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This study investigates the share of open space that maximizes total private property values in urban areas. Open space poses a number of trade-offs to city managers. On the one hand, previous studies have shown that certain kinds of open space can increase property values, which tends to increase tax revenues. On the other hand, open space typically requires substantial capital to establish and perpetual maintenance costs to maintain. This means that in order to keep the city budget balanced, financing open space requires either taking money away from other municipal services, which may be of greater value to residents than open space, or increasing the property tax rate. Both these courses of actions tend to reduce property values, and therefore, lower tax revenues. Open space also incurs an opportunity cost, in that land used for open space could be developed and taxed.

While previous research has modeled these trade-offs, there is still more to be learned by empirically estimating the share of open space that maximizes property values in urban areas. According to the theoretical underpinnings of this study, one of the primary determinants of a city's value-maximizing, or "optimal", share of open space is the price elasticity of housing supply. Therefore, in order to estimate the optimal share of open space, this study estimates the price elasticity of housing supply for 349 U.S. Metropolitan Statistical Areas (MSAs). According to theory, the other factors that determine the optimal share of open space are the price elasticity of

housing demand, the economies of scale in the provision of municipal services, the elasticity of property values with respect to municipal services, and the elasticity of housing demand with respect to open space. For these factors, an example value is establish based on prior research and used commonly among all MSAs to estimate the optimal share.

Once the estimated and example values are determined, they are inserted into the equation that determines the optimal share of open space. The result provides an estimate of this optimal share of open space for 349 MSAs. On average, the model, combined with the estimated and assumed values, produces very low estimates for the optimal share of open space. The mean optimal share was 1.5%, and 95% of the estimates were 5% or less. For shares based on statistically significant supply elasticity estimates, optimal shares ranged from 0.2% to 27%.

In order to gauge how far cities were from their estimated optimal share of open space, this study compared the estimated optimal share to observed shares of open space in 72 MSAs. When compared to observed shares of open space, the model (along with the estimated and assumed values) showed that 89% of the observed MSAs displayed "excesses" of open space, or, an observed share of open space that exceeded their optimal share. The other 11% demonstrated a "shortage" of open space. The average deviation between optimal and actual share was an excess of 6.3 percentage points.

Further analysis was conducted in order to account for the error inherent in the supply elasticity estimates (and subsequently inherent to the estimates of optimal share). Once this error was accounted for, only two cities still showed evidence of having open space shortages: Stockton, CA and Miami, FL. However, both cities were within a percentage point of their optimal share's confidence interval, making it possible these cities are not experiencing meaningful shortages of open space. In contrast, 92% of the cities in the sample set showed statistically significant excesses of open space. Of these, five MSAs exceeded their confidence intervals by 15 or more percentage points: Austin, TX; Albuquerque, NM; Akron, OH; New Orleans, LA; and Anchorage, AK. Because these cities' actual share of open space lies so far above their optimal share, it is very likely that decreasing open space area would increase property values. Two cities in the sample fell within their optimal share's confidence interval: Washington, DC and Virginia Beach, VA. Of all the cities in the sample set, these two are the most likely to be at their optimal share of open space, and therefore, are the most likely to decrease property values by making any changes to their share of open space.

After this primary analysis, a sensitivity analysis was conducted in order to determine how assumptions regarding the variables impacted the estimated optimal share of open space. A reasonable range for each variable was established based on the literature, and this range was used to test each variable's effect on the optimal share of open space. These tests revealed that the optimal share is not especially sensitive to the assumed values for the price elasticity of housing demand, nor to the economy of scale in the provision of municipal services. However, the elasticity of property values with respect to municipal services and the elasticity of housing demand with respect to open space both have large influences on the optimal share. The impact of all the other variables increased as supply elasticity decreased, and as the elasticity of housing demand with respect to open space increased.

Because the elasticity of housing demand with respect to open space has such a disproportionate influence on the optimal share of open space, and because there is very little empirical evidence surrounding its value, further analysis was done to investigate this variable. By assuming that the 72 MSAs for which there is an observed share of open space are at their optimal share, in conjunction with the estimated and assumed values for the other variables, one can estimate the implied value for the elasticity of housing demand with respect to open space.

Using this method, this study found that the average implied elasticity was 0.57. While this result could indicate that open space has a higher-than-assumed effect on housing demand, evidence from the literature suggests this value is too high. It is more likely that this result provides further evidence that the model is indicating actual shares of open space are higher than optimal.

In the final portion of the sensitivity analysis, cities' observed shares of open space were again assumed to be at the optimal level, however, the other variables assume the limits of their reasonable range so as to make the implied elasticity as high or as low as possible. This analysis provided further evidence of discrepancies between actual and optimal shares of open space. While the evidence for open space shortages was fairly slim, the analysis reinforced evidence that some cities have excess open space. Those that presented the highest implied elasticities (and therefore show the strongest evidence of open space excess) are Austin, TX; Akron, OH; and Greensboro, NC.

By comparing optimal shares of open space to observed shares of open space, the results show that the majority of cities could likely increase property values by decreasing their share of open space. This study also sheds new light on the relationship between housing demand and open space. By defining a reasonable value and range for the elasticity of housing demand with respect to open space, this study adds to the scarce information on this variable.

While the results of this study indicate that many urban areas in the U.S. have larger shares of open space than would maximize property values, it is important to emphasize that the value-maximizing share of open space is not the socially optimal share. Open space provides a number of other social benefits that are not capitalized into property values, and are therefore not considered in this study. Environmental benefits are one important example. Further research is needed to determine the socially optimal amount of open space that maximizes social welfare.

The appendices of this study list both the estimates of housing supply elasticity and the estimates of value-maximizing share for the 349 MSAs in the sample set. For the managers of cities that were included in the study, these figures can provide valuable information to help them better understand the implications of open space provision. The housing supply elasticities serve to better illuminate housing markets in their area. The optimal share estimates allow managers to better understand the relationship between property values and open space.

For the managers of cities not included in this study, the methods presented here offer a relatively simple way to calculate their own housing supply elasticity and optimal share. With data on housing prices, housing construction, and population, interested parties can estimate the supply elasticity in their cities. Using this estimate in combination with the values this study assumed for the other variables, they can estimate their own value-maximizing share of open space. By comparing this figure to their present share of open space, city managers can gain a better understanding of the effect open space has on the property values within their city.

Maximizing Urban Property Values Through Open Space Conservation

by

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Winston Oakley, Author

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Chapter 1

Introduction

Open space provides essential benefits to the public in the form of recreation, natural resources (such as timber), jobs, and vital ecosystem services, which include clean water, natural flood control, wildlife habitat, and biodiversity (U.S. Forest Service, 2014). These ecosystem services are even more important in urban areas where high populations depend on clean water, and large areas of impervious surfaces degrade water quality and increase the intensity of flood events (USGS, 2014).

Recognizing the benefits of open space, there have been a number of concerted efforts to expand and protect open spaces. Between 1988 and August 2014, voters across the U.S. passed 1,830 measures to fund open space conservation, totaling over $59 billion (The Trust for Public Land, 2014). In 2007, the U.S. Forest Service developed an Open Space Conservation Strategy in part to "to expand and connect open space in cities, suburbs, and towns" (U.S. Forest Service, 2007).

Despite these efforts, open space is declining at a worrisome rate. Approximately 6,000 acres of open space are lost each day in the U.S., a rate of four acres per minute (U.S. Forest Service, 2014). Urban growth is a major driver in this decrease. For forests alone, researchers estimate that housing density could substantially increase in 44 million acres (over 11 percent) of private forest across the U.S. by 2030 (U.S. Forest Service, 2005). In this same time period, over 21 million acres across the country are projected to change from rural or exurban to urban land (U.S. Forest Service, 2005).

City managers face difficult trade-offs when deciding how much open space to have within their cities. On the one hand, increasing the amount of open space improves the city's amenities and boosts property values, which in turn could increase property tax revenues. On the other hand, open space can incur substantial up-front capital costs and perpetual maintenance costs. These expenditures could be spent on other public goods within the city, which may be of greater value to residents. A less visible trade-off is that the open space imposes an opportunity cost for the city, which may forgo tax revenue from residential or commercial property that would have developed had the open space not been established. Given the significance of open spaces and the complex trade-offs surrounding them, it is important to provide city managers with information to guide their decision making for optimal open space allocation.

Because property values typically determine property taxes (which are a significant source of revenue in many cities), the relationship between open space and property values is especially important for city managers. There have been a number of studies in recent decades that have attempted to measure the effect of open space conservation on property values (Mahan et al. 2000, Irwin 2002, Balsdon 2012). These studies have shown how open space has generally positive but varying impact on property values. However, Wu (2014) is the only study to examine the share of open space that maximizes total private property values (referred to as the "optimal" share throughout this study) within a city under a budget constraint. While Wu (2014) lays out the theoretical conditions for the value-maximizing share of open space, there is room to empirically explore the conditions that optimize open space, the factors that determine this share, and compare the optimal share of open space as estimated by the model to actual shares of open space in urban areas.

Objectives

This study attempts to fill an empirical gap in the literature and aid city manager's decision-making process by investigating the optimal share of open space conservation in urban areas. It does this by estimating the share of open space that maximizes property values for 349 urban areas across the U.S. As shown in Wu

(2014), the price elasticity of housing supply is a primary determinant in the optimal share of open space. Accordingly, this study estimates the price elasticity of housing supply for 349 cities across the U.S. in order to gauge the value-maximizing share of open space for each of the cities. This study also investigates factors that likely affect the price elasticity of housing supply, and, subsequently, the optimal amount of open space. Measuring these factors will help city managers decide not only how much open space to conserve if property values are to be maximized, but how other seemingly unrelated policies can, in fact, affect the optimal amount of open space. Additionally, this study compares actual shares of open space to the estimated optimal share of open space in 72 urban areas. This analysis provides valuable information regarding the current-state relationship between optimal shares of open space and actual shares of open space. Lastly, for cities not included in this study, the methods used here can act as a guide for city managers to estimate the value-maximizing share of open space in their own city, which can further inform their decision-making process.

Organization of Thesis

This thesis is organized into six additional chapters. Chapter Two is a literature review, which covers relevant scientific literature relating to this thesis' topic: the relationship between open space conservation and property values. Chapter Three explains the theory for determining the optimal share of open space in a city, as presented by Wu (2014). This chapter also explains the method developed in Green et al. (2005) for estimating the price elasticity of housing supply. Chapter Four describes the data and methodology used when estimating the price elasticity of housing supply and analyzing the factors that affect it. Chapter Five outlines the results of the empirical analysis and sensitivity analysis. Chapter Six summarizes the findings and details how these findings can be useful to city managers. Appendix A presents a table of the price elasticities of housing supply for 349 Metropolitan Statistical Areas (MSAs) across the U.S. Appendix B presents a table of the estimated optimal shares of open space for the same 349 MSAs, along with the associated confidence intervals. In the 72 MSAs where observed shares of open space are available from Trust for Public Land (2011), this figure is also included. Appendix C contains three supplemental maps that display results from Chapter 5.

Chapter 2

Literature Review

Very little research has been done regarding the share of open space that maximizes property values. However, a fair amount of studies have investigated the relationship between open space and property values, the most relevant of which are outlined in this section. The two studies that are most integral to this thesis, Wu (2014) and Green et al. (2005), will not be covered in this chapter but outlined in greater detail in the next chapter. The studies outlined in this section provide significant insights into the relationship between open space and property values, including: how open space can increase property values, the importance of open space characteristics and distribution, and how open space impacts tax revenues through its influence on property values.

Open Space Conservation and Property Values

The most common empirical method to relate open space to property values has been through hedonic regression. Using hedonic modeling, researchers parse out the difference in property value that results from nearby open space amenities. Numerous studies have a found that open space increases property values. Cheshire and Sheppard (1995) explore the impact of location-specific amenities on land values. Using housing and survey data from a sample of residences in two British towns, the authors apply hedonic regression to estimate the marginal value of local amenities in addition to the typical structural housing variables. The results showed a positive value for open space amenities, providing evidence that open space amenities increase the value of nearby properties.

The size and distance to open space also matters to the impact on property values. Mahan et al. (2000) used hedonic modeling to estimate the value of wetland amenities in Portland, Oregon. In addition to the traditional, structural variables that affect the sale price of owner-occupied, single family residences, the authors also analyzed the distance to and size of wetlands. Their results indicate that property values increase with the size of a nearby wetland. They found that increasing the area of the nearest wetland by one acre increases a residence's value by $24. Distance to a wetland showed an inverse relationship with property value. Reducing the distance to the nearest wetland by 1,000 feet increased the value of a residence by $436. This study demonstrates that size and location of open space amenities matter in its effect on the value of nearby properties.

These conclusions are further supported by Tyrväinen and Meittinen (2000). In this study, the authors used hedonic regression to examine the effect of different kinds of urban forests on housing market transactions in the Finnish district of Salo. Their results showed that as distance to urban forests decreased, property values increased. This effect was especially evident when a property was within walking distance of a forest. Properties with a view of the forest sold for an even higher price. This study supports the inverse relationship between distance and the impact on property values, but also indicates that use values, such as having a view of the open space, are also important.

Thorsnes (2002) offers another perspective on this issue. By studying lot sales from three subdivisions in Grand Rapids, MI, Thorsnes finds the same inverse relationship between distance to open space (in this case forest preserves) and the impact on property values. However, his results indicate that this effect can be limited to a very short distance: Lots bordering the forest preserve showed increased prices while lots located just across from the preserve showed no change in price. He also found evidence of use values: Lots that essentially had a private forest preserve in their backyard sold for an even higher premium.

Irwin and Bockstael (2001) question the positive amenity value of open spaces and explore reasons why these values may not always be empirically uncovered. They explain that identification problem exists in hedonic models where open space land is privately held and developable because this land is part of the market. This causes an identification problem in the model because the land is subject to the same economic forces that influence nearby residential values. To investigate this theory, the authors use data of housing transactions from four counties in Maryland. By using instrumental variables and conducting a Hausman test for endogeneity, the authors find that this identification problem exists and that it biases the marginal value of open space downward. These results indicate that some studies may have underestimated the marginal value of open space due to model misspecification.

