Using Natural Language Processing to Construct a National Zoning and Land Use Database *

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Abstract

As the U.S. housing affordability crisis unfolds, zoning and land use policies are becoming increasingly scrutinized. Most empirical evidence supports the conclusion that exclusionary zoning and land use policies that are widely adopted across the country inflate housing prices and increase residential segregation. Yet, zoning and land use data, particularly longitudinal data, is notoriously difficult to come by. Virtually all of our sources for zoning and land use information come from a handful of cross-sectional surveys that, while useful, can be subject to low response rates and possible measurement error. As an alternative to commissioning surveys that are costly and time intensive, we propose constructing a national zoning and land use database using publicly available information. In this paper, we use this approach to construct a national zoning and land use database with the same sample from the 2006 Wharton Residential Land Use Regulatory Index (WRLURI) survey. We discuss the process of downloading and processing the zoning and land use text data and address how well our output compares to the municipalities and metropolitan areas present in the 2018 update to the WRLURI on several measures – namely, explicit growth controls, minimum lot sizes, open space requirements, and inclusionary zoning requirements. Finally, we discuss the possibility of replicating this process as a way to ensure access to timely, longitudinal zoning and land use data – especially to further explore the role of zoning and land use policies in residential mobility processes.

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1 Introduction

Despite the visibility of federal housing programs, states and localities dictate the bulk of U.S. housing policy. As the housing affordability crisis escalates, one arcane, but nevertheless ubiquitous element of housing policy - zoning and land use policy - is becoming increasingly scrutinized. Several presidential administrations – both Republican and Democratic – have identified burdensome and exclusionary zoning and land use policies as a key factor behind the drastic undersupply of affordable housing in communities across the country.[1]

The bulk of the empirical evidence indicates that restrictive zoning and land use policies inflate housing prices and increase residential segregation. Yet, despite what researchers have uncovered, a lack of data hampers further investigation. Zoning and land use data, particularly longitudinal data, is notoriously difficult to come by. With a few exceptions, the main sources for national zoning and land use information come from a handful of cross-sectional surveys that, while useful, can be subject to low response rates and possible measurement error. While sampling weights can theoretically correct for some of this, constructing the weights depends on correctly modeling the probability of survey response.

As an alternative to commissioning surveys that are costly and time intensive, we propose constructing a national zoning and land use database using publicly available information. Many municipalities now make their zoning and land use policies publicly available. For instance, well over 90 percent of the municipalities in the 2006 Wharton Residential Land Use Regulatory Index (WRLURI) survey – arguably the most widely cited and utilized national zoning and land use database – have made their zoning and land use data available online. Thus, researchers can access source data and utilize natural language processing to construct a national zoning and land use database more efficiently than previous surveys.

In this paper, we use this approach to construct a national zoning and land use database with the same sample from the 2006 WRLURI study. We discuss the process of downloading and processing the zoning and land use text data and address how well our output compares to the municipalities present in the 2018 update to the WRLURI study on several measures – namely, explicit growth controls, minimum lot sizes, open space requirements, and inclusionary zoning requirements. We combine a range of measures to create an exclusionary zoning index - a subset of what constitutes the entire WRLURI - in both our source data and the matching subset of municipalities from the 2018 WRLURI sample. We also create an indicator for municipal inclusionary zoning programs.

The results indicate that our data is reasonably accurate when compared to a subset of matching municipalities present in the 2018 WRLURI sample. We find crossover in the most regulated municipalities across the datsets and the least regulated municipalities match our expectations as do the regions of the country with the highest prevalence of inclusionary zoning programs. Results at the MSA level follow a similar pattern. We explore the demographic and socioeconomic characteristics of places with above and below average exclusionary zoning index scores and regions with and without inclusionary zoning programs. These results suggest what one would expect. Finally, we carry out a series of descriptive OLS regressions that indicate a positive association between both exclusionary and inclusionary zoning and property values net of demographic and socioeconomic controls, but otherwise, no relationship between these zoning indicators and other

[1]The Obama administration released the Housing Development Toolkit in 2016 (https://www.whitehouse.gov/sites/whitehouse.gov/files/images/Housing_Development_Toolkit%20f.2.pdf and the Trump administration established a White House Council on Eliminating Regulatory Barriers to Affordable Housing (https://www.whitehouse.gov/presidential-actions/executive-order-establishing-white-house-council-eliminating-regulatory-barriers-affordable-housing/

outcomes related to housing prices or permitting activity.

While our data are still in need of refining, these preliminary results suggest that utilizing municipal codes to construct a national zoning and land use database is a viable strategy. We conclude by outlining remaining steps for this database and consider the possibility of replicating this process as a way to ensure access to timely, longitudinal zoning and land use data moving forward. This will be especially useful to further explore the role of zoning and land use policies in residential mobility and displacement processes.

2 Literature review

While far less visible than federal housing programs, zoning and land use policies affect far more people and represent arguably the most significant power that local governments wield. Zoning refers to the division of community into zones in which certain activities are permitted or prohibited (Fischel 2015). Minimum lot sizes, use restrictions, and height restrictions represent three universal elements of zoning laws and land use policy, but many others exist, including parking requirements, minimum setbacks, soil quality, the shape of lots, and open space requirements. Zoning can discriminate by age, but not income, ethnicity, or race, though these have never been binding restrictions (Trounstine 2018). Zoning and land use policies can also limit the number of unrelated people sharing a home. The sheer amount of ways municipalities can affect development presents measurement challenges and as Gyourko and Molloy (2015: 1298) note, "Creativity on the part of local governments appears to know virtually no bounds in this instance."

Taken as a whole, zoning and land use policies determine many critical aspects of municipal character, including what kind of development is allowed, where it can be located, how much can exist, and ultimately, who it can serve. The earliest versions of zoning laws sought to promote public health and sensible land uses, but it did not take long for these policies to be co-opted for exclusionary ends (Pendall, Puentes, and Martin 2006). Spearheaded by Baltimore in 1910, municipalities began explicitly segregating by race in their zoning policies (Fischel 2015). Though *Buchanan v. Warley* (1917) struck down the practice of racial zoning, enforcement was weak and municipalities had plenty of avenues around this restriction - for instance, racial covenants - that fell outside the purview of zoning (Massey and Rothwell 2009; Fischel 2015).

Although New York City adopted the first comprehensive zoning ordinance in 1916, researchers who study zoning and land use policy note that exclusionary zoning practices - encapsulated by a myriad of growth controls and density restrictions - did not become commonplace until the 1970s (Schuetz 2008; Fischel 2015; Ganong and Shoag 2017; Gyourko and Molloy 2015). This, scholars note, signaled a shift in land use policy, as previous efforts to control development became increasingly struck down by courts and thus, exhausted (Trounstine 2018; Sahn 2020). Indeed, unlike racial zoning or racial covenants, exclusionary zoning has survived many court challenges and remains quite common today, due in large part to the financial incentives that most homeowners have to increase their property values (Fischel 2005, 2015) along with institutional mechanisms that amplify their preferences (Einstein, Glick, and Palmer 2020).

Much of the empirical evidence clearly establishes a link between exclusionary zoning and higher housing prices, less housing construction, and lower overall welfare (Katz and Rosen 1987; Glaeser, Gyourko, and Saks 2005; Ihlanfeldt 2007; Turner, Haughwout, and Klaauw 2014; Glaeser and Gyourko 2018; Hilber and Robert-Nicoud 2013; Gottlieb et al. 2012; Albouy and Ehrlich 2018; Black and Hoben 1985). Early work on this front hypothesized that the monopoly power of governments enabled the restriction of housing development (Hamilton 1978). Later research qualified this hypothesis (Fischel 1981) and a sizable literature investigating the role of zoning and land use policy in housing market outcomes emerged, particularly in the past two decades. Gyourko and Molloy (2015) provide a through review of this literature.

Glaeser, Gyourko, and Saks (2005) create a proxy measure of zoning and land use restrictiveness in Manhattan by comparing condominium sale prices to construction costs. They detail the growing discrepancy between the two over the past several decades, noting the concomitant plateauing of building permit activity and attribute this to restrictive zoning and land use policies. Notably, they do not find a sufficient economic welfare justification for such restrictive policy. Glaeser and Gyourko (2018) update these findings, this time using national data from the American Housing Survey, but nevertheless reach similar conclusions: zoning and land use restrictions, particularly in a select few metropolitan areas, have led to considerably inflated housing prices, greatly advantaging incumbent homeowners.

Even more emphatic findings emerge across different studies. Ganong and Shoag (2017) demonstrate how restrictive zoning and land use has decreased labor mobility and thus, held back regional income convergence using a unique panel proxy measure of land use restrictions. Similarly, Hsieh and Moretti (2019) indicate that the depressive effect of land use restrictiveness on labor mobility has prevented considerable increases in economic output and average wages, even when relaxing mobility assumptions. Indeed, Rognlie (2015) highlights the scarcity and cost of housing as the driving factor behind the growth in the net capital share over the past few decades that has been of great interest to scholars of economic inequality.

Housing researchers have debated the contribution of availability of developable land and regulatory restrictiveness towards the contemporary growth in housing prices. Saiz (2010) studies the relationship between geographic constraints on housing supply elasticities, noting how geographic constraints predict both lower housing supply elasticities and more restrictive land use regulations. Previous accounts explicitly or implicitly test the competing hypotheses of overly restrictive land use regulations and a lack of developable land, ruling in favor of the former (Glaeser and Ward 2009; Ihlanfeldt 2007), though other researchers have reached opposite or at least more mixed conclusions (Rose 1989a, 1989b; Jackson 2018).

While the bulk of the zoning and land use literature focuses on housing prices and building activity, an important and growing literature emphasizes the effect of these policies on residential segregation. Pendall (2000) offers evidence of a negative relationship between population shares of Black and Hispanic residents and low-density zoning, building moratoria, urban growth boundaries, and permit caps. More recent research has confirmed this link between low-density zoning and residential segregation (Rothwell and Massey 2009; Rothwell 2011; Pendall, Puentes, and Martin 2006). Although the relationship between exclusionary zoning and income segregation is comparatively under-explored, some work does uncover a positive relationship between the two (Lens and Monkkonen 2016).

More recent research more explicitly isolates the role of race in establishing exclusionary zoning. Resseger (2013) analyzes block-level racial composition across municipal borders in Massachusetts and demonstrates that blocks zoned for multi-family use have shares of Black and Hispanic residents that are roughly three and six percentage points higher, respectively. Arguing that municipal governments had strong incentives to maximize property values for white homeowners, Trounstine (2018) shows how early adopters of zoning were areas of high property values and per-capita public expenditures and that early adoption of zoning was associated with racial segregation. Trounstine (2020) also shows how the white population share in 1970 significantly predicts more restrictive WRLURI scores in 2006 and that the white population share of neighborhoods in six California counties significantly predicts support for restrictive land use policies. Using a switch-share instrument approach, Sahn (2020) finds that a one percent increase in Black population share in northern cities during the second Great Migration led to a one percent decrease in land zoned for multi-family housing and a five percent increase in the cost of rental housing. This latter finding breaks from the relative consensus that housing unaffordability due to restrictive zoning is mostly a coastal market phenomenon (Glaeser and Gyourko 2018, Gyourko, Mayer, and Sinai 2013), adding insight into possible root causes of the well-documented rise in the cost of rental housing across the country in recent years (Desmond 2020). After all, zoning decisions in the mid-20th century could plausibly influence present housing market conditions given the demonstrated impact of early zoning laws on long-term development patterns (Shertzer, Twinam, and Walsh 2018).

Finally, inclusionary zoning - the practice of setting aside a certain percentage of a development for below market-rate units - represents another commonly studied topic in the literature. Many economists consider such a practice an implicit tax on development, placing it in the same category as other development disincentives like minimum lot sizes. While there is some empirical evidence of this (Bento et al. 2009; Means and Stringham 2015), most of the research regarding inclusionary zoning is more mixed, noting that its effects depend greatly on the design on the program which can vary dramatically across states and municipalities (Schuetz, Meltzer, and Been 2009; Soltas 2020; Mukhija et al. 2015). Plenty of research shows that inclusionary zoning can not only effectively increase the supply of affordable housing, but also promote residential integration (Schwartz et al. 2012; Calavita, Grimes, and Mallach 1997; Jacobus 2015; Sturtevant 2016; Urban Institute 2012; Williams 2016; Mukhija et al. 2010), which arguably justifies the additional costs it imposes on development.

As Gyourko and Molloy (2015) note, despite all of this knowledge, researchers lack access to national longitudinal zoning and land use data which represents a key hurdle towards uncovering the causal effects of exclusionary zoning (Quigley and Rosenthal 2005). Researchers have made progress on this front in recent years. Gangong and Shoag (2017) built a proxy measure at the state level using a scaled number of land use cases heard in state appellate and supreme courts from 1940 to 2010. Gyourko, Hartley, and Krimmel (2019) detail the second wave of the WRLURI survey, which, when merged with the 2006 wave of the WRLURI survey (Gyourko, Saiz, and Summers 2008), produces data for 850 municipalities across both waves. Though not longitudinal, the data in Sahn (2020) are derived from publicly available zoning ordinances and maps for 273 cities.

