Boundaries Generate Widespread Discontinuities in the Urban Landscape

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October 7, 2024

Abstract

Neighborhood boundaries are often determined by physical topography, transportation networks, or the administration of public goods (e.g., school attendance zones). We present a simple model of boundaries that predicts discontinuities in household demographics, the supply of amenities, and home prices at physical and administrative boundaries. We take these predictions to the data and find abundant evidence of discontinuities in a wide range of observable dimensions – the universe of variables available in the 2020 Census at the Block group level – and six different types of boundaries. We draw two important conclusions from these findings: (1) researchers should implement boundary discontinuity designs with caution because the key identification assumption may not hold except in narrow applications, and (2) even narrowly targeted place-based policies may have much broader impacts if they involve a new administrative boundary.

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1 Introduction

For as long as there have been cities, there have been neighborhoods. For as long as there have been neighborhoods, households, firms, and governments have sorted between them. A rich literature following from Tiebout (1956) has studied both the process of[1] and the consequences of[2] neighborhood sorting. Fundamental to this literature is the idea that neighborhood boundaries matter. They represent more than simply lines on a map, and to the extent that they induce distortions that impact decision makers, we should observe different outcomes across boundaries. As such, boundaries will shape both where people live and how amenities are distributed spatially.

In this paper, we model how boundaries distort the location decisions of households, which in turn distort the amenities supplied by private firms and the public goods provided by local governments. Our key empirical insight is that these distortions will manifest as discontinuities in the demographic and amenity bundle of neighborhoods and ultimately in neighborhood prices. We then test for the existence of spatial discontinuities in the universe of all publicly available variables from the US Census, analyzing Block groups near six very different types of boundaries: historical rail and highway networks, contemporary school district boundaries and attendance zones, county lines, and ZIP code boundaries.

We find overwhelming evidence of discontinuities across a wide range of variables and all types of boundaries. The demographic characteristics of residents, features of the housing stock, labor market profiles, and government assistance take-up all systematically vary discontinuously at boundaries. We perform a series of placebo tests to ensure that the

[1]See, for example, Epple et al. (1984, 2003); Bayer et al. (2004); Caetano (2019); Caetano and Maheshri (2023)

[2]See, for example, Black (1999); Bayer et al. (2007); Chetty et al. (2018)

discontinuities in this large set of variables correspond to boundary effects as opposed to other confounders and that these discontinuities are not merely statistical artifacts of our estimation and testing procedure. The sheer variety of boundaries and neighborhood characteristics that we consider leads us to conclude that this is a general phenomenon, and we should expect to find sharp differences in neighborhoods at most types of boundaries.

Our model is a simple formalization of the insights of two seminal papers on sorting. Following Hotelling (1929), we start from the notion that certain consumers wish to locate close to certain producers in horizontally differentiated markets. We then incorporate Tiebout (1956) sorting stemming from heterogeneous public goods across neighborhoods. Our empirical analysis builds on standard approaches to estimate boundary effects (e.g., Black (1999) and Dell (2010)) with the key difference that we explore whether *every* observed neighborhood attribute varies at the boundary instead of exploiting variation in a single variable at the boundary. Our paper is also related to the empirical literature that leverages historical boundaries for identification. A growing literature expands on the findings of Ananat (2011) to show that historical rail placement subdivides cities and creates more neighborhood options, greater racial segregation, and worse outcomes for non-whites in the present day (Chyn et al. (2022), Cox et al. (2022), Whaley (2024)). In the context of our findings, historic railroad boundaries likely contribute to mobility and crime outcomes through local differentials in the entire bundle of neighborhood characteristics, not simply a low dimensional proxy of racial segregation.

An important implication of our empirical findings is that researchers must be cautious when attempting to use historical boundaries to identify the causal effects of contemporary neighborhood characteristics (e.g., socioeconomic compositions, home prices, pollution, crime, or other urban features) in a boundary discontinuity design (BDD). The key identifying assumption that is common across such studies is that the effects of boundaries are mediated through a single characteristic. Our findings suggest that such an assumption is unlikely to hold since boundaries affect a wide range of neighborhood characteristics. We conjecture that this is likely because households and suppliers of amenities continuously sort, so changes in the features of neighborhoods will beget further changes in features of neighborhoods in a self-reinforcing feedback loop. The upshot is that BDDs may be more appropriate to estimate short-run effects before the sorting process can unfold. Although it is common practice to support the identifying assumptions of a BDD by showing that potentially confounding observable characteristics do not vary discontinuously at neighborhood boundaries, we show that such demonstrations are probably statistically under powered when the analysis covers smaller geographies, e.g., a single city, county or state.

In addition, we encourage researchers to broaden the scope of their assessments of the impact of boundary locations. For instance, a large literature has shown that historical redlining practices in US cities still affects residential segregation today (Zenou and Boccard (2000), Gale (2021)). Our findings indicate that these studies almost certainly understate the scope of the effects of redlining, as these efforts likely affected the urban landscape in a more broadly profound manner. Because school attendance boundaries create the most widespread distortions, our results are in line with recent research translating school boundary effects to residential segregation across housing markets (Monarrez (2023)), which leads to disparaties in educational outcomes and mobility (Reardon (2016),Andrews et al. (2017),Monarrez and Schönholzer (2023)). Our study deepens this literature by extending the analysis of boundary effects to the full slate of demographic and neighborhood amenities that may influence lifetime outcomes.

The remainder of this paper is organized as follows. In Section 2, we present a simple model of consumer location decisions, and we characterize how they are affected by physical and administrative boundaries. In Section 3, we present our empirical approach to estimate discontinuities in a large set of variables with no *a priori* spatial ordering, and in Section 4, we describe the various sources of historical and contemporary data that we use to implement this approach. In Section 5, we present our results. We discuss the implication of these results on the growing literature on boundary discontinuity designs in Section 6 before concluding in Section 7.

2 Conceptual Framework

We motivate how boundaries generate discontinuities in households' location choices in an illustrative model. Boundaries are modeled as either physical distortions that increase the distance between points on opposite sides of the boundary, or mechanisms that allow for different levels of public goods to be supplied (or both). For simplicity, we assume that these boundaries are exogenously located along with two producers who are exogenously located at points $0 < y_0 \leq y_1 < 1$ on the unit interval, and a unit mass of consumers, indexed by i, who endogenously locate at points $x_i \in [0, 1]$. There is also a public good that is supplied exogenously at a level of g.

Let $d_i^j = |x_i - y_j|$ be the distance between consumer i and producer j. Then consumer i's utility is given by

$$U(x_i) = \alpha_i u\left(d_i^0\right) + (1 - \alpha_i) u\left(d_i^1\right) + v(g) \tag{1}$$

where the parameter α_i is drawn from a single peaked distribution over $(0,1)$. We assume that $u' < 0$ and $u'' > 0$. That is, α_i represents consumer i's relative preference for producer 0 to producer 1, and all consumers prefer locating closer to producers (with a diminishing loss in marginal utility in distance to producers). We also assume that $v' > 0$.

Consumer i chooses x_i to maximize the objective in equation (1). The first order condition implies

$$\frac{\alpha_i}{(1-\alpha_i)} \frac{u'\left(d_i^0\right)}{u'\left(d_i^1\right)} = 1 \tag{2}$$

in equilibrium. This has a familiar interpretation, as the left-hand side of equation (2) is the marginal rate of substitution between the two producers. The right-hand side of the equation corresponds to the price ratio if we understand distances to producers to be effective prices since $-\frac{\partial d_i^1}{\partial x_i} / \frac{\partial d_i^0}{\partial x_i} = 1$. No consumer will ever locate outside of the interval $[y_0, y_1]$, as they would be strictly better off moving into the interval. Hence, we can illustrate the spatial equilibrium in the top panel of Figure 1.

