The Global Effects of Housing Policy

Kyle Mangum*

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Abstract

This paper studies the links between housing policies and aggregate energy use in the U.S. I connect two strands of literature on cities–that cities vary in their per capita energy use and in terms of housing supply elasticity–to measure the effects of location choice and housing consumption on aggregate energy use. I build a dynamic spatial equilibrium model of U.S. metropolitan areas, accounting for local heterogeneity in housing demand and supply. Importantly, I decompose the supply restrictions into those naturally-occurring and those policy-induced. After matching the model to data on housing prices, construction activity, and building density, I conduct policy simulations to quantify the effect of various housing policies on energy use. Results indicate that removing the federal tax subsidy for housing would result in a lower aggregate energy use, as would increasing land use regulations in high energy use locations. The primary channel is reducing the amount of housing consumed per person, and the secondary channel is in reallocating population from inefficient to more efficient locations.

Keywords. land use, energy use, housing supply, dynamic spatial equilibrium

JEL codes: R11, R52, Q54, R31

1 Introduction

Carbon emissions may cause significant social harm through climate change. Energy use in the home and in personal transportation, a major source of carbon output, varies significantly over space, suggesting that the nature and location of housing consumption impacts carbon output. This paper studies the links between housing policies and aggregate energy use in the U.S.

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*Department of Economics, Andrew Young School of Policy Studies, Georgia State University. Correspondence to: kmangum@gsu.edu, or Box 3992, Atlanta, GA 30302-3992. Previous versions have circulated under the title "The Global Effects of Local Land Use Restrictions." I thank Jim Alm, Pat Bayer, Bill Gentry, John Gibson, Christian Hilber, Erin Mansur, and Juan Moreno-Cruz for helpful discussions. Taha Kasim and Bret Hewett have provided excellent research assistance. Errors are my own. Comments are welcome.

To do so, I connect two strands of the literature on cities. Glaeser and Kahn (2010) demonstrate that an individual's main contributions of carbon emissions, household and transportation energy use, can vary significantly by metropolitan area of residence. Differences between metropolitan areas in climate, transportation infrastructure, and housing services consumption drive much of the dispersion in energy use across cities.

Cities also vary in housing supply elasticity, a topic studied by Saiz (2010), among others. In some locations, the quantity of housing can expand with little impediment; others are more constrained by natural and artificial restrictions to building. Natural restrictions include geographic barriers such as mountains and water, while artificial barriers include land use regulations such as permit requirements, lot size restrictions, and environmental studies. Thus, at least a portion of the constraints is policy-relevant.

There are reasons to suspect that housing stock expansion in the U.S. has not been optimal with regard to reducing energy use. First, home sizes have been increasing in the postwar U.S. There is a relationship between housing services and energy usage, as larger homes consume more energy and less dense construction increases usage of gasoline. Second, many "easy-building" locations where the stock has expanded are high average energy-use locations.

Regardless of what construction patterns have been, the work of Glaeser and Kahn (2010) suggests what I will call "The Reallocation Hypothesis;" that the movement of population from a high carbon cities to low carbon cities could result in a lower aggregate carbon output.[1] Implicitly, this could happen without any change in a household's behavior within the city, simply because of the more efficient composition of the national average.

This paper quantifies the connection between energy use and the geographic distribution of housing supply. I measure the extent to which housing policies, local or national, affect the amount of housing consumption and the regional allocation of population, which in turn affect aggregate energy use.

The analysis is conducted through a dynamic spatial equilibrium model with an emphasis on housing construction. Through counterfactual policy simulations, I measure the effect of housing policies on the amount of housing constructed and consumed over time in the large metropolitan areas of the U.S. and the resultant energy use and carbon output. This equilibrium-model approach recognizes that altering the housing stock of a city may not only affect the amount consumed per person, but also the number of people who choose to live in that city, and to where they might relocate. The general equilibrium effects may be important because carbon footprints are heterogeneous across space, as Glaeser and Kahn (2010) have shown.

In the model, cities are endowed with amenities and income opportunities, and demand for the location comes from its attractiveness relative to other cities in the economy. Identical workers trade off utility from consumption goods,

[1] Glaeser and Kahn write in their conclusion, "If the urban population lived at higher population density levels closer to city centers in regions of the country with warmer winters and cooler summers in areas whose electric utilities used less coal for producing power, then household greenhouse gas production would be lower" (p. 416).

location amenities, and housing services. Housing prices, population size, and housing services per person are determined endogenously by the standard spatial equilibrium condition that utility must be equalized across space.

In each city, an infinitely lived housing services provider makes housing construction decisions. The builder's decision is dynamic because the stock is durable, thus future prices are affected by past construction decisions, and because land acquisition costs may increase as the land in a city is increasingly employed in construction. Furthermore, the builder accounts for competition from other cities in determining the spatial equilibrium price of housing. The dynamic equilibrium specification is important because I estimate primitive implied costs; failing to account for differences in the option value of land would misstate these costs. This paper relates to recent work (Murphy, 2013, and Paciorek, 2013) on modeling construction as a dynamic decision problem affected by the option value of land.[2]

The dynamic model carries a large state space, complicated exponentially by the spatial equilibrium specification. Much like dynamic games, dynamic spatial equilibrium models are limited by the curse of dimensionality introduced by the number of distinct locations. The technical contribution of the paper is its demonstration of a implementation method for a dynamic equilibrium model of heterogeneous local markets.

The model is implemented empirically using data on local construction activity, housing consumption, housing density, labor and materials cost, and local populations and incomes. Notably, I introduce rich spatially- and temporally-varying housing intensity measures, utilizing detailed tax assessor data on the home and lot sizes by location and time of construction. I am able to leverage variation in amount of construction, its density, and its relationship to changes in demand to identify the primitive cost parameters. Cost parameters are city-specific, and the last step of estimation is to regress these cost primitives on land availability (from Saiz, 2010) and measures of land use regulation (from Gyourko, Saiz, and Summers, 2008). This allows me to decompose the policy-relevant contribution to costs.[3]

Building on the existing descriptive literature, the model's usefulness comes from its ability to predict counterfactual scenarios: the population distribution, housing consumption, and aggregate energy usage under unobserved policy regimes. Using data on household and transportation energy use, I can predict the path of energy use for a given policy regime. Counterfactual experiments study alternative local regulatory regimes and nationwide housing subsidies, and the eventual pass-through effects to aggregate energy use.

[2]Murphy (2013) models individual and owner's decisions to develop, whereas I am modeling the evolution of the city's entire stock. Paciorek (2013) models the stock evolution, but through a dynamic discrete choice model that requires an assumption about the total number of possible units in a city. My flexible continuous stock specification needs no such assumption, and can model the intensive margin of housing consumption as well.

[3]My approach is similar to that of Albouy and Ehrlich (2012) in that I use spatial variation housing market outcomes to identify the average affect of regulation. However, my elasticity measures are identified off of within-city variation over time in the quantity of construction activity, whereas Albouy and Ehrlich (2012) use cross sectional variation in prices.

I find that policies affecting the amount of housing consumed are principally important, and there are second order effects in determining whether the housing is consumed in energy efficient or inefficient locations. Thus, the Reallocation Hypothesis is not rejected, but the intensive margin of housing and its density are the major drivers of carbon savings.[4]

Estimates indicate that the preferential tax treatment of housing (the federal income tax deductions for mortgage interest and property taxes) has increased annual carbon emissions by about 2.7 percent annually, and almost 4.5 percent in new construction, primarily by increasing the amount of housing per person.[5] The federal tax deduction also subsidizes population growth in high per capita housing locations, such as Atlanta, Las Vegas, and Phoenix, many of which are high carbon output locations. Imposing stricter land use regulations in high carbon output cities would decrease the aggregate amount of carbon output by about 1.7 percent (2.7 percent in new construction), again mostly through decreasing the housing consumed per person and secondarily by moving population to low carbon cities. Relaxing regulations in low carbon output cities would have slightly positive net effects on carbon output, as increased housing consumption mitigates reductions from population reallocation.

The rest of the paper proceeds as follows. Section 2 highlights some motivating patterns between construction activity, housing consumption, land use restrictions, and energy use. Section 3 describes the model in detail. Section 4 describes the data and empirical strategy. Section 5 discusses estimation and simulation results. Section 6 concludes.

2 Motivation

2.1 Home Size, Energy Use

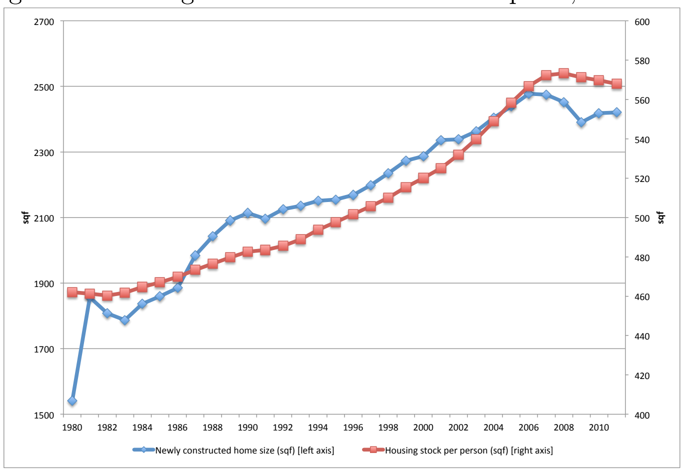
I start by discussing some motivating stylized facts (the data on which these figures are based are described in section 4.2 below). First, home sizes and the amount of housing consumed per person have been trending upward since 1980, as shown in Figure 1.[6] The figure shows that the average size of of newly constructed homes has risen steadily until leveling in the most recent recession. Consequently, housing stock growth has outpaced population growth, and the amount of housing stock per person has grown. The density of new construction (not pictured) fell in the 1980s and 1990s, before becoming somewhat more dense again in the 2000s.

[4]Note that Glaeser and Kahn's (2010) statement suggesting the Reallocation Hypothesis includes, explicitly or implicitly, the intensive margin of housing, population density, and the fuel source of electricity generation (which varies over regions). Each of these dimensions is included in the model and energy calculations below.

[5]For context, the U.S. State Department's energy policy goal for carbon reduction from 2005 to 2020 is 17 percent annually. According to the U.S. Environmental Protection Agency, forested land in the U.S. removes about 18 percent of annual carbon flow. Urban tree cover removes 1.6 percent.

[6]The figure focuses on the estimation period, but the trends predate 1980 as well.

Figure 1: Housing Construction and Consumption, 1980-2011



Notes: The series are the weighted averages for the named cities in the estimation sample below. The 1980 data point includes all housing constructed before 1980.

Figure 2 displays some of the relationships between energy use, housing, and population growth. In the top panel are figures plotting metropolitan area population growth from 1980 to 2011 to per capita gasoline (left) and electricity usage (right), with each dot representing a metro area. The plots show a positive correlation, indicating that quickly growing cities tend to use more energy per person than slowly-growing cities.

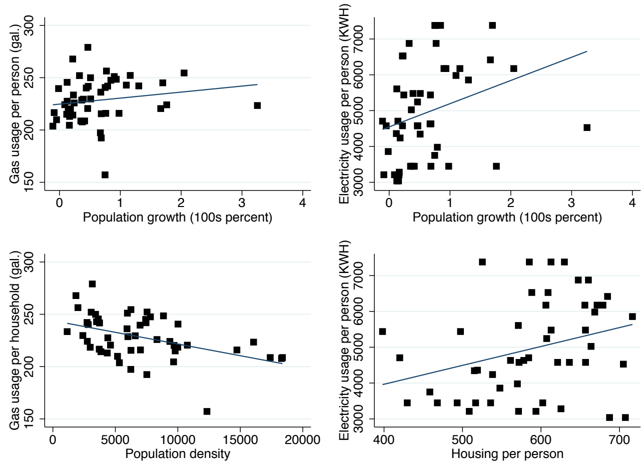
The bottom panel of Figure 2 plots per capita energy use to features of the housing stock in the location. The bottom left plot shows that gasoline use per capita is negatively related to housing density. The bottom right plot shows that higher electricity use per capita is in part due to a more intensive use of housing; cities with more housing area per person use more electricity per person.

Taken together, these figures suggest that energy use can be affected through the extensive and intensive margins. That is, because cities differ in their per capita usage rates, the spatial distribution of population can affect aggregated energy use. At the same time, the characteristics of the housing stock are relevant. A more intensive use of housing will, all else equal, lead to more in-home energy use, and less densely packed housing affects driving patterns and gasoline consumption.

Has the spatial pattern of population growth resulted in higher aggregate carbon output? Figure 3 shows the evidence is mixed. While growth has occurred in higher energy use locations, lower carbon pass-through (due to lower carbon fuel sources for electricity generation) mitigates this to an extent, and the correlation between carbon and population growth is actually slightly negative (though some high carbon locations have grown substantially).[7] Thus, it

[7]Glaeser and Kahn (2010) found virtually no correlation between housing stock growth

Figure 2: Relationship of Energy Use to Population Growth, Housing Density, and Housing Consumption



is important to keep in mind that many sources of spatial heterogeneity are at work.

Table 1 provides a joint summary of the contributors to variation across cities in carbon output per person. Housing per person is a major contributor, even after controlling for population density, climate, and the carbon content of the region's fuel source of electricity (represented by the variable "NERC factor"). All of these contributors are addressed in Glaeser and Kahn (2010), with the exception of housing per person; this component was intentionally ignored in their household-level analysis. In my accounting, I apply energy use rates per unit of housing in order to study the effects of the intensive margin.

2.2 Restrictions to Building

What is the impact of construction barriers, whether naturally occurring or induced by policy? Figure 4 displays scatterplots of population growth, housing per person, and population density against regulatory and natural barriers to construction. Each form of barrier shows a slight negative association with population growth. The associations are stronger with housing per person (negative), and population density (positive). Thus, construction barriers are associated to the nature of the housing stock as much or more than the location.

Finally, Figure (5) shows the correlation between the regulation and land availability of the metro areas. While there is a positive relationship between natural impediments and regulatory barriers, it is far from a perfect correlation. Thus there is variation between the two that I will seek to leverage in identifying

and per capita carbon output.