A number of studies have found the effect of open space can be muted if there is potential for the space to be developed in the future. Irwin (2002) utilizes the method developed in Irwin and Bockstael (2001) to develop unbiased value estimates of different types of open space. Open space types include preserved or developable, private or publicly held, as well as land use type (cropland, pasture, and forests). The study uses hedonic modeling to analyze data from single transactions of owner-occupied residential properties in urban areas in Maryland. The results reveal that open space amenities do impact residential home prices and that the type of open space can determine what this effect is. Preserved open spaces have a larger positive impact on property prices than developable open spaces, implying that the public demands preserved open space more than open areas that may be subject to development (Irwin, 2002). These results indicate that expectations regarding the future presence of open space are important in its effect on property values.

This conclusion is further supported in Geoghegan (2002), which develops a theoretical model for how residential landowners value the open spaces near their homes. Using data on housing sale transactions in a Maryland county, Geoghegan then uses hedonic modeling to test how different types of open space are valued by nearby residents, as evidenced by the price they paid for the property. The study's results indicate that undevelopable open space increases nearby residential land values over three times as much as an equivalent amount of developable open space. These results are relevant because they further support the assertion that future expectations of open space development can vary its effect on property values.

The nature of the open space also seems to determine its relationship with property values. In some cases, open space has been found to decrease property values. Shultz and King (2003) use 1990 U.S. census data to examine the effect of different kinds of open space on property values in Tucson, AZ. Using hedonic regression to investigate the effects of nearby land use, Shultz and King find that urban parks, undeveloped parks, and pristine wildlife habitat reduce property values, while natural areas, golf courses, and less pristine wildlife habitat increase property values. The implication may be that there is an optimal level of use in open space. High traffic or crime in urban parks may reduce property values, as will a lack of use in the open space, which may lead to poor maintenance and decreased usability. However, natural areas that are maintained and allow for some recreational use can increase property values.

Lutzenhizer and Netusil (2001) find similar results. In their study, the authors use hedonic regression on data for single-family homes sales in Portland, OR. Using the Metro Regional Land Information System Geographic Information System, the researchers calculated the distance to the nearest open space. They categorized open space into cemeteries, urban parks, natural area parks, golf courses, and specialty parks/facilities. The results of their analysis showed that all of the open space types positively influenced property values, but urban parks had a much smaller effect than the other types. Natural areas had the greatest impact, and the farthest-reaching.

Bolitzer and Netusil (2000) uses the same data as Lutzenhizer and Netusil (2001), however, the authors defined their variables differently, which lead to different set of conclusions. Open spaces were divided into public parks, private parks, golf courses, and cemeteries. The hedonic regression analysis indicates that public parks and golf courses increase property values, while private parks and cemeteries do not have a definite effect on property values. The authors also tested for reduced property values due to close proximity to highly trafficked open spaces, but they did not find evidence to support that theory. Distance was always associated with either a positive effect or no distinguishable effect.

The differing impacts among natural areas and use levels are supported by other literature. Bin and Polasky (2003) used property sales records to examine how the size of, distance to, and type of wetlands affect property values in Carteret County, North Carolina. The authors distinguish between coastal and inland wetlands. Their results showed that for some areas, inland wetlands tended to decrease property values, while coastal wetlands increased property values. Bin and Polasky hypothesize that this discrepancy may be due to the fact that inland wetlands are likely to have overgrown vegetation, reducing aesthetic and use values, while coastal wetlands may offer fishing and recreating opportunities. This study underlines the importance of use values in the effect open space has on property values.

Open space used for agriculture also appears to have disparate effects on nearby property values. Le Goffe (2000) examines the influence of agriculture on rental rates for tourist cottages in Brittany, France. He distinguishes by land type (forest and grassland) and by agricultural use (crops and livestock). Le Goffe's results indicate that grasslands tend to increase rental rates, while forests, crops, and livestock decrease rental rates. These results indicate that people do not value agriculture in the same way they value other types of open space.

Other studies have found the influence of open space on property values differ by community characteristics, in addition to type. Klaiber and Phaneuf (2010) found this to be the case in the Twin Cities metropolitan area of Minnesota. By examining 17 years of home sales along with land-use types using a sorting model, the authors found that open space was a heterogeneous good, both in terms of the type of open space and in the way communities valued that kind of open space. These results are significant because they suggest that open space will have varying impacts on property values depending on where they are located within a city.

Anderson and West (2006) come to a similar conclusion. These authors use hedonic regression on 1997 home transaction data from Minneapolis-St. Paul area (the data is different from that used by Klaiber and Phaneuf). In addition to the typical factors of open space proximity, size, and type, Anderson and West also test for the effect of neighborhood characteristics on open space's influence on property values. Their results indicated that, in general, neighborhoods with higher population densities and those located near a central business district tend to value open space more than neighborhoods in the suburbs. These results reinforce the conclusion that location and neighborhood characteristics play an important role in determining open space's effect on property values.

Other studies have tried to determine the optimal allocation for open space. Tajibaeva et al. (2007) attempts to characterize the optimal provision of open space across a metropolitan area. They do this by dividing the city into discrete neighborhoods with homogeneous developable land within themselves, but heterogeneous across neighborhoods. They test the effect of open spaces that provide amenities solely to the neighborhood where they are located, and the effect of open spaces that provide amenities to other nearby neighborhoods (known as amenity spillover). Their results show that market equilibrium housing density and after-tax land prices tend to increase with the presence of open space. When open space is a local public good that affects only the immediate neighborhood, it is optimal to provide the same amount of open space in all neighborhoods. With amenity spillover effects, transportation costs determine the optimal location of open space. For high transportation costs, it is optimal to provide open space in a greenbelt at the edge of the city. For low transportation cost, it is optimal to locate open space in a greenbelt within the city (Tajibaeva et al., 2008). These results are relevant because they demonstrate that the distribution of open space affects its optimal provision.

While a positive preference for open space seems to be the primary cause of increased property values, Balsdon (2012) examines other motivations for demanding open space. Most commonly, researchers connect the demand for more open space to the desire for the public amenities that it provides. However, because open space also restricts the supply of available land, it can increase the value of land even if the open space provides no amenities. Using data from the Trust for Public Land on public open space referenda, Balsdon was able find some evidence to suggest that voters support open space referenda for reasons other than environmental amenities. These results are relevant because, as we shall see later in this study, the theoretical underpinnings of this study also support the contention that open space can increase property values without generating any amenities.

Researchers have also examined the ability of open space to fund itself through the increases property values. Geoghegan et al. (2003) use hedonic modeling to estimate the benefit of agricultural preservation programs to nearby residential landowners in three Maryland counties. Following Irwin and Bockstael (2001), the authors test for differences between protected and developable open spaces, and control for endogeneity and spatial autocorrelation. They then use the estimated coefficients to simulate the change in housing values due to additional easements and the subsequent change in county tax revenue. Their results indicate that the increase in tax revenues due to boosts in property values could fund approximately 60% of the easements if the tax increases continued in perpetuity. These results demonstrate how, given certain conditions, land use decision-makers can potentially use open space conservation to generate greater tax revenues, a result that has important connections to the theory used in this study.

In summary, prior research has found that the right kind of open space in right location can increase property values in a city. Only one study has attempted to model the share of open space that maximizing property values for a city facing a budget constraint: Wu (2014). The theoretical framework outlined in Wu (2014) forms the basis for this study, and it is described in the next section.

Chapter 3

Conceptual Framework

The general theoretical framework for estimating the optimal share of open space conservation is based on Wu's (2014) paper on public open space conservation under a budget constraint. This framework is explained in the first part of this chapter. The theoretical framework used in this study to empirically estimate the price elasticity of housing supply for various urban areas is based on Green et al.'s (2005) paper on the sources of price elasticity of housing supply. The underpinnings of this study are discussed in the second part of this chapter.

Optimal Share of Open Space Conservation

Following Wu (2014), by considering a theoretical city we can find the conditions that determine the share of open space that maximizes property values. The following variables represent key aspects of this theoretical city:

A = total land area within the city
S = total area of public open space within the city
τ = property tax rate
g = level of municipal services
P = value of land for residential development
c = non-tax cost of home ownership, such as depreciation and mortgage interest rates
r = rental value of housing services obtained by using the land for residential development
μ = a parameter that reflects the enhancement of residential land value by municipal services such as city water and sewer [$\mu \in (0,1)$]

Wu (2014) uses these variables and a framework from Poterba (1984, 1991) to model the capitalization of municipal services and open-space amenities into urban land value. This technique yields Eq. (1), which states that the value of land for residential development (*P*) equals the present value of the stream of housing services provided by the land, discounted at the rate of user cost of home ownership (Wu, 2014). Intuitively, this equation states that given the property tax rate and the level of municipal services, as open space increases, property values increase. According to the equation, municipal services also increase property values, while higher property tax rates and other costs of home ownership decrease property values.

$$P = \frac{r\big(S, a(S)\big)g^{\mu}}{\tau + c} \tag{1}$$

If we assume that all land within the city (with the exception of public open space) is taxed private land, the total property tax revenue, *T,* can be represented by

$$T = \tau(A - S)P = \frac{\tau(A-S)r\big(S, a(S)\big)g^{\mu}}{\tau + c} \tag{2}$$

Equation (2) is essentially the value of property, multiplied by the amount of property, multiplied by the property tax rate. The city's cost of open space conservation is modeled in Equation (3).

$$C^S = cSP = \frac{cSr\big(S, a(S)\big)g^{\mu}}{\tau + c} \tag{3}$$

Wu (2014) follows Borcherding and Deacon (1972) and represents the costs of municipal services as $C^g = g(A - S)^{\lambda}$. In this equation, $\lambda \in [0,1]$ is a parameter indicating the economy of scale in the provision of municipal services, with λ=1 corresponding to no economy of scale and λ=0 representing the largest economy of scale, with all municipal services being pure non-rival public goods (Wu, 2014).

For a local government seeking to maximize total land value in the city, managers must solve the maximization problem below, choosing the property tax rate and the level of municipal services. This problem is subject to a budget constraint where the combined costs of open space conservation and municipal services must be less than or equal to the total property tax revenue (Wu, 2014).

$$\max_{(\tau,g)} \frac{Ar\big(S,a(S)\big)g^{\mu}}{\tau+c} \ \text{ s.t. } C^S + C^g \leq T \tag{4}$$

Implicit in Equation (4) are the trade-offs inherent to open space. First, the city must have a balanced budget; tax revenues must equal the costs of government services and open space. Second, open space increases property values in the objective function, but also increases costs (C^g) and decreases the tax base in *T*. Because costs must still be less than or equal to total revenue (*T*), additional open space requires either increasing the property tax rate (τ) or decreasing other government services (g^{μ}). Both of these actions cause property values to drop. Equation (4) is designed to maximize total land value in the city, while accounting for these trade-offs. Because the equations that follow are derived from Equation (4), these trade-offs are also inherent to them. Solving this maximization problem yields the value-maximizing level of government services (g*) and property tax rate (τ*):

$$g^* = \left[\frac{\mu r(S,a(S))}{(A-S)^{\lambda-1}}\right]^{\frac{1}{1-\mu}} \tag{5}$$

$$\tau^* = \frac{c}{1-\mu}\left(\mu + \frac{S}{A-S}\right) \tag{6}$$

By substituting Equations (5) and (6) into Equation (4), we can generate the total land value as a function of open space area in Equation (7) (Wu, 2014):

$$TLV = \frac{1-\mu}{c}\left[\frac{\mu^{\mu} r(S,a(S))}{(A-S)^{\lambda\mu-1}}\right]^{\frac{1}{1-\mu}} \tag{7}$$

By differentiating Equation (7) with respect to *S*, we can determine the conditions where open space conservation will increase the total land value:

$$\varepsilon_a^{H^d}\varepsilon_S^a(A-S) > \left[(1-\lambda\mu)\left(\varepsilon_r^{H^d}+\varepsilon_r^{H^s}\right)-1\right]S \tag{8}$$

where:

- $\varepsilon_a^{H^d} = \frac{\partial H^d}{\partial a}\frac{a}{H^d}$, and represents the elasticity of housing demand with respect to municipal amenities;
- $\varepsilon_S^a = \frac{da}{dS}\frac{S}{a}$, and represents the elasticity of amenities with respect to the amount of open space in the city;
- $\varepsilon_r^{H^d} = -\frac{\partial H^d}{\partial r}\frac{r}{H^d}$, and represents the price elasticity of housing demand;
- $\varepsilon_r^{H^s} = \frac{\partial H^s}{\partial r}\frac{r}{H^s}$, and represents the price elasticity of housing supply.

If the city government were to maximize only *private* land values within the city, the maximization solution would become:

$$\varepsilon_a^{H^d}\varepsilon_S^a(A-S) = \left[\left(2-(1+\lambda)\mu\left(\varepsilon_r^{H^d}+\varepsilon_r^{H^s}\right)\right)-1\right]S \tag{9}$$

Rearranging terms yields the share of public open space that maximizes private land value in the city:

$$s^* = \frac{\varepsilon_a^{H^d}\varepsilon_S^a}{\varepsilon_a^{H^d}\varepsilon_S^a+[(2-(1+\lambda)\mu)]\left(\varepsilon_r^{H^d}+\varepsilon_r^{H^S}\right)-1} \tag{10}$$

Because the elasticities in the above equation can change as more land is preserved for open space, Equation (10) only implicitly defines the share of open space that maximizes land value. The equation shows that when all else is equal, more land should be conserved for public open space when:

a) The demand and supply for housing services are less price elastic,

b) The level of amenities is more elastic with respect to the amount of land preserved, and

c) The demand for housing services is more elastic with respect to the level of amenities (Wu, 2014).

Equation (10) will serve as the basis for estimating the optimal share of open space in this thesis.

Price Elasticity of Housing Supply and Its Sources

The foundational theory used in this study to empirically estimate the price elasticity of housing supply for urban areas across the U.S., as well as determine the factors that affect these elasticities, is taken from Green et al.'s (2005) paper on the price elasticity supply of housing. In this paper, Green et al. posit that differences in supply elasticities will stem mainly from differences in urban form and land-use regulation.

