Housing Values and Jurisdictional Fragmentation*

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October 21, 2022

Abstract

We investigate the impact of the number of local governments in a metropolitan area on housing values within the United States. We find that metropolitan areas with one standard deviation more counties have housing values that are almost 11% higher. This difference is largely explained by the presence of higher wages (accounting for worker characteristics) in areas with more local governments. Moreover, we find that areas with more local governments have differences in local policies affecting business and investment. The number of local governments does not seem to have a significant impact on environmental quality, educational outcomes, or crime.

JEL Classification: H11, H77

Keywords: Federalism, Jurisdictional Fragmentation, Interjurisdictional Competition, Government Performance

*The authors thank Sandra Black, Bryan Caplan, Caroline Hoxby, Jonathan Rodden, Jesse Rothstein, James Sallee, Ryan Streeter, Alex Tabarrok, Romain Wacziarg, and several seminar audiences for helpful comments. We are also grateful to Alina Kovalenko for excellent research assistance. Any comments or suggestions are welcome and may be emailed to john.hatfield@utexas.edu, k.kosec@cgiar.org, or lprodgers@fsu.edu

1 Introduction

In 2019, the non-profit advocacy group Better Together collected enough signatures to put on the statewide ballot an audacious plan to consolidate St. Louis City and St. Louis County (geographically and jurisdictionally distinct entities) under one overarching metropolitan government.[1] Indeed, municipal annexation—of both existing, smaller municipalities as well as unincorporated land—is a prominent feature of many metropolitan landscapes; for instance, the city of Houston was 350 square miles in 1960 but is 667 square miles today (Planning & Development Department, 2012).[2] Such jurisdictional consolidation is frequently championed by public officials (Cisneros, 1993; Rusk, 1993, 2006) and pundits (Peirce et al., 1993; Renn, 2017) in addition to urban planning scholars (Barnes and Ledebur, 1991; Briffault, 1992, 1995; Salins, 1993; Savitch et al., 1993; Savitch and Vogel, 2000; Orfield, 2011).[3] Economists, meanwhile, have been particularly "two-handed" in their discussion of jurisdictional consolidation, emphasizing both the costs *and* benefits.[4] Nevertheless, local government—comprising over 10% of GDP in the United States—plays a critical role in residents' lives, and so it is vital to understand how the organization of such political institutions affects residents' welfare.[5]

Understanding the net effect of the level of jurisdictional disassociation (as opposed to consolidation), which we call *jurisdictional fragmentation*, on resident welfare is challenging for two reasons: First, many positive and negative effects of jurisdictional fragmentation have been suggested, and so measuring the net impact of jurisdictional consolidation on resident welfare requires going beyond looking at just one policy outcome, such as wages or educational attainment. But there is no direct way to measure resident welfare to account for how different policy impacts add up. Second, the level of jurisdictional fragmentation may be driven by factors that also affect resident welfare directly, such as rougher terrain—which may have made larger jurisdictional units less cost-effective—and initial settlers who were

[1] The effort ultimately failed due to actions by the Missouri state legislature (Rosenbaum, 2019).

[2] Such annexations have, furthermore, prompted political backlash; e.g., in 2019, HB 347 effectively made it impossible in Texas for a city to annex unincorporated land without the consent of current residents.

[3] A recent overview of the debate over jurisdictional consolidation is provided by Carr and Feiock (2016).

[4] For instance, Tiebout (1956) and Hayek (1945) stressed the importance of adjusting local policy to incorporate local knowledge and tastes, while Oates (1972) and Besley and Coate (2003) noted that externalities between local jurisdictions may lead to inefficient policy outcomes. Similarly, while many economists agree that competition between jurisdictions will drive down tax revenues, they disagree on its implications: Brennan and Buchanan (1978, 1980) saw tax competition as a way to restrain revenue-maximizing "Leviathans," while Zodrow and Mieszkowski (1986) contended that such competition starves local governments of resources needed for local public goods and economic development. A recent overview of the effects of local policy choice is provided by Agarwal et al. (2020).

[5] Local government expenditures in the United States were $1.65 trillion in 2012 (U.S. Census Bureau, 2012b), while the total gross domestic product was $16.1 trillion (Bureau of Economic Analysis, 2018).

both industrious and preferred larger or smaller administrative units.

We address the first problem, the lack of a direct measure of resident welfare, by looking at how housing values vary across metropolitan areas (accounting for housing characteristics).[6] The key idea is that differences in housing prices reflect residents' willingness-to-pay for bundles of various amenities.[7] Indeed, differences in housing prices have long been used to understand how residents value a plethora of policies and policy outcomes: the quality of local education (Black, 1999; Bogart and Cromwell, 2000; Figlio and Lucas, 2004; Kane et al., 2006; Bayer et al., 2007; Ries and Somerville, 2010; Collins and Kaplan, 2017), tax policy (Rosen, 1982; Palmon and Smith, 1998; Fischel, 2001), local environmental quality (Chay and Greenstone, 2005; Currie et al., 2015), policies about natural resource extraction (Muehlenbachs et al., 2015), crime (Gibbons, 2004; Linden and Rockoff, 2008; Pope, 2008; Besley and Mueller, 2012; Adda et al., 2014), and others.[8] Here, we build on this idea by using housing prices to evaluate how *differences in political institutions*—that is, different levels of jurisdictional fragmentation—affect residents' willingness-to-pay. In other words, while we may not be able to measure the quality of local amenities such as parks and roads, or the willingness-to-pay of residents for better local amenities such as parks and roads, we *can* evaluate how much local residents value the bundle of policy outcomes provided in a metropolitan area, and how the value of this bundle varies with jurisdictional fragmentation.

We address the second problem—that the level of jurisdictional fragmentation may be determined by factors that also influence resident welfare directly—by exploiting natural variation in the topography of the United States: We use the total length of small streams in a metropolitan area to instrument for its number of county governments, controlling for the presence of major rivers and other natural characteristics that may be correlated with small streams and may affect housing prices directly.[9,10] Small streams served as natural "breakpoints" between jurisdictions when boundaries were originally defined, often over 200 years ago, but should have no impact on housing values today. Thus, conditional on access to larger bodies of water and rivers, we argue that variation in the length of small streams is exogenous, allowing us to interpret the second stage coefficient on jurisdictional fragmentation

[6]Section 2.2.2 describes how we utilize microdata from the 2012 American Community Survey on housing values and characteristics to estimate the effect of being in each metropolitan area on the value of housing, conditional on these characteristics.

[7]Indeed, the degree to which local amenities are incorporated into housing prices is surprising, even to economists—as Fischel (2001) notes, "Everything seems to be capitalized."

[8]Similarly, structural estimation of the welfare effects of local policies focuses on housing prices—see, e.g., the work of Calabrese et al. (2007, 2012) on Tiebout sorting and zoning.

[9]This strategy builds on the work of Hoxby (2000), who used the number of streams in a metropolitan area as an instrument for the number of school districts; it has also been successfully used to instrument for local political boundaries by Glaeser (1996), Baqir (2001), and Hatfield and Kosec (2013, 2019).

[10]In particular, the streams we use are *not* useful for commerce or transportation.

as representing the long-term effect of jurisdictional fragmentation on housing values.

We find that U.S. metropolitan areas with more local governments, or more jurisdictional fragmentation, have significantly higher housing values (conditional on housing characteristics). Our main results suggest that metropolitan areas with one standard deviation more counties (i.e., 5.4 more counties) have housing values that are nearly 11% higher; this effect is economically large, corresponding to an increased willingness-to-pay for the benefits of these areas of about $1,600 per year.[11] We interpret this result as the long-run effect of jurisdictional fragmentation on property values.[12]

To understand why residents of areas with more jurisdictional fragmentation are willing to pay so much more, we consider factors that local governments can influence and that play a major role in determining residents' willingness-to-pay: wages, air quality, education, and crime. We find that both wages and education predict significantly higher housing values. However, jurisdictional fragmentation has an economically significant effect only on wages; we find that metropolitan areas with one standard deviation more counties have wages that are about 4.6% higher, after accounting for worker characteristics. The effect on wages is economically significant and implies an increase in annual wages of about $1,700 for a worker at the median wage; this can help explain why housing values are higher in areas with more jurisdictional fragmentation. Moreover, we demonstrate that these higher wages are related to differences in local policies affecting business and investment.

Our work also allows us to test a number of theories on the effects of jurisdictional fragmentation on policy outcomes. Brueckner (2006), Hatfield and Padró i Miquel (2012), and Hatfield (2015) all argued that local governments are likely to choose policies that lead to higher economic growth and wages; we find that wages are indeed higher in areas with more jurisdictional fragmentation, and that this is the major explanation of residents' higher willingness-to-pay to live in those areas.[13] We can also evaluate the concerns of

[11] Our results are robust to using other measures of jurisdictional fragmentation, including the sum of municipalities and townships, a population-based Herfindahl-Hirschmann index (i.e., the sum of each county's squared population share) for a metropolitan area, and an earned income-based Herfindahl-Hirschmann index (i.e., the sum of each county's squared earned income share) for a metropolitan area.

[12] Welfare gains due to more jurisdictional fragmentation do not necessarily go to residents; to the degree such welfare gains are capitalized into rents, the gains accrue to landowners. Nevertheless, higher housing values in areas with more jurisdictional fragmentation imply that such fragmentation creates additional value (and to the extent that landowners are also residents, that value is also enjoyed by residents).

[13] We are not the first to study the effects of decentralization on economic outcomes. A number of studies—such as those by Kim (1995), Huther and Shah (1998), Iimi (2005), Davoodi et al. (1998), and Woller and Phillips (1998)—use cross-country regressions to investigate the effects of decentralization on economic growth. However, this approach has been criticized on numerous methodological grounds; see critiques by Oates (1993), Bardhan (2002), Ebel and Yilmaz (2002), and Rodden (2004). Later work by Stansel (2005) and Hatfield and Kosec (2013) sidesteps these critiques by focusing on jurisdictional fragmentation within the United States; they find that economic growth is positively associated with jurisdictional fragmentation. In a similar vein, Grossman et al. (1999) found that metropolitan areas with more competition among jurisdictions

Zodrow and Mieszkowski (1986), Wilson (1986, 1999), Wildasin (1988), and Hoyt (1991) that (imperfect) tax competition will severely hamper the ability of local governments to raise revenue;[14] we do not find any evidence that metropolitan areas with more jurisdictions have lower tax revenues.[15]

Finally, our work contributes to the burgeoning literature on the effect of local jurisdictional consolidation or proliferation. Several papers have considered the effect of jurisdictional consolidation on the cost of service provision in Europe with mixed results (Reingewertz, 2012; Bel and Warner, 2015; Blom-Hansen et al., 2016). Current work by Tricaud (2020) found that forcibly integrated municipalities in France suffer from policies less tailored to local preferences; in a similar vein, Dahis and Szerman (2020) found higher levels of public service provision in administrative units split off from larger municipalities in Brazil. And Grossman et al. (2017) identified an initial increase in the quality of services provision following regional government splits which leveled off at high levels of regional fragmentation in sub-Saharan Africa over 1960–2012. Our work complements these studies by permitting the evaluation of the total effect on resident welfare of jurisdictional fragmentation (by using housing prices) and to consider the long-term effects of jurisdictional fragmentation (as opposed to the immediate effects from jurisdictional consolidations/splits).

The remainder of the paper is organized as follows: Section 2 describes our empirical approach, including our identification strategy and data. Section 3 presents our main results, and Section 4 offers numerous robustness checks. Section 5 explores the mechanisms behind our results. We conclude in Section 6.

2 Empirical Methodology

We investigate the effect of the number of local jurisdictions on housing values using multiple datasets on Core Based Statistical Areas (CBSA) and Combined Statistical Areas (CSAs) in the United States. For simplicity, we will refer to these collectively as CBSAs.[16] A CBSA is comprised of one or more counties; it has an urban nucleus with a population of at least 10,000 and includes nearby communities that, based on commuting patterns, are highly integrated with that central nucleus. In our sample, 16% of CBSAs have only one county, 15% have two counties, 13% have three counties, and 56% have four or more counties.

If all variation in the number of jurisdictions was exogenous, then the long-term causal

are associated with less technically inefficient public sectors.

