of the controls are included in column 10, the coefficient for house value at destination turns negative as the positive effect of income is controlled for.

The coefficients of unemployment rates have the opposite of the expected signs. An SEA with

Table 2 – Push and Pull Factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Logdistance	-1.538***	-1.538***	-1.539***	-1.539***	-1.538***	-1.538***	-1.538***	-1.538***	-0.931***	-1.538***
	(0.0235)	(0.0235)	(0.0235)	(0.0235)	(0.0235)	(0.0235)	(0.0235)	(0.0235)	(0.0303)	(0.0235)
=1 if SEA Contiguous	1.683***	1.683***	1.683***	1.683***	1.683***	1.683***	1.683***	1.683***	2.971***	1.683***
	(0.0481)	(0.0481)	(0.0481)	(0.0481)	(0.0481)	(0.0481)	(0.0481)	(0.0481)	(0.0659)	(0.0481)
Destination: Log(Population)		0.289***							0.950***	0.410***
		(0.0660)							(0.0387)	(0.0734)
Origin: Log(Population)		1.043***							0.981***	1.023***
		(0.0425)							(0.0280)	(0.0455)
Destinatin: Log(Family Income)			0.766***						-1.132***	0.708***
			(0.106)						(0.211)	(0.112)
Origin: Log(Family Income)			0.463***						-0.910***	0.262***
			(0.103)						(0.148)	(0.0697)
Destination: %High school grad				3.004***					4.651***	2.410***
				(0.427)					(0.375)	(0.412)
Origin: %High school grad				1.744***					4.041***	1.047***
				(0.414)					(0.280)	(0.260)
Destination: Log(House Value)					0.268***				0.388***	-0.154**
					(0.0695)				(0.126)	(0.0700)
Origin: Log(House Value)					0.574***				0.344***	0.000206
					(0.0507)				(0.101)	(0.0421)
Destination: % Unemployed						1.412**			3.359***	1.834***
						(0.589)			(1.223)	(0.515)
Origin: % Unemployed						-5.697***			2.339**	-2.739***
						(0.556)			(0.962)	(0.400)
Destination: %Urban							0.193		0.0736	-0.794***
							(0.234)		(0.137)	(0.197)
Origin: %Urban							1.654***		0.0600	-0.429***
							(0.237)		(0.104)	(0.140)
Destination: Manufact. plants								-0.0704*	-0.369***	0.0687
								(0.0408)	(0.0664)	(0.0632)
Origin: Manufact. plants								-0.318**	-0.384***	-0.0268
								(0.123)	(0.0505)	(0.0288)
Observations	1,288,808	1,288,808	1,288,808	1,288,808	1,288,808	1,288,808	1,288,808	1,288,808	1,288,808	1,288,808
R-squared	0.627	0.635	0.629	0.629	0.629	0.628	0.628	0.628	0.476	0.637
Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Destination-FE	Y	Y	Y	Y	Y	Y	Y	Y		Y
Origin-FE	Y	Y	Y	Y	Y	Y	Y	Y		Y

[a] Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Two-way clustering is used at destination-origin SEA level.

increasing unemployment will send less migrants, but receive more. One possible explanation is that the unemployment rate is inversely correlated with the share of rural populations, and areas that are increasingly rural are unattractive destinations but at the same time, there are less migration activities. (It may also be the lagged problem, as contemporaneous values have the expected signal.) The coefficient of urban populations at destination is insignificant, while origin with growing urban populations sends more migrants. This is due to population effect, however, as both coefficients turn negative when population is included. Urban areas are more populated, and after controlling for the positive effect of population, increasingly urban areas have less migration activities.

3.3 Empirical Framework

My empirical strategy is based on Bertoli and Moraga (2015)'s gravity model for migration, which is theoretically micro-founded by the Random utility maximization (RUM) model and yields the migration flow in the gravity-like form (Grogger and Hanson 2011; Beine and Oezden 2011; Beine and Parsons 2015).[10]

Traditionally, this gravity equation was transformed into a log-linear form and estimated using OLS. However, researchers find the OLS estimates ofr log-linear regressions are inconsistent, and suffers from omitted variable bias and selection bias as zero migration flows are dropped from sample.[11] Silva and Tenreyro (2006) show that the Poisson pseudo-maximum likelihood (PPML) estimator performs well in the presence of heteroskedastic error term and accommodates zeros in the dependent variable. As migration data is highly correlated and likely to be heteroskedastic, and 35% of pairs have zero migration flows in the data, PPML should be used for consistent estimate.

[10] The variable m_{ijt}, the bilateral migration flow from origin i to destination j at time t, is a function of the sending ability of origin (s_{it}), the attractiveness of destination (y_{jt}), the accessibility of destination from origin (ϕ_{ijt}), the multilateral resistance to migration (Ω_{it}), and the stochastic term (η_{ijt}).

$$m_{ijt} = \phi_{ijt} \frac{y_{jt}}{\Omega_{it}} s_{it} \eta_{ijt}$$

$$\Omega_{it} = \sum_{k \in D} \phi_{ikt} y_{kt}$$

$$\ln(m_{ijt}) = \beta_0 + \beta_1 \ln(\phi_{ijt}) + \beta_2 \ln y_{jt} - \beta_3 \ln \Omega_{ijt} + \beta_4 \ln s_{it} + \ln \eta_{ijt}$$

[11] Refer to Anderson and Wincoop (2003), Silva and Teneroyo (2006), and Helpman, Melitz, and Rubinstein (2008) for more details.

Thus, follows the baseline specification,

$$m_{ijt} = \exp[\beta_0 + \beta_1 \ln(d_{ij}) + \beta_2 contig_{ij} + \beta_3 border_{ij} + o_{it} + d_{jt}] + \epsilon_{ijt} \quad (1)$$

where $m_{ijt}$is the 5-year bilateral migration from origin SEA i to destination SEA j at census year t; $d_{ij}$is the bilateral distance between the SEAs i and j; $contig_{ij}$is a dummy variable that equals one if the SEAs i and j are contiguous to each other.[12] The variable $border_{ij}$ is a dummy that equals one if origin i and destination j are in different states. Following Wolf (2000), it indicates whether the migration is an intrastate or an interstate movement. The specification also includes time-varying origin and destination dummies to control for SEA-specific unobservables, such as population, unemployment rate, income, area size, climate, and so on.

β_3 is the coefficient of interest that measures the effect of crossing the border at the state line. Similar to trade, the significance and the magnitude of the border effect indicate the home bias for domestic migrants. Because the state border can be a discontinuous function of distance, I include as many distance controls as possible, such as distance-squared and distance-cubed, and a dummy for state contiguity in addition to the baseline regression. For all specifications to follow, the additional distance and contiguity measures are included on top of log-linear distance and SEA contiguity, and will be jointly denoted as X_{ij}. The size of the border effect is the antilog of coefficient β_3.

To understand what drives the border effect, the heterogeneity of the border effect can be explored over different socioeconomic characteristics of destination and origin. I provide measure of the state borders for different subsamples of the data. Also, the baseline specification is extended to include the interaction of the border dummy with bilateral dissimilarity measures of destination and origin SEAs as follows: $dissimilarity_{ijt}$ is a vector of how similar the origin and destination SEAs are on socioeconomic characteristics including race, urbanization, party vote shares, unemployment, and median rent. That is, all $dissimilarity_{ijt}$ variables are defined as $\mid (Variable_{jt} - Variable_{it}) \mid$, the absolute difference in values between destination and origin. The interaction term accommodates for any differential effects of the state border on changes of $dissimilarity_{ijt}$ measures.

