

The Political Economy of Urban Growth

by

Joseph T. Ornstein

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Political Science)
in The University of Michigan
2018

Doctoral Committee:

Professor Robert J. Franzese, Chair
Professor Jenna Bednar
Professor Elisabeth R. Gerber
Professor Scott E. Page

Joseph T. Ornstein

ornstein@umich.edu

ORCID iD: 0000-0002-5704-2098

© Joseph T. Ornstein 2018

*For my girls.
(Carly, Fiona, and Myrtle)*

ACKNOWLEDGEMENTS

It took the efforts of an extraordinary number of people to produce what you, lucky reader, are about to enjoy.

Rob Franzese is a tremendous advisor, and I doubt that there's anyone who has shaped how I think about social science quite like he has ("Lord help us", says Rob). He is generous with his time, a twofer in expertise (political economist *and* empirical methodologist), and a consistent champion for me and my work.

I'm so glad that I've gotten to know Jenna Bednar over the past two years. Her advice has been consistently excellent and thoughtful, and she has a knack for finding the bigger picture in the jumble of math that I produce. It did not take long for my wife to notice that I always returned from meetings with Jenna in a much better mood than when I left the house, and to recommend that I do so more frequently.

Liz Gerber is, of course, my committee's bona fide expert on municipal politics. When Liz tells me that one of my ideas makes sense, I consider it the highest praise. She also taught me how to write a good research paper, and I have tried to craft the following three with Gerberian principles in mind.

Scott Page has one of the most fascinating mental toolboxes I have ever encountered, and getting to work with him has been one of the great joys of my graduate career. He secured his spot on the committee after teaching me the value of intellectual diversity in teams.

Thanks to all the people that sat and listened to me talk about these ideas at the

Michigan Political Economy Workshop, Comparative Politics Workshop, Statistical Learning Workshop, Midwest Political Science Association Meeting, and the APSA Local Political Economy Conference 2017. Particular thanks to everyone who read early drafts and offered their comments: Sarah Anzia, Traviss Cassidy, Jesse Crosson, Jason Davis, Mark Dincecco, Katie Einstein, Mike Hankinson, Ross Hammond, Mai Hassan, Paul Kellstedt, Anil Menon, Brian Min, Jim Morrow, Megan Mullin, Clayton Nall, Noah Nathan, Iain Osgood, Taha Rauf, Albana Shehaj, Jessica Trounstine, Alton Worthington, and Hye Young You. Very special thanks to Jeethi Nair for her insightful and diligent research assistance on Chapter II.

None of this would have been possible without generous financial assistance from Rackham Graduate School and the Carly Ornstein Foundation for Wayward Academic Husbands.

TABLE OF CONTENTS

DEDICATION	ii
ACKNOWLEDGEMENTS	iii
LIST OF TABLES	vii
LIST OF FIGURES	viii
LIST OF APPENDICES	x
ABSTRACT	xi
CHAPTER	
I. Introduction	1
1.1 Zoning in the United States	2
1.1.1 Why It Matters	4
1.2 The New Wave of Local Politics Research	5
1.2.1 Do Local Political Institutions Matter?	6
1.2.2 Municipal Government Responsiveness	7
1.3 Who Decides Urban Land Use Policy?	9
1.3.1 Beyond the Homevoter Hypothesis	10
1.4 Chapter Summary	11
II. Municipal Election Timing and the Politics of Urban Growth	13
2.1 Introduction	14
2.2 Background: Municipal Zoning	17
2.3 Off-Cycle Elections Empower Slow-Growth Interests	22
2.3.1 The Homevoter Hypothesis	24
2.3.2 Voter Demographics	25
2.3.3 Diffuse Benefits, Concentrated Costs	26
2.4 Case Study: Palo Alto's Measure S	27
2.5 Ballot Initiatives	30
2.6 Data	32
2.6.1 The Election Timing Variable	35
2.6.2 Dependent Variables	36
2.6.3 Developable Land	37
2.6.4 Other Covariates	37
2.7 Results	39
2.7.1 Cross-Sectional Correlations: OLS	39
2.7.2 Matching Analysis	40
2.7.3 Difference-in-Difference	41

2.8	Conclusion	43
III. Machine Learning and Poststratification		51
3.1	Introduction	52
3.2	The MLP Procedure	54
3.2.1	First-Stage Model Selection	54
3.2.2	Cross-Validation	56
3.2.3	Poststratification	57
3.2.4	Outline of MLP Procedure	58
3.3	Monte Carlo Simulation	59
3.4	Empirical Application: 2016 US Presidential Election	63
3.5	Conclusion	67
IV. Zone Defense: Why Liberal Cities Build Fewer Houses		72
4.1	Introduction	73
4.2	Municipal Zoning: Background	76
4.3	The Model	79
4.3.1	Setup	79
4.3.2	An Analytic Solution	80
4.3.3	A Computational Solution	84
4.4	Empirical Analysis	88
4.4.1	Data Sources	88
4.4.2	Results	92
4.5	Concluding Thoughts	95
BIBLIOGRAPHY		98
APPENDICES		105

LIST OF TABLES

Table

2.1	Relationship between election timing and success of pro-housing ballot initiatives, by type of development. City-level controls include mean temperature, log population (2000), median income, pct. white, pct. over 65, pct. college graduates, pct. nearby developable land area (2001), school district Academic Performance Index (2003), and debt per capita (2002).	34
2.2	Estimated OLS coefficients and standard errors, regressing log new building permits (2000-2016) on percent off-cycle elections and covariates in a sample of California cities.	46
2.3	Estimated OLS coefficients and standard errors, regressing log new building permits (2010-2016) on percent off-cycle elections and covariates in a sample of California cities.	47
2.4	Estimated OLS coefficients and standard errors, regressing median home value per sqft (2017) on percent off-cycle elections and covariates in a sample of California cities.	48
2.5	Matching Analysis (Home Values): Effect of off-cycle elections and balance statistics.	49
2.6	Matching Analysis: Building Permits (2010-2016). Effect of off-cycle elections and balance statistics.	49
2.7	Matching Analysis: Building Permits (2000-2016). Effect of off-cycle elections and balance statistics.	49
2.8	Difference-in-difference, comparing cities that switched to on-cycle elections (treatment) and those that remained off-cycle (control).	50
3.1	The MLP Procedure	59
3.2	Summary of variables included in first-stage models.	65
3.3	First-stage 10-fold cross-validation results. An ensemble model average of the hierarchical linear model and KNN (italicized) performs best.	67
4.1	Parameter combinations for computational model experiments.	85
4.2	Selected Summary Statistics	88
4.3	Median Home Value Regressions	93
4.4	Building Permit Regressions	94
4.5	Regulatory Index Regressions	96
A.1	Estimated coefficients estimates from the spatial autoregressive lag model.	108
D.1	Assignment procedure for X variables	113
D.2	List of parameter values used in the Monte Carlo Simulation	114
E.1	The CCES public opinion questions used to generate the outcome variable in the empirical application.	115
F.1	Median Home Value Regressions (Robustness Test)	117
F.2	Building Permit Regressions (Robustness Test)	118
F.3	Regulatory Index Regressions (Robustness Tests)	119

LIST OF FIGURES

Figure

2.1	Mean new building permits issued per year, comparing cities with mostly on-cycle elections against those with mostly off-cycle elections, matching on demography, median income, public amenities, and population in the year 2000.	18
2.2	Trajectory of median home value per sqft, comparing cities with mostly on-cycle elections against those with mostly off-cycle elections, matching on demography, median income, public amenities, and population in the year 2000.	19
2.3	Following the switch to on-cycle, Palo Alto city council elections saw much higher turnout (A), and more pro-development city councilmembers were elected (B). Solid lines denote averages before and after the passage of Measure S (dotted line). . . .	29
2.4	New infill development attracts roughly 7-8pp less support when the ballot initiative is held off-cycle.	33
2.5	Map of municipalities in the dataset. Shading denotes whether the majority of municipal elections (1996-2016) were off-cycle or on-cycle.	36
2.6	Median real home prices grew more slowly in cities that moved their city council elections on-cycle than in comparable cities that did not.	41
2.7	Compared to cities that kept their elections off-cycle, cities that shifted to on-cycle elections issued permits for roughly four times as many new housing units between 1996 and 2015.	44
3.1	Representative simulation from Monte Carlo. Disaggregation, MRP, and MLP estimates are plotted against true subnational unit means. Parameter Values: $\alpha = 5$, $\rho = 0.4$, $N = 15000$, $M = 200$, $n = 5000$, $\sigma^2 = 5$	62
3.2	Relative performance of disaggregation, MRP, and MLP estimates, varying α . Parameters Used: $\rho = 0.4$, $n = 2000$, $M = 200$, $N = 15000$, $\sigma^2 = 5$	63
3.3	When machine learning outperforms HLM at individual-level prediction, MLP typically produces better poststratified estimates than MRP. Here, the ratio of root mean square error (RMSE) in the first stage is plotted against the RMSE ratio for the poststratified estimates.	64
3.4	Trump 2016 vote share plotted against disaggregated, MRP, and MLP estimates. Correlations are 0.32, 0.72, and 0.77 respectively.	68
3.5	MLP and MRP estimates in select states, plotted against 2016 presidential vote shares.	69
3.6	MLP and MRP county-level correlations with 2016 presidential vote share by state. In nearly all cases, MLP outperforms MRP, in some cases considerably.	70
4.1	Median home value, as a fraction of median income, is higher on average in liberal cities. Sample consists of all US cities with a population greater than 10,000 (shrinking cities excluded). Solid line is a moving average, with select cities labeled.	73
4.2	With homogeneous income and preferences, the computational model performs as predicted by the analytic solution. When zoning is prohibitively costly (Experiment 1), housing consumption falls below the Pareto optimum. When zoning is costless (Experiment 2), cities attain the Pareto efficient outcome. The dashed line marks the Pareto efficient level of housing consumption $H^* = \beta y$	86

4.3	With heterogeneous preferences (Panel A) and income (Panel B), agents sort into municipalities by ideology, and more liberal cities are more likely to enact restrictive zoning than conservative cities. As a result, average housing consumption is higher in liberal cities.	87
B.1	Estimated effect of off-cycle elections on log new building permits (2000-2016), by type of housing.	110

LIST OF APPENDICES

Appendix

A.	Spatial Econometric Tests	106
B.	Heterogeneous Treatment Effects	109
C.	Synthetic Poststratification Proof	111
D.	Monte Carlo Technical Summary	113
E.	Generating the Outcome Variable (CCES)	115
F.	Robustness Tests	116

ABSTRACT

Why do some US cities strictly limit the growth of their populations, while others are more accommodating to new housing construction? Though this may seem at first glance like a purely parochial concern, the question is of broad national interest. Regulatory barriers to housing construction slow economic growth by impeding the migration of labor. They exacerbate wealth inequality by privileging incumbent landowners over potential newcomers. And they harm the environment by encouraging auto-dependent urban sprawl and prohibiting dense, walkable communities. Understanding the political motivations behind restrictive municipal zoning regulations is therefore of vital national importance.

In my first paper (Chapter II), I show that the timing of city council elections plays an important role in shaping municipal land use policy. Because some residents are deeply involved in municipal politics (e.g. homeowners), while others are not (e.g. renters), the composition of the electorate tends to change depending on the timing of the election. This shapes the reelection incentives of city councilmembers. In an empirical analysis of California cities, I show that cities with off-cycle elections tend to issue fewer new housing permits and have higher home prices than similar cities that hold their elections on-cycle. This result holds in both cross-sectional and difference-in-difference analysis. Cities that shifted their elections from off-cycle to on-cycle subsequently saw a larger increase in permitting, and slower growth in home prices, than comparable cities where elections remained off-cycle. This finding suggests that

election timing can have non-trivial effects on both political representation and land use policy.

In my second paper (Chapter III), I develop a new method for estimating local area public opinion. This method, called Machine Learning and Poststratification (MLP), improves on current practice by modeling public opinion using machine learning techniques like random forest and k-nearest neighbors. The predictions from these models are then poststratified (i.e. reweighted using demographic information) to produce public opinion estimates for local areas of interest. In a Monte Carlo simulation, I show that this technique outperforms classical multilevel regression and poststratification (MRP) and disaggregated survey estimates, particularly when the data generating process is highly nonlinear. In an empirical application, I show that MLP produces superior county-level estimates of Trump support in the 2016 presidential election than either MRP or disaggregation.

In my final paper (Chapter IV), I explore a puzzling feature of US municipal land use politics: cities with more liberal residents tend to enact more restrictive zoning policies than similar conservative cities. In a formal model, I explain this as the result of a public goods provision problem. In liberal cities, where residents value public goods provision more highly, there is a greater incentive to ensure that newcomers do not underinvest in housing, thereby receiving a disproportionate share of public goods relative to property taxes. In an empirical analysis, I show that liberal cities issue fewer new building permits, have higher home prices, and score higher on a survey-based measure of land use policy restrictiveness, a pattern that cannot be explained by differences in geography, demographics, income, or characteristics of the housing stock.

CHAPTER I

Introduction

In the early 20th century, millions of Americans moved to cities in search of economic opportunity. Cities with thriving manufacturing economies – like Detroit, Pittsburgh, and New York – were magnets for rural migrants. Responding to this influx of population, developers constructed enormous new stocks of housing. In the thirty years between 1900 and 1930, Detroit quadrupled in size. Pittsburgh and New York doubled.

Today, the story is very different. Although cities remain the drivers of economic growth, the nation’s most economically successful cities – like San Francisco, New York, Los Angeles, and Washington – are not building enough new housing to satisfy demand. In the thirty years between 1980 and 2010, San Francisco grew by only 16%, New York by 15%, and Ann Arbor by 5%. As a result, home prices in the most economically vibrant US cities are at record highs (in many places exceeding their pre-recession peaks).

The principal barrier to expanding city populations today is not technological, economic, or geographic – it is political. In cities throughout the developed world, land use is tightly regulated, and zoning codes all but prohibit the development of dense new housing. In this dissertation, I explore the political motivations behind

this trend. Why do some US cities strictly limit the growth of their populations, while others are more accommodating to new housing construction? In the process, my research address a number of fundamental questions in political science – on the nature of municipal government responsiveness, and the role that institutions play in shaping policy outcomes.

1.1 Zoning in the United States

New York City adopted the first comprehensive zoning code in 1916. Responding to fears that skyscrapers would shroud the island of Manhattan in perpetual shadow – and diminish the value of property on Fifth Avenue – city planners drew up a map of the city divided into zones. Within each zone, the city designated maximum building heights and permitted land uses (Fischel 2015). Despite early objections that municipal zoning violated the Fifth Amendment’s prohibition on seizure of private property without due process, the Supreme Court ultimately upheld the constitutionality of these ordinances in 1926’s *Ambler Realty v. Village of Euclid* (Wolf 2008). Since that time, municipal governments have been granted broad discretion to regulate land use within their borders. Today, urban land use policy is determined by a patchwork of over 19,000 municipalities, comprising tens of thousands of local legislators, zoning board members, and city planners.

Land use regulation takes many forms, the most common of which is called Euclidean zoning.¹ This type of zoning is intended to separate uses (e.g. residential, commercial, industrial), by permitting a specific designated use for each parcel. In so doing, it curbs some harmful externalities – keeping industrial pollutants away from shopping areas, or prohibiting commercial uses from sprouting up in quiet residential

¹Named after the Village of Euclid, Ohio, litigant in the aforementioned Supreme Court case, not Euclidean geometry. However, the Village of Euclid itself was named after Euclid the geometrician after it was settled by Connecticut Western Reserve cartographers in the late 1700s.

neighborhoods.

In addition to regulating the *type* of land use, zoning also typically regulates the *intensity* of land use. For example, zoning ordinances will often specify a maximum residential density that is allowed within each zone. Other ordinances might mandate a percentage of every lot area that must be dedicated to open space, or a minimum distance that buildings must be set back from the street. Another popular restriction is the maximum floor area ratio (FAR), which limits the total floor area of buildings relative to the size of the lot on which they sit. In practice, these regulations all but ensure that large swaths of US cities are set aside for single-family homes, even when a more intensive land use (townhouses, apartment buildings) would be more appropriate given demand.

Other land use ordinances that are seemingly unrelated to housing can nevertheless limit the number of housing units built in a city. Take, for instance, the near-ubiquitous requirement that developers set aside off-street parking for each new building they construct. Even in cities without formal zoning codes, these requirements can be onerous; the city of Houston mandates that for each studio apartment, developers must set aside 1.25 parking spaces (Lewyn 2005)! Not only does all that mandated parking take up real estate that could be used for housing, but abundant, inexpensive parking further incentivizes urban sprawl, by reducing the cost of automobile commutes (Shoup 1999).

Over time these regulations have accumulated in such a way that building new, affordable housing has become prohibitive in many metropolitan areas. In the century since New York City's zoning code was first implemented, the length of its text has ballooned from 14 pages to 4,126 pages. It has been estimated that roughly 40%

of Manhattan's housing stock would be illegal to build today (Bui et al. 2016).²

1.1.1 Why It Matters

Traditionally, urban land use planning has been considered a parochial concern, of little national importance. If the people of New York City want to limit the density of Manhattan, then that is their right. But over the past two decades, economists have begun to explore the deleterious effects of restrictive zoning in America's cities. The findings of these studies suggest that municipal zoning is of much greater national concern than widely realized.³

Cities exist to facilitate interaction. Even in a world with the Internet, cell phones, and complementary two-day shipping, there is tremendous value that comes from people being in close proximity to other people. Firms prefer to be close to their suppliers, customers, and deep pools of talented labor (Krugman 1991). New York is a hub of finance, Boston of biotechnology, and San Francisco of information technology, precisely because these economies of scale draw industries towards agglomeration (Glaeser 2011).

Regulations that prevent people from moving to cities put a drag on this process. In the same way that barriers to international migration reduce economic growth by preventing workers from moving to where they would be most productive, restrictions on new housing construction have an analogous effect, by imposing a barrier on *domestic* migration. The resulting spatial misallocation in the economy can be tremendously consequential. Hsieh & Moretti (2015) estimate that easing housing restrictions in the three most productive US cities alone would increase GDP by roughly 9.5%, and that housing constraints may have reduced US economic growth

²Although New York City as a whole is twice as populous today as it was in 1910, the population of Manhattan itself peaked in the 1910 Census, just before the introduction of zoning.

³These findings have been the subject of a few recent popular books, and I highly recommend *The Rent Is Too Damn High* by Matthew Yglesias, and *The Gated City* by Ryan Avent.

by as much as 50% over the past sixty years (Hsieh & Moretti 2017).

In addition, a shortage of new housing drives up the price of existing homes in high-demand cities. The most regulated US cities tend to have higher rents than we would expect from construction costs and wages alone (Glaeser & Gyourko 2003, Quigley & Raphael 2005), which spurs homelessness, displacement, and residential segregation, both by race (Rothwell & Massey 2009) and by income (Rothwell & Massey 2010). Such segregation has been shown to affect civic participation (Oliver 1999), public goods provision (Alesina et al. 1999, Trounstein 2015), and even life expectancy (Chetty et al. 2016).

Finally, density restrictions in central cities promote suburban sprawl, by pushing housing farther and farther from city centers (Lewyn 2005). This pattern of development has helped create America's unique car dependence, lengthy commute times, and above average greenhouse gas emissions. (Glaeser & Kahn 2010).

Relaxing municipal zoning regulation is a rare policy idea that would simultaneously boost economic growth, create a more equal distribution of wealth, *and* be good for the environment. Given its substantive importance, it is clear that the topic deserves more attention from political science. Fortunately, the past decade has seen a resurgence in the study of American municipal politics, driven by new datasets and research methods. I consider my dissertation a part of this growing body of work.

1.2 The New Wave of Local Politics Research

Local governments collectively account for 22% of all government revenue, and employ 64% of all public employees (Berry et al. 2015). They pave our roads, run our schools, police our neighborhoods, take out our trash, and provide countless other crucial public services. And yet, when Americans think about government, they

are typically thinking about the federal government. In his recent book, Hopkins (2018) finds that, although Americans tend to agree that local governments have the largest impact on our day-to-day lives, our attention has increasingly shifted to national-level politics.

Fortunately, the past decade has seen a flowering of excellent political science research in American municipal government. These researchers have found new and innovative ways to tap novel sources of data: text analysis of meeting minutes (Einstein et al. 2017), municipal finance records (Ferraz & Finan 2011, Trounstine 2015), news reports from local elections (De Benedictis-Kessner 2017), land value assessments (Sances 2016), mass transit data (Benedictis-Kessner 2018), and emergency service response times (Sances 2018). Methods like MRP – which I refine in chapter III – have allowed political scientists to better understand the link between mass opinion and municipal policy (Tausanovitch & Warshaw 2014). These new datasets and tools have granted political scientists an unprecedented glimpse into the inner workings of municipal government.

And while the activities of local governments are worthy of study in their own right, this research also helps shed light on a number of fundamental questions in political science.

1.2.1 Do Local Political Institutions Matter?

Progressive Era reformers introduced a number of new municipal government reforms in the early 20th century, including the Australian ballot, nonpartisan elections, at-large city council members, the council-manager system, and off-cycle election timing. Reformers at the time hoped that these new institutions would help curb the power of urban political machines and introduce a new era of professionalism in municipal government. But how much do these institutions matter? Some

researchers have found little link between form of government and policy outcomes. Tausanovitch & Warshaw (2014), for instance, find that neither council-manager systems, nonpartisan elections, nor at-large councilmembers appear to be systematically correlated with observable policy outcomes, like taxation and spending.

Other researchers have reached different conclusions. Jensen & Malesky (2018) find that council-manager systems can insulate local leaders from pressures to hand out investment incentives. Trebbi et al. (2008) and Trounstine & Valdini (2008) find that, under some conditions, the choice of at-large or single-member districts can affect the success of minority representation on city councils. And there is now a substantial literature on the effects of municipal election timing. Researchers like Berry (2009), Anzia (2011), and Kogan et al. (2017) find that the timing of elections affects who turns out to vote, which in turn influences the public spending choices by elected officials. Low turnout, off-cycle elections for special districts can partly explain why areas with many overlapping jurisdictions spend more per capita than those with unified governments (Berry 2008).

In this dissertation, I contribute to this literature by exploring another consequence of municipal election timing. In Chapter II, I find that off-cycle elections empower citizens opposed to new housing growth, with significant observable consequences for zoning policy, permitting, and home prices.

1.2.2 Municipal Government Responsiveness

To whom are municipal governments responsive? America's founders designed a federalist system with the expectation that local governments would be more responsive to their citizens than the federal government. In an era where it might take weeks to travel to your state capital, much less Washington, DC, the idea that local politics would be paramount was almost self-evident.

Several classic works in American urban politics reassess that early view (Tiebout 1956, Molotch 1976, Peterson 1981), arguing that city-level government is fundamentally different than state and national level governments, and that the constraints they face result in a different form of responsiveness to citizens. Tiebout (1956) goes so far as to argue that local government *needn't* be responsive to citizens at all: because citizens can physically sort themselves between jurisdictions, “voting with your feet” should be sufficient to attain an efficient equilibrium, with each municipality adopting the preferred policies of its residents, no democracy necessary.

Peterson (1981) argues that city governments are most responsive to business interests. Because capital has the most credible exit threat – it is relatively easy to move operations to another jurisdiction – cities are limited in their ability to enact redistributive tax-and-transfer policies. Instead, municipal governments tend to pursue development oriented policies, investing in public goods that enhance the value of capital and attract businesses (e.g. transportation infrastructure, public safety).

The new wave of scholarship in urban political economy, however, has painted a more nuanced picture, finding that municipal policies are more responsive to mass opinion than previously thought. Regression discontinuity studies find that, in cities with interparty competition, there appears to be meaningful differences between the policies enacted by Republican and Democratic mayors (Gerber & Hopkins 2011, de Benedictis-Kessner & Warshaw 2016). And the types of policies implemented by municipal governments is broadly responsive to local-level ideology: cities with more conservative citizens are likely to tax less and enact more conservative environmental policies Tausanovitch & Warshaw (2014).

1.3 Who Decides Urban Land Use Policy?

To whom are these municipal governments responsive on the subject of land use? Fischel (2001) has written the one of the most prominent works on this subject, called *The Homevoter Hypothesis*. Because of its influence, it is worth recapping this argument in brief. Over the course of the 20th century, homeowners went from viewing their homes as a durable yet depreciating consumer good (like an automobile) to an asset, with an expectation that it appreciate in value. For most middle class families, their home is their largest asset, it is highly leveraged, and it is completely undiversified. Since the policies of municipal governments strongly affect the value of that asset (e.g. Black (1999)), homeowners became highly active in municipal politics. It is not a coincidence that local governments are also known as municipal *corporations*. Like corporations, individuals buy a share (in this case, a home), which confers voting rights. The value of these shares depend on the decisions made by the governing body. There are however, two crucial differences between a business corporation and a municipal corporation.

First, unlike the typical stockholder, the shareholders of municipal corporations (i.e. “homevoters”, Fischel’s neologism) are completely undiversified. For most American families, owning multiple homes is financially out of the question, and to even own one requires substantial debt. As a result, homeowners are keenly interested in the goings-on of their particular municipal government, and how it affects their greatest asset. Second, whereas the business corporation assigns voting rights proportional to the value of one’s shares, each resident in a municipal corporation is entitled to one vote, regardless of home value. As a result, it is the more numerous homeowners, rather than the more wealthy developers and business owners, that

hold political power in local government.

And homeowners, it seems, tend to oppose the construction of new homes. Marble & Nall (2017) show that homeowners are 20 to 30 percentage points more likely to express opposition to new homebuilding than renters in a survey experiment. In his historical case studies of New England towns, von Hoffman (2010) shows that several Boston suburbs developed substantially fewer homes than was originally projected in the 1950s and 1960s. Once homeowners became sufficiently numerous to outvote the original developers, they demanded that new restrictions on building (particularly multifamily housing) be put into place.

1.3.1 Beyond the Homevoter Hypothesis

The Homevoter Hypothesis provides a compelling explanation of how restrictive zoning regulations arose in the late 20th century United States. However, there are a number of questions it leaves unanswered. For one, the Homevoter Hypothesis alone does not provide an explanation for the *variation* in regulatory stringency across municipalities. Why are some cities more *laissez-faire* than others in permitting new building? Without variation in homeowner preferences, historical trajectory, or contemporary political institutions, we cannot explain these patterns. In this dissertation I help fill the gap, and in so doing, provide a glimpse at what sorts of institutional reforms would reduce zoning regulatory stringency.

Another limitation of the Homevoter Hypothesis is that it ascribes a purely financial motivation to opponents of growth, which seems at odds with qualitative evidence on what drives participation in municipal politics. For example, a recent study by Einstein et al. (2017) examines a large collection of meeting minutes from Planning and Zoning Board hearings in Massachusetts. This analysis suggests that, at the very least, the *stated* objections from concerned citizens have very little to do

with home values. Instead, a text analysis of the meeting minutes reveals that residents who engage with local government tend to more concerned with the externalities that new development would impose on the neighborhood. The most frequently voiced concerns included street parking, traffic, safety, strain on water systems, and neighborhood character/aesthetics. Very few opponents explicitly mentioned home values. And indeed, there was a sizable number of *renters* who attend these meetings to voice their opposition to new building. This echoes the findings from Hankinson (2017), who finds that renters in high-price areas are often anxious about the effects of new development, though not quite as much as homeowners.

Now, one might suppose that underlying all of these concerns over parking and schools is a more fundamental concern with property values, left unspoken due to social desirability bias. This could very well be true in some cases, but as I show in the papers of my dissertation, it needn't be the primary motivating factor.