This paper contributes to the literature by detailing the construction of a national zoning and land use database using natural language processing of municipal codes and zoning and land use ordinances. By combining our source data with the 2006 WRLURI data, we can create a panel dataset of 2,522 municipalities, which represents the widest geographic reach to date for longitudinal zoning and land use data. It is our hope that this process can be replicated to establish zoning and land use data for additional municipalities moving forward.

3 Constructing the database

In order to build a panel dataset of zoning and land use information, this project used the 2006 WRLURI sample as the first time period. We replicated selected measures in this data from municipal codes and zoning and land use ordinances between 2019 and 2020 to form the second time period. Thus, we begin with a description of the 2006 WRLURI data as background into our data collection and processing procedure.

The 2006 WRLURI data This dataset represents one of the most comprehensive sets of land use measures and arguably the most widely cited and used land use database to date (Gyourko, Saiz, and Summers 2008). It covers a wide range of measures, from density restrictions and the timeliness of development approvals to the amount of local political pressure and local temperature towards development. While some zoning databases offer even more regulatory detail or multiple years of data, they are generally exclusive to a particular state.[2] Other well-known surveys more directly measure density restrictions (Pendall, Puentes, and Martin 2006), information which we plan to incorporate in future iterations of our database.

To build the dataset, the researchers mailed a survey questionnaire to the planning director or chief administrative officer of 6,896 municipalities across the U.S. from 2004 to 2006. 2,649 responded, yielding a response rate of 38 percent, representing 60 percent of population surveyed. Larger municipalities were more likely to respond to the survey, but with the exception of those with populations under 2,500, municipalities of varying sizes were well-represented.

The survey questionnaire probed three general categories: characteristics of the regulatory process, local land use rules, and outcomes of the regulatory process. The researchers also supplemented these answers with some pre-existing measures of state regulatory environments. Ultimately, they condensed eleven subindices into one overall index of the land use regulatory environment: the WRLURI.

The 2018 update to the WRLURI In 2019, a team of researchers released a new dataset of land use regulations (Gyourko, Hartley, and Krimmel 2019). This survey mirrored the effort in 2006, asking many of the same questions during the 2018 calendar year. Similar to the 2006 wave, 2,472 municipalities answered this wave of the survey. We were able to merge 885 municipalities present in both waves of the WRLURI survey, which give us a subsample of municipalities with which to compare the results of our data collection and processing. According to Gyourko, Hartley, and Krimmel (2019), there was no sea change in land use regulatory regimes between the two survey waves, though regulations were more likely to increase than decrease across municipalities during this time.

Why use source data and natural language processing? For one, fielding surveys like these, particularly national surveys, is expensive and time-consuming. Moreover, while these efforts have yielded very useful information, these surveys have nevertheless demonstrated low response rates, despite the fact that zoning and land use regulations are ubiquitous and oftentimes available online. Over 90 percent of the municipalities in the 2006 WRLURI sample have made their zoning and land use information publicly available online. Finally, possible measurement error is a minor, though not a trivial concern. Researchers may receive different responses depending on which municipal official completes the survey. Indeed, among the small number of duplicated municipalities in the 2006 WRLURI sample, different values were recorded for many measures in the data for the same municipality based on answers from different municipal officials. This was true both for subjective measures like the perception of local political pressure as well as ostensibly objective measures like the existence of minimum lot sizes. Accessing and parsing source data offers some assurances

[2] In particular, Massachusetts (Pioneer Institute's Housing Regulation Database for Massachusetts Municipalities in Greater Boston) and California (Glickfeld et al. 1999; Lewis and Neiman 2000; 2013 California Land Use Survey, 2018 Terner California Residential Land Use Survey), which happen to be two states with highly restrictive zoning and land use policies, have a plethora of zoning and land use information. Florida also has a 2001 land use database used in Ihlanfeldt (2007).

against this type of measurement error by reflecting development laws and rules as they currently exist.

That being said, it is important to note the limitations of this approach. The sheer amount of ways in which local governments can affect the development process presents major hurdles to any zoning and land use data collection process. Accessing zoning and land use ordinances directly further complicates this process for the simple fact that there is virtually no standardization across municipalities in terms of how laws and rules are codified. Even for municipalities in the same state that use the same vendor to codify their regulations (as opposed to the many municipalities who publish their regulations outside of a centralized vendor), the level of detail and organization of the contents in these regulations can be vastly different, which presents immense difficulties in both standardizing data collection and parsing the text data.

Moreover, even if the data collection and parsing process was perfectly seamless, there are many worthwhile measures of land use regulation that this measure cannot easily capture. Determining the average time that project or zoning approvals take or how many regulatory bodies need to approve any project may not necessarily be reflected in municipal regulations. This process also cannot measure perceptions like state government involvement in the process or the local temperature towards development.

Nevertheless, the process described in the remainder of this paper offers a promising method of gathering zoning and land use data. As we expand and perfect this data, it will hopefully help provide centralized, longitudinal zoning and land use information for municipalities across the country. Given the escalating housing affordability problem and the increasing scrutiny aimed at zoning and land use policy, the need for this kind of data will continue to grow.

Current measures The 2006 WRLURI sample provides not only a starting set of target municipalities, but a range of target land use regulation measures. As a first pass through the data, we decided to focus on a range of measures that were likely to be present in municipal zoning and land use regulations. These measures fell into four categories:

- Explicit growth controls: these represent the most restrictive (and rarest) forms of land use regulation. They directly restrict the supply of housing units, which has been shown to increase housing costs (Katz and Rosen 1987; Segal and Srinivasan 1985; Ellickson 1977; Levine 2016). To keep consistency with the WRLURI measures, we captured the six following supply/growth restrictions:
  - Annual limits or caps on single-family permits
  - Annual limits or caps on multi-family permits
  - Annual limits or caps on single-family units
  - Annual limits or caps on multi-family units
  - Annual limits or caps on multi-family dwellings
  - Annual limits or caps on multi-family dwelling units
- Minimum lot size information: the first measure is simply a binary indicator for whether a municipality has any minimum lot size requirement at all. In addition to this, we collected information regarding the sizes of these requirements within municipal boundaries. Larger minimum lot sizes work to restrict housing supply by implicitly restricting density (Fischel

2015). Remaining consistent with the WRLURI measures, minimum lot sizes could fall into one (or more) of four categories:

- Less than one-half acre
- Greater than or equal to one-half acre and less than one acre
- Greater than or equal to one acre
- Greater than or equal to two acres

• Open space requirements: this measure require developers to dedicate or preserve some percentage of the lot(s) to open space or submit an in-lieu payment/fee, which can reduce the amount of land or funds available for development, particularly high-density development and affordable housing (Schmidt and Paulsen 2009).

• Inclusionary zoning requirements: this measure indicates municipalities that operate affordable housing programs, most commonly through the implementation of inclusionary zoning, but also through in-lieu payments or fees that often go into affordable housing trust funds (Schuetz, Meltzer, and Been 2009; Mukhija et al. 2010, Pendall, Puentes, and Martin 2006).

It is worth noting that these measures represent a fraction of the measures that combine to produce the WRLURI. They represent four of the twelve subindices that constitute the overall 2018 WRLURI - the Supply Restriction Index, the Density Restrictions Index, the Open Space Index, and the Affordable Housing Index. While the subindices demonstrate strong correlations with each other and the overall index, our data captures a more narrow scope of land use regulations. Thus, our results will likely be somewhat different, but should still reflect the same general conclusions of Gyourko, Hartley, and Krimmel (2019). Moreover, we treat the Affordable Housing Index - essentially a binary indicator for inclusionary zoning in a given municipality - differently than the WRLURI methodology specifies. While researchers disagree on this point, we do not consider inclusionary zoning an unambiguous development disincentive or restriction and thus treat this indicator separately. We will discuss this further in the next section.

The process We began by downloading municipal codes for 2,716 municipalities in the 2006 WRLURI sample[3][4] We captured the entirety of the municipal codes when possible because early data checks revealed that important zoning and land use information may be located in chapters or sections outside of those specifically related to zoning. In many cases, municipal codes that ostensibly contained a section relating to zoning or land use indicated by a table of contents contained no useful zoning or land use information at all. These were instances in which the municipal codes

[3]We came across several common vendors that store municipal codes. These were Municode, American Legal Publishing Company, Code Publishing Inc, Sterling Codifiers, General Code (eCode360), Franklin Legal Publishing, the Municipal Technical Advisory Service Institute for Public Service at the University of Tennessee, Quality Code Publishing, ClerkBase, and Ranson Citycode. Several other useful websites that hyperlinked to municipal codes for municipalities in particular states were provided by the State of Connecticut Judicial Branch Law Library Services, the Drake University Law Library, and Nebraska Access. The remainder of the municipal codes were downloaded directly from municipal websites.

[4]Scraping these websites, as opposed to downloading the ordinances, is theoretically possible, though not obviously a better solution. The lack of standardization of the content, even within the same vendor, makes the process of web scraping extremely complicated. Furthermore, much of the content is saved in links to PDFs, in which case web scrapping does not help.

referenced regulations that were codified elsewhere. Hurdles like these made the data collection and verification process arguably the most time-consuming part of constructing the database.

Ultimately, we downloaded and verified 2,522 sets of municipal codes, representing about 93 percent of the original target sample. Some of the remaining municipalities simply do not make their codes publicly available. Others have stored their codes in a manner that makes extraction particularly time-consuming. Finally, the last category of remaining municipalities make their codes available, but not in a digitized format. It will likely be possible to include these remaining municipalities in future iterations of this database, but for now, we have a sufficient sample size for our purposes.

With the raw data verified, we then utilized natural language processing to transform the text data into a usable file for analysis. The lack of standardization in the text data also greatly complicated this step of the process. To circumvent this problem, we built a series of regular expression searches that matched on a set of keywords for each of our target measures, capturing the preceding and following 200 characters. Within this text string for a given measure, we then searched for additional keywords, each with an associated weight. We standardized specific words and summed the weights within each additional match in a given string of text. When the sum of the weights was greater than the established threshold, we set the indicator column for a particular measure to 1. If a string had no matches or the sum of matches was not greater than the established threshold, we set the indicator column to 0.[5] This process was repeated for every measure and for each municipality for which we had verified text data. The resulting output was a table of thirteen binary indicators corresponding to the previously discussed measures. See Table 10 in the appendix for a list of keywords used for each measure.

We iterated this process, checking the output values against the municipal codes to verify their accuracy. This resulted in a trial and error method of adjusting the keywords and their weights to minimize both false positive matches and false negative non-matches. We detail the results of this process in the following section.

In order to condense the information conveyed in these thirteen binary indicators, we created an index variable similar to the WRLURI, though with fewer measures as previously discussed. The overall index as it stands (which we label ez.index to measure exclusionary zoning) represents a simple sum of ten of the thirteen binary indicators:

$$\begin{aligned}&\text{ez.index} = \text{restrict SF permit} + \text{restrict MF permit} + \text{limit SF units} + \text{limit MF units} +\\&\text{limit MF dwellings} + \text{limit MF dwelling units} + \text{min lot size} + \text{min lot size } (\geq \text{one acre},\\&< \text{two acres}) + \text{min lot size } (\geq 2 \text{ acres}) + \text{open space}\end{aligned} \tag{1}$$

While our data processing code captures a range of minimum lot sizes per municipality that are not mutually exclusive, we code the minimum lot sizes in the exclusionary zoning index to be mutually exclusive. That is, we capture a municipality's largest minimum lot size, so if it zones for districts with minimum lot sizes of two acres or more, its values for the other minimum lot size indicators will be set to 0 for the purpose of constructing the index. As a departure from the WRLURI methodology, we excluded the indicator for inclusionary zoning from this index. We believe this measure does not neatly align with the other measures, which more clearly indicate

[5]The process for determining specific minimum lot sizes as opposed to just the existence of them was more complicated. Municipalities could store this information in acres or square feet and as digits or as literal words. As it stands, the code is built to convert all numeric (digit or literal word) information into digits and capture ranges of minimum lot sizes in square footage. This undercounts the number of municipalities with one and two acre minimum lot sizes, but we are developing code to futher capture these cases.

impediments to development. Thus, we analyze this binary inclusionary zoning indicator separately in addition to our exclusionary zoning index.

4 Results

Despite the complexity of the process of building a land use database from source text data, we arrived at a database with values that are fairly comparable to the 2018 comparison WRLURI sample. Table 1 displays the results. Comparing means for all thirteen binary indicators across both full samples (All munis), we see that the means for each indicator are quite similar, with the exception of open space requirements and specific minimum lot size variables. Because municipalities often have a range of minimum lot sizes for different jurisdictions (and to remain consistent with the WRLURI methodology), we use the binary indicators to measure the largest minimum lot size that a municipality requires. Thus, each minimum lot size indicator depends in part on the value of the larger minimum lot size indicators. The code used to build the database currently undercounts instances of minimum lot sizes of 2 acres or more, which affects the values for the other three minimum lot size indicators. As for open space requirements, it seems fair to say that our code likely overestimates their prevalence, but based on manual checking of municipal codes against WRLURI values, it is clear that the WRLURI estimate of open space requirements is not entirely accurate either. The true prevalence likely lies somewhere in the middle.