[14]For an excellent review of the literature on local tax competition, see Wilson and Wildasin (2004).

[15]Unfortunately, we lack CBSA-level data on average tax rates.

[16]CSAs are made up of two or more adjacent CBSAs that have substantial employment interchange. We use the 2013 Office of Management and Budget CBSA delineations.

impact of the number of jurisdictions on housing values could be estimated by the following specification:

$$V_i = \beta_0 + \beta_N N_i + \gamma \mathbf{X}_i + \alpha_j + \epsilon_i, \tag{1}$$

where i indexes CBSAs. V_i is the average log housing value in CBSA i in 2012,[17] and N_i is the number of jurisdictions in CBSA i. We also include state fixed effects, α_j, and a vector of controls at the CBSA level, X_i described in detail in Section 2.2.[18]

2.1 Identification Strategy

Generating unbiased estimates of β_N in an ordinary least squares (OLS) framework requires that the number of jurisdictions in a CBSA is exogenous conditional on the other control variables. This exogeneity assumption may be questionable due to concerns of omitted variable bias: First, more densely populated areas are likely to have higher housing values (after accounting for housing characteristics); for example, economies of agglomeration can fuel economic growth and thus raise the cost of residential housing. However, heavily populated areas also tend to have a larger number of different ethnicities and political viewpoints that often live in internally-homogenous communities that create their own, separate jurisdictions. Second, older CBSAs might have more jurisdictions since travel was more difficult hundreds of years ago when their boundaries were drawn—resulting in smaller, and thus more, jurisdictions. However, older CBSAs may be disproportionately prosperous (explaining their establishment as initial sites of economic activity) and thus have higher housing values. Finally, wealthier and more-educated citizens may both induce higher housing values (e.g., though housing quality or neighborhood improvements) as well as be more politically active (e.g., in advocating for improved education and police presence)—and this political activity may be associated with more or fewer local governments. Due to the ambiguous direction of these and other potential concerns, it is not possible to sign the overall bias.

We address these threats to identification by exploiting variation in the natural topography of the United States. Specifically, we use a two-stage least squares (2SLS) estimation strategy in which we instrument for the number of jurisdictions within a CBSA with the total length of small streams in that CBSA, which we calculate using Geographic Information System (GIS) data from the Environmental Systems Research Institute (2008).[19] We ignore larger

[17] We use 2012 as it is the most recent year for which we have data on all outcomes and independent variables considered in this analysis, including data analyzed when considering mediators of the effects.

[18] If a CBSA crosses state borders we assign it to the state where most of its population resides. The results are very similar when allowing for multiple state dummies per CBSA, assigning unique dummies for multi-state CBSAs, or restricting the sample to CBSAs that do not cross state borders.

[19] In particular, we relied on 2008 Data and Maps software for the U.S.A., file name hydroln.sdc (a vector digital dataset). These data are based on the United States National Atlas, published by the United States

rivers when computing the total length of small streams since they may directly impact economic activity and housing values—and we in fact control for their presence in our vector of controls, X_i.[20] Thus, we hypothesize that small streams will only affect housing values and other outcomes of interest through their influence on the number of jurisdictions.

The history of county formation in the United States motivates our identification strategy. The median county was founded in 1848, when geographic obstacles such as streams provided natural "breakpoints" between jurisdictions. Given the lack of modern technology, having more (fewer) streams made it relatively less (more) costly to create jurisdictional boundaries. For example, the Houston and Phoenix CBSAs have roughly comparable land area and not drastically different populations, yet Houston has about 63% more streams; see Table 1. Consistent with the inclusion restriction for our identification strategy, Houston has 14 county governments, while Phoenix has only two. Figure 1 shows how small streams coincide with many of the county borders in the Houston CBSA today.

Table 1: Comparison of Phoenix and Houston

	Land area (sq. miles)	Population	Streams (100s of miles)	# of counties
Phoenix	14,566	4,192,887	13.6	2
Houston	12,527	6,114,562	22.1	14

Notes: Illustrative comparison of Houston–The Woodlands, TX CSA and Phoenix–Mesa–Scottsdale, AZ CBSA. Population, land area, and counties from US Census Bureau (2012). Streams data from ESRI (2008).

In our first stage, we regress the number of jurisdictions in CBSA i, N_i, on the miles of small streams in CBSA i, s_i:

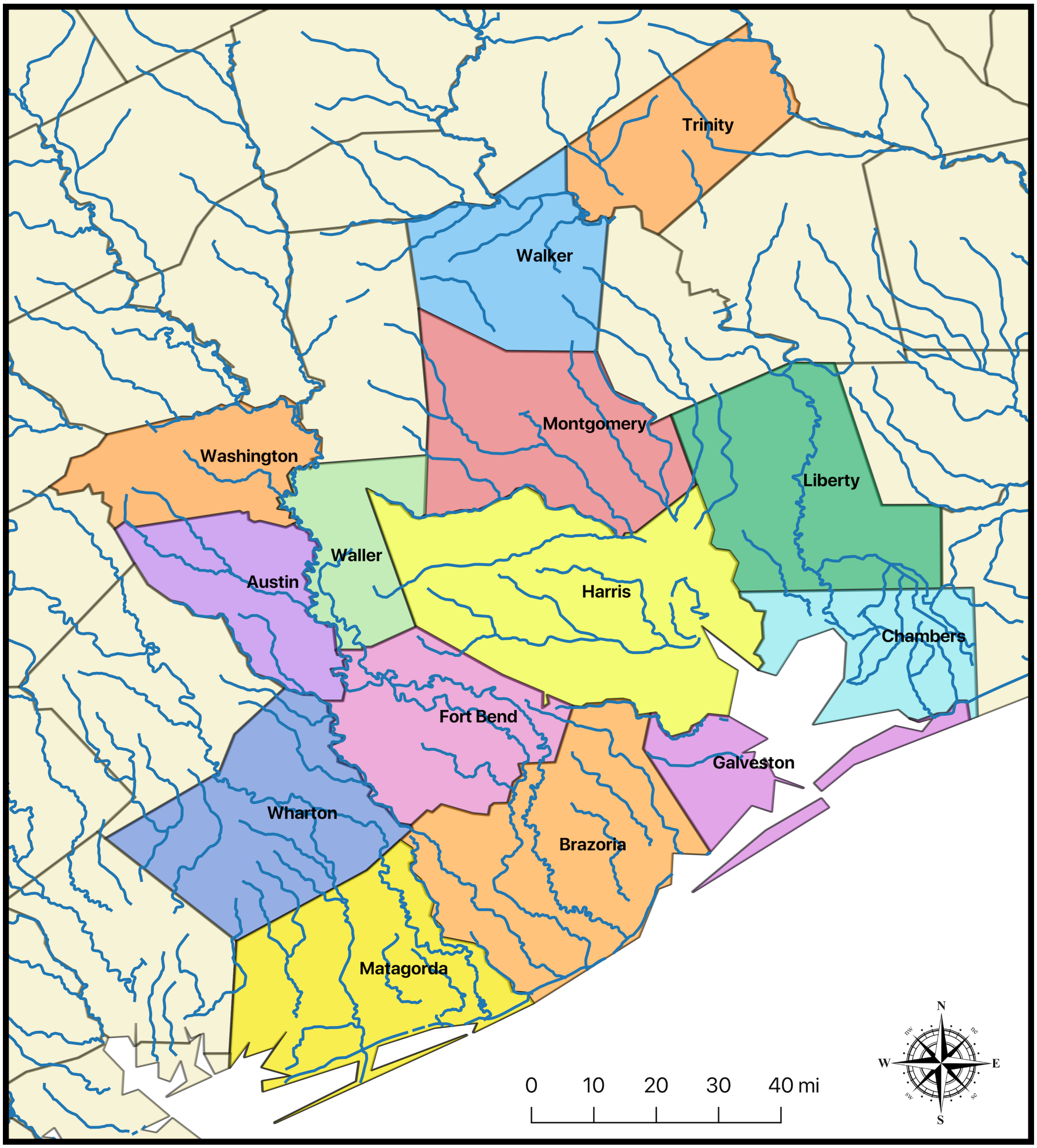
$$N_i = \delta_0 + \delta_s s_i + \theta \mathbf{X}_i + \pi_j + \nu_i \tag{2}$$

where π_j are state fixed effects. Evidence of a strong first stage that satisfies the inclusion restriction is presented in Section 3.

Geological Survey (USGS). This dataset omits major rivers, and includes only streams, intermittent streams, canals, intermittent canals, dams, aqueducts, falls, and intracoastal waterways, as defined by the USGS in the National Atlas of the United States. To compute what we refer to as total miles of small streams—and use as our primary instrument—we excluded canals, intermittent canals, dams, and aqueducts, as these are generally manmade, and may be preferentially built in areas of high growth, thus endogenizing our instrument.

[20] Our focus on small streams and not major rivers or ports addresses concerns raised by Bleakley and Lin (2012) regarding the use of navigable waterways as an instrument; Bleakley and Lin (2012) showed that historical portage sites in the USA—"the intersections between the fall line [the final rapids on rivers before the ocean] and major rivers"—have had a persistent effect on city size and density today. While the distinction between rivers and small streams is clear in the dataset, we do not know the width of each small stream, and thus are unable to experiment with using different thresholds of stream width.

Figure 1: Map of the counties comprising the Houston-The Woodlands, TX CSA, and the CSA's streams (Environmental Systems Research Institute, 2008).



We argue that, largely due to the size of small streams, they neither boost the potential for economic activity nor hinder it; they can easily be avoided, traversed, or built over using affordable modern-day construction methods, and they do not convey the benefits that larger bodies of water do—either by directly stimulating economic activity or forming an enjoyable amenity. As such, small streams are unlikely to appreciably affect housing values today. However, a concern remains that streams are correlated with other geographic features that do affect housing values. We address this concern by including topographic and climatic controls—including access to major rivers, lakes, and oceans—in the vector X_i, described in Section 2.2. We thus exploit natural variation in the number of small streams that is uncorrelated with these other natural features. Our key identifying assumption is that, conditional on these topographic as well as climatic controls, small streams do not affect housing values directly, but rather only through their effect on the number of local governments.

We borrow this strategy from Hoxby (2000), who used small streams as an instrument to investigate how school district fragmentation affects the degree of Tiebout choice over schools in a metropolitan area and, ultimately, school quality.[21] The argument is identical: at the time of school district formation, small streams substantively affected travel time to school and therefore served as natural "breakpoints" for creating more school districts, yet these streams are exogenous to modern-day school productivity. Similar applications of this identification strategy have been used by Cutler and Glaeser (1997), Baqir (2001), and Hatfield and Kosec (2013, 2019).

2.2 Variable Measurement

2.2.1 Number of Jurisdictions

We capture the number of jurisdictions using the number of county governments in a CBSA in 2012. Data on the just over 3,000 county governments in the United States come from the Census Bureau's Census of Governments (U.S. Census Bureau, 2012b). We focus on counties since they are one of the most important and powerful units of subnational governance and represent the primary legal subdivision of states. Counties also have relatively more uniformly defined power than other subnational governments (e.g., municipalities or townships), making them more appropriate for cross-state analysis.[22]

[21] Hoxby's work was criticized by Rothstein (2007) for using a subjective hand count of "small" streams. We circumvent this criticism by algorithmically calculating the number of miles of small streams in a CBSA from GIS data.

[22] As they have county-like control over their territory, we include independent cities (e.g., St. Louis, MO) and consolidated city-counties (e.g., San Francisco, CA) in our count of the total number of counties.

Because counties were formed long ago (1848 at the median), and we exploit that part of the number of counties in a metropolitan area that is due to the prevalence of small streams (a permanent feature), we interpret our estimates of the effects of the number of counties on various outcomes as representing the long-term effect of jurisdictional fragmentation. In sub-section 3.3, we provide empirical evidence supporting our interpretation of this as a long-term effect, following Casey and Klemp (2021).