1.4 Chapter Summary

My dissertation makes several contributions to our understanding of the political economy of urban growth and land use. One contribution highlights the importance of municipal election timing. Studying a sample of California cities (Chapter II), I find that off-cycle elections empower citizens opposed to new housing growth, with significant observable consequences for zoning policy, permitting, and home prices. Another contribution is methodological. I develop a new procedure for estimating local area public opinion (Chapter III), which will allow scholars to better study the link between citizen preferences and local-level policymaking. And finally, in Chapter IV, I explore the relationship between political ideology and land use policy, finding that liberal cities are, on average, more restrictive in their zoning policies than

similar conservative cities. I explain this result using a formal model of public goods provision.

CHAPTER II

Municipal Election Timing and the Politics of Urban Growth

In this paper, I show that the timing of city council elections plays an important role in shaping municipal land use policy. Cities that hold their elections off-cycle (on a date separate from high-profile national elections) tend to place more restrictions on new housing development. This stems from an asymmetry in the costs and benefits of urban growth: the benefits of growth are broadly shared, but the costs are concentrated. As a result, citizens that oppose new growth are likely to form a larger share of the electorate in municipal-specific elections. Using an extensive dataset on local election timing from California, I demonstrate that that cities with off-cycle elections issue fewer building permits and have higher home prices than comparable cities with on-cycle elections. This finding holds both in a cross-sectional matching analysis and a difference-in-difference analysis of cities that shifted their election timing.

2.1 Introduction

In May 2013, the city council of Ann Arbor, Michigan met to discuss the construction of a new high-rise apartment building in the downtown core. Residents packed the council chamber for two hours of debate, voicing concerns that the 150-foot tall building would overshadow the neighborhood’s nearby historic homes. At the end of deliberations, the council narrowly approved the construction, by a 6-5 margin.

“Audience members jeered and literally hissed at council members.” reported the *Ann Arbor News* (Stanton 2013), storming out to shouts of “Shame on you!” and “Disgusting!”

Land use policy is among the most contentious issues in local politics, and municipal governments wield considerable power in determining the rate of population growth within their jurisdictions. But I mention this particular episode to highlight a curious pattern that emerged from the city council vote. At the time, Ann Arbor held its city council elections every year, electing half of the council in odd-numbered years, and half in even-numbered years. When the dust settled, the vote on the new apartment building split the council nearly perfectly by election timing. Of the councilmembers elected in even years, all but one voted to approve the construction. Of those elected in odd years, all but one voted to reject it.¹

In this paper, I argue that the pattern we observe here is not mere coincidence, and that the timing of municipal elections has significant, observable consequences for land use policy and the growth of cities. When elections are held off-cycle (i.e. on a date separate from high profile elections like presidential or congressional races), citizens that oppose new housing development are more likely to turn out to vote

¹Several months later, the lone odd-year city councilmember who voted to approve construction was up for re-election. She was soundly defeated, by nearly 30 percentage points.

than supporters. These citizens, in turn, elect councilmembers that are more willing to use municipal zoning authority to limit urban growth.

Although it may seem like a purely local issue, municipal land use policy has an profound impact on the broader economy. The most tightly regulated US cities tend to have higher rents than we would expect from construction costs and wages alone (Glaeser & Gyourko 2003, Quigley & Raphael 2005). In turn, these excess housing slow economic growth by pricing workers out of cities where they would be most productive. One estimate suggests that easing housing restrictions in the three most productive US cities alone would increase aggregate GDP by roughly 9.5% (Hsieh & Moretti 2015).

In addition, by pricing poorer households out of more affluent areas, restrictive land use policies exacerbate residential segregation, both by race (Rothwell & Massey 2009) and by income (Rothwell & Massey 2010). Such segregation has been shown to affect civic participation (Oliver 1999), public goods provision (Trounstine 2015), and even life expectancy (Chetty et al. 2016). Restrictions on new residential construction are also largely responsible for the recent decline in regional income convergence (Ganong & Shoag 2017), as Americans from poor regions are less able to move to opportunity in growing metropolitan areas. Finally, density restrictions in central cities promote suburban sprawl, which increases both commuting costs and carbon emissions (Glaeser & Kahn 2010).

Given these tremendous costs, why do citizens that oppose population growth so often get their way in municipal politics, at the expense of citizens that would benefit from new housing construction? This fact is particularly puzzling in light of much of the foundational scholarship in American urban politics. Molotch (1976) famously describes the city as a “growth machine”, a political entity whose principal

aim is to promote business interests through population growth. Peterson (1981) makes a similar argument: because labor and capital are mobile across municipal boundaries, city governments are poorly suited to enact redistributive policy, and are instead most likely to pursue developmental policies that grow their property tax base. And yet, in the late 20th and early 21st centuries, many city governments have abandoned this growth machine model, and have instead severely curtailed new housing development through stringent zoning regulations.

I argue that off-cycle election timing provides one explanation for the stringency of municipal land use regulation. Citizens that oppose new residential development are likely to be overrepresented in off-cycle, municipal-specific elections for three reasons. First, **homeowners** are more likely to show up to municipal-specific elections than renters, and homeowners tend to view new development more skeptically. Second, the electorate in off-cycle elections differs **demographically** from on-cycle electorates. And finally, the **concentrated costs** of new housing development suggest that opponents of growth will be more highly motivated to turn out to municipal elections than the beneficiaries, and will form a larger share of the electorate in low-turnout, off-cycle elections. I will expand on these points in Section 2.3.

To test this theory empirically, I employ an extensive dataset on municipal elections from California over the past twenty years. In both OLS and matching analysis, I show that cities where elections are held off-cycle issue fewer new building permits and have significantly higher median home values than comparable cities with on-cycle elections. Because this cross-sectional analysis may not eliminate all city-specific unobserved confounders, I also conduct a difference-in-difference analysis. The pattern holds across time as well; cities that switched to on-cycle elections subsequently issued more new building permits and saw slower home price growth

between 2002 and 2016 than comparable cities that kept their elections off-cycle.

Figures 2.2 and 2.1 preview this empirical analysis. In each panel, I plot the trajectory of cumulative new building permits issued and median home value per sqft for a set of California cities with off-cycle city council elections. This is paired with equivalent trajectories for a set of California cities with on-cycle elections, matched on demographic characteristics, median income, climate, developable land area, local amenities, and population in the initial time period. I will discuss the details of how I construct this matched control group in Section 2.7. For now, note that the off-cycle cities tended to issue fewer new building permits throughout the period, especially during the pre-Recession housing boom. And by the present day, median home prices in these cities were substantially higher, on average \$75 per square foot.

The paper proceeds as follows. In the next section, I briefly sketch the history of municipal zoning in the United States, and discuss the role that city councils play in its implementation. Following that, I review the literature on election timing, and discuss why groups that oppose new residential development are likely to be overrepresented in off-cycle elections. Section four introduces a brief case study on how election timing influenced the politics of land use in Palo Alto, California. In section five, I show that ballot initiatives restricting new infill housing development receive more support when they appear on off-cycle ballots. Section six describes my dataset on land use policy outcomes, and section seven discusses the results of my empirical analysis. Section eight concludes.

2.2 Background: Municipal Zoning

New York City adopted the first comprehensive zoning code in 1916. Responding to fears that skyscrapers would shroud the island of Manhattan in perpetual shadow

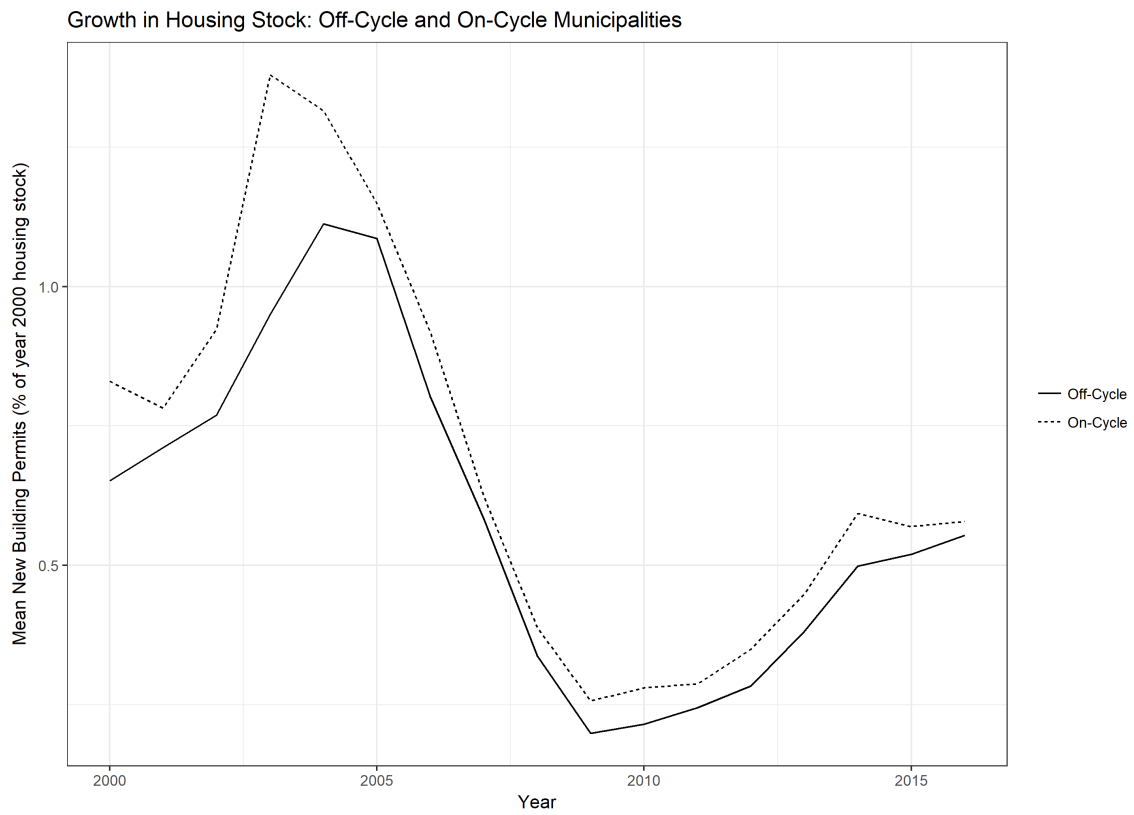


Figure 2.1: Mean new building permits issued per year, comparing cities with mostly on-cycle elections against those with mostly off-cycle elections, matching on demography, median income, public amenities, and population in the year 2000.

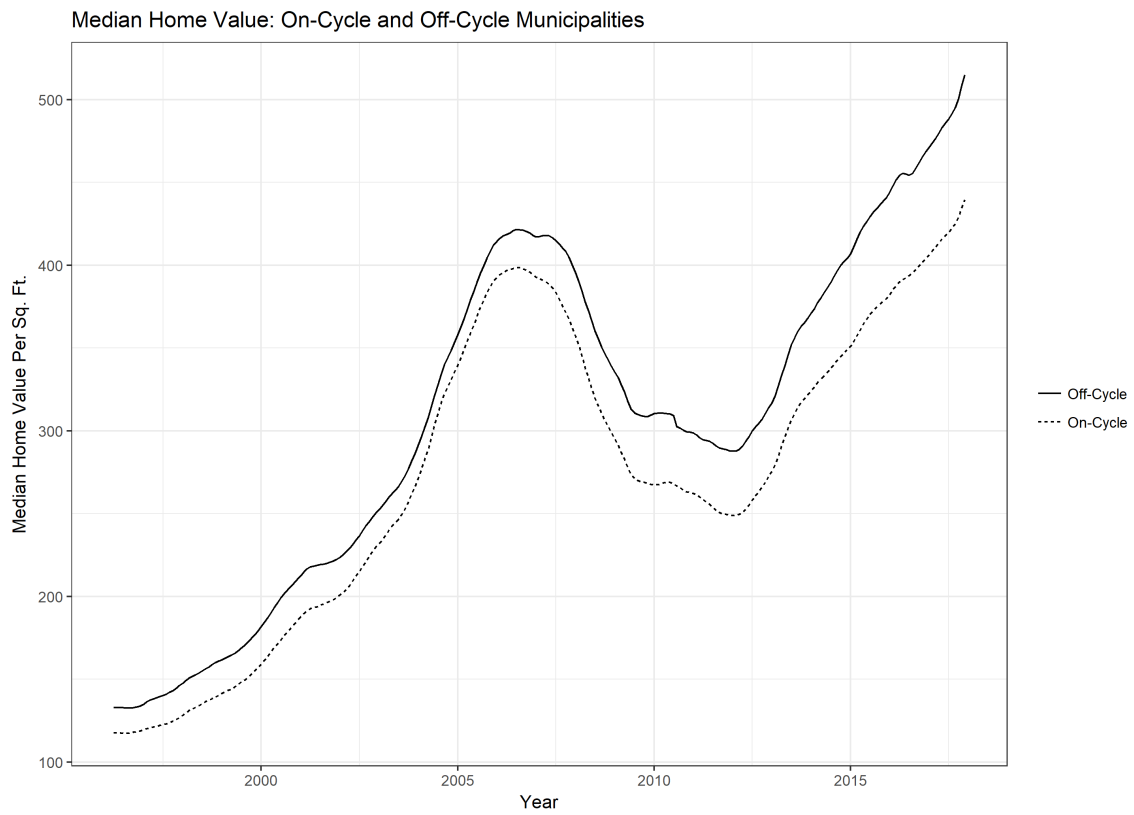


Figure 2.2: Trajectory of median home value per sqft, comparing cities with mostly on-cycle elections against those with mostly off-cycle elections, matching on demography, median income, public amenities, and population in the year 2000.

– and diminish the value of property on Fifth Avenue – city planners drew up a map of the city divided into zones. Within each zone, the city designated maximum building heights and permitted land uses (Fischel 2015). Despite early objections that municipal zoning violated the Fifth Amendment’s prohibition on seizure of private property without due process, the Supreme Court ultimately upheld the constitutionality of these ordinances in 1926’s *Ambler Realty v. Village of Euclid* (Wolf 2008). Since that time, municipal governments have been granted broad discretion to regulate land use within their borders. Today, urban land use policy is determined by a patchwork of over 19,000 municipalities, comprising tens of thousands of local legislators, zoning board members, and city planners.

These regulations take many forms. The most common is to specify permitted land use for each parcel (e.g. residential, commercial, industrial). This type of zoning (“Euclidean”) is intended to separate some activities from others – e.g. keeping industrial pollutants away from shopping areas, or prohibiting commercial uses from sprouting up in quiet residential neighborhoods.

In addition to regulating the *type* of land use, zoning also typically regulates the *intensity* of land use. For example, zoning ordinances will often specify a maximum residential density that is allowed within each zone. Other ordinances might mandate a percentage of every lot area that must be dedicated to open space, or a minimum distance that buildings must be set back from the street. Another popular restriction is the maximum floor area ratio (FAR), which limits the total floor area of buildings relative to the size of the lot on which they sit. In practice, these regulations all but ensure that large swaths of US cities are set aside for single-family homes, even when a more intensive land use (townhouses, apartment buildings) would be more appropriate given demand.

Other land use ordinances that are seemingly unrelated to housing can nevertheless limit the number of housing units built in a city. Take, for instance, the near-ubiquitous requirement that developers set aside parking for each new building they construct. Even in cities without formal zoning codes, these requirements can be onerous; the city of Houston mandates that for each studio apartment, developers must set aside 1.25 parking spaces (Lewyn 2005)! Not only does all that mandated parking take up real estate that could be used for housing, but abundant, inexpensive parking further incentivizes urban sprawl, by reducing the cost of automobile commutes (Shoup 1999).

Over time these regulations have accumulated in such a way that building new, affordable housing has become prohibitive in many metropolitan areas. In the century since New York City's zoning code was first implemented, the length of the text has ballooned from 14 pages to 4,126 pages. It has been estimated that roughly 40% of Manhattan's housing stock would be illegal to build today (Bui et al. 2016).²

How is municipal land use policy determined? In practice, much of the regulatory authority lies with the elected city council. In nearly every US municipality, the city council is responsible for adopting and amending the city's comprehensive plan. Of 2,729 municipalities surveyed by the Wharton Residential Land Use Regulation Survey (Gyourko et al. 2008), 94% reported that rezoning decisions require a majority (or supermajority) vote in city council. In addition, 70% of municipalities surveyed require planning commission approval for any new building. These committees tend to be appointed rather than elected (there are no instances in my dataset of an elected zoning board or planning commission member), so any group looking to influence the composition of those committees would have to do so through mayoral or city

²Although New York City as a whole is twice as populous today as it was in 1910, the population of Manhattan itself peaked in the 1910 Census, just before the introduction of zoning.

council elections.

Who shows up to these elections depends in part on when they are held. We turn to this topic in Section 2.3.

2.3 Off-Cycle Elections Empower Slow-Growth Interests

Although “Election Day” in the United States is officially the Tuesday following the first Monday in November, most US elections are not held on that day (Berry & Gersen 2010). The United States comprises tens of thousands of local governments, including roughly 3,000 counties, 19,000 municipalities, 14,000 school districts, and 35,000 special districts (Berry 2009). At this lower level, elections are commonly held *off-cycle*, on a date separate from presidential, congressional, or gubernatorial elections.

The historical roots of this practice are deep. As Anzia (2012*a*) documents, several city governments experimented with election timing in the late 19th century as a play for partisan political advantage. In the decades that followed, the Progressive movement advocated off-cycle elections as part of a package of reforms designed to weaken urban political machines. The institution has proven remarkably sticky. Today, roughly 80% of US municipalities continue to hold their elections off-cycle (Anzia 2012*a*).

The most prominent consequence of holding elections off-cycle is lower voter turnout. Because voting entails a non-trivial time cost, citizens are more likely to vote when there are multiple concurrent elections on the ballot, particularly high-profile national elections like the presidency. Berry & Gersen (2010) document a 20 percentage point decrease in turnout when California municipal elections are held off-cycle. This finding is replicated in quasi-experimental studies as well; local govern-

ments that were compelled to shift the timing of their elections saw large subsequent changes in voter turnout (Anzia 2012*b*, Garmann 2016).

But this decrease in turnout is not uniform. Kogan et al. (2017) compile an extensive dataset drawn from voter files to examine the differences between on-cycle and off-cycle electorates. They find that the electorate in off-cycle elections is very different demographically from those that turnout to vote in presidential years. In particular, the off-cycle electorate is much older (roughly 10-20 percentage points more senior citizens than in presidential years).

Citizens that have a larger stake in local politics are more likely to show up to local-specific elections. For example, when school district elections are held off-cycle, members of teachers unions are more likely to turn out to vote than those with smaller stakes in school district policymaking. In such districts, there is a significant increase in the average teacher's salary (Anzia 2011, Berry & Gersen 2010). Similarly, because most special districts (e.g. water districts, library districts) hold their elections off-cycle, groups that benefit from the district's services are more likely to show up to vote than those that do not, resulting in higher levels of taxes and spending (Berry 2008).

In the two examples above, we see the classic Olsonian logic of collective action at work (Olson 1965). A small group receives concentrated benefits from additional government spending (e.g. teachers receive higher salaries; library patrons get better libraries). But the larger bulk of the population bears very small per capita costs from the necessary increase in taxes or debt. This produces an enthusiasm gap when it comes to turning out supporters (Anzia 2012*b*). The beneficiaries of additional spending are much more likely to organize and turn out their supporters than those that oppose it.

But how does all this relate to the politics of local land use? To complete my argument, I argue that restrictions on housing development generate a similar pattern of concentrated benefits and diffuse costs. As such, off-cycle elections produce a differential mobilization of three groups: homeowners, older voters, and neighbors of proposed new development. These three explanations are not mutually exclusive, and I suspect that each one explains part of the empirical relationship I present in Section 2.7.

2.3.1 The Homevoter Hypothesis

In his influential book, *The Homevoter Hypothesis*, Fischel (2001) describes how resident homeowners came to dominate American municipal politics during the late 20th century. Because their financial portfolio largely consists of a single, highly-leveraged, undiversified, immobile asset, homeowners develop a (wholly justified) concern for maintaining home values in their community. And municipal government policy is an important determinant of home values. Studies have repeatedly demonstrated that home prices respond to factors like local tax policy (Hamilton 1976), public school quality (Black 1999), transportation infrastructure (Hess & Almeida 2007), placement of public parks (Troy & Grove 2008), and crime risk (Linden & Rockoff 2008, Pope & Pope 2012).

But arguably it is zoning policy, by regulating the overall supply of housing, that exerts the most direct influence on home values. Homeowners tend to support greater restrictions on new construction than renters. Marble & Nall (2017) conduct a series of survey experiments to assess urban residents' views towards new housing development. In these surveys, homeowners consistently report stronger opposition to new housing construction than renters. This effect is stronger than that of any other demographic variable or experimental manipulation. Hankinson (2017) finds a

similar result. Although there is some support for building restrictions among renters in gentrifying neighborhoods, homeowners consistently support these policies more strongly than renters.

All of this suggests that homeowners will be more likely than renters to turnout to municipal-specific elections, and vote for candidates that share their concern for maintaining home values and limiting new construction. Dipasquale & Glaeser (1999), for example, find that homeowners are 25 percentage points more likely to report voting in local elections. Einstein et al. (2017) find that homeowners are more than twice as likely to speak at local zoning board meetings than renters. In municipalities with such a large gap in political participation, municipal governments are likely to be more responsive to homeowners' concerns. But when municipal elections are held on-cycle, this turnout discrepancy may disappear, as renters turn out for the more high-profile elections.³

2.3.2 Voter Demographics

However, the Homevoter Hypothesis does not tell the entire story. In many suburban municipalities, homeowners make up a decisive majority of residents. Renters in these communities are not be a sufficiently large voting bloc to swing municipal elections, even when they show up. In such places, election timing can only influence outcomes if there are heterogeneous preferences *among homeowners*.

One possible source of this heterogeneity is age. In their overlapping-generations model on the political economy of urban growth, Ortalo-Magne & Prat (2014) identify age as an important determinant of zoning policy preferences. Older agents are more likely to oppose new construction because they have made greater investments

³De Benedictis-Kessner (2017) documents an increase in mayoral incumbency advantage when municipal elections are held on-cycle, suggesting that on-cycle voters – drawn to the polls for other reasons – are less informed on average about municipal politics.

in real estate over the course of their lives, and are less able to recoup a loss in the value of that capital.

As we've already mentioned, Kogan et al. (2017) find that off-cycle electorates are much older than on-cycle electorates on average. If older residents prefer slow growth, then this could be another channel through which election timing affects the incentives of city councilmembers. It remains to be seen whether this trend, identified during the years of a Democratic presidency, remains true during a Republican presidential administration. Nevertheless, this relationship holds true during the period I investigate in the empirical analysis (my dataset concludes in 2016).

2.3.3 Diffuse Benefits, Concentrated Costs

There is one final mechanism through which opponents of growth may be over-represented in off-cycle elections: the asymmetry between the concentrated costs of new development and its more diffuse benefits. In the same manner that teachers are more likely to show up to school board elections – because they have more to gain – the neighbors of potential new development are more likely to show up to municipal elections – because they have more to lose.

New housing development imposes concentrated costs on nearby residents. A larger population can increase neighborhood traffic congestion and compete for scarce parking spaces. New residents crowd local public amenities like libraries, parks, or beaches. Tall apartment buildings block neighbors' sunlight and impede their views.

By comparison, the benefits that come from new housing are diffuse and uncertain. Building additional housing stock puts downward pressure on rents. Denser, walkable development in the urban core reduces average commute times (Wheaton 1998). Larger cities may benefit from economies of scale in administrative costs (Blom-Hansen et al. 2014). But each of these benefits accrue to the metropolitan area at

large, and the marginal benefit that any individual voter reaps from a new housing development is minuscule. These diffuse benefits are unlikely to motivate citizens to turn out and vote in city council elections.

Einstein et al. (2017) compile a novel dataset of meeting minutes from local zoning board meetings in the Boston area. They find that the residents who attend these meetings were more likely to be older, male, and homeowners. And they overwhelmingly spoke out in opposition of new development (63% opposed compared to 15% in favor). The reasons cited for this opposition include a number of concentrated costs imposed on the neighborhood, including: traffic, environmental degradation, flooding, public safety, aesthetics, and parking. By matching these records to individual-level voter files, they also determine that the residents who comment at local zoning board meetings are also more likely to turn out to local elections.

Taken together, these three mechanisms suggest that off-cycle electorates will be, on average, more skeptical of new housing development, and are likely to elect city councilmembers that share this skepticism. Before turning to more systematic empirical evidence on this proposition, let us briefly discuss an illustrative case study.

2.4 Case Study: Palo Alto's Measure S

The city of Palo Alto, California lies in the heart of Silicon Valley. Over the past two decades, demand for housing in the area has caused home values to nearly quintuple. The question of how to create affordable housing – and whether to permit large amounts of new supply – is a very salient issue in local politics.

It was amidst this controversy that, in November 2010, the residents of Palo Alto passed Measure S, a referendum shifting the city's elections on-cycle. Although Palo Alto is an outlier in terms of home prices, its experience with the change in election

timing offers an instructive case study into the political dynamics described in the last section. Prior to 2010, Palo Alto city council members were elected during odd-numbered years. But following the referendum's passage, city council elections were moved to coincide with national elections on even-numbered years. Proponents of the change argued that it would boost voter turnout and decrease the cost of administering municipal elections.

The first claim was certainly proven true. As Figure 2.3 (panel A) illustrates, on average 47% of registered voters turned out to vote for city council in the three elections prior to Measure S. Afterwards, turnout increased dramatically. About 85% of registered voters turned out in 2012 and 2016, and 60% turned out during the congressional midterm in 2014.⁴

But did the *composition* of the electorate change, to the advantage of pro-development candidates? To explore this question, I consulted the archives of the local newspaper (The Palo Alto Observer), which has conducted interviews with each candidate for city council going back to 2005. Because housing policy is such a prominent issue, the candidates have typically been asked to state their opinion on local zoning and housing development policies. For every candidate between 2005 and 2016, I manually code whether each candidate's platform is pro-development (+1), slow-growth (-1) or unclear (0). Pro-development candidates express willingness to relax height restrictions, deregulate accessory dwelling units, lower density requirements, and build new housing near transit corridors. Slow-growth candidates emphasize maintaining Palo Alto's character, express concerns about overcrowding in schools, etc.