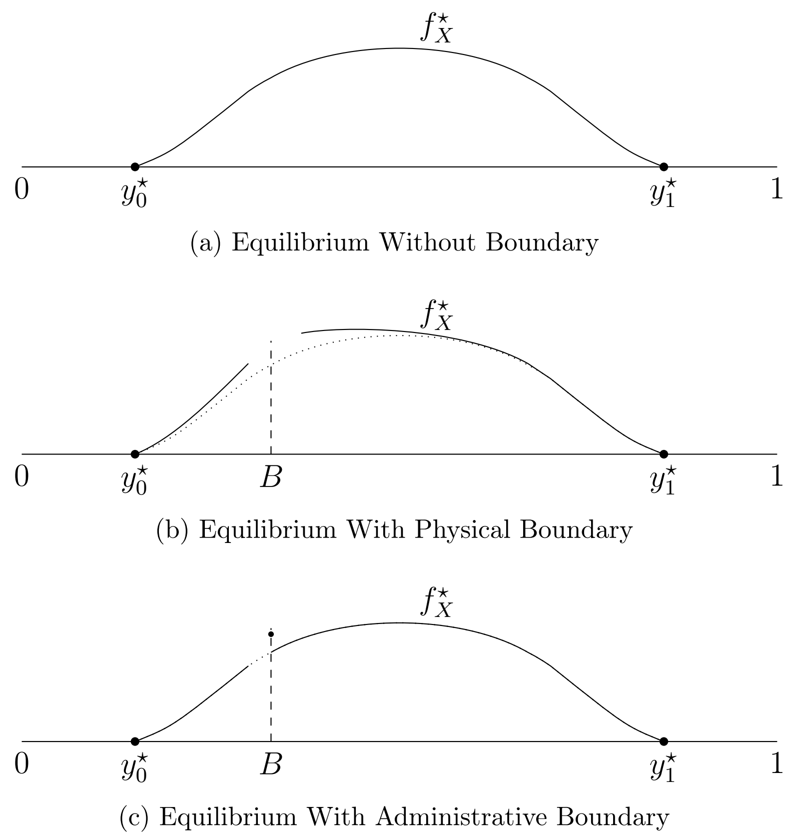
We now introduce an exogenous boundary at some point $B \in (y_0, y_1)$. A basic characteristic of many boundaries such as highways or rivers is that they distort the physical environment. We capture this by modeling the distance between any two points on opposite sides of B increased by $\beta \geq 0$. Consumer i's first order condition is now

$$\frac{\alpha_i}{(1-\alpha_i)} \frac{u'\left(d_i^0\right)}{u'\left(d_i^1+\beta\right)} = 1 \qquad x_i < B \tag{3}$$

$$\frac{\alpha_i}{(1-\alpha_i)} \frac{u'\left(d_i^0+\beta\right)}{u'\left(d_i^1\right)} = 1 \qquad x_i > B \tag{4}$$

All consumers with $x_i^\star < B$ before the introduction of the boundary remain to the left of the boundary and vice versa. The distortion has the effect of shifting the mass of consumers away

Figure 1: Spatial Equilibrium



Notes: Panel A illustrates the distribution of optimal consumer location choices $f_X^\star$, given heterogeneous preferences over distance to producers $y_0^\star$ and $y_1^\star$. Panel B and C illustrate predictions from a model of consumer behavior when a boundary occurs at point B, relative to the initial distribution shown by the dotted line.

from the boundary with a greater shift for those consumers who are located farthest from the boundary. We illustrate this in panel (b) of Figure 1. In general, physical boundaries generate discontinuities in the locations of consumers.

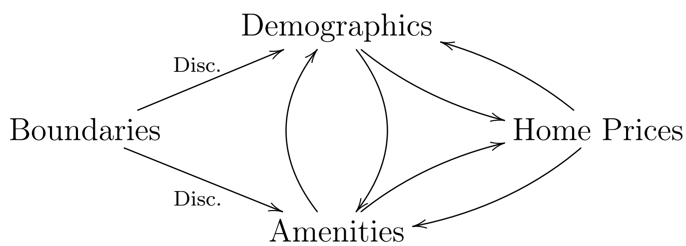
A second characteristic of many boundaries such as school zones or political borders is that they allow for public goods to be differentiated.[3] We model this by specifying $g(x) = g_0$ at all points $x \leq B$ and $g(x) = g_1$ at all points $x > B$ where $g_0 < g_1$ without loss of generality. This has the effect of shifting a mass of consumers just to the left of B across the boundary. We illustrate the effects of an administrative boundary on spatial equilibrium in panel (c) of Figure 1. In general, administrative boundaries also generate discontinuities in the locations of consumers. Of course, many boundaries are both physical and administrative. For example, political boundaries may coincide with rivers or school district boundaries may coincide with roadways. This does not affect the qualitative conclusions of our analysis. We should note that these conclusions are likely to persist – or even strengthen – if we endogenized the locations of boundaries or producers or if we endogenized the levels of public goods since this would increase incentives for sorting.

If consumers belonged to different demographic groups and these groups had systematically different tastes for the producers (the distributions of α_i differed across groups) or different tastes for public goods ($v(\cdot)$ differed across groups) then this simple analysis would yield further insights. Because boundaries would generate discontinuities in the locations of both groups of consumers, then we would generically observe discontinuities in demographic compositions across boundaries. Moreover, if producers adjusted their outputs to cater to their clientele, then this would imply discontinuities in the amenities supplied across

[3] To simplify notation, we assume consumers exactly at the boundary can choose the side of the boundary to which they locate.

boundaries. Similarly, to the extent that governments respond to the preferences of their constituencies, then this would imply discontinuities in the public goods supplied across boundaries. Finally, as amenities and public goods are capitalized into home prices, this may affect the demographics of new consumers.

We summarize how each of these mechanisms contributes to the positive feedback loops shown in the following diagram:



Boundaries generate discontinuities in demographics and amenities. Demographics and amenities are then co-determined with home prices through the sorting of households (consumers) and adjustments made by the suppliers of private amenities (producers) and public amenities (governments). Even if this sorting process is continuous, the ultimate effect of a boundary on the urban landscape will be discontinuities in the characteristics of residents, characteristics of the amenity bundle, and prices.

3 Empirical Approach

To test for these predicted discontinuities, we propose a scalable approach to estimate discontinuous boundary effects on a large set of variables. We observe a boundary network (e.g., the interstate highway network) as a series of curves in space, and we observe characteristics (e.g., population demographics or house prices) at a set of discrete points in space, which, in an abuse of nomenclature, we refer to as neighborhoods. We index neighborhoods with j.

Standard approaches to estimate boundary effects require researchers to know which side of a boundary is treated and which side of a boundary is untreated. These approaches then can then identify treatment effects in a regression discontinuity framework where the running variable is distance to boundary (untreated neighborhoods are usually assigned negative distances, and treated neighborhoods are usually assigned positive distances). In our setting, we do not have *a priori* treated and untreated sides of boundaries; our goal is simply to identify discontinuities and estimate their magnitudes. Moreover, we seek to estimate these effects on vast, highly intersecting boundary networks that span the entire United States. For these reasons, we must modify the standard approach.