2.2.2 Housing Values and Wages

We use detailed data from the 2012 American Community Survey (ACS) (U.S. Census Bureau, 2012a) to generate CBSA-level measures of housing values and wages. Rather than use raw averages of these variables in our analysis, we employ a method for netting out important differences in underlying characteristics of houses and workers:[23] Using the individual-level ACS data, we regress log housing values on a set of housing characteristics and CBSA fixed effects.[24] The sum of the constant and the CBSA fixed effect provides the "residualized housing value" for that CBSA. This variable captures the difference in housing values across CBSAs net of important housing characteristics. Similarly, we regress log hourly wages on a set of individual worker characteristics and CBSA fixed effects.[25] The "residualized wage" is the sum of the constant and the CBSA fixed effect, representing the wage level in a CBSA net of important worker characteristics.[26] We employed this method to avoid overstating the significance of the results (i.e., the identifying variation is at the CBSA-level, not the individual-level) as well as due to the fact that other outcome variables (beyond housing values) were only available at higher levels of aggregation. Regressions using individual-level data are included in Table A6 and are very similar to the main results.

Table A5 shows that our results are robust to alternative definitions of jurisdictional fragmentation.

[23] Our methodology follows that of Albouy (2018) and Notowidigdo (2019).

[24] These characteristics include number of rooms, number of bedrooms, lot size in acres, year built, type of plumbing, number of units in structure, type of kitchen, and farm status. Housing values are a monthly flow, either rent paid or the value of an owner's house multiplied by 0.0785 and divided by 12. For an explanation of this methodology, see Albouy (2018).

[25] Individual characteristics include sex, age, age squared, veteran status, whether someone immigrated in the last five years, race, marital status, education, occupation, industry, and interactions of all of the above with a male dummy. Hourly wages are defined as annual earned income divided by hours worked per year. For an explanation of this methodology, see Notowidigdo (2019).

[26] The primary geographic identifier in the ACS data is the Public Use Microdata Area (PUMA), though some observations also include CBSA and county identifiers. Most observations were therefore directly linked to the appropriate CBSA in order to estimate coefficients on the fixed effects. Rarely, the PUMA was the only available geographic identifier and the PUMA spanned multiple CBSAs. In these cases, the CBSA where the majority of the PUMA was located was assigned to the individual.

2.2.3 Educational Test Scores

We use data from the National Center for Education Statistics (2012), organized by the Stanford Education Data Archive, to capture differences in average educational outcomes. The National Assessment of Education Progress (NAEP) is known as "The Nation's Report Card" because its test scores are designed for cross-country comparisons in multiple subjects. We aggregate county-level data, weighted by the number of test takers in that county, up to the CBSA level to generate a CBSA average of the math and English/language arts scores. We use 4^{th} grade scores because this age group covers the largest number of CBSAs in our sample, although the results are robust to using other grades.

2.2.4 Environmental Quality

Our primary measure of environmental quality is the Environmental Protection Agency's (EPA) Air Quality Index (AQI) (Environmental Protection Agency, 2012). The AQI measures the level of air pollution based on the presence of the five pollutants regulated under Title I of the Clean Air Act (1970): ground-level ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, and particulate matter (also known as particle pollution). The EPA has established maximum levels at which each of these pollutants is thought to harm public health if breathed for an extended period of time. The range of the AQI is 0 to 500.[27] The EPA reports AQI levels daily for each county. The variable used in Section 5 is the average AQI during 2012. County-level data were combined using population weighting to generate CBSA-level measures.

2.2.5 Criminal Activity

We also investigate whether crime is an additional channel by which the number of jurisdictions may affect housing values using the Federal Bureau of Investigation (2012) Crime Index. The FBI Crime Index for a CBSA is simply the number of violent or property crimes per capita in that CBSA in that year.[28] Since the FBI only releases statistics at the CBSA level, CSA averages were calculated via population weighting of the component CBSAs.

[27]The EPA considers values below 100 healthy and values over 100 unhealthy; values over 100 trigger EPA recommendations for children and those with respiratory problems to limit outdoor activity.

[28]These data are voluntarily submitted through the FBI's Uniform Crime Reporting (UCR) program by various law enforcement agencies (e.g., city, county, and state).

2.2.6 Additional Controls

We control for a range of additional CBSA characteristics, X_i, in both stages of our 2SLS framework. As discussed in Section 2.1, unbiased results require that our instrument be uncorrelated with the error term in Equation (1). The inclusion of additional controls and their relatively inconsequential effect on our results alleviates concerns that the impact of the number of jurisdictions on housing values was driven by some other factor correlated with our instrument. Many of our controls are motivated by the work of Saiz (2010), who noted that residential development can be influenced by geographic region, land area availability, and the presence of steep-sloped terrain. Our full set of additional controls includes the standard deviation of elevation as well as dummy variables for whether a CBSA borders different oceans, the Great Lakes, and major rivers, all obtained from Environmental Systems Research Institute (2008) data or the National Oceanic and Atmospheric Administration (2011). We control for the total land area in a CBSA as recorded by the U.S. Census Bureau (2012c). Weather controls include the average number of cooling and heating degree days per month[29] and average monthly rainfall, both from the National Climatic Data Center (2010) for the years 1970-2010. We control for the average hours of sunshine in January between 1940-1970 using GIS data in the 2002 Climate Atlas of the United States, also provided by the National Climatic Data Center (2002).[30] In general, we find that the inclusion of these observable controls is relatively inconsequential for our results, alleviating concerns that unobservables which impact both the number of jurisdictions and housing values are driving our results.

Summary statistics for all variables described above are displayed in Table 2, where each observation is a CBSA or CSA. The sample is restricted to CBSAs with non-missing values for all variables used in the regression analysis.[31]

The counties used in the analysis, which can be seen in Figure A1, include nearly 77% of the population of the United States in 2012. Variation in the number of counties within a CBSA is presented in Figure A2.

[29] A cooling degree day is the number of degrees that a day's average temperature is above 65°F; a heating degree day is the number of degrees that a day's average temperature is below 65°F.

[30] Each of these variables are sums or unweighted averages. See Table A1.

[31] Given our use of state fixed effects, and to avoid overstating our sample size, we drop observations from CBSAs which are the only ones in their state. FBI data were available for fewer CBSAs then were other data and so we use the larger sample size (with some observations missing FBI data) in most regressions, except those using FBI data; see Section 4 for more details.

Table 2: Summary Statistics

	mean	median	standard deviation
Average monthly housing value	1245	1145	465
Log residualized housing value	5.01	4.94	0.27
Number of county governments	5.65	4.00	5.36
100s of miles of streams	6.06	4.53	5.26
Average Air Quality Index (AQI)	38.70	38.26	14.74
Dummy - on Pacific Ocean	0.05	0.00	0.23
Dummy - on Atlantic Ocean	0.15	0.00	0.36
Dummy - on Great Lakes	0.07	0.00	0.26
Dummy - on major river	0.29	0.00	0.46
Square miles of land (1000s)	4.73	3.19	4.91
Cooling degree days (100s)	1.09	0.84	0.78
Heating degree days (100s)	3.81	3.81	1.86
Sunshine percentage in January	50.96	51.00	11.59
Monthly rainfall	3.32	3.53	1.16
Standard deviation of elevation	0.20	0.08	0.27
Average hourly wage	22.11	21.52	3.00
Log residualized wage	1.28	1.28	0.08
Average NAEP score (math + ELA) G4	228.55	229.08	6.39
FBI crime index: violent + property crime	3.49	3.44	0.87

Notes: There are 201 observations at CBSA (or CSA) level used in the main analysis. Housing value is monthly rent for renters and monthly-adjusted home value for owners ($0.0785 \times \text{value} \times \frac{1}{12}$) from the 2012 American Community Survey (ACS). Residualized housing values are the CBSA fixed effects plus the estimated constant from a regression of housing values on housing characteristics in the ACS. Residualized wages are similarly calculated using hourly wages after controlling for worker-level characteristics. The number of county governments is taken from the 2012 Census of Governments. 100s miles of small streams comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. The EPA's Air Quality Index (AQI) is on a scale from 0 to 500 and reflects the presence of five pollutants. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, divided by 100. The percentage of sunshine is recorded in January. Rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. The average math and English/language arts scores in grade 4 are from the National Assessment of Education Progress (NAEP). The FBI crime index is the number of violent or property crimes in an CBSA rescaled to be per 100 inhabitants.

Sources: Census ACS, COG (2012, 2013), NCES (2012), EPA (2012), ESRI (2008), FBI (2012), NCDC (2002, 2010)

3 Results

3.1 OLS Results

We first present the results of our OLS regressions estimating the impact of the number of jurisdictions on residualized housing values in Table 3. The coefficient on the number of county governments is stable as controls are iteratively added. Focusing on our preferred specification with the full set of controls (Column 3), a CBSA with one more county government is expected to have housing values approximately 1.4% higher. However, the concerns raised in Section 2.1 highlight the possibility that these estimates are capturing other factors that both directly affect housing values and are correlated with the number of county governments, thus motivating our IV strategy.

3.2 IV First Stage Results

Figure 2 plots the number of county governments in a CBSA (on the vertical axis) against our instrumental variable, the total miles of small streams (on the horizontal axis); it reveals a positive correlation. In Table 4, we present our first stage specification as we iteratively add our set of control variables; in each specification, the F-statistic is no smaller than 45. Column 3 indicates that a 100 mile increase in the length of small streams in a CBSA predicts 0.82 more county governments in that CBSA. Thus, the total length of small streams indeed affects the number of jurisdictions, independent of other geographic or climatic characteristics for which we control.

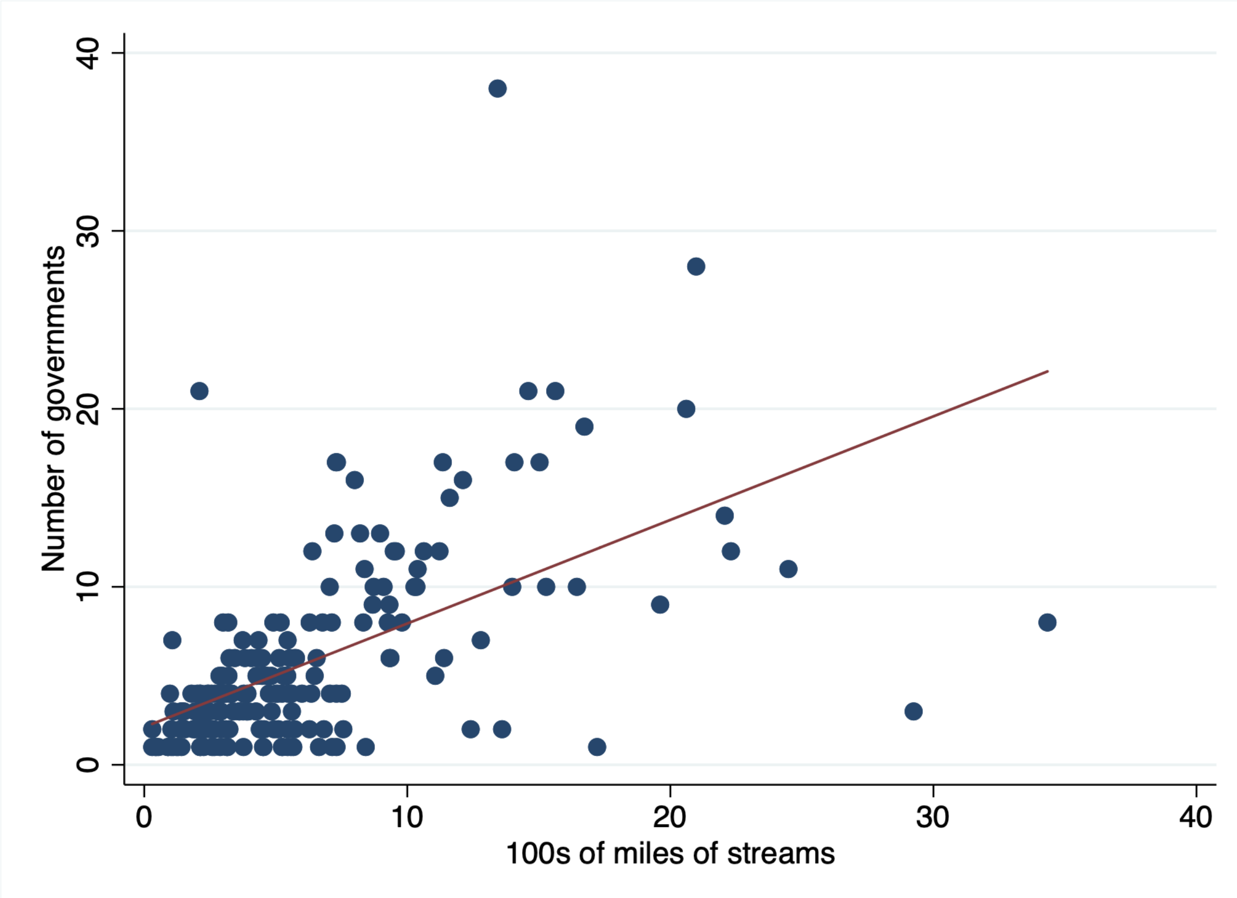
Table 3: OLS Results, Showing the Effect of the Number of County Governments on Housing Values