Table 1: Comparison of output to WRLURI 2018 sample

Measure	All munis		Munis in both WRLURI samples		
	Source data N = 2,522	WRLURI 2018 N = 2,843	Source data N = 822	WRLURI 2018 N = 822	matching values
Restrict SF permits	0.01	0.02	0.01	0.02	0.99
Restrict MF permits	0.01	0.03	0.01	0.03	0.97
Limit SF units	0.01	0.03	0.01	0.01	0.98
Limit MF units	0.01	0.03	0.01	0.03	0.97
Limit MF dwellings	0.01	0.03	0.01	0.02	0.97
Limit MF dwelling units	0.01	0.04	0.02	0.03	0.96
Minimum lot size	0.98	0.91	0.98	0.96	0.94
Less than $\frac{1}{2}$ acre	0.42	0.38	0.42	0.5	0.59
Between $\frac{1}{2}$ acre and 1 acre	0.2	0.15	0.19	0.17	0.72
Between 1 and 2 acres	0.17	0.12	0.18	0.12	0.75
2 acres or more	0.15	0.24	0.15	0.22	0.73
Open space	0.91	0.54	0.93	0.59	0.62
Inclusionary zoning	0.1	0.14	0.08	0.12	0.9

However, while comparing the mean values of these binary indicators gives us some sense of the relative prevalence of these regulations in both datasets, it does not indicate how individual municipalities compare across datatsets. Luckily, we were able to match 822 municipalities that are present in both the WRLURI 2006 and 2018 samples and recreate our measures using the actual survey responses to compare individual values for all thirteen indicators. These results are also displayed in Table 1 (Munis in both WRLURI samples). Again, we note the similarities in mean values across the datasets, with the exception of open space and minimum lot size requirements. Moreover, the percentage of matching values across the datasets is quite high for most of the measures, indicating that most municipalities have the same values across the datasets rather than both datasets simply having similar aggregate instances of each measure. While there is still room for improvement in future iterations of this dataset, these initial results are promising.

Turning now to an analysis of our exclusionary zoning index, Figures 1 and 2 plot the densities of our exclusionary zoning indices across the different samples. When compared to the index in the WRLURI data, the index in our source data demonstrates a similar mean value, but slightly less variance. The mean index value in our full sample is 2.266 with a standard deviation of 0.885 compared to a mean of 1.975 and a standard deviation of 1.17 in the full WRLURI 2018 sample. The results are very similar for the subset of matching municipalities. In our source data for this subset, the mean value and standard deviation for the exclusionary zoning index are 2.31 and 0.91, respectively, compared to 1.991 and 1.02 for the same values in the WRLURI 2018 subset.

Figure 1

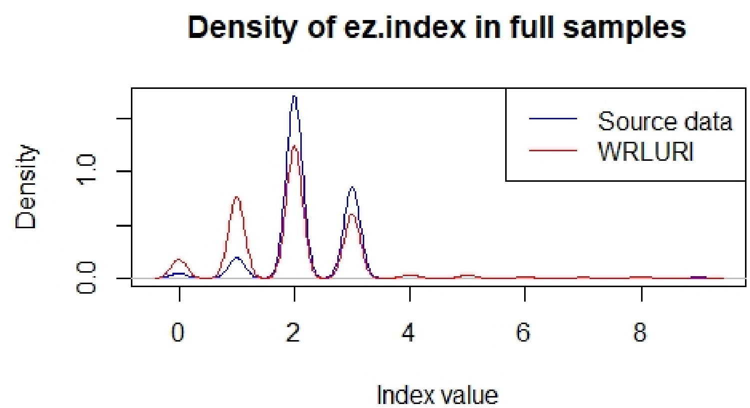


Table 2 displays the top 10 regulated municipalities across the samples - the municipalities with the highest exclusionary zoning index values. The regions present here are consistent with prior research and reflect the usual suspects in terms of restrictive land use regulations. Moreover, there is noticeable cross-over between our data and the WRLURI 2018 data for some of these municipalities. Table 3 displays ten of the least regulated municipalities. Unsurprisingly, the regions present in Table 3 differ considerably from those in Table 2. However, Table 3 contains municipalities from states with notoriously restrictive land use regulations and tight housing markets, an observation that is also consistent with prior research (Gyourko, Saiz, and Summers 2008).[6].

Table 4 details the top five states by number of municipalities with inclusionary zoning programs. The presence of New Jersey, California, and Massachusetts in all of these results corresponds to prior research that notes the concentration of inclusionary zoning programs in these states. Our data seem to suggest that these programs are more heavily concentrated in these three states than does the WRLURI data. The remaining states in Table 4 pass face validity with the possible exception of Illinois, though this will require further investigation.

[6]One should not read into the lack of cross-over in Table 3 since the exclusionary index values for all municipalities present are all 0

Figure 2

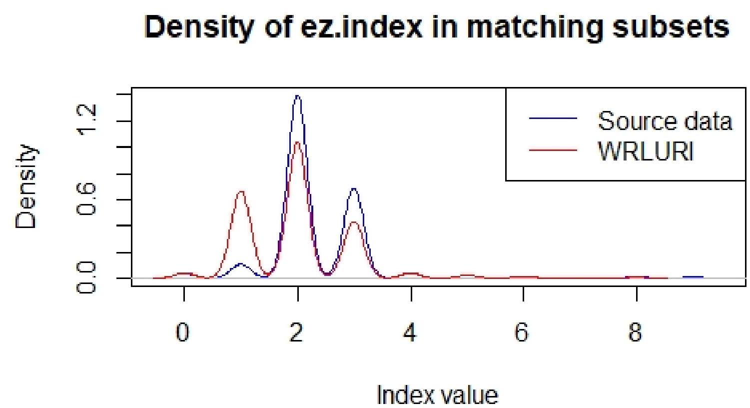


Table 2: Comparison of most regulated municipalities

Rank	All municipalities			
	Source data (N=2,522)		WRLURI 2018 (N=2,843)	
	Municipality name	ez.index	Municipality name	ez.index
1	Morro Bay, CA	9	Needles, CA	9
2	Rohnert Park, CA	9	Merton, WI	9
3	Santa Paula, CA	9	Alfred, ME	9
4	Barnstable, MA	9	Franklin, PA	9
5	Harwich, MA	9	Exeter, RI	8
6	Litchfield, NH	9	Lakehurst, NJ	8
7	Old Bridge, NJ	9	Hopkinton, NH	8
8	Carson City, NV	9	Menands, NY	8
9	West Greenwich, RI	9	Akron, NY	8
10	Normandy Park, WA	9	Tobyhanna, PA	8
Rank	Municipalities in both WRLURI samples			
	Source data (N=822)		WRLURI 2018 (N=822)	
	Municipality name	ez.index	Municipality name	ez.index
1	Morro Bay, CA	9	Morro Bay, CA	8
2	Rohnert Park, CA	9	Exeter, RI	8
3	Harwich, MA	9	Rockingham, VT	8
4	Normandy Park, WA	9	Stow, MA	7
5	Calistoga, CA	8	West Jordan, UT	7
6	Lodi, CA	8	Lodi, CA	6
7	St. Helena, CA	8	St. Helena, CA	6
8	Windsor, CA	8	Milford, MA	6
9	Palm Beach Gardens, FL	8	Clarksdale, MS	6
10	Portsmouth, RI	6	Strongville, OH	6

Table 3: Sampling of least regulated municipalities

All munis		Munis in both WRLURI samples	
Source data N = 2,522	WRLURI 2018 N = 2,843	Source data N = 822	WRLURI 2018 N=822
Opp, AL	Derry, PA	Lamar, CO	Forest Park, OH
Clarksville, AR	St. Francis, WI	American Falls, ID	Manorhaven, NY
Forrest, AR	Mount Pleasant, TX	Shelley, ID	Yorkville, NY
Lamar, CO	Mexia, TX	Flora, IL	Marshall, MI
Bethany, CT	Pampa, TX	Rensselaer, IN	Brentwood, MD
Bartow, FL	Danielson, CT	Camanche, IA	Americus, GA
Springfield, FL	Garwood, NJ	Fort Dodge, IA	Donalsonville, GA
West Miami, FL	Manorhaven, NY	Beverly Hills, MI	Lighthouse Point, FL
Camanche, IA	Yorkville, NY	Centerville, MN	Vestavia Hills, AL
Charles, IA	Hopewell, PA	Springfield, TN	Crestview Hills, KY

**Note*: all ez.index values are 0

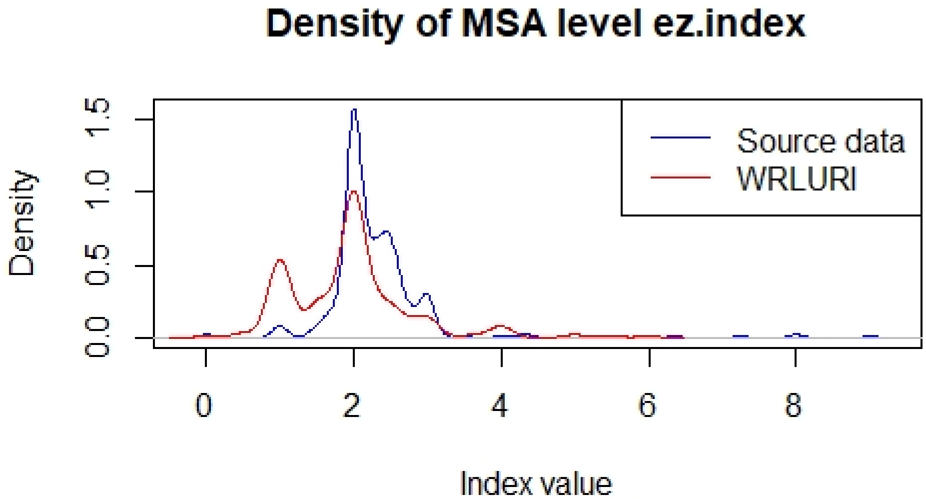
Table 4: States with most inclusionary zoning programs

Rank	All municipalities			
	Source data (N=2,522)		WRLURI 2018 (N=2,843)	
	State	# munis	State	# munis
1	NJ	74	CA	69
2	CA	64	MA	36
3	MA	39	NY	35
4	WA	10	NJ	33
5	CT	8	IL	28
Rank	Municipalities in both WRLURI samples			
	Source data (N=822)		WRLURI 2018 (N=822)	
	State	# munis	State	# munis
1	CA	21	CA	20
2	MA	10	MA	12
3	FL	5	IL	8
4	NJ	5	NY	7
5	CT	4	NJ	5

Aggregating to the metropolitan statistical area (MSA) level by taking the mean values across municipalities within the same MSA does not substantively change the results. For all MSA level analyses, we compare results from MSAs present in the full sample of our source data (N=324) and the MSAs present in the matching subset of municipalities in the 2018 WRLURI data (N=208). Figure 3 displays the density of the exclusionary zoning index at the MSA level. As with the results at the municipal level, our exclusionary zoning index is more tightly concentrated around 2 with a mean value of 2.304 and a standard deviation of 0.834. By comparison, the MSA-level exclusionary zoning index in the WRLURI data registers a mean of 1.94 and a standard deviation of 0.874.

Table 5 compares exclusionary zoning index scores for the most regulated MSAs across the datasets, revealing some interesting findings. As in Table 2, we predictably find MSAs in California, Massachusetts, and other coastal markets well-represented. Yet, several non-coastal markets are present as well. In fact, the Carson City MSA registers as the most tightly regulated MSA in

Figure 3



our data, which strikes us as surprising, yet plausible given its mountainous terrain and proximity to Lake Tahoe. Also notable is the presence of MSAs anchored in fast-growing areas with major research universities - Boulder, CO in our data and San Jose-Sunnyvale-Santa Clara, CA, Lafayette, IN, and Providence, RI in the WRLURI data.

When observing MSAs with at least 10 responding municipalities in Table 5, we again observe MSAs in our data that we would expect - Boston, MA and Seattle, WA - but also some surprises - Akron, OH and Grand Rapids-Wyoming, MI. The presence of MSAs like Atlanta-Sandy Springs-Marietta, GA and Chicago-Joliet-Naperville, IL-IN-WI among the top ten most regulated MSAs in the WRLURI may strike some as surprising, but it is worth keeping in mind that this exclusionary index captures a fraction of what the WRLURI measures. The results in the bottom portion of Table 5 suggest that these MSAs rank highly compared to other large MSAs in the areas of supply restrictions and open space requirements, but likely do not exhibit other land use restrictions that are more difficult to measure via municipal codes alone. Moreover, the highest average exclusionary index for MSAs with at least 10 responding municipalities in the WRLURI data is 2.51, suggesting that even these MSAs are not that tightly regulated.

Table 6 displays exclusionary zoning index values for the least regulated MSAs across datasets. Among all MSAs, the least regulated are geographically dispersed and exhibit a very low average level of land use regulations. Interestingly, the Bremerton-Silverdale, WA MSA - located just outside the Seattle metro area - appears in the list of ten least regulated MSAs according to the WRLURI data, yet this MSA registers as the seventh most regulated MSA out of all MSAs in our data.