First, for a given boundary network, we divide all boundaries into small, equal length pieces. We denote these as boundary segments indexed by b. For each boundary segment, we consider a set of nearby neighborhoods denoted as J_b. We locate the nearest neighborhoods in J_b on either side of the boundary and refer to them as index neighborhoods. For each neighborhood characteristic C, boundary segment b, and neighborhood $j \in J_b$, we construct a dummy $H_{Cbj} = 1$ for all neighborhoods that are on the same side of the boundary as the index neighborhood with a higher value of C (i.e., the "high side") and $H_{Cbj} = 0$ otherwise.

For each $j \in J_b$ on the high side, we define d_{Cbj} to be the distance from j to the boundary, and for each j on the low side, we define d_{bj} to be -1 times the distance from j to the boundary. We then estimate the following regression:

$$C_{bj} = \delta_C H_{Cbj} + f_{-}\left(d_{Cbj}\right) \times 1\left(d_{Cbj} < 0\right) + f_{+}\left(d_{Cbj}\right) \times 1\left(d_{Cbj} > 0\right) + \epsilon_{Cbj} \tag{5}$$

where $f_{-}(\cdot)$ and $f_{+}(\cdot)$ are flexible functions of the distance to the boundary and ϵ_{Cbj} is an error term. The parameter δ_C corresponds to the boundary effect for characteristic C. Under the assumption that the unobservable determinants of C_{bj} vary continuously at the $d_{Cbj} = 0$ threshold, δ_C will be identified and can be estimated by least squares. We implement the discontinuity model with bandwidth selection procedures formalized by Imbens and Kalyanaraman (2012), Calonico et al. (2014), and Calonico et al. (2017).

Placebo Validation Exercise

We consider the following placebo exercise to validate our empirical strategy. To simulate placebo boundaries, we shift every neighborhood in a boundary segment by 0.5 miles to the left or right in the two dimensional boundary space with the direction of the shift determined randomly. That is, we reshuffle the position of each neighborhood $j \in J_b$ by $\xi_{Cb} = \{-0.5, 0.5\}$ with equal probability. For each characteristic C we estimate the placebo regression

$$C_{bj} = \delta_C^p H_{Cbj} + f_{-}^p\left(d_{Cbj} + \xi_{Cb}\right) \times 1\left(d_{Cbj} + \xi_{Cb} < 0\right) + f_{+}^p\left(d_{Cbj} + \xi_{Cb}\right) \times 1\left(d_{Cbj} + \xi_{Cb} > 0\right) + \epsilon_{Cbj}^p \tag{6}$$

which can be understood as an analog to equation (5) in which the location of each boundary segment has been randomly assigned across the map containing neighborhoods $j \in J_b$. If our identifying assumption is satisfied, then we would expect our estimate of δ_C^p to be zero.

4 Data

To estimate the boundary discontinuities δ_C, we construct a dataset that is comprised of Census Block groups geospatially merged to nearby boundaries. Latitude and longitude estimates for the center of population of each Block group is provided by the National Historical Geographic Information System (NHGIS), and we use ARCGIS software to map population centers to 2 mile segments of each boundary type. The rich set of publicly available data at the Census Block group level allows us to describe the area near each boundary segment along more than one thousand dimensions. We describe both the boundary network data and neighborhood variables in further detail.

4.1 Boundary Networks

We analyze three types of boundaries: transportation networks, educational boundaries, and administrative boundaries. Transportation networks form physical boundaries as they deform the urban landscape,are costly to cross, and often delineate distinct neighborhoods. We consider historical rail and highway networks. The US railway network peaked at 254,000 miles of track in the early twentieth century, and today it is comprised of approximately 160,500 miles of track.[4] We measure the historical US rail network using the Atack (2013) historic GIS transportation database created from the New Century Atlas maps published in 1911. This includes all passenger and freight rail lines that were in operation circa 2011. The Interstate Highway System stretches nearly 50,000 and is part of a larger network that includes state highways. For the analysis we employ a digitized map of only interstate highways made publicly available by the US Department of Transportation as of 2020.[5]

School district and school attendance zone boundaries are constructed using shapefiles provided by NHGIS. The National Center for Education Statistics (NCES) conducts an

[4] American Association of Railroads, *Chronology of America's Freight Railroads. https://www.aar.org/chronology-of-americas-freight-railroads/.*

[5] Our analysis omits segments of interstate < 0.5 mile long. Additionally, state managed highways are not present in the shape file.

annual update of school district boundaries dating back to 1995, and we obtain boundaries from the 2020 update. Unlike school districts, there is scant nationally representative spatial data for school attendance zones. NHGIS hosts the 2009-2010 shapefiles created by the NSF funded SABINS project. The analysis of school attendance boundaries is restricted to elementary schools, which are defined as those enrolling third grade students (and none above ninth grade). Because the best available data for US school boundaries are from the 2009-2010 school year, we estimate this model with Census Block group data from 2010.

We also consider administrative boundaries in the form of 2020 county lines and ZIP code boundaries. A large share of county boundaries exist in remote areas with few nearby Block groups, however, our sample is restricted to boundary segments with descriptive Census data on both sides. Such a restriction results in smaller samples for county line regressions, despite the near 100% geographic coverage. ZIP code shapefiles also have extensive geographic coverage, but they contrast with county lines in that the data restriction is far less binding.

4.2 Sample Description

We provide summary statistics of our data in Appendix Table 3, where we compare selected neighborhood characteristics in each boundary network. All Block groups are within one mile of each boundary type, with the sample restricted to boundaries with at least two block groups on either side. For five of the six boundaries we use Block group data from the 2020 Decennial Census and the 2016-2020 American Community Survey (ACS). For school zones we use 2010 Decennial Census Block group data. For 2020, there are over 1,700 variables characterizing the people, housing, and amenities for each Block group in the sample contiguous 48 states (with over 2,000 for 2010). Tens of millions of people live within a mile of our sample boundaries with the most being near railroads (98.7 million) and the least living near county lines (25.9 million). On average, Block group population means range from 1,674 to 1,859 compared to a population average of 1,776.The variation in home values and income across boundary types reflect the exclusion of boundaries in rural areas that do not meet the sampling restriction. Incomes for the sample ($77,768) are relatively higher than US national averages ($67,521) at the time.

5 Results

For each boundary type, we present histograms of all estimated boundary effects in Figure 2 overlaid with histograms of those effects that are significant at the 95% level. In order to facilitate comparison across estimates, we normalize the standard deviation of all dependent variables to 1.[6]

For the two physical boundaries, railroads and highways, all statistically significant boundary effects are positive, which supports our selection procedure for H_{Cbj} (the "high side"). Moreover, the vast majority of economically significant effects (defined as $\hat{\delta}_C > 0.05$) are statistically significant. The range of effects for highways and railroads is similar, though railroad effects tend to be slightly larger than highway effects.

For the two educational boundaries, we estimate even larger effects than for the physical boundaries. Once again, all statistically significant boundary effects are positive, and the vast

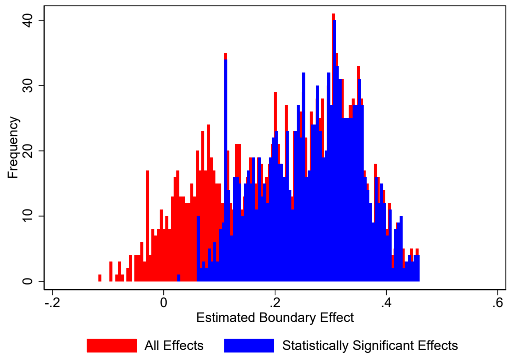
[6]For all results in the main text, we model the relationship between each outcome and distance to the boundary as a third order polynomial function (i.e., f_+ and f_- are cubic polynomials).