To investigate this hypothesis, the authors begin by manipulating a model that was developed by Mayer and Somerville (2000), which was an extension of Capozza and Helsley (1989). This theory is based on the concept of a monocentric city where lot sizes are homogeneous. In this theoretical city, the price of housing is comprised of the opportunity cost of land (i.e. the value of using the land for agriculture), the cost of capital used to convert the land, transportation costs, and rent increases due to population growth. New housing construction occurs only at the city boundary when value of housing is greater than the value of using the land for agricultural plus the cost of converting the land into housing (Mayer and Somerville, 2000). The market for housing is assumed to be in perfect competitive equilibrium, implying home buyers and builders earn the same rate of return on capital as they can from other investments (Capozza and Helsley, 1989). Green et al. use this model to derive

Equation (11), which relates the elasticity of housing supply to the factors that affect the value of housing.

$$\eta = \left(\frac{2}{\phi\sqrt{n}}\right)\frac{(i-g)}{k}p \tag{11}$$

η = price elasticity of housing supply
i = cost of capital
g = growth rate for the city
n = population of the city
p = house price at some fixed point in the city
k = transportation cost
ϕ = factor of proportionality that is increasing in density

Green et al. (2005) further expands Equation (11) to better reflect the real cost of owning a home in a city by incorporating marginal tax rates and property taxes. This manipulation results in the following equation:

$$\eta = \left(\frac{2}{\phi\sqrt{n}}\right)\frac{(i+\tau_p)(1-\tau_y)-g}{k}p \tag{12}$$

τ_p = property tax rate
τ_y = marginal tax rate

According to Equation (12), an increase in the following factors would cause the price elasticity of housing supply to become more elastic (i.e. the elasticity would increase): Cost of capital, property taxes, and housing prices. An increase in the following factors would cause supply elasticity to become more inelastic (elasticity would decrease): Growth rate in the city, marginal tax rate, transportation costs, population density, and total population.

While Green et al. (2005) does not explain the intuition behind the relationships in Equation (12), some insight can be inferred from a draft of the paper (Green et al., 2004). The derivations in this paper imply that the expansion of the city boundary is equivalent to the number of housing starts, since depreciation, demolition, and construction within the city boundary are not incorporated into the model (Mayer and Somerville, 2000). Because land is inelastically supplied in the long run, factors that increase the city boundary decrease the supply elasticity. This explains why increases in total population and population growth cause reductions in the supply elasticity. It also explains why higher transportation costs and higher population density, both of which inhibit the city boundary, also reduce the supply elasticity.

Factors that increase the costs of home ownership, including real interest rates, property tax rates, and housing prices, increase the supply elasticity. This appears to be due to the assumption that the market is in competitive equilibrium, and market participants earn the same return on property as they do on other investments. Because increasing the return on the investment also means increasing the opportunity costs of building a home, supply becomes more elastic. This also explains why the marginal tax rate has a negative relationship with the supply elasticity. Since increasing the marginal tax rate reduces the influence of the user costs of owning a home, it also reduces the supply elasticity.

In order to verify the relationship between price elasticity of housing supply and the factors that theoretically that affect it, Green et al. employs a two-stage process, which is mimicked with updated data in this study. In the first stage, the authors estimate the price elasticity of housing supply for 45 U.S. Metropolitan Statistical Areas (MSAs). In the second stage, they use the elasticity estimates as the dependent variable and regress them onto the variables on the right-hand side of Equation (12) to determine what effect each variable has on supply elasticity.

To estimate the price elasticities of housing supply, Green et al. utilize the simplest definition of elasticity: $\varepsilon = \frac{Percentage\ change\ in\ Quantityi}{Percentage\ change\ in\ Price} = \frac{\%\Delta Q}{\%\Delta P}$.

Rearranging the terms of this equation yields: $\%\Delta Q = \varepsilon(\%\Delta P)$. Green et al. use this this equation and Ordinary Least Squares (OLS) regression with time series data to estimate the supply elasticity for the 45 MSAs. The regression equation for each MSA is as follows:

$$\gamma_t = \beta_0 + \beta_1(\rho_{t-1}) + \varepsilon_t \tag{13}$$

γ = Proxy for the percentage change in the quantity of housing. Calculated by multiplying the number of new housing permits issued in the MSA by the average number of people per household in the U.S. (2.5) and dividing by the population. This transformation is equivalent to dividing the number of new households by the approximate stock of housing. The stock of housing is represented by 2.5 divided by the population. Because multiplying by 2.5 over population is equivalent to dividing by population over 2.5, and because population divided by 2.5 approximates the stock of housing, the transformation represents the change in the housing stock divided by the estimated stock of housing. In this way, γ represents the percentage change in the quantity of housing.

ρ = Represents the percentage change in housing prices in each MSA. The parameter ρ is calculated by taking the first difference in natural logs of the Freddie Mac Housing Price Index average for each year. The first difference in natural logs is calculated by taking the natural log of the index value in one time period and subtracting the natural log of the index value in the previous period. This transformation provides a close approximation of the percentage change in the index. In the regression, the first lag of ρ is used to avoid simultaneity problems.

β_0 = constant term

β_1 = estimate of the price elasticity of housing supply

ε = random error term

t = year

After estimating the supply elasticities, Green et al. use these estimates in the dependent variable in the following second-stage OLS regression (using variable notation from Equations (11) and (12)):

$$\ln(\eta_j + 1) = \beta_0 + \beta_1 r_j + \beta_2 \ln(p_j) + \beta_3 \ln(n_j) + \beta_4 g_j + \beta_5 \ln(k_j) + \beta_6 \ln(\phi_j) + \beta_7 \ln\left(\tau_{p_j}\right) + \beta_8 \ln\left(\tau_{y_j}\right) + \varepsilon_j \tag{14}$$

r = an index measuring the stringency of land-use regulation developed in Malpezzi (1996), increasing with more stringent land-use regulation

j = a variable representing each MSA

As the dependent variable, Green et al. (2005) use the natural log of the elasticity estimates plus one. They justify this transformation by stating that some of their elasticity estimates are negative, and so must add one to be able to take the natural log of every estimate. In the regression results, the sign and significance of each beta coefficient indicates the effect of each factor on supply elasticity. Green et al. use three model specifications, each with a different measure of population density. The measure used in this thesis, average density, corresponds to Model (i) in Figure 3.A.

Figure 3.A: Green et. al. (2005) Second-Stage Regression Results

TABLE 2—SUPPLY ELASTICITY EXPLAINED

Variable	(i)	(ii)	(iii)
Intercept	16.7	15.5	15.6
	(5.3)	(7.5)	(5.8)
Intercept of SUM			−0.65
			(0.30)
Regulatory index	−0.07	−0.08	−0.08
	(0.03)	(0.04)	(0.03)
Change in population	3.07	2.73	2.63
	(0.9)	(1.1)	(1.0)
Log property tax	−0.389	−0.340	−0.29
	(0.2)	(0.3)	(0.3)
Log commute	−1.40	−1.24	−0.783
	(1.4)	(1.5)	(1.5)
Log median density	−0.547		
	(0.2)		
Log average density		−0.306	
		(0.2)	
Log population	0.540	0.473	0.534
	(0.2)	(0.3)	(0.2)
Log house price	−0.848	−0.904	−0.814
	(0.3)	(0.5)	(0.4)
Log marginal tax rate	0.943	0.979	1.27
	(0.9)	(1.0)	(0.9)
R^2:	0.702	0.659	0.686

Note: Standard errors are in parentheses.

According to Equation (13), the following variables should have positive signs in Green et al.'s second-stage regression: Property taxes and housing prices. Conversely, the following variables by theory would have negative signs: Change in population, marginal tax rate, commute, population density, and total population. Green et al. also theorize that more stringent land use regulation should cause the price elasticity of housing supply to become more inelastic. Therefore, the variable for regulatory index is expected to be negative.

Looking at Green et al.'s results in Figure 3.A, we see that the regulatory index and population density are both significant and have the expected negative sign. However, total population, population growth, and house price levels are also significant but do not have the sign that would be expected by theory. Property taxes and marginal tax rates have the wrong sign but are not significant. Commute has the correct sign but is also not significant. Green et al. attempt to explain the unexpected behavior of population growth by stating that their elasticity estimates for slow-growth cities are likely wrong, and that the simultaneity of population growth and housing supply contributes to the problem. They also state that simultaneity likely lead to unexpected results for the housing price variable.

Chapter 4

Data and Empirical Methods

This chapter presents the empirical methods and data used in this study. The first section describes the type and sources of the data used in the empirical analysis. The second section describes how some the data were transformed to create variables used in subsequent regression analyses. The third section covers the regression models used and the procedures followed to obtain the empirical results.

Data

The data collected this study was used for two purposes: 1) To estimate the price elasticity of housing supply for 349 urban areas across the U.S., and 2) To determine how various attributes of the city affect the supply elasticity. This section describes the data used to estimate the elasticities and the data used to analyze the factors that affect the elasticity.

As an administrative note, all of the data used in this study are aggregated to statistical areas by the U.S. Office of Management and Budget. Prior to 2003, these areas were referred to as MSAs. From 2003 onward, the names of these areas were changed to Core Based Statistical Areas (CBSA). Despite the fact that some of the data used in this study pertain to MSAs or CBSAs, for simplicity, the statistical area will always be referred to as MSA.

Following Green et al. (2005), this thesis calculates variables to represent the percentage change in the quantity and price of housing, and then uses these variables in an OLS regression to estimate the price elasticity of housing supply of the urban area. The proxy variable representing the percentage change in housing quantity, hereafter referred to as γ, is generated using the number of new housing permits and the MSA's total population. Both the housing permit data and population data were obtained from the U.S. Census. The data are annual, extending from 1980-2012. The housing permit data represent building permits for new, privately owned, residential construction, and are based upon reports submitted by local building permit officials in response to a mail survey (U.S. Census, 2004).

The variable representing the percentage change in price, hereafter referred to as ρ, is calculated using data from the Freddie Mac Housing Price Index (FMHPI). This data is monthly and is aggregated for 367 MSAs. The FMHPI is based on repeat transactions on one-family detached and townhome properties serving as collateral on loans originating between January 1, 1975 and the end of the most recent index month. These transactions are only recorded for loans that have been purchased by Freddie Mac or Fannie Mae. Because it is a repeated sales index, the FMHPI measures the underlying rate of appreciation since housing type and location are fixed. The FMHPI does not adjust for seasonality or inflation (Freddie Mac, 2009).

The MSA factors that affect supply elasticity are also taken from Green et al. (2005). These factors include the price of housing, population level, population change, commute time, population density, property tax, marginal tax rate, and stringency of land-use regulation. In some cases, a direct value could be used to represent the variable; in other cases, a suitable proxy variable was used.

In this study, the price of housing was represented by the median housing price in the MSA in 2010. This value was acquired directly from the 2010 U.S. Census American Community Survey (ACS) dataset, as was the average commute time (in minutes) for each MSA. The population level and change in population were calculated using U.S. Census figures from the years 2000 and 2010. The change in population is represented by units of one hundred thousand people. Population density, represented by the average population density in the MSA, was calculated using the total MSA area and population, both taken from U.S. Census data.

The property tax and marginal tax rates in the MSA were both calculated using data from the 2010 U.S. Census Public Use Microsamples (PUMA) dataset.

The PUMA dataset is compiled using survey responses from individuals across the U.S. at 1-, 3-, and 5-year intervals. The survey contains questions on both the individual and household level. Questions at the individual level include topics such as demographics, employment status, family composition, educational history, and income. Questions at the household level include topics such as household structure, family income, housing costs, household amenities, and family structure. To calculate the property tax variable, two PUMA's responses were used: the self-reported value of the property in 2010, and the self-reported amount of property tax paid in 2010. To calculate the marginal tax rate variable, the following PUMA's responses were used: the self-reported household income, state of residence, marital status, and number of children in the household.

In both Green et al. (2005) and this study, the variable representing land use regulation was created using survey data. Green et al. used a regulatory index from Malpezzi (1996), which was developed from survey data presented in Linneman et al. (1990). To construct this variable, Malpezzi took the unweighted sum of seven survey responses that measured the regulatory environment in 56 MSAs.

In this study, two different metrics were used to measure the stringency of land-use regulation in each MSA. Using two metrics provided an opportunity to test the robustness of the results on the regulatory measure used, as well as a chance to test the relationship in a larger number of MSAs. Because both of these indices were created using a method similar to Malpezzi (1996), it is difficult to argue that one is more accurate than another.

The first index used in this study was created by Saks (2005), which listed land-use regulation levels for 83 MSAs. This index was generated using data from six different surveys that asked questions about local land use regulations. The earliest survey was conducted in 1975 and the latest was in 1990. For each survey, responses reflecting more stringent regulation are coded with a higher value. The Saks (2005) index takes a simple average of these survey response scores to generate a final regulatory metric (Saks, 2008).

Gyourko et al. (2008) created the second land-use regulation index used in this study. This index, called the Wharton Residential Land Use Regulation Index

(WRLURI), was generated by surveying over 2000 jurisdictions across the U.S. The survey included questions about the regulatory process for housing, the rules for residential land use, and outcomes of the regulatory process (Gyourko et al., 2008). Responses to the surveys were used to generate 10 sub-indices, which Gyourko et al. used in a factor analysis to generate an overall index value for 47 MSAs.