The bottom portion of Table 6 displays the same results, but for MSAs with at least 10 responding municipalities. Our data captures the San Francisco-Oakland-Fremont, CA MSA and the WRLURI data contains the New York - Northern New Jersey - Long Island, NY-NJ-PA MSA. These two MSAs are widely regarded as the most restricted and expensive housing markets in the country

Table 5: Comparison of most regulated MSAs

Rank	All MSAs			
	Source data (N=324)		WRLURI 2018 (N=208)	
	MSA name	ez.index	MSA name	ez.index
1	Carson City, NV	9	San Luis Obispo-Paso Robles, CA	6
2	Napa, CA	8	Stockton, CA	6
3	Stockton, CA	8	Providence-New Bedford-Fall River, RI-MA	5.67
4	Barnstable, MA	7.25	Akron, OH	5
5	Santa Rosa-Petaluma, CA	6.33	Napa, CA	5
6	Boulder, CO	4.33	Lafayette, IN	4
7	Bremerton-Silverdale, WA	4.33	Santa Rosa-Petaluma, CA	4
8	San Luis Obispo-Paso Robles, CA	4	Worcester, MA	4
9	Oxnard-Thousand Oaks-Ventura, CA	3.5	Salt Lake City, UT	3.67
10	Manchester-Nashua, NH	3.09	San Jose-Sunnyvale-Santa Clara, CA	3.5
Rank	MSAs with at least 10 responses			
	Source data (N=47)		WRLURI 2018 (N=15)	
	MSA name	ez.index	MSA name	ez.index
1	Manchester-Nashua, NH	3.09	Atlanta-Sandy Springs-Marietta, GA	2.51
2	Providence-New Bedford-Fall River, RI-MA	3	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	2.5
3	Portland-South Portland-Biddeford, ME	2.97	Minneapolis-St. Paul-Bloomington, MN-WI	2.39
4	Bridgeport-Stamford-Norwalk, CT	2.91	Boston-Cambridge-Quincy, MA-NH	2.33
5	Boston-Cambridge-Quincy, MA-NH	2.83	Dallas-Fort Worth-Arlington, TX	2.29
6	Seattle-Tacoma-Bellevue, WA	2.78	Pittsburgh, PA	2.2
7	Hartford-West Hartford-East Hartford, CT	2.75	Kansas City, MO-KS	2.2
8	Akron, OH	2.73	Chicago-Joliet-Naperville, IL-IN-WI	2.04
9	Springfield, MA	2.62	Miami-Fort Lauderdale-Pompano Beach, FL	1.96
10	Grand Rapids-Wyoming, MI	2.58	Seattle-Tacoma-Bellevue, WA	1.95

**Note*: We removed the Monroe, MI MSA from these calculations. It registers as the most regulated MSA according to the WRLURI data and one of the least regulated MSAs according to our data. A quick check confirmed that one municipality (Milan, MI) represents the entire MSA in both datasets. The source data for Milan, MI is missing critical zoning information, which explains its ez.index of 0. The ez.index value of 6 in the WRLURI data seems suspect after cross-referencing with the municipal codes.

(with the Los-Angeles-Long-Beach-Santa Ana, CA and Seattle-Tacoma-Bellevue, WA MSAs not far behind), so their presence in Table 6 seems suspect at first. However, one should keep in mind that this exclusionary zoning index currently measures only a small subset of land use restrictiveness and thus does not capture other elements of zoning and land use policy that contribute to intense cost pressures in these particular MSAs. One should also note that the WRLURI data only contain 15 metros with more than 10 responding municipalities, so the largest MSAs are bound to appear in either the top 10 most or least regulated MSAs. Indeed, several MSAs appear in both.

Finally, Table 7 displays information regarding the prevalence of inclusionary zoning programs across MSAs. The top portion of Table 7 ranks the top five MSAs in terms of the fraction of municipalities with inclusionary zoning programs. These are MSAs in which all responding municipalities

Table 6: Comparison of least regulated MSAs

Rank	All MSAs			
	Source data N=324)		WRLURI 2018 (N=208)	
	MSA name	ez.index	MSA name	ez.index
1	Panama City-Lynn Haven-Panama City Beach, FL	0	Utica-Rome, NY	0
2	Texarkana, TX-Texarkana, AR	0	Battle Creek, MI	0.5
3	Cleveland, TN	1	Wichita Falls, TX	0.5
4	Enid, OK	1	Youngstown-Warren-Boardman, OH-PA	0.5
5	Fort Smith, AR-OK	1	Albany-Lebanon, OR	1
6	Glens Falls, NY	1	Bay City, MI	1
7	Pocatello, ID	1	Beaumont-Port Arthur, TX	1
8	Sioux City, IA-NE-SD	1	Binghamton, NY	1
9	Terre Haute, IN	1	Bowling Green, KY	1
10	Tulsa, OK	1.43	Bremerton-Silverdale, WA	1
Rank	MSAs with at least 10 responses			
	Source data (N=47)		WRLURI 2018 (N=15)	
	MSA name	ez.index	MSA name	ez.index
1	Kansas City, MO-KS	2.03	Detroit-Warren-Livonia, MI	1.55
2	St. Louis, MO-IL	2.05	St. Louis, MO-IL	1.58
3	Houston-Sugar Land-Baytown, TX	2.06	Cincinnati-Middletown, OH-KY-IN	1.61
4	Detroit-Warren-Livonia, MI	2.06	New York-Northern New Jersey-Long Island, NY-NJ-PA	1.73
5	San Antonio-New Braunfels, TX	2.08	Los Angeles-Long Beach-Santa Ana, CA	1.83
6	Rochester, NY	2.08	Seattle-Tacoma-Bellevue, WA	1.95
7	Columbus, OH	2.09	Miami-Fort Lauderdale-Pompano Beach, FL	1.96
8	Anderson, IN	2.11	Chicago-Joliet-Naperville, IL-IN-WI	2.04
9	San Francisco-Oakland-Fremont, CA	2.14	Kansas City, MO-KS	2.2
10	Minneapolis-St. Paul-Bloomington, MN-WI	2.15	Pittsburgh, PA	2.2

**Note*: We removed the Monroe, MI MSA from these calculations. It registers as the most regulated MSA according to the WRLURI data and one of the least regulated MSAs according to our data. A quick check confirmed that one municipality (Milan, MI) represents the entire MSA in both datasets. The source data for Milan, MI is missing critical zoning information, which explains its ez.index of 0. The ez.index value of 6 in the WRLURI data seems suspect after cross-referencing with the municipal codes.

operate some form of inclusionary zoning. There are slightly more than five of these MSAs for both our data and the WRLURI data. Most of these MSAs have a small number of responding municipalities, so they are not necessarily reflective of other municipalities in these MSAs.

The bottom portion of Table 7 displays the same information, but for MSAs with at least ten responding municipalities. Here, we see results that more closely align with expectations. Most, if not all of the MSAs present in this portion of Table 7 are consistent with where prior research would suggest inclusionary programs concentrate. As with Table 4, our results suggest a higher prevalence of these programs in several regions of the country. Interestingly, the WRLURI data suggest a very high concentration of inclusionary zoning programs in the New York-Northern New

Jersey-Long Island, NY-NJ-PA and Boston-Cambridge-Quincy, MA-NH MSAs, but a sharp drop-off in prevalence beyond these two MSAs. Our data also indicates a considerably higher degree of inclusionary zoning programs in the Los Angeles-Long Beach-Santa Ana, CA MSA than does the WRLURI data.

Table 7: MSAs with most inclusionary zoning programs

Rank	All MSAs			
	Source data (N=324)		WRLURI 2018 (N=208)	
	MSA	frac. munis	MSA	frac. munis
1	Farmington, NM	1	Bend, OR	1
2	Longview, WA	1	Florence, SC	1
3	Napa, CA	1	Iowa City, IA	1
4	San Jose-Sunnyvale-Santa Clara, CA	1	Ann Arbor, MI	1
5	San Luis Obispo-Paso Robles, CA	1	Louisville/Jefferson County, KY-IN	1
Rank	MSAs with at least 10 responses			
	Source data (N=47)		WRLURI 2018 (N=15)	
	MSA	frac. munis	MSA name	frac. munis
1	San Francisco-Oakland-Fremont, CA	0.667	New York-Northern New Jersey-Long Island, NY-NJ-PA	0.8
2	New York-Northern New Jersey-Long Island, NY-NJ-PA	0..633	Boston-Cambridge-Quincy, MA-NH	0.667
3	Boston-Cambridge-Quincy, MA-NH	0.579	Chicago-Joliet-Naperville, IL-IN-WI	0.178
4	Bridgeport-Stamford-Norwalk, CT	0.545	Seattle-Tacoma-Bellevue, WA	0.167
5	Los Angeles-Long Beach-Santa Ana, CA	0.417	Los Angeles-Long Beach-Santa Ana, CA	0.167

The following tables - Tables 8 and 9 - reveal demographic and socioeconomic information for these MSAs. We retrieved this data from 2014-2018 ACS estimates.[7] Table 8 displays this demographic and socioeconomic data for MSAs with above and below-average exclusionary zoning index scores. MSAs with higher exclusionary zoning index scores tend to be more populated and have higher shares of Latinx and Asian residents. They are also characterized by higher percentages of households with kids along with higher median household incomes, median property values, median gross rents, and average housing prices, which falls in line with our expectations. There does not seem to be any noticeable difference in average levels of segregation (measured by the multi-group entropy index) across MSAs by these exclusionary zoning index scores. MSAs with more land use restrictions tend to have higher average building permit activity for all kinds of permits, which likely reflects their larger populations.

Table 9 displays similar results to Table 8, except these results are stratified by whether or not an MSA has at least one responding municipality with an inclusionary zoning program. The same observations for Table 8 remain true for Table 9 and in many cases, they are magnified. As discussed previously, MSAs with some degree of inclusionary zoning are concentrated in states like California, Massachusetts, and New Jersey, which we know to be wealthier and more expensive.

[7] Our source data was collected between 2019 and 2020, while the WRLURI data was collected in 2018. 2014-2018 ACS estimates are not the ideal data to use in combination with this zoning and land use data, but it represents the most recently available data for these measures. ACS 2015-2019 estimates will be an improvement and we plan to update this analysis once those estimates become available.

Table 8: Summary statistics for MSAs by ez.index

	Below average ez.index-Source N=195	Below average ez.index-WRLURI N=75	Above average ez.index-Source N=125	Above average ez.index-WRLURI N=133
Total population	627,198.69 (1,187,642.70)	1,072,762.68 (2,826,535.28)	1,134,586.93 (2,384,451.43)	1,160,233.95 (1,641,634.91)
Median Age	38.50 (4.37)	38.41 (4.72)	37.69 (4.20)	38.00 (4.32)
Pct. Black	10.94 (11.12)	10.23 (9.19)	9.67 (10.07)	10.29 (10.29)
Pct. Latinx	9.61 (12.25)	11.06 (13.29)	16.27 (16.22)	15.97 (16.60)
Pct. Asian	2.53 (2.70)	2.79 (2.72)	4.18 (5.23)	4.08 (4.36)
Pct. white	72.92 (16.03)	71.84 (15.69)	65.29 (18.28)	65.65 (18.42)
Multigroup entropy index	0.18 (0.08)	0.19 (0.09)	0.18 (0.07)	0.18 (0.07)
Pct. owner occupied	66.04 (5.46)	65.90 (6.25)	64.38 (5.69)	64.70 (5.42)
Median hhld. income	54,642.66 (8,243.55)	55,610.03 (9,300.28)	60,824.47 (12,521.96)	60,928.92 (11,948.18)
Median property value	173,549.74 (82,121.84)	179,422.67 (92,470.22)	236,274.02 (127,443.72)	229,291.60 (123,751.24)
Median gross rent	871.49 (169.63)	876.75 (195.23)	1,008.54 (254.14)	1,005.37 (238.45)
Pct. rent burdened	44.67 (4.37)	45.01 (4.53)	46.53 (5.19)	46.19 (4.85)
Pct. sev rent burdened	22.30 (3.59)	22.32 (3.53)	23.06 (3.94)	23.01 (3.62)
FHFA Housing Price Index	208.54 (45.12)	205.22 (47.13)	233.59 (58.32)	236.30 (61.68)
Median year structure	1977 (9.73)	1975 (9.80)	1979 (9.60)	1979 (8.95)
Pct. bachelors or more	27.43 (7.81)	28.26 (7.74)	31.07 (8.88)	31.41 (8.69)
Pct. no HS degree	11.22 (4.42)	11.21 (4.51)	11.61 (5.24)	11.43 (5.08)
Hhld. poverty rate	14.41 (3.19)	14.24 (3.21)	13.38 (3.79)	13.28 (3.75)
Unemp. rate	5.88 (1.55)	5.84 (1.20)	5.85 (1.73)	5.84 (1.75)
Pct. hhlds w/kids	29.78 (4.50)	29.95 (4.42)	31.28 (4.86)	30.99 (5.13)
All building permits	1,821.11 (4,059.27)	1,865.12 (3,187.34)	2,726.30 (4,540.60)	3,508.25 (5,836.97)
SF building permits	1,768.18 (3,968.00)	1,781.84 (3,020.53)	2,618.47 (4,403.91)	3,394.75 (5,711.35)
MF building permits	52.93 (110.42)	83.28 (270.25)	107.83 (241.60)	113.50 (171.35)

5 Preliminary regression analyses

Rounding out the overall analysis of our data, we conduct a series of regression analyses with our source data and the WRLURI data on a range of outcomes commonly used in studies of zoning and land use policy. Each cross-sectional regression can be characterized by the following equation:

$$Y_i = \alpha_i + \beta_1 Z_i + \beta_2 X_i + \epsilon_i \qquad (2)$$

In equation (2), i represents an individual MSA, indicating that we run each regression at the