	Dependent Variable: Log residualized housing value		
	(1)	(2)	(3)
# of county governments	0.016***	0.015***	0.014***
	(0.004)	(0.005)	(0.004)
Dummy - on Pacific Ocean		0.445***	0.385***
		(0.089)	(0.096)
Dummy - on Atlantic Ocean		0.121**	0.164***
		(0.047)	(0.042)
Dummy - on Great Lakes		-0.027	-0.005
		(0.050)	(0.050)
Dummy - on major river		-0.067**	-0.045
		(0.031)	(0.029)
Square miles of land (1000s)		0.002	-0.000
		(0.003)	(0.003)
Cooling degree days (100s)			-0.224***
			(0.076)
Heating degree days (100s)			-0.079*
			(0.048)
Sunshine percentage in January			0.005*
			(0.003)
Monthly rainfall			-0.014
			(0.027)
Standard deviation of elevation			0.050
			(0.095)
State FE	✓	✓	✓
Observations	201	201	201
R^2	0.612	0.724	0.760

Notes: Observations are at the CBSA (or CSA) level. Residualized housing values are the CBSA fixed effects from a regression of housing costs, defined as rent for renters or monthly-adjusted home value for owners, on housing characteristics using the 2012 American Community Survey (ACS). Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, over 100. Land area is in 1000s of square miles. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. Robust standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sources: Census ACS, COG (2012), EPA (2012), ESRI (2008), NCDC (2002, 2010)

Figure 2: First stage relationship between county governments and miles of small streams



See Section 2.2 for more details.

3.3 IV Second Stage Results

The second stage results of our 2SLS strategy are presented in Table 5. In each specification, the effect of the number of county governments on housing values is strongly significant. The estimate in Column 3 of Table 5, which includes the entire set of geographic controls and state fixed effects, indicates that the same CBSA with one additional county government would be expected to have housing values that are 2.0% higher. Compared to the OLS results in Table 3, the IV point estimates are slightly larger.

We interpret our results here as estimates of the long-run effect of jurisdictional fragmentation. To justify our interpretation, we follow the methodology of Casey and Klemp (2021), who showed how to correctly use historical instruments for contemporary endogenous variables. Casey and Klemp (2021) showed that one can use the persistence of the endogenous variable to assess whether the IV estimates are biased; when persistence of the endogenous

Table 4: IV First Stage Results, Showing the Effect of Miles of Small Streams on the Number of County Governments

	Dependent Variable: # of county governments		
	(1)	(2)	(3)
100s of miles of streams	0.800***	0.778***	0.823***
	(0.098)	(0.116)	(0.123)
Dummy - on Pacific Ocean		0.239	0.078
		(0.972)	(1.568)
Dummy - on Atlantic Ocean		1.246	1.549
		(1.124)	(1.113)
Dummy - on Great Lakes		0.021	0.021
		(0.895)	(0.867)
Dummy - on major river		0.380	0.426
		(0.509)	(0.528)
Square miles of land (1000s)		0.016	-0.007
		(0.151)	(0.184)
Cooling degree days (100s)			-1.343
			(1.464)
Heating degree days (100s)			-0.321
			(0.996)
Sunshine percentage in January			0.032
			(0.036)
Monthly rainfall			-0.376
			(0.463)
Standard deviation of elevation			-1.489
			(1.820)
State FE	✓	✓	✓
Observations	201	201	201
R^2	0.656	0.661	0.668
F-stat	67	45	45

Notes: Observations are at the CBSA (or CSA) level. 100s miles of small streams comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, over 100. Land area is in 1000s of square miles. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. Robust standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sources: Census ACS, COG (2012), EPA (2012), ESRI (2008), NCDC (2002, 2010)

variable is high, bias is low. In our setting, we find a very high degree of persistence, consistent with our interpretation of our estimate as the long-run effect of jurisdictional fragmentation. Specifically, adjusting our IV estimates using the method described in Casey and Klemp (2021) reduces our point estimates by only 10% (see Table A3). We attribute the similarity in our results to the relative stability of the number of county governments over the last two centuries. Because the two methods produce statistically indistinguishable estimates, we focus on the traditional IV results for the remainder of the paper.

To put our estimate into context, a metropolitan area with a standard deviation more counties (i.e., 5.4 more counties) has, on average, home values that are 11% greater; at the median home value, this implies a value that is $20,000 higher.[32] Converting housing prices to annualized rents for owner-occupied housing, our results indicate that someone would be willing to pay about $1,600 more per year to live in a location with a standard deviation more jurisdictions—approximately 4.4% of the median annual wage.[33] Put another way, living in a location with a standard deviation more local governments is worth about five times as much as living in a school district with test scores that are one standard deviation higher.[34] While this seems a very substantial premium to pay to live in a place with more local governments, we also estimate that such places have significantly higher wages; see Section 5.1.

4 Robustness

4.1 Additional Controls

Table 6 shows the robustness of our main results to the inclusion of numerous additional controls. We add controls, both separately and in concert, for area covered in water, hundreds of miles of major rivers,[35] founding year of the CBSA divided by 100,[36] a dummy for the CBSA including a state capital, and a dummy for the CBSA having a major university. In all of our specifications, the first stage F-statistic remains over 21 and the coefficient on the number of county governments remains strongly statistically significant and stable

[32]The median home value in our sample, as reported in the ACS, is $175,000, and so we calculate $(e^{5.4\times.020} - 1) \times \$175{,}000 = \$19{,}958$.

[33]Based on the same method described in Footnote 24, we calculate the increase in annualized rent for the median home as $19{,}958 \times 0.0785 = \$1{,}567$. The median annual wage in the sample of CBSAs is approximately $36,000.

[34]According to Black (1999), parents are willing to spend nearly $4,000 more on a house for a one standard deviation increase in elementary school test scores.

[35]Water and river variables were generated using the Environmental Systems Research Institute (2008) data.

[36]We take the earliest founding year of any county in the CBSA as the CBSA's founding year. Information on when counties were founded was provided by the National Association of Counties (2009).

Table 5: IV Second Stage Results, Showing the Effect of Number of County Governments on Housing Values

	Dependent Variable: Log residualized housing value		
	(1)	(2)	(3)
# of county governments	0.017***	0.018***	0.020***
	(0.004)	(0.005)	(0.005)
Dummy - on Pacific Ocean		0.449***	0.405***
		(0.079)	(0.085)
Dummy - on Atlantic Ocean		0.116***	0.156***
		(0.041)	(0.036)
Dummy - on Great Lakes		-0.028	-0.007
		(0.042)	(0.040)
Dummy - on major river		-0.067**	-0.047*
		(0.028)	(0.025)
Square miles of land (1000s)		-0.000	-0.005
		(0.004)	(0.005)
Cooling degree days (100s)			-0.210***
			(0.068)
Heating degree days (100s)			-0.074*
			(0.042)
Sunshine percentage in January			0.005**
			(0.002)
Monthly rainfall			-0.020
			(0.023)
Standard deviation of elevation			0.057
			(0.083)
State FE	✓	✓	✓
Observations	201	201	201
R^2	0.612	0.722	0.753
F-stat	67	45	45

Notes: Observations are at the CBSA (or CSA) level. Residualized housing values are the CBSA fixed effects from a regression of housing costs, defined as rent for renters or monthly-adjusted home value for owners, on housing characteristics using the 2012 American Community Survey (ACS). 100s miles of small streams comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, over 100. Land area is in 1000s of square miles. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. Robust standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sources: Census ACS, COG (2012), EPA (2012), ESRI (2008), NCDC (2002, 2010)

at around 0.02.[37] That controlling for water area leaves the coefficient on miles of small streams unchanged—and itself is a statistically insignificant predictor of housing values—is inconsistent with water bodies (which include small streams) simply being a sought-after amenity, and increases our confidence that a correlation between small streams and this variable does not itself account for the results. This may be unsurprising given that the median percentage of area covered in water is only 2 percent for the CBSAs in our sample. We also demonstrate that our results are not driven by outlier observations of the number of miles of small streams (Table A4).

4.2 Alternative Measures of Competition

While our main results use the number of county governments in a CBSA, there are alternative ways to represent the level of jurisdictional fragmentation: First, it may be the case that the number of municipal or township governments is more important than the number of counties. Second, a CBSA with many counties but where only one county dominates in terms of population or income may affect housing values differently than a CBSA with the same number of counties and a more equal distribution of population and income: Having one large county and many small counties may have a much different effect on policy than having several mid-sized counties, and this in turn may imply differences in outcomes with respect to housing values.

These considerations motivate the use of five alternative measures of jurisdictional fragmentation: First, we omit consolidated city-counties and independent cities from the total number of county governments in a CBSA. Second, we use the number of municipalities and townships in a CBSA. Third, we create two different Herfindahl-Hirschmann Indexes (HHIs), one using the sum of squared shares of the 2012 population and the other using the sum of squared shares of earned income at the county level in the CBSA.

Table A5 presents the results using these alternative measures of jurisdictional fragmentation. Panel A shows the OLS results and Panel B shows the second stage results, once again using our instrumental variable of small streams in a CBSA. The narrow definition of the county government variable is very similar to the variable used in the main analysis based on functional county governments, which explains the similarity of Column 1 to the results presented in Table 3 and Table 5. Column 2's OLS estimates using the number of municipalities and townships reflect qualitatively similar findings.[38] Column 3 shows

[37] Although population is endogenous, the results are also not meaningfully affected by its inclusion as a control.

[38] We estimate an effect size of having one standard deviation more counties of $5.4 \times 0.02 = 0.108$, whereas we estimate a slightly larger effect size of having one standard deviation more municipalities and townships of $123 \times 0.0011 = 0.135$.

Table 6: IV Second Stage Results, Showing the Effect of Number of County Governments on Housing Values is Robust to Additional Controls

	Dependent Variable: Log residualized housing value					
	(1)	(2)	(3)	(4)	(5)	(6)
# of county governments	0.020***	0.023***	0.019***	0.018***	0.020***	0.023***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.008)
Water area (1000s of sq. miles)	0.029					0.025
	(0.020)					(0.024)
Total miles of major rivers		-0.001				-0.001
		(0.000)				(0.000)
Earliest county founding year, over 100			-0.089*			-0.069
			(0.052)			(0.057)
State capital				0.035		-0.010
				(0.035)		(0.044)
Largest public university in state					0.059	0.053
					(0.037)	(0.038)
State FE	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓
Observations	201	201	201	201	201	201
R^2	0.756	0.752	0.761	0.759	0.758	0.760
F-stat	67	33	46	28	44	21

Notes: Observations are at the CBSA (or CSA) level. Residualized housing values are the CBSA fixed effects from a regression of housing costs, defined as rent for renters or monthly-adjusted home value for owners, on housing characteristics using the 2012 American Community Survey (ACS). 100s miles of small streams comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. Baseline controls include the following: Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, over 100. Land area in 1000s of square miles. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. Robust standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sources: Census ACS, COG (2012), ESRI (2008), NACO (2009), NCDC (2002, 2010) that having a one standard deviation lower (0.28 unit lower) population-based HHI predicts housing values that are about 7.5% higher using the OLS specification and 24% using the IV approach. Column 4, which uses the earned income-based HHI, shows that when this measure of jurisdictional fragmentation is one standard deviation (0.25 units) lower, housing values are about 6.1% (OLS) and 27% (IV) higher, although the F-statistic for this IV specification is lower than those using other measures of jurisdictional fragmentation. That estimates generated using alternative measures of competition are of similar magnitude and significance as our main results serves as evidence of the robustness of our findings.