Table 4.1: Descriptive Statistics for Each Variable

Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
Total MSA Population 1980-2012	7,314	792,921	1,536,239	54,616	2,020,000
Permits 1980-2012	7,314	4,255	8,012	10	111,271
FMHPI 1980-2012	7,314	105	35.11	22.44	254.53
Median House Value in 2010	366	172,292	81,855	73,200	631,400
Total MSA Population in 2010	366	705,786	1,579,549	55,274	1,890,000
Population Change 2000-2010 (in hundreds of thousands)	281	0.861	1.91	-1.621	12.298
Average Commute Time in 2010	302	22.42	3.20	14.2	34.6
Average Population Density in 2010	366	288.83	326.82	7.22	2,825.99
Property Tax Average in 2010	207	0.012	0.005	0.002	0.030
Average Marginal Tax Rate in 2010	207	0.204	0.025	0.135	0.264
Saks (2008) Regulatory Index	85	0.029	1.005	-2.4	2.21
Gyourko et al. (2008) Regulatory Index	47	0.273	0.581	-0.8	1.79

Variable Creation

This section describes how the variables used in the supply elasticity estimations and elasticity factor regression were calculated. As in Green et al. (2005), the variables γ and ρ were used in an OLS regression to estimate the supply elasticity for each MSA. *Gamma (γ)*, which is a proxy for the percentage change in housing quantity, was generated using the population and housing permit data in Equation

(15) below. In the equation, the number of housing permits is multiplied by the average number of people per household in the U.S. (2.5).

$$\gamma_t = \frac{2.5h_t}{n_t} \tag{15}$$

h = number of new housing permits issued in the MSA in the given year
n = total MSA population
t = year

The parameter ρ represents the percentage change in housing price. Because ρ is generating using monthly FMHPI data when an annual value is need for the regression, the mean value of the 12 months in the calendar year was used. The ρ value for each MSA in each year is calculated using Equation (16):

$$\rho_t = \ln(f_t) - \ln(f_{t-1}) \tag{16}$$

f = Average FMHPI value for the calendar year

In analyzing the factors that affect supply elasticity, the following variables required calculation: the change in population, average population density, property tax average, and the average marginal tax rate. The change in population was calculated simply by subtracting the total MSA population in the year 2000 from the total MSA population in 2010. The average population density was calculated by dividing the total MSA population in 2010 by the total MSA area (in square miles). To generate an observable regression coefficient result, the units for population change are in hundreds of thousands of people.

The average property tax rate is calculated in the manner of Green et al. (2004). For each household in the 2010 PUMA dataset, the reported amount of property taxes paid is divided by the reported value of the property. The average of these ratios for all households in an MSA represents the average property tax.

The method for calculating average marginal tax rate is also taken from Green et al. (2004). For each household in the 2010 PUMS dataset, the federal and state standard deductions and personal exemptions were subtracted from total household income to estimate the taxable income for both the federal and state level. Some states allow federal taxes to be deducted from state taxable income; in these cases, the estimated federal tax amounts were also subtracted from household income to calculate state taxable income. Federal standard deduction and personal exemption amounts were taken from the 2010 Instructions for IRS Form 1040 Standard Deductions Worksheet. State standard deduction amounts and personal exemption were acquired from Tax Foundation (2010), the Tax Policy Center, and individual state tax forms.

The marginal tax rate for each household was assigned based on household taxable income. Federal marginal tax brackets were acquired from IRS 2010 Publication 17. State marginal tax brackets were attained from Tax Foundation (2010), the Tax Policy Center, and individual state tax forms. Once the state and federal marginal tax rates were imputed, they were added together to estimate the household's overall marginal tax rate. However, for states that allow federal taxes to be deducted from state taxable income, the following, more complicated formula was used to generate the household's overall marginal tax rate:

$$FMTR + (1-FMTR) \times SMTR = MTR$$

FMTR = federal marginal tax rate for each household
SMTR = state marginal tax rate for each household
MTR = total marginal tax rate for each household

Once each household's overall marginal tax rate was obtained, a weighted average was calculated for all households in an MSA. This metric was used as the average marginal tax rate for each MSA. Because this method only considers federal and state taxes, local taxes are not included in this analysis. While local taxes are likely to impact the price elasticity of housing supply within an MSA, the effort required to compile tax rates for 356 MSAs was beyond the scope of this study.

Estimating Price Elasticity of Housing Supply

As in Green et al. (2005), the price elasticity of housing supply for each MSA is estimated by OLS regression using Equation (17):

$$\gamma_t = \beta_0 + \beta_1(\rho_{t-1}) + \varepsilon_t \tag{17}$$

Because the data is time series, there is potential for serial correlation to bias the standard errors of the estimates. If the error terms are correlated, the results will be overly significant. A test for serial correlation presented by Woodridge (2002) shows evidence of serial correlation, both in the dataset used in this study and in the dataset used in Green et al. (2005). While Green et al. do not address this potential problem in their study, I use Newey-West standard errors in the regressions in order to control for serial correlation and heteroskedasticity.

Another potential issue with using Equation (17) to estimate the supply elasticities is the equation implicitly suggests price is the only factor that impacts the supply of housing. All other factors that may affect housing supply are included in the error term. A problem arises if there are indeed other factors that affect supply across time periods, but are not included as variables in the regression equation. The cost of construction materials and labor are two factors that likely fit this description. If this is the case, improper model specification resulting from omitted variables could bias the supply elasticity estimate (Wooldridge, 2002).

While this potential issue is not addressed in Green et al. (2005) or in this study, further research into this subject may benefit from expanding Equation (17) to include other factors that impact the supply of housing. If data on such factors are unavailable, another solution for gaining an unbiased estimate of the supply elasticity would be to use an instrumental variable (IV) in two stage least squares regression (Wooldridge, 2002). In this case, a proper IV would be a factor that affects the price of new housing but does not affect supply, such as a factor that shifts the demand for new housing.

Also following Green et al. (2005), this study analyzed the factors that affect supply elasticity by regressing elasticity estimates on the eight factors posited to influence supply elasticity. In this second stage, three different model specifications were used to test the robustness of the results. Each specification uses a different form of elasticity as the dependent variable. The first model uses the same transformation as Green et al. (2005): The natural log of the elasticity estimate plus one. This allows each point estimate (including negative estimates) to be included in the regression.

However, this method has the potential to be misleading since many of the estimated elasticities are not statistically different than zero, and therefore it may not be appropriate to treat them as point estimates in subsequent analysis. For this reason, in the second model, all estimates that are statistically insignificant have been replaced with zeros. Because none of the negative estimates are statistically significant, there is no longer justification for adding one before taking the natural log of the estimate. Consequently, the dependent variable in the second model is simply the natural log of the estimate. The third model uses the untransformed elasticity estimates as the dependent variable to test whether or not the transformation affects the results. For each of the three model specifications, the two regulatory indices (Gyourko et al. and Saks) are tested separately, for a total of six different models.

In all six models, robust standard errors were used. While Green et al. (2005) did not use robust standard errors, some of the independent variables in the second-stage regression did show evidence of heteroskedasticity. If left uncontrolled, this could cause bias the standard errors of the estimated coefficients. To avoid this potential problem, this study uses robust standard errors in the second-stage regression as a cautionary measure.

The models have the following regression forms (again using notation from Equations (13) and (14)):

Model A1:

$$\ln(\eta_i + 1) = \beta_0 + \beta_1 r_i^G + \beta_2 \ln(p_i) + \beta_3 \ln(n_i) + \beta_4 g_i + \beta_5 \ln(k_i) + \beta_6 \ln(\phi_i) + \beta_7 \ln\left(\tau_{p_i}\right) + \beta_8 \ln\left(\tau_{y_i}\right) + \varepsilon_i \tag{18}$$

Model A2:

$$\ln(\eta_i + 1) = \beta_0 + \beta_1 r_i^S + \beta_2 \ln(p_i) + \beta_3 \ln(n_i) + \beta_4 g_i + \beta_5 \ln(k_i) + \beta_6 \ln(\phi_i) + \beta_7 \ln\left(\tau_{p_i}\right) + \beta_8 \ln\left(\tau_{y_i}\right) + \varepsilon_i \tag{19}$$

Model B1:

$$\ln(\eta_i^*) = \beta_0 + \beta_1 r_i^G + \beta_2 \ln(p_i) + \beta_3 \ln(n_i) + \beta_4 g_i + \beta_5 \ln(k_i) + \beta_6 \ln(\phi_i) + \beta_7 \ln\left(\tau_{p_i}\right) + \beta_8 \ln\left(\tau_{y_i}\right) + \varepsilon_i \tag{20}$$

Model B2:

$$\ln(\eta_i^*) = \beta_0 + \beta_1 r_i^S + \beta_2 \ln(p_i) + \beta_3 \ln(n_i) + \beta_4 g_i + \beta_5 \ln(k_i) + \beta_6 \ln(\phi_i) + \beta_7 \ln\left(\tau_{p_i}\right) + \beta_8 \ln\left(\tau_{y_i}\right) + \varepsilon_i \tag{21}$$

Model C1:

$$\eta_i^* = \beta_0 + \beta_1 r_i^G + \beta_2 \ln(p_i) + \beta_3 \ln(n_i) + \beta_4 g_i + \beta_5 \ln(k_i) + \beta_6 \ln(\phi_i) + \beta_7 \ln\left(\tau_{p_i}\right) + \beta_8 \ln\left(\tau_{y_i}\right) + \varepsilon_i \tag{22}$$

Model C2:

$$\eta_i^* = \beta_0 + \beta_1 r_i^S + \beta_2 \ln(p_i) + \beta_3 \ln(n_i) + \beta_4 g_i + \beta_5 \ln(k_i) + \beta_6 \ln(\phi_i) + \beta_7 \ln\left(\tau_{p_i}\right) + \beta_8 \ln\left(\tau_{y_i}\right) + \varepsilon_i \tag{23}$$

r^G = Gyourko et al. regulatory index

r^S = Saks regulatory index

η^* = All statistically insignificant elasticity estimates have been changed to zero values

Chapter 5

Empirical Results and Analysis

This section outlines the results of the empirical procedures used to estimate the price elasticity of housing supply, and the factors that affect supply elasticity. The first part of the section discusses the estimates of the supply elasticity. The second part of this section summarizes the results of the regression used to assess how various MSA factors impact housing supply elasticity. The third section outlines the estimated optimal shares of open space. The fourth section compares the estimated optimal shares to observed shares of open space. The fifth and final section presents a sensitivity analysis, which tests the assumed values used to estimate the optimal share of open space.

Price Elasticity of Housing Supply

The regressions used to recover housing supply elasticities resulted in estimates for 349 MSAs. Of those, 288 estimates were statistically different than zero. Descriptive statistics for the elasticity estimates are provided in Table 5.1. It is noteworthy that none of the statistically significant observations are negative. According to economic theory, which states that price and supply quantity should rise and fall together, supply elasticities should always be positive, lending the method some construct validity. A list of all supply elasticity estimates by MSA is provided in Appendix A.

Comparing the elasticity estimates to Green et al. (2005), the results of this study show improved reliability. Only 51% of the estimates in Green et al. (2005)

were statistically different than zero. In this study, 82% of estimates are statistically significant. This improvement is, no doubt, due to the increased number of observations for each MSA (17 in Green et al. versus up to 32 in this study). The results of this study also lend to support Green et al.'s method of estimating supply elasticities. Among the 43 MSAs that appear in both datasets there is a 66% correlation between the estimates. If one only compares the 20 estimates that are statistically significant in both studies, this correlation increases to 99%. These results indicate that the method established by Green et al. (2005) and adopted in this study provide consistent estimates.

Table 5.1: Descriptive Statistics of Housing Supply Elasticity Estimates

	Observations	Mean	Std. Dev.	Minimum	Maximum
All Supply Elasticity Estimates	349	9.024	7.097	-11.75	37.47
Statistically Significant Supply Elasticity Estimates [a]	288	10.271	6.901	1.142	37.47

[a] Estimated coefficient has a p-value ≤ 0.05

Figure 5.A: Estimates of the Elasticity of Housing Supply

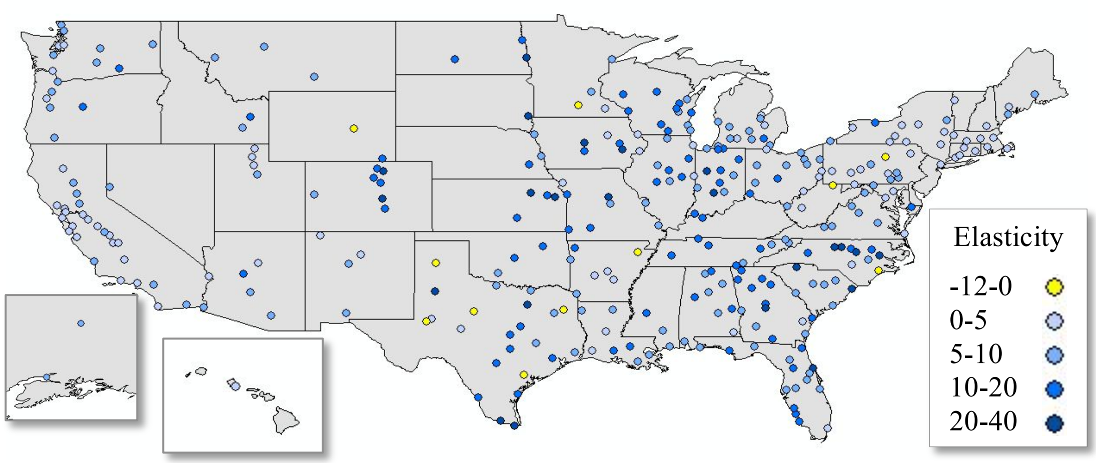


Figure 5.A displays the elasticity estimates geographically. Displaying the results this way reveals some spatial pattern to the elasticity of housing supply. In general, urban areas in the West Coast and Northeast regions show lower supply elasticities, while cities in the Midwest and South show higher supply elasticities. When only the statistically significant estimates are examined, this pattern remains intact, but the negative estimates drop out (this map is shown in Appendix C).

Factors That Affect Supply Elasticity

Table 5.2 displays the results of the second-stage regression that analyzes the factors hypothesized to affect the price elasticity of housing supply. From the results, it is clear that population change clearly affects supply elasticity, regardless of model specification and always in the direction theory predicts: As the urban population grows, housing supply becomes more price elastic. These results also align with Green et al. (2005).

For land-use regulation, the Saks index is consistently significant and negative, as was predicted. The Gyourko et al. index is also consistently negative, however, it is only significant in Model B1. This is likely due to the fact that there are almost half as many observations for the Gyourko et al. index than the Saks index. Regardless, the results provide good evidence that more stringent land-use regulation causes housing supply to become more inelastic.