Table 9: Summary statistics for MSAs by inclusionary zoning

	No IZ-Source N=265	No IZ-WRLURI N=163	IZ-Source N=57	IZ-WRLURI N= 43
Total population	497,952.31 (811,810.05)	746,893.77 (1,091,523.09)	2,358,577.58 (3,467,807.37)	2,574,515.44 (3,889,118.94)
Median age	38.08 (4.44)	38.09 (4.71)	38.63 (3.70)	38.36 (3.39)
Pct. Black	10.73 (11.14)	10.04 (9.87)	9.08 (8.45)	11.12 (10.00)
Pct. Latinx	10.51 (13.60)	13.32 (16.05)	20.28 (14.83)	17.43 (13.58)
Pct. Asian	2.49 (3.04)	2.69 (1.96)	6.38 (5.87)	7.09 (6.58)
Pct. white	72.25 (16.39)	69.95 (17.39)	59.04 (17.59)	60.15 (16.84)
Multigroup entropy index	0.18 (0.08)	0.18 (0.07)	0.20 (0.08)	0.22 (0.09)
Pct. owner occupied	65.92 (5.41)	65.69 (5.71)	62.91 (5.85)	63.05 (5.47)
Median hhld. income	54,554.12 (7,790.56)	56,339.25 (8,322.55)	68,827.81 (13,561.40)	69,049.81 (15,111.35)
Median prop value	170,607.17 (60,448.56)	181,082.21 (66,153.39)	326,984.21 (166,133.32)	325,058.14 (177,816.56)
Median gross rent	867.73 (146.63)	898.29 (157.28)	1,194.32 (283.01)	1,186.93 (314.70)
Pct. rent burdened	44.70 (4.42)	45.02 (4.57)	48.67 (5.16)	48.55 (4.47)
Pct. sev rent burdened	22.24 (3.63)	22.20 (3.47)	24.28 (3.85)	24.87 (3.29)
FHFA Housing Price Index	207.90 (42.09)	215.09 (50.16)	267.35 (65.23)	262.49 (72.55)
Median year structure	1978 (9.73)	1979 (9.51)	1976 (9.49)	1,975 (9.00)
Pct. bachelors or more	27.53 (7.58)	28.76 (7.90)	35.05 (9.40)	35.97 (8.23)
Pct. no HS degree	11.27 (4.71)	11.40 (5.11)	11.87 (4.98)	11.14 (3.86)
Hhld. poverty rate	14.43 (3.42)	13.97 (3.62)	12.02 (2.99)	12.32 (3.16)
Unemp. rate	5.86 (1.65)	5.85 (1.62)	5.92 (1.47)	5.83 (1.35)
Pct. hhlds. w/kids	30.24 (4.74)	30.60 (5.15)	30.96 (4.47)	30.65 (3.85)
All building permits	1,706.98 (3,870.85)	2,620.06 (4,866.96)	4,348.65 (5,290.36)	4,006.09 (5,791.68)
SF building permits	1,658.84 (3,787.44)	2,548.10 (4,764.13)	4,152.26 (5,121.31)	3,789.05 (5,590.91)
MF building permits	48.14 (96.86)	71.96 (121.32)	196.39 (337.87)	217.05 (380.88)

MSA level, consistent with prior research (Rothwell 2011; Rothwell and Massey 2009). We do this for two reasons. One, we had more success merging outcome data at the MSA rather than the municipal level. Moreover, for many of these outcomes, but particularly racial segregation, it is possible for one municipality's zoning regime to affect outcomes in neighboring municipalities, which would violate SUTVA conditions.

Y_i represents the outcome of interest, which for our purposes includes the Federal Housing Finance Agency (FHFA) Housing Price Index (HPI), median property values, median gross rent, the natural logarithm of building permits (all, single-family, and multi-family permits separately) obtained from the Census Bureau Building Permit Survey, and racial segregation as measured by the multi-group entropy index (composed of four groups - Black, Latinx, Asian, and white). Z_i represents a placeholder for either an MSA's average exclusionary zoning score or an indicator for whether at least one responding municipality operates an inclusionary zoning program. X_i is a vector of covariates, all of which are included in Tables 8 and 9, and ϵ_i is an individual MSA error term. See the appendix for the full regression tables for each analysis.

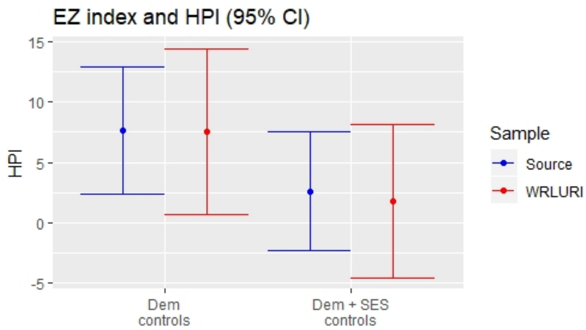
Figures 4 and 5 contain 95 percent confidence intervals for each analysis. We ran four regressions for each outcome of interest, each with a different combination of input data and covariates: (1) our source data and demographic controls, (2) the WRLURI data with demographic controls, (3) our source data with demographic and socioeconomic controls, and (4) the WRLURI data with demographic and socioeconomic controls. We present the results side-by-side to see how well our results compare to the results of matching MSAs in the WRLURI 2018 sample.

The results suggest a few takeaways regarding the exclusionary zoning index. One, results using our source data are very similar when using the WRLURI data, which satisfies another accuracy check of our data. Two, there does not seem to be any meaningful association between this exclusionary zoning index and racial segregation or building permit activity. We did not expect the latter result, but the former has been confirmed in prior empirical work when distinguishing between the WRLURI and more specific measures of anti-density zoning (Rothwell 2011; Rothwell and Massey 2009). Finally, the exclusionary zoning index is associated with higher housing prices, median property values, and median gross rents net of demographic factors, though this association is generally not statistically significant at the 0.05 level after controlling for additional socioeconomic variables (with the exception of median property values in our source data). In other words, after accounting for factors like median household income and the percentage of the population with a 4-year college education or more, the association between markers of higher housing costs and this exclusionary zoning indicator is not statistically different from zero (at the 0.05 level). Given that exclusionary zoning can affect the household income or educational attainment composition of a municipality, this is expected. These results are meant to be entirely descriptive, but future work should consider the many ways that post-treatment bias can alter analyses of exclusionary zoning's impact on housing market and residential mobility and displacement patterns. This is particularly relevant for research with longitudinal data, which our work enables.

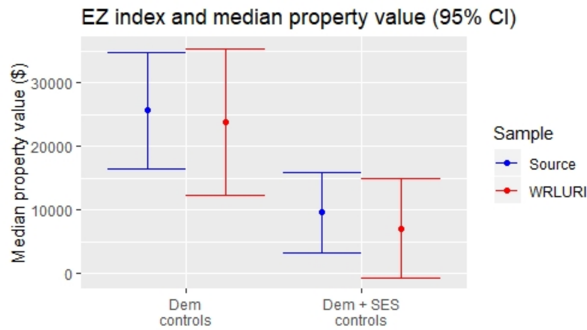
The results of the analyses of inclusionary zoning and our selected outcomes reveal many of the same takeaways, with a few caveats. The difference between the results using our data and the WRLURI data are more noticeable here, but the gap closes with the inclusion of socioeconomic factors. Moreover, as with the previous set of results, no discernible relationship exists between an MSA with at least one municipal inclusionary zoning program and racial segregation or building permit activity. Finally, as with the exclusionary zoning results, the association between an MSA with at least one municipal inclusionary zoning program and median property values remains significant at the 0.05 level with demographic and socioeconomic controls included. Moreover, this association is quite large. The difference in property values between an MSA with and without at least one municipal inclusionary zoning program is roughly \$25,000. This likely reflects the fact that MSAs with at least one municipal inclusionary zoning program are concentrated in the nation's most expensive and supply-restricted housing markets.

Figure 4: OLS regression results: ez.index

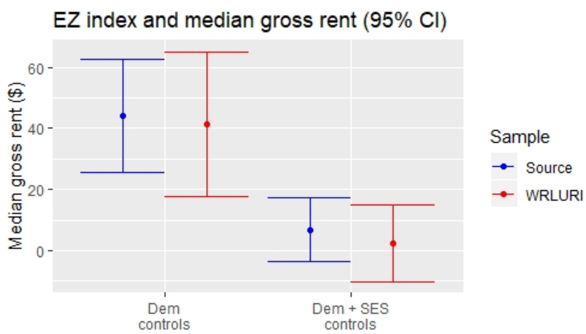
(a)



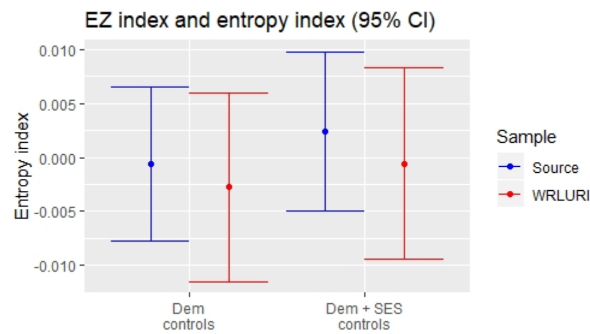
(b)



(c)



(d)



(e)

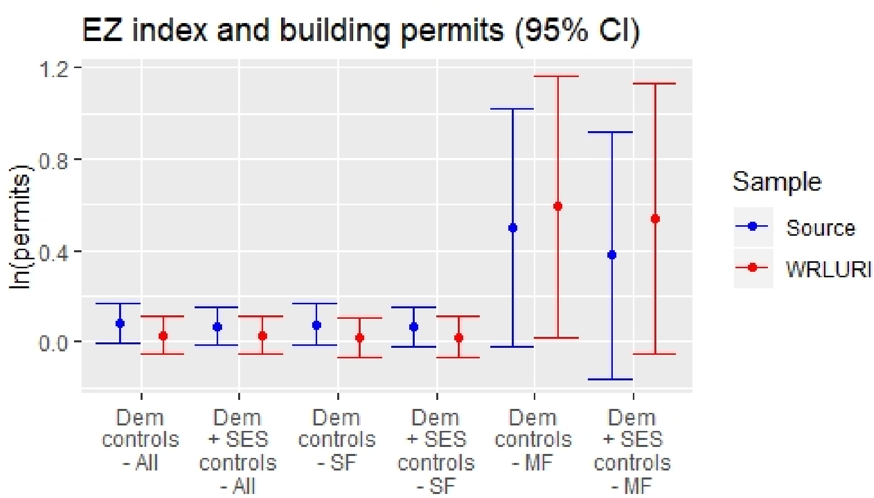
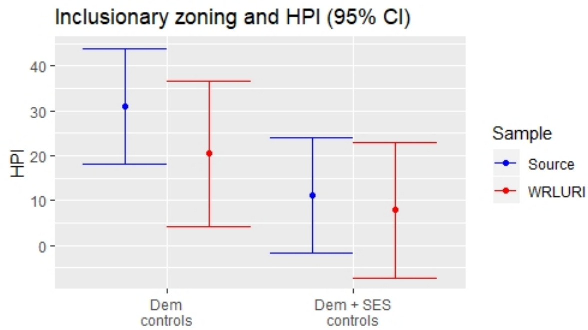
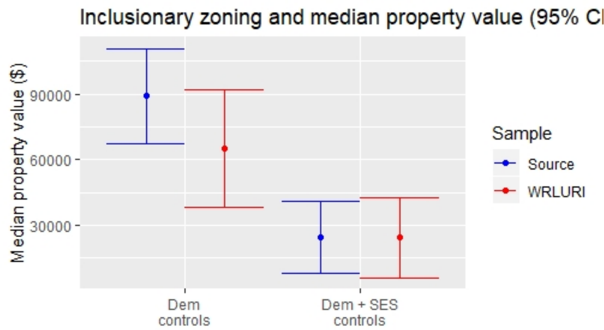


Figure 5: OLS regression results: inclusionary zoning

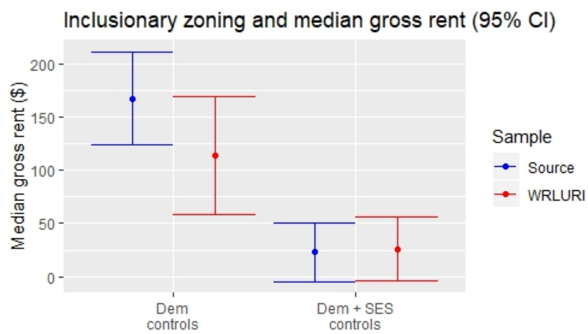
(a)



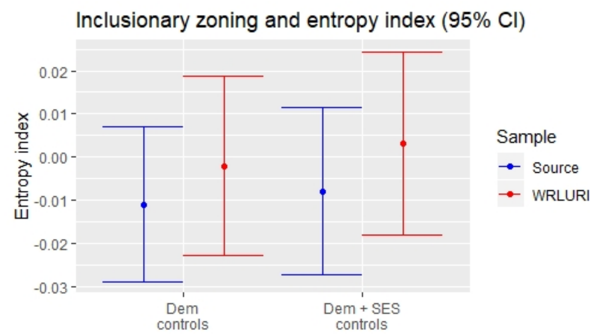
(b)



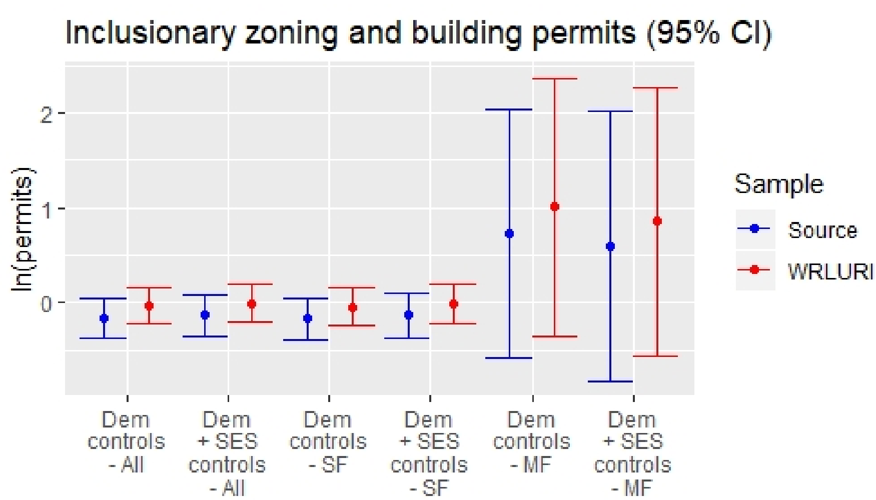
(c)



(d)



(e)



6 Discussion and next steps

Taken together, these results indicate that our data, though in need of refinement and supplemental measures, compare well to survey data that has been the most frequent form of zoning and land use measurement up until this point. Our data currently capture only a fraction of the myriad of different zoning and land use policies, but we have proven our process to be viable and accurate for the most readily identifiable forms of land use regulation in municipal codes. With this confirmation, future iterations of this data can expand to other measures such as building heights or floor area ratios and other municipalities that are not captured in the WRLURI samples. Ideally, this process could eventually be refreshed at regular intervals to provide consistent panel data, though this would likely require a more systematic data storage and collection process.