[12] Unlike previous studies on bilateral intranational trade or interstate migration where intrastate moves are always coded as contiguous or as non-contiguous, the variable $contig_{ij}$ measures the contiguity of the SEA-pairs separately due to availability of data at disaggregated level.

$$m_{ijt} = \exp[\beta_0 + \beta_1 X_{ij} + \beta_2 border_{ij} + \beta_3 dissimilarity_{ijt} + \beta_4 border_{ij} * dissimilarity_{ijt} + o_{it} + d_{jt}] + \epsilon_{ijt} \quad (2)$$

By exploiting the panel structure of the data, I provide estimates for the temporal pattern of the border. The cross-section of baseline regressions estimate the border for each decade. The data also allows me to use the most rigorous specification possible and destination-origin pair fixed effects are included to capture all time-invariant pair-specific effects. For this regression, only time-interacted border survives.

$$m_{ijt} = \exp[\beta_0 + \beta_{2t} border_{ij} * Year_t + o_{it} + d_{jt} + pair_{ij}] + \epsilon_{ijt} \quad (3)$$

All regressions are estimated using PPML and the standard errors are two-way clustered at the destination and origin SEA level.[13]

Lastly, the land use regulation at destination state is added to the specification (3) and interacted with time-varying borders.

$$m_{ijt} = \exp[\beta_0 + \beta_{2t} border_{ij} * Year_t + \beta_{3t} border_{ij} * Year_t * landuse_{jt} + o_{it} + d_{jt} + pair_{ij}] + \epsilon_{ijt} \quad (4)$$

The estimates indicate whether regulations at destination affects the border effect over time.

4 Empirical Results

4.1 Baseline Results

Table 3 presents the measure of the state border effect estimated from the equation (1). The regressions include time-varying destination and origin fixed effects, which will capture all of the unobserved push and pull factors shown in the previous section. The fixed effects are also necessary

[13]Estimation results with clustered standard errors at SEA-pair level are also available upon request. The t-statistics are inflated by almost an order of magnitude. Table A2 presents OLS results with different level of clustering.

Table 3 – Baseline Regressions

	All			Contiguous
	(1)	(2)	(3)	(4)
Logdistance	-0.855***	2.958***	1.588**	2.644**
	(0.0412)	(0.790)	(0.753)	(1.236)
Logdistance2		-0.791***	-0.508***	-0.809***
		(0.144)	(0.140)	(0.299)
Logdistance3		0.0512***	0.0346***	0.0505**
		(0.00864)	(0.00846)	(0.0238)
=1 if SEA Contiguous	0.797***	0.651***	0.746***	
	(0.0406)	(0.0727)	(0.0631)	
=1 if State Contiguous			0.490***	
			(0.0529)	
=1 if State Border	-1.342***	-1.235***	-1.171***	-0.989***
	(0.0436)	(0.0418)	(0.0419)	(0.0360)
Observations	1,292,860	1,292,860	1,292,860	13,970
R-squared	0.692	0.691	0.704	0.961
Destination*Year-FE	Y	Y	Y	Y
Origin*Year-FE	Y	Y	Y	Y
Border Effect	3.827	3.439	3.224	2.689
Border(distance)	3,589	4,983	8,801	82

[a] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-way clustering is used at destination-origin SEA level.

to control for the effect of alternative destinations, which Bertoli and Fernandez-Huertas Moraga (2013) refer to as the multilateral resistance to migration. In column 1, the traditional gravity variables, such as the log of distance and the contiguity of the SEAs, are included with the state border dummy. In column 2 and 3, the distance polynomial terms are added to control for the potentially non-linear relationship between migration and distance (Davies et al. 2001). Column 3 also includes a state contiguity dummy in addition to the SEA contiguity. The last column shows results for contiguous SEAs only.

The first column shows that the elasticity of distance to migration is -0.855. One percent increase in distance decreases -0.855% of the migration flow. Also consistent with the previous studies that include the quadratic distance term (Davies et al. 2001;Arzaghi and Rupasingha 2013), column 2 and 3 show that distance is indeed non-linear, indicating a declining negative elasticity of distance on migration. This implies that migration is decreasing in distance at a diminishing rate, and once a fixed cost of a long distance move has incurred, be it economical or psychological, the distance elasticity is reduced. Intuitively, an additional increase of one mile in distance between places that are 10 miles apart and those that are 1,000 miles apart will not have the same effect.

The contiguity variable is defined at the SEA level and the coefficient of SEAs being adjacent to each other is 0.797 in column 1. This indicates that given all else equal, on average the migration flows between contiguous SEAs are $exp(0.797) = 2.22$ times higher than between non-contiguous SEAs. In column 3, another variable is introduced to control for the effect of states sharing the same border. While all contiguous SEAs are in adjacent states, there are also some non-contiguous SEA pairs between contiguous states. Even after controlling for the non-linearity of distances, the result in column 3 implies that the migration flows across non-contiguous states are on average $exp(0.490) = 1.63$ times lower.

The size and the significance of the state border effect, the variable of interest for this study, is highly significant and robust across all specifications. The size of the border effect ranges between $exp(1.342) = 3.83$ and $exp(1.171) = 3.22$ depending on specifications. Column 1 shows that there are on average 3.83 times less migration flows across states than within. After including distance polynomial and contiguity terms in column 3, the border effect is reduced to 3.22, but still remains strongly significant.[14]

The deterring effect of border on migration can be expressed in distance (miles) by $\overline{D} \times [\exp(\beta_{StateBorder}/\beta_{Distance}) - 1]$, where $\overline{D}$ is the sample mean distance (Parsley and Wei 2001). That is, the border "width" is the distance from mean which produces the equivalent negative effect of crossing the border. As reported in the bottom of column 1, the border width is 3,589 miles,

[14]Comparison of border effects for intranational migration: Kone et al. (2016) uses 2001 Census of India and finds that between neighboring districts, migration across states is 1.56 times lower. Between non-neighboring districts, the border effect is close to 2. Compared to non-neighboring districts across states, migration flows are each 5.6 and 8.8 times larger if moving between different but neighboring districts and between neighboring districts in same state. Poncet (2006) uses inter-provincial migration data in China between 1985-1990 and 1990-1995, and the size of the estimated province border effect is between 21 and 25.

Comparison of border effects for trade in U.S.: Wolf (2000)'s estimated state border effect is 4.39 using U.S. intranational trade data for 1993. The size ranges from 4.39 to 3.15 depending on the specifications and all are estimated without the fixed effects. Millimet and Osang (2007)'s estimates also range between 4.9 and 7.14 in 1993, and between 5.91 and 8.45 in 1997.

which means crossing the state border has the same negative effect as being 3,589 miles apart.[15] As this measure is sensitive to the coefficient estimates, it changes across specifications. In column 2 and 3, the border width increases up to 4,983 and 8,801 miles.[16] One of the reason why the number is so large is because this is the effect of border at the sample mean distance, 943 miles, which is not a short-distance migration. As the relationship between distance and migration is nonlinear, the negative effect of distance diminishes for long-distance moves and hence, the border is "wider." The distance effect is even smaller as additional control for contiguity is included in column 3, and this further increases the border width despite the smaller border size.

In column 4, the sample is restricted to the contiguous SEAs only. Although distance and contiguity are controlled for, a large share of total migration takes place between contiguous areas, and given the proximity, the contiguous pairs are likely to share common natural amenities or labor markets, and may be more comparable. The migrants are also likely to be better informed. Thus, between more comparable pairs of contiguous SEAs, the border effect drops by $exp(0.989-1.171)-1=16.6\%$. The size of the border effect is 2.689, and this is equivalent of being 82 miles apart at the mean distance for contiguous SEAs.[17] Even for the SEAs that are adjacent to each other, the state boundaries inhibit migration flows substantially.

In Appendix Table 1, the OLS estimates of the same specifications are also reported for each column. Although OLS estimates of log-linear equation is known to be biased, it allows more flexibility in adding fixed effects or using different levels of clustering. The PPML estimates are mostly smaller than the OLS estimates, which is the typical result of PPML (Silva and Tenreyro 2006).[18] The border effect is highly significant and robust, ranging from 4.6 to 3.76. The border width from the OLS estimates, however, is much lower than PPML estimates at 1,874 miles, and this is due to a higher OLS distance elasticity.