The results also provide some evidence that property taxes affect supply elasticity, however, not in the direction predicted. Green et al. (2005) showed a similar odd result but it was not statistically significant. The variables for commute, population density, total population, house value, and marginal tax rate show little to no evidence of impacting housing supply elasticity.

Table 5.2: Regression Results for Factors That Affect Supply Elasticity

Variable	A1	A2	B1	B2	C1	C2
Gyourko et al. Regulatory Index	-0.3313*		-0.4517**		-1.8155	
Saks Regulatory Index		-0.2479***		-0.3034***		-2.6014***
Population Change	0.0792**	0.1115***	0.0858**	0.1297***	1.0434**	1.4229***
Property Tax	-0.6783**	-0.1850	-0.8121**	-0.3110*	-4.6497*	-1.6500
Commute	-1.1191	-1.2618	-1.3387	-0.8306	-16.8755	-24.2691
Average Population Density	-0.1683	-0.2269	-0.2071	-0.2653	-0.6828	-0.3015
Total Population	0.0809	-0.0329	0.0832	-0.0328	1.2378	-0.1062
Median House Value	-0.2969	-0.2559	-0.1941	-0.7657*	-2.3684	0.8474
Average Marginal Tax Rate	-1.1307	-0.4432	-1.5567	0.0517	-13.3696	-8.8303
Constant	4.2438	8.3178	2.4917	14.3209**	33.8791	54.7061
Observations	29	51	28	47	29	51

* indicates a p-value ≤ 0.1
** indicates a p-value ≤ 0.5
*** indicates a p-value ≤ 0.01

Optimal Share of Open Space Conservation

Using the estimated price elasticities of housing supply, we can return to Equation (10) to investigate the share of open space that maximizes total private land value. Following Wu (2014), we can assume values for the other variables in (10) based on relevant literature. These variables include the price elasticity of housing demand ($\varepsilon_r^{H^d}$), the economies of scale in municipal services (λ), and elasticity of land value with respect to municipal services (μ).

For empirical evidence of economies of scale in municipal services (λ), Wu (2014) cites two studies: Carruthers and Ulfarsson (2008) and Hortas-Rico and Sole-Olle (2010). The results from both suggest that that the value of λ is close to 1.

Another study further supports these results: Holcombe and Williams (2009) examines per capita expenditures in 487 municipalities with populations larger than 50,000 people. The authors find that once population density is controlled for, there appear to be neither economies nor diseconomies of scale in municipal government expenditures. This study reaffirms constant returns to scale in municipal services, and a value of λ close to 1.

For the elasticity of land value with respect to municipal services (μ), there is less empirical work examining this value. However, Wu (2014) cites Potepan (1996), who analyzes variation in housing prices, rents and land prices for 58 MSAs. Potepan finds a statistically significant value of 0.68 for μ.

The price elasticity of housing demand ($\varepsilon_r^{H^d}$) has been the subject of many studies. The results of these studies provide strong evidence that demand for housing is inelastic with respect to price (Wu, 2014). This makes intuitive sense, as housing is a good essential to life, people are likely to consume housing regardless of price changes, so demand should be inelastic. In Mayo (1981), the author lists 21 unbiased price elasticity estimates from other studies. As an approximation for this variable, we use the median value of these 21 estimates, which is 0.56.

Unfortunately for the two remaining variables, there are no known studies that have explicitly estimated the elasticity of housing demand with respect to amenities ($\varepsilon_a^{H^d}$), or the elasticity of housing demand with respect to open space (ε_S^a). However, by first combining these elasticities into a single term, we can derive an estimate of this variable. The two elasticities can be combined using the method shown in Equation (24). This transformation results in a single term: The elasticity of housing demand with respect to open space.

$$\varepsilon_a^{H^d}\varepsilon_S^a = \frac{\Delta H^d}{\Delta a}\frac{a}{H^d}\times\frac{\Delta a}{\Delta S}\frac{S}{a} = \frac{\Delta H^d}{\Delta S}\frac{S}{H^d} = \varepsilon_S^{H^d} \tag{24}$$

Unfortunately, there is very little evidence from the literature regarding the value of $\varepsilon_S^{H^d}$. However, because elasticities are unitless measures, it is possible to compare their relative values, and by examining the influence of other factors that affect housing demand, we can gain some information on the value of $\varepsilon_S^{H^d}$. The two most well-documented factors that influence demand for housing are price and income. It would be safe to argue that open space would have a smaller impact on the demand for housing than either of these factors, and therefore its elasticity should be smaller than the elasticities of price and income. In this way, the elasticities of price and income can act as an upper limit to the elasticity with respect to open space.

In Table 1 of "Theory and Estimation in the Economics of Housing Demand" (1981), Mayo lists the elasticities of price and income that have been estimated in 27 different studies. Additionally, he indicates which estimates were gained through incorrect model specification that may have lead to bias in the results. By treating these estimates as the range of likely values for the elasticities of income and price, we can gain some information about the elasticity of open space. Of the estimates that were not subject to bias, Mayo provides 21 estimates for the price elasticity and 52 estimates for the income elasticity. Descriptive statistics for these estimates are shown in Table 5.3.

As Table 5.3 shows, according to the studies Mayo cited, the lowest estimate for the price or income elasticity is 0.08. Since we can expect the open space elasticity to be below this figure, to calculate an estimate of s^* I will use a value of 0.05 for $\varepsilon_S^{H^d}$.

Table 5.3: Descriptive statistics for estimates of price and income elasticity listed in Table 1 of Mayo (1981)*

Elasticity	Mean	Median	Minimum	Maximum
Price	0.51	0.56	0.17	0.89
Income	0.41	0.39	0.08	0.87

* Estimates generated in studies Mayo marked as subject to bias are not included

In accordance with the evidence cited above, we assume the following values for all MSAs in the calculation of their optimal share of open space: $\varepsilon_S^{H^d} = 0.05$, $\lambda = 1, \mu = 0.68$, and $\varepsilon_r^{H^d} = 0.56$. In order to test the implications of these assumed values, a sensitivity analysis is in the last section of this chapter. When the assumed values are inserting into Equation (10), the formula for the optimal share of open space simplifies to Equation (25):

$$s^* = \frac{0.05}{0.64\,\varepsilon_r^{HS} - 0.5916} \tag{25}$$

Equation (25) shows how, once the other variable values have been assumed, the optimal share of open space becomes a function of the price elasticity of housing supply. An important feature of this equation is that for sufficiently low supply elasticities, the optimal share of open space will be negative. This happens when the denominator of Equation (25) is less than zero. For the values we have assumed to estimate $s*$, this happens when $\varepsilon_r^{HS} < 0.924$. This characterizes 15 MSAs (none of which are statistically significant at the 5% level). Another important aspect of this equation is that it can produce estimates of optimal share that are 100% or higher. Again, for the values that we have assumed, this happens when $0.924 < \varepsilon_r^{HS} < 1.0025$. While no MSA in the dataset has a supply elasticity estimate within this small range, it is an important facet of the equation and it will be relevant in later analysis.

By inputting the 349 MSAs supply elasticity estimates into Equation (25), we can now estimate the optimal share of open space for those MSAs. Each MSA's estimated optimal share of open space is listed in Appendix B. Descriptive statistics are outlined in Table 5.4.

Table 5.4: Descriptive statistics for estimates of the optimal share of open space

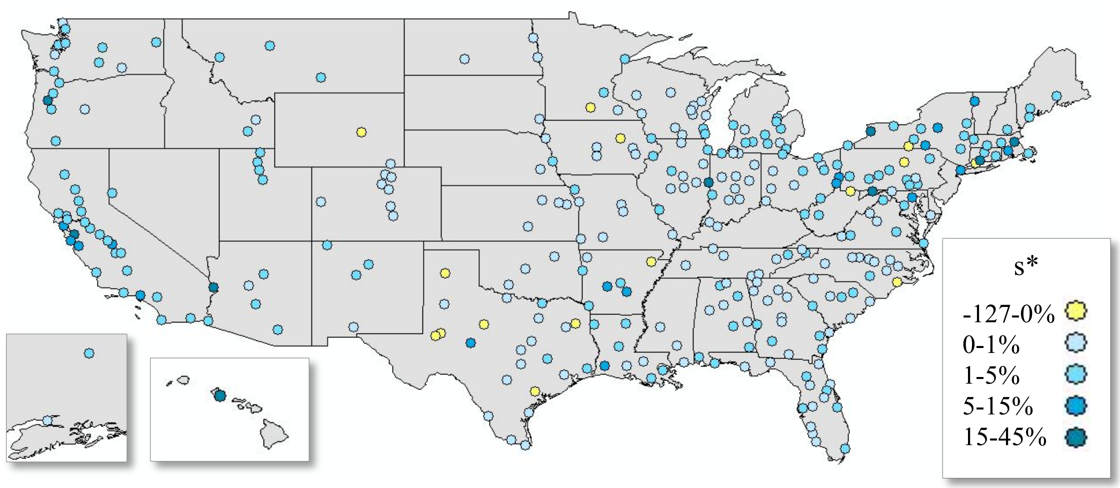
	Observations	Mean	Std. Dev.	Minimum	Maximum
All Estimates	349	0.0165	0.0893	-1.2729	0.4423
Statistically Significant Estimates [a]	288	0.0179	0.0300	0.0021	0.2726

[a] Optimal shares based on statistically significant supply elasticity estimates

Table 5.4 shows that the mean optimal share of open space is very low: Around 1.5% of the total area. The median value is near 1%. While the range for all estimates includes some nonsensical values (such as a -127% optimal share), once insignificant estimates have been removed the range of estimates becomes more reasonable: From essentially 0 to 27%. Of the statistically significant estimates, 95% have an optimal share of 5% or less.

Figure 5.B shows the optimal share estimates geographically. Because supply elasticity is the distinguishing factor in the optimal share, Figure 5.B shows a spatial pattern similar to the map of supply elasticities (Figure 5.A). Higher optimal shares appear more frequently on the West Coast and Northeast regions, while lower optimal shares tend to characterize the Midwest and South. As with the supply elasticity, the spatial pattern remains unchanged if only the statistically significant estimates are considered, but, once again, the negative estimates disappear.

Figure 5.B: Estimates of the Optimal Share of Open Space



Comparing Optimal Shares of Open Space to Actual Shares

To better understand how these estimates of optimal share compare to the real world, it is helpful to compare them to observed shares of open space. The Trust for Public Land (TPL) cites this type of information in their report "2011 City Park Facts." The report lists the percent of total land that is park space for the 100 U.S.

cities that were the most populous in 2009. The park area figures were based on data from the year 2000, and included all publicly owned and operated parks within city limits that were managed by a government body at any level, from municipal to federal. Descriptive statistics on the TPL's figures are listed in Table 5.5.

Table 5.5: Descriptive statistics for observed shares of open space as listed in Trust for Public Land (2011)

	Observations	Mean	Std. Dev.	Minimum	Maximum
Percent of total city area that is park space	100	0.0977	0.0711	0.014	0.399

It is appropriate to compare the estimates of optimal open space to percentages listed in the TPL report if a number of assumptions can be made. First, we must assume there is not a significant amount of public open space that was not accounted for in the report. Second, we must assume that the share of open space does not change drastically from the municipality to the larger MSA, since the optimal share estimates are based on the larger MSA and the TPL figures are based on the smaller municipality. Lastly, we must assume that the share of park space cited in the TPL report has not changed significantly since 2000. While these assumptions are not unreasonable, if a city violates any one of them it is possible the subsequent analysis for that city will not be valid.

With the TPL report providing some basis for the actual shares of open space, we can now make meaningful comparisons with our estimates of optimal share. This is most simply done by subtracting the estimated optimal share from the observed actual share. There are 72 urban areas that were included in both TPL report and this study's dataset. Of these, 61 MSAs had statistically significant supply elasticity estimates. Table 5.6 shows the descriptive statistics for the difference between the optimal share and actual share of open space. A map displaying this information is shown in Appendix C.

Table 5.6: Descriptive statistics for difference between the optimal share of open space and the actual share as listed in Trust for Public Land (2011)

	Observations	Mean	Std. Dev.	Minimum	Maximum
Optimal share minus the actual share	72	-0.063	0.101	-0.389	0.342
Statistically Significant Estimates [a]	61	-0.079	0.077	-0.389	0.111

[a] Optimal shares based on statistically significant supply elasticity estimates

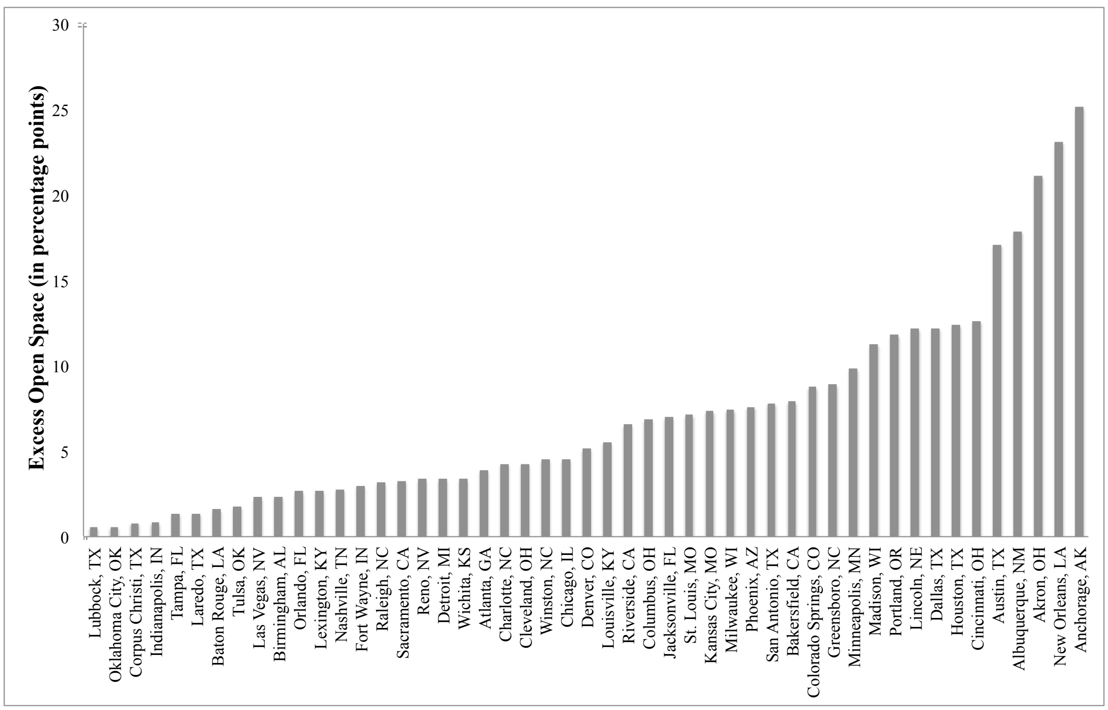
Because of the method of calculation, differences with negative values represent MSAs where the actual share of open space is larger than the estimated optimal share, or an "excess" of open space. Positive differences represent an actual share that is lower than the optimal share, or a "shortage" of open space. Excesses account for 89% of the observations, while shortages account for 11% of the observations. This result is unsurprising given that the most optimal shares were very small (almost all below 5%), while the actual shares of open space averaged over 9%. However, the results indicate both large shortages (34 percentage points) and large excesses (39 percentage points) of open space. The average deviation is an excess of 6.3 percentage points.