Moreover, supplementing our data with additional measures will be necessary to gain a more complete picture of the impact of zoning and land use policy on housing market outcomes, residential segregation, and residential mobility and displacement. As it stands, our data mostly reflect the use of explicit growth controls, minimum lot sizes, and open space requirements. These are certainly important aspects of land use policy, but they are necessarily limited in scope. For instance, large minimum lot sizes capture some element of anti-density zoning, but they do not capture more comprehensive measures of a municipality's openness towards density, such as the percentage of land zoned for multi-family development or maximum permitted density (Rothwell 2011; Rothwell and Massey 2009). Moreover, explicit growth controls are exceedingly rare and, as some research suggests, not nearly as effective at halting development as more informal barriers like neighborhood opposition to development (Landis 1992).

Our contribution is notable for its use of natural language processing techniques to uncover zoning and land use policies across the country, but it is not the only effort to improve the quality and accessibility of zoning and land use data. The Urban Institute is utilizing machine learning techniques to predict permitted municipal densities from geospatial zoning data and zoning ordinances with promising initial results (Tyagi and MacDonald 2019). Furthermore, advocacy groups such as Desegregate Connecticut are raising awareness about the prevalence exclusionary zoning and land use policies and promoting housing policy reforms that can improve housing affordability, reduce residential segregation, and prevent residential displacement.[8] Finally, although zoning and land use policies fall within the purview of local governments, researchers have articulated steps that the federal government can take to curb exclusionary zoning and incentivize more equitable development (Greene and Ellen 2020).

One small, but obvious way governments can improve the status quo is by making data publicly available online and in a standardized format. There are several states that require localities to establish growth management plans (Pendall, Puentes, and Martin 2006) and some go as far as to forbid mandatory inclusionary zoning[9], so there is precedent for state governments dictating local zoning and land use guidelines. If governments continue to implement byzantine zoning and land use policies, they should be required to not only make them available, but to do so in a way that is useful to researchers and accessible to the public.

Without considerable reform at all levels of government, the current housing crisis will only worsen. Necessary federal and state policies have been identified and rightly receive a great deal of

[8]See the homepage for Desegregate Connecticut here `https://www.desegregatect.org/` and an overview of their data analysis here `https://www.desegregatect.org/ourdata`

[9]This comes from Grounded Solutions Network's analysis of inclusionary housing programs: `https://inclusionaryhousing.org/inclusionary-housing-explained/what-are-the-downsides/is-it-legal/`

research attention and advocacy. Researchers and advocates should also continue to pay attention to zoning and land use policies, not only due to their increasingly clear role in inflating housing prices and preserving residential segregation, but also as an avenue for bottom-up reform. Building majority support for housing policy reform requires far fewer votes at the city council level than at the state or federal level. Indeed, several major U.S. cities such as Minneapolis, MN and Portland, OR have demonstrated this by recently enacting major zoning and land use reforms. Yet, in order to assess and identify the disparate impact of zoning and land use policies and to actively monitor reform, researchers need more complete and timely access to data. Our work helps fill this need.

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7 Appendix

Table 10: Keywords used in construction of zoning database

Measure	Initial match	Weighted match
Restrict SF permits	Residential subdivision building permits Unit ceiling, Growth management, Growth control Growth rate, Development approvals	building permit(s) (1), permits (1), unit (0.5) restricted (1), allowable (1), limit (1), single-family (0.5), growth management (3) growth control (3), subdivision control (3) scheduled development (1), maximum (2), no more (1), population (1), annual (1), year (1), fixed (2), limited (1), controlled (2), quota (2), moratorium (0.5), allot (2), allocate (2) cap (2), approved (1), calculation (1) ceiling (2), annual affordable distribution (3.5) annual market distribution (3.5), growth rate limit (3.5) issue (1), unit ceiling (2)
Restrict MF permits	Residential subdivision building permits Unit ceiling, Growth management, Growth control Growth rate, Development approvals	Same as row 1, except multi-family (0.5) instead of single-family (0.5)
Limit SF units	Unit ceiling, Growth management, Growth control Growth rate, Development approvals	Same as row 1, except also construction (1), unit (0.5), dwelling (0.5)
Limit MF units	Unit ceiling, Growth management, Growth control Growth rate, Development approvals	Same as row 2, except also construction (1), unit (0.5), dwelling (0.5)
Limit MF dwellings	Unit ceiling, Growth management, Growth control Growth rate, Development approvals	Same as row 4
Limit MF dwelling units	Unit ceiling, Dwelling units per building, Growth management, Growth control, Growth rate Development approvals, Minimum additional lot area	Same as row 4 except also dwelling units per building (2), minimum additional lot area (2), commercial (-2), nonresidential (-2), industrial (-2), agricultural (-2), shall be (1)
Minimum lot size	Lot area, Lot size, Building area, Building site area Acres/dwelling unit, Square feet/dwelling unit	minimum (3), lot size (2), lot area (2) building area (2), acreage (2) shall be (1), requirement (1), permitted (1) square feet per dwelling unit (3)
Open space	Open space	open space (3), in lieu (1), payment (1), fee (1), preserve (2), maintain (2), require (1), minimum (1), no less (1) shall be (1), designate (1), incorporate (1), dedicate (2), acres/dwelling unit (3), square feet/dwelling unit (3)
Inclusionary zoning	Inclusionary, Affordable	inclusionary (3), affordable (3), set-aside (2), in lieu (2), require (1), reserve (1)

Note: weights are shown in parentheses

Table 11

	Dependent variable:			
	hpi			
	(1)	(2)	(3)	(4)
ez.index	7.643***		2.582	
	(2.678)		(2.505)	
ez.index.w		7.579**		1.754
		(3.487)		(3.218)
log(pop_total_metro)	18.368***	18.945***	12.535***	15.522***
	(2.256)	(2.934)	(2.450)	(3.088)
median_age	1.807**	2.684**	2.383**	2.020
	(0.878)	(1.202)	(1.132)	(1.675)
per_Black_metro	−1.715***	−2.086***	−1.115***	−1.422***
	(0.240)	(0.348)	(0.257)	(0.360)
per_Latinx_metro	−0.120	−0.354	0.167	−0.035
	(0.228)	(0.282)	(0.280)	(0.349)
per_Asian_metro	2.459***	4.223***	−1.330*	−0.569
	(0.687)	(0.961)	(0.764)	(1.188)
pct_owner_occupied	−1.576**	−1.869**	−2.660***	−3.068***
	(0.623)	(0.841)	(0.587)	(0.824)
median_hhld_income			0.004***	0.004***
			(0.001)	(0.001)
median_yr_structure	1.834***	2.391***	2.012***	2.584***
	(0.240)	(0.329)	(0.230)	(0.321)
pct_bachelors			−1.637***	−1.933**
			(0.597)	(0.785)
dropout_rt			−0.590	0.040
			(0.990)	(1.453)
hhld_poverty_rt			3.918**	2.517
			(1.515)	(2.029)
unemp_rt			−4.136**	−4.454*
			(1.861)	(2.595)
pct_hhlds_wkids	−1.077	−0.762	−2.308**	−2.941*
	(0.779)	(1.077)	(1.055)	(1.575)
Constant	−3,582.949***	−4,714.426***	−3,961.936***	−5,041.961***
	(482.045)	(659.789)	(473.761)	(656.668)
Observations	322	206	322	206
R^2	0.477	0.541	0.592	0.645
Adjusted R^2	0.461	0.520	0.574	0.619
Residual Std. Error	38.242 (df = 312)	40.636 (df = 196)	34.032 (df = 307)	36.192 (df = 191)
F Statistic	31.564*** (df = 9; 312)	25.665*** (df = 9; 196)	31.834*** (df = 14; 307)	24.805*** (df = 14; 191)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 12

	Dependent variable:			
	median_prop_value			
	(1)	(2)	(3)	(4)
ez.index	25,655.410***		9,586.639***	
	(4,629.022)		(3,202.410)	
ez.index.w		23,889.050***		7,100.260*
		(5,864.221)		(3,953.767)
log(pop_total_metro)	11,578.020***	4,743.130	−8,224.010***	−8,524.173**
	(3,898.942)	(4,935.595)	(3,131.859)	(3,794.001)
median_age	5,388.161***	8,511.490***	7,381.501***	8,830.638***
	(1,517.927)	(2,021.093)	(1,447.260)	(2,058.172)
per_Black_metro	−2,103.524***	−2,346.192***	−1,206.412***	−1,433.827***
	(414.555)	(586.143)	(328.505)	(442.960)
per_Latinx_metro	154.112	−107.606	70.563	20.234
	(393.872)	(474.241)	(358.458)	(429.107)
per_Asian_metro	15,252.230***	18,417.160***	4,251.416***	3,530.840**
	(1,186.996)	(1,616.184)	(976.529)	(1,459.444)
pct_owner_occupied	−2,991.210***	−3,932.744***	−5,226.981***	−6,677.321***
	(1,077.555)	(1,415.270)	(749.681)	(1,012.527)
median_hhld_income			9.772***	9.838***
			(0.757)	(1.013)
median_yr_structure	1,480.282***	1,562.717***	1,753.266***	1,884.693***
	(414.854)	(552.622)	(294.357)	(395.012)
pct_bachelors			−777.286	−920.154
			(763.228)	(964.731)
dropout_rt			2,296.410*	2,471.227
			(1,265.771)	(1,784.908)
hhld_poverty_rt			8,433.984***	7,381.775***
			(1,936.728)	(2,493.332)
unemp_rt			−810.971	−686.925
			(2,378.083)	(3,188.192)
pct_hhlds_wkids	117.151	1,377.648	−1,830.015	−1,476.045
	(1,346.861)	(1,811.618)	(1,348.333)	(1,934.894)
Constant	−2,978,889.000***	−3,139,838.000***	−3,747,092.000***	−3,950,407.000***
	(833,267.600)	(1,109,728.000)	(605,557.100)	(806,873.500)
Observations	322	206	322	206
R^2	0.627	0.666	0.841	0.862
Adjusted R^2	0.616	0.651	0.834	0.852
Residual Std. Error	66,105.030 (df = 312)	68,347.190 (df = 196)	43,498.830 (df = 307)	44,470.680 (df = 191)
F Statistic	58.329*** (df = 9; 312)	43.448*** (df = 9; 196)	116.138*** (df = 14; 307)	85.401*** (df = 14; 191)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 13

	Dependent variable:			
	median_gross_rent			
	(1)	(2)	(3)	(4)
ez.index	43.929***		6.818	
	(9.382)		(5.356)	
ez.index.w		41.424***		2.428
		(11.983)		(6.386)
log(pop_total_metro)	47.377***	36.858***	2.676	6.959
	(7.902)	(10.085)	(5.238)	(6.128)
median_age	8.560***	12.017***	7.836***	7.863**
	(3.076)	(4.130)	(2.420)	(3.324)
per_Black_metro	−0.915	−0.963	1.504***	1.242*
	(0.840)	(1.198)	(0.549)	(0.715)
per_Latinx_metro	2.122***	1.730*	3.610***	3.591***
	(0.798)	(0.969)	(0.600)	(0.693)
per_Asian_metro	28.568***	34.834***	5.310***	2.197
	(2.406)	(3.302)	(1.633)	(2.357)
pct_owner_occupied	−4.011*	−4.325	−8.404***	−10.192***
	(2.184)	(2.892)	(1.254)	(1.635)
median_hhld_income			0.020***	0.021***
			(0.001)	(0.002)
median_yr_structure	4.197***	4.346***	4.654***	5.068***
	(0.841)	(1.129)	(0.492)	(0.638)
pct_bachelors			−3.625***	−3.893**
			(1.276)	(1.558)
dropout_rt			−1.168	−0.943
			(2.117)	(2.883)
hhld_poverty_rt			8.367**	7.501*
			(3.239)	(4.027)
unemp_rt			14.219***	15.728***
			(3.977)	(5.149)
pct_hhlds_wkids	−3.683	−2.969	−10.748***	−11.606***
	(2.730)	(3.702)	(2.255)	(3.125)
Constant	−8,144.038***	−8,427.577***	−9,065.259***	−9,823.219***
	(1,688.785)	(2,267.554)	(1,012.772)	(1,303.169)
Observations	322	206	322	206
R^2	0.631	0.653	0.893	0.910
Adjusted R^2	0.620	0.637	0.888	0.904
Residual Std. Error	133.975 (df = 312)	139.657 (df = 196)	72.750 (df = 307)	71.824 (df = 191)
F Statistic	59.206*** (df = 9; 312)	40.896*** (df = 9; 196)	182.732*** (df = 14; 307)	138.686*** (df = 14; 191)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14