Table 1: Carbon Output Per Person Across Cities

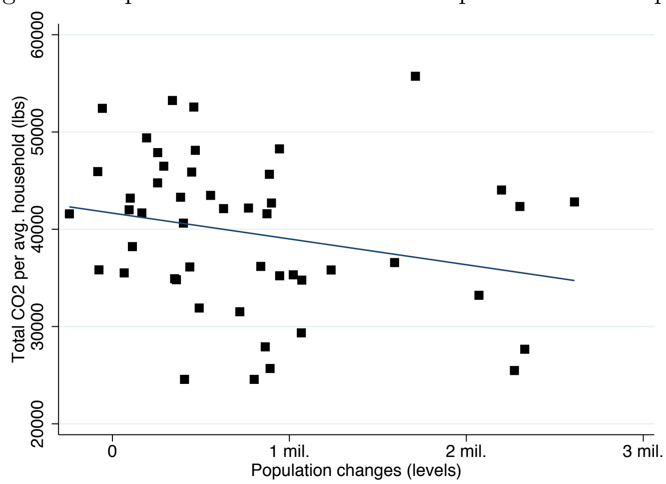
	(1)	(2)
Housing per person (sqft)	16.86***	16.46***
	(4.493)	(4.410)
Population density (pop/sqmi)	-0.180	-0.181
	(0.121)	(0.115)
NERC factor	2,662***	2,555***
	(529.2)	(478.9)
Log Population	-67.29	-57.76
	(404.6)	(396.7)
Mean July Hi Temp (deg F)	63.49	
	(45.27)	
Mean January Lo Temp (deg F)	16.27	
	(27.89)	
Cooling degree-days (1000s)		699.5**
		(340.3)
Heating degree-days (1000s)		100.3
		(174.3)
Constant	-2,119	2,445
	(7,190)	(6,686)
Observations	49	49
R-squared	0.702	0.715

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The dependent variable is metro area average of annual carbon output per person. Mean carbon per person is 14,628 lbs per year. See also Table 3. Mean housing per person is 584 sq ft. The NERC factor is the rate at which a kilowatt hour of electricity generation produces a pound of carbon; its mean is 1.32.

Figure 3: Population Growth and Per Capita Carbon Output



their impact of housing construction costs.

With these stylized facts as background, I proceed to develop a model of housing construction in spatial equilibrium, which will yield predictions for the extensive and intensive margins of housing consumption across space.

3 Model

3.1 Setting

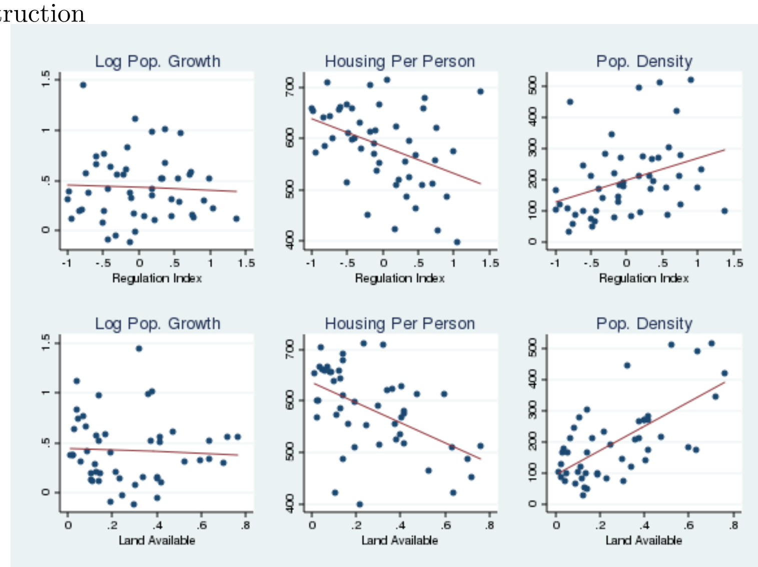
This section describes a dynamic spatial equilibrium model of location and housing consumption choices. Time is discrete and the horizon is infinite. The economy is a closed system of a finite number J of distinct locations. These locations are allowed to be heterogeneous in amenities, labor markets, and housing supply. National population at time t is given by P_t, and workers are freely mobile across cities.

In each location, housing is produced by a single agent whom I call the builder.[8] The construction decision is a stock-and-flow problem in which the builder faces a continuous choice of how much housing to build, and at what density. Construction is durable and irreversible. There is a one period lag between the decision to construct new housing and its arrival in the livable housing stock.

I note from the outset that agents receive no direct utility impact of energy use or carbon output. That is, energy use is completely an externality with no internal cost, simply a byproduct of housing services, density, and location

[8] In reality, the construction sector has many firms. This is the planner's solution to a decentralized model, as described in Ljungvist and Sargent (2001).

Figure 4: Population Growth, Housing Stock Characteristics, and Barriers to Construction



choices. Thus I focus my model on the latter two choices, but return to apply the model's predictions on housing to energy usage.

3.2 Housing Demand

Housing demand comes from a spatial equilibrium in the demand for locations. I assume a resident of the the economy has the following utility function over consumption and housing services:[9]

$$u(c, h) = log(c) + \gamma log(h)$$

where γ governs the elasticity of substitution of housing and consumption (numeraire) goods.

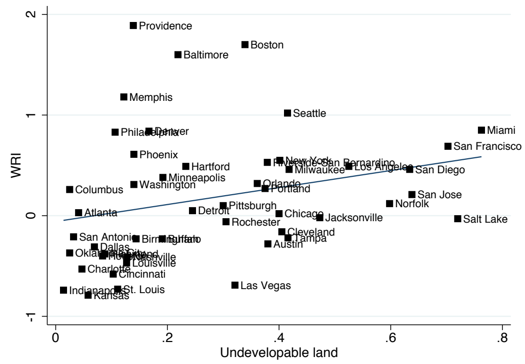
For each unit of housing services, the resident pays price r. Incomes in each location are taken to be exogenous. The agent's budget constraint in each location is

$$c + r_j h = y_j$$

The first-order condition for optimization yields $h = c\frac{\gamma}{r_j}$. Using the first-order condition for optimization and the budget constraint, we have the individual's inverse demand equation for housing services:

[9]Note that this is a Cobb-Douglas utility function in natural logs. Davis and Ortalo-Magne (2011) argue for a Cobb-Douglas utility function based on the temporal and spatial consistency of the expenditure share of housing.

Figure 5: Land Availability and Local Land Use Regulation



$$r_j = \frac{y}{h} \frac{\gamma}{1+\gamma} \qquad (1)$$

3.3 Housing Supply and Equilibrium

The housing supply in period t, H_t, is the result of past construction decisions by the builder. I describe the housing supply decision in more detail below, but for the purpose of determining equilibrium rents and population in period t, it is predetermined.

Within an arbitrary city, two conditions must hold. First, the residents must be at their optimal tradeoff of housing services and the consumption good, given by (1). Second, the housing market must clear: the housing services per resident sum to the total stock of housing in the city.

$$pop\, h = H \qquad (2)$$

Equations (1) and (2) can be combined to obtain the city-wide demand curve

$$r_j = y \frac{\gamma}{1+\gamma} \frac{pop}{H} \qquad (3)$$

That is, ceteris paribus, rents rise in income and population, but fall with the supply of housing stock.

It is not necessarily the case, however, that the price elasticity of housing is unity, because the population term is determined endogenously by a spatial equilibrium, and therefore it depends on the housing stocks and incomes of all locations. Between cities, full mobility implies zero arbitrage in utility: residents must be indifferent between any two arbitrary cities (Roback [1982])

$$\begin{aligned} u_j(c_j, h_j, \mu_j) = log(y_j - r_j h_j) + \gamma log(h_j) + log(\tfrac{\mu_j}{p_j^{\nu}}) = \\ log(y_k - r_k h_k) + \gamma log(h_k) + log(\tfrac{\mu_k}{p_k^{\nu}}) = u_k(c_k, h_k, \mu_j) \end{aligned} \qquad (4)$$

where μ_j is the flow utility from location j-specific amenities. The amenity congests in population at rate ν.

A spatial equilibrium obtains when (3) and (4) hold for all cities j, k. For an economy of J cities, there are $2J$ endogenous variables, the rents r_j and the population sizes pop_j. These are determined by the $2J$ equilibrium conditions: J "within city" conditions (3), $J-1$ relative "between city" conditions (4), and 1 adding-up constraint on the national population, $\sum_j^J pop_j = P_t$.

3.4 The Builder's Problem

The previous subsection described the equilibrium conditional on housing stock. I now describe how the builder chooses the housing stock.

The builder is endowed with ownership of all vacant land in the city. On his land, he can produce a continuous and divisible stock of housing; the housing stock is built atop land A_t, the current stock of land employed. Constructed housing, and the land that it is built upon, is sold to a risk neutral middleman at the price of the net present value of the current rent rate in perpetuity.[10] The builder's revenue is

$$b_t = v_t i_t = \frac{1}{1-\delta\beta} r_t i_t \tag{5}$$

where i_t is the new construction.

The builder can decide to add to housing stock, but cannot intentionally remove it. Housing and land stock depreciate at rate δ, and depreciated land returns to ownership of the builder.[11] The evolution of the land and housing stock is then

$$\begin{aligned} H_t &= (1-\delta)H_{t-1} + i_t \\ A_t &= (1-\delta)A_{t-1} + a_t \end{aligned} \tag{6}$$

$$s.t.\ i_t,\ a_t \geq 0$$

The builder decides in t how much housing stock to build, sold at a contract price determined in t, but the new stock does not become available for consumption until $t+1$. This delay is meant to reflect the considerable time involved in constructing housing, obtaining permits, and the like.[12] The density of new construction is $\frac{i_t}{a_t}$, and the density of the stock is $\frac{H_t}{A_t}$.

[10] This essentially reverses a user-cost rental calculation back to a value.

[11] It is a simplification to assume that the land employed decays at the same rate of housing depreciation; that is, the housing stock depreciates equally at all densities.

[12] The assumption that the contract price is determined in t simplifies the solution of the spatial equilibrium price vector. Prices are determined by current states (i.e. the history of construction decisions in all locations), not simultaneously determined by all current construction policy functions. Future prices will however be affected by decisions today, and the builder will take this into account in his dynamic decision problem.

3.4.1 Production Function for Housing

New housing i_t is constructed using land a and capital k; when producing an addition to the housing stock i_t, the builder decides the factor intensities. Capital is the combination of the physical materials (wood, brick, drywall, etc), and the labor and equipment used to install them, which are perfect complements: $k = min\{materials, labor, equipment\}$. The production function for housing is given by a constant returns to scale Cobb-Douglas specification.[13]

$$i = \phi_j k^{1-\alpha} a^{\alpha} \tag{7}$$

The total factor productivity of the housing production function, ϕ_j is specific to the location, as are the costs of the inputs. I denote the cost of land as c_j and capital as cc_j.[14] The first-order conditions of an expenditure minimization problem of

$$min_{k,a}[cck + ca] \; s.t. \; i = \bar{i}$$

yield the demand function for capital: $k = \frac{1-\alpha}{\alpha}\frac{c_j}{cc_j}a$. Substituting for k gives the production to be

$$i = \phi_j (\frac{1-\alpha}{\alpha}\frac{c_j}{cc_j})^{1-\alpha} a \tag{8}$$

Thus, the density of housing construction, $\frac{i}{a}$, is determined by the productivity parameters ϕ, α and the relative costs of land and capital.

3.4.2 Costs

As mentioned, the capital costs are the costs of materials, labor and installation. The land cost is the expense of the technology of converting vacant land into plots suitable for construction. I specify the cost of land to be $c_j = c_{1j}A_t$ to reflect a finite amount of land available to the builder. That is, the marginal cost of new land may increase as more land is occupied by housing. The dynamic nature of the land cost is meant to reflect that presumably the best (lowest cost) land was developed first, and more difficult land (forested, steeply sloped, swamp, etc) is only developed later.[15]

Additionally, new housing comes at a convex cost of $c_{2j}i^2$. That is, an infinite amount of housing cannot be added in a single period. This is intended to reflect anything inelastically supplied in the city (a limited supply of contractor labor, backlog at the permit office, local opposition to “excessive” new building).[16]

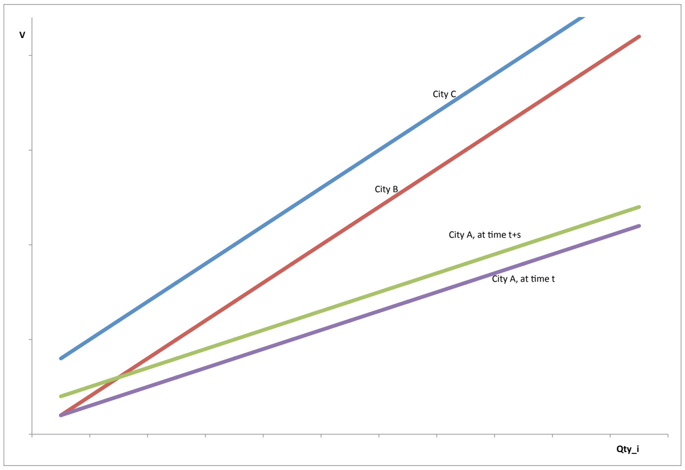
[13] Recent work on the topic has found that a constant returns to scale Cobb-Douglas function to be a good approximation to the production function for housing. See Ahlfeldt and McMIllan (2014) and Epple, Gordon, and Sieg (2010).

[14] The cost of capital implicitly includes the labor cost of installing materials as well. My data source for construction costs reports values for “materials” and “labor and installation.”

[15] When assuming a uniform price for the city, this cost could also represent that additional land is at the city edge and is therefore less valuable.

[16] The finding of the literature, and in my data, is that materials and labor are elastically supplied, as material and wage costs do not seem to move with the amount of construction activity. See Wheaton and Simonton (2007), Gyourko and Saiz (2006).

Figure 6: Comparing Housing Supply Curves



Together, these costs form the housing supply curve, as illustrated in Figure 6. Given the current state of the economy, the marginal revenue unit of i is v. The parameter c_2 governs the slope of the supply curve. City A has a flatter slope (i.e. more price elastic, a lower c_2) than B or C; for a given demand shock, quantities will increase more in A than B. In a given time period, the land and capital costs, $\{c_1, cc\}$, form the intercept to the supply curve. City C has a higher intercept than A or B; relative to B, a higher price will result at each quantity. The line "City A, at time t+s" illustrates how the supply curve may shift as the stock of available land diminishes (i.e. as A_t increases). Thus, these supply curves illustrate the marginal cost at a point in time, which may shift. Furthermore, the slope of the supply curve at time t will reflect the option value of land–the builder's interest in withholding land for future use–so that the shape of the supply curve also depends on the amount of land employed, the demand states, their expected transitions, the stock of housing in other locations, and so on. Static specifications of the housing supply curve may attribute all of this to a slope parameter like c_2, when it may actually be a combination of within-period costs and dynamic considerations.

3.4.3 The Return Function

Resulting from the two previous subsections, the per-period payoff function is then

$$\pi_t = v_t i_t - cc_j k_t - c_{1j} A_t a_t - c_{2j} i^2 \tag{9}$$

3.4.4 Dynamic Decision Problem

The housing supplier's decision problem is dynamic because both revenues and costs are affected by state variables, as construction is durable and irreversible. The builder's control state variables, which result directly from previous choices, are the current stock of housing, H_t (which includes the lagged construction about to come online, i_{t-1}), and land employed in the provision of housing services, A_t. With the optimal substitution of capital and land in (8), this reduces to a single control in A_t.The exogenous demand state is the income of the location, y_t, and the national population. The other determinant of r_t, the local population, pop_t is determined by spatial equilibrium, a function of the builder's and other locations' states.