While this kind of analysis is interesting, it is also does not account for an important consideration given the methods used here: The error associated with the supply elasticity estimates. Because the supply elasticities were generated using OLS, they have an associated 95% confidence interval, which is likely to contain the "true" supply elasticity. Since the supply elasticity is likely to lie somewhere between the highest and lowest levels of this confidence interval, it is only appropriate to use these high and low levels to generate a confidence interval around the optimal share of open space. By determining these upper and lower limits of $s*$ and comparing them to the observed shares of open space, we can determine which cities have shares of open space that are significantly higher or lower than their estimated optimal share.

However, in calculating the lowest confidence interval of $s*$, we again run into the practical limitations of Equation (23): When $\varepsilon_r^{H^s} < 0.924$ the estimate of optimal open space is negative, and when $0.924 < \varepsilon_r^{H^s} < 1.0025$ the estimate of the optimal share is greater than 100%. Of the 72 MSAs with an observed share of open space, 18 (25%) have a lower confidence interval below 0.924. Of the 61 MSAs with statistically significant elasticity estimate, 7 (11%) have a lower confidence interval below 0.924. One MSA has a confidence interval limit between 0.924 and 1.0025. While the limitations of the model make it impossible to include these cities in this analysis, the sensitivity analysis in the next section will allow us to explore the relationship between these cities' observed and optimal shares of open space.

Of the 53 remaining MSAs, only two showed statistically significant shortages of open space: Stockton, CA and Miami, FL. However, neither city appears to be experiencing large shortages of open space: Miami misses its lowest confidence interval by only one-third of a percentage point, and Stockton by less than that. While their observed share of open space does lie below their optimal share, both cities are still very close to being within their confidence intervals for optimal open space.

Figure 5.C: Cities that show statistically significant excesses of open space



Compared to those MSAs that showed shortages, the excesses are much more dramatic. Figure 5.C shows the 49 MSAs that exhibited statistically significant excesses of open space. Of these, five MSAs are above their confidence intervals by 15 percentage points or more: Austin, TX; Albuquerque, NM; Akron, OH; New Orleans, LA; and Anchorage, AK. Because their actual share of open space is significantly higher than their estimated optimal share, it is much more likely that these cities are experiencing large surpluses of open space and could increase property values by decreasing the amount of open space in their cities.

The two remaining MSAs have actual shares of open space that lie within the confidence intervals of the estimated optimal share. These are Washington, DC and Virginia Beach, VA. Statistically speaking, of the 53 MSAs considered in this analysis, these two cities are the most likely to be at their optimal share of open space. Consequently, they are also the most likely to experience a decline in property values if they change their share of open space.

Sensitivity Analysis

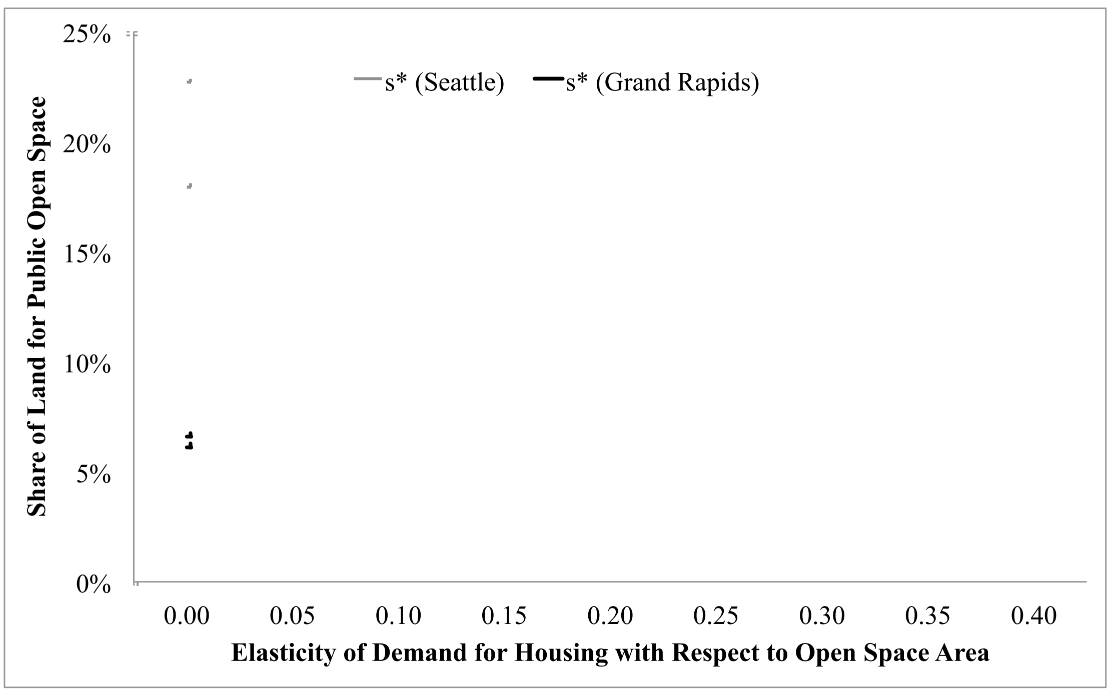
In order to test how robust the results are to changes in our assumptions, we conduct sensitivity tests on each of the variables for which we have used example values: $\varepsilon_S^{H^d}$, λ, μ, and $\varepsilon_r^{H^d}$. By calculating the optimal share across the reasonable range of these variables, we can get a sense of the weight of assuming their value. We begin with the price elasticity of housing demand ($\varepsilon_r^{H^d}$).

Returning to Table 5.3, the studies cited by Mayo (1981) produce a range for $\varepsilon_r^{H^d}$ between 0.17 and 0.89. This is how we will define its reasonable range. Because the effect of $\varepsilon_r^{H^d}$ also depends heavily upon on value of $\varepsilon_S^{H^d}$, we must also determine the reasonable range for the elasticity of housing demand with respect to open space. For this, I will also use Mayo (1981). Because people are unlikely to respond more strongly to changes in open space than to changes in price, it is reasonable to say that the value for $\varepsilon_S^{H^d}$ is less than the price or income elasticities of housing demand.

Therefore, I define the upper limit of $\varepsilon_S^{H^d}$ as being the below the average of these two elasticities: 0.41. Since this model assumes people have a positive preference for open space, $\varepsilon_S^{H^d}$ must be positive. Therefore, I define the reasonable limit of $\varepsilon_S^{H^d}$ to be from 0 to 0.40.

Now that we have defined the range of values for both variables, we can determine the influence of $\varepsilon_r^{H^d}$. Figure 5.D shows the optimal share of open space for two MSAs over the range of $\varepsilon_S^{H^d}$ values. The two MSAs, Seattle (the grey lines above) and Grand Rapids (the black lines below), represent cities with relatively low and high supply elasticities (3.5 and 10, respectively). Each city has two lines representing the optimal share of open space: One line where $\varepsilon_r^{H^d} = 0.17$, the other where $\varepsilon_r^{H^d} = 0.89$. The values for λ and μ remain the same as before (1 and 0.68, respectively).

Figure 5.D: Impact of changes in the price elasticity of housing demand



By looking at Figure 5.D and comparing the distance between the lines in either city, we can draw a number of conclusions regarding the influence of $\varepsilon_r^{H^d}$.

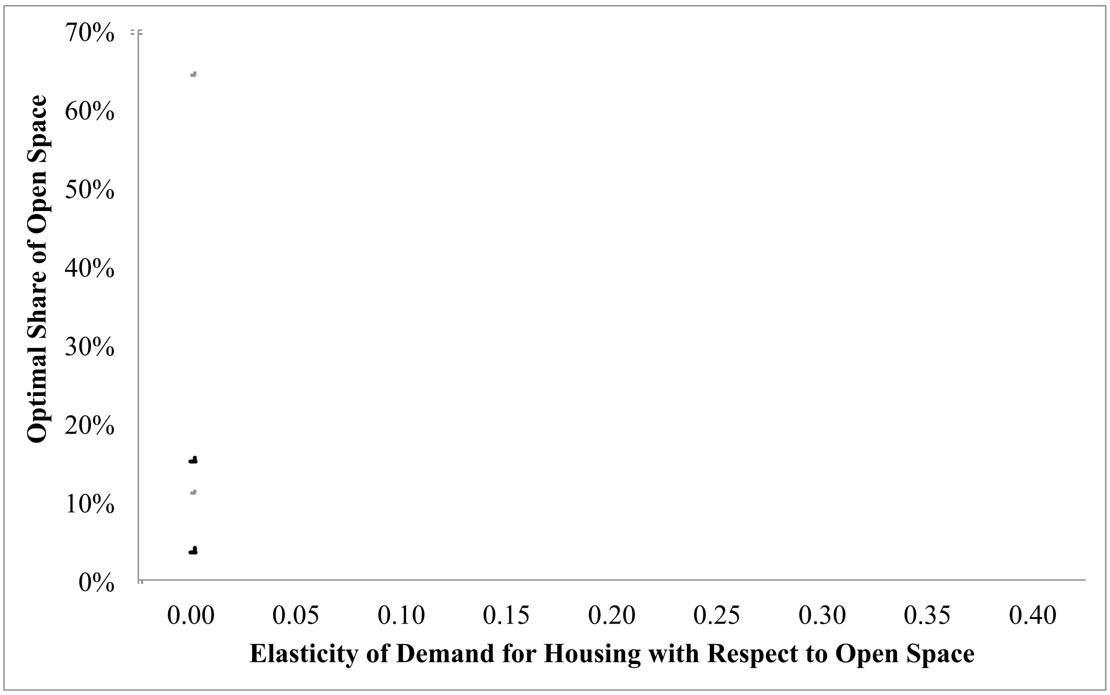
First, $\varepsilon_r^{H^d}$ has the largest influence on optimal share when the supply elasticity is low and when the value for $\varepsilon_S^{H^d}$ is high. This is apparent from the fact that the distance between Seattle's lines is much greater than the distance between Grand Rapids' lines at any value of $\varepsilon_S^{H^d}$, and especially at higher values. Second, at low values of $\varepsilon_S^{H^d}$, the price elasticity of housing demand has very little influence on the optimal share of open space. For example, when $\varepsilon_S^{H^d} = 0.05$, changing $\varepsilon_r^{H^d}$ from its lowest to highest value alters $s*$ by only one percentage point. In fact, even with a low supply elasticity (represented by Seattle) and high values of $\varepsilon_S^{H^d}$, the entire range of price elasticity values vary $s*$ by only five percentage points. Lastly, if the supply elasticity is high (as it is in Grand Rapids), $\varepsilon_r^{H^d}$ has almost no impact on the optimal level of open space, even at high levels of $\varepsilon_S^{H^d}$. This is evident from the fact that lines for Grand Rapids remain close over the entire range of values. Based on this evidence, we can conclude that the optimal share of open is space is not very sensitive to assumptions regarding the price elasticity of housing demand.

We can use a similar technique to examine the elasticity of property values with respect to municipal services (μ). Because of the limited empirical evidence surrounding μ, it is more difficult determine a reasonable range of values for this variable. For the purposes of this analysis, we will simply increase and decrease μ by 25% and examine the effects on optimal share. This provides a low value of μ=0.5 and a high value of μ=0.85. Figure 5.E shows the effect of this change in the same manner as the previous analysis. Once again, values for the other variables (λ and $\varepsilon_r^{H^d}$) remain the same as in the original analysis.

As with Figure 5.D, Figure 5.E shows Seattle (grey lines) and Grand Rapids (black lines) at the low and high values of μ. When comparing Figure 5.E to Figure 5.D, it is clear that μ has a much greater impact on the optimal share of open space, as the distance between each city's lines is much greater. As with $\varepsilon_r^{H^d}$, this effect increases with higher $\varepsilon_S^{H^d}$ values. Even at the low $\varepsilon_S^{H^d}$ level we used as our example value (0.05), in city with a low supply elasticity (such as Seattle), changing μ from 0.5 to 0.85 increases the optimal share by 17 percentage points. At higher levels of

$\varepsilon_S^{H^d}$, it increases $s*$ by more than 50 percentage points. This effect is diminished in cities that have high elasticities (such as Grand Rapids), resulting in an increase of only one percentage point at low levels of $\varepsilon_S^{H^d}$. However, it is clear that the estimate of the optimal share of open space is sensitive to assumptions regarding μ, especially when open space has a strong impact on housing demand and when the price elasticity of housing supply is not very elastic.