4.3 Relaxing the Exogeneity Assumption

The validity of our IV results rests on the assumption that the length of small streams in a CBSA is exogenous; we make explicit our argument for why this is the case in Section 2.1. However, Imbens (2003) and Harada (2013) described a method for quantifying the degree to which omitted variable bias could impact IV results. In our setting, this means relaxing the exogeneity assumption by allowing for correlation between the length of small streams and both housing values and the number of county governments. We generate 201 pseudo-unobservables which would explain away half of the OLS coefficient from Column 3 of Table 3; the inclusion of such a covariate would meaningfully affect our results. The marginal increase in the R^2 from controlling for this variable in both the reduced form and the first stage are plotted against each other, shown in Figure A3. On the same figure, we have also plotted the marginal increase in R^2 when we add

- Large body of water dummies and land area controls;
- Our weather control variables.

The location of these points relative to the curve generated from controlling for pseudo-unobservables indicates that an unobservable would not only have to be highly correlated with both housing values and the number of county governments in order to meaningfully alter our results, but that it would also need to be substantially more influential than our current set of controls. This analysis supports our causal interpretation of the IV results.[39]

4.4 Local Government Finances

Our main result—that metropolitan areas with more jurisdictional fragmentation have higher housing values—suggests that local government finance may depend on the degree of jurisdic-

[39] We include additional checks related to the exclusion restriction in Table A10. Notably, our instrument does not predict higher levels of historical economic activity. Our instrument is associated with slightly earlier county founding years, but the effect is small.

tional fragmentation. Table 7 presents results where the outcome variable in Equation (1) is replaced with per capita measures of local government finances. Column 1 shows that overall tax revenue per capita is not lower due to competition with neighboring jurisdictions, unlike the predictions of Zodrow and Mieszkowski (1986), Brennan and Buchanan (1978), and others; this may be because local governments have access to tax instruments, such as property taxes, that are not subject to even local tax competition. Indeed, although statistically insignificant, the sign on the coefficient in Column 2 suggests that more jurisdictional fragmentation leads to higher property tax revenue.[40] Moreover, our results here indicate that CBSAs with more jurisdictional fragmentation are not acquiring more resources from state governments or from the federal government: CBSAs with more jurisdictional fragmentation do not have significantly higher revenue from external sources or higher deficits.

Table 7: IV Second Stage Results, Showing the Effect of Number of County Governments on Per Capita Local Government Finances

Dependent Variable:	Total tax revenue	Property tax revenue	Revenue from external sources	Expenditures	Deficit
	(1)	(2)	(3)	(4)	(5)
# of county governments	0.002	0.004	-0.005	-0.017	-0.002
	(0.004)	(0.003)	(0.005)	(0.015)	(0.003)
State FE	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓
Observations	201	201	201	201	201
R^2	0.744	0.727	0.921	0.793	0.511
F-stat	45	45	45	45	45

Notes: Each observation is an CBSA (or a CSA in the case of larger metropolitan areas). The same sample is used for all regressions. Dependent variables are in 1000s of dollars per capita. The instrumental variable is 100s miles of small streams in the CBSA and comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. Baseline controls include the following: Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, divided by 100. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. Dependent variables are in units of 1000s of dollars per capita. Robust standard errors: *** p < 0.01, ** p < 0.05, * p < 0.1.

Sources: Census ACS, COG (2012), EPA (2009-2012), ESRI (2008), NCDC (2002, 2010)

[40]Note that this effect is *not* mechanical given higher housing prices, since jurisdictions in those areas could reduce property tax rates to compensate for the higher housing costs.

4.5 Land Use Regulation

Another possibility is that jurisdictional fragmentation leads to more restrictive land use and zoning policies. If this were the case, supply constraints could be responsible for higher housing values in areas with more jurisdictional fragmentation, as opposed to higher demand to live in such areas. We carry out two analyses to assess whether or not this is the case. For the first, we consider the impacts of the number of county governments on the Wharton Residential Land Use and Regulation Index (WRLURI) from Gyourko et al. (2019), a measure of the degree to which regulatory restrictions contain the supply of housing.[41] For the second, we consider the effects of the number of county governments on the housing stock (i.e., the number of housing units, defined as a house, an apartment, a group of rooms, or a single room occupied or intended for occupancy as separate living quarters) in 2012, and on the growth in the housing stock during 2010–14, a period centered on the year of our dataset for the main analysis of 2012 (U.S. Census Bureau, 2020). Table A9 shows that jurisdictional fragmentation does not have an impact on the WRLURI. Additionally, the number of county governments has no impact on the housing stock itself, but is actually associated with a higher growth rate of housing stock over 2010–14. We thus conclude that land use regulations, or any other factors restricting the level or growth in the housing stock, are not an important mediator for the effect of jurisdictional fragmentation on housing prices. In particular, we take this as evidence that jurisdictional fragmentation does not harm resident welfare through decreased access to housing.

5 Mechanisms

5.1 Explaining the Effects of Jurisdictional Fragmentation

The number of jurisdictions in a CBSA has the potential to affect housing values in many ways. For example, if a larger number of jurisdictions engenders competition for business that takes the form of weaker environmental standards, lower air quality may result; this negative externality may then be capitalized into lower housing values in the area. Similarly, competition between jurisdictions may increase wages and enhance economic growth, increasing housing values. In this section, we quantify the importance of these and a number of other channels in understanding the effect of jurisdictional fragmentation on housing values.

While there are myriad factors which influence housing values, we focus on those which have been shown in the literature to be economically meaningful and for which we can

[41] This includes hard caps on permitting or building of new housing units as well as policies that raise costs via delays and restrictions.

get data. People naturally desire to live in areas that pay higher wages, and this effect is an obvious candidate given the results of Stansel (2005) and Hatfield and Kosec (2013) showing that jurisdictional fragmentation leads to higher wages and wage growth. Evidence that environmental quality is capitalized into housing values continues to grow;[42] moreover, Hatfield and Kosec (2019) showed that jurisdictional fragmentation lowered air quality in U.S. metropolitan areas using data from the late 1990s.[43] Extensive literatures on the relationship between housing values and both school quality (Black, 1999; Figlio and Lucas, 2004; Bogart and Cromwell, 2000; Kane et al., 2006; Bayer et al., 2007; Ries and Somerville, 2010; Collins and Kaplan, 2017) and crime (Gibbons, 2004; Linden and Rockoff, 2008; Pope, 2008; Besley and Mueller, 2012; Adda et al., 2014) motivate our investigation of these additional channels. While there are additional channels that have been previously studied in the context of housing values, to our knowledge there are no data on these mechanisms available at the CBSA level (or which can be aggregated to the CBSA level) for our study year.[44]

We estimate the relationship between the number of jurisdictions and these outcomes using 2SLS.[45] Table 8 shows the results of the second stage regressions of Equation (1), where housing value has been replaced by a different outcome in each column—either log residualized wage, average Air Quality Index (AQI), education test scores, or the FBI crime index. We find that inter-jurisdictional competition has a statistically significant impact on wages (Column 1). The effect of jurisdictional fragmentation on wages is highly economically significant as well: Metropolitan areas with one standard deviation more jurisdictions have wages that are about 4.6% higher. At the median annual wage this is equivalent to about $1,700.[46]

Interestingly, Column 2 shows that jurisdictional fragmentation has effectively zero impact on air quality, in contrast to what was found by Hatfield and Kosec (2019) using 1999–2002 data; possible reasons for this divergence include appreciably cleaner air throughout the country in the more recent data (making differences in air quality harder to detect) and more modern (2012) boundaries for metropolitan areas in some way changing the results.

[42] See, among other studies, work by Leggett and Bockstael (2000), Kim et al. (2003), and Chay and Greenstone (2005).

[43] A number of other works have studied the effects of decentralization on environmental outcomes, with many finding negative effects (List and Co, 2000; Gray and Shadbegian, 2002; Sigman, 2002, 2005; Whitford and Helland, 2003; McWhinnie, 2009; Burgess et al., 2012; Lipscomb and Mobarak, 2017); meanwhile, others have shown null (Sigman, 2007; List and Gerking, 2000) or even positive effects (Levinson, 1999; Millimet, 2003).

[44] Amenities and local characteristics other than those considered here likely impact housing values (Albouy and Lue, 2015), but many of these features, such as the quality of local infrastructure, are difficult to measure.

[45] OLS versions of these regressions are qualitatively similar.

[46] The median annual wage in our data was $36,000, and so we calculate $(e^{5.4\times 0.0083}-1)\times \$36{,}000 = \$1{,}650$.

Another possibility is that as areas with more jurisdictional fragmentation became relatively richer, residents put more emphasis on environmental amenities, and so the air quality in areas with more jurisdictional fragmentation has improved more over time.[47] Column 3 of Table 8 presents a positive impact of the number of county governments on average NAEP test scores, but it is small and statistically insignificant. Finally, Column 4 of Table 8 shows that jurisdictional fragmentation has a statistically insignificant effect on violent and property crime (as measured by the FBI crime index).

Table 8: IV Second Stage Results, Showing the Effect of the Number of County Government on Mediator Outcomes

Dependent Variable:	Log residualized wage	Air Quality Index	Test scores	FBI crime index
	(1)	(2)	(3)	(4)
# of county governments	0.0083***	-0.211	0.147	-0.014
	(0.0013)	(0.272)	(0.119)	(0.023)
Controls and state fixed effects	✓	✓	✓	✓
Observations	201	201	201	170
First Stage F-Stat	45	45	45	42

Notes: Each observation is a CBSA (or a CSA in the case of larger metropolitan areas). The same sample is used for all regressions. The instrumental variable is 100s miles of small streams in the CBSA and comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. All regressions include dummies for bordering oceans, major rivers, or the Great Lakes. Controls for land area, heating degree days, cooling degree days, hours sunshine in January, rainfall, and the standard deviation of elevation are always included, as are state fixed effects. Residualized wages are the CBSA fixed effects from a regression of wages on worker-level demographic controls. The EPA's Air Quality Index (AQI) is on a scale from 0 to 500 and reflects the presence of five pollutants. The average math and English/language arts scores in grade 4 are from the National Assessment of Education Progress (NAEP). The FBI crime index is the number of violent or property crimes in a CBSA per 100 inhabitants. Robust standard errors: *** indicates $p < .01$; ** indicates $p < .05$; * indicates $p < .1$.

Sources: BEA (2012), Census ACS, COG (2012, 2013), NCES (2012), EPA (2012), ESRI (2008), FBI (2012), NCDC (2002, 2010)

5.2 Explaining Higher Wages

Our analysis thus far has shown that higher wages are the primary explanation for higher housing values in CBSAs with more jurisdictional fragmentation. One possible explanation of our results is that jurisdictional fragmentation leads to more "business-friendly" policies: if fragmentation generates policies that attract more business activity, this could partially

[47]We investigate the reason for the differences between our results and those of Hatfield and Kosec (2019) in Appendix B, and find that the choice of metropolitan boundaries is not important; rather, air quality is worse in areas with more jurisdictional fragmentation before 2000 and statistically indistinguishable after 2000.

explain higher wages and thus higher housing values. Another, potentially linked explanation is that jurisdictional fragmentation changes the industrial composition of a CBSA, making residents more likely to work in higher-skilled occupations. And a third explanation is that wages are simply higher because employer- and government-provided benefits are reduced, and higher wages simply compensate for fewer benefits. We consider all three of these explanations below.

First, we consider the policy explanation for higher wages. Quantifying local policies affecting economic activity is difficult; however, two separate indices have been developed to do so. Stansel (2013) outlined how a CBSA-level Economic Freedom Index (EFI) can be generated using information from the Bureau of Economic Analysis (BEA), the U.S. Census Bureau, and UnionStats.com; this is a modified version of the more well-known global index produced annually by the Heritage Foundation.[48] We use appropriate data to create a 2012 EFI index and ranking to match our main dataset. Alternatively, Area Development Magazine produces an index (ADI) based on various measures of local economic conditions; this index is typically used by the business community to help inform site selection and relocation. However, the relevant data are not available for all CBSAs, slightly reducing our sample size when using these measures.