[15]Comparison of the state border width for trade: Millimet and Osang (2007)'s estimate ranges between 6,450 to 7,174 miles in 1993, and over 10,000 miles in 1997.

[16]The border width is calculated by solving for $d^*$from $\beta_{StateBorder} = [\ln(\overline{D}+d^*) - \ln(\overline{D})](\beta_{Distance} + 2\ln\overline{D} \times \beta_{Distance^2} + 3\ln\bar{D}^2 \times \beta_{Distnace^3})$.

[17]The sample mean distance for the contiguous SEAs is 95 miles. For the pooled sample, the sample mean is 943 miles. If 943 is used instead, the border 'width' would be 1,039 miles.

[18]Silva and Tenreyro (2006) state "OLS greatly exaggerates the roles of colonial ties and geographical proximity. Using the Anderson–van Wincoop (2003) gravity equation, we find that OLS yields significantly larger effects for geographical distance. The estimated elasticity obtained from the log-linearized equation is almost twice as large as that predicted by PPML."

4.2 Understanding the Border

To understand why the state border effect is so significant, I now calculate the border effects for different sub-groups of the data. The idea is to observe border heterogeneity, as the barrier that migrants face at the state border may not be the same between places that have higher income, for instance. I divide the sample by the distributions of income, education, and urbanization at destination and origin SEAs.

The first column in Table 4 is the benchmark regression from Table 3 column 3. In column 2, I limit the sample to SEAs whose per capita income are in the top 25 percentile. I find that the border effect falls by $exp(0.998 - 1.171) - 1 = -15.88\%$ compared to the benchmark estimate. The SEAs that have more educated population also have lower state borders. High education SEAs are defined as those in the top 25 percentile when ranked by the share of population who attained high school education or more. Column 3 shows that between high education SEAs , the size of the border effect falls by $exp(0.919 - 1.171) - 1 = -22.28\%$. For highly urban SEAs, the border coefficient is the lowest at -0.692, dropping by close to 40% ($exp(0.692 - 1.171) - 1 = -38.05\%$). On the contrary, low income, low education or low urbanized SEAs (bottom 25 percentile) in column 5, 6, and 7 have similar or larger border sizes. Thus, there is more free mobility across states between SEAs with high income, high share of educated population, and especially between urban SEAs. This is also consistent with well-known findings that individuals who are educated and have high incomes are more likely to migrate.

While this exercise alone does not help explain the driver of the state border effect, it shows differential border effects. The border heterogeneity can further be examined by using the $dissimilarity_{ijt}$ vector following specification (2). The interacted border terms estimate to what extent the level of the state borders is affected by the social and economic differences between the areas and are reported in Table 5. All regressions include distance polynomial terms, contiguity measures, and time-varying destination, origin fixed effects as before, and while not included in the table, the elasticities of the traditional gravity variables are robust and do not differ largely from the estimates of the baseline regression. As explained earlier, the dissimilarity measures are defined as the absolute differences in socioeconomic factors such as population, income, rent, house prices, unemployment, urbanization, race, and party vote shares are reported in each column. The effect of the state bor-

Table 4 – Border for Different Groups

	(1) All	(2) High Income	(3) High Education	(4) High Urban	(5) Low Income	(6) Low Education	(7) Low Urban
Logdistance	1.588**	-4.389***	1.718	-3.468***	-3.245**	-4.341**	-0.0169
	(0.753)	(1.058)	(1.119)	(0.950)	(1.325)	(1.970)	(1.653)
Logdistance2	-0.508***	0.579***	-0.442**	0.406**	0.127	0.293	-0.389
	(0.140)	(0.192)	(0.198)	(0.180)	(0.245)	(0.353)	(0.288)
Logdistance3	0.0346***	-0.0281**	0.0267**	-0.0185*	0.00309	-0.00236	0.0288*
	(0.00846)	(0.0115)	(0.0115)	(0.0110)	(0.0149)	(0.0207)	(0.0164)
=1 if SEA Contiguous	0.746***	0.136	0.629***	-0.0685	0.550***	0.565***	0.554***
	(0.0631)	(0.125)	(0.127)	(0.144)	(0.0472)	(0.0522)	(0.0582)
=1 if State Contiguous	0.490***	0.285***	0.471***	0.252***	0.378***	0.434***	0.424***
	(0.0529)	(0.0683)	(0.0539)	(0.0625)	(0.0453)	(0.0480)	(0.0424)
=1 if State Border	-1.171***	-0.998***	-0.919***	-0.692***	-1.145***	-1.180***	-1.303***
	(0.0419)	(0.0936)	(0.0798)	(0.0865)	(0.0404)	(0.0420)	(0.0412)
Observations	1,292,860	80,010	80,010	79,758	80,010	80,518	80,518
R-squared	0.704	0.807	0.811	0.832	0.887	0.926	0.933
Destination*Year-FE	Y	Y	Y	Y	Y	Y	Y
Origin*Year-FE	Y	Y	Y	Y	Y	Y	Y
Border Effect	3.224	2.714	2.506	1.998	3.142	3.253	3.680

[a] Robust t-statistics in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Two-way clustering is used at destination-origin SEA level.

Table 5 – Heterogeneity of the Border Effect

<table>
<tr><th></th><th>(1)</th><th>(2)</th><th>(4)</th><th>(5)</th><th>(6)</th><th>(7)</th><th>(8)</th><th>(9)</th></tr>
<tr><td>=1 if State Border</td><td>-3.676***</td><td>-0.698***</td><td>-1.065***</td><td>-1.377***</td><td>-1.047***</td><td>-0.780***</td><td>-1.022***</td><td>-1.129***</td></tr>
<tr><td></td><td>(0.305)</td><td>(0.121)</td><td>(0.0634)</td><td>(0.108)</td><td>(0.0479)</td><td>(0.0685)</td><td>(0.0543)</td><td>(0.0550)</td></tr>
<tr><td>|Population(Dest. - Origin)|</td><td>-0.187***</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>(0.0259)</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Border X |Population(Dest. - Origin)|</td><td>0.195***</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>(0.0244)</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>|Family Income Med.(Dest. - Origin)|</td><td></td><td>0.0174</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td>(0.0145)</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Border X |Family Income Med.(Dest. - Origin)|</td><td></td><td>-0.0651***</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td>(0.0155)</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>|Rent(Dest. - Origin)|</td><td></td><td></td><td>-0.0256</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td>(0.0165)</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Border X |Rent(Dest. - Origin)|</td><td></td><td></td><td>-0.0393**</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td>(0.0156)</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>|House Value(Dest. - Origin)|</td><td></td><td></td><td></td><td>-0.0421**</td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td></td><td>(0.0170)</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Border X |House Value(Dest. - Origin)|</td><td></td><td></td><td></td><td>0.0237*</td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td></td><td>(0.0121)</td><td></td><td></td><td></td><td></td></tr>
<tr><td>|%Unemployed(Dest. - Origin)|</td><td></td><td></td><td></td><td></td><td>2.269</td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td>(1.461)</td><td></td><td></td><td></td></tr>
<tr><td>Border X |%Unemployed(Dest. - Origin)|</td><td></td><td></td><td></td><td></td><td>-7.831***</td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td>(1.667)</td><td></td><td></td><td></td></tr>
<tr><td>|%Urban(Dest. - Origin)|</td><td></td><td></td><td></td><td></td><td></td><td>0.627***</td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td>(0.124)</td><td></td><td></td></tr>
<tr><td>Border X |%Urban(Dest. - Origin)|</td><td></td><td></td><td></td><td></td><td></td><td>-1.326***</td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td>(0.173)</td><td></td><td></td></tr>
<tr><td>|%Black(Dest. - Origin)|</td><td></td><td></td><td></td><td></td><td></td><td></td><td>0.348</td><td></td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>(0.335)</td><td></td></tr>
<tr><td>Border X |%Black(Dest. - Origin)|</td><td></td><td></td><td></td><td></td><td></td><td></td><td>-2.167***</td><td></td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>(0.402)</td><td></td></tr>
<tr><td>|%Republican Vote(Dest. - Origin)|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>-0.981***</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>(0.335)</td></tr>
<tr><td>Border X |%Republican Vote(Dest. - Origin)|</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>-0.494</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>(0.347)</td></tr>
<tr><td>Observations</td><td>1,288,808</td><td>1,288,738</td><td>1,286,462</td><td>1,288,008</td><td>1,288,808</td><td>1,288,808</td><td>1,288,808</td><td>1,288,808</td></tr>
<tr><td>R-squared</td><td>0.715</td><td>0.709</td><td>0.707</td><td>0.700</td><td>0.708</td><td>0.732</td><td>0.713</td><td>0.708</td></tr>
<tr><td>Destination*Year-FE</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td></tr>
<tr><td>Origin*Year-FE</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td><td>Y</td></tr>
</table>