	Dependent variable:			
	log(allb.n)			
	(1)	(2)	(3)	(4)
ez.index	0.083*		0.069	
	(0.042)		(0.043)	
ez.index.w		0.030		0.031
		(0.042)		(0.043)
log(pop_total_metro)	1.219***	1.162***	1.152***	1.133***
	(0.036)	(0.035)	(0.042)	(0.041)
median_age	−0.011	0.0002	−0.013	−0.006
	(0.014)	(0.015)	(0.020)	(0.023)
per_Black_metro	−0.019***	−0.020***	−0.008*	−0.015***
	(0.004)	(0.004)	(0.004)	(0.005)
per_Latinx_metro	−0.011***	−0.013***	0.0001	−0.008
	(0.004)	(0.003)	(0.005)	(0.005)
per_Asian_metro	−0.029***	−0.026**	−0.003	−0.013
	(0.011)	(0.012)	(0.013)	(0.016)
pct_owner_occupied	0.008	−0.003	0.001	−0.007
	(0.010)	(0.010)	(0.010)	(0.011)
median_hhld_income			−0.00004***	−0.00002
			(0.00001)	(0.00001)
median_yr_structure	0.072***	0.073***	0.065***	0.070***
	(0.004)	(0.004)	(0.004)	(0.004)
pct_bachelors			0.016	0.002
			(0.010)	(0.011)
dropout_rt			−0.008	−0.001
			(0.017)	(0.020)
hhld_poverty_rt			−0.110***	−0.056**
			(0.026)	(0.027)
unemp_rt			−0.034	−0.022
			(0.032)	(0.035)
pct_hhlds_wkids	0.009	0.014	0.023	0.015
	(0.012)	(0.013)	(0.018)	(0.021)
Constant	−152.075***	−153.066***	−134.337***	−144.561***
	(7.735)	(8.053)	(8.167)	(8.929)
Observations	320	204	320	204
R^2	0.855	0.899	0.869	0.903
Adjusted R^2	0.851	0.894	0.863	0.895
Residual Std. Error	0.606 (df = 310)	0.488 (df = 194)	0.580 (df = 305)	0.484 (df = 189)
F Statistic	203.065*** (df = 9; 310)	191.230*** (df = 9; 194)	144.983*** (df = 14; 305)	125.114*** (df = 14; 189)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 15

	Dependent variable:			
	log(sfb.n)			
	(1)	(2)	(3)	(4)
ez.index	0.079*		0.066	
	(0.045)		(0.045)	
ez.index.w		0.021		0.023
		(0.043)		(0.045)
log(pop_total_metro)	1.226***	1.163***	1.159***	1.136***
	(0.038)	(0.036)	(0.044)	(0.043)
median_age	−0.010	0.002	−0.013	−0.006
	(0.015)	(0.015)	(0.021)	(0.024)
per_Black_metro	−0.019***	−0.019***	−0.008*	−0.014***
	(0.004)	(0.004)	(0.005)	(0.005)
per_Latinx_metro	−0.011***	−0.013***	0.0002	−0.008
	(0.004)	(0.004)	(0.005)	(0.005)
per_Asian_metro	−0.030***	−0.027**	−0.002	−0.013
	(0.011)	(0.012)	(0.014)	(0.016)
pct_owner_occupied	0.009	−0.003	0.002	−0.007
	(0.010)	(0.011)	(0.011)	(0.012)
median_hhld_income			−0.00004***	−0.00002
			(0.00001)	(0.00001)
median_yr_structure	0.074***	0.075***	0.067***	0.072***
	(0.004)	(0.004)	(0.004)	(0.005)
pct_bachelors			0.018	0.002
			(0.011)	(0.011)
dropout_rt			−0.007	−0.002
			(0.018)	(0.020)
hhld_poverty_rt			−0.117***	−0.060**
			(0.027)	(0.028)
unemp_rt			−0.029	−0.015
			(0.033)	(0.036)
pct_hhlds_wkids	0.010	0.016	0.023	0.015
	(0.013)	(0.013)	(0.019)	(0.022)
Constant	−155.429***	−156.040***	−136.946***	−147.447***
	(8.117)	(8.327)	(8.586)	(9.242)
Observations	320	204	320	204
R^2	0.845	0.893	0.860	0.897
Adjusted R^2	0.840	0.888	0.853	0.889
Residual Std. Error	0.636 (df = 310)	0.504 (df = 194)	0.610 (df = 305)	0.501 (df = 189)
F Statistic	187.564*** (df = 9; 310)	179.884*** (df = 9; 194)	133.543*** (df = 14; 305)	117.491*** (df = 14; 189)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 16

	Dependent variable:			
	log(mfb.n)			
	(1)	(2)	(3)	(4)
ez.index	0.501*		0.380	
	(0.265)		(0.273)	
ez.index.w		0.591**		0.539*
		(0.291)		(0.299)
log(pop_total_metro)	2.216***	2.018***	1.928***	1.687***
	(0.223)	(0.245)	(0.267)	(0.287)
median_age	−0.180**	−0.203**	0.057	−0.010
	(0.088)	(0.102)	(0.125)	(0.159)
per_Black_metro	−0.123***	−0.097***	−0.075***	−0.060*
	(0.024)	(0.029)	(0.028)	(0.034)
per_Latinx_metro	−0.050**	−0.033	−0.006	−0.018
	(0.023)	(0.024)	(0.031)	(0.032)
per_Asian_metro	−0.053	−0.041	−0.074	−0.042
	(0.068)	(0.080)	(0.083)	(0.110)
pct_owner_occupied	−0.014	0.028	−0.094	−0.043
	(0.062)	(0.071)	(0.064)	(0.077)
median_hhld_income			0.00002	−0.00005
			(0.0001)	(0.0001)
median_yr_structure	0.074***	0.054*	0.065**	0.031
	(0.024)	(0.028)	(0.025)	(0.030)
pct_bachelors			−0.009	0.071
			(0.065)	(0.073)
dropout_rt			−0.163	0.002
			(0.108)	(0.136)
hhld_poverty_rt			0.177	−0.047
			(0.165)	(0.189)
unemp_rt			−0.686***	−0.514**
			(0.203)	(0.241)
pct_hhlds_wkids	−0.103	−0.079	0.068	0.090
	(0.077)	(0.090)	(0.115)	(0.147)
Constant	−160.376***	−122.377**	−147.479***	−76.623
	(48.190)	(56.010)	(52.256)	(61.916)
Observations	320	204	320	204
R^2	0.312	0.347	0.347	0.376
Adjusted R^2	0.292	0.316	0.317	0.329
Residual Std. Error	3.776 (df = 310)	3.392 (df = 194)	3.710 (df = 305)	3.359 (df = 189)
F Statistic	15.642*** (df = 9; 310)	11.433*** (df = 9; 194)	11.564*** (df = 14; 305)	8.124*** (df = 14; 189)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 17

	Dependent variable:			
	metro_H			
	(1)	(2)	(3)	(4)
ez.index	−0.001		0.002	
	(0.004)		(0.004)	
ez.index.w		−0.003		−0.001
		(0.004)		(0.004)
log(pop_total_metro)	0.028***	0.032***	0.032***	0.032***
	(0.003)	(0.004)	(0.004)	(0.004)
median_age	−0.003**	−0.003*	−0.003**	−0.003
	(0.001)	(0.002)	(0.002)	(0.002)
per_Black_metro	0.004***	0.003***	0.003***	0.003***
	(0.0003)	(0.0004)	(0.0004)	(0.001)
per_Latinx_metro	0.001***	0.001***	−0.0001	0.0001
	(0.0003)	(0.0004)	(0.0005)	(0.001)
per_Asian_metro	−0.001	−0.001	−0.0004	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
pct_owner_occupied	0.003***	0.002**	0.003***	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
median_hhld_income			−0.00000	−0.00000
			(0.00000)	(0.00000)
median_prop_value			0.00000	−0.000
			(0.00000)	(0.00000)
median_gross_rent			−0.00002	−0.0001
			(0.0001)	(0.0001)
pct_rent_burdened			−0.001	0.002
			(0.001)	(0.001)
median_yr_structure	−0.004***	−0.004***	−0.004***	−0.004***
	(0.0003)	(0.0004)	(0.0004)	(0.001)
pct_bachelors			0.001	0.002*
			(0.001)	(0.001)
dropout_rt			0.006***	0.008***
			(0.001)	(0.002)
hhld_poverty_rt			0.001	−0.003
			(0.002)	(0.003)
unemp_rt			−0.002	−0.003
			(0.003)	(0.004)
pct_hhlds_wkids	−0.003***	−0.003**	−0.004**	−0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
Constant	7.415***	8.070***	7.135***	7.662***
	(0.656)	(0.839)	(0.822)	(1.081)
Observations	322	206	322	206
R^2	0.565	0.583	0.608	0.630
Adjusted R^2	0.552	0.564	0.586	0.596
Residual Std. Error	0.052 (df = 312)	0.052 (df = 196)	0.050 (df = 304)	0.050 (df = 188)
F Statistic	44.963*** (df = 9; 312)	30.486*** (df = 9; 196)	27.678*** (df = 17; 304)	18.793*** (df = 17; 188)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 18

	Dependent variable:			
	hpi			
	(1)	(2)	(3)	(4)
affordable.n	31.057***		11.246*	
	(6.547)		(6.558)	
affordable.w.n		20.425**		7.895
		(8.218)		(7.664)
log(pop_total_metro)	14.610***	18.815***	11.369***	15.387***
	(2.315)	(2.923)	(2.418)	(3.082)
median_age	1.698**	2.943**	2.375**	2.007
	(0.855)	(1.194)	(1.117)	(1.671)
per_Black_metro	−1.704***	−2.304***	−1.102***	−1.485***
	(0.234)	(0.347)	(0.256)	(0.361)
per_Latinx_metro	−0.235	−0.465	0.160	−0.066
	(0.225)	(0.284)	(0.279)	(0.350)
per_Asian_metro	2.143***	3.622***	−1.201	−0.719
	(0.677)	(1.019)	(0.766)	(1.190)
pct_owner_occupied	−1.493**	−2.103**	−2.619***	−3.127***
	(0.609)	(0.839)	(0.583)	(0.820)
median_hhld_income			0.004***	0.004***
			(0.001)	(0.001)
median_yr_structure	1.981***	2.590***	2.048***	2.643***
	(0.235)	(0.328)	(0.231)	(0.320)
pct_bachelors			−1.600***	−1.944**
			(0.591)	(0.783)
dropout_rt			−0.722	0.042
			(0.988)	(1.450)
hhld_poverty_rt			3.649**	2.275
			(1.515)	(2.043)
unemp_rt			−4.292**	−4.438*
			(1.858)	(2.589)
pct_hhlds_wkids	−0.832	−0.337	−2.104**	−2.821*
	(0.762)	(1.085)	(1.046)	(1.577)
Constant	−3,820.356***	−5,097.615***	−4,005.347***	−5,142.270***
	(472.517)	(658.172)	(473.083)	(652.291)
Observations	322	206	322	206
R^2	0.499	0.544	0.595	0.647
Adjusted R^2	0.485	0.523	0.576	0.621
Residual Std. Error	37.412 (df = 312)	40.490 (df = 196)	33.928 (df = 307)	36.120 (df = 191)
F Statistic	34.533*** (df = 9; 312)	26.008*** (df = 9; 196)	32.162*** (df = 14; 307)	24.959*** (df = 14; 191)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 19