How well did pro-development candidates perform in Palo Alto city council elections before and after the shift in election timing? Figure 2.3 (panel B) provides

⁴Santa Clara Registrar of Voters: <https://www.sccgov.org/sites/rov/resources/pages/pasterresults.aspx>

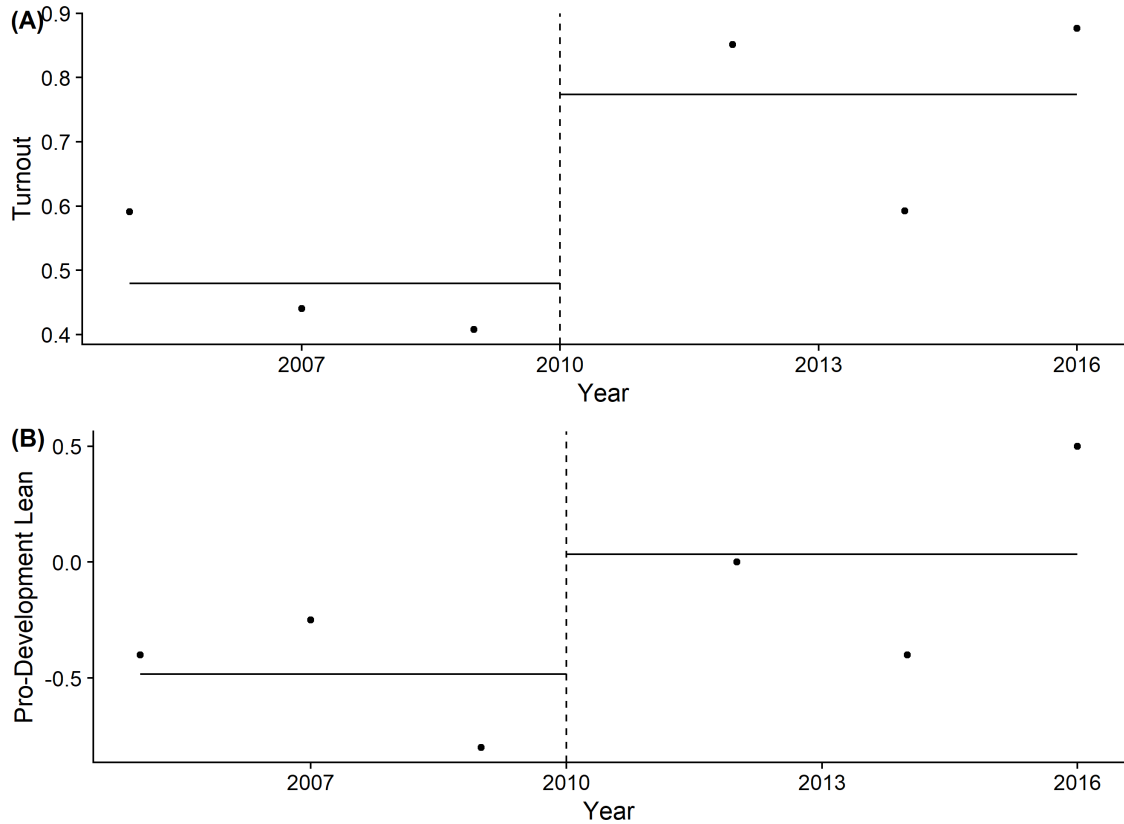


Figure 2.3: Following the switch to on-cycle, Palo Alto city council elections saw much higher turnout (A), and more pro-development city councilmembers were elected (B). Solid lines denote averages before and after the passage of Measure S (dotted line).

some suggestive evidence. Prior to Measure S, roughly 25% of the candidates elected to city council were pro-development. That fraction increased to 50% after the city shifted to on-cycle elections. The most dramatic result was in 2016, when a slate of candidates running on an explicitly pro-development platform won an unprecedented victory. Three out of the four elected councilmembers that year expressed pro-development opinions in their interviews.

Of course, this single case is far from conclusive. There are a number of reasons why more city councilmembers would have expressed pro-development sentiments toward the end of this period (the housing market collapse and its aftermath spring to mind). But it seems likely that the shifting election timing played some role in the

election of these new development-minded candidates. To investigate this proposition in a more systematic fashion, we'll now turn to evidence from a comprehensive elections dataset in California cities, and explore how election timing affects popular support for pro-development ballot initiatives, as well as observable land use policy outcomes, including permitting and median home prices.

2.5 Ballot Initiatives

Over the past two decades, California has stood out among US states for its unique reliance on the ballot initiative to shape land use policy. Slow-growth citizen groups frequently resort to direct democracy to constrain the ability of city councils to permit new development (Gerber & Phillips 2004). There are several popular tools in this arsenal. One is the Urban Growth Boundary (UGB), a requirement that all new residential development take place within a specified boundary, beyond which the municipality will not extend city services (Gerber 2005). As of writing, at least 85 municipalities in California have adopted some form of UGB via ballot measure. Another tool is the initiative requirement, a rule that prohibits certain types of development (particularly multifamily housing) unless expressly approved by ballot initiative. Finally, California voters will often use ballot measures to directly shape the city's zoning code: imposing restrictions on building heights, setbacks, parking requirements, environmental review, traffic impacts, etc.

As a result, there is now a large set of data on how voters react when asked to weigh in on municipal land use decisions. In this section, I investigate whether the timing of those elections affected the electorate's willingness to permit new development. To do so, I employ the California Election Data Archive, an extensive database of every election held in the state of California since 1996.⁵ For each ballot measure,

⁵Available at <http://www.csus.edu/isr/projects/ceda.html>.

the CEDA database includes the municipality, election date, ballot question, and number of voters that voted for and against the measure. Using the text of the ballot question, I manually code whether the measure restricted or approved new residential development, removing initiatives that did not pertain to land use, or only applied to nonresidential development. I also categorize each measure based on the type of housing development (Infill or Greenfield), and the type of restriction (UGB, initiative requirement, height restriction, etc.).

Before I proceed with the analysis, two caveats are in order. First, it is important to note that the timing of ballot initiatives is endogenous. When deciding to place an initiative on the ballot, citizen groups deliberately attempt to do so during a time when it is most likely to attract supporters.⁶ This selection bias should attenuate the observed effect of election timing on pro-development outcomes.

Second, bear in mind that the existence of popular initiatives on land use is *itself* a development control. Municipalities that require new development to face the voters before it can go forward are placing an additional (ornery) veto player into the permitting process. As such, the types of housing development that are proposed tend to be significantly watered down, and likely to come paired with developer-funded public goods Gerber (2005). For example, many of the ballot initiatives in the CEDA dataset allow new housing, but on the condition that a portion of the land area be preserved as permanent open space. I code these initiatives as “pro-housing” because they expand the housing stock relative to current law, but that is a coding decision upon which reasonable people may disagree.

Using this coding scheme, I identify 59 initiatives that were placed on the ballot to approve or prohibit new infill development, and 157 initiatives pertaining to

⁶For example, 80% of the initiatives proposing UGBs are placed *on-cycle*, and on average, 62% of the electorate votes in favor. Curbing sprawl, it seems, is quite popular among Californians at large.

greenfield development on the urban fringe (this includes UGBs and open space requirements). 74 initiatives did not obviously fall into either category (e.g. annual permit caps). As Table 2.1 reports, initiatives to block urban sprawl are highly popular in California. Of the ballot measures analyzed, the pro-housing share averaged 40% for greenfield measures, regardless of election timing. Initiatives to permit new infill development were significantly more popular, but their success depended on election timing. Figure 2.4 illustrates the vote share garnered by the pro-housing side of these initiatives, broken down by election timing. Among infill development initiatives, the pro-housing side received roughly 7 percentage points more support when the election was held on-cycle (corresponding to a 14pp swing). This effect holds even when controlling for city-level characteristics and metropolitan area fixed effects in an OLS regression (Table 2.1). However, among initiatives relating to greenfield development and urban sprawl, election timing does not appear to affect support for development.

All of this tentatively suggests that off-cycle voters are less likely to support new development that intensifies land use within existing neighborhoods. In the land-constrained cities on the California coast, where any new housing development is necessarily infill development, this eliminates the potential for new housing entirely. In the next section, we will discuss the effects this has on observable land use policy outcomes, including new building permits and median home prices.

2.6 Data

Owing to its extensive records on municipal election timing going back two decades, the empirical evidence in this paper comes entirely from the state of California. So it is worth noting the ways in which California cities differ from their counterparts

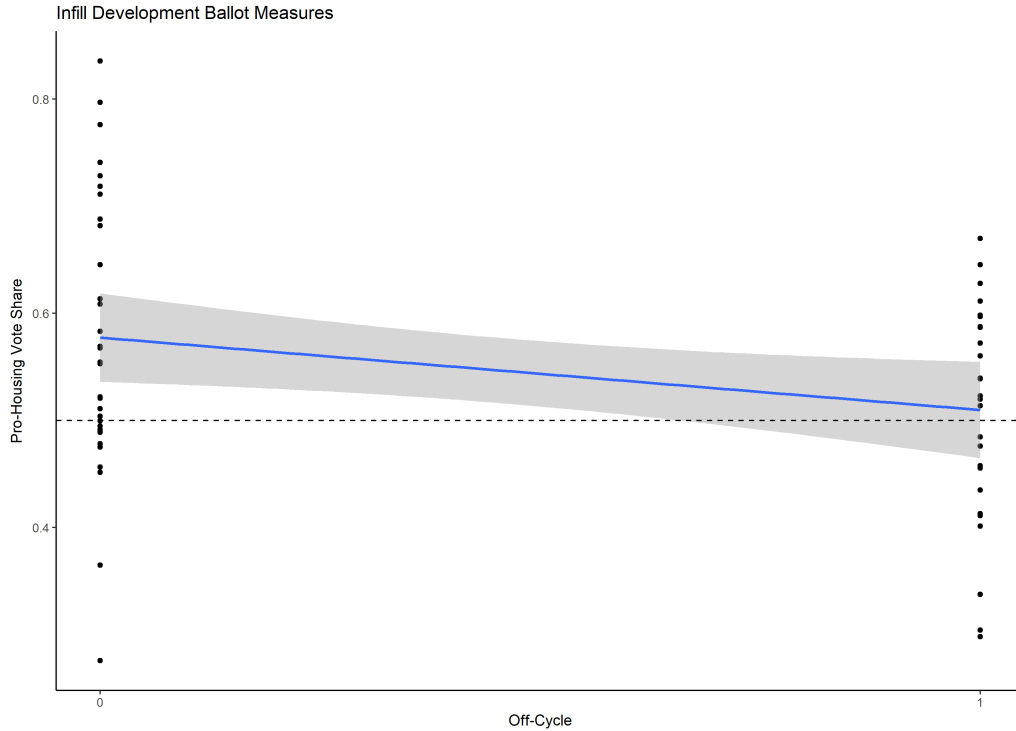


Figure 2.4: New infill development attracts roughly 7-8pp less support when the ballot initiative is held off-cycle.

in the rest of the United States. First, California has experienced consistent, rapid population growth throughout its history as a state. Since 1840, there has not been a single decade during which its population grew by less than 10%.⁷ This is significant, because it has required a continual expansion of the housing supply to accommodate new migrants. This trend has largely been reflected at the city level as well. Unlike other areas of the country, where cities have experienced protracted population decline, 78% of California's cities are currently at their population peak, and only six cities are below 90% of their population peak (author's calculations). As a result, there is no overhang of housing supply in shrinking cities to drive down home prices (Glaeser & Gyourko 2005). In nearly every city, new construction is required to keep up with expanding demand.

⁷<https://www.census.gov/population/www/censusdata/files/table-16.pdf>

Table 2.1: Relationship between election timing and success of pro-housing ballot initiatives, by type of development. City-level controls include mean temperature, log population (2000), median income, pct. white, pct. over 65, pct. college graduates, pct. nearby developable land area (2001), school district Academic Performance Index (2003), and debt per capita (2002).

	<i>Dependent variable:</i>		
	Percent Pro-Housing		
	(1)	(2)	(3)
Off-Cycle	0.02 (0.03)	0.02 (0.03)	0.04 (0.03)
Infill	0.19*** (0.03)	0.20*** (0.03)	0.15*** (0.04)
Off-Cycle * Infill	-0.09 (0.05)	-0.10 (0.05)	-0.12* (0.05)
Academic Performance Index (2003)			-0.001** (0.0003)
Constant	0.39*** (0.01)	0.32*** (0.03)	-1.76 (1.36)
CBSA Fixed Effects	No	Yes	Yes
City-Level Controls	No	No	Yes
Observations	216	200	194
R ²	0.17	0.27	0.36
<i>Note:</i>	*p<0.05; **p<0.01; ***p<0.005		

Second, California has a unique situation regarding local public finance, owing to a 1976 measure called Proposition 13. Passed by referendum as part of the broader “tax revolt”, Prop 13 places strict limits on municipal governments’ ability to raise property taxes. All property tax rates are statutorily capped at 1% of assessed property value, and assessments can only increase at a maximum of 2% per year. As a result, the effective tax rate paid in high-demand real estate markets is substantially below 1% (Ferreira 2010). The effect that Proposition 13 has on homeowner behavior is well-researched: people are simply less likely to move. Because purchasing a new home results in a reassessment by the local government, many residents

are "locked-in" to their homes, paying favorable property tax rates (Ferreira 2010). There is less scholarly agreement, however, on how Prop 13 affects municipal land use policies. Some scholars suggest that Prop 13 makes new residential development less attractive, because their property taxes will be insufficient to pay the cost of new public services (Quigley & Rosenthal 2005). However, because new housing is assessed at market value rather than the statutorily constrained assessments of older housing stock, this could *increase* the incentive to build new housing, particularly in areas that have undergone rapid home price growth.

Finally, California consists of two very distinct regions. The coastal cities are land-constrained, wealthy, liberal, and most have recovered easily from the housing price collapse in 2007. The inland and north coast cities are more land-abundant, conservative, and have had greater difficulty recovering from the Great Recession. In the empirical analysis, I conduct a matching analysis to ensure that we are comparing cities within, rather than across, these regions.

2.6.1 The Election Timing Variable

To generate my measure of municipal election timing, I refer once again to the California Election Data Archive. Subsetting the data so that I only consider elections for mayor and city council (or the equivalent legislative body, like County Supervisor in San Francisco)⁸, I then determine whether each election was held on November during an even-numbered year: if yes, I code it on-cycle, if no, off-cycle.

Once that step is complete, I compute for each municipality the fraction of elections between 1996 and 2016 that were held off-cycle. This measure, `pct.off.cycle`, is my primary independent variable. The measure reveals a substantial amount of heterogeneity in election timing. 25% of the cities in my sample held all of their elec-

⁸I include mayoral elections in the measure as well, because mayors typically vote on the city council and appoint members to municipal zoning and land use committees.

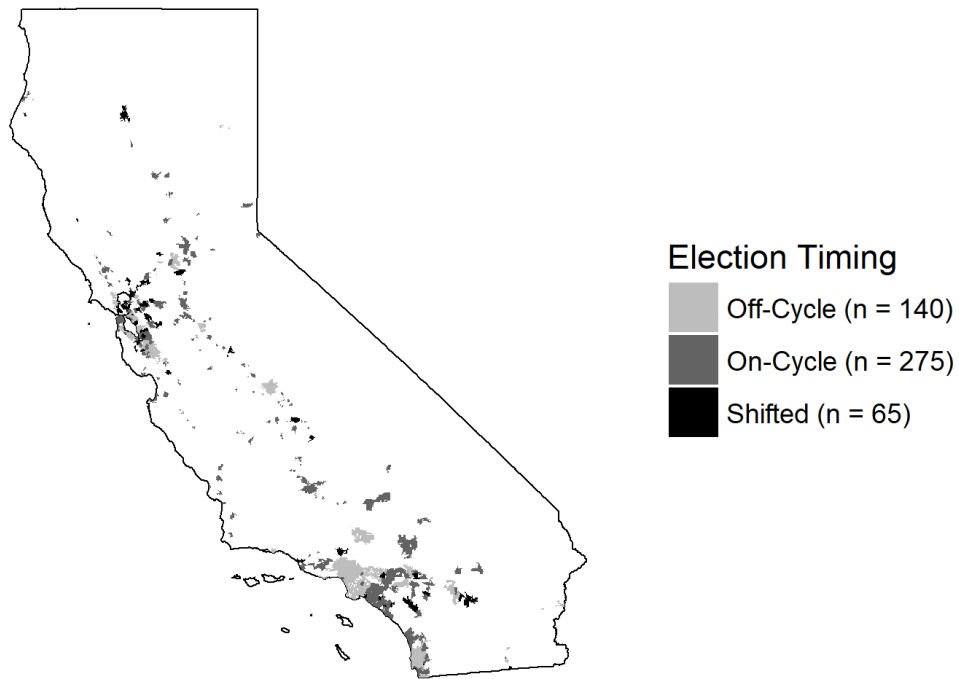


Figure 2.5: Map of municipalities in the dataset. Shading denotes whether the majority of municipal elections (1996-2016) were off-cycle or on-cycle.

tions off-cycle during this period, while 41% held their elections on-cycle. Roughly 13% of cities switched the timing of their elections during the survey period, a fact that will prove useful for the difference-in-difference analysis (Section 2.7.3). Figure 2.5 maps the cities in my dataset, shaded by election timing.

2.6.2 Dependent Variables

In my empirical analyses, I employ three outcome variables. The first is a direct measure of regulatory stringency, the number of new building permits issued each year by the municipal government. These data come from the Census Bureau's Building Permits Survey, conducted annually since 1980. The other two outcome variables are measures of median home prices. Although not a direct measure of

land use regulation, prices provide a useful proxy for the elasticity of housing supply in an area, after accounting for demand-side factors like median income and urban amenities.⁹ In all of the following analyses, I use a measure of median sale price per square foot from the real-estate website Zillow.¹⁰

2.6.3 Developable Land

Municipalities with an abundance of nearby developable land are likely to have an easier time expanding their housing supply than land-constrained cities, because it merely requires building out, rather than building up (Saiz 2010). To account for this potential confounder, I generate a measure of nearby developable land for each municipality in my dataset. This entails a three-step process. First, I use the National Land Cover Dataset (NLCD) to identify the parcels of land within a 20km radius of the city center that are undeveloped. I then identify which of those parcels are *developable*, following criteria from Saiz (2010). I exclude any land that is classified as wetlands in the NLCD, as well as any terrain that is too steep to build on (grade greater than 15 percent), which I compute from USGS Digital Elevation Model (90 sq. meter grid cells).¹¹ Finally, I compute the fraction of land within 20km of the city center that matches these criteria (undeveloped, not-too-steep, and not wetlands). The result is my `percent.developable` variable.

2.6.4 Other Covariates

From the American Community Survey I collect covariate data on population, median income, educational attainment, and demographic composition for every city in California with a population greater than 10,000.

⁹See Saiz (2010) for a more thorough explanation on how supply elasticity affects home price levels, and Glaeser et al. (2005) for an example of an empirical analysis using home prices relative to construction costs to infer the stringency of land use regulation.

¹⁰<https://www.zillow.com/research/data/>

¹¹Data available from the US Geological Survey, accessed through the FedData package in R (Bocinsky 2017).

Because many municipalities cite cost savings as a motivation for changing their election timing, omitting data on local fiscal conditions may bias my estimates. Cities with large per capita debt burdens may be more likely to switch to on-cycle elections, and also to pursue tax-base enhancing real estate developments. To account for this possibility, I collect data on outstanding debt per capita, expenditures per capita, and taxes per capita from the US Census of Governments.¹²

I also employ a measure of city-level ideology developed by Tausanovitch & Warshaw (2014) using multilevel regression and poststratification. If liberal cities – in an effort to turn out Democratic voters – are more likely to hold their elections on-cycle, and liberal cities also have more restrictive zoning policies – as Kahn (2011) documents in California – then omitting local-level ideology could bias my estimates. Note that this estimate is only available for cities with population greater than 20,000.

Hedonic models of urban quality of life (e.g. Roback (1982)) suggest that amenities like pleasant climate are likely to affect median home values. So I also compute average January and July temperatures for each municipality from the high-resolution WorldClim dataset (Hijmans et al. 2005).

Home prices are also sensitive to the quality of local public goods. In particular, the performance of nearby public schools is strongly capitalized into property values, as border discontinuity studies reveal (Black 1999). A review of the literature suggests that one standard deviation increase in test scores is associated with home prices that are four percent higher (Nguyen-Hoang & Yinger 2011). To account for this effect, I include school district-level data on the Academic Performance Index, a measure computed annually by the California Department of Education to track school district performance and hold local officials accountable. Payson (2017) docu-

¹²Available at <http://www2.census.gov/pub/outgoing/govs/special60/>. The filename is “IndFin1967-2012.zip”.

ments the importance of this measure in local school board elections; see that paper for a more detailed description of the measure. For each city in my dataset, I assign an API score based on the school district with the most territorial overlap.¹³

2.7 Results

My empirical analysis proceeds in three parts. First, I estimate the relationship between off-cycle elections, home prices, and building permits using cross-sectional OLS. As predicted, off-cycle elections are associated with higher home values and fewer new building permits. Second, I perform a matching analysis, comparing cities with off-cycle elections against a matched set of cities that hold their elections on-cycle. This analysis yields a similar result. Finally, to hold unobserved city effects constant, I restrict my focus to those cities that switched their election timing between 1996 and 2016. This difference-in-difference analysis is consistent with the cross-sectional results: cities that switched to on-cycle elections had slower growth in home prices and issued roughly three times as many building permits as those that did not.

2.7.1 Cross-Sectional Correlations: OLS

To begin, I estimate the a series of linear regression models of the following form:

$$Y_i = \beta_1 T_i + \beta_2 X_i + \varepsilon_i$$

where Y_i is either a measure of median home prices in 2014 or the logarithm of new units permitted by city i between 2010 and 2016. The variable T_i is the percentage of elections in city i held off-cycle between 1996 and 2016, X_i is a matrix of city-level covariates, and ε_i is an iid error term.

¹³Where multiple school districts overlap with a municipality, I assign the API scores for the unified school district, and use scores from secondary or elementary districts only if there is no unified school district. Data files available at <https://www.cde.ca.gov/ta/ac/ap/apidatafiles.asp>.

As reported in Tables 2.2 and 2.3, the estimated relationship between off-cycle election timing and building permits is negative across all specifications of the model. The magnitude of the effect is striking: the estimate reported in Column (4) suggests that off-cycle cities issued just half as many building permits between 2010 and 2016 as comparable cities with on-cycle elections. A similar pattern shows up in the median home price regressions (Table 2.4). Median home prices are roughly \$61 higher per square foot in cities with off-cycle elections.

2.7.2 Matching Analysis

To complement the OLS estimation above, I also conduct a matching analysis (Rubin 1973). This estimation strategy compares treated observations (cities with off-cycle elections) to a matched sample of control observations (cities that hold elections on-cycle). The objective of the matching algorithm is to ensure that both samples, while differing on treatment condition, are on average balanced across potential confounding variables. I define the “treatment” group as those cities with a majority of city council elections between 1996 and 2016 held off-cycle, and all other cities as the control group. Dichotomizing the treatment in this manner is not terribly problematic, since most cities in my sample hold either 100% or 0% of their elections off-cycle. As before, I include as covariates each city’s median income, population, nearby developable land, per capita debt burden, and the percentage of residents that are white, college-educated, and over 65 years of age as covariates. I also perform an exact match on metropolitan statistical area, so that each treated city is compared to a matched control city within the same CBSA.¹⁴

The two groups are well-balanced on the matching covariates, as indicated by

¹⁴In all specifications, I identify the matched control group using Diamond & Sekhon’s Genetic Matching algorithm (Diamond & Sekhon 2012), courtesy of the `Matching` package in R (Sekhon 2011). Owing to the heavily right-skewed city size distribution, I drop three cities with population greater than 500,000.

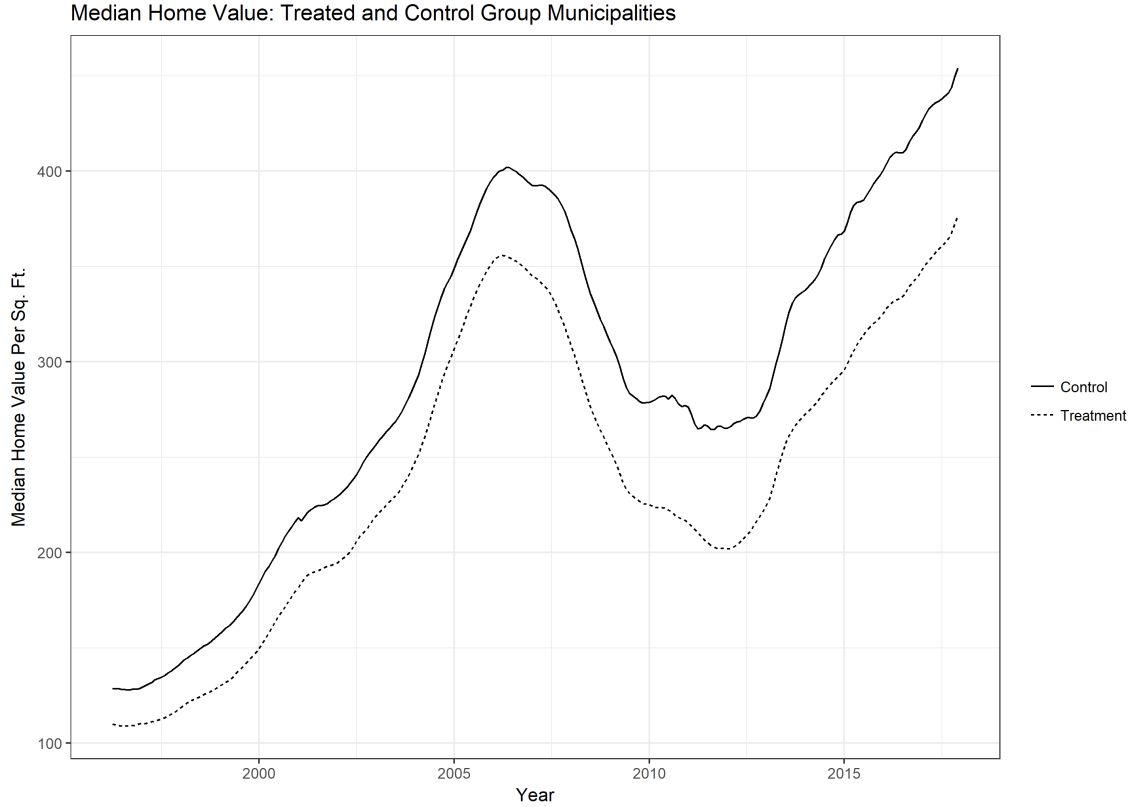


Figure 2.6: Median real home prices grew more slowly in cities that moved their city council elections on-cycle than in comparable cities that did not.

the Kolmogorov-Smirnoff statistics in the second half of Tables 2.5 through 2.7. For each outcome variable, I compute the average treatment effect on the treated units (ATT). These estimates are similar to those from the OLS: the median home value in treated cities is roughly \$75 higher per square foot than in control cities, and they issued half as many building permits.

2.7.3 Difference-in-Difference

Matching ensures that the treatment and control groups are balanced on *observed* covariates, but there may yet be unobserved city-level characteristics affecting housing policy. To adjust for these unobserved covariates, we will now investigate within-city variation through a difference-in-difference analysis.

To do so, I compare the growth in home prices between cities that shifted their election timing from off-cycle to on-cycle, and those cities where elections remained off-cycle the entire period. As before, I create a matched control group, balancing on median income, population, demographics, developable land, and per capita debt burden.¹⁵ I perform a similar analysis for the growth of newly permitted housing stock.

In total, I identify 65 cities that shifted their election timing from off-cycle to on-cycle during the period of study. As illustrated in Figure 2.5, these cities are located throughout the state, although a plurality are within or around the San Francisco metropolitan area. Their mean population is roughly 55,000, median income is on average \$55,000, and roughly 30% of their population is college educated. These and other covariate balance statistics are listed in Table 2.8.

The cities that shifted their election timing are broadly similar to the cities that did not, with three notable exceptions. First, they tend to have a greater share of nearby developable land (26% compared to 9%). Second, they tend to have a larger percentage of white residents (54% and 44%, respectively). And finally, they hold more municipal debt per capita (\$2000 compared to \$1400). Because each of these characteristics may affect the price and growth of the housing stock, I opt for the more conservative approach of creating a matched control group prior to estimating the difference-in-difference. Post-match, there are no significant differences between the groups, as measured by a Kolmogorov-Smirnoff statistic.

Figures 2.6 and 2.7 illustrate the results. Both groups begin with roughly the same average sale price per square foot (only a \$24 difference). But home prices grow

¹⁵This matching is not strictly necessary for a difference-in-difference analysis as long as one assumes that the potential outcomes in both groups follow “parallel trends”. However, the parallel trends assumption is more plausible after matching on observed covariates, so one could consider this test even more conservative than a standard difference-in-difference. See Abadie (2005) for a detailed discussion of semi-parametric difference-in-difference estimators.

much more slowly in the treatment group, and by 2015, the difference is nearly \$100. This coincides with a large difference in the number of new building permits issued between the treatment and control group. Collectively, the control group permitted roughly 50,000 new housing units between 1996 and 2016, while the treatment group issued nearly 200,000 during that same period.