[a] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-way clustering is used at destination-origin SEA level.
[b] All specifications include distance polynomial, contiguity measures, and time-varying destination and origin fixed effects.

ders now equals the coefficient of the border plus the interaction term, and a negative coefficient of the interaction indicates that the deterring effect of the border is increasing in the corresponding dissimilarity measure. Almost all of the coefficients of interacted terms are negative, implying that crossing state borders is more difficult between areas that are dissimilar.

Compared to the benchmark result of in Table 4 column 3, the border coefficient ranges from -0.698 to -3.676, depending on how similar the destination and origin are to each other. Consistent with the results in Table 4, income and urbanization have the largest effects on border. If a pair of SEAs are perfectly similar in median family income and urbanization rate, the border effects will each drop by 37% and 32% given all else equal. This indicates that the economic disparities between urban and non-urban areas explain a significant part of the border. The result in column 7 shows that urbanization has a different effect within and across states. Positive coefficient for within state moves implies that there are more moves between rural to urban, or urban to rural areas while for across states, moves between urban areas or rural areas dominate.

Population differences have an opposite effect on border, and the border is smaller for areas that are more different in population. This may be driven by the fact that as the variance for population is large, and small differences are mostly between less populated areas, this systematically lowers migration flows in between. Once pair-specific factors are controlled for, like other control variables, migration is decreasing in population differences. The coefficient for interacted border with house value differences is also positive but weakly significant. I will discuss this in the later section.

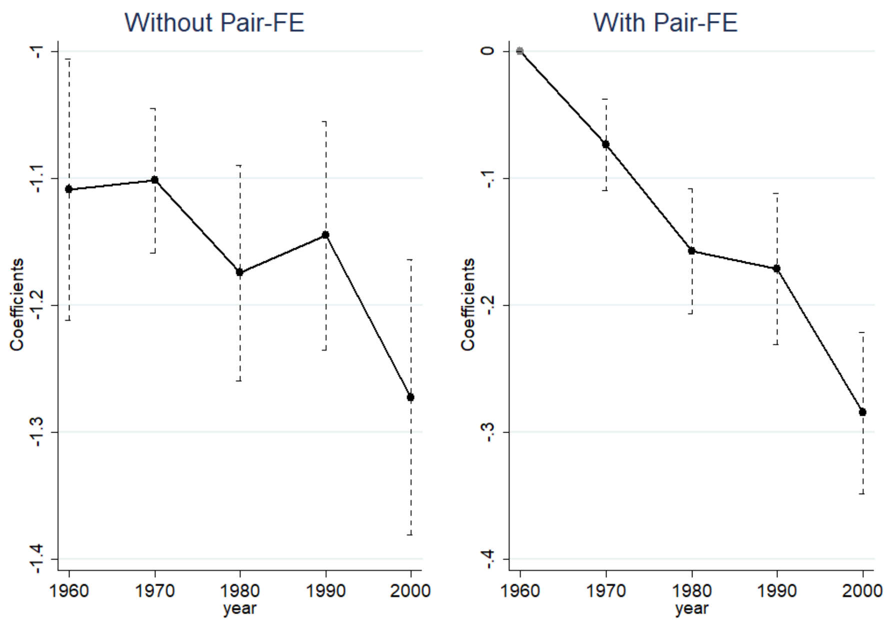
Non-economic controls, such as share of blacks and the votes for the Republican Party, are also included in the last two columns. Similar share of black population also lowers the border effect by 13.84%. The border is higher between areas that are more different in racial compositions, and at the maximum difference of 73.97%, the border coefficient will increase up to -2.62. Interaction with vote share differences is not significant, but interestingly, migration flows are smaller for SEAs with different party preferences within states, suggesting evidence of political sorting.

4.3 Border Trend

I have established a substantial level of the border effect at the state line. In this section, the panel structure of the data is utilized to examine the temporal pattern of the state border effect.

Given lower transportation costs and improved accessibility over time, barrier of crossing the state is expected to decrease over time.[19]

Figure 3 – Border Trend



Note: Border coefficients are from regression results in Table 8 column 1 and 2.

Figure 5 depicts the state border trend. The left panel plots the antilog coefficients of time-interacted border from column 2 with pair fixed effects. It is possible that this strong increase in border trend shown in the left panel is because the effects of other gravity variables, such as distance and contiguity variables, are fixed over time. The right panel shows that even after interacting the distance and contiguity variables with year, the growing border trend is significant and the size of the increase is even larger. Thus, I find that the size of the state border effect has increased over the period parallel with the growing difference between aggregate migration trend for within and across states, shown in Figure 1.

In the first two columns in Table 6, the interaction term between year and the border dummy are reported, and the cross-section PPML outputs for each census year are included in the following columns. In both columns 1 and 2, I find that contrary to expectations, the border has actually

[19]The fall in transportation and communication cost is well documented in Rhode and Strumpf (2003).

increased over time. The state lines act as higher barriers on migration over time, and there are less migrants crossing state lines. Column 1 shows that between 1960 and 2000, the border effect has increased by $exp(1.273-1.109)-1 = 17.82\%$. In column 2, the pair fixed effects are introduced following specification (3). This is the most rigorous specification demanded of my data controlling for all unobservables specific to an origin-destination pair, and the only available variability for identifying coefficients is within-pair across time. Thus, all other variables are collinear with the fixed effects, and only the interaction terms between border and year dummies survive. The coefficients of time-interacted border are relative to the base level in 1960, which is omitted, and the increasing trend is more obvious. The magnitude of the border effect increases by $exp(0.285) - 1 = 32.97\%$ in 2000 compared to the border in 1960.[20]

For the cross-section regressions in the following columns, the pair fixed effects can no longer be included, as there are no time variation within each sample, and the destination and origin characteristics are static and absorbed by the destination and origin fixed effects. The results show that the size of the border effect ranges from 2.646 in 1960 to 3.583 in 2000, and has increased by $exp(1.276 - 0.973) - 1 = 35.39\%$, which is consistent with the increase found in column 2. The border width also increases greatly from 4,360 miles in 1960 to 11,123 miles in 2000. This big jump in width is due to increasingly discounted long-distance moves relative to rising border effect over time.

One concern is the zero flows. Out of all possible SEA pairs, close to half of the pairs have zero migration flows and are mostly interstate pairs excepting few. Large number of zero flows may have an upward bias on the border effect as zero migration will imply high border barrier, but there were more no-flow pairs in the earlier periods. To address this concern, I also separately estimate the pooled and cross-sectional baseline regression for SEA pairs with positive migration flow only. If it is the zero migration flows that drive the border barrier, limiting sample will significantly affect both the level and the trend of the border estimate. I find that the results are similar.[21] I also find the trend is even stronger when limited to contiguous SEAs only.

[20]The sample size is smaller because with pair fixed effect, the origin-destination pairs that have zero migrant flows for all five decades are dropped for PPML regression. This is in total 119,845 observations, 23,969 origin-destination pairs. (But this does not affect the results.)

[21]Results are available upon request.