The builder's problem is written recursively as

$$V(H, A, y, X) = max_a[\pi(H, A, y, X) + \beta EV(H', A', y', X'|a, i(a))] \tag{10}$$

where H, y, A are the state variables in the city, and X are state variables in other cities. The builder's cost component of $\pi(H, A, y, X)$ depends on how much housing stock he adds today and how much new land he employs to do it, with the land cost depending on the current state of land employed in housing. The builder's revenue component of $\pi(H, A, y, X)$ depends on the housing stock carried over from previous periods, and the level of demand for the location. The notation X is used to represent the states of demand and housing stock for *other* cities in the economy. The states of other cities are relevant for revenue because the population and rent are determined by the spatial equilibrium.

The builder also factors in the expected continuation value, $EV(\cdot)$, the value of acting optimally in the future. Choices today affect the transitions to future states, so the "shadow value" of these choices in factored into the dynamic decision problem; for example, optimally waiting for a higher expected output price is such a dynamic consideration. The builder's choice of a will determine the next period's values of H and A, and he forms expectations over the demand-determining states y and X.

With many locations in the economy, the state space represented by X will be very large. This is the "system of cities" problem which makes dynamic spatial equilibrium models extremely difficult to analyze and implement. I discuss in the next section how I approach this problem.

4 Empirical Implementation

4.1 Model Solution

With the large state space of the problem in (10), solving the model to yield a policy function is not a trivial task. Because the demand for any one city is determined by a spatial equilibrium, it is affected by the income, amenity, and housing supply conditions of all the other cities in the economy. With K state variables for each location, the full state space is of size KJ, meaning that under standard value function iteration methods, the curse of dimensionality bites very quickly. For any interesting number of cities, standard solution methods are infeasible.

4.1.1 Aggregation

In accounting for even basic features of local heterogeneity in dynamic spatial equilibrium models, one encounters this "system of cites" dimensionality problem similar to the solution of dynamic games.[17] My approach here will be similar to my earlier work (Mangum [2012]), which was inspired by the work of Krusell and Smith (1998) and Weintraub, Benkard, and Van Roy (2008). The equilibrium concept is an approximated rational expectations equilibrium. Instead of literally accounting for every other state in the economy, I approximate the full solution by assuming that a local agent accounts for his own state variables, and a summary of the "elsewhere" states. This makes the state space $K_{local} + K_{other} << KJ$ with large J. The point is to use an aggregate state as a proxy for the conditions of the economy, without the combinatorial explosion created by separate treatment of other locations.

State aggregation is computationally convenient, but it has an appealing "bounded rationality" intuition as well–a builder factors in demand in his city relative to others, but is not competing with other cities individually like an oligopoly market. In a sense, the mathematical solution to the model is difficult for artificial reasons, and the approximated solution may well be closer to reality anyway. Section A in the appendix elaborates the argument for the aggregate state simplification.

The summary states I use are the average per capita income (y_{-j}) and aggregate housing stock (H_{-j}) of the rest of the economy, in addition to the national population. The approximated problem is now

$$V_j(H_j, A_j, y_j, P, H_{-j}, y_{-j}) = max_{h,a}[\pi(H, A, y, P, H_{-j}, y_{-j}$$

$$\beta EV_j(H'_j, A'_j, y'_j, P', H'_{-j}, y'_{-j}|H_j, A_j, y_j, P, H_{-j}, y_{-j};\ \omega(y_{-j}), \rho(S);\ h, a)] \quad (11)$$

I preserve the local heterogeneity by solving each agent's dynamic problem separately (note the index of j on the value function itself). That is, while I may be summarizing the "elsewhere" states similarly for each agent, the impact those states have on one's value function varies across agents, as the value of the "elsewhere" states depends on what policies the states imply for the other agents in the economy.

The future value term $\beta EV(\cdot)$ depends on the expected next-period value of the summarized states, Y'_{-j}, H'_{-j}. Thus the summarized states need their own laws of motion, represented respectively by $\omega(y_{-j})$ and $\rho(S)$, which affect the value function. Because local incomes are taken to be exogenous, the expected

[17]For early work on this topic in the games literature, see Pakes and McGuire (1994)

"other income" term $E(y'_{-j}|y_{-j}) = \omega(y_{-j})$ is simple to find using the individual cities' transition laws for y and the joint distribution of the error terms. In practice, I use a Monte Carlo procedure. The other aggregate state, H'_{-j}, is the summarized outcome of the individual cities' choices. Consistent with the approximated rational expectations equilibrium, I assume the agent expects H_{-j} to follow the law of motion $H'_{-j} = (1-\delta)H_{-j}+i_{-j}$, where the construction policy rule $i_{-j} = \rho_j(S)$ is a parameterized policy rule in the states.[18] In practice, a log-linear specification of $\rho(S) = \rho_0 + \rho_1 Y_{-j} + \rho_2 H_{-j} + \rho_3 P$ fits the construction activity in the data quite well, yielding R^2 terms around 0.90.[19]

Note that $\rho_j(S)$ is merely an aggregation of individual builders' optimal decision rules, and as such is an outcome of the costs that the cities face. When simulating the model for counterfactual values of parameters, the policy rule needs to be updated for the new cost regime. To do this, I simulate the construction choices of each city's builder at the hypothetical new cost parameters, but at the original policy rule, $\rho_j^0(S)$. I then use the simulated choices to determine a new guess of the policy rule, $\rho_j^1(S)$, which I then use to simulate the city's builders' choices again. I iterate on this process until all builder's policy functions have converged, at which point the aggregated policy update rule will converge as well. The algorithm is:

1. Solve (11) using new parameter values of $\{c'_1, c'_2\}$, and a guess of the policy rule $\rho_j^0(S)$. This yields the policy rules for each city: $i_j(H_j, A_j, y_j, P, H_{-j}, y_{-j};\ \rho_j^0(S); c'_1, c'_2)$.
2. Use $i_j(\cdot)$ to update the expected "other cities" policy rule, $\rho_j^1(S)$.
3. Solve step 1 again using $\rho_j^1(S)$ instead of $\rho_j^0(S)$).
4. Repeat 1-3 until convergence in $i_j(\cdot),\ \rho_j(S)\ \forall j$.

4.1.2 Acceleration

Aggregation reduces the problem to six states, regardless of the size of J. While the reduced problem is now feasible, it is still not a trivial problem to solve, so I use acceleration or further approximation techniques to speed convergence. In practice, I speed the solution algorithm by using a projection method, approximating the value function as a linear-in-parameters function of the states, $V(S) \approx \sum_k \lambda_k g(S_k)$ at a sampling of possible points in the state space of the economy.[20] By choosing a "good basis" of functions $g(S_k)$, one can achieve an arbitrarily good approximation of the true function.[21] After much specification

[18] Note that the policy rule is indexed by j; that is, it may have different parameters depending on which cities make of the "other cities" in $-j$.

[19] The rule's fit is worst in the recent recession, where housing construction fell off much more than income. The rule fits extremely well in the first 25-26 years of data.

[20] For more on projection methods, see Judd (1998), ch. 11 and Miranda and Fackler (2002), ch. 6.

[21] Projection methods behave particularly well in smooth continuous state problems such as this. See Aruoba, Fernandez-Villaverde, and Rubio-Ramirez (2006).

testing, I settled on first-order terms, second order interactions, and a quadratic in local incomes.

4.2 Data

In the empirical implementation, the "city" level of geography is the metropolitan area as defined by Core-Based Statistical Area (CBSA). I focus on the 49 largest CBSAs and aggregate all others into a single "outside option."[22] Data is limited for rural areas, so these are ignored. The data comes from several sources enumerated below.

4.2.1 Local Housing Demand

Determinants of housing demand include local income and population sizes. I use annual county population estimates from the Census, and per-capita income from the regional economic accounts data by the Bureau of Economic Analysis. County-level data is aggregated to the CBSA level.

4.2.2 Housing Stock and Construction

For housing stock, I focus on the total living area occupied by single family units (detached and attached). This is for data availability reasons: the size and density data are not available for multi-unit buildings, and construction activity data for single family homes are more precise. Population sizes are scaled to be the fraction living in single-family homes by metropolitan area, taken from the 5 percent subsample of the decennial census (Ruggles et all [2010]).[23]

I use housing units by county from the decennial Censuses of 1980, 1990, 2000, and 2010, aggregated to the CBSA level. For intercensal years, I allocate the decadal change in the housing stock by the level of building permit activity in the CBSA, as collected by the Census and provided by Housing and Urban Development's State of the Cities Database (SOCD). I use permitting activity as an index because building permits are a noisy estimate of building activity, and do not simply sum to the change in housing stock. Some permits may be abandoned, while other construction may exceed the officially permitted level. Further, I allocate the permits to their expected arrival in the inventory of housing, which may vary spatially and temporally, using annual regional summaries of permit-to-completion rates and times from the Census.

I scale the units by living area and lot size using detailed county tax assessor records, provided by real estate data firm Dataquick. The tax assessor records are collected in 2012 (2011 in some cities), but contain year of construction. Thus, I can subset the data by year of construction to find the average living

[22]IIdentifieid cities comprise approximately two-thirds the national urban population, with the outside option the remaining third. The three smallest specified cities in my data are Salt Lake CIty, UT (49), Rochester, NY (48), and Birmingham, AL (47).

[23]The share of population in single family homes varies substantially between cities, but negligibly within a city over time. I use the simple average proportion.

area and lot size of units constructed in a particular year in the county. Thus my measure of housing density is the actual flooring area ratio (FAR), $\frac{living\ area}{lot\ area}$, and not a proxy such as population or housing units per square mile. To my knowledge, this level of detail at such a wide geographic coverage is unique to this paper. This allows me to implement the model using construction densities and the intensive margin of housing services consumption.

4.2.3 Rents and Costs

Rents are found using the user cost method of Poterba (1992), applied to home value data. The implied rent is $r = uc \cdot v$, where uc is the user cost and v is the house value. Poterba suggests the user cost formula $uc = [(1-t)(m+\tau) + \phi + \psi] - \pi$, where t is the income tax rate, m is the nominal mortgage rate, τ is the property tax rate, ϕ is maintenance cost and depreciation, ψ is the risk premium associated with housing, and π is expected inflation. Following Poterba, I set $\tau = 0.025, \phi = .04, \psi = .04$. I use Albouy's (2009) calibration of $t = 0.251$. I take m as the average 30-year fixed mortgage rate from 1980-2011, using Freddie Mac's Primary Mortgage Market Survey (PMMS). Finally, π is the CBSA's average nominal house value appreciation rate.

Because I am considering the value of newly constructed housing, home values per square foot are obtained from averaging transaction prices from 2004 and 2005 sales of new homes in Dataquick transaction registers. In counties for which no transactions data were available, I used median value for homes built 2005 or later in the 2008-2010 American Community Survey (ACS). The values were converted to 2000 dollars, and averaged across CBSA using housing units by county as weights. The values were then pegged to the Federal Housing Finance Administration's (FHFA) all-transactions housing price index for the CBSA.

The capital component of construction costs is obtained from the RS Means Company. The RS Means data provide the cost per square foot of several typical categories of homes, annually by city, for 1988-2013. The construction costs include materials and installation, which means labor and equipment. I use the construction costs per square foot for an average quality, 2000-square foot home.

4.2.4 Land Use Restrictions

For local land use restrictions, I take the land availability measure published in Saiz (2010). The land availability measure is based on GIS analysis of a 50 mile radius from the city center, quantifying the degree to which land is unsuitable for building. This accounts for coastal and inland water and terrain too steeply sloped for building.

The Wharton Residential Land Use Regulatory Index (WRLURI, or WRI) is a survey of the practices of local building authorities assembled and published by Gyourko, Saiz, and Summers (2008). It contains several sub-surveys related to types of land use regulation, such as permitting and project approval practices, zoning, lot size restrictions, open space requirements, and the like. Gyourko et al (2008) note that the subindices tend to be highly correlated.[24] The subindices rate the propensity of a community to impede building, yet one subindex in particular stands out in the context of the current paper: minimum lot size restrictions. While these are in a sense an impediment to building, conditional on a unit being built, these *increase* the amount land employed. To account for this, I build an aggregate regulation index absent the lot size indices, using the factor loadings reported by Gyourko et al (2008).[25] The modified index is rescaled to have a mean of 0 and standard deviation of 1 across communities, and then I take the metro-level average using the community sampling weights provided.[26]

4.2.5 Energy Use

To relate housing stock to energy use, I want to predict the energy usage for a typical household, controlling for location, amount of housing consumed, and housing stock age (since newer homes are typically more energy efficient). The assumption is that there is no permanent individual heterogeneity–a relocating resident will become the type of energy user that the destination city already hosts. For this reason, many possible "controls" are intentionally omitted and subsumed in the averages, including price of the energy. That is, I ignore sorting between cities based on energy use preferences.I focus on personal energy use most directly related to housing stock decisions: in-home electricity and home heating fuels, and gasoline used by personal cars. For household surveys of energy use, I follow and expand upon Glaeser and Kahn (2010).[27]

Detailed gasoline consumption for households is collected by the National Highway Transportation Survey (NHTS) in survey years 1983, 1990, 1995, 2001, and 2009. The data include household attributes such as number of drivers, vehicle attributes (detail varies by survey year), and self-reports of gallons consumed and expenditures per year. I limited analysis to unleaded gasoline vehicles. The NHTS includes specific metropolitan area location for the large cities used in my data. To find average usage per resident, I pool the data and run a regression of gasoline usage on location and time dummies.

In-home energy use is collected by the Residential Energy Consumption Survey (RECS) for survey years 1987, 1990, 1993, 1997, 2001, 2005, and 2009. The

[24] From p. 695 of Gyourko et al.: "[T]here is a strong positive correlation across the component indexes that make up the aggregate WRLURI....Thus, there is little evidence of targeted regulation at the local level. The data are more consistent with communities deciding on the degree of regulation they want and then imposing that desire across the board."

[25] I also omit the "Local Assembly" subindex (LAI), representing the degree of direct democracy (e.g. town hall meeting votes) in project approval. This is peculiar to New England and may not be well represented in the index. (Gyourko et al note that this subindex was not part of the survey questions, but information was volunteered by some communities.) Inclusion of the LAI makes Boston and Providence in particular notable outliers, though even without the LAI, Boston and Providence are some of the most highly regulated markets.

[26] The metro level index for the large cities in my sample has a mean near 0 but a standard deviation of 0.59.

[27] I thank Erin Mansour for additional guidance on these data sources.

data include household attributes such as number of members, and importantly, the size of the living area. The data include self-reports of in-home utility usage (electricity, natural gas), as well as home heating fuels such as oil, propane, and kerosene. I limit analysis to the common utilities: electricity, natural gas, and fuel oil. I find the average usage per square foot of housing for each energy type. Geographic detail is more limited in RECS than NHTS, as the survey reports only metropolitan status (an indicator) and census region or, in the 2009 survey, sub-region. To assign metro-level energy usage rates, I assign the metro areas to their respective census sub-regions, using the sub-region means in 2009 to infer differences in within-region means in earlier survey years.