Our results, presented in Columns 1–3 of Table 9, show that having more county governments leads to a significantly higher index and better (lower) ranking. In particular, having one standard deviation more county governments in a CBSA results in an EFI that is $5.4 \times 0.023 = 0.12$ higher, which represents 13% of the EFI's standard deviation (0.91).

Furthermore, we separately measure the impact of jurisdictional fragmentation on each of the three component areas of the EFI: size of government, takings and discriminatory taxation, and labor market freedom.[49] In results available upon request, we find that each component appears to be significantly affected, with the largest effect coming through the labor market component. This pattern appears consistent with the strong wage channel discussed above; however, policies in each of these areas are likely to be related and even complementary. Either way, these results support the supposition that jurisdictional fragmentation, which can also be described as a greater degree of competition between local governments, may affect housing values and wages by creating a more "business-friendly" environment.[50]

[48] Hobbs et al. (2019) documented the positive relationship between the number of local governments and the EFI.

[49] The size of government is proxied for by various measures of expenditures and transfers by state and local governments. Takings and discriminatory taxation is proxied for by how much tax revenue is raised through income and sales taxation. Labor market freedom is proxied for by union density, annual minimum wage income as a percentage of per capita personal income, and the percent employed in government. See Stansel (2013) for more details.

[50] There are, of course, many other policy dimensions along which CBSAs differ that affect the business environment than those considered by Hobbs et al. (2019) and the Area Development Magazine. For instance,

Table 9: "Business-friendliness" outcomes

Dependent Variable:	Economic Freedom Index	Economic Freedom Index Rank	Area Development Rank
	(1)	(2)	(3)
# of county govts	0.023***	-1.64***	-5.46***
	(0.010)	(0.608)	(2.39)
Baseline controls and state FE	✓	✓	✓
Observations	196	196	187
R^2	0.92	0.93	0.49
F-stat	46	46	41

Notes: Observations are at the CBSA (or CSA) level. The same sample restrictions from the main analysis are used for each regression. Residualized housing values are the CBSA fixed effects from a regression of housing costs, defined as rent for renters or monthly-adjusted home value for owners, on housing characteristics using the 2012 American Community Survey. The instrumental variable is 100s miles of small streams in the CBSA and comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. Baseline controls include the following: Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, divided by 100. Land area in 1000s of square miles. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. The CBSA-level Economic Freedom Index (EFI) was generated following the work of Stansel (2013) using additional information from the Bureau of Economic Analysis (BEA), U.S. Census Bureau, and UnionStats.com; data limitations reduce the sample for the regressions in Columns 1 and 2. Area Development Magazine produces an index (ADI) which is used by the business community to help inform site selection and relocation. The ADI ranks locations based on various measures of local economic conditions and is used in Column 3 as the outcome variable. A lower value in Columns 2 and 3 corresponds to a more favorable ranking. Robust standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sources: Area Development Magazine (2012), BEA (2012), Census ACS, COG (2012), EPA (2012), ESRI (2008), NCDC (2002, 2010), UnionStats (2012)

Second, we consider the industrial composition and work skill explanation for higher wages. Table A7 shows that jurisdictional fragmentation indeed contributes to significant decreases in the share of the population working in manufacturing and in retail trade, and significant increases in the share of the population working in professional, scientific, and technical occupations, finance and insurance, wholesale trade, and educational services. This suggests that another reason for higher wages is changes in industrial composition that accompany jurisdictional fragmentation, whereby residents become more likely to work in higher-skilled occupations.[51]

Finally, we consider whether jurisdictional fragmentation simply raises wages because it simultaneously reduces employer- and government-provided benefits, with the higher wages compensating for the reduced benefits. To do this, we consider the prevalence of health insurance, as it is one of the most important benefits employees receive from their employer. Table A8 considers as outcomes indicator variables for having any health insurance, employer-provided health insurance, individually-purchased health insurance, or publicly-provided health insurance. We find that more county governments leads to less public health insurance and more employer-provided health insurance, and leads to a net increase in the likelihood of having any health insurance at all. Further, having more county governments does not affect the likelihood of having purchased health insurance. We interpret these findings as evidence against jurisdictions competing through social dumping, in which workers become less likely to be insured.

5.3 Distributional Outcomes

We also investigated the possibility that the number of jurisdictions could lead to sorting which—due to higher income or education inequality—could affect housing values. We found limited evidence that this was the case: Column 1 of Table A2 shows that the standard deviation of housing values is not higher in places where there is more jurisdictional fragmentation. Additionally, it appears that there may be higher levels of racial diversity in CBSAs with more jurisdictional fragmentation, shown in Column 2.[52] The level of aggregation in our analysis conceals possible within-CBSA segregation (e.g., Cutler and Glaeser, 1997; Boustan, 2011), yet these higher levels of diversity arguably reduce the likelihood that sorting is a significant driver of our results.

CBSAs may use more or less efficient tax instruments; but see Section 4.4, where we find that CBSAs with a greater degree of jurisdictional fragmentation do not have statistically different government finances.

[51] Our residualized wage results net out education. Hatfield and Kosec (2013) found that more educated workers accompany this shift in industrial composition.

[52] Ethnic fractionalization was calculated using the method of Alesina et al. (1999): Ethnic index $= 1 - \sum_i \rho_i^2$, where ρ_i is the fraction of the CBSA population of race i, calculated using the 2012 ACS.

6 Conclusion

Our results show that metropolitan areas with more jurisdictional fragmentation have economically significant and robustly higher housing values; this increase in housing values reflects consumers' increased willingness-to-pay to live in such areas. Our work also explains why consumers are willing to pay more to live in areas with more jurisdictional fragmentation: Wages are substantially higher in areas with greater jurisdictional fragmentation, while air quality, crime, and education vary little with jurisdictional fragmentation. Finally, we find that these higher wages can be (at least partially) explained by local policy conducive to investment by firms.

Our work also sheds new light on the empirical importance of many of the mechanisms by which jurisdictional fragmentation could influence outcomes. In particular, our work is consistent with a number of theories that predict that jurisdictional fragmentation will induce higher wages.[53] By contrast, we find little evidence that metropolitan areas with more jurisdictional fragmentation have lower tax revenues via tax competition, à la Brennan and Buchanan (1978) and Zodrow and Mieszkowski (1986). Nor do we find evidence that metropolitan areas with greater degrees of fragmentation systematically under-provide public goods à la Oates (1972)—though this can be explained if either public goods with significant spillovers are not an important component of citizens' welfare or if local governments are able to coordinate the production of such goods, as in the work of Ostrom (1990).

Finally, our work cautions that recent advocacy to consolidate local governments in large metropolitan areas may be ill-advised:[54] our work indicates that jurisdictional fragmentation has benefits as well as the costs identified by scholars such as Savitch and Vogel (2000) and Rusk (2006). By merging local jurisdictions, we may lessen competition between local governments—and that competition between local governments, like competition between firms, may play a vital role in disciplining local governments to provide better value for their citizens.

[53]For instance, jurisdictional fragmentation may induce competition for private investment between jurisdictions, raising the rate of return on capital and thus generating more private investment, and that private investment may increase wages.

[54]See, for instance, the celebrated book by David Rusk (1993), "Cities without Suburbs," as well as more recent arguments by Orfield (2011).

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A Additional Results

Table A1: Variable Aggregation Details

Variable(s)	Source	Initial Level of Observation	Aggregation Method
Miles of rivers, streams, etc.	ESRI 2008	County	Unweighted summation
Employee earnings	BEA 2012	County	Unweighted summation, then divided by total population in CBSA
Elevation	ESRI 2008	County	Unweighted summation of county variance
Air quality	EPA 2012	County	Population weighted summation
Land area	Census Gazetteer 2012	County	Unweighted summation
Precipitation, temperature, heating/cooling days	NCDC 2010	Climatic region	Data was mapped to counties via NCDC-provided crosswalk, then used to generate unweighted means
Residualized housing value and wage	ACS 2012	County, PUMA, or CBSA	CBSA fixed effect estimated via regressions described in Section 2.2.2
Education test score	NCES 2012	County	Weighted average based on the number of students who took the NAEP tests
Crime index	FBI 2012	CBSA	Some CBSAs were combined via population weights to generate CSA-level estimates
Area Development Index	AD Magazine 2012	CBSA	Some CBSAs were combined via population weights to generate CSA-level estimates
Economic Freedom Index	BEA, Census, UnionStats 2012	County	Combined via population weights. See Stansel (2013) for more details.
Wharton Residential Land Use and Regulation Index (WRLURI)	Gyourko et al. (2019)	County	Population weighted summation

Note: The primary level of observation for most of the data is the county. However, some variables were only available at higher levels of aggregation. The Office of Management and Budget (OMB) released CBSA boundaries in 2013 based on the 2010 Census. The NBER county-to-CBSA crosswalk is used to map county variables to the 2013 CBSA boundaries.

Table A2: Sorting Outcomes

Dependent Variable:	St. Dev. of Log Residualized Housing Value	Ethnic Fraction-alization
	(1)	(2)
# of county govts	0.001	0.005**
	(0.002)	(0.002)
Baseline controls and state FE	✓	✓
Observations	201	201
R^2	0.541	0.695
F-stat	45	45

Notes: Observations are at the CBSA (or CSA) level. The same sample restrictions from the main analysis are used for each regression. Residualized housing values are the CBSA fixed effects from a regression of housing costs, defined as rent for renters or monthly-adjusted home value for owners, on housing characteristics using the 2012 American Community Survey. The instrumental variable is 100s miles of small streams in the CBSA and comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. Baseline controls include the following: Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, divided by 100. Land area in 1000s of square miles. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. Ethnic fractionalization was calculated using the method of Alesina et al. (1999): Ethnic index $= 1 - \sum Race_i{}^2$, where $Race_i$, the fraction of the CBSA population of race i, was calculated using the 2012 ACS. Robust standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sources: Census ACS, COG (2012), EPA (2012), ESRI (2008), NCDC (2002, 2010)

Table A3: Results comparison - persistence of county governments

	Baseline	Adjusting for persistence
	(1)	(2)
# of county governments	0.020***	0.020***
	(0.004)	(0.008)
Persistence of county govts		0.92***
		(0.25)
Long-run effect		0.018*
		(0.010)

Notes: All data notes match those of the main paper. Column 1 reproduces our main result (Column 3 of Table 5 using only county governments as the measure of JF. Column 2 shows how that estimate is affected by the method described in Casey and Klemp (2021). We performed a seemingly unrelated regression where the first row represents the impact of predicted county governments on housing values while the second row shows the estimated persistence of county governments between 1875 and 2012. The product of the coefficients in the first two rows gives us the long-run effect of county governments on housing values in the third row. Robust standard errors in Column 1 and bootstrapped standard errors in Column 2: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: IV Second Stage Results, Showing the Effect of Number of County Governments on Housing Values when Winsorizing or Trimming the Top and Bottom 5% of Observations of Miles of Small Streams

	Baseline	Winsorize top and bottom 5%	Trim top and bottom 5%
	(1)	(2)	(3)
# of county govts	0.020***	0.018***	0.018***
	(0.005)	(0.004)	(0.005)
Baseline controls and state FE	✓	✓	✓
Observations	201	201	179
R^2	0.753	0.757	0.752
F-stat	45	91	31

Notes: Observations are at the CBSA (or CSA) level. The same sample restrictions from the main analysis are used for each regression. Residualized housing values are the CBSA fixed effects from a regression of housing costs, defined as rent for renters or monthly-adjusted home value for owners, on housing characteristics using the 2012 American Community Survey. The instrumental variable is 100s miles of small streams in the CBSA and comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. Column 2 replaces the top and bottom 5 % of streams with the 95th and 5th percentile value, respectively. Column 3 drops those observations from the sample. Baseline controls include the following: Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, divided by 100. Land area in 1000s of square miles. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. Robust standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sources: Census ACS, COG (2012), EPA (2012), ESRI (2008), NCDC (2002, 2010)

Table A5: OLS and IV Second Stage Results, Showing the Effect of Several Measures of Jurisdictional Fragmentation on Housing Values