Table 6 – Border over Time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All	1955-60	1965-70	1975-80	1985-90	1995-00
Logdistance	1.573**		2.208***	2.833***	1.068	1.067	1.231*
	(0.753)		(0.819)	(0.849)	(0.877)	(0.762)	(0.717)
Logdistance2	-0.505***		-0.641***	-0.725***	-0.410**	-0.405***	-0.449***
	(0.140)		(0.153)	(0.156)	(0.164)	(0.142)	(0.133)
Logdistance3	0.0344***		0.0427***	0.0469***	0.0289***	0.0282***	0.0314***
	(0.00845)		(0.00937)	(0.00934)	(0.00997)	(0.00856)	(0.00800)
=1 if SEA Contiguous	0.744***		0.719***	0.666***	0.754***	0.762***	0.784***
	(0.0634)		(0.0803)	(0.0717)	(0.0691)	(0.0637)	(0.0599)
=1 if State Contiguous	0.491***		0.512***	0.538***	0.504***	0.465***	0.453***
	(0.0529)		(0.0601)	(0.0572)	(0.0580)	(0.0501)	(0.0544)
=1 if State Border			-0.973***	-1.135***	-1.214***	-1.174***	-1.276***
			(0.0461)	(0.0420)	(0.0466)	(0.0453)	(0.0424)
Border1960	-1.109***						
	(0.0524)						
Border1970	-1.102***	-0.0738***					
	(0.0448)	(0.0184)					
Border1980	-1.175***	-0.158***					
	(0.0458)	(0.0251)					
Border1990	-1.145***	-0.171***					
	(0.0458)	(0.0303)					
Border2000	-1.273***	-0.285***					
	(0.0469)	(0.0325)					
Observations	1,292,860	1,173,015	258,572	258,572	258,572	258,572	258,572
R-squared	0.706	0.981	0.578	0.670	0.661	0.745	0.762
Destination*Year-FE	Y	Y	Y	Y	Y	Y	Y
Origin*Year-FE	Y	Y	Y	Y	Y	Y	Y
Pair-FE		SEA					
Border effect			2.646	3.110	3.365	3.234	3.583
Border(distance)			4,360	8,270	10,813	8,389	11,123

[a] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-way clustering is used at destination-origin SEA level.

4.4 Understanding Border Trend

In Table 7, as with the level of the border, I interact the border trend with the dissimilarity in control variables to see whether border across time is affected by differences between destination and origin characteristics. The results show that the divergence in population, income, and housing costs can explain the increase in border effects. The changes in border effect over time are canceled out when interacted with differences in population and median house values. This implies that the border barrier increases with population sizes and house values for a given pair of destinations and origins over time. For example, in the 1990 census, the maximum difference in median house value was $267,700 between Santa Clara county in California and a SEA in Kansas that includes Smith, Jewell, Norton, Phillips, Republic, Marshall, and Washington counties.

While the border effect was decreasing in house value differences in the previous table, this effect has reversed when controlled for pair-specific time-invariant factors. This may be driven by the fact that while large house price differences induce less migration for all, this negating effect is smaller across states because within state moves are more sensitive to house prices.Once the pair-specific unobservables are controlled for, within-pair increase in house values will further increase border. The border effect also increases based on income differences. Between destination and origin with similar median family incomes, the border will only increase by half as much. Thus, I find the increasing disparities in population, income and housing costs can explain the border trend.

4.5 Land Use Regulations

4.5.1 Land Use Regulations

Ganong and Shoag (2017) find that the effect of income on outcomes such as housing constructions, house prices, population growth differs as land use regulations increase. This section provides some descriptive facts in line with the literature that the land use regulations are associated with increasing house prices and discouraging migration.

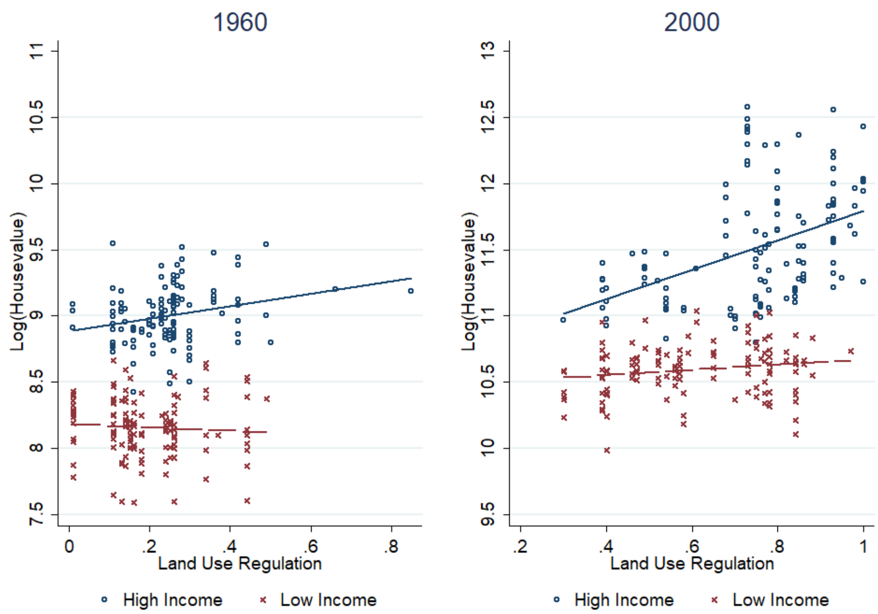
In order to see this relationship between house prices and regulations, Figure 3 plots the log of house value on the land use regulation measures for two groups, the high income and low income SEAs, defined by areas with income in the top and the bottom quartiles. Income and house values

Table 7 – Border Trend Interactions

Control Variable	(1) Population	(2) Income	(3) Rent	(4) House Value	(5) Urban	(6) Black
Border1970	-0.134*	-0.127**	-0.0939***	-0.286***	-0.0914***	-0.0578***
	(0.0787)	(0.0498)	(0.0240)	(0.0571)	(0.0235)	(0.0217)
Border1980	0.141	-0.0367	-0.0975***	-0.0718	-0.105***	-0.148***
	(0.101)	(0.0421)	(0.0214)	(0.0437)	(0.0280)	(0.0286)
Border1990	0.377***	-0.0810*	-0.0692***	0.0783	-0.135***	-0.188***
	(0.132)	(0.0467)	(0.0253)	(0.0759)	(0.0354)	(0.0360)
Border2000	0.153	-0.130**	-0.127***	-0.0789	-0.250***	-0.309***
	(0.158)	(0.0638)	(0.0380)	(0.103)	(0.0387)	(0.0379)
$\lvert$Control(Dest. - Origin)$\rvert$	-0.00266	0.0201***	0.00770	0.0183***	-0.104	-0.960***
	(0.00501)	(0.00619)	(0.00545)	(0.00637)	(0.0647)	(0.170)
Border1970X$\lvert$Control(Dest. - Origin)$\rvert$	0.00451	0.00806	0.00911	0.0274***	0.0496	-0.542***
	(0.00666)	(0.00699)	(0.00774)	(0.00741)	(0.0546)	(0.161)
Border1980X$\lvert$Control(Dest. - Origin)$\rvert$	-0.0234***	-0.0167***	-0.0210***	-0.0105*	-0.175***	-0.569***
	(0.00881)	(0.00627)	(0.00609)	(0.00623)	(0.0580)	(0.161)
Border1990X$\lvert$Control(Dest. - Origin)$\rvert$	-0.0423***	-0.0115*	-0.0293***	-0.0267***	-0.125**	-0.212
	(0.0113)	(0.00673)	(0.00797)	(0.00976)	(0.0635)	(0.200)
Border2000X$\lvert$Control(Dest. - Origin)$\rvert$	-0.0334**	-0.0177**	-0.0346***	-0.0193*	-0.126*	-0.125
	(0.0131)	(0.00858)	(0.0106)	(0.0114)	(0.0737)	(0.222)
Observations	1,168,927	1,168,864	1,166,613	1,168,153	1,168,927	1,168,927
R-squared	0.981	0.981	0.981	0.981	0.981	0.981
Destination*Year-FE	Y	Y	Y	Y	Y	Y
Origin*Year-FE	Y	Y	Y	Y	Y	Y
Pair-FE	SEA	SEA	SEA	SEA	SEA	SEA

[a] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-way clustering is used at destination-origin SEA level.