Eyeballing the data, it appears that the most dramatic leap in new homebuilding occurred in the run-up to the housing collapse (2000-2007). This accords with intuition, but it is striking how much steeper that line during this period is for the cities that switched to on-cycle elections. Homebuilding in the control municipalities ticks up only slightly, while in the treatment group, the housing stock expands nearly 5% each year, before converging with the control group by 2009. Nearly all of the difference in new housing stock between the two groups came about during that period.¹⁶ In Table 2.8, I report the estimates, balance statistics, and measures of uncertainty. Median home value per square foot grew, on average, by \$17 less in the cities that moved their elections on-cycle. And those treated cities issued roughly two-and-a-half times as many permits as the control group between 2000 and 2016 (about 4,300 new units per city on average).

2.8 Conclusion

The debate over land use policy is often framed as a choice between local self-determination and broader economic efficiency. Should a city like Palo Alto be compelled to permit more housing in order to benefit people that do not currently live there, but would like to? Or do the current citizens have a right to determine for themselves the density and character of their own community? Indeed, much of

¹⁶Nine of the cities in the treatment group switched their election timing on or after 2010, too late to have explained this pattern. However, the difference-in-difference estimate is robust to dropping those observations.

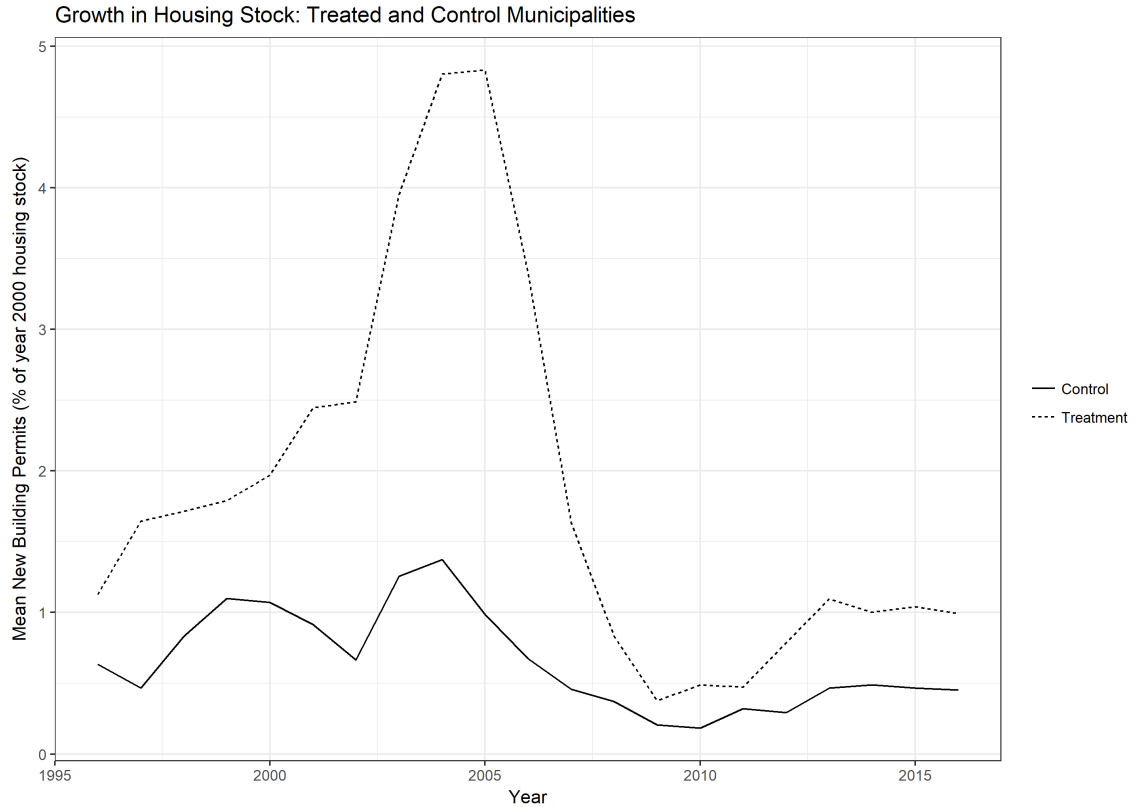


Figure 2.7: Compared to cities that kept their elections off-cycle, cities that shifted to on-cycle elections issued permits for roughly four times as many new housing units between 1996 and 2015.

the formal modeling literature on this topic proceeds from this assumption as well: residents of a municipality vote on the amount of new housing they want in their jurisdiction, and the median voter result holds. The evidence I present here suggests that this is not quite the right framing. Because municipal elections are poorly attended affairs, and the actors with the most political influence in city government are disproportionately drawn from groups that oppose new housing construction. As a result, the equilibrium housing policy reflects neither the will of the median voter, nor the optimal growth of the housing supply that a benevolent urban planner would pursue.

There are at least two ways I hope to expand this study in future work. First,

the empirical analysis is restricted to California, due to the lack of a comprehensive dataset on municipal election timing in other states. For many of the reasons discussed above, California is a unique case, and findings in this region may not generalize more broadly. A concerted effort to collect data on city council election timing outside of California would help establish the external validity of the findings presented here.

Finally, although I have done what I could to alleviate endogeneity concerns, the fact remains that my sample consists of cities that self-selected into their institutional rules. An interesting avenue for future research would be to identify cities where election timing is assigned exogenously (e.g. by state-level mandate). Fortunately, we've recently observed such an exogenous treatment assignment. In September 2018, California passed SB 415, a law requiring that lower-level governments hold their elections currently with statewide elections (wherever off-cycle elections attract 25% lower voter turnout than the average on-cycle election). Over the next several years, we should begin to see how this shock to election timing affects municipal-level public policy. Readers are encouraged to remind me to write a follow-up paper in 2028.

Despite these limitations, the evidence presented here provides a compelling glimpse at yet another significant consequence of election timing. If restrictive land use policy is partly the product of organized interests mobilizing during low-turnout elections, then it raises fundamental questions about the nature of representation in municipal government. And it suggests that a relatively simple institutional reform could yield broad welfare gains.

Table 2.2: Estimated OLS coefficients and standard errors, regressing log new building permits (2000-2016) on percent off-cycle elections and covariates in a sample of California cities.

	<i>Dependent variable:</i>		
	Log Permits (2000-2016)		
	(1)	(2)	(3)
Pct. Off-Cycle	-1.17*** (0.18)	-0.55*** (0.16)	-0.36* (0.17)
Log Population	0.94*** (0.06)	1.07*** (0.05)	1.06*** (0.05)
Median Income		0.00 (0.00)	0.00 (0.00)
January Median Temp.		-0.04 (0.02)	-0.06 (0.04)
July Median Temp.		0.04*** (0.01)	0.06** (0.02)
Pct. White		1.20*** (0.42)	1.17* (0.48)
Pct. Over 65		-0.93 (1.64)	-2.44 (1.67)
Pct. College Grad		-0.40 (0.78)	0.16 (0.84)
Debt Per Capita (2002)		0.25*** (0.04)	0.24*** (0.04)
Pct. Developable (2001)		2.25*** (0.43)	2.36*** (0.57)
Academic Performance Index (2003)		0.001 (0.001)	0.001 (0.001)
Constant	-3.29*** (0.95)	-9.51*** (1.48)	-9.97*** (2.76)
CBSA Fixed Effects	No	No	Yes
Observations	330	324	317
R ²	0.44	0.69	0.74

Note: *p<0.05; **p<0.01; ***p<0.005

Table 2.3: Estimated OLS coefficients and standard errors, regressing log new building permits (2010-2016) on percent off-cycle elections and covariates in a sample of California cities.

	<i>Dependent variable:</i>			
	Log Permits (2010-2016)			
	(1)	(2)	(3)	(4)
Pct. Off-Cycle	-1.02*** (0.19)	-0.79*** (0.19)	-0.71*** (0.21)	-0.52* (0.23)
Log Population	1.15*** (0.06)	1.20*** (0.06)	1.19*** (0.06)	1.21*** (0.08)
Median Income		0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
January Median Temp.		-0.01 (0.02)	-0.01 (0.04)	0.01 (0.05)
July Median Temp.		0.02 (0.02)	0.07* (0.03)	0.08* (0.03)
Pct. White		0.35 (0.50)	0.56 (0.62)	0.39 (0.72)
Pct. Over 65		-4.27* (2.06)	-5.31* (2.13)	-8.97*** (2.62)
Pct. College Grad		3.01*** (1.00)	2.53* (1.08)	4.71*** (1.45)
Debt Per Capita		0.14*** (0.03)	0.14*** (0.03)	0.17*** (0.05)
Pct. Developable		1.76*** (0.50)	1.75* (0.72)	2.04* (0.86)
Academic Performance Index		0.002 (0.002)	0.003 (0.002)	0.002 (0.002)
Ideology Score				1.19 (0.62)
Constant	-8.95*** (0.97)	-13.84*** (1.89)	-18.03*** (3.55)	-19.03*** (3.97)
CBSA Fixed Effects	No	No	Yes	Yes
Observations	358	351	342	266
R ²	0.50	0.61	0.65	0.66

Note:

*p<0.05; **p<0.01; ***p<0.005

Table 2.4: Estimated OLS coefficients and standard errors, regressing median home value per sqft (2017) on percent off-cycle elections and covariates in a sample of California cities.

	<i>Dependent variable:</i>			
	Median Home Value Per Sqft (2017)			
	(1)	(2)	(3)	(4)
Pct. Off-Cycle	150.45*** (30.09)	99.97*** (19.84)	69.35*** (19.19)	61.47** (21.75)
Log Population		-2.27 (6.29)	-13.21* (5.71)	-16.73* (7.69)
Median Income		0.005*** (0.0003)	-0.0002 (0.001)	0.001 (0.001)
January Median Temp.		7.40*** (1.87)	14.90*** (4.08)	11.10* (4.50)
July Median Temp.		-14.82*** (1.35)	-13.34*** (2.65)	-14.30*** (3.07)
Pct. White			-24.49 (55.26)	-45.71 (66.87)
Pct. Over 65			-85.06 (144.84)	272.87 (243.07)
Pct. College Grad			664.51*** (97.42)	525.85*** (134.87)
Debt Per Capita			-1.86 (2.88)	5.27 (4.26)
Pct. Developable			-15.78 (65.87)	-25.97 (80.04)
Academic Performance Index			0.24 (0.17)	0.23 (0.20)
Ideology Score				-162.25** (57.92)
Constant	343.19*** (17.40)	780.31*** (162.42)	536.64 (323.94)	816.69* (369.62)
CBSA Fixed Effects	No	No	Yes	Yes
Observations	362	361	338	264
R ²	0.06	0.63	0.79	0.80

Note:

*p<0.05; **p<0.01; ***p<0.005

Table 2.5: Matching Analysis (Home Values): Effect of off-cycle elections and balance statistics.

	Mean, Treatment	Mean, Control	Difference in Means	T-Test p-value
<i>Outcome Variables</i>				
Median Home Value (per sqft)	499.6	423.8	75.8	0.0003
Number of Cities	126	67		
	Mean, Treatment	Mean, Control	K-S Statistic	K-S Bootstrap p-value
<i>Balance Statistics</i>				
Median Income	73,243	72,605	0.119	0.314
Population (2010)	71,608	70,842	0.142	0.118
Jan. Mean Temp	52.38	52.02	0.158	0.052
Jul. Mean Temp	72.71	72.39	0.134	0.126
Pct. White (2010)	0.38	0.39	0.174	0.046
Pct. College Grad	0.34	0.32	0.159	0.06
Pct. Over 65	0.124	0.122	0.087	0.666
Academic Performance Index	793.6	803.7	0.190	0.012
Pct. Developable (2011)	0.131	0.147	0.214	<2e-16
Debt Per Capita (2007)	2.23	1.84	0.134	0.148

Table 2.6: Matching Analysis: Building Permits (2010-2016). Effect of off-cycle elections and balance statistics.

	Mean, Treatment	Mean, Control	Difference in Means	T-Test	p-value
<i>Outcome Variables</i>					
Log Permits (2010-2016)	7.91	8.56	-0.65		0.025
Number of Cities	127	67			
	Mean, Treatment	Mean, Control	K-S Statistic	K-S Bootstrap p-value	
<i>Balance Statistics</i>					
Median Income	73,032	72,046	0.118	0.298	
Population (2010)	71,208	71,531	0.150	0.1	
Jan. Mean Temp	52.4	52.2	0.157	0.098	
Jul. Mean Temp	72.9	72.6	0.126	0.226	
Pct. White (2010)	0.38	0.39	0.173	0.026	
Pct. College Grad	0.34	0.32	0.150	0.114	
Pct. Over 65	0.124	0.122	0.087	0.656	
Academic Performance Index	793	801	0.181	0.03	
Pct. Developable (2011)	0.137	0.159	0.204	0.008	
Debt Per Capita (2007)	2.23	1.91	0.118	0.292	

Table 2.7: Matching Analysis: Building Permits (2000-2016). Effect of off-cycle elections and balance statistics.

	Mean, Treatment	Mean, Control	Difference in Means	T-Test	p-value
<i>Outcome Variables</i>					
Log Permits (2000-2016)	10.11	10.67	-0.56		0.014
Number of Cities	124	69			
	Mean, Treatment	Mean, Control	K-S Statistic	K-S Bootstrap p-value	
<i>Balance Statistics</i>					
Median Income	55,604	55,947	0.144	0.154	
Population (2000)	68,082	64,230	0.096	0.566	
Pct. White (2000)	0.44	0.45	0.12	0.292	
Pct. College Grad	0.30	0.30	0.112	0.38	
Pct. Over 65	0.111	0.111	0.088	0.638	
Pct. Developable (2001)	0.148	0.165	0.272	<2e-16	
Debt Per Capita (2002)	1.41	1.46	0.144	0.134	

Table 2.8: Difference-in-difference, comparing cities that switched to on-cycle elections (treatment) and those that remained off-cycle (control).

	Mean, Treatment	Mean, Control	Difference in Means	T-Test p-value
<i>Outcome Variables</i>				
Δ Median Value per Sq. Ft. (2002-2014)	78.2	95.8	-17.6	0.026
New Units Permitted (2000-2016)	4,300	2,545	1,755	0.024
Number of Cities	27	27		
	Mean, Treatment	Mean, Control	K-S Statistic	K-S Bootstrap p-value
<i>Balance Statistics</i>				
Median Income (2000)	56,392	54,395	0.222	0.484
Population (2000)	53,187	55,053	0.148	0.89
Mean Jan. Temp	50.6	50.9	0.185	0.658
Mean Jul. Temp	74.0	73.0	0.222	0.472
% White (2000)	50.0	56.2	0.222	0.482
% College Grad (2000)	28.7	32.1	0.222	0.48
% Over 65 (2000)	12.0	13.0	0.296	0.174
API (2003)	696	706	0.222	0.436
% Developable (2001)	22.4	18.4	0.259	0.282
Debt Per Capita (2002)	2,655	1,858	0.296	0.168

CHAPTER III

Machine Learning and Poststratification

I develop a procedure for estimating local-area public opinion called machine learning and poststratification (MLP), a generalization of classical multilevel regression and poststratification (MRP). This procedure incorporates an expanded set of predictive models, including random forest and k-nearest neighbors, improving the cross-validated fit of the first-stage model. In a Monte Carlo simulation, MLP significantly outperforms MRP when there are deep interactions in the data generating process, without requiring the researcher to specify a complex parametric model in advance. In an empirical application, MLP produces county-level estimates of Trump support that correlate better with 2016 presidential vote share than classical MRP or disaggregated survey data.

3.1 Introduction

Subnational public opinion data is often difficult or costly to obtain. For political scientists who focus on lower-level units of government (e.g. legislative districts, counties, cities), this lack of local area public opinion data can be a significant impediment to empirical research. And so, over the past decade and a half, political methodologists have refined techniques for estimating subnational public opinion data from national-level surveys. A now standard approach is multilevel regression and poststratification (MRP), first introduced by Park et al. (2004).

MRP proceeds through a two-stage process. First, the researcher estimates a hierarchical linear model from individual-level survey data, using demographic and geographic variables to predict public opinion. Typically, this model takes the following form, where the outcome is a function of individual-level demographic variables (here, x_1 and x_2), and a region-specific intercept (α_n^{region}), itself a function of region-level characteristics (z_n):

$$\begin{aligned}\hat{y}_i &= \beta^0 + \alpha_j[i]^{x_1} + \alpha_k[i]^{x_2} + \alpha_n^{region}; \\ \alpha_j^{x_1} &\sim N(0, \sigma_j^2); \\ \alpha_k^{x_2} &\sim N(0, \sigma_k^2); \\ \alpha_n^{region} &\sim N(\beta^z \times z_n, \sigma_{region}^2)\end{aligned}$$

The predictions from this first stage model can then be used to estimate average opinion in each local-area of interest. To do so, the researcher takes each demographic group's predicted opinion, and computes a weighted average using the observed demographic distribution. This second stage is called poststratification. If the predicted value for each demographic group is \hat{y}_r , and the frequency of that group

in region s is N_{rs} , then the following equation gives the MRP estimate for region s :

$$Y_s^{MRP} = \frac{\sum_{r \in s} N_{rs} \hat{y}_r}{\sum_{r \in s} N_{rs}}$$

MRP has enabled a flowering of new research on political representation in states (Lax & Phillips 2012), Congressional districts (Warshaw & Rodden 2012), and cities (Tausanovitch & Warshaw 2014). But the method is not without its critics. Buttice & Highton (2013) find that MRP performs poorly in a number of empirical applications, particularly when the first-stage model is a poor fit for the public opinion of interest. In particular, they find that MRP works best for predicting opinion on cultural issues (like support for gay marriage), where there is greater geographic heterogeneity in opinion. In these cases, public opinion is more strongly predicted by geographic-level variables, yielding better poststratified estimates. But for opinions on economic issues, MRP yields a poorer fit. The authors conclude by emphasizing the importance of model selection, noting that “predictors that work well for cultural issues probably will not work well for other issue domains and vice versa”. This finding echoes Lax & Phillips (2009), who urge researchers to optimize their first-stage model for the issue of interest.

In this paper, I introduce a refinement of classical MRP, called Machine Learning and Poststratification (MLP). This technique improves first-stage model selection by expanding the set of candidate models to include machine learning techniques, like random forest and K-Nearest Neighbors. MLP then selects the model (or ensemble of models) that minimizes cross-validation prediction error at the individual level. I show, in both a Monte Carlo simulation and empirical application, that this technique produces superior estimates of subnational public opinion under certain conditions. I conclude with guidelines for best practice and some suggestions for future research.

3.2 The MLP Procedure

3.2.1 First-Stage Model Selection

Fundamentally, MRP is an exercise in out-of-sample prediction, using observed opinions from survey respondents to make inferences about the opinions of similar individuals who were not surveyed. As such, first-stage model should be selected on the basis of its out-of-sample predictive performance. Though classical MRP relies on hierarchical linear models, there is no reason *ex ante* to believe that such models will perform best at this task. Indeed, there is a large collection of models from the machine learning literature that may do better.

One potential downside of adopting machine learning techniques is that they tend to be “black box” approaches to prediction. A complicated model may produce better predictions than a simple linear model, but do a poor job explaining the outcome that it is modeling – at least in a manner that is interpretable by a human researcher. The most complex machine learning techniques (e.g. artificial neural networks, random forests) may be intuitive in theory, but in practice it becomes arduous to interrogate such models to determine *why* they reach the conclusions they do. For political science applications where the objective is explanation, such an approach falls short. But since subnational public opinion estimation is fundamentally a *prediction* problem, black box models are perfectly suitable, so long as they produce good predictions.

In what follows, I will introduce two machine learning techniques, K-Nearest Neighbors and Random Forests. I will give a brief overview of their properties in this section, then will demonstrate how to apply them to subnational public opinion estimation.

Random Forests

Random forests, first introduced by Breiman (2001*a*), are an ensemble approach to classification and regression. Rather than estimating a single model, the procedure constructs a large collection of models, then aggregates their predictions together. Each component model is a regression tree, a model that generates predictions by successively partitioning the data on the X variables, taking the average outcome of observations at each terminal node. To ensure that these trees are not all identical, each tree is trained on a bootstrap sample of the dataset (thus the “random” in random forest). The forest prediction is then equal to the mean prediction of the constituent trees. See Breiman (2001*b*) for an excellent primer on these types of models.

One advantage of this approach is that the researcher need not assume that public opinion obeys a prespecified model in order for the poststratified predictions to make sense. Random forest is a popular technique among machine learning algorithms, because it requires few tuning parameters or data preprocessing.

K-Nearest Neighbors

K-Nearest Neighbors (KNN) is an intuitive nonparametric approach to regression. For each observation i , KNN predicts an outcome \hat{y}_i by taking the k most similar observations in the training data (according to some predefined distance metric) and computing the mean of their observed outcomes. In classical KNN, this is an unweighted average of the k -nearest neighbors, but a more general approach uses a weighted average, with weights proportional to inverse distance. In the following exercise, I use the weighting scheme proposed by (Samworth 2012).

As with random forests, the researcher need not assume a model of the DGP in or-

der to produce estimates. Instead, KNN requires a more easily-accepted assumption: that similar people who live in similar places are likely to hold similar opinions.

Another advantage of this approach is that KNN can easily incorporate spatial predictors. For example, if each survey respondent provides their county of residence, then a prediction using KNN could incorporate the latitude and longitude of that county's centroid as predictors. Predictions would then be generated by a weighted average of nearest neighbors in *physical* space as well as some abstract variable-space. If black respondents in Tennessee have systematically different opinions than black respondents in Minnesota, then the KNN prediction would reflect that, without the researcher having to specify a battery of interaction terms in advance.

3.2.2 Cross-Validation

Now that we've introduced a number of possible models that one could use for the first-stage prediction, what is a principled way to go about model selection? If MRP is fundamentally a problem of out-of-sample prediction, then one should go about model selection with this criterion in mind. This naturally leads us to cross-validation.

Cross-validation is a common machine learning technique designed to guard against overfitting. A model is overfit if it produces good predictions for the dataset that was used to estimate it, but performs poorly out-of-sample. This is most likely to occur when a model is overly complex, picking up on chance patterns in the training data. Consider a common case of overfitting in political science research: models that include unit-specific or time period-specific fixed effects. Though these models may be useful for estimating causal effects, they are incapable of generating predicted values for observations outside the time periods or regions found in the training dataset.

To combat this, cross-validation partitions the data into two subsets: the training

set, used to estimate the model’s parameters, and the test set, against which the model’s predictions are compared. By “hiding” part of the data from the model, this procedure allows the researcher to quantify how well a model performs at out-of-sample prediction. K-fold cross validation assigns $\frac{n}{k}$ observations to the test set and the remaining observations to the training set. The researcher then repeats this process k times, until each observation has been in the test set once. In the limit, where $k = n - 1$, this procedure is known as “leave out one” cross-validation (LOO).

Because cross-validation error provides a measure of out-of-sample predictive accuracy, it is a principled way to select from among multiple predictive models (Stone 1974). In the following sections, I will demonstrate that models with better cross-validated predictive accuracy typically produce better poststratified estimates than those that do not.

3.2.3 Poststratification

In addition to guiding the first-stage model selection process, cross-validation can help inform the researcher how best to generate the poststratification frame. Lee-mann & Wasserfallen (2017) introduce a promising refinement to MRP, which they call multilevel regression and *synthetic* poststratification (MrsP). Rather than creating poststratification estimates using the true joint distribution of the demographic variables in the individual-level model, this approach proceeds as if the demographic variables were statistically independent. Then, the poststratification weights can be derived from the product of the marginal distributions, a process they call synthetic poststratification. The authors conduct a Monte Carlo test of this procedure, demonstrating that, so long as the demographic variables are not too strongly correlated with one another, MrsP estimates do not significantly diverge from those of classical MRP.

The advantage of synthetic poststratification is that the first-stage model can include a larger set of individual-level predictors, for which we may not have joint distributions in the poststratification stage. This, however, presents a new problem. How does a researcher know if it's appropriate to use synthetic poststratification? In empirical applications where the joint distribution of interest is unavailable, then we cannot know how correlated the demographic variables are, so we don't know how badly MrsP would perform relative to MRP. In this paper, I propose a remedy for that problem.

In Appendix C, I present a general proof that MrsP and classical MRP produce identical estimates if the first-stage model is additively separable. This suggests a straightforward decision rule for when to use synthetic poststratification. If a linear-additive model outperforms more complex machine learning techniques in the cross-validation stage, then the researcher should proceed with synthetic poststratification, because it allows for the inclusion of more individual-level predictors. If not, then one should use classical MRP or MLP.

3.2.4 Outline of MLP Procedure

Putting it all together, the MLP procedure is summarized in Table 3.1. This procedure varies from classical MRP in two places: (1) choosing a first-stage model based on cross-validated predictive accuracy, and (2) generating the poststratification frame synthetically if the best first-stage model is additively separable. How well does this procedure perform relative to classical MRP? To answer this question, I now turn to a Monte Carlo analysis.

Table 3.1: The MLP Procedure

Step	Procedure
1	Collect individual-level survey data on outcome of interest and predictors.
2	Select the model that minimizes cross-validated prediction error (or maximizes cross-validated R^2). Note: This could include HLM, or an ensemble average!
3	Fit the selected model to the entire dataset.
4	Generate predictions for each respondent type (demographics \times geographic variables)
5	Poststratify by weighting these predictions against the known frequency of each type at the subnational level.
5a	If the best first-stage model is additively separable, then the poststratification frame may be generated synthetically.

3.3 Monte Carlo Simulation

For the following analysis, I simulate a data generating process where the outcome variable (\mathbf{y}) is a function of three demographic variables ($\mathbf{z}_1, \mathbf{z}_2, \mathbf{z}_3$), and geographic location. For simplicity, the DGP is linear-additive, except in two geographic regions, where the Z variables have a multiplicative effect. This produces a nonlinearity we might expect to observe in real data, where some demographic subgroups have very different opinions depending on their geography (e.g. white females in Vermont compared to white females in Georgia).

More formally, the data are generated through the following process. First, I create NM individuals, where M is the number of subnational units, and N is the number of observations per unit. Each individual has four latent (unobserved) characteristics, z_1 through z_4 , drawn from a multivariate normal distribution with mean zero and variance-covariance matrix equal to

$$\begin{bmatrix} 1 & \rho & \rho & \rho \\ \rho & 1 & \rho & \rho \\ \rho & \rho & 1 & \rho \\ \rho & \rho & \rho & 1 \end{bmatrix}$$

The variable \mathbf{z}_4 is used to assign each observation to a subnational unit, which ensures that there is cross-unit variation on the latent characteristics. Each subnational unit, in turn, is assigned a random latitude and longitude, drawn from a bivariate uniform distribution between (0,0) and (1,1). Once I assign each observation a \mathbf{z} vector and subnational unit, I generate the outcome variable, y , using the following equation:

$$y_i = z_{1i} + z_{2i} + z_{3i} + (\alpha D_i^0 z_{1i} z_{2i}) - (\alpha D_i^1 z_{1i} z_{3i}) + \varepsilon_i$$

D^0 is a function that is decreasing in distance from (0,0), and D^1 is decreasing in distance to (1,1) so that multiplicative effects are strongest near those points. ε_i is an iid normal error term with mean zero and variance σ^2 . The parameter α governs the strength of the threeway interaction effect. When $\alpha = 0$, the DGP is simply a linear-additive combination of the demographic variables, but as α increases, the conditional effect of geography becomes stronger. Finally, I create discretized versions of the demographic variables \mathbf{z}_1 through \mathbf{z}_3 , called \mathbf{x}_1 through \mathbf{x}_3 . Although the outcome variable y is a function of the latent variables, Z , the researcher can only observe the discrete variables X .