4.3 Estimation

Given data on local income and national population, the model predicts the endogenous level of construction, land employed, rents, and population shares by city. I fit the parameters of the model to these data moments.

4.3.1 First-Stage Parameters

Many model parameters are found in a first stage, without simulation of the model. These include state transitions, local construction costs, and structural parameters calibrated a priori.

First, I find the transition process by which income evolves for each location. This is done through fitting an AR(1) time series process on local per-capita income. Next, I calibrate the housing demand elasticity parameter γ using the average housing expenditure from my calculation of user costs and incomes. I find a value of $\gamma = 0.238$, effectively the same as the Davis and Ortalo-Magne's (2011) calibration of 0.24.

Then using the actual data on rents, income, housing services consumed, population size, and the calibrated γ, I back out the local amenity fixed effect parameters μ and its associated congestion term, ν, from condition (4). I do this through an iterative routine. For a guess of ν, I run a fixed effects regression of the spatial equilibrium condition (4), subject to a normalization of the outside option $\mu_0 = 0$; this yields the amenity terms best implied by the spatial equilibrium condition under a calibration of ν. I then update the guess of ν to find the value which yields the lowest mean-squared error in the regression. There is some tradeoff in matching rents or population shares, but because I am interested in the revenues of the builder's problem, I use the ν which fits rents the best. I find $\nu = 0.47$.

I find the deprecation rate of the housing stock δ from a regression of (6) using the national housing stock time series and construction activity (which is far less noisy than the local permit data). I find $\delta = .012$.[28]

In the construction cost data from RS Means, there is significant spatial heterogeneity but virtually no evidence that these fluctuated with the level of

[28] Note that this is physical depreciation, not value depreciation. That is, δ governs how quickly housing decays and falls out of the stock, not how buildings may lose value with age.

building activity. That construction labor and materials are elastically supplied is not an uncommon finding in the literature.[29] But because the costs are largely affected by construction sector wages, the costs do seem to trend with income. I run a regression of construction costs on incomes, pooling the data across cities and including city fixed effects. Doing so yields city-specific intercepts and a wage coefficient: $cc_{jt} = cc_{0,j} + cc_1 y_{jt}$, for which I find $cc_1 = 1.36$.

Finally, I set the builder's discount rate to $\beta = 0.95$.

4.3.2 Second Stage Parameter Estimation

I find the structural parameters $\theta = \{c_1, c_2, \phi\}$ via the method of simulated moments (MSM) for each city (i.e. for each agent/builder). That is, I choose parameters that yield a policy function as near as possible to the data. The moments to match are the choice variables i, a, so the moment conditions are

$$M = E\left[\begin{pmatrix} \hat{i}_t(\theta) \\ \hat{a}_t(\theta) \end{pmatrix} - \begin{pmatrix} i \\ a \end{pmatrix} \right] = 0 \tag{12}$$

The objective function is then $L = min_\theta\{\frac{1}{2t}M'M\}$, and the estimates are $c_1, c_2\phi = argmin_\theta L$. The admissible set of values is constrained to the non-negative real numbers.

The intuition for identification is to use observed temporal variation in quantities of housing and its density relative to prices to infer parameter values. Essentially, the model asks, given the revenues available to the builder, why does he build as much as he does? Conditional on prices, the average amount of building and the degree to which this changes with the stock of land identifies the land cost parameter c_{1j}. The parameter ϕ_j is identified by the density of construction, conditioning on cost parameters (since the builder optimally choose the factor intensities, these are affected by c_1). The extent to which building activity fluctuates with demand (i.e. the supply elasticity) identifies the convexity cost parameter c_{2j}. All of this is done controlling for differences between cities in physical construction (capital) costs, cc.[30]

MSM requires many evaluations of the value function in (11). Even after the acceleration methods, a large J still makes the problem difficult since all the individual housing suppliers' value functions are solved separately but must converge jointly in equilibrium. Therefore, it is very useful to make an additional simplification in the process of estimation. I estimate the policy function $H_{-j,t+1} = \rho(P_t, H_{-j,t}, y_{-j,t})$ directly from the data. That is, I use the "elsewhere" state transitions in the data, rather than jointly solving the dynamic spatial equilibrium for each guess of parameters for all cities. This allows me to estimate the model separately for each city as a single agent problem, a major

[29]See Wheaton and Simonton (2007), Gyourko and Saiz (2006). Discussions with data engineers at RS Means confirmed the finding.

[30]Technically, the parameters are jointly identified, so it is a bit casual to discuss piecemeal identification, but the discussion should illuminate how moments of the data inform the parameter selection.

savings in computational time as well as a way to break the correlation of errors between the parameters for different cities. In counterfactual simulations, I cannot make this simplification.

4.3.3 Effect of Land Use Restrictions

Given estimates of the structural parameters on construction costs, $\{c_1, c_2\}$ and productivity ϕ for each city j, the next task in estimation is to relate these to the land use restrictions: land availability and local regulation indices. My simple approach is to treat the structural parameters as outcome variables caused by land availability and regulation. For parameter θ_n, I assume

$$\theta_{nj} = f(LA_j, WRI_j, \epsilon_{nj}) \tag{13}$$

where LA is the Saiz land availability measure and WRI is the Wharton Regulation Index in j, and the term ϵ_{nj} is the unexplained component of the cost parameter for city j. This specification leverages spatial variation in the structural parameter estimates to identify the average impact of land use restrictions on the residual costs. In practice, I run linear regressions.

Policy simulations input counterfactual values of WRI to yield counterfactual values of $\{c_1, c_2, \phi\}$ and simulate the model under these. The projections of counterfactual cost parameters retain the city's unique cost heterogeneity through the residual ϵ_{nj}. Because the model finds the equilibrium population distribution and housing services consumed under each counterfactual simulation, this can be done for one, several, or all locations at a time, making for a very flexible policy simulator.

5 Results

5.1 Energy Use

Before discussing the structural cost estimates and model simulations, I report the results for spatial differences in energy use. The discussion is brief because the analysis mostly replicates Glaeser and Kahn (2010).

Table (2) reports the results for in-home energy use, as a usage rate per square foot of housing. The findings are in line with Glaeser and Kahn (2010). Warmer climates tend to use more electricity but less heating fuel. Newer construction tends to be more energy efficient. The last column reports the average gasoline consumption per household in 2009, estimated from the NHTS sample. Housholds in cities in the south (and Detroit, MI) tend to use the most gasoline, roughly 30 percent more than low use cities.

It is useful to consolidate the energy usage information into a single index of carbon output, as in Glaeser and Kahn (2010), to summarize the net impact of different forms of energy use and their intensity. This requires a "carbon factor" which converts a unit of energy usage to the amount of carbon its consumption adds to the atmosphere. I use the factors of Glaeser and Kahn (2010) for gasoline

Table 2: Energy Use by Residential Location

MSA	Electricity(kWh) (old constr.)	Electricity(kWh) (new constr)	Natural gas (100cuft) (old constr)	Natural gas (100cuft) (new constr)	Fuel Oil (gal)	Gasoline (gal/hhld)
New_York_NY_NJ	3.12	3.09	0.42	0.27	0.35	1,053
Los_Angeles_CA	3.24	3.35	0.34	0.28	0.18	1,159
Chicago_Gary_IL	4.50	3.55	0.67	0.41	0.28	1,072
Philadelphia_PA	4.18	4.14	0.41	0.26	0.35	1,023
Dallas_FW_TX	7.36	6.79	0.39	0.25	0.00	1,237
Miami_FL	7.01	6.10	0.18	0.13	0.24	1,038
Washington_DC	5.58	4.86	0.51	0.38	0.24	1,346
Houston_TX	7.36	6.79	0.39	0.25	0.00	1,249
Detroit_MI	3.85	3.04	0.72	0.44	0.28	1,225
Boston_MA	2.91	2.87	0.33	0.36	0.34	1,170
Atlanta_GA	5.29	4.60	0.44	0.33	0.24	1,245
San_Francisco_CA	3.24	3.35	0.34	0.28	0.18	1,046
Riverside_SB_CA	3.24	3.35	0.34	0.28	0.18	1,089
Phoenix_AZ	7.18	5.67	0.21	0.15	0.02	1,058
Seattle_WA	6.77	7.00	0.53	0.43	0.18	1,099
Minneapolis_MN	3.59	3.26	0.53	0.32	0.19	1,190
San_Diego_CA	3.24	3.35	0.34	0.28	0.18	1,196
St_Louis_MO	4.95	4.49	0.39	0.23	0.19	1,149
Baltimore_MD	5.58	4.86	0.51	0.38	0.24	1,162
Pittsburgh_PA	4.18	4.14	0.41	0.26	0.35	920
Tampa_St_Pete_FL	7.01	6.10	0.18	0.13	0.24	991
Denver_Boulder_CO	3.67	2.90	0.64	0.45	0.02	1,154
Cleveland_OH	4.40	3.48	0.42	0.26	0.28	1,060
Cincinnati_OH	4.40	3.48	0.42	0.26	0.28	1,197
Portland_OR	6.77	7.00	0.53	0.43	0.18	1,021
Kansas_City_MO	4.96	4.50	0.54	0.33	0.19	1,148
Sacramento_CA	3.24	3.35	0.34	0.28	0.18	1,092
San_Jose_CA	2.92	3.02	0.49	0.39	0.18	1,092
San_Antonio_TX	7.36	6.79	0.39	0.25	0.00	1,197
Orlando_FL	7.01	6.10	0.18	0.13	0.24	1,132
Columbus_OH	4.40	3.48	0.42	0.26	0.28	1,100
Providence_RI	2.93	2.89	0.38	0.41	0.34	1,048
Norfolk_VA_Bch_VA	5.49	4.77	0.40	0.30	0.24	1,188
Indianapolis_IN	4.40	3.48	0.42	0.26	0.28	1,154
Milwaukee_WI	2.85	2.26	0.38	0.23	0.28	1,152
Las_Vegas_NV	5.54	4.38	0.41	0.29	0.02	1,014
Charlotte_NC	6.96	6.06	0.39	0.29	0.24	1,257
Nashville_TN	7.58	6.01	0.34	0.20	0.06	1,307
Austin_TX	7.36	6.79	0.39	0.25	0.00	1,204
Memphis_TN	7.58	6.01	0.34	0.20	0.06	1,238
Buffalo_Niagara_NY	3.12	3.09	0.42	0.27	0.35	966
Louisville_KY	6.98	5.53	0.47	0.28	0.06	1,170
Hartford_Bristol_CT	2.93	2.89	0.38	0.41	0.34	1,117
Jacksonville_FL	7.01	6.10	0.18	0.13	0.24	1,155
Richmond_VA	5.49	4.77	0.40	0.30	0.24	1,126
Oklahoma_City_OK	9.09	8.39	0.63	0.40	0.00	1,187
Birmingham_AL	6.98	5.53	0.47	0.28	0.06	1,115
Rochester_NY	3.12	3.09	0.42	0.27	0.35	1,068
Salt_Lake_City_UT	4.13	3.26	0.49	0.35	0.02	1,068
Other/OO	4.96	4.56	0.45	0.30	0.33	1,176

Notes: Usage rates are annual per square foot of housing, except gasoline, which is in gallons per year per household.

(23.47 lbs per gallon), natural gas (14.47 lbs per 100cu ft), and fuel oil (26.86 lbs per gallon). The carbon output per kilowatt hour of electricity depends on how the electricity is generated, which varies by region. The U.S. Environmental Protection Agency reports the North American Electric Reliability Corporation (NERC) state-by-state conversion factors, which convert the electricity drawn from the grid to emissions from its typical source of generation. Glaeser and Kahn (2010) use a similar conversion; the only difference is that the geographic detail reported is somewhat finer than what was available to those authors.

Table 3 reports my calculation of the carbon output of a typical resident of each city, ranked from lowest to highest. The results are quite comparable to Glaeser and Kahn (2010). I find that California cites, with temperate climate and relatively clean electricity generation, tend to produce less carbon. High carbon use cities are a mixture of southern cities with high gasoline and air-conditioning use, and northern cities with more home heating and dirtier electricity generation, but they tend to be inland cities, not coastal.

The motivation for the Reallocation Hypothesis is clear from a review of Table 3. There are substantial differences in carbon output per person, with the high carbon cities contributing twice as much per person as the low carbon cities.

5.1.1 Gasoline Usage and Population Density

Gasoline usage is largely due to city structure, including size, shape, density, and the nature of the transportation infrastructure. While many of these attributes are outside the scope of the current model, population density is one of the central features. It will be useful to have an estimate of the effect of population density on gasoline consumption while controlling for the un-modeled features of the cities. The literature contains detailed treatments of the relationship between city structure and gasoline use. Brownstone and Golob (2009) is the most relevant.[31] They use 2001 NHTS data for California to estimate an endogenous three equation model of home location (in dense or nondense areas), vehicle ownership, and gasoline usage.[32] Unfortunately, in their reported results, the density measure is the housing units per square mile of the respondent's home census block group, which is not directly comparable to the density measured predicted by the current model, the average population density of the city in residential areas.[33] Thus, I resort to my own analysis of a proportional effect: if the city were to become X% more or less dense, how would gasoline consumption be affected?

[31]See also Bento et al (2005), who develop a multi-step model of transportation mode choice, vehicle ownership, vehicle miles traveled (VMT), and gasoline usage, which they relate to many features of city structure. They find population density to affect the decision to drive or not, but do not find a significant effect of density on VMT, conditional on driving, after controlling for several other features correlated with city density.

[32]One of Brownstone and Golob's concerns is the selection of "car people" into suburban neighborhoods, hence the specification of a multi-equation model of endogenous variables.

[33]Brownstone and Golob (2009) also limit their analysis to the state of California in 2001 instead of a nationwide sample.