	Dependent Variable: Log Residualized Housing Value			
	(1)	(2)	(3)	(4)
Panel A: OLS				
# of county governments	0.014***			
	(0.005)			
# of municipalities and townships		0.0007***		
		(0.0001)		
HHI, county population-based			-0.259***	
			(0.069)	
HHI, county income-based				-0.235***
				(0.072)
Panel B: IV, Second Stage				
# of county governments	0.020***			
	(0.005)			
# of municipalities and townships		0.0011***		
		(0.0002)		
HHI, county population-based			-0.760***	
			(0.195)	
HHI, county income-based				-0.950***
				(0.272)
Baseline controls and state fixed effects	✓	✓	✓	✓
First Stage F-Stat	50	16	13.6	9.3

Notes: Observations ($N = 201$) are at the CBSA (or CSA) level. Residualized housing values are the CBSA fixed effects from a regression of housing costs, defined as rent for renters or monthly-adjusted home value for owners, on housing characteristics using the 2012 American Community Survey (ACS). 100s miles of small streams comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. HHI is a Herfindahl-Hirschmann Index for the CBSA, computing by summing the squared shares of CBSA population (column 3) or CBSA earned income (column 4) pertaining to each county in the CBSA. Baseline controls include the following: Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, over 100. Land area in 1000s of square miles. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. Robust standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sources: Census ACS, COG (2012), EPA (2012), ESRI (2008), NCDC (2002, 2010)

Table A6: Individual Level Regressions

Dependent Variable:	Log Housing Value			Log Hourly Wage	
	All	Owners	Renters	All	No part time
	(1)	(2)	(3)	(4)	(5)
# of county govts	0.020***	0.021***	0.015***	0.009***	0.010***
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
Baseline controls and state FE	✓	✓	✓	✓	✓
Housing Characteristics	✓	✓	✓		
Individual Characteristics				✓	✓
Observations	1,523,927	1,311,650	212,277	967,905	798,688
R^2	0.431	0.448	0.360	0.335	0.366
F-stat	142	148	107	137	138

Notes: Observations are at the CBSA (or CSA) level. The same sample restrictions from the main analysis are used for each regression. Housing values, defined as rent for renters or monthly-adjusted home value for owners, and wages are taken from the 2012 American Community Survey. The instrumental variable is 100s miles of small streams in the CBSA and comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. Baseline controls include the following: Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, divided by 100. Land area in 1000s of square miles. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. Housing characteristics include number of rooms, number of bedrooms, number of household acres, year built, type of plumbing, number of units in structure, type of kitchen, and farm status. Individual characteristics include sex, age, age squared, veteran status, whether someone immigrated in the last five years, race, marital status, education, occupation, industry, and interactions of all of the above with a male dummy. Robust standard errors clustered at the CBSA level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sources: Census ACS, COG (2012), EPA (2012), ESRI (2008), NCDC (2002, 2010)

Table A7: Effect of the Number of County Government on Industrial Composition

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Wholesale trade	Retail trade	Finance and insurance	Professional, scientific, and technical	Educational services	Health and social assistance
# of county govts	0.087***	-0.128***	0.234***	0.285***	0.080**	-0.110
	(0.031)	(0.037)	(0.045)	(0.059)	(0.022)	(0.088)
Panel B	Manufacturing	Construction	Real estate, rental, and leasing	Mining/quarrying, oil/gas, transport., and forestry/fishing	Accommodation, food services, arts, info, and other	
# of county govts	-0.305***	-0.054*	0.059**	-0.028	-0.124	
	(0.085)	(0.031)	(0.025)	(0.119)	(0.078)	

Notes: All data notes match those of the main regressions. Each result is the second stage result using the same 2SLS framework and set of control variables from the main 2SLS regressions. Data from the Bureau of Economic Analysis (BEA); employment shares in percentages. We combine multiple, related categories in Columns 4-5 of Panel B to conserve space. N = 200 and the first stage F-stat is 47 for each regression. Robust standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Effect of the Number of County Government on Health Insurance

	Any health insurance	Employer insurance	Purchased insurance	Public insurance
	(1)	(2)	(3)	(4)
# of county governments	0.002***	0.003***	-0.0003	-0.0005***
	(0.0003))	(0.0007)	(0.0002)	(0.0002)

Notes: All data notes match those of the main paper. Each result is the second stage result using the same 2SLS framework and set of control variables from the main paper. Additional individual controls include age, age squared, and dummies for male, veteran status, and if the individual immigrated within the last 5 years. Data on health insurance are from the same 2012 American Community Survey (ACS) used to residualize wages in the main paper. N = 4,891,455 and F-stat = 70 for each regression. Standard errors clustered at the state level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Land Use Regulation and Housing Stock Results

Dependent Variable:	Wharton Residential Land Use and Regulation Index (WRLURI)	Housing stock	Housing stock growth
	(1)	(2)	(3)
# of county governments	0.014	56.0	0.066**
	(0.013)	(42.0)	(0.033)
State FE	✓	✓	✓
Baseline controls	✓	✓	✓
Observations	201	201	201
R^2	0.325	0.675	0.600
F-stat	45	45	45

Notes: Observations are at the CBSA (or CSA) level. Residualized housing values are the CBSA fixed effects from a regression of housing costs, defined as rent for renters or monthly-adjusted home value for owners, on housing characteristics using the 2012 American Community Survey (ACS). 100s miles of small streams comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. Baseline controls include the following: Dummies for being next to large bodies of water are indicator variables. Heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2010, over 100. Land area in 1000s of square miles. The percentage of sunshine is recorded in January. Monthly rainfall is average monthly precipitation during 1970-2010, in inches. The standard deviation of elevation is in 1000s of feet. The WRLURI index at the CBSA-level is created by weighting the county-level index by population. County housing stock ((i.e., the number of housing units, defined as a house, an apartment, a group of rooms, or a single room occupied or intended for occupancy as separate living quarters) from the U.S. Census. The outcome in Column (3) is the amount of housing stock in 2012 while the outcome in Column (4) is the percent change in housing stock between 2010 and 2014. Robust standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

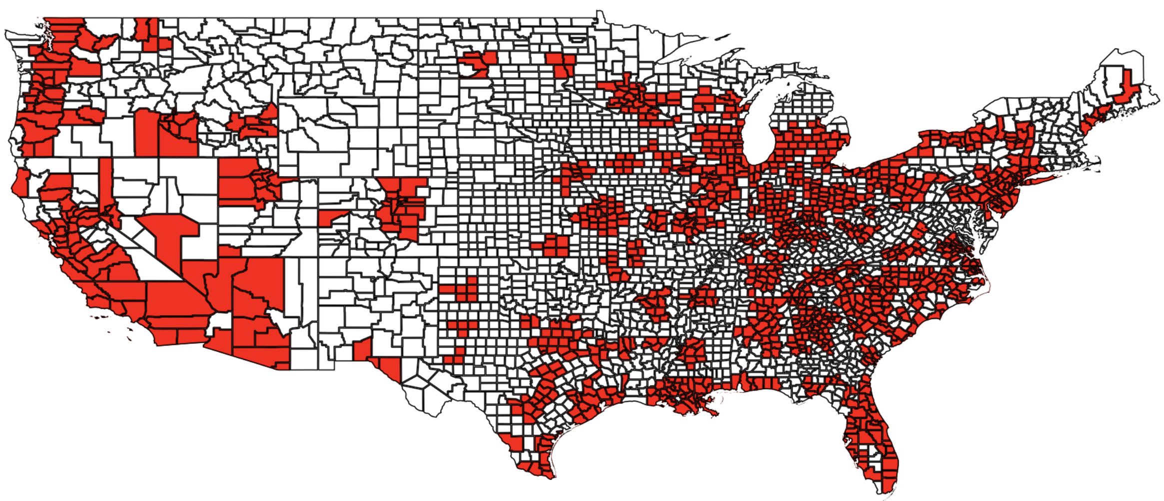
Sources: Census ACS, COG (2012), PEP (2020), ESRI (2008), NACO (2009), NCDC (2002, 2010), Gyourko et al. (2019)

Table A10: Relationship between streams and historical outcomes

	Agricultural output (1)	Manufacturing capital (2)	Founding year (3)
100s of miles of streams	64.9	68.3	-0.012**
	(63.7)	(59.8)	(0.006)
Baseline controls and state FE	✓	✓	✓
Observations	123	123	201

Notes: All data notes match those of the main tables. Agricultural output is the value of all production of wheat, barley, oats, rye, buckwheat, corn, hops, Irish potatoes, sweet potatoes, hay, hemp, flax, tobacco, rice, cotton, and sugar (Haines et al., 2018). Manufacturing capital is the value of all buildings, equipment, and cash held by manufacturing enterprises (Haines, 2010). We take these 1840 county values, the earliest year for which these data are available, and adjust them for inflation (2012 dollars). We then aggregate them to the CBSA level. Historical data only available for 123 of the original 201 CBSAs. Founding year is the earliest county founding year in the CBSA, divided by 100 for readability. Robust standard errors: *** p < 0.01, ** p < 0.05, * p < 0.1.

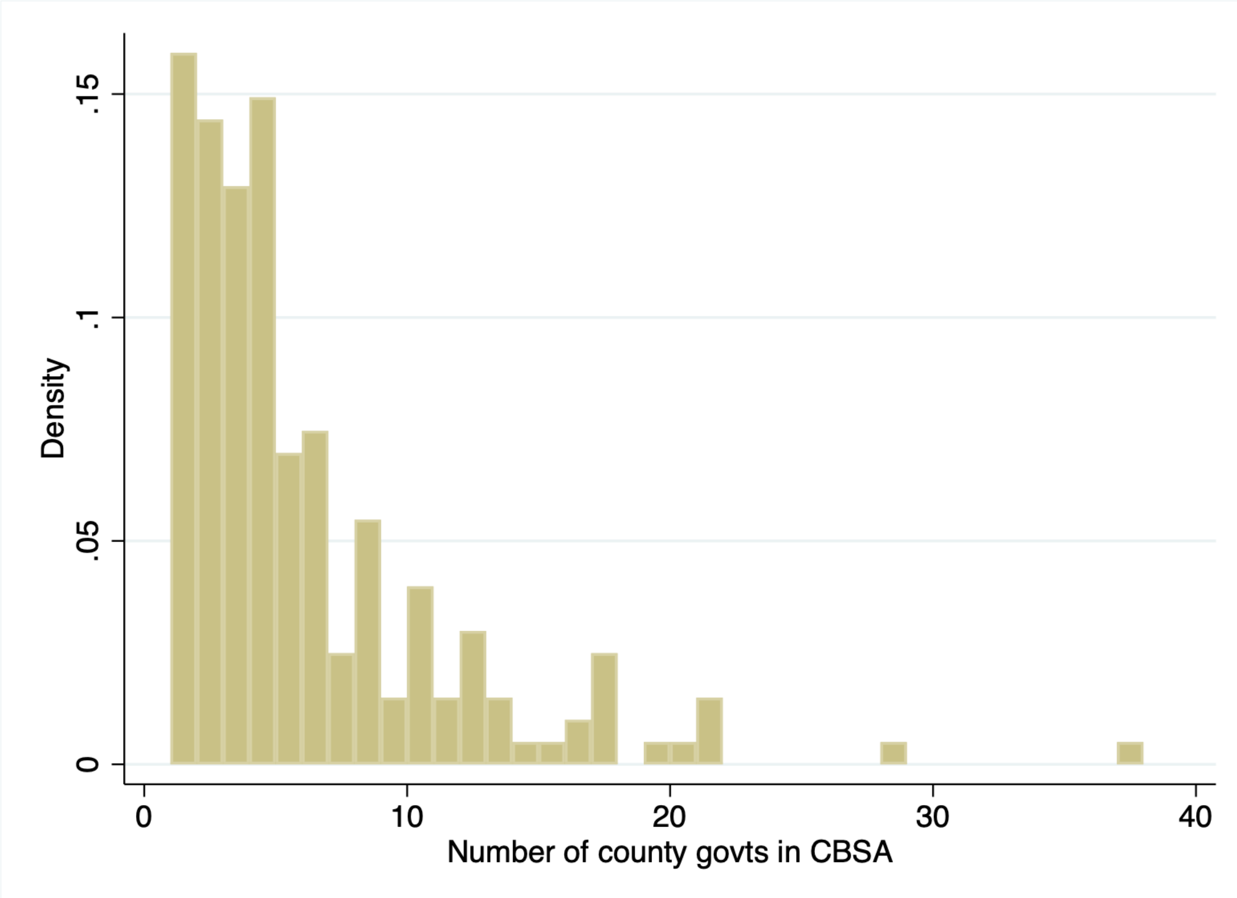
Figure A1: Counties in sample CBSAs



Counties included in regression analysis in red.