I repeatedly simulate this data generating process, varying the parameters ρ and α .¹ For each simulated population, I then draw a random sample of size n , and

¹Appendix D provides a more detailed technical description of the simulation. Table D.2 in that appendix lists the combinations of parameter values used.

generate three subnational estimates: disaggregation, classical MRP, and MLP. The first stage equation for the MRP estimation is a hierarchical linear model of the following form:

$$y_i = b_0 + X_{1i}b_1 + X_{2i}b_2 + X_{3i}b_3 + \alpha_j^{unit} + e_i$$

$$\alpha_j^{unit} \sim N(0, \sigma_{unit}^2)$$

For the first stage of the MLP, I train a KNN model using \mathbf{x}_1 , \mathbf{x}_2 , \mathbf{x}_3 , latitude, and longitude as predictors, and LOO cross-validation to select the optimal value of k . I also train a random forest model using the same predictors. I then select the first-stage model, or ensemble average, that minimizes RMSE in 10-fold cross-validation.

Figure 3.1 illustrates the results of a representative run from the Monte Carlo simulation. Under certain conditions, MLP dramatically outperforms both disaggregation and classical MRP. When α is large, the machine learning models are better able to predict individual-level opinion than the hierarchical linear model, which in turn produces better poststratified estimates.

However, the machine learning algorithms do not perform strictly better than HLM under all conditions. When α is small – and thus the true DGP is linear-additive – KNN and random forest provide no prediction advantage over HLM. Indeed, the flexibility of KNN is a detriment when the sample size of the survey is small, as KNN performs poorly when the number of predictors is large relative to the size of the training set (Beyer et al. 1999).²

Nevertheless, the benefits of MLP can be dramatic under some conditions. In cases where α and ρ are large, MRP performs modestly better than disaggregation,

²More precisely, Beyer et al. (1999) show that KNN on high dimensional data will perform poorly regardless of the size of n , owing to the “curse of dimensionality”. Euclidean distance does not meaningfully measure “closeness” in spaces with more than 10-15 dimensions.

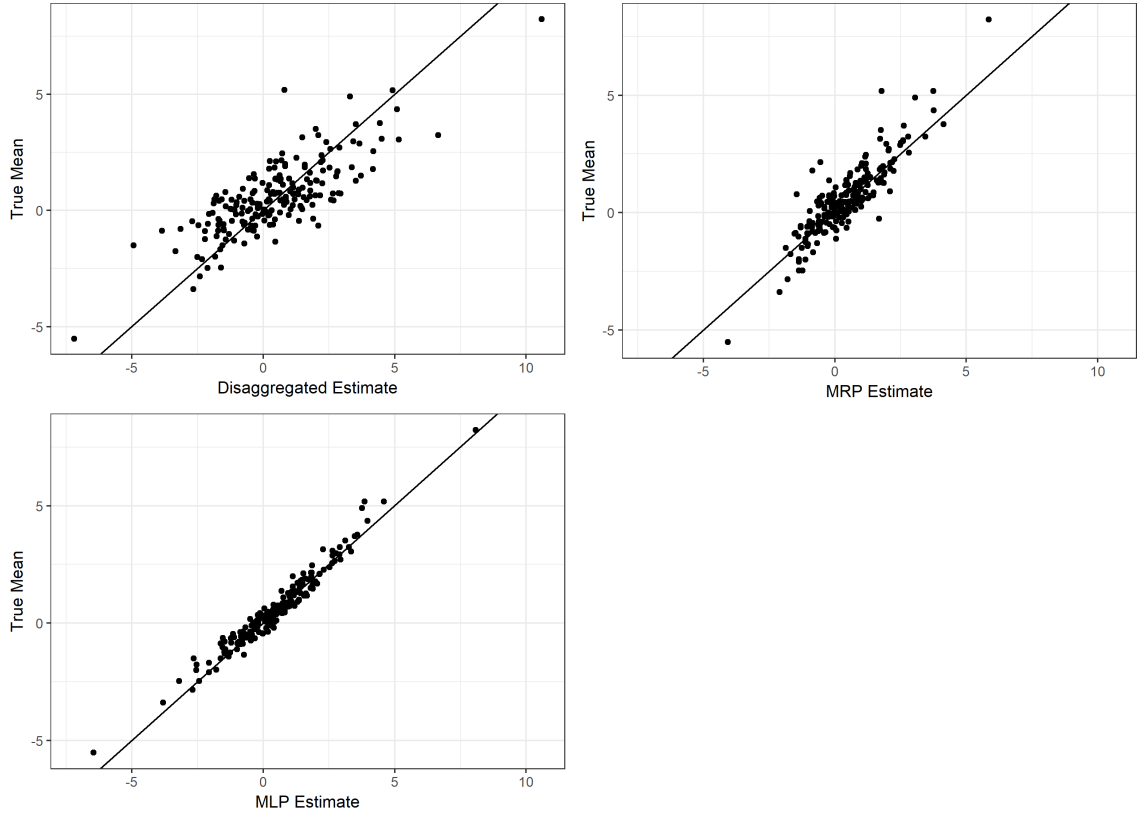


Figure 3.1: Representative simulation from Monte Carlo. Disaggregation, MRP, and MLP estimates are plotted against true subnational unit means. Parameter Values: $\alpha = 5$, $\rho = 0.4$, $N = 15000$, $M = 200$, $n = 5000$, $\sigma^2 = 5$.

while MLP produces estimates that are well-correlated with the true unit means. Figure 3.2 illustrates these relative performance gains for varying levels of α . And the Monte Carlo demonstrates the value of selecting a first-stage model through cross-validation. As Figure 3.3 shows, the model that provides better first-stage predictions typically produces better poststratified estimates as well. And even when MLP underperformed MRP, it never performed *poorly*: the worst correlation produced across all simulations was a 0.92, compared to 0.79 for MRP and 0.35 for disaggregation.

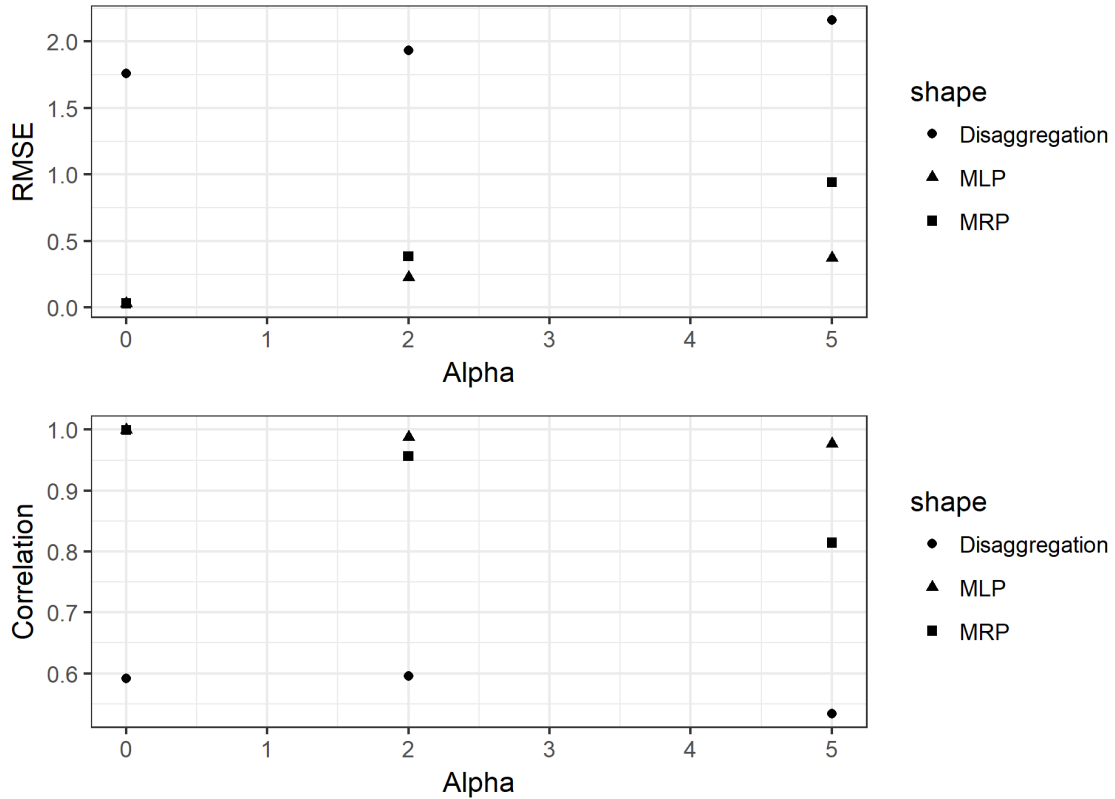


Figure 3.2: Relative performance of disaggregation, MRP, and MLP estimates, varying α . Parameters Used: $\rho = 0.4$, $n = 2000$, $M = 200$, $N = 15000$, $\sigma^2 = 5$.

3.4 Empirical Application: 2016 US Presidential Election

How does MLP perform in an empirical application? In this section, I demonstrate that US county-level MLP estimates of “Trumpist” public opinion (which I will define in a moment) correlate very well with actual county-level presidential vote share in 2016, outperforming disaggregation and classical MRP.

For individual-level survey data, I draw on the 2016 Cooperative Congressional Election Survey (CCES), an extensive survey of over 64,000 Americans conducted prior to the 2016 presidential election (Ansolabehere & Schaffner 2018). From that survey, I collect responses on vote choice, demographics, and geography, as listed in Table 3.2. Note that, even in such a large survey, estimating county-level public

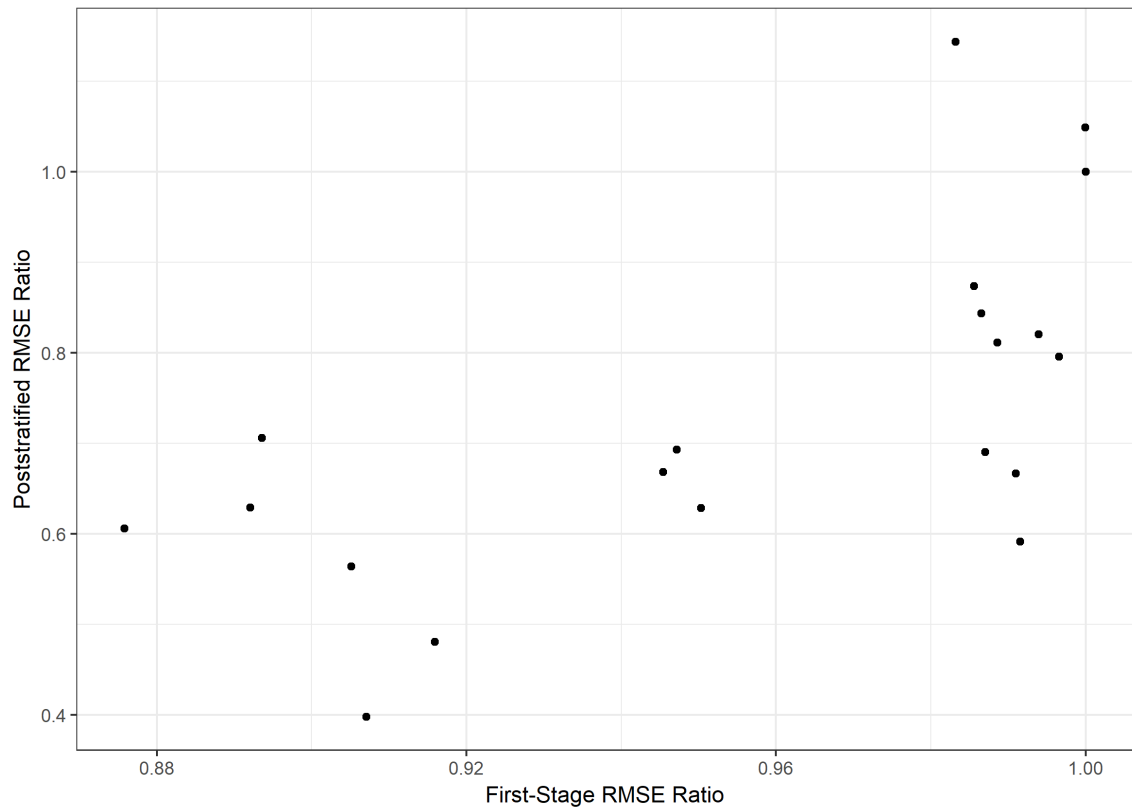


Figure 3.3: When machine learning outperforms HLM at individual-level prediction, MLP typically produces better poststratified estimates than MRP. Here, the ratio of root mean square error (RMSE) in the first stage is plotted against the RMSE ratio for the poststratified estimates.

Table 3.2: Summary of variables included in first-stage models.

Variable	Level	Values	Source
Trumpism	Individual	See Appendix 3	CCES 2016
Race	Individual	{White, Black, Hispanic, Other}	CCES 2016
Age	Individual	{18-29, 30-44, 45-64, 65+}	CCES 2016
Female	Individual	{0,1}	CCES 2016
Education	Individual	{No HS, HS, Assoc's Degree, Bachelor's Degree, Postgraduate}	CCES 2016
Latitude/Longitude	County		Census US Gazetteer Files (2016)
Percent Veterans	County		American Community Survey (2012-2016)
Percent Urban	County		Decennial Census (2010)
Median Household Income	County		American Community Survey (2012-2016)
Percent Evangelical or Mormon	State		Pew Religious Landscape Survey (2014)

opinion through disaggregation alone is impractical. With over 3,000 counties in the United States, CCES contains roughly 20 observations per county on average. Since respondents are not drawn uniformly across counties, nearly half of the counties have five or fewer respondents in the CCES sample.

And so, if we want to estimate county-level public opinion, we will need a model-based approach. To begin, I first generate the outcome variable. One approach would be to simply use a dichotomous variable indicating whether the respondent planned to vote for Trump in 2016. For this exercise, however, I will instead generate a continuous variable measuring “Trumpist” public opinion. In this way, I am not throwing out large amounts of useful information on preference intensity.

To generate this continuous variable, I first collect the responses to twenty questions on some of the most salient issues of the 2016 presidential campaign: immigration, gun control, criminal justice, trade, healthcare, and environmental regulation. These variables are catalogued in Appendix E, Table E.1. I then conduct a principal component analysis, taking the first component as my measure of Trumpism. This measure is strongly correlated with self-reported intention to vote for Trump.

With this measure in hand, I then use the cross-validation procedure to select the best-fitting individual-level model. The hierarchical linear model is of the following form:

$$\begin{aligned}
y_i &= \alpha_0 + \alpha_{j[i]}^{female} + \alpha_{k[i]}^{race} + \alpha_{l[i]}^{education} + \alpha_{m[i]}^{age} + \alpha_c^{county} + \varepsilon_i \\
\alpha_{j[i]}^{female} &\sim N(0, \sigma_{female}^2) \\
\alpha_{k[i]}^{race} &\sim N(0, \sigma_{race}^2) \\
\alpha_{l[i]}^{education} &\sim N(0, \sigma_{education}^2) \\
\alpha_{m[i]}^{age} &\sim N(0, \sigma_{age}^2) \\
\alpha_c^{county} &\sim N(\alpha_s^{state} + \beta X_c, \sigma_{county}^2) \\
\alpha_s^{state} &\sim N(\beta X_s, \sigma_{state}^2)
\end{aligned}$$

X_c and X_s are matrices of county-level and state-level variables, respectively, as reported in Table 3.2. I also train a KNN model (optimal cross-validated fit at $k = 23$) and a random forest, using the predictor variables in Table 3.2.

The cross-validated prediction error and correlations for each of these models are listed in Table 3.3. Of the three models, HLM performs the best. However, the best fitting predictions overall come not from a single model, but from an *ensemble model average*, taking the mean prediction of the hierarchical linear model and KNN. This reflects the advantages of combining diverse models into a single prediction (Page 2008, Montgomery et al. 2012).

Poststratifying the predictions from the HLM at the county-level yields my MRP estimates, and poststratifying the EMA predictions yields my MLP estimates. I also generate disaggregated estimates, taking the county-level mean of my outcome variable. Figure 3.4 compares these estimates against the true 2016 presidential vote

Table 3.3: First-stage 10-fold cross-validation results. An ensemble model average of the hierarchical linear model and KNN (italicized) performs best.

Model	RMSE	Correlation
Hierarchical Linear Model	1.022	0.332
K-Nearest Neighbors	1.043	0.302
Random Forest	1.058	0.289
<i>Ensemble Model Average (HLM + KNN)</i>	<i>1.019</i>	<i>0.338</i>
Ensemble Model Average (HLM + KNN + RF)	1.023	0.333

shares by county. Clearly, disaggregation fares worst, particularly in small counties with few CCES respondents. MRP and MLP both perform significantly better, while MLP is the most strongly correlated of the three.

Although MLP’s performance improvement seems modest when looking at the country as a whole, the difference is striking at the state-level. Figure 3.5 plots a few illustrative examples, while Figure 3.6 gives a more comprehensive overview. Within nearly every state, MLP correlates better with 2016 results than does MRP, and in some cases dramatically so.

3.5 Conclusion

In this paper, I have developed a generalization of MRP, which expands set of candidate first-stage models. Machine learning algorithms can produce significant improvements in local area public opinion estimates, particularly when the relationship between opinion and demographic variables is nonlinear. It is important to note, however, that MLP does not always produce better estimates than classical MRP. As the Monte Carlo analysis demonstrates, MLP will only outperform MRP when the data generating process is complex, with nonlinear interactions that are unlikely to be specified in advance by the researcher’s model. Fortunately, cross-validation provides a principled method to determine whether MLP is likely to outperform MRP, and to select from among this new menagerie of first-stage models.

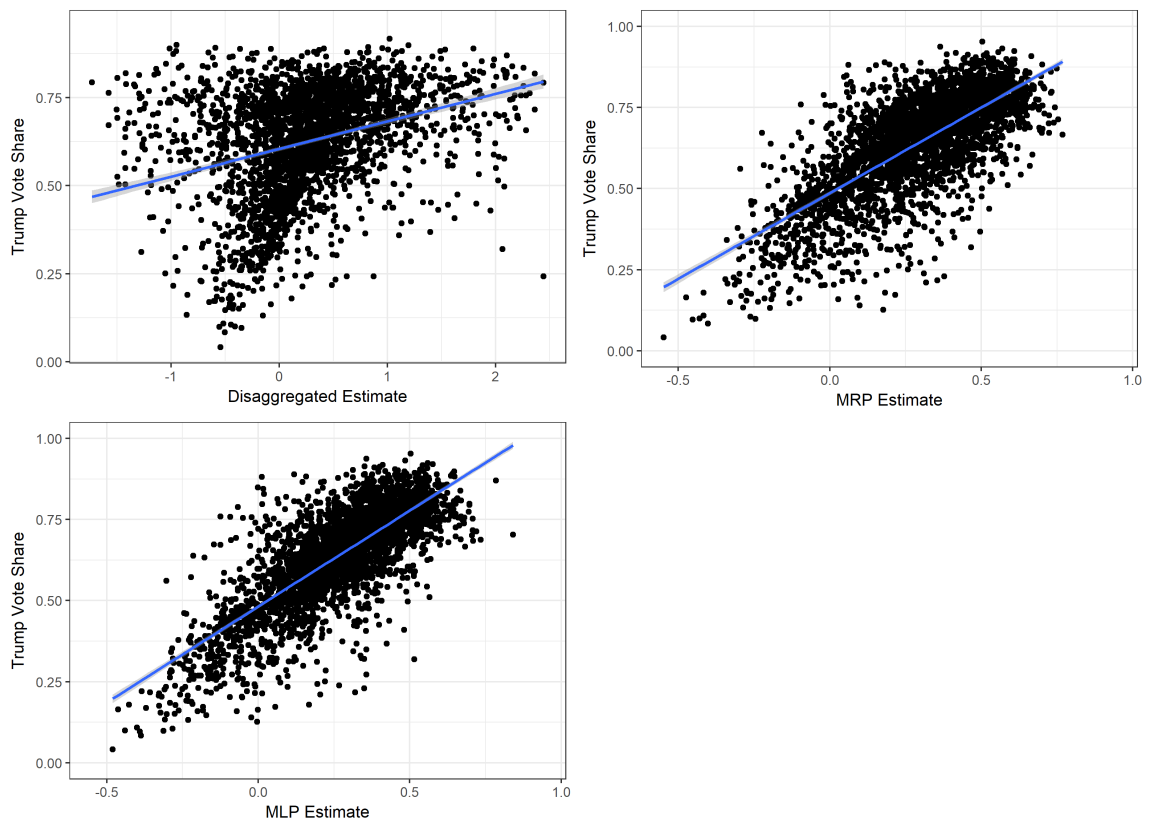


Figure 3.4: Trump 2016 vote share plotted against disaggregated, MRP, and MLP estimates. Correlations are 0.32, 0.72, and 0.77 respectively.

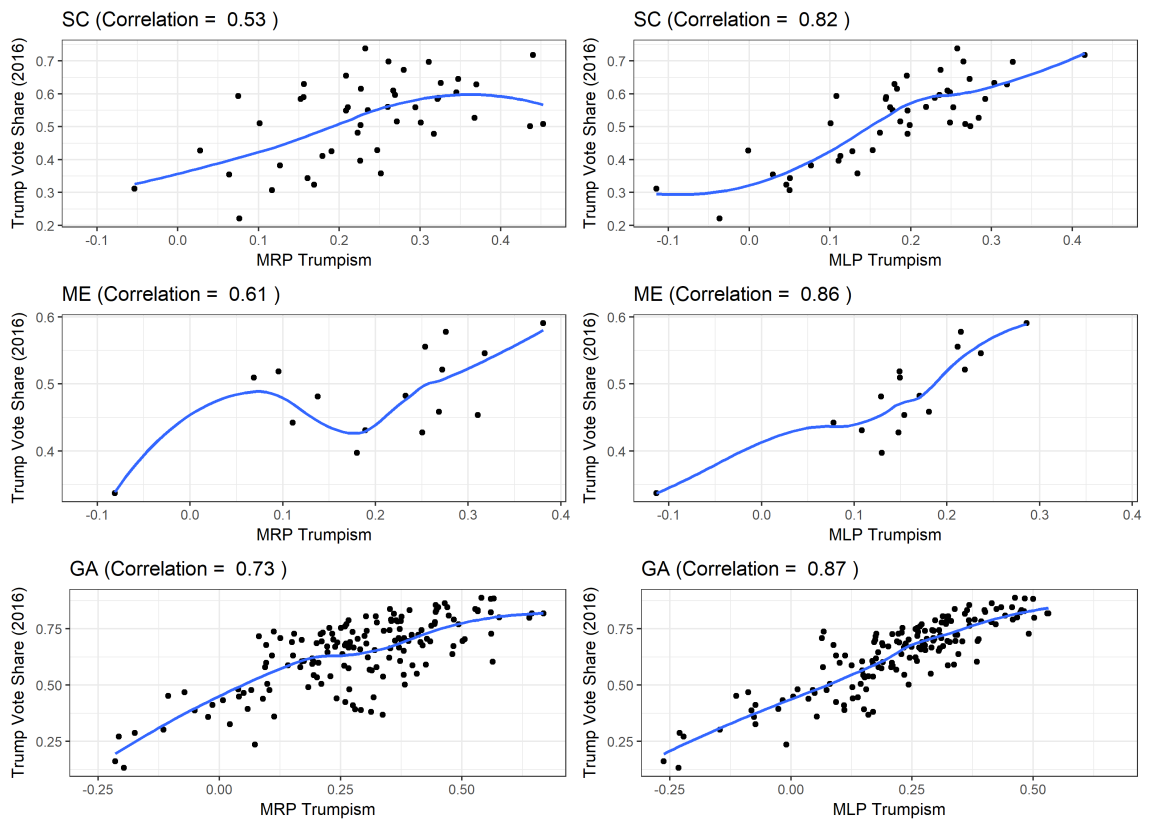


Figure 3.5: MLP and MRP estimates in select states, plotted against 2016 presidential vote shares.

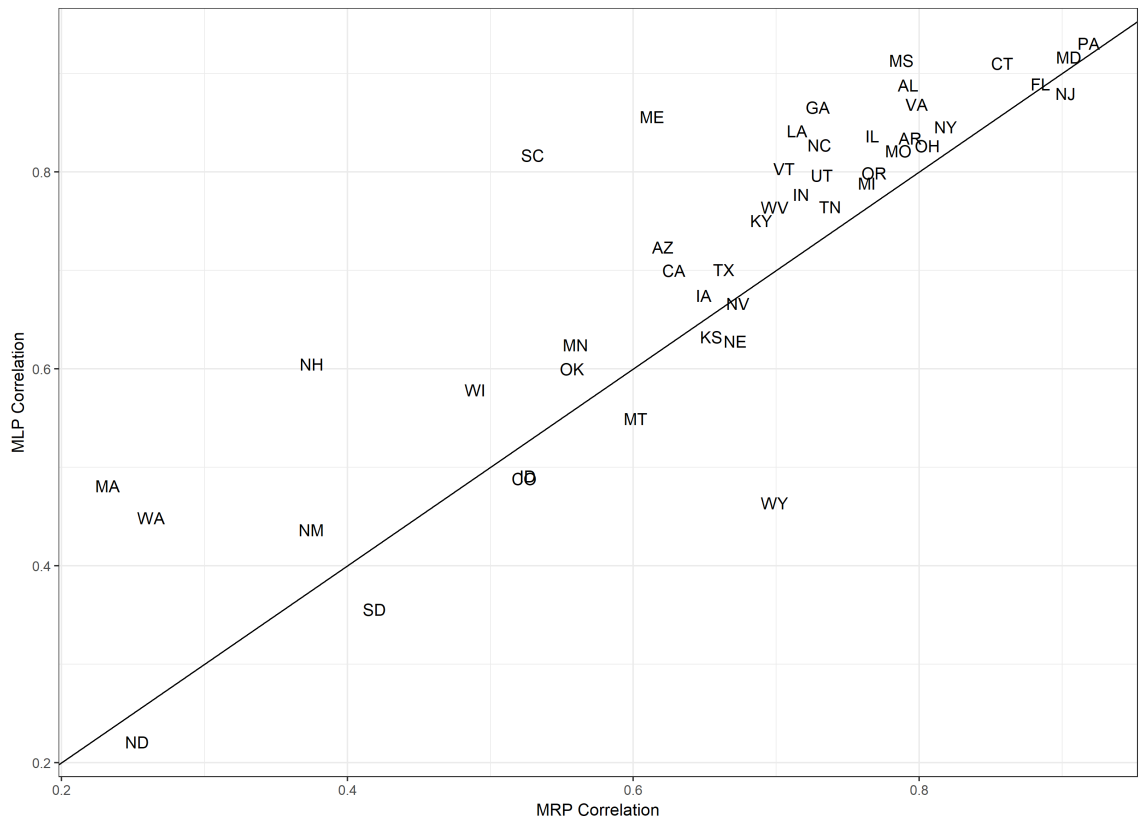


Figure 3.6: MLP and MRP county-level correlations with 2016 presidential vote share by state. In nearly all cases, MLP outperforms MRP, in some cases considerably.