Appendix Figure 7 suggests that our estimates of δ_C might be sensitive to this modeling assumption, so we replicated all results assuming f_+ and f_- were linear and summarized them in Appendix Table **??**. A comparison with our main results in Table 1 shows that the cubic model is more conservative in the sense that we estimate fewer statistically significant outcomes.

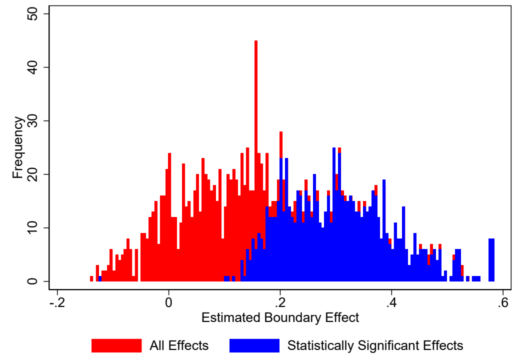
majority of economically significant effects are statistically significant. We estimate fewer statistically significant effects at county boundaries, but a substantial fraction of statistically significant effects at ZIP code boundaries. This is likely due to the fact that the majority of county borders are in rural areas that offer fewer observations for estimation, a drawback that does not apply to ZIP code boundaries.

Figure 2: Boundary Effects

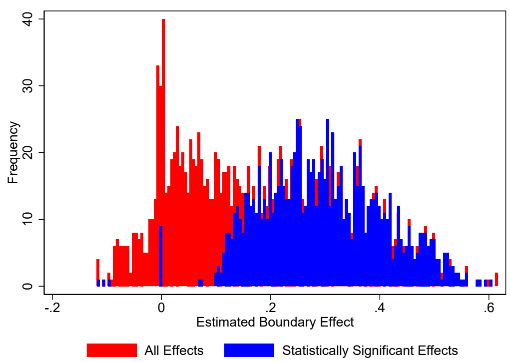
(a) Railroads



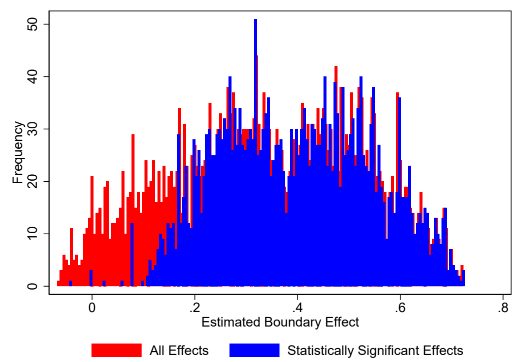
(b) Highways



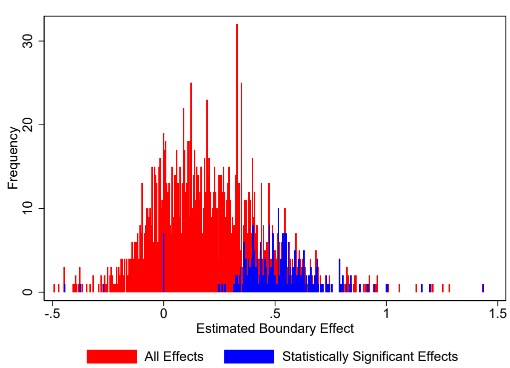
(c) School Districts



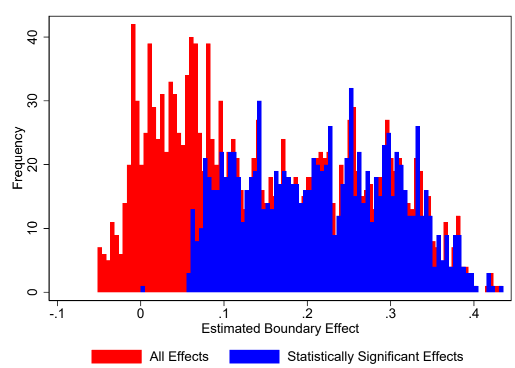
(d) School Attendance Zones



(e) Counties



(f) Zip Codes



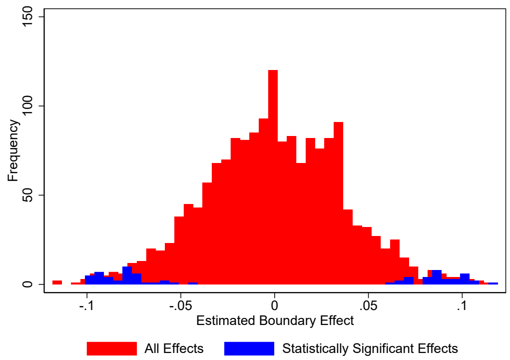
Note: Statistical significance is determined at the 95% level. Each histogram contains the frequency of statistically significant and insignificant effects arranged by the magnitude of the boundary effect (x-axis). For comparison across estimates, the standard deviation of all dependent variables is normalized to 1.

In order to ensure that our results are not simply a statistical artifact of our estimation and testing procedure, we reproduce these histograms using estimated effects from our placebo validation exercise in Figure 3. Three observations are immediate for all boundary types: (1) The overwhelming majority of placebo effects are not statistically significantly different than zero. (2) The distributions of placebo effects are roughly symmetric around zero.[7] (3) The magnitudes of estimated placebo effects are substantially smaller than the magnitudes of the estimated boundary effects. All three observations strongly support our identification strategy.

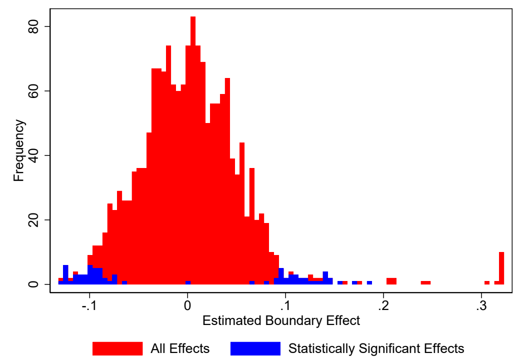
[7] The slight skew to the right is likely due to our selection procedure for the "high side."