Figure 4 – House Value and Land Use Regulation

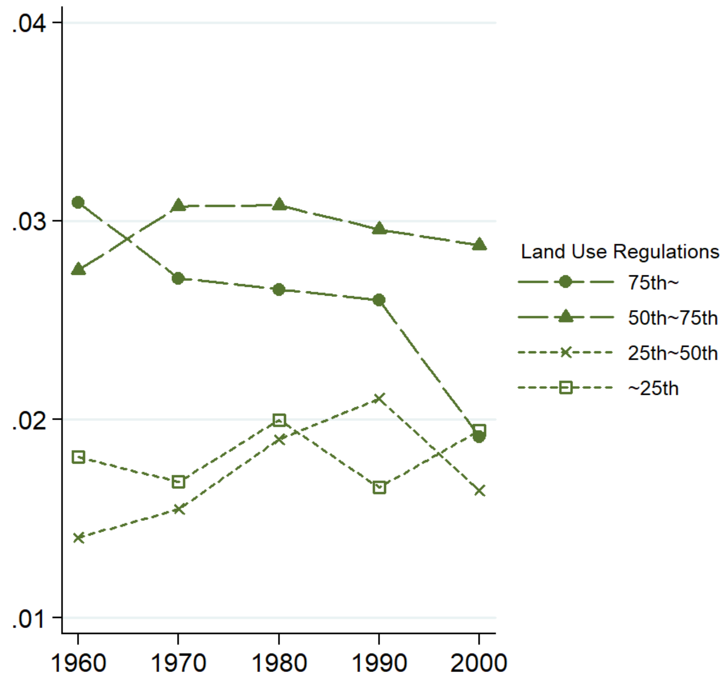


Note: The SEAs with median family income above 75th percentile and below 25th percentile are defined as the high income and the low income groups. Author's calculation using data from Census and Ganong and Shoag (2017).

are observed at the SEA level, and the regulation data is defined at the state level. High income areas will always have larger house prices, but with the implementation of land use regulations, this relationship is further strengthened as higher income feeds into house prices for tightly regulated states due to limited housing supply. A positive slope indicates that the more regulated a state is, the larger the increase in house prices. The steeper slope in 2000 for high income group suggests this correlation has grown over time as the number of land use regulations increase. For the low income group, the land use regulations are positively associated with house prices in 2000, but the relationship is much weaker as the housing demand will be lower. This implies that within state, the land use regulations will have different effects on areas as there are stronger effects for higher income areas consistent with Ganong and Shoag (2017).

Figure 4 displays the aggregate cross-state migration in population shares by the land use regulation measures at destination states. The states are grouped in quartiles and the sum of all four lines will be identical to the hump-shaped interstate migration line shown in the right panel of Figure 1. This demonstrates that there is a clear drop in cross-state migration flows to the most highly regulated states. The total decrease in the top quartile group accounts for 1.18% of the total

Figure 5 – Between State Migration by Land Use Regulation at Destination State



Note: Author's calculation using data from Census and Ganong and Shoag (2017).

population migrating less. Between 1980-2000, 0.7% of the population move less to highly regulated states, and this accounts for more than half of the drop (1.26%) in total interstate migration. While the migration from other states are on a declining trend by 1990 for most states, the bottom quartile group of states with low land use regulation displays no such decline.

4.5.2 Land Use Regulations and the Border Effect

The proliferation of land use restrictions constrains the housing supply, reducing housing affordability, and consequently, migration. Figure 3 and 4 have shown the effect of land use regulations on house prices and migration. Using the land use regulation data from Ganong and Shoag (2017), this section examines the effects of the regulations on the actual migration over the periods 1960-2000. Consistent with their findings, I expect that the more land use regulations are adopted by states, the more discouraged the incoming migration will be. This effect is also expected to be stronger for high income areas where the housing demand is not met due to the limited housing supply. In short, I test for the following claims: 1) highly regulated states have lower in-migration; 2) the effect of state border is increasing in land use regulations; and 3) this effect is stronger for high income areas.

The regression outputs of specification (4) are reported in Table 8.[22] As with other controls, I use the average of the regulation measures over the nearest 5 years that does not overlap with migration years for each census year.[23] The interaction terms between the border and the land use regulation measure at destination states indicate whether the state border is "wider" for the more regulated states. Negative coefficients of the interaction terms imply that regulations increase the border effect, and it is on average more difficult to move to a tightly regulated state.

Column 1 shows the results for total sample. The interaction coefficient is negative and significant in 1990, and the border increase is weaker post-1980 if there are no regulations at the destination state. In the following columns 2 and 3, the sample is limited to all migration flows to high income SEAs whose median family income is above the 50th and the 25th quantiles, and the negative effects of high regulations are even larger and increasing as expected. What is more, the growing effects of regulations completely absorb all of the increase in border trend. Land use regulations, however, will have no impact on migration inflows if the housing supply is not constrained due to low housing demand, and this is what the results show in columns 4 and 5. For low income SEAs, the land use regulations have no effect on border or if any, a positive effect, and fails to explain the border trend. The positive interaction effect may be due to an increased attractiveness of low income SEAs in more regulated states, as migrants substitute toward places with more affordable housing options.

As this paper uses bilateral migration data, I can decompose the negative effect of the land use regulations on net migration found in Ganong and Shoag (2017), and also investigate the effect of regulations at the origin. Consistent with their findings, the results in Table 8 have shown that the interstate migration inflow is reduced as regulation at destination state increases. At origin, the state residents may exit as the cost of living rises due to land use regulations. On the other hand, the

[22]The regression outputs with the measure of zoning restrictions from Ganong and Shoag (2017) are also reported in the Appendix Table 2. The results are similar. I also repeat their placebo exercise using using total number of cases and find no effect in the Appendix Table 3. Border effect is not increasing in the general litigious environment.

[23]Ganong and Shoag (2017) use the average over the last ten years for decennial data. I find the effects are stronger if the average over the previous decade is used.

Table 8 – Land Use Regulations

Destination SEAs by Income	(1) All	(2) Above Median	(3) Above 75th	(4) Below Median	(5) Below 25th
Border1970	-0.166***	-0.0936***	-0.121***	-0.128***	-0.157**
	(0.0307)	(0.0339)	(0.0453)	(0.0432)	(0.0629)
Border1980	-0.162***	-0.0386	-0.0223	-0.198***	-0.279***
	(0.0416)	(0.0545)	(0.0826)	(0.0414)	(0.0594)
Border1990	-0.0203	0.0951	0.215	-0.0777	-0.0702
	(0.0644)	(0.0941)	(0.149)	(0.0588)	(0.0791)
Border2000	-0.187**	-0.0145	-0.0123	-0.307***	-0.285***
	(0.0783)	(0.108)	(0.155)	(0.0848)	(0.110)
LanduseXBorder1970	0.274***	0.220***	0.268***	0.0520	0.225
	(0.0639)	(0.0730)	(0.0849)	(0.134)	(0.201)
LanduseXBorder1980	0.00616	-0.147*	-0.213*	0.134*	0.396***
	(0.0563)	(0.0793)	(0.129)	(0.0753)	(0.111)
LanduseXBorder1990	-0.232***	-0.372***	-0.559***	-0.0371	0.00302
	(0.0789)	(0.119)	(0.188)	(0.0856)	(0.115)
LanduseXBorder2000	-0.145	-0.335**	-0.336*	0.0994	0.0700
	(0.0972)	(0.132)	(0.182)	(0.118)	(0.162)
Observations	1,166,923	582,570	291,524	555,136	270,369
R-squared	0.981	0.985	0.988	0.982	0.981
Destination*Year-FE	Y	Y	Y	Y	Y
Origin*Year-FE	Y	Y	Y	Y	Y
Pair-FE	SEA	SEA	SEA	SEA	SEA

[a] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-way clustering is used at destination-origin SEA level. Data is from Ganong and Shoag (2017).

land use regulations are often in favor of the incumbents, and induce residents to stay. In Appendix Table 4, I find that the land use regulations at origin have a similar but a weaker effect as the regulations at destination, and if significant, the regulation decreases the interstate outflow relative to the intrastate flows. In column 2 and 3, the regulations at high income origin areas will have reduced the interstate outflow of migration, whereas for low income origins, the interstate outflow weakly increases in regulation in Column 4. This may be driven by the demographic profiles of the existing residents, and for high income areas, the incumbents can still afford the higher living cost, but the middle or lower income earners in low income areas are affected. The land use regulations are largely insignificant for low income origins in Column 4 and 5, and the insignificant border effects for the areas with income in the bottom quantile in column 5 seem to be driven more by the sample itself than the land use regulations, as the coefficients are largely inisignificant.