In future work, I hope to further expand the set of MLP first-stage models. Although I focus in this paper on random forest and KNN, there may perhaps be other techniques better-suited to modeling public opinion. Other methodological research could test the technique on a broader range of issue areas, and see if there are particular public opinion topics where it performs poorly relative to MRP. And I hope that MLP proves to be a useful addition to the empirical social scientist's toolbox, spurring further research into subnational politics.

CHAPTER IV

Zone Defense: Why Liberal Cities Build Fewer Houses

In this paper, I investigate a puzzling feature of American urban politics: cities with more liberal residents tend to permit fewer new housing units each year than similar conservative cities. Empirically, I show that this relationship is not attributable to differences in income, demographics, geography, or characteristics of the housing stock. To help explain this puzzle, I develop a formal model of municipal zoning policy. In this model, liberal cities are characterized by generous levels of public goods spending. This, in turn, attracts new households, who have an incentive to construct inexpensive housing. If permitted to do so, the added property tax revenue from these new households would be insufficient to cover their share of public spending. In a spatial sorting equilibrium, any city that offers generous public goods spending must also enact restrictive zoning to defend it.

4.1 Introduction

This paper is motivated by a puzzling feature of contemporary American urban politics. In the decade since the Great Recession, home prices have once again reached record highs in cities across the United States. But the cities with the most acute housing affordability problems are overwhelming liberal, while conservative cities remain quite affordable by comparison. Figure 4.1 illustrates this stylized fact: cities that voted for Obama in 2008 tend to have more expensive housing relative to their median income. The average home in Mesa, Arizona costs three years of the median household's income, while in San Francisco, that figure is closer to ten years.

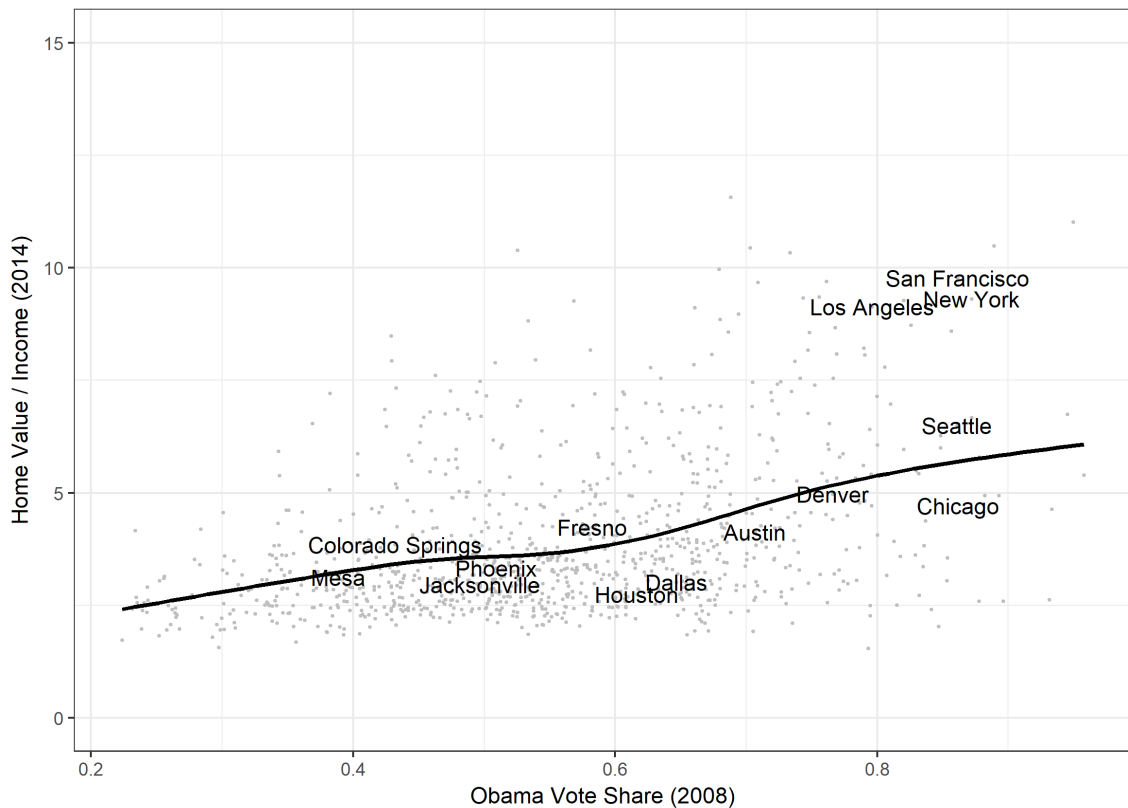


Figure 4.1: Median home value, as a fraction of median income, is higher on average in liberal cities. Sample consists of all US cities with a population greater than 10,000 (shrinking cities excluded). Solid line is a moving average, with select cities labeled.

There are, of course, a large set of confounding factors that might explain this

pattern: liberal cities tend to be coastal, more historic, have higher incomes, have more educated residents, and less available land for housing development, all of which tend to increase home prices. But in this paper's empirical analysis, I show that these confounding factors alone cannot fully explain the home price difference between liberal and conservative cities. Instead, this effect appears attributable to differences in housing supply elasticity: liberal city governments permit fewer new housing units when faced with increasing demand, and they impose more stringent zoning regulations on new residential development.

The ill effects of such regulations are, at this point, well-documented. Because home prices must rise when increasing demand for housing is not met by increasing supply, the most regulated US cities tend to have higher rents than we would expect from construction costs and wages alone (Glaeser & Gyourko 2003, Quigley & Raphael 2005). In turn, these excess housing costs can have profound effects on the broader economy. For one, they slow economic growth by pricing workers out of cities where they would be most productive. One estimate suggests that easing housing restrictions in the three most productive US cities alone would increase aggregate GDP by roughly 9.5% (Hsieh & Moretti 2015). Second, by pricing poorer households out of more affluent areas, growth control policies exacerbate residential segregation, both by race (Rothwell & Massey 2009) and by income (Rothwell & Massey 2010). Such segregation has been shown to affect civic participation (Oliver 1999), public goods provision (Alesina et al. 1999, Trounstein 2015), and even life expectancy (Chetty et al. 2016). Third, density restrictions in central cities promote suburban sprawl, which increases both commuting costs and carbon emissions (Glaeser & Kahn 2010). Finally, such restrictions may contribute to widening income inequality. Rognlie (2015) finds that the increase in capital's share of income

since 1948 can be attributed *entirely* to an increase in the return to housing, something that could not have occurred if the housing supply were more flexible over that period.

Why then, do liberal cities implement more restrictive zoning than their conservative counterparts? On its face, the fact seems paradoxical, given American liberalism's emphasis on raising wages, combating segregation, reducing carbon emissions, and promoting public transit.

To help explain this puzzle, I develop a formal model of municipal zoning. Agents in the model consume three types of goods: public goods, housing, and non-housing private goods. City governments tax housing and supply public goods, and agents allocate their income net of taxes on housing and the bundle of private goods. Liberal agents place a higher value on public goods relative to private consumption, and seek out municipalities that tax and spend generously. However, in a world with free migration, cities with generous public spending tend to attract low-income households. If these new migrants are permitted to construct inexpensive housing, then the property tax revenue they contribute would be insufficient to cover their share of public services. This provides liberal cities with an incentive to impose restrictive zoning policies, mandating that newcomers consume some minimum amount of housing in order to live in the jurisdiction.

The paper proceeds in five parts. In the next section, I provide a brief introduction to municipal zoning policies, and review the existing explanations in the literature for their existence. In section three, I develop the formal model, and in section four I present my empirical analysis, demonstrating that liberal cities issue fewer new building permits, have more expensive housing, and score higher on a survey-based measure of land use regulation. Section five concludes.

4.2 Municipal Zoning: Background

Residential construction in the United States is heavily regulated by municipal governments. Zoning authority, upheld as constitutional by the landmark 1926 Supreme Court case *Euclid v. Ambler*, grants municipal governments broad discretion to regulate land use within their boundaries. This zoning power takes many forms. The most common is Euclidean zoning, which divides the entire municipality into zones, within which there is a single permitted land use (e.g. residential, commercial, industrial).¹ This separation of uses, de rigeur among mid-century urban planners, has largely fallen out of fashion of late, but nearly all US municipal governments maintain some form of Euclidean zoning.

Even cities without explicit Euclidean zoning codes retain many of its features. Other forms of land use regulation include permit limits, open space requirements, minimum lot sizes, setback requirements, parking minimums, and building height restrictions. Houston, for example, is notable for being the only major American city without a Euclidean zoning code. Nevertheless, the city strictly regulates residential land use, requiring minimum lot sizes, setbacks, and off-street parking for all new residential developments. These regulations have promoted a sprawling, auto-dependent pattern of residential development (Lewyn 2005).

Why do municipal governments enact these policies restricting new housing growth? This question is itself puzzling, especially in light of much of the foundational work in American urban politics. Molotch (1976) famously describes the city as a “growth machine”, a political entity whose principal aim is to promote business interests

¹A common misconception is that the name “Euclidean zoning” is an homage to Euclid the ancient Greek geometrician. It is actually a reference to the town of Euclid, Ohio, whose pioneering zoning code was the subject of the aforementioned Supreme Court case. In a twist on the twist, however, the town of Euclid was itself named for Euclid the mathematician after it was settled by Case Western Reserve cartographers in the 1700s. So the original misconception is, in a way, partly correct (Wolf 2008).

through population growth. Broadly speaking, there are three prominent explanations in the literature for the widespread prevalence of municipal zoning.

In the urban economics literature, zoning regulations are often depicted as a form of benevolent urban planning. Euclidean zoning can separate polluting industries from residential areas, improving public health. Unplanned urban growth produces negative externalities like traffic congestion, environmental degradation, loss of historic buildings, and crowding of natural amenities. Given these externalities, a local government can increase social welfare within its boundaries by limiting the rate of population growth (Cooley & LaCivita 1982, Brueckner 1990).

The most prominent political economy explanation for restrictive zoning policies is the “Homevoter Hypothesis” (Fischel 2001), which views zoning as a means through which homeowners can insure the value of their property. For many Americans, a house is the single most valuable item in their investment portfolio, it is financed heavily by debt, and its value is strongly tied to local economic shocks. Given this precarious financial situation, homeowners are likely to support public policies that protect the value of their greatest asset (Scheve & Slaughter 2001). Empirically, American homeowners are much more likely to be involved in municipal politics than renters, for whom financial security is not as closely tied to the health of the local real estate market (Dipasquale & Glaeser 1999). Although the evidence for this hypothesis is compelling, the Homevoter Hypothesis itself does not explain why liberal cities would zone more strictly than conservative cities, particularly given that conservative cities tend to have a larger share of homeowners.

Finally, there is the literature on “fiscal zoning”, which motivates this paper’s model. According to this theory, restrictive zoning policies arise as a response to the fiscal constraints faced by local governments. As Peterson (1981) notes, cities

are inherently limited in their choice of public spending policies. Due to labor and capital mobility, redistributive transfers are particularly difficult to enact at the local level, except when there are relatively few jurisdictions (Epple & Romer 1991) or substantial sources of intergovernmental revenue (Craw 2010). Hamilton (1975) proposes a solution to this problem: if cities restrict housing development, they can increase the cost of housing in their jurisdictions, deterring entry by poor households. This allows residents to enact their preferred package of taxes and spending without concern that it will spark new migration.

Subsequent political economists have developed this hypothesis further. Brueckner (1997) argues that exactions – up-front fees paid by developers to finance local public services – are an efficient way to finance the fixed costs of new infrastructure. Ding et al. (1999) suggest that if local public goods are congestible, then instituting an urban growth boundary, a boundary beyond which development must be low-density, can increase aggregate welfare. In many municipalities, planning documents explicitly cite strains on public service provision as the reason for enacting growth controls (Molotch 1976). Empirical studies suggest that this proposed link between growth controls and citizens’ preferences for public goods has merit. Gerber & Phillips (2003) find that San Diego residents are more likely to support pro-growth ballot initiatives if they result in increased local public goods provision, and that developers are more likely to finance new public goods in cities with direct democracy requirements for new housing development (Gerber & Phillips 2004). The formal model I develop in the next section proceeds from this insight.

4.3 The Model

4.3.1 Setup

The model consists of n agents and m cities. Agents are free to migrate between cities, and each agent seeks to maximize a utility function of the following form:

$$(4.1) \quad U_i = g_i^{\alpha_i} H_i^{\beta_i} c_i^{1-\alpha_i-\beta_i}$$

where g_i denotes public goods consumption, H_i is housing consumption, and c_i is consumption of non-housing private goods.² The parameters β_i and α_i denote agent i 's ideal share of spending on housing and public goods, respectively. We can think of the α_i parameter as an agent's "liberalism": agents with higher α are more willing to forego private consumption in exchange for public goods.

Each city taxes housing consumption and supplies public goods, the value of which is divided equally among city residents. Rewriting equation 4.1 yields the following utility for agent i living in city j :

$$(4.2) \quad U_{ij} = (t_j \bar{H}_j)^{\alpha_i} H_i^{\beta_i} (y_i - t_j H_i - H_i)^{1-\alpha_i-\beta_i}$$

where t_j is the tax rate in city j , \bar{H}_j is average housing consumption of residents in city j , and y_i is agent i 's exogenous pre-tax income.

Upon moving to a new jurisdiction, agent i chooses its optimal level of housing consumption, taking the city's current tax and spending policies as fixed. Solving the first order condition yields this optimal H_i^* .

$$\begin{aligned} \frac{\partial U_i}{\partial H_i} &= (t_j \bar{H}_j)^{\alpha_i} \beta_i H_i^{\beta_i-1} (y_i - t_j H_i - H_i)^{1-\alpha_i-\beta_i} \\ &+ (t_j \bar{H}_j)^{\alpha_i} H_i^{\beta_i} (1 - \alpha_i - \beta_i)(-1 - t_j) (y_i - t_j H_i - H_i)^{-\alpha_i-\beta_i} = 0 \end{aligned}$$

²For the purpose of this model, housing consumption can represent either rented housing or mortgage payments by a homeowner.

$$(1 + t_j)(1 - \alpha_i - \beta_i)H_i = \beta_i(y_i - t_jH_i - H_i)$$

$$(4.3) \quad H_i^* = \frac{\beta_i y_i}{(1 - \alpha_i)(1 + t_j)}$$

Each city's tax and spending policy is determined by majority vote, setting t_j to the median voter's ideal tax rate (equation 4.4).

$$\begin{aligned} \frac{\partial U_i}{\partial t_j} &= \alpha_i \bar{H}_j (t_j \bar{H}_j)^{\alpha_i - 1} H_i^{\beta_i} (y_i - t_j H_i - H_i)^{1 - \alpha_i - \beta_i} \\ &+ (t_j \bar{H}_j)^{\alpha_i} H_i^{\beta_i} (1 - \alpha_i - \beta_i)(-H_i) (y_i - t_j H_i - H_i)^{-\alpha_i - \beta_i} = 0 \end{aligned}$$

$$(1 - \alpha_i - \beta_i)t_j H_i = \alpha_i (y_i - t_j H_i - H_i)$$

$$(4.4) \quad t_i^* = \frac{\alpha_i (y_i - H_i)}{(1 - \beta_i)H_i}$$

All else equal, citizens with higher α_i prefer higher taxes, as do citizens with greater disposable income $(y_i - H_i)$.

Finally, citizens also vote on whether to enact a zoning policy, represented in the model by a housing consumption floor, requiring new residents to consume some minimum amount of housing. This is the model's analogue to policies like minimum lot sizes, parking requirements, or other density restrictions that increase the amount of housing a person must consume in order to live in a jurisdiction.

4.3.2 An Analytic Solution

I will solve the full model with heterogeneous income and preferences computationally. But to first grasp the intuition for why liberal jurisdictions may be more willing to enact restrictive zoning policies, let us solve a simplified version of the model analytically. Suppose that every agent has identical income and preferences

($y_i = y$, $\alpha_i = \alpha$, $\beta_i = \beta$ for all i). Using this simplified model we can prove a series of propositions.

Proposition 1. *There exists a Pareto efficient outcome in which each citizen consumes $\frac{(\alpha+\beta)y}{1+t}$ units of housing.*

Proof of Proposition 1. When each citizen has identical income and preferences, a Benevolent Urban Planner would set a uniform H_i to maximize utility (equation 4.2).

$$\begin{aligned} \frac{\partial U}{\partial H} &= \alpha t (tH)^{\alpha-1} H^\beta (y - tH - H)^{1-\alpha-\beta} \\ &\quad + (tH)^\alpha \beta H^{\beta-1} (y - tH - H)^{1-\alpha-\beta} \\ &\quad + (tH)^\alpha H^\beta (1 - \alpha - \beta)(-1 - t) (y - tH - H)^{-\alpha-\beta} = 0 \\ (1 + t) (1 - \alpha - \beta) H &= (\alpha + \beta) (y - tH - H) \end{aligned}$$

$$(4.5) \quad H^* = \frac{(\alpha + \beta)y}{1 + t}$$

Note that, substituting the preferred tax rate from (4.4) into (4.5) yields $H^* = \beta y$, $t^* = \frac{\alpha}{\beta}$, and $t^* H^* = \alpha y$, which equals the allocation of income that maximizes the Cobb-Douglas utility function. No agent can increase its utility by consuming more than H^* . And if any agent consumed less than H^* , it would harm every other agent by reducing \bar{H} . Therefore, this is a Pareto efficient outcome.

Proposition 2. *The social optimum is not a stable equilibrium. Agents have an incentive to consume less than the Pareto efficient quantity of housing (i.e. $H_i^* < H^*$).*

Proof of Proposition 2. We have already shown that an agent selecting its optimal housing consumption (taking \bar{H}_j as fixed) will select H_i^* from equation 4.3. To see

that this quantity is strictly less than the Pareto efficient quantity, note that $H_i^* < H^*$ is equivalent to:

$$\begin{aligned}\frac{\beta y}{(1-\alpha)(1+t)} &< \frac{(\alpha+\beta)y}{1+t} \\ \frac{\beta}{1-\alpha} &< \alpha+\beta \\ \alpha+\beta &< 1\end{aligned}$$

which is true by construction.

Proposition 2 implies that the Pareto efficient outcome is unattainable in equilibrium without zoning controls. New migrants (even those with identical income and preferences to incumbent households!) have an incentive to spend less than incumbent residents on housing consumption, thereby receiving proportionally more in public goods than they contribute in taxes.

The next proposition demonstrates that incumbent residents are harmed by a reduction in \bar{H} , and therefore have an incentive to implement a housing consumption floor. This incentive is strongest in cities with high α , where residents place a higher value on public goods consumption.

Proposition 3. *Decreasing \bar{H} below H^* harms incumbent households (i.e. $\frac{\partial U}{\partial \bar{H}} > 0$), and this disutility is larger for communities with higher α (i.e. $\frac{\partial^2 U}{\partial \bar{H} \partial \alpha} > 0$).*

Proof of Proposition 3. Taking the first order condition of (4.2) with respect to \bar{H} yields:

$$\frac{\partial U}{\partial \bar{H}} = \alpha t (t\bar{H})^{\alpha-1} H^\beta (y - tH - H)^{1-\alpha-\beta}$$

Substituting the values of H^* and t^* from the Pareto efficient outcome reduces this

equation to:

$$\begin{aligned}\frac{\partial U}{\partial \bar{H}} &= \alpha \frac{\alpha}{\beta} (\alpha y)^{\alpha-1} (\beta y)^\beta ((1-\alpha-\beta)y)^{1-\alpha-\beta} \\ &= \alpha^{\alpha+1} (1-\alpha-\beta)^{1-\alpha-\beta} \beta^{\beta-1}\end{aligned}$$

This expression is strictly greater than zero, implying that incumbent households would be willing to incur some cost to ensure that newcomers do not consume less than H^* units of housing. The magnitude of this marginal disutility, in turn, depends on the value of α .

$$\frac{\partial^2 U}{\partial \bar{H} \partial \alpha} = [\alpha^\alpha (\alpha + \alpha \ln \alpha + 1) (1-\alpha-\beta)^{1-\alpha-\beta} - \alpha^{\alpha+1} (1-\alpha-\beta)^{1-\alpha-\beta} (\ln(1-\alpha-\beta) + 1)] \beta^{\beta-1}$$

This expression is positive if:

$$\begin{aligned}\alpha + \alpha \ln \alpha + 1 &> \alpha (\ln(1-\alpha-\beta) + 1) \\ \ln \alpha + \frac{1}{\alpha} &> \ln(1-\alpha-\beta) \\ \alpha e^{\frac{1}{\alpha}} &> 1-\alpha-\beta\end{aligned}$$

The left hand side of this expression is strictly greater than 1 for positive values of α , and the right hand side is strictly less than 1 by construction, completing the proof.

Putting this all together, we have demonstrated two important results. First, even in a model with homogeneous income and preferences, new migrants to a city have an incentive to consume less than the Pareto efficient quantity of housing. This suggests that there is some level of “optimal zoning”, which raises average housing consumption and produces a Pareto improvement relative to the noncooperative equilibrium. Second, the disutility from a decrease in average housing consumption is strongest in liberal jurisdictions, where residents place a greater value on public goods consumption. This suggests that liberal cities will be more willing to impose zoning restrictions than conservative cities, all else equal.

4.3.3 A Computational Solution

What if income and preferences are heterogeneous? Do the results we've proven above still hold? To address this question, we will solve a heterogeneous preferences version of the model computationally. The behavior of agents and city governments is identical to that described above, and the computational model proceeds as follows:

Setup.

1. Create n agents with random values of y_i , α_i , and β_i , subject to the condition that $\alpha_i + \beta_i < 1$. These parameters are uncorrelated.
2. Assign m agents to m cities. These agents are the “founders”, and they set each city's initial policy to their personal optimum: $H_i = \beta_i y_i$, $t_j = \frac{\alpha_i}{\beta_i}$.
3. Let the exogenous parameter z denote the cost of implementing a zoning restriction. Each resident in the jurisdiction compares this cost against their marginal disutility from a reduction in \bar{H}_j . If $\frac{\partial U_i}{\partial H_j} > z$, they vote to impose a housing consumption floor at \bar{H}_j . Majority rules.

Main Loop.

1. One agent is randomly selected to move.
2. The agent moves to the jurisdiction where it would receive the highest utility (taking \bar{H}_j and t_j as fixed). The agent consumes housing equal to H_i^* or the minimum housing consumption floor set by that jurisdiction, whichever is largest.
3. All agents vote for their preferred tax rate and zoning policy. Each city implements the median policy preference of its residents.

The main loop executes until no agent can improve its utility by moving to a new

Experiment	y	α	β	z	n	m
1	100	0.25	0.5	Large	10,000	50
2	100	0.25	0.5	0	10,000	50
3	100	\sim Uniform (0, 0.5)	0.5	0.15	10,000	50
4	\sim Uniform (0, 200)	\sim Uniform (0, 0.5)	0.5	0.15	10,000	50

Table 4.1: Parameter combinations for computational model experiments.

city. To explore the behavior of the model, I conduct four computational experiments, summarized in Table 4.1.

Experiments 1 and 2 replicate the conditions of our simplified analytic model, and it produces the expected outcomes. In Experiment 1, zoning is prohibitively costly, so no jurisdiction implements it. As a result, agents consume a quantity of housing below the Pareto optimum ($\beta y = 50$). In Experiment 2, zoning is costless, so every city implements it. This yields a Pareto improvement, as illustrated in Figure 4.2.

In Experiment 3, agents have heterogeneous values of α_i . As in Tiebout (1956), agents sort themselves into communities with similar values of α , seeking their preferred mix of taxation and public spending. Zoning is costly, but not prohibitively so. As a result, the cities with higher average values of α_i are more willing to bear the cost of zoning, and are therefore more likely to impose zoning restrictions. Figure 4.3 plots this relationship.

The relationship between mean α_i and zoning restrictions is even more pronounced when we introduce heterogeneous income in Experiment 4 (Panel B). All else equal, lower income agents are more attracted to wealthy, liberal cities that offer generous public goods provision. This comes at a greater cost for liberal households than it does in comparatively wealthy conservative cities. And so the model generates the relationship we observe in the empirical analysis, described in the following section.

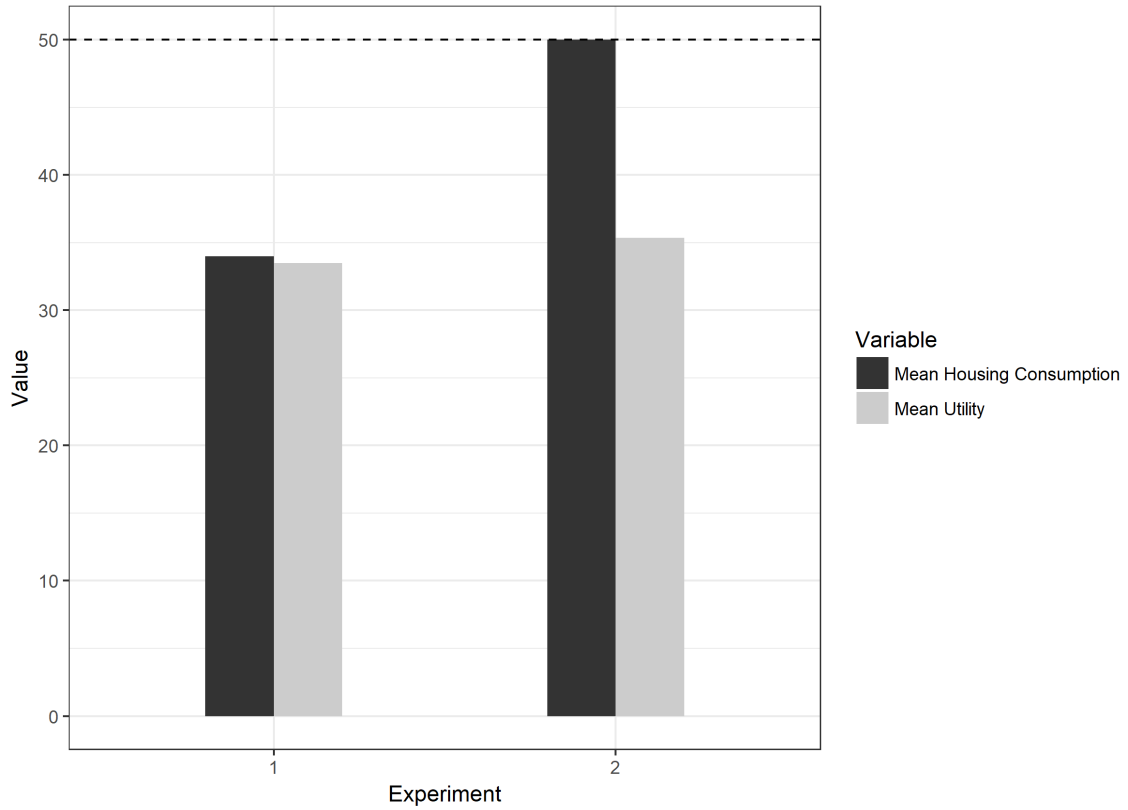


Figure 4.2: With homogeneous income and preferences, the computational model performs as predicted by the analytic solution. When zoning is prohibitively costly (Experiment 1), housing consumption falls below the Pareto optimum. When zoning is costless (Experiment 2), cities attain the Pareto efficient outcome. The dashed line marks the Pareto efficient level of housing consumption $H^* = \beta y$.