Table 3: Annual Carbon Output Per Person, by Metro Area
(units are annual 1000 lbs. per person)

Rank	Metro	Carbon	Rank	Metro	Carbon
1	San_Jose_CA	8.61	26	Norfolk_VA_Bch_VA	13.80
2	Riverside_SB_CA	8.70	27	Pittsburgh_PA	14.24
3	Los_Angeles_CA	8.84	28	Washington_DC	14.28
4	San_Francisco_CA	9.27	29	Tampa_St_Pete_FL	14.32
5	Sacramento_CA	10.08	30	Detroit_MI	14.45
6	San_Diego_CA	10.15	31	San_Antonio_TX	14.77
7	New_York_NY_NJ	10.67	32	Orlando_FL	14.82
8	Buffalo_Niagara_NY	11.06	33	Atlanta_GA	15.09
9	Rochester_NY	11.31	34	Jacksonville_FL	15.10
10	Salt_Lake_City_UT	11.57	35	St_Louis_MO	15.15
11	Baltimore_MD	11.59	36	Birmingham_AL	15.29
12	Philadelphia_PA	11.66	37	Houston_TX	15.72
13	Portland_OR	12.06	38	Columbus_OH	15.99
14	Miami_FL	12.43	39	Austin_TX	16.01
15	Seattle_WA	12.45	40	Dallas_FW_TX	16.09
16	Milwaukee_WI	12.46	41	Phoenix_AZ	16.26
17	Boston_MA	12.74	42	Charlotte_NC	16.43
18	Hartford_Bristol_CT	12.80	43	Memphis_TN	16.46
19	Minneapolis_MN	12.83	44	Cleveland_OH	16.66
20	Providence_RI	12.86	45	Kansas_City_MO	17.52
21	Chicago_Gary_IL	12.89	46	Nashville_TN	17.79
22	Other Cities	13.45	47	Cincinnati_OH	17.93
23	Denver_Boulder_CO	13.51	48	Indianapolis_IN	18.09
24	Richmond_VA	13.77	49	Louisville_KY	18.67
25	Las_Vegas_NV	13.79	50	Oklahoma_City_OK	19.09

Table 4: Gasoline Use and Population Density

Coef.	(1)	(2)	(3)	(4)	(5)
Log(density)	-0.092***	-0.082***	-0.083***	-0.078***	-0.058***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
MSA FE	X	X	X	X	X
Year	X	X	X	X	X
Race		X	X	X	X
Number of adults		X	X	X	X
Number of children		X	X	X	X
Income			X	X	X
Number of drivers				X	X
Number of vehicles					X
Number of workers				X	X

Notes: The outcome variable is the log of gallons of gasoline consumed per household per year. Controls are categorical dummies.

Table 4 addresses this issue; a full table of results is in the appendix (Table 12). Using the full sample of NHTS data, I regress the log of reported annual gallons per household on the log of respondent's neighborhood density, year dummies, and importantly, metro area dummies to pick unobserved city attributes that may otherwise be correlated with density. Each specification progressively adds more controls, following Brownstone and Golob (2009). Note that as indicated above, in doing energy use predictions, I am not interested in the controls per se, but acknowledge that omitted variables may bias the point estimate on density.

The initial estimate is that 100 log point difference in density results in 9 log points less gasoline used.[34] In column 2, adding controls for "permanent" household attributes, such as race, number of children and adults, (i.e. things unlikely to change were the household to be relocated) reduces this only slightly. Controlling for household income (column 3) changes the point estimate little. Columns 4 and 5 add, respectively, controls for number of drivers and number of vehicles; the latter especially attenuating the estimate on density. I will use the -.058 estimate from column 5 as the proportional effect of density on gasoline use. I do this in the interest of being conservative, but reluctantly so, as the choice to drive and to own vehicles may be endogenous to city structure, including density, and so the "control" for number of vehicles may be biasing downward the effect of interest in the present task.

5.2 Cost Estimates

Table 5 reports the estimates for the model's structural parameters, with the average capital cost component, *cc*, for reference. The interpretations of the parameters are straightforward: (1) higher c_1 means more costly land, and

[34] Brownstone and Golob's (2009) estimate of the impact of density was 64.7 gallons per 1000 housing units per mile. The mean usage for a California household in 2001 is about 1400 gallons per household.

hence less building, though the construction effect is mitigated somewhat by construction occurring at a higher density; (2) c_2 means less construction occurs as prices rise; and (3) higher values of ϕ mean more building per unit of land, all else equal.

Table 6 relates the cost estimates to measures of building restrictions well-known to the literature on housing supply. There is a panel each for c_1 and c_2.[35] The specifications for c_2 include a measure of the metro area size ("Pop rank") to control for the fact that the model is estimated in levels, and as such, there is a clear negative relationship between initial city size and the parameter estimate; this control is important for the elasticity parameter (c_2) more so than the land cost (c_1). The regulation index I use is a modified version of the index published by Gyourko et al (2008), as discussed above, which excludes the lot size restriction index.

Both panels show a similar pattern. The regulation index shows a positive and significant correlation with the cost estimates. Adding the Saiz land availability metric–itself positively associated with the cost parameters–causes the regulation index estimate to fall and lose significance. However, adding a separate control for lot size restrictions (column 3) is important. This is intuitive: lot size restrictions themselves increase land usage and are negatively related to cost parameter estimates, but are also correlated with other restrictions, so failure to control for this attenuates the point estimate on the regulation index. The last column of panel A shows the slight effect of population size controls on the the land cost (c_1). The last column in panel B shows the effect of dropping one particular outlier, Baltimore, Maryland, from the elasticity estimate regression; Baltimore has a relatively high regulation index (1.04), yet one of the smallest c_2 point estimates.

Column 4 of panel A and column 3 of panel B, the specifications controlling for land availability, lot size, and population size, are my preferred point estimates which I use in simulations below.

5.3 Model Fit

In this section, I briefly discuss the fit of the baseline simulation of the model to the data. I report the model's predictions from the estimation and from a baseline simulation. The difference between the two is the assumption on the "other cities" strategy function $\rho(S)$. In the estimation's predictions, I use the $\rho(S)$ function derived from the data; essentially, this is a partial equilibrium simulation, and it displays the predicted moments on which the estimation routine is based. The baseline simulation updates $\rho(S)$ based on predicted other cities' policy functions until convergence to the approximated rational expectations equilibrium. This is the baseline simulation to which the counterfactual simulations are compared.

Figure 7 displays the model's predicted housing stock added versus the actual figures from the data. (Figure 12 in the appendix does the same for land stock.)

[35] No clear relationships were found between ϕ and the land use restrictions, so analysis of ϕ is omitted.

Table 5: Parameter Estimates

Metro	Avg CC	c_1	c_2(1000s)	ϕ
New York Nor NY	123.85	0.40	1.31	1.58
Los Angeles CA	102.40	1.32	1.30	1.57
Chicago Gary IL	105.00	0.33	1.31	1.40
Philadelphia PA	105.62	1.62	1.26	0.62
Dallas Fort TX	81.49	0.25	1.50	1.64
Miami Hialea FL	79.96	0.97	3.49	1.58
Washington DC	87.54	0.11	4.02	1.49
Houston Braz TX	81.20	0.47	1.69	1.63
Detroit MI	99.69	0.20	2.79	1.04
Boston MA	109.58	0.08	2.81	1.48
Atlanta GA	79.69	0.05	1.52	1.58
San Francisc CA	114.30	1.82	2.18	1.64
Riverside Sa CA	103.36	0.51	2.85	1.64
Phoenix AZ	84.31	0.47	1.95	1.84
Seattle Ever WA	93.46	0.29	4.24	1.32
Minneapolis MN	104.39	0.27	2.79	0.47
San Diego CA	101.17	0.42	3.03	0.48
St Louis MO	93.30	0.51	2.24	0.49
Baltimore MD	85.55	0.87	0.83	0.65
Pittsburgh B PA	94.67	0.09	4.30	1.52
Tampa St Pe FL	80.43	0.55	1.50	1.14
Denver Bould CO	89.40	0.40	5.37	1.15
Cleveland OH	99.58	0.11	4.64	1.61
Cincinnati OH	90.44	0.10	3.35	1.07
Portland Van OR	130.58	1.99	4.34	0.76
Kansas City MO	94.55	0.22	2.23	1.55
Sacramento CA	104.17	0.39	4.84	1.54
San Jose CA	113.39	1.98	5.05	1.60
San Antonio TX	76.18	0.11	4.25	1.64
Orlando FL	81.31	0.30	4.06	1.60
Columbus OH	89.76	0.18	4.26	0.91
Providence F RI	97.05	0.61	2.78	0.48
Norfolk VA B VA	80.81	0.17	3.06	1.51
Indianapolis IN	89.77	0.21	5.40	1.25
Milwaukee WI	95.63	0.86	7.70	1.01
Las Vegas NV	97.97	1.16	5.67	1.84
Charlotte Ga NC	73.49	0.11	4.66	1.64
Nashville TN	78.43	0.07	5.93	1.00
Austin TX	75.30	0.16	4.72	1.64
Memphis TN	79.16	0.38	6.32	0.52
Buffalo Niag NY	99.05	0.07	11.84	1.06
Louisville KY	86.07	0.01	6.25	1.10
Hartford Bri CT	98.21	0.52	4.19	0.45
Jacksonville FL	77.74	0.65	7.29	1.13
Richmond Pet VA	82.81	0.04	4.31	1.02
Oklahoma Cit OK	76.08	0.05	4.97	1.36
Birmingham AL	79.03	0.17	5.51	0.47
Rochester NY	92.59	0.04	13.38	1.07
Salt Lake Ci UT	80.62	0.97	14.06	1.02

Table 6: Relationship of Cost Estimates to Land Use Barriers

Panel A: $ln(c_1)$

	(1)	(2)	(3)	(4)
Reg Index	0.749***	0.395	0.567*	0.522
	(0.255)	(0.269)	(0.309)	(0.328)
Land Availability (Saiz)		2.087***	1.608*	1.623*
		(0.743)	(0.855)	(0.863)
Lot Size Restr			-1.061	-1.017
			(0.943)	(0.957)
Pop Size				-0.00489
				(0.0111)
Constant	-1.208***	-1.811***	-1.442***	-1.372***
	(0.147)	(0.254)	(0.415)	(0.448)
Observations	49	49	49	49
R-squared	0.155	0.279	0.299	0.302

Panel B: $ln(c_2)$

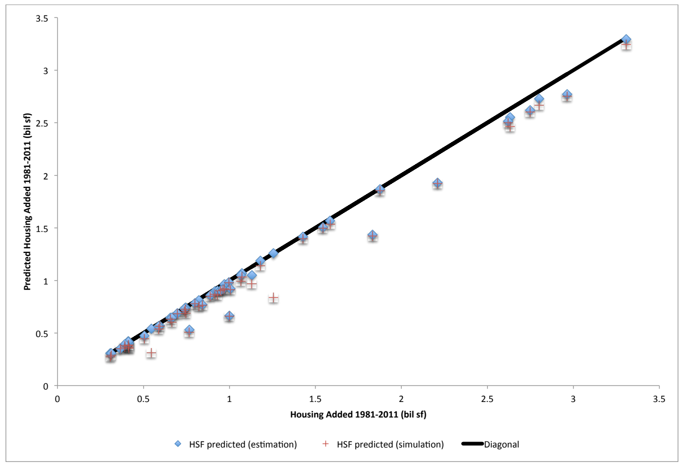
	(1)	(2)	(3)	(4)
Reg Index	0.161*	0.109	0.197*	0.256**
	(0.0900)	(0.1000)	(0.114)	(0.109)
Land Availability (Saiz)		0.309	0.0770	-0.0377
		(0.263)	(0.299)	(0.284)
Lot Size Restr			-0.514	-0.618*
			(0.332)	(0.314)
Pop Size	0.0413***	0.0413***	0.0420***	0.0427***
	(0.00391)	(0.00390)	(0.00386)	(0.00364)
Constant	7.191***	7.101***	7.269***	7.317***
	(0.0826)	(0.113)	(0.155)	(0.147)
Observations	49	49	49	48
R-squared	0.714	0.723	0.737	0.768

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: All specifications include an unreported constant. Specifications with 48 observations exclude Baltimore, MD.

Figure 7: Actual and Predicted Construction of Housing, by Location



Each point represents the total stock added for a city for the period 1981-2011. The model, in estimation and in the baseline equilibrium simulation, does quite well at matching the spatial heterogeneity in housing and land stock growth in the last three decades, with the points fitting very nearly along the 45-degree line. The average predicted densities, reported in Figure 8 also match quite well. However, the model's exact timing of the stock additions is imperfect. Figure 9 is year-by-year plot of predicted housing added to actual housing added. While the points still line up reasonably well along the 45-degree line, there are a few instances of significant prediction error. The model's stock-and-flow structure does contain a self-correcting mechanism, however; for instance, if it predicts too low a stock in period t for whatever reason, the model will try to "catch up" with demand in later periods. I note that this year-over-year prediction error is most serious in cities with large population growth and construction volatility that dwarfs income volatility, such as Las Vegas and Phoenix.

Figure 10 compares predicted end of simulation population to the data. Again, the model overall does well at matching the spatial variation in city size. Under-prediction happens in cities where the housing stock prediction is worst; notably, Phoenix and Las Vegas. Note that unlike housing prices or construction quantities, population is *not* a targeted moment of the estimation routine, yet the model does well at recovering this moment.

5.4 Counterfactual Simulations

I now turn to counterfactual simulations which will alter housing policies in various ways, predicting the housing construction, population distribution, density, and resultant energy use under each counterfactual. First, I highlight what is and what is not permitted to change in these simulations.

In the experiments below, I am altering the level of local regulation, which

Figure 8: Actual and Predicted Construction Density, by Location

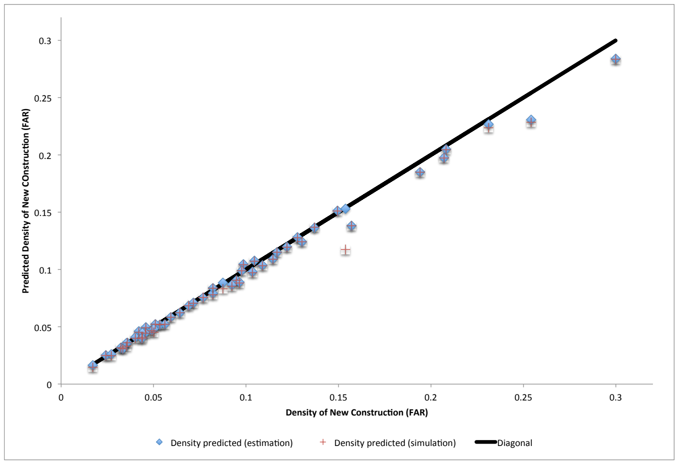


Figure 9: Actual and Predicted Construction of Housing, by Location and Year

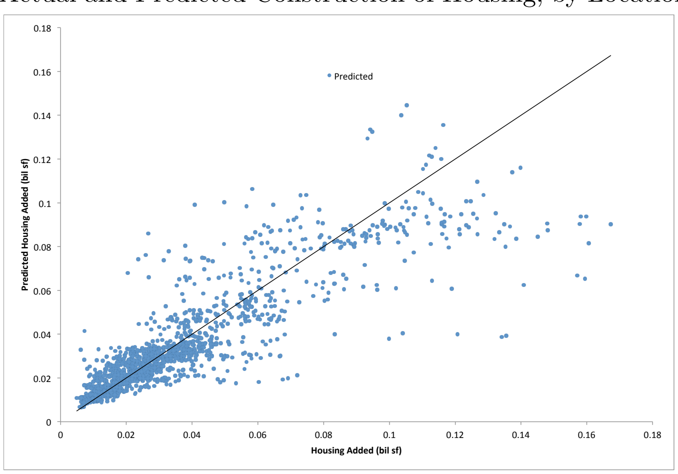
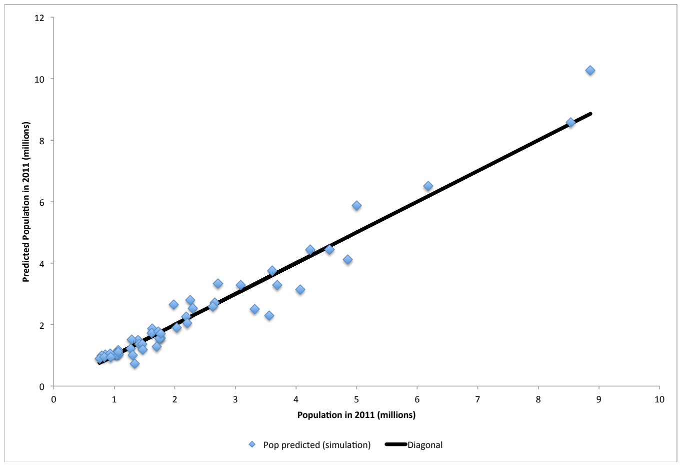


Figure 10: Actual and Predicted Construction of Housing, by Location



manifests in an alternative values of parameter $\{c_1, c_2\}$ for the cities affected. Another experiment is to remove the federal tax subsidy for housing, the mortgage interest and property tax deductions. Each experiment affects the equilibrium supply of housing across locations, and as a consequence, the spatial distribution of population.