Figure 3: Placebo Boundary Effects

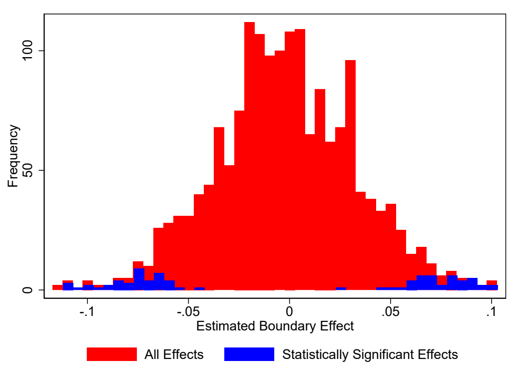
(a) Railroads



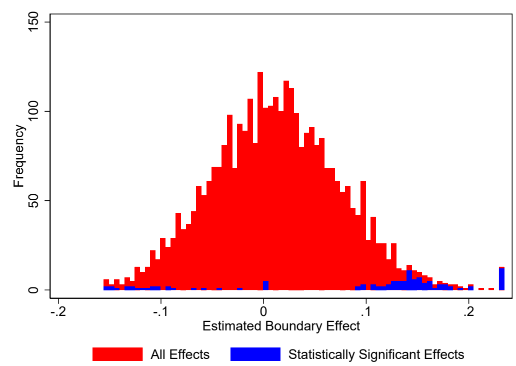
(b) Highways



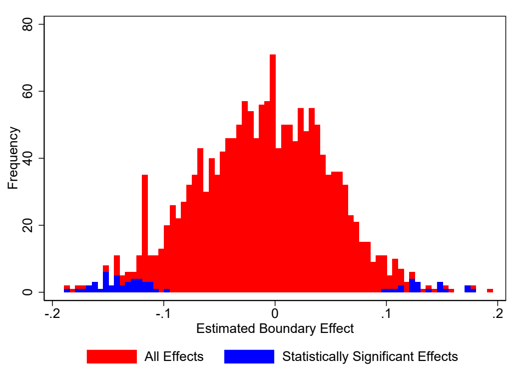
(c) School Districts



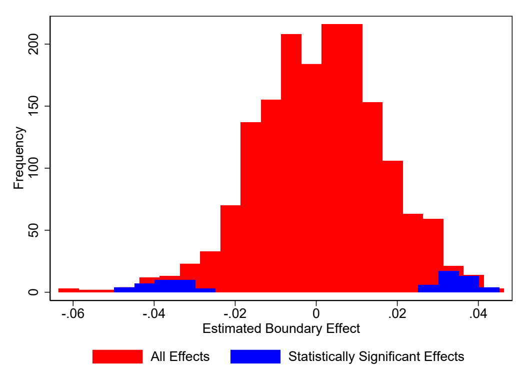
(d) School Attendance Zones



(e) Counties



(f) Zip Codes



Note: Statistical significance is determined at the 95% level. Each histogram contains the frequency of statistically significant and insignificant effects arranged by the magnitude of the boundary effect (x-axis). For comparison across estimates, the standard deviation of all dependent variables is normalized to 1.Detailed description of the placebo boundary exercise is in Section 3.

We summarize these results in Table 1. The fraction of statistically significant effects in column (1) of panel A is substantially greater than 5%, which supports our theory that boundaries should generate systematically generate discontinuities in neighborhood characteristics. In column (3), we see that these effect sizes are of similar size for railroads and highways, slightly larger for school districts and counties, and roughly 50% larger for school attendance zones. This may capture a greater degree of household sorting across school zones than other boundaries. To ensure that these results are not driven by a large number of Census variables being uninformative, in columns (2) and (4) we consider only a subset of variables for which fewer than 10% of observations are missing, all entries are numeric, no observations accidentally take on negative values, and no variables contain extreme outliers (a coefficient of variation over 2000). This eliminates roughly 20% of all neighborhood characteristics from our analysis. Nevertheless, we find a similar prevalence and size of significant effects as we did in the unrestricted sample of columns. The results of our placebo tests are summarized in Panel B of Table 1. All entries in columns (1) and (2) are close to 5%, which is what we would expect when considering significance at the 95% level. Meanwhile, columns (3) and (4) shows that even the few statistically significant placebo effects that we do find are not economically significant.

6 Discussion

Our finding of robust, widespread boundary discontinuities invites caution to practitioners seeking to implement regression discontinuity designs at geographical boundaries, which are commonly known as boundary discontinuity designs or geographic regression discontinuity

Table 1: Summary of Results

	Frac. Significant Effects		Avg. Significant Effect Size	
	All Vars.	Selected Vars.	All Vars.	Selected Vars.
	(1)	(2)	(3)	(4)
Panel A: Actual Boundaries				
School Attendance Zone	0.810	0.841	0.403	0.406
Railroad	0.756	0.783	0.264	0.270
School District	0.610	0.643	0.262	0.304
Highway	0.508	0.531	0.307	0.311
County	0.167	0.178	0.471	0.499
Zip Code	0.635	0.683	0.219	0.219
Panel B: Placebo Boundaries				
School Attendance Zone	0.040	0.036	0.086	0.075
Railroad	0.046	0.045	-0.012	-0.007
School District	0.050	0.050	-0.045	-0.019
Highway	0.053	0.047	-0.037	-0.003
County	0.039	0.043	-0.027	-0.025
Zip Code	0.048	0.048	-0.001	0.006

Notes: In columns (1) and (3), we present statistics for $\hat{\delta}_C$ for the entire sample of neighborhood characteristics. In columns (2) and (4), we present statistics for $\hat{\delta}_C$ for the subsample of non-negative neighborhood characteristics that have fewer than 10% missing observations and no extreme outliers. Each row summarizes the results of independent regressions taking each Census descriptive variable as an outcome, grouped by the particular boundary used in each set of regressions. Statistical significance is reported at the 95% level.

designs. In the notation above, researchers implement such a design in order to estimate the effect of a treatment on an outcome C_{bj} in which treated units j lie to one side of a boundary b ($H_{Cbj} > 0$) and untreated units lie to the other side of that boundary ($H_{Cbj} < 0$). The central identifying assumption in such a design is that the average treatment effect should be continuous as we approach the boundary from either side (Keele and Titiunik (2015)). A common test of this assumption is to demonstrate that other potential confounders C'_{bj} that are observed by the researcher do not vary discontinuously at the boundary with the implication being that any discontinuity that is estimated at the boundary can then be attributed to treatment.

Our results suggest that such an assumption is unlikely to be satisfied in the practice. This is seemingly at odds with the covariate balance tests that often accompany such designs (e.g., Bayer et al. (2007); Gibbons et al. (2013)). We argue that this is due to the fact that tests of discontinuities in neighborhood characteristics are likely to be under-powered when the sample is a single city, metropolitan area or even state. To support this, we replicate our analysis separately for 9 large Core-based statistical areas (CBSA) in the United States using school attendance areas as boundaries and summarize our results in Table 2. We select these 9 CBSAs because they have the largest share of total Census population residing within school attendance zones available in the data shapefiles. In this sense, these results should be seen as conservative since they are the most statistically powered subsamples. While the estimated effect sizes for each CBSA are similar to those of the nation as a whole, the precision of these estimates is dramatically smaller. Instead of finding statistically significant discontinuities in over 80% of neighborhood characteristics, we find statistically significant discontinuities in only 10-25% of neighborhood characteristics depending on city. Hence, researchers should be careful when relying on such tests of (the lack of) discontinuities in potential confounders to validate their research designs.

Our findings do not imply that boundary discontinuity designs are never appropriate. Instead, they indicate that these designs are better suited for estimating certain classes of treatment effects. The fact that we find discontinuities in such a broad set of neighborhood characteristics suggests some (endogenous) relationship between these characteristics. As alluded to in Section 2, an attractive basis for this relationship is some endogenous process of sorting of households and suppliers of amenities. Of course, such a process takes time to unfold. As a result, boundary discontinuity designs may be more successful at identifying short-run treatment effects where the outcome is observed fairly soon after the introduction (or removal) of a boundary.

Table 2: School Attendance Zone Boundary Discontinuities by City

City (CBSA)	Observations	(1) Fraction of Statistically Significant Effects (All)	(2) Fraction of Statistically Significant Effects, Selected Variables
All US (Pooled)	53966	0.810	0.841
Miami	2203	0.101	0.109
Philadelphia	1598	0.088	0.087
Minneapolis	1371	0.228	0.237
Houston	1344	0.223	0.234
Tampa	1141	0.184	0.188
Atlanta	1104	0.371	0.397
Riverside	1010	0.287	0.288
Washington, DC	958	0.163	0.163
Denver	855	0.118	0.102

Notes: In column (1) we present statistics for $\hat{\delta}_C$ for the entire sample of neighborhood characteristics, and in column (2) we present statistics for $\hat{\delta}_C$ for the subsample of non-negative neighborhood characteristics that have fewer than 10% missing observations and no extreme outliers. Selected cities are chosen based on data coverage, ie the share of MSA population residing in a school zone available in GIS shapefiles. Sample cities are sorted in the table by total number of observations. Statistical significance is reported at the 95% level.