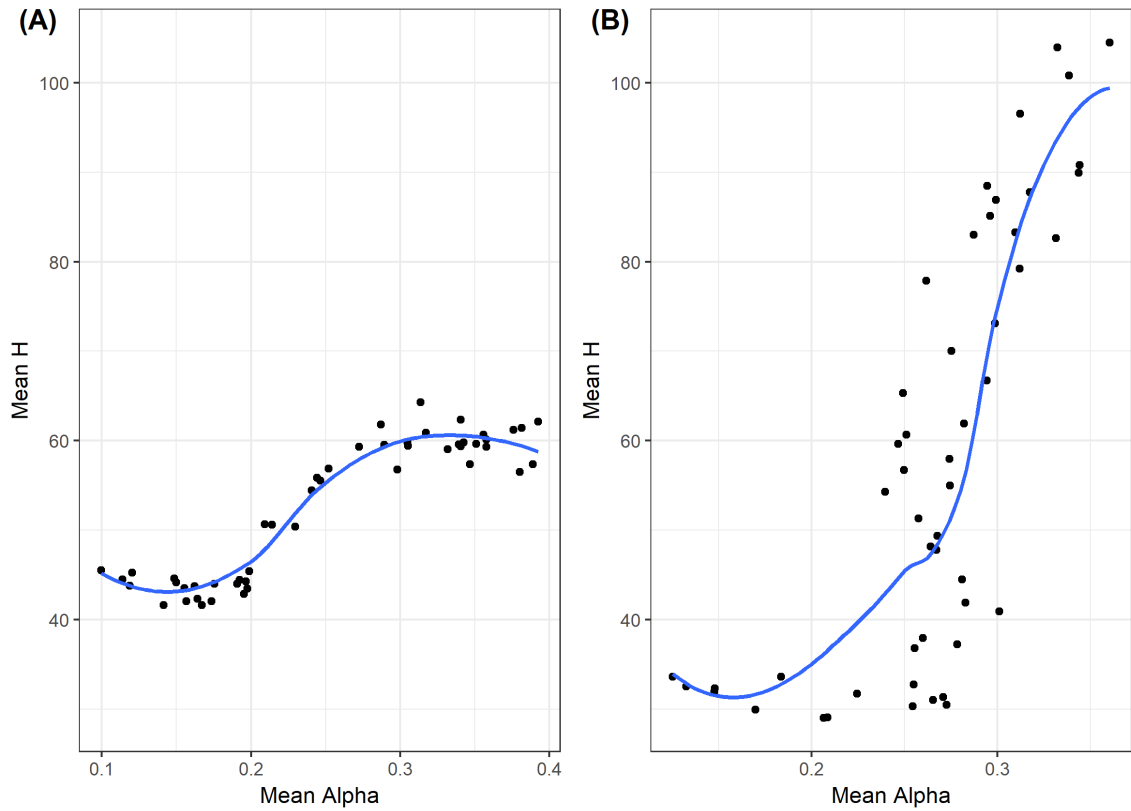


Figure 4.3: With heterogeneous preferences (Panel A) and income (Panel B), agents sort into municipalities by ideology, and more liberal cities are more likely to enact restrictive zoning than conservative cities. As a result, average housing consumption is higher in liberal cities.

Table 4.2: Selected Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Population (2010)	3,907	47,719	174,603	10,001	8,175,133
Housing Units (2010)	3,907	19,860	72,399	1,362	3,371,062
Mean Jan. Temperature	3,907	36.7	14.0	-11.5	76.4
Mean Jul. Temperature	3,907	75.5	5.5	50	95
Median Home Value (2010-2014)	3,819	221,660	147,841	34,200	999,100
Median Household Income (2010-2014)	3,858	60,195	26,665	13,608	241,453
MRP Ideology	3,840	-0.032	0.202	-0.988	0.691
MRP Ideology (Tausanovitch & Warshaw)	1,545	-0.044	0.263	-1.019	0.669
Pct. White (2010)	3,878	0.640	0.251	0.007	0.983
Pct. Black (2010)	3,878	0.121	0.171	0.001	0.980
Pct. Hispanic (2010)	3,878	0.164	0.195	0.004	0.987
Pct. Over 65 (2010)	3,878	0.131	0.058	0.000	0.836
Pct. College Graduates (2010)	3,878	0.295	0.159	0.006	0.898
Pct. Housing Constructed before 1959	3,709	0.330	0.230	0.000	0.930
Pct. Developable Land within 20km (2011)	3,332	44.723	27.607	0.012	96.8
Building Permits (2000-2016)	2,696	4,115	12,383	0	368,111
WRLURI	1,276	-0.077	0.874	-2.091	3.759
Modified WRLURI	1,276	0.032	0.960	-1.998	4.740
Zoning Veto Players	1,275	1.496	1.029	0.000	6.000

4.4 Empirical Analysis

My empirical analysis proceeds in three parts. First, I explore whether home values are higher than we would expect (given income, demographic characteristics, and amenities) in liberal cities. Due to endogeneity concerns, I also measure policy outcomes directly: do more liberal cities issue fewer building permits than similar conservative cities? Finally, I test my predictions against an extensive survey-based measure of urban land use regulation. Throughout this analysis, I restrict my attention to cities with a population greater than 10,000.

4.4.1 Data Sources

Outcome Variables

My outcome variables come from three sources. For my survey-based measure of land use policy, I use the Wharton Residential Land Use Regulation Index (WRLURI) (Gyourko et al. 2008). In 2004, Gyourko, Saiz, and Summers conducted an

extensive survey of US municipal governments regarding local land use regulation. City planning officials from 2,649 municipalities (out of 6,896 in the International City Managers Association database) supplied data on: (1) the number of veto players in the zoning approval process, (2) existing rules restricting supply or density of housing, and (3) the length of time required for building permit approval. The authors then use factor analysis to construct their summary measure of the stringency of local housing regulation (WRLURI).

In the analysis that follows, I slightly modify this measure. The original WRLURI is generated in part using survey questions on state-level variables (e.g. state court involvement) and institutional variables (e.g. number of veto players whose approval is required to permit new development). To generate a dependent variable that measures city-level regulations alone – and allows me to include veto players as an explanatory variable – I remove those subcomponents. I generate this new regulatory measure using principal component analysis, as in the original study. In Appendix F, I show that my results do not depend on this choice, and that the results go through using the original WRLURI measure as well.

Because the regulatory measure is constructed from multiple factors, it is somewhat difficult to interpret. However, the following benchmarks can serve as a rough guide. The index ranges from roughly -2 to $+4$, and 85% of the distribution lies between -2 and $+1$. An exemplar town in the -2 range is Lake Arthur, LA. There are no formal restrictions on density or housing supply in Lake Arthur, and there is no planning commission or environmental review required to approve new construction. On average, new housing stock is approved by the local government within one month. Contrast this with Charleston, SC, which scores a 0. Charleston has a Euclidean zoning code, including stringent height restrictions in the downtown

core. Changes to the zoning plan must be approved by the city council. However, there are no statutory limits on new construction, and on average it takes 3 months to approve new single family units.

On the higher end of the regulatory index we find Los Angeles, CA (+2) and Mashpee, MA (+3.5). Los Angeles has a formal zoning code, and any rezoning requires the approval of the planning commission, a city council majority, and an environmental board. There are no formal construction or permit limits, but the city government reports that it takes 6 months on average to approve new single family housing. Mashpee, meanwhile, has among the most restrictive land use policies in the nation. There is a statutory limit on new building permits each year, a minimum lot size of 1 acre for residential development, and any change in the zoning code requires a majority vote at an all-citizen town meeting.

For my measure of new building permits by city, I consult the US Census Building Permits Survey, merging annual counts of new building permits by Census Designated Place between 2000 and 2016. My measure of median home price comes from the 2016 five-year American Community Survey.

Ideology

For data on city-level ideology, I rely on the invaluable dataset compiled by Tausanovitch & Warshaw (2013). Combining public opinion data from the Cooperative Congressional Election Study, they create a city-level measure of conservatism using multilevel regression and poststratification for over 1600 US cities. The ideology measure ranges from roughly -1 (Berkeley, CA liberal) to about 0.5 (Amarillo, TX conservative). As Tausanovitch & Warshaw (2014) document in a subsequent paper, this measure of conservatism is a significant predictor of city-level taxes and expenditures per capita. For this reason, I believe it is a reasonable measure of the

population’s preference for local public spending – the model’s α_i parameter. The original Tausanovitch & Warshaw measure was constructed only for cities with population greater than 20,000, so I extend their procedure to create ideology measures for each city in my sample.³

Other Covariates

Many large US cities are “built out”, and have little available land for residential development. In such cities, constructing new housing stock is relatively more difficult, and we would expect to observe fewer new building permits and more expensive land prices. Because these cities tend to be older, coastal, and more liberal, excluding this covariate is likely to bias our estimates. So I compute a measure of developable land for each city. Combining the USGS Digital Elevation Model⁴ and National Land Cover Dataset (NLCD), I identify the percentage of land area within a 20km radius of each city center that is (1) undeveloped, and (2) not geographically inhospitable to residential development, e.g. a wetland or steep terrain with greater than 15% grade (Saiz 2010). Using this information, I generate a measure for each city (`pct.developable`), denoting the percentage of nearby land that is available for development.

For demographic and housing data, I consult the 2000 and 2010 Decennial Census (U.S. Census Bureau, Summary File 3). Finally, I compute the mean January and July temperatures in each municipality using the WorldClim dataset (Hijmans et al. 2005). Table 4.2 reports selected summary statistics for these variables.

³To replicate the city-level estimates, I first construct an individual-level ideology measure by taking the first component from a principal component analysis of twenty-two policy questions in the 2010 Cooperative Congressional Election Study. I then estimate city-level ideology measures using multilevel regression and poststratification (MRP), as in Tausanovitch & Warshaw (2013). I verify that the final measure is capturing average city-level ideology by regressing it against the Democrat’s presidential vote share in 2008. The correlation between presidential vote share and Tausanovitch and Warshaw’s original measure is -0.76, and with the replicated measure is -0.77. This and all other replication materials will be made available at the author’s website.

⁴Data available from the US Geological Survey, accessed through the `elevatr` package in R (Hollister & Tarak Shah 2017).

4.4.2 Results

Home Prices

Table 4.3 reports the coefficient estimates from a set of linear regressions predicting median home values by city. As Glaeser & Gyourko (2005) document, a two-factor linear model including median income and average temperature explains a large share of the variation in median home values (R^2 roughly 0.6). The results from Table 4.3 suggest that liberal cities tend to be more expensive than income and climate alone would predict. This relationship holds if we include state fixed effects (column 3), additional demographic/geographic covariates (column 4), and CBSA-level fixed effects. On average, the median home value in a moderately liberal city (Ideology Score: -0.15) is about \$25,000 to \$50,000 higher than in a similar conservative city (Ideology Score: 0.15).

Building Permits

For my second measure of local growth controls, I investigate the number of new housing units approved in each city from 2000 to 2016. I adopt the empirical estimation strategy from (Kahn 2011), regressing $\log(\text{new units} + 1)$ on $\log(\text{units})$, median home value, and state fixed effects. Table 4.4 reports the coefficient and standard error estimates from these regressions. Liberal cities issue fewer building permits than we would expect given their size, housing costs, and demographic variables. Depending on how we specify the model, a moderately conservative city (+0.15) issued on average 13% to 38% more building permits than a moderately liberal city (-0.15) during the period in question.

Table 4.3: Median Home Value Regressions

	<i>Dependent variable:</i>				
	Median Home Value (2010-2014)				
	(1)	(2)	(3)	(4)	(5)
MRP Ideology	-132,855*** (11,712)	-106,816*** (6,428)	-77,737*** (7,703)	-136,259*** (14,274)	-170,893*** (19,621)
Median Household Income		4.35*** (0.05)	4.05*** (0.05)	3.03*** (0.08)	2.97*** (0.12)
Mean Jan. Temperature		3,612*** (105.4)	5,544*** (331.6)	4,082*** (317.1)	7,646*** (1,154.7)
Mean Jul. Temperature		-8,374*** (277.6)	-9,042*** (396.8)	-6,016*** (373.0)	-5,680*** (890.8)
Log Population (2010)				-2,289** (890)	-3,056*** (1,107)
Pct. White				-92,982*** (17,269)	-26,092 (22,562)
Pct. Black				-186,766*** (19,429)	-145,109*** (25,470)
Pct. Hispanic				-79,536*** (17,191)	-41,630* (22,614)
Pct. Over 65				258,796*** (22,440)	412,081*** (39,423)
Pct. College Grad				238,907*** (12,065)	253,350*** (16,749)
Pct. Housing Built Pre-1959				77,227*** (5,753)	72,563*** (8,221)
Pct. Developable (20km)				-288.11*** (53.03)	-45.97 (101.21)
Constant	217,525*** (2,399)	460,945*** (20,156)	396,519*** (40,144)	382,879*** (34,472)	92,915 (100,259)
State Fixed Effects	No	No	Yes	Yes	No
CBSA Fixed Effects	No	No	No	No	Yes
Observations	3,782	3,782	3,782	3,259	2,017
R ²	0.03	0.74	0.80	0.86	0.90

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 4.4: Building Permit Regressions

	<i>Dependent variable:</i>					
	Log Building Permits (2000-2016)			Log Building Permits (2010-2016)		
	(1)	(2)	(3)	(4)	(5)	(6)
MRP Ideology	3.25*** (0.19)	0.60* (0.33)	1.41*** (0.41)	4.24*** (0.20)	0.77* (0.44)	1.56*** (0.55)
Log Housing Units (Initial)	0.91*** (0.03)	0.99*** (0.02)	1.01*** (0.02)	1.30*** (0.03)	1.23*** (0.03)	1.25*** (0.03)
Median Home Value	0.38*** (0.05)	0.88*** (0.08)	0.93*** (0.13)	0.71*** (0.05)	0.94*** (0.10)	1.21*** (0.16)
Mean Jan. Temperature		0.01 (0.01)	0.02 (0.03)		0.03*** (0.01)	0.01 (0.03)
Mean Jul. Temperature		0.05*** (0.01)	0.05** (0.02)		0.03** (0.01)	0.04 (0.03)
Pct. White		1.07** (0.54)	-0.45 (0.62)		1.39** (0.56)	0.18 (0.67)
Pct. Black		0.49 (0.58)	-0.08 (0.66)		-0.02 (0.64)	-0.24 (0.75)
Pct. Hispanic		0.74 (0.54)	-0.14 (0.62)		0.77 (0.56)	0.44 (0.67)
Pct. Over 65		-0.07*** (0.01)	-0.07*** (0.01)		-8.92*** (0.87)	-9.66*** (1.10)
Pct. College Grad		-1.30*** (0.33)	-1.07** (0.44)		0.79* (0.43)	0.44 (0.57)
Pct. Housing Built Pre-1959		-3.34*** (0.17)	-2.29*** (0.21)		-2.21*** (0.20)	-1.62*** (0.24)
Pct. Developable (20km)		0.02*** (0.001)	0.04*** (0.002)		0.03*** (0.002)	0.03*** (0.003)
Constant	-8.12*** (0.86)	-21.20*** (1.75)	-23.68*** (3.12)	-21.61*** (0.89)	-28.90*** (2.07)	-33.44*** (3.87)
State Fixed Effects	No	Yes	No	No	Yes	No
CBSA Fixed Effects	No	No	Yes	No	No	Yes
Observations	2,670	2,438	2,034	2,648	2,421	2,017
R ²	0.31	0.70	0.76	0.45	0.69	0.74

Note:

*p<0.1; **p<0.05; ***p<0.01

Wharton Residential Land Use Regulation Index

Finally, I use the Wharton regulatory measure as my outcome variable. Table 4.5 reports the coefficient estimates and standard errors from five OLS models. As expected, liberal cities have more restrictive housing regulations than one would predict given their income, demographics, and geography. A one-unit increase in the conservatism measure is associated with a 0.55 unit decrease in the regulatory index. These results are not, however, robust to adding additional state-level fixed effects (Column 4) or CBSA-level fixed effects (Column 5).

4.5 Concluding Thoughts

In this paper, I have investigated the systematic difference in home prices and zoning policies between liberal and conservative US cities. I develop a theory to explain the puzzle: if cities with liberal residents place a greater value on public goods provision, then restrictive zoning policy can enable generous public expenditures by ensuring that newcomers pay their fair share of property taxes. In an empirical analysis, I show that the observed relationship between city-level ideology and zoning policy is robust to conditioning on a number of confounding factors. All else equal, liberal cities are more expensive, issue fewer new building permits, and score higher on the survey-based measure of land use regulatory stringency.

The current study faces several limitations that I hope to address in future work. Firstly, the empirical analysis is purely cross-sectional, and while I have done what I can to control for likely confounding factors, a time series analysis of some sort may be more convincing from a causal inference perspective. Unfortunately, our current survey-based measures of zoning policy are solely cross-sectional. In future work, I plan to develop new and improved measures of zoning stringency, based on GIS

Table 4.5: Regulatory Index Regressions

	<i>Dependent variable:</i>				
	Modified Wharton Residential Land Use Index (2004)				
	(1)	(2)	(3)	(4)	(5)
MRP Ideology	-0.31** (0.14)	-0.53*** (0.13)	-1.24*** (0.20)	-0.33 (0.35)	-0.09 (0.48)
Log Median Income (2000)		1.04*** (0.07)	0.82*** (0.12)	0.64*** (0.14)	0.30 (0.23)
Log Population (2000)			0.07** (0.03)	0.10*** (0.03)	0.17*** (0.04)
Mean Jan. Temperature			0.02*** (0.003)	0.02** (0.01)	0.03 (0.03)
Mean Jul. Temperature			-0.02*** (0.01)	-0.03*** (0.01)	-0.02 (0.02)
Pct. White			2.30*** (0.57)	2.50*** (0.66)	2.27*** (0.86)
Pct. Black			1.36** (0.58)	2.12*** (0.69)	1.89** (0.90)
Pct. Hispanic			2.44*** (0.59)	2.64*** (0.65)	1.71** (0.86)
Pct. Over 65			-0.004 (0.01)	-0.02** (0.01)	-0.01 (0.01)
Pct. College Grad			0.14 (0.24)	0.47* (0.27)	0.56 (0.40)
Pct. Housing Built Pre-1959			-1.05*** (0.16)	-0.93*** (0.18)	-0.64*** (0.23)
Pct. Developable (20km)			0.004*** (0.001)	0.004** (0.002)	0.01*** (0.003)
Veto Players			0.21*** (0.02)	0.20*** (0.02)	0.19*** (0.03)
Constant	0.02 (0.03)	-11.06*** (0.77)	-10.38*** (1.56)	-8.92*** (1.74)	-7.70** (3.39)
State Fixed Effects	No	No	No	Yes	No
CBSA Fixed Effects	No	No	No	No	Yes
Observations	1,271	1,269	1,141	1,141	924
R ²	0.004	0.14	0.30	0.35	0.49

Note:

*p<0.1; **p<0.05; ***p<0.01

remote sensing or text analysis of zoning code changes over time.

Second, the current analysis focuses entirely on US cities. A useful test of the theory would be to compare conservative and liberal cities in countries where zoning authority is devolved to municipal authorities, but *taxation* is collected at the national level. If zoning restrictions are in part a response to the fiscal incentives outlined in this paper's model, then we should expect to see a weaker relationship between ideology and zoning in these countries.

BIBLIOGRAPHY

Bibliography

- Abadie, A. (2005), ‘Semiparametric Difference-in-Difference Estimators’, *Review of Economic Studies* **72**, 1–19.
- Alesina, A., Baqir, R. & Easterly, W. (1999), ‘Public Goods and Ethnic Divisions’, *The Quarterly Journal of Economics* **114**(4), 1243–1284.
- Ansolabehere, S. & Schaffner, B. F. (2018), ‘CCES Common Content, 2016’.
URL: <https://doi.org/10.7910/DVN/GDF6Z0>
- Anzia, S. F. (2011), ‘Election Timing and the Electoral Influence of Interest Groups’, *Journal of Politics* **73**(2), 412–427.
- Anzia, S. F. (2012a), ‘Partisan Power Play: The Origins of Local Election Timing as an American Political Institution’, *Studies in American Political Development* **26**(1), 24–49.
- Anzia, S. F. (2012b), ‘The Election Timing Effect: Evidence from a Policy Intervention in Texas’, *Quarterly Journal of Political Science* **7**, 209–248.
- Benedictis-Kessner, J. D. (2018), ‘How Attribution Inhibits Accountability: Evidence from Train Delays’, *Journal of Politics* **80**(4).
- Berry, C. (2008), ‘Piling on: Multilevel government and the fiscal common-pool’, *American Journal of Political Science* **52**(4), 802–820.
- Berry, C., Grogger, J. & West, M. (2015), ‘The Growth of Local Government’, *Working Paper* .
- Berry, C. R. (2009), *Imperfect Union: Representation and taxation in multilevel governments*, Cambridge University Press.
- Berry, C. R. & Gersen, J. E. (2010), ‘The Timing of Elections’, *The University of Chicago Law Review* **77**(37), 37–64.
- Beyer, K., Goldstein, J., Ramakrishnan, R. & Shaft, U. (1999), ‘When Is “Nearest Neighbor” Meaningful?’, *International conference on database theory* pp. 217–235.
- Black, S. E. (1999), ‘Do Better Schools Matter? Parental Valuation of Elementary Education’, *Quarterly Journal of Economics* **114**(2), 577–599.
- Blom-Hansen, J., Houlberg, K. & Serritzlew, S. (2014), ‘Size, Democracy, and the Economic Costs of Running the Political System’, *American Journal of Political Science* **58**(4), 790–803.
- Bocinsky, R. K. (2017), ‘FedData: Functions to Automate Downloading Geospatial Data Available from Several Federated Data Sources’, *R package version 2.4.7* .
- Breiman, L. (2001a), ‘Random forests’, *Machine Learning* **45**(1), 5–32.
- Breiman, L. (2001b), ‘Statistical Modeling: The Two Cultures’, *Statistical Science* **16**(3), 199–231.
- Bru Eckner, J. K. (1990), ‘Growth Controls and Land Values in an Open City’, *Land Economics* **66**(3), 237–248.

- Brueckner, J. K. (1997), 'Infrastructure financing and urban development: The economics of impact fees', *Journal of Public Economics* **66**(3), 383–407.
- Bui, Q., Chaban, M. A. & White, J. (2016), '40 Percent of the Buildings in Manhattan Could Not Be Built Today', *The New York Times* (May 20, 2016).
- Buttice, M. K. & Highton, B. (2013), 'How does multilevel regression and poststratification perform with conventional national surveys?', *Political Analysis* **21**(4), 449–467.
- Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., Bergeron, A. & Cutler, D. (2016), 'The Association Between Income and Life Expectancy in the United States, 2001-2014', *Journal of the American Medical Association* **315**(16), 1750–1766.
- Cooley, T. F. & LaCivita, C. J. (1982), 'A theory of growth controls', *Journal of Urban Economics* **12**(2), 129–145.
- Craw, M. (2010), 'Deciding to Provide: Local Decisions on Providing Social Welfare', *American Journal of Political Science* **54**(4), 906–920.
- De Benedictis-Kessner, J. (2017), 'Off-Cycle and Out of Office: Election Timing and the Incumbency Advantage', *Journal of Politics* (Forthcoming).
- de Benedictis-Kessner, J. & Warshaw, C. (2016), 'Mayoral Partisanship and Municipal Fiscal Policy', *The Journal of Politics* **78**(4), 1124–1138.
- Diamond, A. & Sekhon, J. (2012), 'Genetic Matching for Estimating Causal Effects', *The Review of Economics and Statistics* **95**(July), 932–945.
- Ding, C., Knaap, G. J. & Hopkins, L. D. (1999), 'Managing Urban Growth with Urban Growth Boundaries: A Theoretical Analysis', *Journal of Urban Economics* **46**(1), 53–68.
- Dipasquale, D. & Glaeser, E. L. (1999), 'Incentives and Social Capital: Are Homeowners Better Citizens?', *Journal of Urban Economics* **45**(2), 354–384.
- Einstein, K. L., Palmer, M. & Glick, D. (2017), 'Who Participates in Local Government? Evidence from Meeting Minutes', *Working Paper* pp. 1–28.
- Epple, D. & Romer, T. (1991), 'Mobility and Redistribution', *Journal of Political Economy* **99**(4), 828–858.
- Ferraz, C. & Finan, F. (2011), 'Electoral Accountability and Corruption: Evidence from the Audits of Local Governments', *The American Economic Review* **101**(4), 1274–1311.
- Ferreira, F. (2010), 'You can take it with you: Proposition 13 tax benefits, residential mobility, and willingness to pay for housing amenities', *Journal of Public Economics* **94**(9-10), 661–673.
- Fischel, W. A. (2001), *The homevoter hypothesis: How home values influence local government taxation, school finance, and land-use policies*, Harvard University Press, Cambridge, MA.
- Fischel, W. A. (2015), *Zoning Rules!*, Lincoln Institute of Land Policy.
- Ganong, P. & Shoag, D. (2017), 'Why Has Regional Income Convergence in the U.S. Declined?', *Journal of Urban Economics* **102**, 76–90.
- Garmann, S. (2016), 'Concurrent elections and turnout: Causal estimates from a German quasi-experiment', *Journal of Economic Behavior and Organization* **126**, 167–178.
- Gerber, E. R. (2005), 'Evaluating the Effects of Direct Democracy on Public Policy: California's Urban Growth Boundaries', *American Politics Research* **33**(2), 310–330.

- Gerber, E. R. & Hopkins, D. J. (2011), ‘When Mayors Matter: Estimating the Impact of Mayoral Partisanship on City Policy’, *American Journal of Political Science* **55**(2), 326–339.
- Gerber, E. R. & Phillips, J. H. (2003), ‘Development Ballot Measures, Interest Group Endorsements, and the Political Geography of Growth Preferences’, *American Journal of Political Science* **47**(4), 625–639.
- Gerber, E. R. & Phillips, J. H. (2004), ‘Direct democracy and land use policy: exchanging public goods for development rights’, *Urban Studies* **41**(2), 463–479.
- Glaeser, E. L. (2011), ‘Cities, Productivity, and Quality of Life’, *Science* **333**(6042), 592–594.
- Glaeser, E. L. & Gyourko, J. (2003), ‘The Impact of Building Restrictions on Housing Affordability’, *Economic Policy Review* **2**, 21–39.
- Glaeser, E. L. & Gyourko, J. (2005), ‘Urban Decline and Durable Housing’, *Journal of Political Economy* **113**(2), 345–375.
- Glaeser, E. L., Gyourko, J. & Saks, R. E. (2005), ‘Why have housing prices gone up?’, *NBER Working Paper* pp. 1–36.
- Glaeser, E. L. & Kahn, M. E. (2010), ‘The greenness of cities: Carbon dioxide emissions and urban development’, *Journal of Urban Economics* **67**(3), 404–418.
- Gyourko, J., Saiz, A. & Summers, A. A. (2008), ‘A new measure of the local regulatory environment for housing markets: The Wharton Residential Land Use Regulatory Index’, *Urban Studies* **45**(3), 693–729.
- Hamilton, B. W. (1975), ‘Zoning and Property Taxation in a System of Local Governments’, *Urban Studies* **12**, 205–211.
- Hamilton, B. W. (1976), ‘Capitalization of Intra-jurisdictional Differences in Local Tax Prices’, *The American Economic Review* **66**(5), 743–753.
- Hankinson, M. (2017), ‘When Do Renters Behave Like Homeowners? High Rent, Price Anxiety, and NIMBYism’, *Working Paper* pp. 1–63.
- Hess, D. B. & Almeida, T. M. (2007), ‘Impact of proximity to light rail rapid transit on station-area property values in Buffalo, New York’, *Urban Studies* **44**(5-6), 1041–1068.
- Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. & Jarvis, A. (2005), ‘Very high resolution interpolated climate surfaces for global land areas’, *International Journal of Climatology* **25**(15), 1965–1978.
- Hollister, J. & Tarak Shah (2017), *elevatr: Access Elevation Data from Various APIs*.
URL: <http://github.com/usepa/elevatr>
- Hopkins, D. J. (2018), *The Increasingly United States: How and Why American Political Behavior Nationalized*, University of Chicago Press.
- Hsieh, C.-T. & Moretti, E. (2015), ‘Why Do Cities Matter? Local Growth and Aggregate Growth’, *NBER Working Paper* .
- Hsieh, C.-T. & Moretti, E. (2017), ‘Housing Constraints and Spatial Misallocation’, *NBER Working Paper* .
- Jensen, N. M. & Malesky, E. J. (2018), *Incentives to Pander: How Politicians Use Corporate Welfare for Political Gain*, Cambridge University Press.
- Kahn, M. E. (2011), ‘Do liberal cities limit new housing development? Evidence from California’, *Journal of Urban Economics* **69**(2), 223–228.