There are two main concerns regarding the possible endogeniety of land use regulations: omitted variables and simultaneity. The way in which Ganong and Shoag (2017) address the endogneity issues for land use regulation on the income convergence is twofold. First, the authors run a placebo test using the total number of court cases, and show that the effects of regulations are not driven by some change in the general litigious climate. Second, they test for reverse causality by using the regulation measure in 1965, the period after which the land use regulations begin to gain popularity. The results show that the level of regulations in 1965 do not have differential effects on the income convergence rates in the pre-period, but in the post-period, there is a significant negative effect on income convergence. This shows that the increase in regulations cannot have been driven by the lower income convergence. Following their paper, I also provide the results for the placebo test in Appendix Table 2, and show that the total number of cases, which reflect the legal climate of the state, have insignificant or a positive effect on the border. This is the opposite of the effect of land use regulations, and if any, it will downward bias my results.

The pre-trend test, unfortunately, is not possible for this paper, as the migration data starts from 1960 and there are not enough data to test prior to the increased regulatons. But my migration data is at the SEA level while the regulation measure is at the state level. There is a large heterogeneity in migration within states, and I also use lagged land use regulation data, to reduce some of reverse causality issues. Also, the use of pair fixed effects will abosrb much of omitted variables as only within-pair over time variations are used.

Endogeneity concerns remain if there are any changes that are correlated with both regulation changes and migration changes. There is a possibility of some unobservables that are correlated with the increase of land use regulation, and at the same time, reduce migration. To address this, in Appendix Table 5, I include the border interaction terms with dissimilarity measures in addition to the specification in Column 3 in Table 8, to test whether the effect of land use regulations are absorbed by other socioeconomic differences. I find that the land use regulation at destination survives. For example, one possible concern is racially segregating and culturally conflicting places may have been more likely to implement regulations, and this may drive the results. Researchers argue that the change in climate toward land use regulations in 1960s can be attributed to racial desegregation in the aftermath of the Civil Rights Act (Fischel 2004). By including the difference in share of blacks as a control, I find that the effect of regulations on border effect survives.

5 Conclusion

The bilateral migration data from the decennial Census Published Volumes show that the decline in interstate migration led to an overall decrease in internal migration since the 1980s, but conversely, intrastate migration has increased since the 1960s. By using the gravity framework, I measure the border effect at the state line and quantify the home bias for migrants. Following Silva and Tenreyro (2006), I employ the PPML estimator with fixed effects to account for bias in the traditional OLS estimates. Despite lack of any formal border barriers, a significant and substantial border effect is found, and it is robust to different specifications. What is more, the estimates show that the border effect has increased over time and it has expanded with the differences in house prices. By using measures of land use regulations, I show that the more land use restricted states have higher borders for incoming migrants, and for high income areas, the increase of land use regulations can explain all of the growth from the border effect. My findings suggest that the popularity of land use regulations hinder migration, but further research is needed to fully understand the root of the border effect.

While this paper has addressed the decline in cross-state migration, the increase in within state migration has not been explained. The findings of this study suggest that non-economic factors such as party preferences affect intrastate migration, but further research is needed to identify the determinants of short-distance moves.

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Table A.1 – Baseline Regressions: OLS(ln(Migrants+1))

	(1)	All (2)	(3)	Contiguous (4)
Logdistance	-1.396***	4.879***	2.650***	3.441***
	(0.0226)	(0.919)	(0.908)	(1.093)
Logdistance2		-1.179***	-0.734***	-1.099***
		(0.158)	(0.156)	(0.257)
Logdistance3		0.0711***	0.0443***	0.0772***
		(0.00893)	(0.00887)	(0.0201)
=1 if SEA Contiguous	1.012***	0.950***	1.009***	
	(0.0428)	(0.0510)	(0.0506)	
=1 if State Contiguous			0.396***	
			(0.0205)	
=1 if State Border	-1.527***	-1.396***	-1.324***	-1.077***
	(0.0467)	(0.0486)	(0.0499)	(0.0322)
Observations	1,292,860	1,292,860	1,292,860	13,930
R-squared	0.666	0.668	0.670	0.885
Destination*Year-FE	Y	Y	Y	Y
Origin*Year-FE	Y	Y	Y	Y
Border Effect	4.604	4.041	3.759	2.935
Border(distance)	1874	1899	1980	79
Standardized Beta(%)	-71.27	-65.17	-61.80	
Standardized Beta(%)contig	47.25	44.33	47.09	
Standardized Beta(%)statecontig			18.50	

[a] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-way clustering is used at destination-origin SEA level.

Table A.2 – Zoning Regulations

Destination SEAs by Income	(1) All	(2) Above Median	(3) Above 75th	(4) Below Median	(5) Below 25th
Border1970	-0.138***	-0.0872**	-0.0841	-0.0930**	-0.119**
	(0.0350)	(0.0401)	(0.0544)	(0.0401)	(0.0475)
Border1980	-0.186***	-0.0747	0.00533	-0.199***	-0.250***
	(0.0533)	(0.0602)	(0.0701)	(0.0474)	(0.0559)
Border1990	-0.131*	-0.0533	0.0455	-0.0933*	-0.0771
	(0.0745)	(0.0874)	(0.122)	(0.0551)	(0.0702)
Border2000	-0.303***	-0.172**	-0.134	-0.340***	-0.313***
	(0.0701)	(0.0829)	(0.111)	(0.0664)	(0.0876)
ZoningXBorder1970	0.149**	0.158**	0.140	-0.0639	0.0581
	(0.0618)	(0.0744)	(0.0886)	(0.0892)	(0.121)
ZoningXBorder1980	0.0523	-0.0745	-0.256**	0.123*	0.295***
	(0.0730)	(0.0904)	(0.105)	(0.0731)	(0.0927)
ZoningXBorder1990	-0.0706	-0.171	-0.347**	-0.0137	0.0160
	(0.0909)	(0.108)	(0.151)	(0.0833)	(0.108)
ZoningXBorder2000	0.0291	-0.139	-0.203	0.177*	0.142
	(0.0841)	(0.0988)	(0.133)	(0.0994)	(0.142)
Observations	1,166,923	582,570	291,524	555,136	270,369
R-squared	0.981	0.985	0.988	0.982	0.981
Destination*Year-FE	Y	Y	Y	Y	Y
Origin*Year-FE	Y	Y	Y	Y	Y
Pair-FE	SEA	SEA	SEA	SEA	SEA

[a] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-way clustering is used at destination-origin SEA level. The measure of zoning cases is from Ganong and Shoag (2017).