7 Conclusion

Boundaries are ubiquitous and unavoidable. Physical structures, both natural and man-made, distort the urban landscape. So too do administrative boundaries that allow for the differentiation of public goods. In this paper, we present a simple model that yields the prediction that these distortions will manifest as discontinuities in neighborhood characteristics across boundaries of many types. We then show that a comprehensive set of neighborhood characteristics – the universe of publicly available characteristics in the decennial Census – exhibit discontinuities at a broad set of physical, educational and administrative boundaries. These discontinuities are sizable, systematic, and not merely statistical artifacts of how spatial data are collected.

In addition to highlighting the sheer durability of urban transportation structures, the existence of railroads and highways installed decades (or centuries) ago suggests that physical boundaries may predate overlapping administrative boundaries observed today. In practice, this implies, for example, that the variation in tax rates at state and county lines is potentially associated with the latent attributes of neighborhoods that were shaped by railroads and highways. This in turn should affect how we think about fiscal competition at political boundaries (Agrawal (2015), Yu et al. (2016)), and the effects of fiscal policy on local economic growth (Peltzman (2016)).[8] In the case of school attendance boundaries, educational and labor market disparities may be amplified when contemporary school zones enhance existing segregation caused by physical boundaries.

Given these findings, we argue that the popular boundary discontinuity design should be

[8]Indeed, Dalgaard et al. (2022) show that even Roman roads dating back well over a millenium are linked to the provision of public goods today.

applied with caution as its core identifying assumption may not hold in certain settings, and a standard validation exercise of this assumption is, in practice, probably under-powered to draw a meaningful conclusion. This yields an insight that should be taken to heart by both policymakers and researchers. Although the short-run effects of boundaries may be narrow, the long-run effects of boundaries are likely to be broad in scope, even if the treatment induced by the boundary is very narrow. Shifting a school attendance boundary has the scope to affect far more than educational outcomes; adding a highway will affect neighborhoods in far more profound ways than changing traffic patterns; past institutional boundaries such as redlines that are no longer in effect may still generate dramatic discontinuities in the present day. Policymakers would be wise to consider these knock-on effects when assessing if and where to place boundaries. And researcher should perhaps trade-off the hope of using boundaries for the sharp identification of narrow treatment effects for the prospect of using boundaries to explain a broader set of spatial phenomena.

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Online Appendix

A Data and Sampling

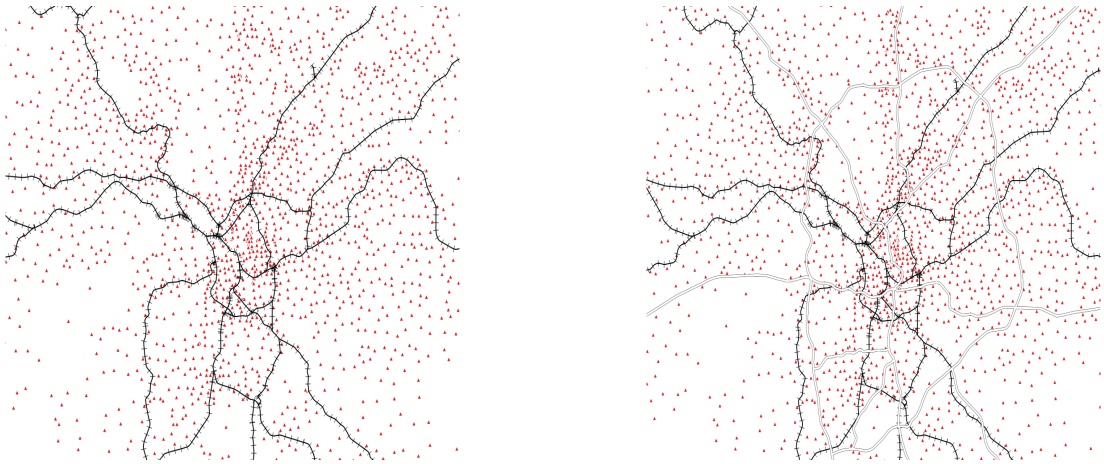
The general approach to constructing our data is the same for each of the six boundaries. Original source data shapefiles are loaded into ArcGIS, and each boundary is cut into segements at maximum two miles in length. Block groups are assigned to nearby boundary segments using the latitude and longitude coordinates of each Block group population center. For each boundary type, we allow Block groups to be assigned to multiple boundary segments. Although Block groups are discrete points across space, the data proxy for a continuous distribution of amenities near each boundary. In that sense, a single Block group that is 0.75 miles from one boundary and 0.1 miles from another can provide valuable information about each. The sample is restricted to Block groups less than a mile from a boundary, and boundary segments must have data on both sides to be included.

A.1 Physical Boundaries

The data for railroad and highway networks is comprehensive and covers the entire United States. The sum total of railroad mileage is greater than highway mileage, and the arrangement of both networks may differ in urban and rural areas. As an example, Figure 4 contains a comparison of railroad and highway coverage in a large urban area (Atlanta, GA) and a suburan/rural county (Anderson, SC) in the same region. Evident from the upper panel are transportation networks serving as major arteries in the city structure, with substantial clustering of neighborhoods near both railroads and highways. Economic activity in rural areas is more likely to be clustered near railroads, as shown in the the lower panel of Figure 4.

Figure 4: Railroads and Highways

(a) Urban Transportation Networks (Atlanta, GA)



(b) Rural Transportation Networks (Anderson, SC)

Notes: In each panel, the left Figure includes only railroad lines, while the right Figure includes both railroad and highway lines. Railroad lines are colored solid black and highway lines are outlined in grey.

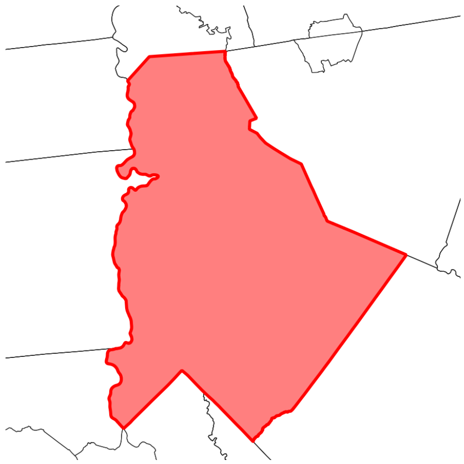
A.2 School Boundaries

There is an extensive body of research on the formation and consequences of school boundaries. There is substantial heterogeneity in the political economy behind how school district and attendance zone boundaries are drawn by state. For the two school boundary types, we try to use the broadest definition possible. The school district sample includes unified districts that do not solely serve charter schools. School attendance zones in the sample include those that contain third grade students and are intended to have open enrollment. Open enrollment school zones allow students with the cachment area to choose from two or more schools that share the same boundary.