	Dependent variable:			
	median_prop_value			
	(1)	(2)	(3)	(4)
affordable.n	89,231.210***		24,535.060***	
	(11,022.050)		(8,414.129)	
affordable.w.n		65,043.310***		24,451.490***
		(13,680.430)		(9,349.494)
log(pop_total_metro)	594.808	4,294.338	−11,572.350***	−8,802.745**
	(3,896.644)	(4,865.651)	(3,102.501)	(3,759.644)
median_age	5,268.747***	9,327.462***	7,697.542***	8,821.142***
	(1,438.995)	(1,988.024)	(1,432.949)	(2,038.681)
per_Black_metro	−2,091.994***	−3,036.040***	−1,166.757***	−1,645.132***
	(394.741)	(577.102)	(328.649)	(440.592)
per_Latinx_metro	−151.353	−459.857	109.474	−71.448
	(378.696)	(472.816)	(357.435)	(426.913)
per_Asian_metro	14,467.740***	16,491.620***	4,528.882***	3,038.496**
	(1,139.477)	(1,695.561)	(982.187)	(1,451.429)
pct_owner_occupied	−2,846.878***	−4,675.113***	−5,277.612***	−6,896.093***
	(1,025.311)	(1,396.578)	(748.173)	(999.726)
median_hhld_income			9.284***	9.599***
			(0.782)	(1.011)
median_yr_structure	1,922.761***	2,193.857***	1,833.315***	2,086.863***
	(396.423)	(546.198)	(295.802)	(390.534)
pct_bachelors			−584.756	−971.236
			(758.857)	(955.106)
dropout_rt			1,956.146	2,475.667
			(1,268.021)	(1,768.526)
hhld_poverty_rt			7,768.726***	6,684.488***
			(1,943.913)	(2,492.107)
unemp_rt			−1,040.855	−605.349
			(2,384.273)	(3,158.186)
pct_hhlds_wkids	869.405	2,729.331	−1,200.336	−1,125.950
	(1,282.979)	(1,805.448)	(1,342.464)	(1,923.811)
Constant	−3,691,589.000***	−4,354,490.000***	−3,837,558.000***	−4,304,158.000***
	(795,472.700)	(1,095,626.000)	(606,971.900)	(795,724.700)
Observations	322	206	322	206
R^2	0.662	0.675	0.841	0.865
Adjusted R^2	0.652	0.660	0.834	0.855
Residual Std. Error	62,982.610 (df = 312)	67,401.110 (df = 196)	43,530.440 (df = 307)	44,062.550 (df = 191)
F Statistic	67.778*** (df = 9; 312)	45.292*** (df = 9; 196)	115.938*** (df = 14; 307)	87.245*** (df = 14; 191)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 20

	Dependent variable:			
	median_gross_rent			
	(1)	(2)	(3)	(4)
affordable.n	167.382***		23.016	
	(22.328)		(14.038)	
affordable.w.n		113.898***		25.739*
		(28.041)		(15.132)
log(pop_total_metro)	26.986***	36.016***	−0.022	6.241
	(7.894)	(9.973)	(5.176)	(6.085)
median_age	8.115***	13.435***	7.950***	7.758**
	(2.915)	(4.075)	(2.391)	(3.300)
per_Black_metro	−0.872	−2.165*	1.535***	1.069
	(0.800)	(1.183)	(0.548)	(0.713)
per_Latinx_metro	1.522**	1.114	3.617***	3.488***
	(0.767)	(0.969)	(0.596)	(0.691)
per_Asian_metro	26.957***	31.444***	5.573***	1.765
	(2.308)	(3.475)	(1.639)	(2.349)
pct_owner_occupied	−3.635*	−5.620*	−8.374***	−10.310***
	(2.077)	(2.863)	(1.248)	(1.618)
median_hhld_income			0.020***	0.021***
			(0.001)	(0.002)
median_yr_structure	5.006***	5.446***	4.729***	5.217***
	(0.803)	(1.120)	(0.494)	(0.632)
pct_bachelors			−3.505***	−3.897**
			(1.266)	(1.546)
dropout_rt			−1.458	−0.929
			(2.116)	(2.862)
hhld_poverty_rt			7.786**	6.615
			(3.243)	(4.033)
unemp_rt			13.942***	15.723***
			(3.978)	(5.111)
pct_hhlds_wkids	−2.327	−0.604	−10.259***	−11.176***
	(2.599)	(3.701)	(2.240)	(3.114)
Constant	−9,446.199***	−10,545.300***	−9,152.458***	−10,065.350***
	(1,611.436)	(2,245.741)	(1,012.651)	(1,287.840)
Observations	322	206	322	206
R^2	0.665	0.660	0.893	0.912
Adjusted R^2	0.655	0.644	0.888	0.905
Residual Std. Error	127.588 (df = 312)	138.154 (df = 196)	72.625 (df = 307)	71.313 (df = 191)
F Statistic	68.841*** (df = 9; 312)	42.266*** (df = 9; 196)	183.440*** (df = 14; 307)	140.877*** (df = 14; 191)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 21

	Dependent variable:			
	log(allb.n)			
	(1)	(2)	(3)	(4)
affordable.n	−0.163		−0.133	
	(0.107)		(0.113)	
affordable.w.n		−0.027		−0.003
		(0.099)		(0.103)
log(pop_total_metro)	1.232***	1.168***	1.145***	1.136***
	(0.038)	(0.035)	(0.041)	(0.041)
median_age	−0.004	0.001	−0.004	−0.006
	(0.014)	(0.015)	(0.019)	(0.023)
per_Black_metro	−0.020***	−0.020***	−0.008*	−0.015***
	(0.004)	(0.004)	(0.004)	(0.005)
per_Latinx_metro	−0.010***	−0.012***	0.002	−0.008
	(0.004)	(0.003)	(0.005)	(0.005)
per_Asian_metro	−0.023**	−0.023*	−0.004	−0.014
	(0.011)	(0.012)	(0.013)	(0.016)
pct_owner_occupied	0.004	−0.003	−0.003	−0.008
	(0.010)	(0.010)	(0.010)	(0.011)
median_hhld_income			−0.00004***	−0.00001
			(0.00001)	(0.00001)
median_yr_structure	0.072***	0.073***	0.065***	0.071***
	(0.004)	(0.004)	(0.004)	(0.004)
pct_bachelors			0.019*	0.002
			(0.010)	(0.011)
dropout_rt			−0.008	−0.001
			(0.017)	(0.020)
hhld_poverty_rt			−0.108***	−0.055**
			(0.026)	(0.028)
unemp_rt			−0.029	−0.021
			(0.032)	(0.035)
pct_hhlds_wkids	0.009	0.014	0.025	0.015
	(0.012)	(0.013)	(0.018)	(0.021)
Constant	−152.012***	−153.457***	−133.857***	−145.296***
	(7.762)	(8.075)	(8.194)	(8.907)
Observations	320	204	320	204
R^2	0.854	0.898	0.869	0.902
Adjusted R^2	0.850	0.894	0.863	0.895
Residual Std. Error	0.607 (df = 310)	0.488 (df = 194)	0.581 (df = 305)	0.485 (df = 189)
F Statistic	201.972*** (df = 9; 310)	190.728*** (df = 9; 194)	144.334*** (df = 14; 305)	124.742*** (df = 14; 189)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 22

	Dependent variable:			
	log(sfb.n)			
	(1)	(2)	(3)	(4)
affordable.n	−0.171		−0.134	
	(0.112)		(0.118)	
affordable.w.n		−0.042		−0.013
		(0.103)		(0.107)
log(pop_total_metro)	1.241***	1.169***	1.153***	1.139***
	(0.039)	(0.036)	(0.044)	(0.043)
median_age	−0.002	0.003	−0.005	−0.006
	(0.015)	(0.015)	(0.020)	(0.024)
per_Black_metro	−0.019***	−0.019***	−0.008*	−0.015***
	(0.004)	(0.004)	(0.005)	(0.005)
per_Latinx_metro	−0.010***	−0.013***	0.002	−0.008
	(0.004)	(0.004)	(0.005)	(0.005)
per_Asian_metro	−0.024**	−0.024*	−0.004	−0.013
	(0.012)	(0.013)	(0.014)	(0.017)
pct_owner_occupied	0.005	−0.003	−0.002	−0.008
	(0.010)	(0.011)	(0.011)	(0.011)
median_hhld_income			−0.00004***	−0.00002
			(0.00001)	(0.00001)
median_yr_structure	0.074***	0.075***	0.066***	0.072***
	(0.004)	(0.004)	(0.004)	(0.005)
pct_bachelors			0.020*	0.002
			(0.011)	(0.011)
dropout_rt			−0.007	−0.002
			(0.018)	(0.020)
hhld_poverty_rt			−0.115***	−0.058**
			(0.027)	(0.028)
unemp_rt			−0.025	−0.014
			(0.033)	(0.036)
pct_hhlds_wkids	0.010	0.015	0.026	0.015
	(0.013)	(0.014)	(0.019)	(0.022)
Constant	−155.283***	−156.070***	−136.461***	−147.929***
	(8.136)	(8.342)	(8.610)	(9.213)
Observations	320	204	320	204
R^2	0.844	0.893	0.859	0.897
Adjusted R^2	0.840	0.888	0.853	0.889
Residual Std. Error	0.637 (df = 310)	0.504 (df = 194)	0.610 (df = 305)	0.502 (df = 189)
F Statistic	187.028*** (df = 9; 310)	179.808*** (df = 9; 194)	133.107*** (df = 14; 305)	117.313*** (df = 14; 189)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 23

	Dependent variable:			
	log(mfb.n)			
	(1)	(2)	(3)	(4)
affordable.n	0.725		0.598	
	(0.665)		(0.720)	
affordable.w.n		1.005		0.857
		(0.693)		(0.717)
log(pop_total_metro)	2.111***	2.042***	1.816***	1.702***
	(0.235)	(0.246)	(0.265)	(0.288)
median_age	−0.165*	−0.187*	0.077	−0.008
	(0.088)	(0.103)	(0.124)	(0.159)
per_Black_metro	−0.125***	−0.110***	−0.074***	−0.070**
	(0.024)	(0.029)	(0.028)	(0.034)
per_Latinx_metro	−0.050**	−0.038	−0.003	−0.021
	(0.023)	(0.024)	(0.031)	(0.033)
per_Asian_metro	−0.050	−0.061	−0.068	−0.064
	(0.069)	(0.086)	(0.084)	(0.111)
pct_owner_occupied	−0.020	0.015	−0.100	−0.057
	(0.062)	(0.071)	(0.064)	(0.077)
median_hhld_income			0.00001	−0.00004
			(0.0001)	(0.0001)
median_yr_structure	0.079***	0.066**	0.067***	0.042
	(0.024)	(0.028)	(0.026)	(0.030)
pct_bachelors			−0.0002	0.066
			(0.065)	(0.073)
dropout_rt			−0.174	0.003
			(0.109)	(0.136)
hhld_poverty_rt			0.158	−0.064
			(0.166)	(0.191)
unemp_rt			−0.687***	−0.506**
			(0.204)	(0.242)
pct_hhlds_wkids	−0.093	−0.058	0.090	0.097
	(0.077)	(0.091)	(0.115)	(0.148)
Constant	−169.002***	−145.596**	−149.868***	−95.816
	(48.434)	(56.388)	(52.432)	(61.975)
Observations	320	204	320	204
R^2	0.307	0.340	0.344	0.370
Adjusted R^2	0.287	0.309	0.314	0.323
Residual Std. Error	3.790 (df = 310)	3.410 (df = 194)	3.718 (df = 305)	3.375 (df = 189)
F Statistic	15.261*** (df = 9; 310)	11.096*** (df = 9; 194)	11.429*** (df = 14; 305)	7.918*** (df = 14; 189)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 24

	Dependent variable:			
	metro_H			
	(1)	(2)	(3)	(4)
affordable.n	−0.011		−0.008	
	(0.009)		(0.010)	
affordable.w.n		−0.002		0.003
		(0.010)		(0.011)
log(pop_total_metro)	0.029***	0.032***	0.033***	0.032***
	(0.003)	(0.004)	(0.004)	(0.004)
median_age	−0.003**	−0.003*	−0.003*	−0.003
	(0.001)	(0.002)	(0.002)	(0.002)
per_Black_metro	0.004***	0.003***	0.003***	0.003***
	(0.0003)	(0.0004)	(0.0004)	(0.001)
per_Latinx_metro	0.001***	0.001***	−0.00002	0.0001
	(0.0003)	(0.0004)	(0.0004)	(0.001)
per_Asian_metro	−0.001	−0.001	−0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
pct_owner_occupied	0.003***	0.002**	0.003***	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
median_hhld_income			−0.00000	−0.00000
			(0.00000)	(0.00000)
median_prop_value			0.00000	−0.000
			(0.00000)	(0.00000)
median_gross_rent			−0.00002	−0.0001
			(0.0001)	(0.0001)
pct_rent_burdened			−0.001	0.002
			(0.001)	(0.001)
median_yr_structure	−0.004***	−0.004***	−0.004***	−0.004***
	(0.0003)	(0.0004)	(0.0004)	(0.001)
pct_bachelors			0.001	0.002*
			(0.001)	(0.001)
dropout_rt			0.006***	0.008***
			(0.001)	(0.002)
hhld_poverty_rt			0.001	−0.003
			(0.002)	(0.003)
unemp_rt			−0.002	−0.003
			(0.003)	(0.004)
pct_hhlds_wkids	−0.003***	−0.003**	−0.004**	−0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
Constant	7.482***	8.154***	7.214***	7.642***
	(0.656)	(0.840)	(0.825)	(1.081)
Observations	322	206	322	206
R^2	0.567	0.583	0.608	0.630
Adjusted R^2	0.554	0.563	0.586	0.596
Residual Std. Error	0.052 (df = 312)	0.052 (df = 196)	0.050 (df = 304)	0.050 (df = 188)
F Statistic	45.328*** (df = 9; 312)	30.392*** (df = 9; 196)	27.712*** (df = 17; 304)	18.804*** (df = 17; 188)
Note:				*p<0.1; **p<0.05; ***p<0.01