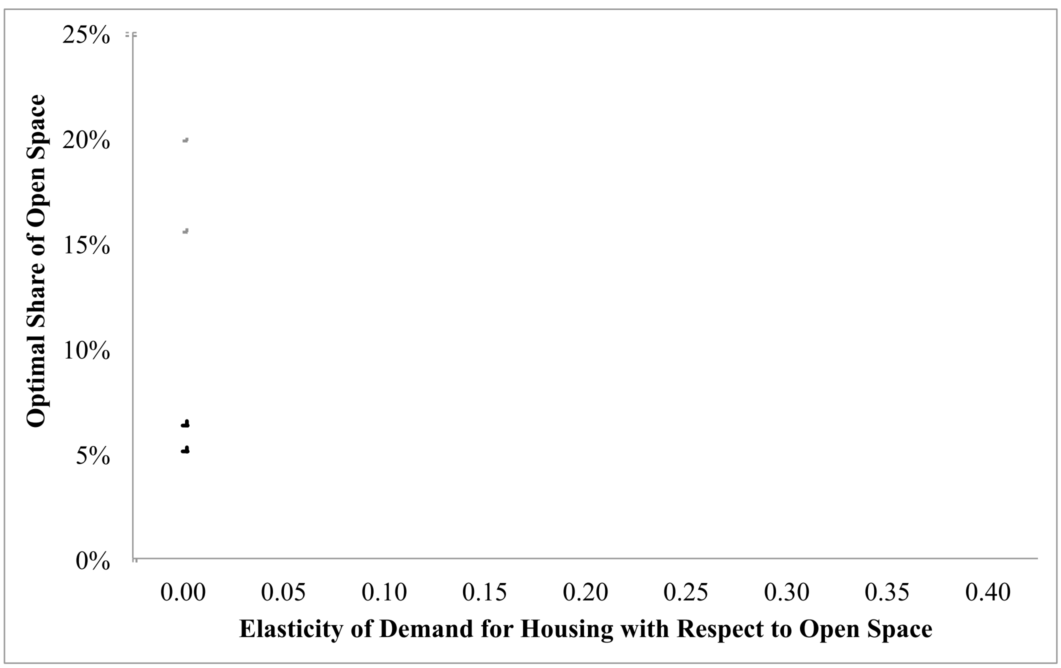
Figure 5.E: Impact of changes in the elasticity of property values with respect to municipal services



Using the same kind analysis, we can assess the influence of the economy of scale in municipal services (λ). As with μ, empirical evidence provides little help in determining the range of λ since all the available empirical evidence suggest there are no economies of scale in municipal services. However, for the purposes of this analysis, we will assume a lower bound of λ=0.8, which indicates that there are some economies of scale in the provision of municipal services. Since by definition $\lambda \in [0,1]$, the upper limit of λ is 1.

Figure 5.F shows the impact of changing λ from 1 to 0.8. Comparing Figure 5.F to Figures 5.D and 5.E, λ shows slightly more influence on optimal share than $\varepsilon_r^{H^d}$, but still much less influence than μ. As with the previous two variables, λ has more of an impact when the supply elasticity is low, and when housing demand is more responsive to changes in open space. When $\varepsilon_S^{H^d} = 0.4$, having some economies of scale in municipal services can increase the optimal share of open space by four percentage points in cities with relatively low supply elasticities. However, at lower levels of $\varepsilon_S^{H^d}$, or when supply elasticities are high, λ only modifies $s*$ by one percentage point. Based on this evidence, we can conclude that the assumptions made regarding the economies of scale in municipal services do not have a strong impact on the estimation of the optimal share of open space.

Figure 5.F: The impact of changes in the economy of scale in municipal services



We do not need to replicate similar graphs to analyze $\varepsilon_S^{H^d}$ since the three figures above provides sufficient insights into the significance of this variable. By comparing the difference between $s*$ at low and high values of $\varepsilon_S^{H^d}$, it is clear that the elasticity of housing demand with respect to open space has a substantial impact on the optimal share of open space. The effect of $\varepsilon_S^{H^d}$ is strongest when supply elasticities are low and property values are more responsive to the level of municipal services (μ has a higher value). Under these conditions, changing $\varepsilon_S^{H^d}$ from 0.05 to 0.4 causes $s*$ to increase by more than 50% (as is evident in Figure 5.E). In fact, it is reasonable to state that assumptions regarding $\varepsilon_S^{H^d}$ have a greater impact on the estimated optimal share of open space than any of the other three variables (λ, μ, or $\varepsilon_r^{H^d}$).

Because of its disproportionate influence, and because there is a shortage of empirical evidence surrounding this variable, it is beneficial to conduct further analysis into the elasticity of housing demand with respect to open space. One way to examine $\varepsilon_S^{H^d}$ is to assume that a city's actual share of open space (s') is the value-maximizing share ($s*$), and then see what value of $\varepsilon_S^{H^d}$ is implied by this assumption. Equation (26) illustrates this supposition. If we solve Equation (26) for $\varepsilon_S^{H^d}$, we get Equation (27), which shows how $\varepsilon_S^{H^d}$ can become of function of the other variables.

$$s' = s^* = \frac{\varepsilon_S^{H^d}}{\varepsilon_S^{H^d} + [(2-(1+\lambda)\mu)]\left(\varepsilon_r^{H^d} + \varepsilon_r^{H^s}\right) - 1} \tag{26}$$

$$\varepsilon_S^{H^d} = \frac{s'\left\{\left(\varepsilon_r^{H^d} + \varepsilon_r^{H^s}\right)[2-(1+\lambda)\mu] - 1\right\}}{1-s'} \tag{27}$$

$$\varepsilon_S^{H^d} = \frac{s'\left(0.64\varepsilon_r^{H^s} - 0.6416\right)}{1-s'} \tag{28}$$

By inputting the previously assumed values for λ, μ, and $\varepsilon_r^{H^d}$ (1, 0.68, and 0.56, respectively), Equation (27) reduces to Equation (28). Inserting each city's estimated supply elasticity and observed share of open space into Equation (28) reveals the value of $\varepsilon_S^{H^d}$ that is implied if a city is at its optimal share of open space. Table 5.7 shows descriptive statistics of the results when this procedure is used on the 72 MSAs that have an observed share of open space. This information is further summarized in Figure 5.G, which displays each city's implied value of $\varepsilon_S^{H^d}$.

Table 5.7: Descriptive statistics for the implied elasticity of housing demand with respect to open space

	Observations	Mean	Std. Dev.	Minimum	Maximum
Implied value of $\varepsilon_S^{H^d}$	72	0.576	0.666	0.001	3.299
Only statistically significant estimates [a]	61	0.648	0.696	0.021	3.229

[a] Implied values based on statistically significant supply elasticity estimates

Figure 5.G: The implied value of the elasticity of housing demand with respect to open space

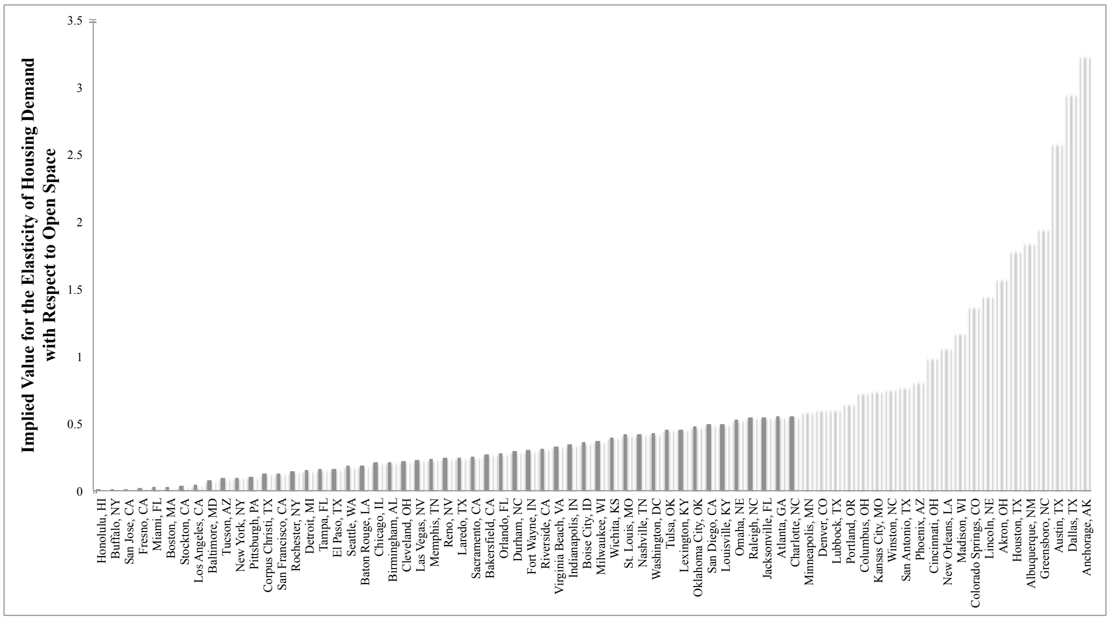


Table 5.7 provides some interesting insights into the value of $\varepsilon_S^{H^d}$ and how the model relates to observed shares of open space. First, the mean value of all estimates is 0.57, which is higher than the upper limit we established for $\varepsilon_S^{H^d}$ (0.4). In fact, a value of 0.57 would suggest that open space and price have the same effect on housing demand (price elasticity has median value of 0.56 in the studies cited by Mayo). However, we also see from the maximum value that some estimates of $\varepsilon_S^{H^d}$ are unrealistically high. Of the 72 MSAs in the dataset, 11 have values that exceed a value of 1 (implying housing demand is elastic with respect to open space), and 34 MSAs have estimates that lie above the reasonable range we established (0.4). From

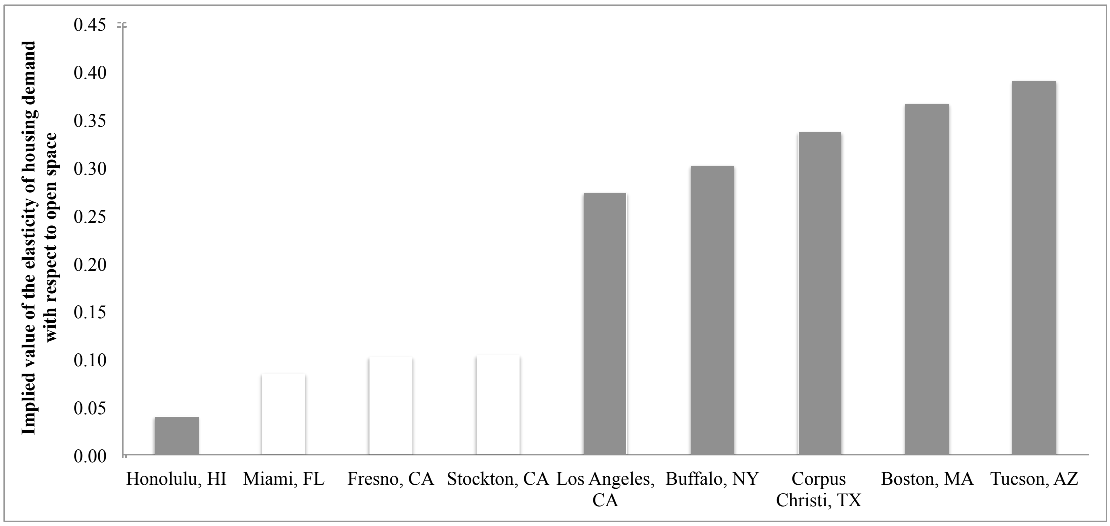
these facts, one could infer that the assumed value for $\varepsilon_S^{H^d}$ (0.05) is much too low, or that the upper limit of our reasonable range for $\varepsilon_S^{H^d}$ should be higher. But given the evidence from Mayo (1981), it is much more likely that these cities' are not experiencing such high levels of $\varepsilon_S^{H^d}$, and that their observed share of open space is higher than their value-maximizing share.

For the final part of the sensitivity analysis, we continue to assume that the 72 MSAs are at their optimal share of open space in order to explore the implications for the value of $\varepsilon_S^{H^d}$. However, in this evaluation the other variables with take on the extreme values of their reasonable range so as to make $\varepsilon_S^{H^d}$ as large or as small as possible. Exploring these extreme values of $\varepsilon_S^{H^d}$ can provide further insights into the relationship between the observed and optimal shares of open space. For example, if the implied value of $\varepsilon_S^{H^d}$ is at its lowest reasonable level and it still lies above the reasonable range of $\varepsilon_S^{H^d}$, this indicates the city is likely experiencing an excess of open space. This analysis also provides further value because it incorporates the confidence interval around the housing supply elasticity estimates.

We begin with exploring the conditions that will produce the highest implied values for $\varepsilon_S^{H^d}$. If the implied value of $\varepsilon_S^{H^d}$ is still excessively low, this will indicate a shortage of open space. This will occur when $\varepsilon_r^{H^d}$ and $\varepsilon_r^{H^s}$ are at their highest levels, while λ and μ are at their lowest levels. This results in the following values being used in Equation (27): $\lambda = 0.8$, $\mu = 0.5$, and $\varepsilon_r^{H^d} = 0.89$. The variable $\varepsilon_r^{H^s}$ will take on the highest value in its 95% confidence interval. Figure 5.H shows the MSAs that exhibit the lowest implied values of $\varepsilon_S^{H^d}$.

Looking at Figure 5.H, it is apparent that none of the MSAs exhibit an exceptionally low value for the elasticity of housing demand with respect to open space. Even the lowest value, represented by Honolulu, is close to the value we assumed for $\varepsilon_S^{H^d}$. However, this does not mean that a city like Honolulu is not experiencing a shortage of open space. What these results indicate is that, in order for its observed share of open space to be at optimal level, all the variables need to be near their extreme values: The price elasticity of housing supply must be near the highest limit of its confidence interval, residents' demand for housing must be more responsive than normal to price, municipal services must exhibit some economies of scale, and property prices must be more responsive to municipal services than the best available evidence indicates. While it is theoretically possible that a city could be experiencing all these conditions at once, it is unlikely.