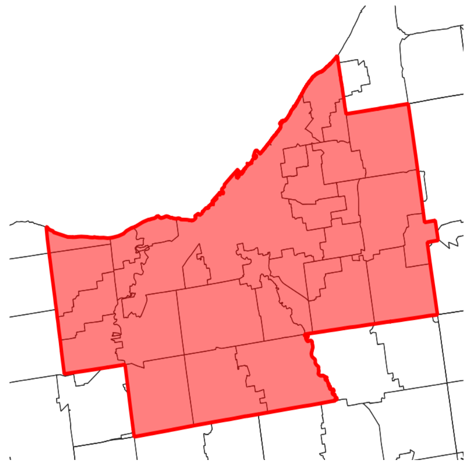
School district maps can vary substantially by state, and are a classic example of variation in the political economy that has historically shaped school districts. On one extreme are school districts drawn synonomously with county lines, covering large spatial areas and governed by a single school board. Such design is prominent is southern states. By contrast, other counties are fragmented with smaller school districts each managed by an independent school board. In the latter case school district lines may coincide with municipal boundaries at a lower geography than the county. As an example, Figure 5 contains two counties (shaded areas) with similar populations in 2020. On the left is Mecklenberg County, population 1.13 million, in which Charlotte is center city. On the right is Cuyahoga County, population 1.23 million, where Cleveland is the center city. As of 2020, Cuyahoga county is served by over 25 school districts.

Figure 5: School District Heterogeneity

(a) Charlotte, Mecklenburg County, NC (1 District)



(b) Cleveland, Cuyahoga County, OH (25+ Districts)



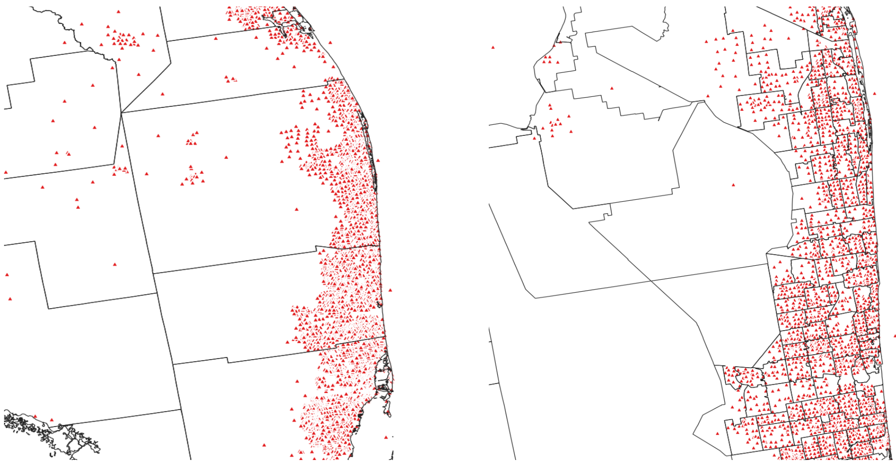
Notes: Mecklenburg County, NC (4.1) has a population of 1.13 million in 2020, in comparison to the 1.23 million residents of Cuyahoga County, OH (4.2). The upper panel illustrates the single unified Charlotte-Mecklenburg school district in contrast to the many districts serving the Cleveland-Cuyahoga County area.

A.3 Administrative Boundaries

Data for county lines and ZIP codes cover nearly entire lower 48 geographic area. As Figure 6 shows, counties have broader administrative geography with boundary sections in both urban and remote areas. There are over 3,000 US counties, and across county lines are predicted changes in tax rates levied on property and sales, municipal service quality, and school quality. There is substantial heterogeneity in county population sizes, with the average US county being approximately 100,000 people.

Figure 6: Example: Greater Miami MSA

(a) County Lines (b) ZIP Codes



Notes: Census Block group locations are overlaid with spatial data for county lines and ZIP code boundaries in the Greater Miami metropolitan area, including Dade, Broward, and Palm Beach counties.

As of the 2020 census there are 41,500 zip codes containing an average 8,340 people in each. As shown in the second panel of Figure 6, the spatial correlation between ZIP code density and populaton density combined with a contiguous ZIP code map yields a substantially larger analysis sample of ZIP code boundaries. The primary purpose of ZIP codes is to delineate federal postal routes, in theory an otherwise meaningless distinction that in practice is used to faciliate other locally provided services. Public school cachments, police and fire precincts, county lines and other municipal boundaries have the potential to overlap with ZIP codes to produce statistically significant amenity differentials in our analysis.

A.4 Real and Placebo Boundaries

The location choice of residents and the endogenous production of heterogenous neighborhood amenities tie the data describing block group population centers to boundary segments in the spatial data. It is the location choices, not the endogeneity of amenities and neighborhood demographics, that result in the observed boundary effects. If the statistical correlation between neighborhood amenities remained constant but the location of neighborhoods were randomly assigned, there would be a much weaker boundary effect, particularly for physical boundaries.

To implement our placebo test, we map neighborhoods to the same boundary segment but randomize the position of population centers relative to the threshold. In doing so we preserve the statistical correlation between neighborhood amenities to simulate a world absent the specific type of spatial segregation that generates boundary effects. Alternatively, if consumers (producers) have within-neighborhood preferences for proximity to a specific producer (consumer) type, but are indifferent about the characteristics of nearby neighborhoods, boundaries will have no effect on the spatial distribution of amenities.

A.5 Summary Statistics

Table 3: Block Group Summary Statistics

Variables	Full Data	Railroad	Highway	School District	School Zone	County Line	ZIP Code
Home Value	304,807.22	298,811.16	340,305.52	329,255.35	307,648.80	340,140.41	331,725.58
	(249299.8)	(257542.2)	(275536.2)	(263742.7)	(211625.8)	(266735.6)	(271314.8)
Income	77,768.43	74,642.87	79,372.11	85,446.41	74,813.60	87,853.63	81,567.33
	(40300.6)	(39464.3)	(40816.8)	(42854.5)	(38145.6)	(43871.7)	(41879.6)
Share White	0.60	0.59	0.53	0.61	0.62	0.63	0.58
	(0.302)	(0.305)	(0.305)	(0.300)	(0.298)	(0.291)	(0.304)
Share Latino	0.19	0.19	0.21	0.17	0.18	0.14	0.19
	(0.235)	(0.239)	(0.245)	(0.227)	(0.227)	(0.180)	(0.237)
Share Black	0.12	0.12	0.14	0.11	0.13	0.13	0.12
	(0.201)	(0.207)	(0.217)	(0.194)	(0.213)	(0.219)	(0.201)
Rooms / Unit	5.82	5.65	5.61	5.97	5.78	6.01	5.85
	(1.374)	(1.316)	(1.399)	(1.471)	(1.272)	(1.562)	(1.447)
Age of Housing	52.96	55.73	56.00	60.05	35.33	60.69	59.06
	(159.1)	(143.3)	(152.9)	(184.4)	(17.98)	(190.6)	(181.3)
Obsevations	65639	56815	39875	33685	35604	14266	45765

Notes: Means and standard deviations (in parentheses) for the full sample of Census Block groups that lie within 1 mile of any boundary (column (2)), and the six subsamples of Block groups for each corresponding boundary network.) Because school zone boundaries reflect the 2009-2010 school year, Census data for this column come from the 2010 Census. For all other boundaries the data are from the 2020 census. Income and home value measures displayed are in 2020 dollars.