I assume that there are no changes to national population, local income, or local amenities; only the spatial distribution of housing supply, and in response, population, are changing. Note that this means there is not a perfectly elastic supply of population–any one city is still "competing" with other cities for residents who are offered income, amenities, and housing in other locations, and there is an "adding up" constraint from the national population being fixed.

I apply the energy usage rates in the data. This assumes that energy consumption behavior does not change, except through the margins affected by the simulation (housing location, housing consumption, population density). This assumes, for example, that in-home technology adoption is unaffected, local governments offer the same transportation infrastructure, consumers buy the same types of vehicles conditional on location, and so on. Furthermore, because energy consumption is driven to large degree by climate, housing consumption, and transportation infrastructure, I assume there are no preferences in energy consumption that are portable across cities. For instance, a counterfactual Los Angeles resident will consume energy like an observed Los Angeles resident, and does not bring, say, "Chicago habits" with her.

The spatial equilibrium model presented does not contain a governmental sector. Thus, I am assuming government policies do not change beyond the imposed policy counterfactual. I ignore, for example, possible changes in government spending when federal tax deductions change, local changes in property taxes when regulations tighten or relax, and the like.

All of the above may be interesting avenues for study in future research, but each would require direct treatment in the model, and they are simply beyond the scope of the current paper.

Finally, I note that a household's expenditure share of housing will remain constant across scenarios. As the supply of housing changes and its price changes, households adjust through the quantity of housing consumed to maintain constant expenditure. This in turn means the numeraire consumption is unchanged, and therefore I ignore carbon output from tradables. The constancy of expenditure share is a result of the Cobb-Douglas functional form for utility. This functional form was not chosen lightly, however: there is direct empirical support for it in the literature (Davis and Ortalo-Magne, 2011).

5.4.1 Energy Use Accounting

For each simulation, I calculate the amount of each type of energy consumed and the resulting carbon output using the location's usage rates from Tables 4 and 2 in each year of the simulation. Because housing is highly durable, even large changes to the construction flow can have small impacts on the aggregate stock. To get a sense of the impact, I report separately for end-of-simulation and cumulative sums, where the former compares the energy flow given by the housing stock in year 2011 across simulations, and the latter totals the energy use flows of each period's stock. I also separately report the energy coming from new construction, defined as housing not pre-existing in 1980 but constructed during the simulation period (1981-2011).

Energy efficiency may have changed over time. To account for this, I separately calculate the energy use per square foot of housing for each of four vintages of housing in the RECS data: pre-1980, 1980s, 1990s, and 2000 and following. The stock of each vintage evolves according to depreciation rate δ and the amount of addition to stock in a given year.

Gasoline calculations use the metropolitan specific average, accounting for time effects. I scale the average gallons per household by the metropolitan-specific probability of owning at least one car,[36] and the average number of persons in a household, obtained from the 5 percent public use samples of the census (Ruggles et al [2010])

Finally, I multiply the city's total energy usage by its respective carbon factor to calculate total carbon output, as in Table 3. Gasoline and natural gas use carbon factors are taken from Glaeser and Kahn (2010), while electricity is weighted by NERC factors reflecting the carbon output of the transmission source. Home fuel oil is a small share of energy usage, and is virtually never present in new construction during the study period, so it is not reported, though the total carbon number includes it.

[36] In doing so, I am effectively assuming that the probability of owning zero cars is unchanged in the counterfactual simulations. That is, the effects of a counterfactual (such as a change in density) on gasoline consumed must come through changes in vehicle miles traveled, mileage per vehicle, or in the number of vehicles, conditional on owning at least one. The share of households in single family homes without any cars is small in all metro areas, from 1.6% in Salt Lake City, UT to 10% in Philadelphia, PA, and under 6% for all but two of the cities considered here.

Table 7: Baseline Simulation: Housing, Population, and Energy Use Totals

	Housing Stock	Density	Electricity	Nat. Gas	Gasoline	In-home Carbon	Total Carbon
	(bil sf)	(FAR)	(bil kwh)	(100 bl cuft)	(bil gal)	(tril lbs)	(tril lbs)
Housing Stock and Energy Flow Use at End of Simulation (2011) ("Snapshot")							
National	104.769	0.090	494.724	24.361	55.792	0.978	2.297
ID'ed Cities	69.918	0.091	326.574	16.353	35.380	0.644	1.481
High Carbon Use	33.505	0.076	183.108	7.596	16.361	0.383	0.768
Low Carbon Use	36.414	0.106	143.467	8.757	19.020	0.261	0.714
Construction Flow and Accumulated Energy Use over Simulation (1981-2011) ("Summary")							
	(bil sf)	(FAR)	(tril kwh)	(100 bl cuft)	(bil gal)	(tril lbs)	(tril lbs)
National	79.060	0.092	12.245	755.317	1,479.840	26.434	61.536
ID'ed Cities	52.162	0.093	8.089	507.325	944.777	17.452	39.896
High Carbon Use	26.572	0.077	4.541	233.876	438.245	10.156	20.477
Low Carbon Use	25.590	0.109	3.548	273.450	506.532	7.297	19.419

Table 7 reports the statistics from the baseline simulation: populations, housing stock, construction, stock density, energy use and carbon output. The first panel–the "snapshot"–reports population stocks and energy use flows for the last year of the simulation, 2011. The second panel–the "summary"–reports total construction flows, the density of new construction, and accumulated energy use over the entire simulation (all years 1981-2011). Counterfactual experiments will later be reported as relative to the baseline simulation, viewing the differences in percentage terms.

As a benchmark for scale in what follows, consider some facts from U.S. government reports on carbon output and climate change.

- The U.S. State Department's Climate Action Report calls for a 17 percent reduction in emissions from 2005 levels by 2020.[37] The report focuses on technological improvements to energy production and efficiency improvements in consumption.

- From the U.S. Environmental Protection Agency's (EPA) "Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2012"[38]

  - Total carbon output from all sources in 2011: 5,592 million metric tons, or 12.33 trillion pounds. About 94% of this is from fossil fuels. Smaller contribution sources include, by way of example, natural gas distribution systems, 35.1 metric tons, or 77.38 billion pounds in 2011; and, trash incineration, 12.1 metric tons, or 26.7 billion pounds in 2011.

  - Of fossil fuel consumption sources, transportation accounts for about 34%, of which about 62% is passenger cars and light trucks/SUVs. Of in-home energy use, electricity accounts for about 14% of all carbon emissions, and direct use of fossil fuels account for 5.7%. Combined,

[37]See http://www.state.gov/e/oes/rls/rpts/car6/219259.htm
[38]http://www.epa.gov/climatechange/ghgemissions/usinventoryreport.html

personal vehicles plus in-home energy use accounts for about 41% of emissions.

- Carbon sinks, such as forested land, remove 979 metric tons per year, about 18% of carbon emissions. Of this forest, 9% consists of urban trees. So, urban trees remove about 1.64% of annual total carbon flow.

5.4.2 Changes to Land Use Regulations

The first set of experiments make changes to regulations in all or in subsets of cities. The first of this set removes heterogeneity between cities in regulation; effectively, this is testing whether high carbon output results as an unintended consequence of the spatial distribution of local land use restrictions. The correlation between the regulation index and carbon per person is -0.61, indicating that less regulated cities have larger footprints. If all cities were equally regulated, would aggregate carbon output be reduced?

To operationalize this, I set the WRI at the scaled mean of zero. The parameters are reset to $c_{1j}^{'} = c_{1j} - 0.522 * WRI_j$, $c_{2j}^{'} = c_{2j} - .197 * WRI_j$, using the parameter from specifications in Table 6, which projects the costs under new levels of regulation, while retaining unobserved cost differences unique to the city. Table 8 displays the city-by-city results from this simulation in terms of housing stock and population change. The cities in Table 8 are sorted by size of the housing stock/population change relative to the baseline simulation. Unsurprisingly, the population "winners" are the cities with high regulation, and the "losers" are those with low regulation, as the degree of change is largest in these. But note that the correlation is not perfect, as the equilibrium model makes this less than a mechanical relationship: some cities may be more desirable for labor or amenity reasons, and the level of regulation is a binding constraint. Also note the changes in the nature of consumption of housing: (1) the increase in housing construction is larger than the response of population, as housing consumed per person increases, and (2) density varies inversely to population.

As the last column of Table 8 shows, any decrease in carbon in one location is offset by an increase in another. The Reallocation Hypothesis is that the aggregate carbon output can be reduced through more efficient composition of population over space. This regulation experiment reallocates housing and population over space, but the effects on the housing consumption patterns mean that this experiment shows no net reduction in energy use.

This is shown in Table 9, which displays the percentage changes in the aggregate energy accounting–the experiments relative to Table 7. The first row of each panel shows the difference relative to the "snapshot" at the end of the simulation period (2011), and the second row shows the difference relative to the accumulated totals (1981-2011). The third row shows energy use in new (post-1980) construction only, ignoring stock put in place before the simulation period. Finally, the fourth row of each panel shows an energy accounting that would result had only population been reallocated according to the experiment, and the intensity and density of housing consumption is as in the baseline.

Panel 1, marked "Same Regulations" displays the results for this first experiment. The net effect on aggregate carbon output is essentially zero. There are two broad reasons for this null result. First, as alluded to, there is an intensive margin response in cities that relax constraints: not only are the cities bigger than the baseline in terms of population share, but each resident consumes a larger home. Any reallocation from high energy use locations to low is overwhelmed by the increase in the intensity of consumption or the decrease in density. The last row of the "Same Regulations" panel displays the energy accounting without the intensive margin response; that is, the accounting assumes the same housing per person and density as the baseline, but uses the population allocation of the counterfactual. While electricity and natural gas usage would decline after the reallocation without the intensive margin response, the net carbon savings would still only be about one half of one percent.

This finding highlights the second reason. Even with substantial differences in carbon output rates in Table 3, very large population changes would be necessary to "move the needle" for aggregate carbon output. This consideration should be kept in mind for other experiments as well. Using the figures of Table 3, even if *all* residents of Oklahoma City (the highest carbon city) were moved to San Jose (the lowest), the aggregate carbon savings would be a mere 0.8 percent.

The results indicate that high carbon output is not a mere accident of the web of land use regulations. But can such regulations still be used as an environmental policy tool? The next three panels of Table 9 display the energy accounting from three experiments to this point. The first of these, in panel 2, labeled "Low Carbon City Reg Subsidy," simulates an economy in which the lowest carbon cities have more lax regulations. Specifically, I remove one standard deviation of regulation (i.e. a change in WRI of 1) from cities below the median carbon output per person, altering their $\{c_1, c_2\}$ parameters accordingly. The results from Table 9 show that this experiment "backfires," actually raising carbon output by 1.35%, as the intensive margin response overwhelms any carbon savings from reallocation of population. While population is reallocated somewhat from high carbon cities to low, the low carbon cities have greater housing stock and use more energy. Furthermore, the last row of the panel indicates that even without the intensive margin response carbon savings would be slight.

The next experiment, in panel 3, marked "High Carbon City Reg Tax," I do the opposite: I add one standard deviation of regulation (i.e. a change in WRI of 1) from cities above the median carbon output per person, altering their $\{c_1, c_2\}$ parameters accordingly. This "stick" approach instead of the "carrot" is more effective in reducing carbon output, with a 1.66 percent in the simulation (2.69% in new construction). Much of this is due to the decrease in the intensity of housing consumption and increase in density: had these remained the same, carbon savings would have been 0.72%.

The last regulation experiment, in panel 4, marked "Carbon-proportional reg tax/subsidy," I use a continuous measure of carbon intensity. I impose a change to the $\{c_1, c_2\}$ parameters relative to the carbon output per person as in Table 3. The story is much as before: population reallocation would make a small change to carbon output, but even this is mitigated by associated intensive margin responses.

In summary, despite the obvious intuition of it, the Reallocation Hypothesis seems of relatively small consequence, though not entirely rejected. The foregoing experiments have, however, highlighted the importance of the nature of housing consumption: the intensive margin matters. The next experiment explores a national policy impacting the intensive margin of housing.

5.4.3 The Federal Tax Treatment of Housing

In the U.S., payments for mortgage interest and local property tax are deductible from federal income taxes, reducing the tax burden for homeowners and effectively subsidizing payments for housing. Given the importance of the intensive margin of housing consumption in the previous experiments, I now ask, what would happen if this subsidy were removed?

In the following experiment, I modify the economy by removing the tax subsidy for housing. The tax treatment of housing increases demand for housing services, ceteris paribus, by decreasing the user cost of housing. While this is a national policy, the effect of the subsidy may not be homogenous across markets, a point emphasized by Hilber and Turner (2013). In the model, no city is either perfectly elastic or inelastic. Increased demand for housing is passed through to developers, to which they respond by adding supply at degrees that vary with the magnitude of the cost parameters and the housing stocks and attributes of the other cities in the economy. Absent the subsidy, the developers add less housing. This experiment measures the effect of housing stocks, populations, and consequently, carbon output across markets.