Table A.3 – Total Cases

Destination SEAs by Income	(1) All	(2) Above Median	(3) Above 75th	(4) Below Median	(5) Below 25th
Border1970	-0.00977	0.0421	0.0603	-0.0596**	-0.102**
	(0.0277)	(0.0283)	(0.0385)	(0.0290)	(0.0444)
Border1980	-0.200***	-0.145***	-0.0954**	-0.165***	-0.194***
	(0.0390)	(0.0380)	(0.0408)	(0.0390)	(0.0475)
Border1990	-0.256***	-0.205***	-0.158**	-0.139**	-0.0996
	(0.0593)	(0.0560)	(0.0680)	(0.0553)	(0.0699)
Border2000	-0.328***	-0.207**	-0.199**	-0.268***	-0.199**
	(0.0783)	(0.0833)	(0.0965)	(0.0836)	(0.101)
TotalXBorder1970	-0.220***	-0.200***	-0.307***	-0.168**	0.00700
	(0.0604)	(0.0754)	(0.107)	(0.0659)	(0.0946)
TotalXBorder1980	0.0955*	0.0719	-0.120	0.0537	0.158**
	(0.0552)	(0.0686)	(0.0779)	(0.0623)	(0.0747)
TotalXBorder1990	0.140**	0.0800	-0.0263	0.0583	0.0423
	(0.0702)	(0.0702)	(0.0794)	(0.0712)	(0.0879)
TotalXBorder2000	0.0621	-0.0807	-0.102	0.0302	-0.0642
	(0.0919)	(0.0997)	(0.110)	(0.104)	(0.118)
Observations	1,166,923	582,570	291,524	555,136	270,369
R-squared	0.981	0.986	0.988	0.982	0.981
Destination*Year-FE	Y	Y	Y	Y	Y
Origin*Year-FE	Y	Y	Y	Y	Y
Pair-FE	SEA	SEA	SEA	SEA	SEA

[a] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-way clustering is used at destination-origin SEA level. The measure of the total number of cases is from Ganong and Shoag (2017).

Table A.4 – Land Use Regulations at Origin State

Destination SEAs by Income	(1) All	(2) Above Median	(3) Above 75th	(4) Below Median	(5) Below 25th
Border1970	-0.165***	-0.203***	-0.228***	-0.127***	-0.00677
	(0.0306)	(0.0412)	(0.0520)	(0.0406)	(0.0575)
Border1980	-0.160***	-0.226***	-0.277***	-0.185***	-0.0412
	(0.0418)	(0.0550)	(0.0757)	(0.0435)	(0.0488)
Border1990	-0.0208	-0.0451	0.0398	-0.0675	0.0469
	(0.0645)	(0.107)	(0.168)	(0.0564)	(0.0709)
Border2000	-0.185**	-0.243**	-0.227	-0.298***	-0.108
	(0.0783)	(0.121)	(0.164)	(0.0739)	(0.0988)
Landuse at OriginXBorder1970	0.270***	0.290***	0.293***	0.187	0.0831
	(0.0634)	(0.0748)	(0.0857)	(0.122)	(0.190)
Landuse at OriginXBorder1980	0.00180	0.00475	-0.00617	0.271***	0.235**
	(0.0571)	(0.0775)	(0.114)	(0.0780)	(0.0923)
Landuse at OriginXBorder1990	-0.231***	-0.297**	-0.479**	0.0544	0.0990
	(0.0790)	(0.135)	(0.224)	(0.0817)	(0.117)
Landuse at OriginXBorder2000	-0.147	-0.160	-0.207	0.190*	0.0467
	(0.0973)	(0.145)	(0.198)	(0.104)	(0.164)
Observations	1,166,931	585,143	293,434	473,381	268,928
R-squared	0.981	0.985	0.989	0.983	0.977
Destination*Year-FE	Y	Y	Y	Y	Y
Origin*Year-FE	Y	Y	Y	Y	Y
Pair-FE	SEA	SEA	SEA	SEA	SEA

[a] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-way clustering is used at destination-origin SEA level. The measure of the land use regulations is from Ganong and Shoag (2017).

Table A.5 – Land Use Regulations And Controls

	(1) Population	(2) Income	(3) Education	(4) Rent	(5) House Value	(6) Unemployment	(7) Urban	(8) Black	(9) Republican
Border1970	-0.0306	-0.125	-0.148***	-0.126**	-0.295***	-0.0662	-0.148***	-0.114**	-0.121**
	(0.144)	(0.0800)	(0.0485)	(0.0518)	(0.0828)	(0.0497)	(0.0567)	(0.0488)	(0.0563)
Border1980	0.379**	-0.103	-0.0825	-0.00449	-0.0367	-0.0322	-0.0324	-0.0107	0.00255
	(0.150)	(0.107)	(0.0933)	(0.0832)	(0.121)	(0.0806)	(0.0869)	(0.0831)	(0.0858)
Border1990	0.777***	0.185	0.110	0.267	0.287	0.156	0.189	0.145	0.214
	(0.222)	(0.212)	(0.177)	(0.164)	(0.194)	(0.138)	(0.161)	(0.160)	(0.156)
Border2000	0.714***	0.00128	-0.246	0.158	0.150	-0.0626	-0.0410	-0.107	-0.0198
	(0.255)	(0.209)	(0.184)	(0.162)	(0.197)	(0.159)	(0.171)	(0.159)	(0.161)
LanduseXBorder1970	0.289***	0.261***	0.271***	0.276***	0.276***	0.242***	0.270***	0.256***	0.263***
	(0.0875)	(0.0845)	(0.0827)	(0.0857)	(0.0847)	(0.0841)	(0.0840)	(0.0847)	(0.0882)
LanduseXBorder1980	-0.200	-0.217	-0.188	-0.210	-0.213*	-0.200	-0.218*	-0.204	-0.229*
	(0.129)	(0.132)	(0.129)	(0.129)	(0.128)	(0.126)	(0.128)	(0.128)	(0.130)
LanduseXBorder1990	-0.558***	-0.564***	-0.505**	-0.556***	-0.556***	-0.484***	-0.561***	-0.486***	-0.562***
	(0.190)	(0.191)	(0.202)	(0.192)	(0.185)	(0.170)	(0.188)	(0.188)	(0.187)
LanduseXBorder2000	-0.361**	-0.345*	-0.205	-0.337*	-0.313*	-0.303*	-0.340*	-0.256	-0.350*
	(0.182)	(0.182)	(0.192)	(0.182)	(0.184)	(0.179)	(0.186)	(0.178)	(0.182)
|Control(Dest. - Origin)| XBorder1970	-0.00743	0.000819	0.281	0.000251	0.0221*	-3.421***	0.0884	-0.329	0.0172
	(0.0114)	(0.0108)	(0.215)	(0.0150)	(0.0118)	(1.302)	(0.0768)	(0.402)	(0.322)
|Control(Dest. - Origin)| XBorder1980	-0.0297***	0.0117	0.495*	-0.00726	0.00170	0.744	0.0541	-0.635	-0.240
	(0.0100)	(0.00957)	(0.282)	(0.0124)	(0.0114)	(1.277)	(0.0842)	(0.400)	(0.254)
|Control(Dest. - Origin)| XBorder1990	-0.0409***	0.00420	0.873**	-0.0164	-0.00762	-0.0439	0.101	-0.0263	0.0346
	(0.0135)	(0.0122)	(0.403)	(0.0125)	(0.0129)	(0.745)	(0.104)	(0.445)	(0.256)
|Control(Dest. - Origin)|XBorder2000	-0.0512***	-0.000868	2.139***	-0.0380**	-0.0167	1.686	0.108	0.183	0.225
	(0.0171)	(0.0136)	(0.628)	(0.0165)	(0.0166)	(1.491)	(0.131)	(0.421)	(0.320)
Observations	291,524	291,495	291,524	290,605	291,249	291,524	291,524	291,524	291,524
R-squared	0.989	0.988	0.989	0.988	0.988	0.988	0.988	0.988	0.988
Destination*Year-FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Origin*Year-FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pair-FE	SEA	SEA	SEA	SEA	SEA	SEA	SEA	SEA	SEA

[a] Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Two-way clustering is used at destination-origin SEA level. The measure of the land use regulations is from Ganong and Shoag (2017).