- Kogan, V., Lavertu, S. & Peskowitz, Z. (2017), ‘Election Timing, Electorate Composition, and Policy Outcomes: Evidence from School Districts’, *Forthcoming* .
- Krugman, P. (1991), ‘Increasing Returns and Economic Geography’, *Journal of Political Economy* **99**(3), 483–499.
- Lax, J. R. & Phillips, J. H. (2009), ‘How Should We Estimate Public Opinion in The States?’, *American Journal of Political Science* **53**(1), 107–121.
- Lax, J. R. & Phillips, J. H. (2012), ‘The Democratic Deficit in the States’, *American Journal of Political Science* **56**(1), 148–166.
- Leemann, L. & Wasserfallen, F. (2017), ‘Extending the Use and Prediction Precision of Subnational Public Opinion Estimation’, *American Journal of Political Science* **61**(4), 1003–1022.
- Lewyn, M. (2005), ‘How Overregulation Creates Sprawl (Even in a City without Zoning)’, *Wayne Law Review* **50**(1171).
- Linden, L. & Rockoff, J. E. (2008), ‘Estimates of the Impact of Crime Risk on Property Values from Megan ’ s Laws’, *American Economic Review* **98**(3), 1103–1127.
- Marble, W. & Nall, C. (2017), ‘Beyond “NIMBYism”: Why Americans Support Affordable Housing But Oppose Local Housing Development’, *Working Paper* .
- Molotch, H. (1976), ‘The City as a Growth Machine: Toward a Political Economy of Place’, *American Journal of Sociology* **82**(2), 309–332.
- Montgomery, J. M., Hollenbach, F. & Ward, M. D. (2012), ‘Improving Predictions Using Ensemble Bayesian Model Averaging’, *Political Analysis* .
- Nguyen-Hoang, P. & Yinger, J. (2011), ‘The capitalization of school quality into house values: A review’, *Journal of Housing Economics* **20**(1), 30–48.
- Oliver, J. E. (1999), ‘The Effects of Metropolitan Economic Segregation on Local Civic Participation’, *American Journal of Political Science* **43**(1), 186–212.
- Olson, M. (1965), *The Logic of Collective Action: Public Goods and the Theory of Groups*, Harvard University Press, Cambridge, MA.
- Ortalo-Magne, F. & Prat, A. (2014), ‘On the political economy of urban growth: Homeownership versus affordability’, *American Economic Journal: Microeconomics* **6**(1 D), 154–181.
- Page, S. E. (2008), ‘Uncertainty, Difficulty, and Complexity’, *Journal of Theoretical Politics* **20**(2), 115–149.
- Park, D. K., Gelman, A. & Bafumi, J. (2004), ‘Bayesian multilevel estimation with poststratification: State-level estimates from national polls’, *Political Analysis* **12**(4), 375–385.
- Payson, J. A. (2017), ‘When Are Local Incumbents Held Accountable for Government Performance? Evidence from US School Districts’, *Legislative Studies Quarterly* **42**(3), 421–448.
- Peterson, P. E. (1981), *City Limits*, University of Chicago Press.
- Pope, D. G. & Pope, J. C. (2012), ‘Crime and property values: Evidence from the 1990s crime drop’, *Regional Science and Urban Economics* **42**(1-2), 177–188.
- Quigley, J. M. & Raphael, S. (2005), ‘Regulation and the high cost of housing in California’, *The American Economic Review* **95**(2), 323–328.
- Quigley, J. M. & Rosenthal, L. a. (2005), ‘The Effects of Land-Use Regulation on the Price of Housing: What Do We Know? What Can We Learn?’, *Cityscape: A Journal of Policy Development and Research* **8**(1), 69–137.

- Roback, J. (1982), ‘Wages, Rents, and the Quality of Life’, *Journal of Political Economy* **90**(6), 1257–1278.
- Rognlie, M. (2015), ‘Deciphering the fall and rise in the net capital share’, *Brookings Papers on Economic Activity* .
- Rothwell, J. & Massey, D. S. (2009), ‘The Effect of Density Zoning on Racial Segregation in U.S. Urban Areas’, *Urban Affairs Review* **44**(6), 779–806.
- Rothwell, J. T. & Massey, D. S. (2010), ‘Density zoning and class segregation in U.S. metropolitan areas’, *Social Science Quarterly* **91**(5), 1123–1143.
- Rubin, D. B. (1973), ‘Matching to Remove Bias in Observational Studies’, *Biometrics* **29**(1), 159–183.
- Saiz, A. (2010), ‘The Geographic Determinants of Housing Supply’, *The Quarterly Journal of Economics* **125**(3), 1253–1296.
- Samworth, R. J. (2012), ‘Optimal weighted nearest neighbour classifiers’, *Annals of Statistics* **40**(5), 2733–2763.
- Sances, M. W. (2016), ‘The Distributional Impact of Greater Responsiveness: Evidence from New York Towns’, *The Journal of Politics* **78**(1), 105–119.
- Sances, M. W. (2018), ‘Something for Something: How and Why Direct Democracy Impacts Service Quality’, *Quarterly Journal of Political Science* **13**(1), 29–57.
- Scheve, K. F. & Slaughter, M. J. (2001), ‘What determines individual trade-policy preferences?’, *Journal of International Economics* **54**, 267–292.
- Sekhon, J. S. (2011), ‘Multivariate and Propensity Score Matching Software with Automated Balance Optimization: The Matching Package for R’, *Journal of Statistical Software* **42**(7), 127–210.
- Shoup, D. C. (1999), ‘The trouble with minimum parking requirements’, *Transportation Research A* **33**(7/8), 549–574.
- Stanton, R. J. (2013), ‘Ann Arbor City Council approves 14-story high-rise at Huron and Division’, *The Ann Arbor News* (May 14, 2013).
- Stone, M. (1974), ‘Cross-Validatory Choice and Assessment of Statistical Predictions’, *Journal of the Royal Statistical Society, Series B (Methodological)* **36**(2), 111–147.
- Tausanovitch, C. & Warshaw, C. (2013), ‘Measuring Constituent Policy Preferences in Congress, State Legislatures, and Cities’, *The Journal of Politics* **75**(02), 330–342.
- Tausanovitch, C. & Warshaw, C. (2014), ‘Representation in Municipal Government’, *The American Political Science Review* **108**(03), 605–641.
- Tiebout, C. M. (1956), ‘A pure theory of local expenditures’, *The Journal of Political Economy* **64**(5), 416–424.
- Trebbi, F., Aghion, P. & Alesina, A. (2008), ‘Electoral Rules and Minority Representation in U.S. Cities’, *The Quarterly Journal of Economics* **123**(1), 325–357.
- Trounstine, J. (2015), ‘Segregation and Inequality in Public Goods’, *American Journal of Political Science* **60**(3), 709–725.
- Trounstine, J. & Valdin, M. E. (2008), ‘The context matters: The effects of single-member versus at-large districts on city council diversity’, *American Journal of Political Science* **52**(3), 554–569.

- Troy, A. & Grove, J. M. (2008), 'Property values, parks, and crime: A hedonic analysis in Baltimore, MD', *Landscape and Urban Planning* **87**(3), 233–245.
- von Hoffman, A. (2010), 'Wrestling with Growth in Acton, Massachusetts: The Possibilities and Limits of Progressive Planning', *Joint Center for Housing Studies of Harvard University* (January).
- Warshaw, C. & Rodden, J. (2012), 'How Should We Measure District-Level Public Opinion on Individual Issues?', *The Journal of Politics* **74**(1), 203–219.
- Wheaton, W. C. (1998), 'Land Use and Density in Cities with Congestion', *Journal of Urban Economics* **43**(2), 258–272.
- Wolf, M. A. (2008), *The Zoning of America: Euclid v. Ambler*, University Press of Kansas, Lawrence, KS.

APPENDICES

APPENDIX A

Spatial Econometric Tests

In Chapter II, I assumed that median home prices in one city are statistically independent of home prices in neighboring jurisdictions. This is, however, a heroic assumption. Because homebuyers are not constrained by buy homes within a single municipality, factors that affect the price of housing in one city are likely to affect nearby municipalities as well. As a result, land use policies are likely to exhibit spillover effects. A supply restriction in one city can increase home prices throughout the metropolitan area.

The good news is that these spillover effects are likely to bias *against* my hypothesis. If off-cycle elections cause City A to enact restrictive zoning, which increases home prices in both City A and neighboring City B, then I should be more likely to observe a null result when comparing home prices within a metro area. Nevertheless, it is a useful robustness test to explicitly model the spillover effect between jurisdictions, and see if it alters my substantive conclusion. To do so, I model home prices with a spatial autoregressive lag model, as follows:

$$Y_i = \rho WY + \beta X_i + \varepsilon_i$$

where Y is a vector of median home values and W is a spatial weights matrix, with each W_{ij} containing a measure of “closeness” between city i and j . In the following

analysis, I populate the W matrix using the inverse distance between the centroids of each pair of municipalities (Column 1) and a 50km threshold (Column 2).¹ A positive ρ implies that median home values are positively correlated across space, holding X_i constant. In the presence of such autocorrelation, omitting the ρWY term would bias the estimates of β . Table A.1 reports the coefficient estimates from this model; despite the addition of the spatial lag term, the estimated coefficient on Off-Cycle elections remains significant. Bear in mind that the β coefficient reported here is not, as in an OLS, equivalent to the estimated effect size. Rather, one can think of it as the “pre-spatial feedback” impulse, analogous to a coefficient estimate in a lagged-dependent variable time series model.

¹I have also estimated the model using a threshold distance matrix, spatial contiguity matrix, and a shared-CBSA matrix, without meaningfully altering the results.

Table A.1: Estimated coefficients estimates from the spatial autoregressive lag model.

	<i>Dependent variable:</i>	
	median.hv.sqft.2017	
	(1)	(2)
Pct. Off-Cycle	35.83** (14.23)	44.14*** (16.66)
Log Population	-13.68*** (3.77)	-17.19*** (4.35)
Median Income	0.001*** (0.0003)	0.001** (0.0004)
January Median Temp.	7.85*** (1.36)	4.55** (1.99)
July Median Temp.	-4.32*** (1.06)	-3.95*** (1.52)
Pct. White	-74.88** (36.00)	-95.90** (42.24)
Pct. Over 65	86.16 (103.89)	104.99 (119.92)
Pct. College Grad	605.91*** (69.27)	738.92*** (78.63)
Debt Per Capita	-1.16** (0.46)	-1.11** (0.51)
Pct. Developable Land	-1.69 (16.96)	80.15** (40.48)
Test Scores	0.02 (0.13)	-0.10 (0.14)
ρ	0.97*** (0.02)	0.52*** (0.05)
Observations	412	405
LR Test (df = 1)	165.44***	75.41***
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01	

APPENDIX B

Heterogeneous Treatment Effects

The effect of off-cycle election timing may vary depending on context. For example, new single family developments may provoke less political opposition in off-year elections than multifamily housing. As the ballot initiative results suggest, public support for urban sprawl restrictions do not vary with election timing, but support for new infill developments does. To test this hypothesis, I recompute the cross-sectional regression analysis separately for single family and multifamily housing. As Figure B.1 shows, the estimated effect of election timing is slightly stronger for multifamily housing than for single-family housing, but this difference is not statistically significant. Note that 24% of the municipalities in my dataset permitted zero multifamily units between 2010-2016, so I drop those observations when multifamily permits are the dependent variable below.

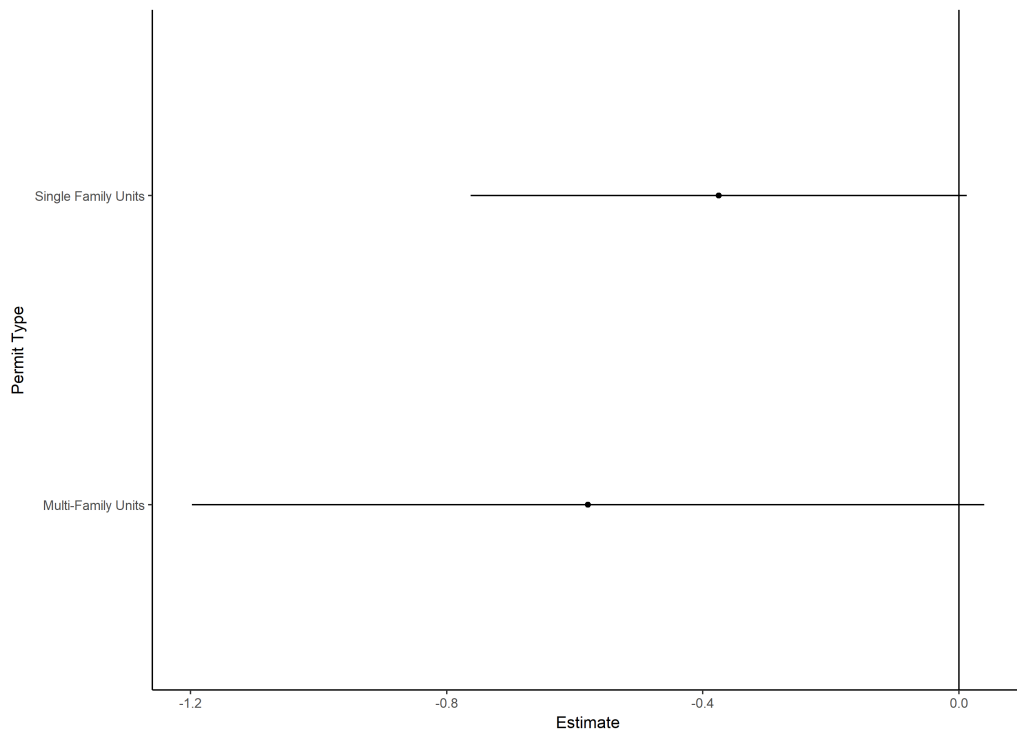


Figure B.1: Estimated effect of off-cycle elections on log new building permits (2000-2016), by type of housing.

APPENDIX C

Synthetic Poststratification Proof

In this appendix, I demonstrate that synthetic poststratification and classical MRP produce identical estimates if the first-stage model is additively-separable. Let $\hat{\mathbf{y}}$ be the vector of predictions for each type of respondent, and \mathbf{p} be the true empirical pmf for each type. The classical MRP poststratified estimate is the dot-product $\hat{\mathbf{y}} \cdot \mathbf{p}$. MrsP uses the same vector of predictions $\hat{\mathbf{y}}$, but uses a synthetic joint probability distribution, where each entry is the product of marginal probabilities. I will denote this synthetic poststratification vector as $\boldsymbol{\pi}$. Therefore, the poststratified MrsP estimates will be $\hat{\mathbf{y}} \cdot \boldsymbol{\pi}$.

Let X_1 through X_m be discrete random variables, and the $c \times m$ matrix X be a matrix in which the each row is one of the c possible combinations of values that X_1 through X_m can take. Crucially, we are not assuming that X_1 through X_m are independent, so $P(X_1 = x_{1i}, \dots, X_m = x_{mk})$ need not equal $P(X_1 = x_{1i}) \dots P(X_m = x_{mk})$.

Suppose the model is additively separable, such that $\hat{\mathbf{y}} = X\hat{\boldsymbol{\beta}}$. The vector of MrsP predictions for each unit is therefore $\boldsymbol{\pi}'\hat{\mathbf{y}}$, where $\boldsymbol{\pi}$ is the synthetic distribution vector. To complete the proof, we must show that $p'X\hat{\boldsymbol{\beta}} = \boldsymbol{\pi}'X\hat{\boldsymbol{\beta}}$. Because $\boldsymbol{\beta}$ is a vector, this

is equivalent to showing that $p'X = \pi'X$.

$$\begin{aligned}
 p'X &= \begin{bmatrix} \sum_i \dots \sum_k P(X_1 = x_{1i}, \dots, X_m = x_{mk})x_{1i} \\ \vdots \\ \sum_i \dots \sum_k P(X_1 = x_{1i}, \dots, X_m = x_{mk})x_{mk} \end{bmatrix} \\
 &= \begin{bmatrix} \sum_i P(X_1 = x_{1i})x_{1i} \\ \vdots \\ \sum_k P(X_m = x_{mk})x_{mk} \end{bmatrix} \\
 &= \begin{bmatrix} \sum_i \dots \sum_k P(X_1 = x_{1i}) \dots P(X_m = x_{mk})x_{1i} \\ \vdots \\ \sum_i \dots \sum_k P(X_1 = x_{1i}) \dots P(X_m = x_{mk})x_{mk} \end{bmatrix} = \pi'X
 \end{aligned}$$

This completes the proof. If our underlying first-stage model is additively separable, then our poststratified estimates will be identical whether we use MrsP or classical MRP.

APPENDIX D

Monte Carlo Technical Summary

This appendix provides an overview of some of the technical specifications from the Monte Carlo simulation in Chapter III.

The X variables are generated by discretizing each Z variable, according to procedure in Table D.1. Subnational units are assigned using the Z_4 variable. The N observations with the smallest value of Z_4 are assigned to Unit 1, the next smallest N observations assigned to Unit 2, and so on.

Table D.1: Assignment procedure for X variables

Z	X
Less than 1 SD below mean	1
1 SD below mean to mean	2
Mean to 1 SD above mean	3
More than 1 SD above mean	4

The functions D^0 and D^1 in the data-generating process are defined as follows, so that the former is increasing as it approaches $(0,0)$, while the latter is decreasing.

$$D_i^0 = \sqrt{2} - \sqrt{\text{lat}_i^2 + \text{lon}_i^2}$$
$$D_i^1 = \frac{\sqrt{\text{lat}_i^2 + \text{lon}_i^2}}{2}$$

Table D.2 lists the parameter values swept in the Monte Carlo. All simulation code will be made available at the author's website.

Table D.2: List of parameter values used in the Monte Carlo Simulation

Parameter	Values	Description
ρ	{0.2, 0.4, 0.6}	Correlation between Z variables
α	{0, 2, 5}	Strength of the threeway interaction effect
n	{2000, 5000, 10000}	Sample size drawn for disaggregation, MRP, and MLP estimates
N	15000	Observations per unit
M	200	Number of units
σ^2	5	Error term variance in DGP

APPENDIX E

Generating the Outcome Variable (CCES)

The outcome variable for the empirical application in Chapter III is generated from the twenty variables reported in Table E.1. Each variable has a binary outcome (with 1 representing the “Trumpist” opinion), producing a vector of length 20 for each respondent. Taking the first component from a principal component analysis maps each individual onto a unidimensional measure of Trumpism.

Table E.1: The CCES public opinion questions used to generate the outcome variable in the empirical application.

Opinion	CCES Code	Category
Background Checks	CC16_330a	Gun Control
Publishing Gun-Owners Names	CC16_330b	Gun Control
Assault Rifle Ban	CC16_330d	Gun Control
Concealed Carry	CC16_330e	Gun Control
Legal Status for Employed Immigrants	CC16_331.1	Immigration
More Border Patrol	CC16_331.2	Immigration
DACA	CC16_331.3	Immigration
Deportation	CC16_331.7	Immigration
CO2 Regulation	CC16_333a	Environment
Fuel Efficiency Standards	CC16_333b	Environment
Renewable Energy	CC16_333c	Environment
Clean Air Act	CC16_333d	Environment
Mandatory Minimums	CC16_334a	Criminal Justice
Police Body Cameras	CC16_334b	Criminal Justice
Increase Police Force	CC16_334c	Criminal Justice
Three Strike Laws	CC16_334d	Criminal Justice
TPP	CC16_351B	Trade
Iran Sanctions	CC16_351G	Foreign Policy
Repeal ACA	CC16_351I	Healthcare
Minimum Wage	CC16_351K	Economy

APPENDIX F

Robustness Tests

To ensure the robustness of my empirical results from Chapter IV, I re-estimate each regression using different measures for my key variables. Appendix Tables F.1-F.3 report the results from this reanalysis using (a) the original Tausanovitch & Warshaw measure of ideology, and (b) the original WRLURI measure from Gyourko et al. (2008). The main results reported above hold, with a few exceptions. Notably, the original Tausanovitch & Warshaw ideology measure is *not* a statistically significant predictor of median home price or new building permits when CBSA-level fixed effects are included. Note that using the original ideology measure requires us to drop roughly 1,500 cities from the sample, which could explain the discrepancy.

Table F.3 reports the results of the reanalysis using both the original measure of ideology *and* the original Wharton Residential Land Use Regulation Index. In all specifications, ideologically liberal cities score higher on WRLURI, even when including state-level and CBSA-level fixed effects.

Table F.1: Median Home Value Regressions (Robustness Test)

	<i>Dependent variable:</i>				
	Median Home Value (2010-2014)				
	(1)	(2)	(3)	(4)	(5)
MRP Ideology (T&W)	-148,925*** (14,211)	-119,681*** (7,611)	-109,722*** (8,407)	-32,821*** (10,401)	-15,727 (13,170)
Median Household Income		4.79*** (0.09)	4.53*** (0.09)	2.95*** (0.13)	2.71*** (0.18)
Mean Jan. Temperature		4,260*** (150.9)	5,342*** (515.6)	4,938*** (496.2)	8,503*** (1,464.8)
Mean Jul. Temperature		-8,814*** (399.2)	-8,506*** (560.7)	-6,527*** (547.3)	-7,085*** (1,081.6)
Log Population (2010)				-2,255.33 (1,422.32)	-44.30 (1,649.13)
Pct. White				-137,168*** (23,179)	-69,495*** (25,736)
Pct. Black				-149,781*** (25,432)	-86,294*** (28,345)
Pct. Hispanic				-107,981*** (23,519)	-94,447*** (26,971)
Pct. Over 65				293,370*** (43,445)	248,323*** (57,917)
Pct. College Grad				310,202*** (18,982)	302,616*** (25,578)
Pct. Housing Built Pre-1959				98,359*** (9,846)	91,905*** (12,005)
Pct. Developable (20km)				-204.41** (83.86)	-114.10 (153.79)
Constant	214,252*** (3,777)	459,193*** (29,792)	360,403*** (48,769)	353,142*** (51,043)	151,376 (120,903)
State Fixed Effects	No	No	Yes	Yes	No
CBSA Fixed Effects	No	No	No	No	Yes
Observations	1,530	1,530	1,530	1,376	1,202
R ²	0.07	0.77	0.83	0.88	0.92

Note:

*p<0.1; **p<0.05; ***p<0.01

Table F.2: Building Permit Regressions (Robustness Test)

	<i>Dependent variable:</i>					
	Log Building Permits (2000-2016)			Log Building Permits (2010-2016)		
	(1)	(2)	(3)	(4)	(5)	(6)
MRP Ideology (T&W)	2.85*** (0.17)	0.02 (0.21)	-0.13 (0.27)	3.10*** (0.19)	0.01 (0.27)	-0.42 (0.35)
Log Housing Units (Initial)	1.18*** (0.04)	1.14*** (0.03)	1.13*** (0.03)	1.52*** (0.04)	1.36*** (0.04)	1.32*** (0.05)
Median Home Value	0.35*** (0.06)	0.69*** (0.11)	0.84*** (0.17)	0.71*** (0.06)	0.89*** (0.14)	1.06*** (0.23)
Mean Jan. Temperature		0.01 (0.01)	-0.01 (0.03)		0.04*** (0.01)	-0.02 (0.04)
Mean Jul. Temperature		0.06*** (0.01)	0.07*** (0.02)		0.03** (0.02)	0.07** (0.03)
Pct. White		0.66 (0.56)	-0.44 (0.62)		0.80 (0.63)	0.15 (0.73)
Pct. Black		-0.27 (0.60)	-1.10* (0.67)		-1.11 (0.70)	-1.60* (0.82)
Pct. Hispanic		0.46 (0.57)	-0.38 (0.66)		-0.15 (0.64)	-0.20 (0.77)
Pct. Over 65		-0.05*** (0.01)	-0.05*** (0.01)		-7.23*** (1.17)	-6.70*** (1.57)
Pct. College Grad		-0.53 (0.43)	-0.63 (0.60)		0.61 (0.60)	0.32 (0.86)
Pct. Housing Built Pre-1959		-2.88*** (0.22)	-1.97*** (0.27)		-1.91*** (0.27)	-1.62*** (0.34)
Pct. Developable (20km)		0.02*** (0.002)	0.04*** (0.003)		0.03*** (0.002)	0.03*** (0.004)
Constant	-11.50*** (1.13)	-21.20*** (2.32)	-24.72*** (3.76)	-25.18*** (1.22)	-29.70*** (2.95)	-32.52*** (5.11)
State Fixed Effects	No	Yes	No	No	Yes	No
CBSA Fixed Effects	No	No	Yes	No	No	Yes
Observations	1,459	1,316	1,213	1,446	1,305	1,202
R ²	0.43	0.74	0.81	0.49	0.73	0.78

Note:

*p<0.1; **p<0.05; ***p<0.01

Table F.3: Regulatory Index Regressions (Robustness Tests)

	<i>Dependent variable:</i>				
	Wharton Residential Land Use Regulation Index (2004)				
	(1)	(2)	(3)	(4)	(5)
MRP Ideology (T&W)	-0.74*** (0.12)	-0.91*** (0.12)	-1.08*** (0.17)	-0.65*** (0.19)	-0.59** (0.27)
Log Median Income (2000)		1.02*** (0.09)	0.77*** (0.14)	0.67*** (0.15)	0.73*** (0.27)
Log Population (2000)			0.07* (0.04)	0.06* (0.04)	0.10** (0.04)
Mean Jan. Temperature			0.02*** (0.003)	0.01 (0.01)	0.01 (0.03)
Mean Jul. Temperature			-0.05*** (0.01)	-0.03** (0.01)	-0.03 (0.02)
Pct. White			2.00*** (0.65)	2.18*** (0.71)	1.17 (0.86)
Pct. Black			1.18* (0.66)	1.80** (0.73)	1.03 (0.86)
Pct. Hispanic			2.29*** (0.69)	2.54*** (0.71)	1.21 (0.85)
Pct. Over 65			-0.004 (0.01)	-0.01 (0.01)	-0.004 (0.01)
Pct. College Grad			0.19 (0.29)	0.84*** (0.30)	0.60 (0.45)
Pct. Housing Built Pre-1959			-0.63*** (0.19)	-0.63*** (0.21)	-0.49* (0.27)
Pct. Developable (20km)			0.002 (0.002)	0.003 (0.002)	0.01** (0.003)
Constant	-0.03 (0.03)	-10.95*** (0.96)	-8.00*** (1.88)	-8.78*** (2.04)	-8.24** (3.79)
State Fixed Effects	No	No	No	Yes	No
CBSA Fixed Effects	No	No	No	No	Yes
Observations	735	735	653	653	588
R ²	0.05	0.19	0.34	0.49	0.65

Note:

*p<0.1; **p<0.05; ***p<0.01