The user cost calculation accounts for the federal tax deductions for mortgage interest and property tax. I operationalize a removal of this subsidy by making an adjustment to the effective rent, changing the consumer's budget constraint to

$$y = c + \kappa r h$$

where κ is the ratio of the user cost formula without the tax subsidy to the formula with tax subsidy. Based on the implementation parameters described in section 4.2.3, I use $\kappa = 1.17$. (The exact magnitude is debatable, and I conduct sensitivity analyses with respect to subsidy size.) The change becomes effective at the start of the simulation in 1980.

$$r_j = \frac{1}{\kappa}\frac{y}{h}\frac{\gamma}{1+\gamma}$$

Table 10 shows the winners and losers of population in the no-tax-subsidy regime. The population losers tend to be cities that would had the most expansion in housing supply and the higher per capita consumption of housing in

Table 8: Same Regulations in All Cities: Simulation Results *For Each City*

City	WRI	% Δ Hsf	% Δ Pop	% Δ Hsf_pp	% Δ Pop Density	% Δ Carbon
Providence_RI	1.375	10.62	3.19	7.19	-3.37	6.61
Baltimore_MD	1.042	10.30	3.05	7.04	-2.28	5.64
Seattle_WA	0.993	9.43	2.85	6.40	-1.24	5.63
Denver_Boulder_CO	0.738	7.06	2.11	4.85	-1.68	4.53
Miami_FL	0.707	6.84	2.03	4.71	-1.35	4.83
Phoenix_AZ	0.589	5.90	1.74	4.09	-1.31	4.43
San_Diego_CA	0.555	5.40	1.57	3.78	-1.53	3.01
Memphis_TN	0.577	4.63	1.33	3.25	-0.13	3.05
Boston_MA	0.751	3.78	1.04	2.71	-1.63	2.25
Philadelphia_PA	0.767	3.73	1.03	2.68	-1.42	2.57
Riverside_SB_CA	0.365	3.59	0.99	2.57	-0.74	2.10
Sacramento_CA	0.367	3.39	0.93	2.43	-0.77	1.93
Washington_DC	0.338	3.11	0.84	2.25	-0.79	1.92
New_York_NY_NJ	0.456	2.55	0.64	1.89	-0.88	1.60
San_Francisco_CA	0.909	2.53	0.62	1.89	-1.29	1.60
Portland_OR	0.312	2.30	0.58	1.72	-0.14	1.35
Los_Angeles_CA	0.464	2.03	0.48	1.55	-0.72	1.16
Orlando_FL	0.181	1.76	0.39	1.36	-0.41	1.22
Minneapolis_MN	0.190	1.27	0.23	1.04	-0.50	0.72
Milwaukee_WI	0.229	1.05	0.16	0.89	-0.41	0.57
San_Jose_CA	0.177	0.71	0.05	0.67	-0.24	0.29
Hartford_Bristol_CT	0.068	0.23	-0.11	0.34	-0.17	0.04
Other/OO	0.000	0.00	-0.19	0.19	-0.02	-0.10
Detroit_MI	-0.044	-0.31	-0.29	-0.02	0.08	-0.31
Chicago_Gary_IL	-0.077	-0.37	-0.31	-0.06	0.13	-0.35
Austin_TX	-0.048	-0.51	-0.36	-0.16	0.09	-0.45
Columbus_OH	-0.119	-0.54	-0.36	-0.18	0.23	-0.48
Norfolk_VA_Bch_VA	-0.100	-0.74	-0.43	-0.31	0.18	-0.60
Pittsburgh_PA	-0.118	-0.78	-0.44	-0.34	0.22	-0.65
Tampa_St_Pete_FL	-0.306	-0.89	-0.48	-0.41	0.51	-0.78
Cleveland_OH	-0.328	-1.64	-0.73	-0.92	0.61	-1.26
Atlanta_GA	-0.169	-1.66	-0.74	-0.93	0.40	-1.28
Jacksonville_FL	-0.176	-1.76	-0.77	-0.99	0.34	-1.33
Birmingham_AL	-0.487	-1.95	-0.83	-1.13	0.94	-1.53
Salt_Lake_City_UT	-0.212	-2.12	-0.89	-1.24	0.41	-1.51
Richmond_VA	-0.438	-2.28	-0.95	-1.35	1.03	-1.72
Buffalo_Niagara_NY	-0.435	-2.45	-0.99	-1.47	0.93	-1.78
Louisville_KY	-0.806	-2.56	-1.04	-1.54	1.53	-2.12
Rochester_NY	-0.507	-2.81	-1.12	-1.71	1.10	-1.96
Oklahoma_City_OK	-0.713	-3.08	-1.22	-1.89	1.40	-2.39
Kansas_City_MO	-1.002	-3.16	-1.24	-1.94	1.70	-2.52
San_Antonio_TX	-0.392	-3.77	-1.45	-2.35	0.88	-2.73
Cincinnati_OH	-0.835	-3.94	-1.50	-2.47	1.76	-2.97
Dallas_FW_TX	-0.499	-4.80	-1.80	-3.05	1.09	-3.55
Charlotte_NC	-0.604	-5.51	-2.05	-3.53	1.15	-4.05
St_Louis_MO	-0.939	-5.53	-2.04	-3.56	1.99	-3.91
Houston_TX	-0.608	-5.71	-2.12	-3.67	1.17	-4.12
Nashville_TN	-0.748	-6.81	-2.50	-4.42	1.64	-5.00
Las_Vegas_NV	-0.784	-7.25	-2.66	-4.72	1.57	-5.56
Indianapolis_IN	-0.988	-8.91	-3.23	-5.87	1.87	-6.48

Table 9: Simulation Results: Percent Changes to Aggregate Housing Stock and Energy Use

	Housing stock	Population	Electricity	Natural Gas	Gasoline	In-home Carbon	Total Carbon
1 - Same Regulation							
End Period of Sim (2011)	0.59		0.31	0.68	0.16	0.01	0.09
Cumulative (1980-2011)	0.91		0.12	0.44	0.08	-0.04	0.03
In New Construction (2011)	0.93		0.51	1.07	0.64	0.01	0.08
Pop. Reallocation Only (2011)	-1.20		-1.33	-1.11	0.05	-1.38	-0.59
2 - Low Carbon City Reg Subsidy							
End Period of Sim (2011)	2.98		2.27	2.95	0.63	2.30	1.35
Hi-carbon cities	-0.14	-0.95	-0.14	-0.10	-0.90	-0.12	-0.51
Lo-carbon cities	5.85	0.95	5.36	5.59	1.94	5.86	3.36
Cumulative (1980-2011)	4.75		1.66	1.94	0.36	1.63	0.91
In New Construction (2011)	4.73		3.77	4.65	2.65	3.74	2.06
Pop. Reallocation Only (2011)	-1.16		-1.49	-1.09	0.07	-1.42	-0.60
3 - High Carbon City Reg Tax							
End Period of Sim (2011)	-2.56		-2.75	-2.56	-0.58	-3.06	-1.66
Hi-carbon cities	-5.36	-1.07	-4.92	-5.54	-2.06	-5.15	-3.60
Lo-carbon cities	0.03	0.74	0.03	0.02	0.69	0.00	0.43
Cumulative (1980-2011)	-4.13		-2.24	-1.90	-0.37	-2.36	-1.24
In New Construction (2011)	-4.06		-4.55	-4.04	-2.28	-4.97	-2.69
Pop. Reallocation Only (2011)	-1.36		-1.37	-1.36	-0.13	-1.49	-0.72
4 - Carbon-proportional reg tax/subsidy							
End Period of Sim (2011)	-0.14		-0.81	-0.38	0.03	-0.92	-0.39
Hi-carbon cities	-2.79	-0.91	-2.76	-2.93	-1.26	-2.82	-2.04
Lo-carbon cities	2.29	0.72	1.68	1.84	1.13	1.86	1.39
Cumulative (1980-2011)	-0.26		-0.73	-0.41	-0.01	-0.78	-0.35
In New Construction (2011)	-0.23		-1.34	-0.60	0.12	-1.50	-0.67
Pop. Reallocation Only (2011)	-1.29		-1.50	-1.35	-0.05	-1.54	-0.71
5 - Without Federal Tax Subsidy for Housing							
End Period of Sim (2011)	-5.77		-5.63	-5.99	-0.35	-5.77	-2.70
Cumulative (1980-2011)	-9.35		-4.57	-4.43	-0.14	-4.52	-2.05
In New Construction (2011)	-9.16		-9.34	-9.46	-3.83	-9.36	-4.26
Pop. Reallocation Only (2011)	-1.31		-1.09	-1.54	-0.08	-1.26	-0.57

the baseline. That is, "big house" cities such as Las Vegas, Phoenix, Orlando, Atlanta and Dallas lose residents, and housing per person falls substantially in these locations. (The correlation between population change and initial housing per person is -0.66.) Housing per person falls everywhere, and population densities increase.

Table 9, in panel 5, labeled "Without Federal Tax Subsidy for Housing," reports the energy statistics for the no tax subsidy experiment. Removing the tax subsidy has substantial effects on the amount of construction and housing stock as of 2011, reducing them by 9.35% and 5.77%, respectively. In-home energy use decreases in proportion with the decline in housing per person, and gasoline consumption–the stickiest needle in previous experiments–declines due to increased population density. The result is carbon output that is 2.7% lower in 2011, or 4.26% lower in newer construction. (Recall that construction before 1980 would not be affected.) Interestingly, the population reallocation effect in this experiment (a 0.57% reduction) is nearly as large as those experiments targeting low or high carbon cities.

These results used a particular value of the subsidy according to my calibration. The actual user cost impact of the mortgage interest and property tax deductions for any particular housing consumer will depend upon her personal income and marginal tax rates, as well as (endogenous) decisions such as whether she owns or rents, how much of the home is financed, and whether deductions are itemized, all of which are beyond the scope of this paper. The use of a single parameter is a way to simply incorporate the aggregate effect of the tax subsidy on housing demand, but the exact magnitude is debatable.

To address this concern, I treat the user cost adjustment parametrically in multiple simulations. This exercise is both sensitivity check and a demonstration of the functional relationship between the magnitude of the housing subsidy and the carbon impact. Figure 11 plots the estimated total and in-home carbon changes (in Table 9, final two columns, first line of each panel) as I vary the size of the subsidy removed (the center point, 17% was used for the results of Tables 9 and 10 above). Unsurprisingly, there is a clear monotonic (and slightly concave) relationship: less subsidy means less carbon.

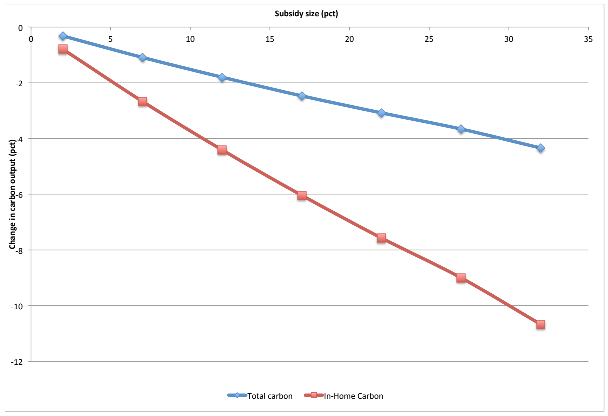
5.4.4 Summary of Simulation Findings

Back-of-the-envelope calculations help to put the figures in context. The 2.70% reduction in experiment 5 would be about one-sixth of the U.S. State Department goal for 2020, and the 4.32% reduction on new housing would be over one-quarter the goal. The 48 billion pounds in carbon savings (from the 49 named cities alone) is roughly twice the amount of carbon contributed nationwide by trash incineration. Or consider that urban tree cover absorbs 1.64% of carbon emissions; with slightly less than half of emissions represented in this experiment, the reduction is roughly equivalent to absorption of urban trees. That is, the entirety of urban tree cover is needed to offset the increase in additional emissions imposed by the federal tax subsidy for housing. Simulation 3, increasing regulations in high carbon output cities, would have similar but

Table 10: Removal of Federal Tax Subsidy: Simulation Results For Each City

City	Hsf_pp	% Stock Growth (baseline)	% Δ Hsf	% Δ Pop	% Δ Hsf_pp	% Δ Pop Density	% Δ Carbon
San_Jose_CA	440	62	-2.090	1.130	-3.180	0.270	0.290
San_Francisco_CA	486	65	-2.770	0.900	-3.640	0.320	-0.170
Norfolk_VA_Bch_VA	548	76	-3.130	0.780	-3.880	0.400	-0.820
Baltimore_MD	348	76	-3.130	0.760	-3.860	0.360	-0.630
Tampa_St_Pete_FL	601	74	-3.640	0.610	-4.220	0.420	-1.630
Louisville_KY	585	64	-3.730	0.580	-4.290	0.570	-1.890
Philadelphia_PA	382	69	-4.120	0.430	-4.530	0.450	-1.680
Boston_MA	561	63	-4.230	0.410	-4.620	0.570	-1.200
Milwaukee_WI	509	63	-4.300	0.380	-4.670	0.480	-1.310
Oklahoma_City_OK	583	72	-4.520	0.300	-4.810	0.560	-2.310
Los_Angeles_CA	512	62	-4.780	0.220	-4.990	0.470	-1.270
Richmond_VA	688	80	-4.750	0.220	-4.960	0.600	-2.030
Birmingham_AL	573	65	-4.950	0.160	-5.110	0.620	-2.320
Pittsburgh_PA	500	56	-5.020	0.150	-5.160	0.650	-2.460
Other/OO	549	77	-5.000	0.130	-5.120	0.020	0.070
Cleveland_OH	606	64	-5.040	0.130	-5.170	0.610	-2.550
Chicago_Gary_IL	552	71	-5.070	0.120	-5.180	0.550	-2.280
New_York_NY_NJ	530	60	-5.130	0.110	-5.230	0.590	-2.010
Buffalo_Niagara_NY	518	58	-5.260	0.070	-5.330	0.740	-2.070
Cincinnati_OH	632	73	-5.240	0.060	-5.300	0.630	-2.680
Rochester_NY	498	65	-5.370	0.020	-5.390	0.700	-1.950
Detroit_MI	597	63	-5.430	0.000	-5.430	0.700	-2.360
Columbus_OH	623	75	-5.510	-0.030	-5.480	0.620	-2.870
Kansas_City_MO	688	74	-5.510	-0.040	-5.470	0.550	-2.920
Providence_RI	627	65	-5.900	-0.180	-5.730	0.710	-2.530
St_Louis_MO	565	67	-5.960	-0.190	-5.780	0.710	-2.800
Minneapolis_MN	550	75	-6.120	-0.250	-5.880	0.720	-2.530
Hartford_Bristol_CT	672	69	-6.110	-0.250	-5.870	0.720	-2.420
Seattle_WA	602	76	-6.630	-0.430	-6.230	0.600	-2.890
Washington_DC	504	83	-6.740	-0.470	-6.290	0.610	-3.010
Indianapolis_IN	719	79	-6.720	-0.470	-6.280	0.580	-3.900
Nashville_TN	687	81	-6.740	-0.470	-6.290	0.630	-3.720
Miami_FL	595	76	-6.800	-0.490	-6.340	0.530	-3.860
Charlotte_NC	811	88	-6.800	-0.500	-6.330	0.530	-3.830
San_Diego_CA	528	74	-6.840	-0.510	-6.360	0.790	-2.290
Denver_Boulder_CO	625	82	-6.930	-0.540	-6.430	0.610	-3.240
Sacramento_CA	678	86	-6.900	-0.540	-6.400	0.540	-2.640
Houston_TX	675	83	-6.980	-0.560	-6.450	0.550	-3.850
San_Antonio_TX	620	86	-7.000	-0.570	-6.470	0.620	-3.790
Memphis_TN	667	76	-7.060	-0.590	-6.510	0.720	-4.020
Jacksonville_FL	637	86	-7.050	-0.590	-6.490	0.550	-3.810
Salt_Lake_City_UT	468	80	-7.080	-0.590	-6.520	0.570	-3.490
Dallas_FW_TX	774	86	-7.090	-0.600	-6.530	0.610	-4.100
Atlanta_GA	897	92	-7.080	-0.600	-6.510	0.630	-4.000
Austin_TX	797	95	-7.050	-0.600	-6.490	0.580	-4.120
Riverside_SB_CA	691	89	-7.230	-0.650	-6.620	0.520	-3.040
Orlando_FL	775	92	-7.300	-0.680	-6.670	0.570	-4.370
Las_Vegas_NV	870	103	-7.370	-0.700	-6.710	0.500	-4.550
Phoenix_AZ	808	95	-7.580	-0.780	-6.850	0.560	-4.910
Portland_OR	651	73	-7.690	-0.810	-6.930	0.640	-3.890

Figure 11: Change in Carbon Output As Function of Tax Subsidy Size



slightly smaller effects than the no tax subsidy experiment.