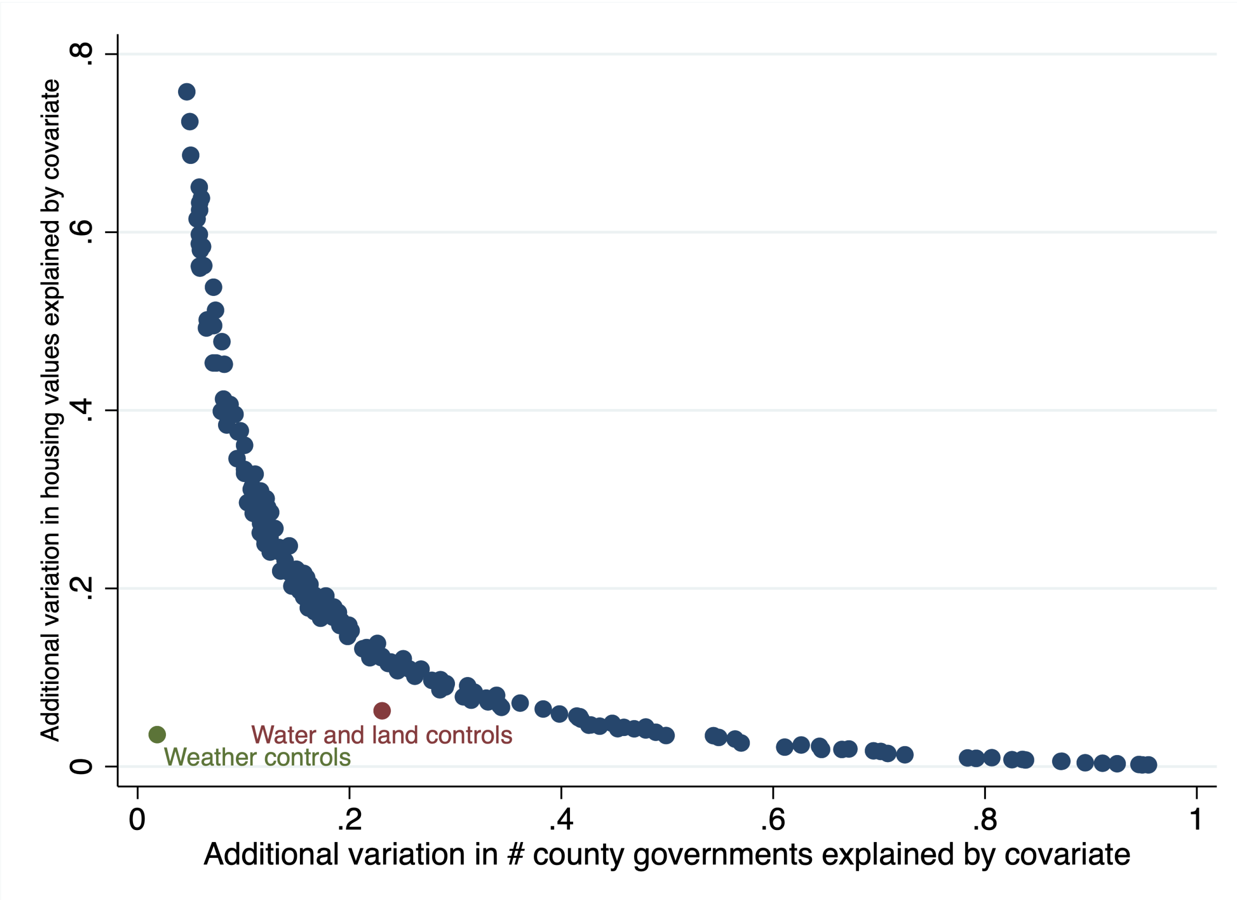
The restricted sample is the result of data requirements and limitations discussed in Section 2.2.

Figure A2: Number of counties within a CBSA



See Section 2.2 for more details.

Figure A3: Exogeneity Analysis

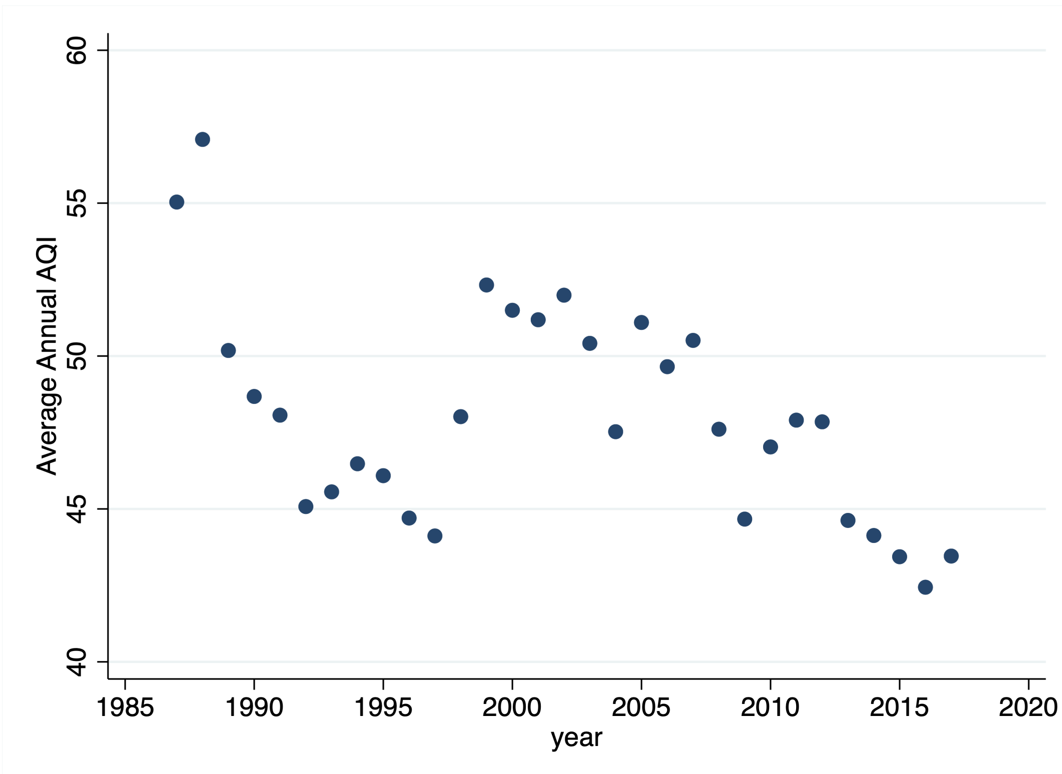


This figure shows how correlated an unobservable would need to be in order to reduce the estimated effect of county governments on housing values by half. Based on Imbens (2003) and Harada (2013), this analysis is used to test the exogeneity assumption of our instrument. The vertical axis represents the marginal increase in R-squared from including such a covariate in the reduced form regression; the horizontal axis does the same with the first stage. The 201 points in the curve are based on the results of including generated pseudo-unobservables. The two labeled points highlight the change in R-squared from adding the main control estimates. The position of the labeled points relative to the curve indicate that an unobservable would have to be substantially more influential than our current controls to reduce the main effect size by half.

B Air Quality Discussion

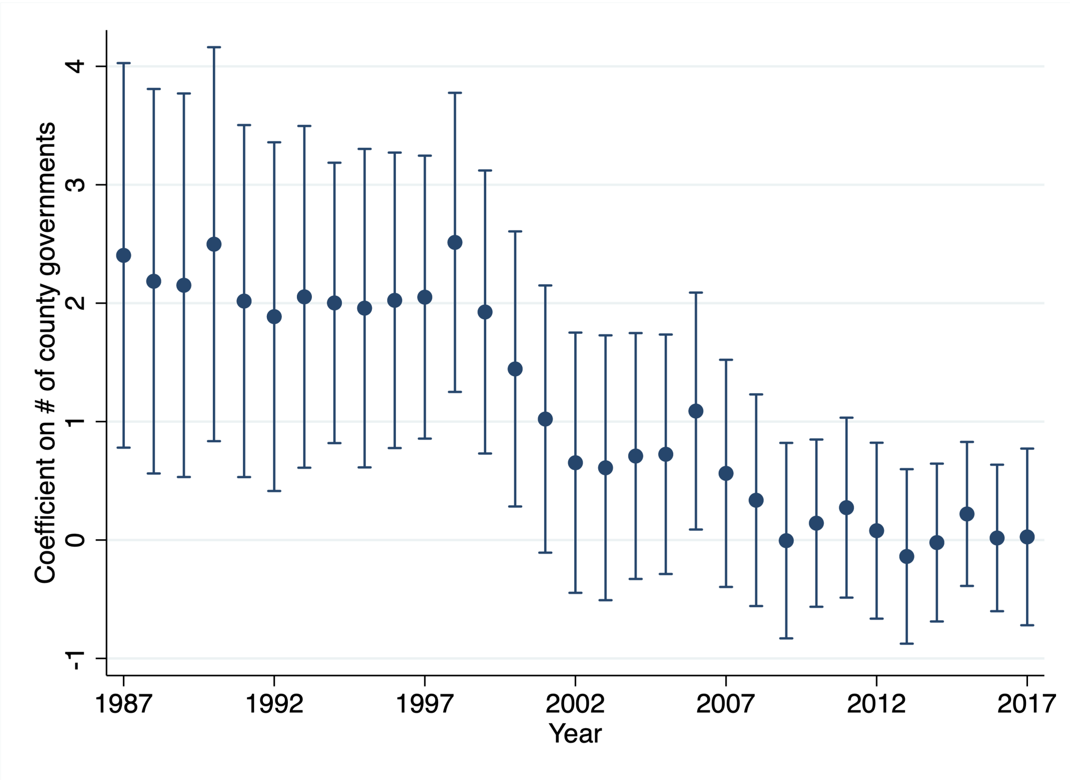
The main conclusion of Hatfield and Kosec (2019) was that jurisdictional fragmentation could lead to lower air quality, yet the results presented in Section 5 suggest a weaker relationship than previously measured. There are multiple possible explanations for the difference: First, this project uses updated data from 2012 (to be consistent with other data used in this project) instead of a 1999–2002 average. General improvements in air quality over this decade might make it more difficult to detect the same relationship; Figure A4 demonstrates the decrease in AQI levels over the last four decades. Moreover, CBSAs with more jurisdictional competition have become richer faster than CBSAs with less jurisdictional competition; this increase in wealth may have induced residents to become more concerned with local environmental amenities, thus resulting in better air quality relative to before. Second, we use updated CBSA boundaries in our analysis in the main text; while this change should affect the results, it seems unlikely to be the primary reason for the updated finding. Figure A5 plots the coefficient of interest from regressions based on the boundaries in Hatfield and Kosec (2019) and different years of air quality data. We see that while places with more jurisdictional fragmentation suffered from lower air quality in the past, that no longer seems to be the case today. Thus, we conclude that it is primarily improvements in air quality, particularly in areas with more jurisdictional fragmentation, rather than changes in boundary definitions that have weakened the relationship between jurisdictional fragmentation and air quality.

Figure A4: Average Air Quality Index



Average Air Quality Index (AQI) over time for the CBSAs in our sample. The pattern is unchanged if all CBSAs or county-level averages are used. A steady decrease in pollution over the last 30 years may explain why results using more recent data does not find a negative relationship between jurisdictional fragmentation and air quality.

Figure A5: Estimated effected of fragmentation using pollution data from different years



Using different years of AQI data generates different estimates of the importance of the number of county governments on air quality. Estimates were based on aggregating county-level air quality data from the EPA up to the 1999 boundaries used in Hatfield and Kosec (2019). 90% confidence intervals are shown.