B Application: Hedonic Prices at School Boundaries

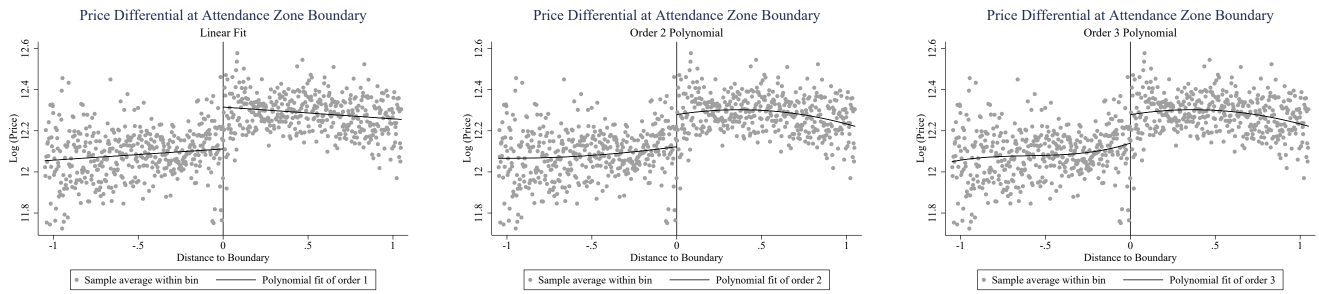
In this section we stress test the results for robustness to specification choices in the boundary discontinuity design. We focus on school attendance zones, which produce the most widespread amenity effects in our analysis and have been a focus in the literature for quite some time. In a setting where house prices capitalize changes in school quality and endogenous amenities at the boundary, bandwidth selection involves choosing the distance from the boundary used to restrict the estimation sample. Further, modelling the change in prices relative to distance to the boundary involves choosing the order of polynomial used to fit the regression. Through this analysis we illustrate how results of boundary - hedonic price regressions are sensitive to research design, and discuss the limitations of causal claims in the absence of high frequency data for both prices and amenities.

B.1 Bandwidth and Local Polynomial Selection

Figure 7 includes raw data scatter plots of census block group home prices for owner-occupied housing. Prices are displayed in logs on the y-axis, and the x-axis arranges block groups by distance to the boundary. For each boundary segment, the median house price is computed for each side, and block groups on the higher income side take positive values. Each panel includes identical underlying data but vary by the polynomial degree chosen for the line of best fit. In a sharp RD design, the point estimate is the difference between two regression functions evaluated at the boundary, represented by the vertical difference the two fit lines. Comparing the panels illustrates how the potential for misspecification if non-linearities in the house price gradient go unmodeled.

Figure 7: Mean Home Values by Distance to the Boundary, 2010 Census

(a) (b) (c)



Notes: Scatterplots of raw data for Census Block groups arranged by distance to a school attendance zone boundary. Each Figure varies only by the polynomial selected to model the local regression on each side of the boundary. Point estimates in a hedonic model of prices are computed as the vertical distance between the two regression lines as they intersect the boundary.

As in traditional RD settings, the primary hurdle in spatial RD design is determination of the bandwidth, defined by the distance from the boundary on either side that determines which data points to be included in the estimation sample. A common practice is to repeatedly estimate the sharp RD model, reducing the sample each iteration by shrinking the bandwidth. We follow Imbens and Kalyanaraman (2012) bandwidth selection process that minimizes an empirical approximation of the mean squared error. Using Calonico et al. (2017) RDRobust package implements Imbens and Kalyanaraman (2012) optimal bandwidth selection for each regression outcome in the main analysis and in the hedonic price regressions that follow.

B.2 Sensitivity of Hedonic Models to Research Design

The bandwidth selection problem is related to a core endogeneity problem in hedonic price regressions. A wider bandwidth increases sample size and statistical power but introduces a particular form of omitted variables bias that increases in the bandwidth radius. The standard assumption is that unobserved amenity quality is held reasonably constant across a small space, allowing for unbiased estimates of the house price capitalization of the only amenity, school quality, that changes at the boundary.

To estimate the price differential across a small spatial area usually involves transaction level data for homes on both sides of a school boundary. More often than not, the high-frequency price data is paired with amenity data that is far less refined spatially. The implication is that balance tests will not detect variation in amenities because the model is underpowered. Indeed, credible identification of potential confounders over a small area near the boundary requires high frequency amenity data to match the rich variation in transaction price data. As shown in the main results, statistically significant patterns in pooled amenity data disappear in smaller samples describing individual cities. This point is made concrete by the results in Table 4, which take house prices as an outcome in the discontinuity model. The pattern is qualitatively similar to the results for all amenities. When the data requirements are met and the model is suffiently powered, there is a 21% premium for the high quality school under the most restrictive model assumptions (column 3).

Table 4: Hedonic Price Regressions

	(1) Degree 1 Polynomial Optimal Bandwidth	(2) Degree 1 Polynomial 0.5 Mile Bandwidth	(3) Degree 3 Polynomial Optimal Bandwidth	(4) Degree 3 Polynomial 0.5 Mile Bandwidth
Full Sample	0.180***	0.183***	0.214**	0.202***
Miami	0.218	0.251**	0.110	0.195
Philadelphia	0.251	0.263	-0.201	0.074
Minneapolis	0.508*	0.350**	0.535	0.576
Houston	0.196	0.269*	0.343	0.226
Tampa	0.204	0.155	0.302	0.288
Atlanta	0.161	0.149	0.166	0.170
Riverside	0.252	0.248	0.141	0.148
Washington, DC	-0.031	0.188*	-0.162	-0.083
Denver	-0.124	-0.038	-0.157	-0.162

Notes: Estimates of price differentials at school attendance zone boundaries under different RD specification choices. Selected cities are chosen based on data coverage, ie the share of MSA population residing in a school zone available in GIS shapefiles. Sample cities are sorted in the table by total number of observations.

The results of this exercise open the black box of boundary fixed effects assumed to hold unobserved amenities constant across the boundary space. Indeed, with rich variation in the data at school boundaries we find that house prices likely capitalize changes in a bundle of amenities that includes school quality. The nature of this process may vary from city to city.

B.3 The Interaction of School and Physical Boundaries

An extension of the theoretical model is the case where neighborhoods on the opposite sides of physical boundaries have access to different public goods. For example, railroads and highways may facilitate the drawing of a new school zone by serving as a pre-existing neighborhood boundary. Given the evidence of race and income demographic sorting at train tracks independent of school zones Whaley (2024), existing train tracks may lower the political cost of drawing a new school boundary overlapping a railroad.

Table 5: Cross-Tab of School and Physical Boundaries

Percent Attending Different Schools			
Boundary	All	City	Suburb
Railroad	45.14% (53,025)	63.87% (26,801)	32.41% (19,803)
Highway	60.32% (32,413)	72.07% (19,342)	45.04% (12,135)
Percent Attending Different Districts			
Boundary	All	City	Suburb
Railroad	17.67% (53,025)	11.51% (26,801)	30.45% (19,803)
Highway	25.48% (32,413)	16.67% (19,342)	40.55% (12,135)

Notes: For the railroad and highway samples, each cell contains the percentage share of Block groups assigned to physical boundaries that overlap with school boundaries. The top panel reflects the incidence of railroads and highways with school attendance zones, and the bottom panel reflects the incidence of railroads and highways with school districts.

Table 5 tabulates the instances in which railroad and highway boundaries also delineate school administrative units. In the upper panel, each cell is the percentage of observations (within 1-mile of a railroad or highway) where the two sides are zoned to different elementary schools. Similarly, the lower panel shows the percentage of observations where the two physical boundary types overlap with school districts. Both tabulations are broken down across city and suburban locales.

There are clear behavioral patterns in the descriptive data of Table 5. First, the interaction of physical boundaries with school zones is more prevalent than with school districts. Second, highways are more likely to serve as facilitators of both school and district maps relative to railroads.Third, physical boundaries are more likely to overlap school zone line in cities relative to the suburbs, while being more likely to overlap a school district line in suburbs (relative to cities).