In summary, policies affecting the intensive margin of housing–the amount consumed per person–are the drivers of carbon savings. Reallocation of population results in some carbon savings, but the equilibrium effects are complicated, with decreases in one location offset by increases elsewhere. The results suggest that had the general equilibrium effects been ignored, carbon savings may have been overstated.

6 Conclusion

This paper has designed and implemented a dynamic spatial equilibrium model of housing construction and consumption, and the growth of population across metropolitan areas. The estimation yields residual costs for housing construction and the intensity of land use, after controlling for the option value of a local builder and the competitive effects between cities. These residual costs are then related to land use regulation as measured by the Wharton Regulation Index.

Counterfactual simulations affect local land use regulation, projecting the equilibrium outcomes for housing construction, the spatial distribution of population, and ultimately, the implications for energy use. I find there is some scope for reducing energy use by targeting high energy use cities with increased regulation. The carbon savings come primarily by reducing housing consumed, and secondarily by reallocating population from inefficient locations to more efficient locations. I find that the federal tax treatment of housing has added a nontrivial amount of carbon output by increasing housing consumption.

My results indicate that the Reallocation Hypothesis is not false, but is not large. Despite apparent large differences between cities in carbon per person, simply moving population from one location to another without any changes to within-city housing consumption patterns has limited scope for reducing carbon output. An implication is that because significant carbon savings require changes in consumption patterns, carbon reductions are likely to come at some utility cost. However, I note that I have conducted simulation and accounting exercises and not welfare calculations. True welfare analyses, which would likely have to address the complicated issue of the utility impacts of carbon output, are left for future work.

Finally, the energy accounting of this study is short of a full accounting. Future work could incorporate the carbon footprint of consumption goods, whether tradable or nontradeable across markets, and the impacts of energy use by firms commercial and industrial, and how the spatial distribution of employment contributes. Water use is also a growing environmental concern, and a model of this type may be useful in analyzing the efficiency of water allocation.

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A Examining the Aggregate State Simplification

How dangerous is the aggregate state assumption? A direct comparison of the full solution to the approximated solution would be desirable, but the very problem is the inability to calculate the full solution in finite time, so the true answer is effectively unknowable. However, consideration of the structure of the problem can shed light on the question.

I argue that, especially under the structure of the utility function and the spatial equilibrium, this is a relatively innocuous simplification. Consider the payoff function to the builder and how it is affected by states through the spatial equilibrium. First, notice that the impact of own-city income y_j on rents is first order, affecting rent directly and through population (see equation (3) and (4)), while the effect of another city's income is second order, affecting rents only indirectly through population. The derivatives of (4) are cumbersome, but Table 11, panel A shows the numerical calculations of the population and rent elasticities evaluated at the means of income, housing stock, and population in the data. I show this for cities of different size: the (second) largest in my data, New York City,[39] the median, Cincinnati, OH, and the smallest in my data, Salt Lake City, UT. The own-income elasticities of population and housing price (column 1 of panel A) are orders of magnitude larger than the cross-income elasticities (column 2). The same is true for own-housing stock elasticity of population and rent (column 3) versus cross-city elasticity with respect to housing stock (column 4). Panel A suggests that while other city's states may matter for demand conditions in a city, they are far less important than local demand and supply conditions.

Note that cross-city elasticities are symmetric. That is, New York's effect on Cincinnati and Salt Lake City, as well as Chicago, Los Angles, Baltimore, etc, is the same.[40] A one percent increase in income in New York will decrease populations and rent in other cities by 0.0076 percent. The size of the city matters, however: New York City's income has a larger effect on other cities than does Salt Lake City's.

Thus, a true examination of the approximation assumption asks how the *spatial distribution* of the states affects the payoff. After all, the model is designed to allow heterogeneous locations to interact in a spatial equilibrium, whereas the state aggregation assumption is, for the dynamic decision maker, throwing away the detailed heterogeneity and taking an average. One might worry that the payoff to the builder might be affected by the exact location of the averaged state; whether, e.g. there are two cities with average income, or one with high and another with low, and which is which. Panel A's elasticities do little to address this concern. Panel B of Table 11 investigates this concern more di-

[39]New York is the second-largest because an aggregate of all smaller cities, the "outside-option," is the largest.

[40]The symmetry result is also aided by the spatial equilibrium holding in a Cobb-Douglas functional form for utility. Cobb-Douglas is not merely common and convenient, but also has empirical support in the literature. See Davis and Ortalo-Magne (2011).

Table 11: Relative Importance of Own, Cross, and Aggregated States for Population and Rent

A: Elasticities of Own- and Cross-City States

	$\frac{dlogP_j}{dlogy_j}$	$\frac{dlogP_j}{dlogy_k}$	$\frac{dlogP_j}{dlogH_j}$	$\frac{dlogP_j}{dlogH_k}$
(2) New York	0.1328	-0.0076	0.0317	-0.0018
(25) Cincinnati	0.1391	-0.0014	0.0331	-0.0003
(50) Salt Lake City	0.1398	-0.0007	0.0333	-0.0002

	$\frac{dlogr_j}{dlogy_j}$	$\frac{dlogr_j}{dlogy_k}$	$\frac{dlogr_j}{dlogH_j}$	$\frac{dlogr_j}{dlogH_k}$
(2) New York	0.2328	-0.0076	-0.0683	-0.0018
(25) Cincinnati	0.2391	-0.0014	-0.0669	-0.0003
(50) Salt Lake City	0.2398	-0.0007	-0.0667	-0.0002

B: Variation with Respect to Location Dispersion Within Aggregated States

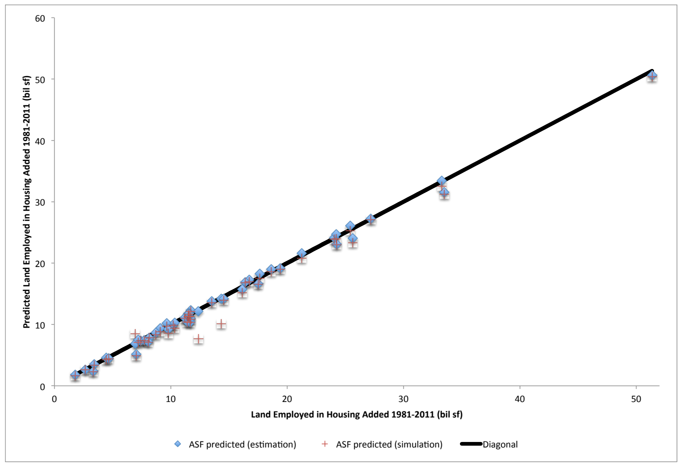
CV of Rent or Pop	Income y				Housing Stock H			
Perturbation size:	0.01	0.05	0.10	0.20	0.01	0.05	0.10	0.20
(2) New York	0.0004	0.0021	0.0040	0.0082	<0.0001	0.0002	0.0005	0.0010
(25) Cincinnati	0.0006	0.0028	0.0057	0.0120	<0.0001	0.0003	0.0005	0.0011
(50) Salt Lake City	0.0006	0.0029	0.0060	0.0118	<0.0001	0.0003	0.0005	0.0011

Notes: Panel A reports the empirical elasticities of population and rent at the mean values of income, housing stock, and population. Panel B reports for the city listed the coefficient of variation (CV) over 1000 simulations of the spatial equilibrium in which the distribution of the aggregate state is varied by perturbing by the given size the local values of income and housing stock. Rents and populations have the same CV, so they are reported in the same table.

rectly. In panel B, I have simulated at the mean values of the states alternative spatial dispersions of the aggregate states, holding the summary statistic fixed, and solved the spatial equilibrium to find populations and rents for the example cities. That is, for a fixed y_{-j}, I randomly draw whether city k has a 1% higher or lower value of y_k, whether city l has a 1% higher or lower value of y_l, and so on. The perturbation sizes vary and are listed separately. Panel B then reports the coefficient of variation (the CV, standard deviation divided by mean) for the payoff-relevant variables over the simulations. This exercise is meant to illustrate the degree to which imprecision regarding the spatial distribution of the aggregate state matters for the payoff.

The CVs show variation orders of magnitude smaller than the perturbations. Even when the agent in New York is systematically 20% wrong (a large error) about each city's level of income, but knows the economy-wide average, his rent varies by a mere 0.82%. This is slightly more severe for smaller cities, but still an error small relative to the degree of information thrown away. Thus, the aggregate state assumption, despite its massive simplification in terms of computational solution, seems relatively innocuous.

Figure 12: Actual and Predicted Land Employed in Housing Construction, by Location



B Additional Tables and Figures

Table 12: Gasoline Use Regressions

Coef.	(1)	(2)	(3)	(4)	(5)
Log(density)	-0.092***	-0.082***	-0.083***	-0.078***	-0.058***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
MSA FE	X	X	X	X	X
New York	0.017	-0.075***	-0.189***	-0.168***	-0.100***
Los Angeles	0.180***	0.102***	0.013	0.023*	0.013
Chicago	0.065***	0.002	-0.069***	-0.051**	-0.015
Phoenix	0.023	-0.016	-0.060***	-0.058***	-0.015
Dallas	0.173***	0.135***	0.061***	0.062***	0.082***
Miami	0.058***	-0.003	-0.048**	-0.043**	-0.013
Washington	0.210***	0.129***	-0.009	-0.002	-0.001
Houston	0.207***	0.153***	0.068***	0.070***	0.104***
Detroit	0.190***	0.149***	0.084***	0.080***	0.098***
Boston	0.142***	0.061***	-0.025	-0.017	0.031*
Atlanta	0.167***	0.129***	0.056**	0.059***	0.056***
San Francisco	0.049***	0.018	-0.106***	-0.093***	-0.097***
Rochester	-0.020	-0.062**	-0.010***	-0.097***	-0.048**
Pittsburgh	-0.178***	-0.181***	-0.178***	-0.165***	-0.122***
Seattle	0.058*	-0.001	-0.079***	-0.074***	-0.103***
Minneapolis	0.152***	0.109***	0.031	0.033	0.027
San Diego	0.189***	0.123***	0.033**	0.038***	0.028**
Tampa	-0.053**	-0.039*	-0.40**	-0.037*	0.029
Baltimore	0.151***	0.093***	-0.028	-0.024	-0.005
Portland	0.052	0.007	-0.58	-0.062	-0.89**
VA Beach	0.120***	0.087***	0.023	0.028*	0.013
Denver	0.106**	0.096**	-0.025	-0.024	-0.055
Cleveland	0.033	-0.012	-0.045	-0.039	-0.046
Cincinnati	0.080	0.010	0.003	0.016	-0.001
Providence	-0.038	-0.116**	-0.143***	-0.136***	-0.106**
Kansas City	0.111**	0.071*	0.023	0.010	0.017
St. Louis	0.063	0.056	0.023	0.022	0.040
San Jose	0.049***	0.018	-0.106***	-0.093***	-0.097***
San Antonio	0.129***	0.107***	0.064***	0.072***	0.101***
Philadelphia	-0.023	-0.077***	-0.170***	-0.016***	-0.105***
Columbus	0.021	0.009	-0.055	-0.054	-0.055
Richmond	0.045***	0.041***	0.005	0.008	-0.003
Oklahoma	0.186***	0.195***	0.187***	0.173***	0.154***
Indianapolis	0.092***	0.076***	0.031	0.033	0.022
Milwaukee	0.084**	0.007	-0.070**	-0.071**	-0.060*
Las Vegas	0.077	0.033	-0.037	-0.030	-0.018
Charlotte	0.109***	0.078**	0.047	0.048	0.026
Nashville	0.180***	0.180***	0.121***	0.121***	0.104***
Austin	0.104***	0.084***	0.004	0.010	0.038**
Memphis	0.136***	0.131***	0.078*	0.084**	0.075*
Buffalo	-0.107***	-0.117***	-0.128***	-0.120***	-0.069***
Louisville	0.044	0.079	0.053	0.061	0.008
Hartford	0.067	0.041	-0.083**	-0.074*	-0.050
Jacksonville	0.059*	0.049*	-0.009	-0.004	0.030
Riverside	0.028	0.001	-0.022	-0.011	-0.016
Orlando	0.056*	0.030	0.009	0.009	0.050**
Birmingham	-0.102**	-0.024	-0.018	-0.017	-0.013
Sacramento	0.067**	0.045**	-0.043*	-0.037	-0.044**
Salt Lake	0.129***	-0.020	-0.033	-0.037	-0.065
Year					
1995	-0.342***	-0.237***	-0.323***	-0.394***	-0.341***
2001	0.096***	0.227***	0.081***	0.009	0.044***
2009	0.017*	0.198***	-0.011	-0.078***	0.016**
Race					
African-American		-0.148***	-0.042***	-0.015	-0.019**
Asian		-0.134***	-0.114***	-0.090***	-0.080***
Other		-0.092***	0.027***	0.046***	0.028***
Number of adults					
2		0.748***	0.536***	0.183***	0.061***
3 or more		1.064***	0.854***	0.327***	0.101***
Number of children					
1		0.356***	0.277***	0.217***	0.135***
2		0.398***	0.300***	0.242***	0.173***
3 or more		0.427***	0.367***	0.304***	0.236***
Income					
5000-9999			0.091***	0.080***	0.043***
10000-19999			0.299***	0.269***	0.162***
20000-29999			0.460***	0.413***	0.237***
30000-39999			0.584***	0.524***	0.297***
40000-49999			0.668***	0.600***	0.341***
50000-74999			0.727***	0.652***	0.362***
75000-99999			0.757***	0.679***	0.371***
10000 or more			0.872***	0.782***	0.432***
Number of drivers					
1				0.041	-0.021
2				0.460***	0.045
3 or more				0.700***	0.095**
Number of vehicles					
2					0.612***
3 or more					0.937***
Number of workers					
1					0.270***
2					0.348***
3 or more					0.391***
Constant	7.356***	6.361***	6.170***	6.192***	5.890***

Notes: The outcome variable is the log of gallons of gasoline consumed per household per year. Controls are categorical dummies. Standard errors are omitted, but parameter significance is flagged as: *** p<0.01, ** p<0.05, * p<0.1.