Figure 5.H: Highest implied value for the elasticity of housing demand with respect to open space



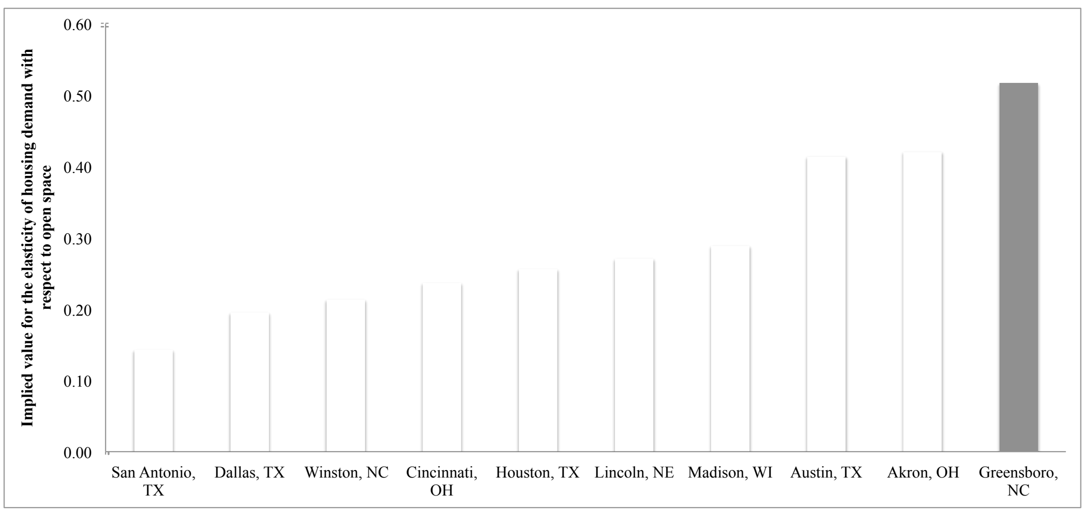
Alternatively, one could argue that the city's residents simply have a weaker preference for open space, which results in a lack of response in housing demand. However, such drastic variation in people's preferences for open space is doubtful, especially when the implied elasticities differ by orders of magnitude. It is more probable that these cities are experiencing shortages of open space and could increase property values by increasing open space.

We now use a similar procedure to gain the lowest implied value for $\varepsilon_S^{H^d}$. If this value excessively high, this will indicate an excess of open space. The lowest implied value occurs when $\varepsilon_r^{H^d}$ and $\varepsilon_r^{H^s}$ are at their lowest levels, while λ and μ are at their highest levels. Therefore, the following values are used in Equation (27): $\lambda = 1$, $\mu = 0.85$, and $\varepsilon_r^{H^d} = 0.17$. The variable $\varepsilon_r^{H^s}$ will take on the lowest value in its 95%

confidence interval. Figure 5.I displays the 10 MSAs that exhibit the greatest potential for experiencing excesses of open space.

Figure 5.I shows three cities with $\varepsilon_S^{H^d}$ values that lie above the reasonable range: Austin, Akron, and Greensboro. Even at their lowest possible implied level of $\varepsilon_S^{H^d}$, these cities show evidence of having excessive open space. In order for these cities to be at the optimal share of open space, not only would all they have to been experiencing the extreme values of every input factor, but their residents demand for housing would have to be as responsive to open space as the average city is to price and income. This is very unlikely.

Figure 5.I: Lowest implied value for the elasticity of housing demand with respect to open space



For the other cities in Figure 5.I, as in the previous group of cities, it is possible these cities are at their optimal share of open space. However, this would simultaneously require that their supply elasticities are at the lowest limit of their confidence interval, residents' demand for housing is less responsive to price than normal, and municipal services have a smaller impact on property prices than is likely. Once again, experiencing all these qualities at the same time is improbable. It is more plausible that these cities are experiencing excesses of open space, and could increase property values by decreasing their share of open space.

Chapter 7

Summary and Conclusion

Numerous previous studies have examined the relationship between property values and open space. Many have found that right kind of open space increases property values (Mahan et al., 2000; Shultz and King, 2001; Riddel, 2001, Lutzenhizer and Netusil, 2001; Tyrväinen, 2007; Geoghenan et al., 2003). The value increase arises not just from a positive preference for open space, but also because open space reduces the available land for residential development, restricting the supply of housing and driving up costs (Balsdon, 2012).

Cities face trade-offs in deciding how much open space area to maintain. Increasing open space area can lead to higher property values and increased amenities for residents. However, establishing new open space and conducting perpetual maintenance both require money from city. This money could be spent on other government services that may be of greater value to residents. Open space also poses an opportunity cost to cities, since the space could be used for development that generates tax revenue. Only Wu (2014) attempts to model these trade-offs faced by cities under a budget constraint in order to determine the share of open space that maximizes property values. While Wu (2014) derives these value-maximizing conditions, his empirical analysis is limited. This study attempts to fill that empirical gap by estimating the value-maximizing share of open space for urban areas across the U.S.

According to the theory explained in Wu (2014), the price elasticity of housing supply is a key determinant of the value-maximizing, or "optimal", share of open space. Therefore, in order to estimate the optimal share of open space for urban areas, this study first estimated the housing supply elasticities for 349 MSAs using a method outlined in Green et al. (2005). In their study, Green et al. estimated the supply elasticities of 45 U.S. MSAs. By comparing this study's estimates to Green et al.'s, it is clear that this method for estimating supply elasticity provides consistent results.

Additionally, Green et al. conducted further analysis to determine how various factors influenced the supply elasticity. This study also replicated this analysis. Findings that were consistent between Green et al. (2005) and this study are that stringent land use regulation is associated with lower supply elasticities, and that higher levels of population growth are associated with higher supply elasticities. The implication for property values is that cities with more stringent land use regulation and/or lower levels of population growth will tend to have higher optimal shares of open space.

This study estimated the optimal share of open space for 349 U.S. MSAs. The model, along with both the estimated and assumed variable values, on average produced fairly low estimates of the optimal share of open space. The average was around 1.5%, and 95% of estimates were 5% or less. Of the optimal shares that were based on statistically significant estimates of the supply elasticity, the smallest optimal shares of open space belonged to Myrtle Beach, SC (0.25%), Ames, IA (0.24%) Burlington, NC (0.21%). The largest shares belonged to New Haven, CT (23%), Boston, MA (26%), and Danville, IL (27%).

Of course, the estimates of the optimal share of open space are most interesting when compared to observed shares of open space. Using figures from a 2011 report by the Trust for Public Land, and by making a few reasonable assumptions about the data, this study was able to make such a comparison. Calculating the difference between the observed and optimal shares of open space revealed that the majority of cities exhibit an excess of open space (89% of the observations). This result is unsurprising given that the model does not take into account other benefits of open space that are not capitalized into property values, such as environmental benefits. The largest excesses of open space belonged to Anchorage, AK (38 percentage points); Albuquerque, NM (27 percentage points); and New Orleans (24 percentage points). The largest shortages of open space were observed in Buffalo, NY (23 percentage points); San Jose, CA (23 percentage points); and Honolulu, HI (34 percentage points).

Because these simple differences do not account for the standard error in the estimate of the supply elasticity, further analysis was conducted to determine which cities had actual shares of open space that lie outside their 95% confidence interval. For the 53 MSAs that were studied, only two showed statistically significant shortages of open space: Stockton, CA and Miami, FL. However, both cities were within one percentage point of their confidence interval, making it possible they are close to their optimal shares. The vast majority of cities (49 out of 53) showed statistically significant excesses of open space. Of those, Anchorage, New Orleans, and Akron presented the largest deviations (25, 23, and 21 percentage points, respectively). Only two cities lied within the confidence interval of their optimal share: Washington, DC and Virginia Beach, VA. Of all the cities in the sample set, these two are the most likely to be at their value-maximizing share of open space.

After the primary analysis of the empirical results, a sensitivity analysis was conducted to determine the influence of the assumptions made regarding the values of the other four variables that codetermine optimal share: The price elasticity of housing demand, the elasticity of property values with respect to the level of municipal services, the economy of scale in municipal services, and the elasticity of housing demand with respect to open space. The sensitivity analysis revealed that the optimal share of open is not particularly sensitive to the price elasticity of housing demand or to the economy of scale in municipal services. However, it was sensitive to the elasticity of property values with respect to municipal services and the elasticity of housing demand with respect to open space. Changes in these two variables lead to large differences in the optimal share of open space. Consequently, the conclusions regarding differences between optimal and observed shares of open space are heavily dependent on the assumed values of these two variables. Also, when the supply elasticity is low, the optimal share is more sensitive to changes in any of the four variables.

Because of the disproportionate influence of the elasticity of housing demand with respect to open space, as well as the lack of empirical evidence surrounding its value, the second part of the sensitivity analysis explored this variable further. By assuming that a city’s observed share of open space is its optimal share, and by assuming the same likely values for the other variables, we calculated an implied value for the elasticity of housing demand with respect to open space. The implied values averaged 0.57, which is near the average estimate of the price elasticity of housing demand. Because it is very unlikely that demand for housing is as responsive to changes in open space as it is to changes in price, these results provide further evidence that many of the cities have shares of open space much higher than their value-maximizing levels. The highest implied elasticity values belonged to Austin, TX (2.57), Dallas, TX (2.94), and Anchorage, AK (3.23). The lowest implied values were Honolulu, Buffalo, and San Jose (0.001, 0.010, and 0.014, respectively).

The final part of the sensitivity analysis also calculated the implied value for the elasticity of housing demand with respect to open space. However, this process differed in that the other variables took on the extreme values of their reasonable range so as to make the implied elasticity as high or low as possible. The process has the additional advantage of incorporating the confidence interval of the supply elasticity estimates.

This final analysis reinforced the fact that the model projects very few shortages of open space. The lowest implied elasticity values belonged to Honolulu (0.04), Miami (0.10), Fresno (0.10), and Stockton (0.10). The values themselves are not so low as to indicate certain shortages of open space. However, if the true value of the elasticity of housing demand with respect to open space is between 0.04 and 0.10, in order for their observed share of open space to be the value-maximizing share, these cities would have to be experiencing the extreme values of all the other variables simultaneously. In other words, the price elasticity of housing supply must be near the highest limit of its confidence interval, demand for housing must be responsive to price, municipal services must have some economies of scale, and property prices must be more responsive to municipal services than evidence indicates. Because it is very unlikely these cities would experience all these qualities at once, the implied elasticity suggests that their actual share of open space lies below the optimal level, and these cities could increase property values by increasing their share of open space.

Using a similar procedure to find the lowest likely implied elasticity value resulted in even more evidence of excessive shares of open space. Even at their lowest implied value, Austin, TX, Akron, OH, and Greensboro, NC all showed elasticity values above the reasonable range (implied values of 0.41, 0.42, and 0.52, respectively). This provides strong evidence that these cities have excessive shares of open space, and could increase property values by decreasing the amount of open space.

For the other cities that have an observed share of open space, it is difficult to determine exactly where they lie in relation to their value-maximizing share. Because of the uncertainty surrounding the variables, especially the elasticity of housing demand with respect to open space, as well as the error inherent in the estimation of the supply elasticities, it is difficult to say whether these cities are close their optimal share or not. Further research on the value of these variables would allow for a more precise estimation of these cities' value-maximizing share of open space.

In summary, this study has provided a number of contributions to the body of knowledge surrounding the relationship between property values, open space, and housing markets. It has tested the implications of a theoretical model designed to maximize property values based on the share of open space. It has showed, based on the best available evidence, the model tends to predict that the value-maximizing share of open space is quite small, and consequently, that most cities could increase their total private property value by decreasing their share of open space.

It is important to reiterate that this study has only examined the share of open space that maximizes property values in the urban area. While this share has repeatedly been referred to as the "optimal" share, it is only optimal in the sense that total private property values are maximized. This share does not represent the socially optimal share of open space, or the share that maximizes total social welfare. Open space provides benefits that are not capitalized into property values, such as environmental benefits, which are not considered in this study. In all likelihood, the socially optimal share of open space is different than the value-maximizing share. City managers should bear this in mind while using the information presented in this study to inform their decision-making. Finding the share of open space that maximizes total social welfare is an area for further research.

This study also contributes to sparse knowledge surrounding housing demand and open space. To the author's knowledge, there has been no research that has explicitly examined the direct affect of open space on housing demand. This study has provided some insight into this relationship by justifying a reasonable value and range for this elasticity, and then testing those assumptions.

For the cities included in the study, this report has the potential to inform city managers' decision-making process regarding open space. For cities not included in this study, the methods used here present a fairly simple way of calculating their own value-maximizing share of open space. With some data regarding housing prices, new construction, and population, interested decision-makers could calculate the housing supply elasticity in their city. Combining this estimate with the example values for the other variables, managers could estimate their own optimal share. With some additional data regarding the amount of open space currently in the city, managers could compare this to their estimated optimal share and determine how changes in open space are likely to affect property values.

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APPENDICIES

Appendix A

Estimates of Price Elasticity of Housing Supply by MSA

MSA	Elasticity Estimate		MSA	Elasticity Estimate	
Abilene, TX	-0.43		Biloxi, MS	9.74	***
Akron, OH	9.62	***	Boise City, ID	8.54	**
Albany, GA	6.39	***	Boston, MA	1.22	***
Albany, NY	3.90	***	Boulder, CO	14.07	***
Albuquerque, NM	8.35	***	Bowling Green, KY	26.86	**
Alexandria, LA	4.30	*	Bremerton, WA	3.54	***
Allentown, PA	5.12	***	Bridgeport, CT	0.69	
Altoona, PA	3.96		Brownsville, TX	28.73	***
Amarillo, TX	-0.02		Brunswick, GA	8.19	***
Ames, IA	33.79	***	Buffalo, NY	1.18	
Anchorage, AK	8.60	**	Burlington, NC	37.47	***
Ann Arbor, MI	10.88	***	Burlington, VT	2.46	*
Anniston, AL	4.45	**	Canton, OH	5.04	***
Appleton, WI	18.37	***	Cape Coral, FL	18.04	**
Asheville, NC	9.83	***	Cape Girardeau, MO	8.83	
Athens, GA	18.50	***	Carson City, NV	1.78	*
Atlanta, GA	18.81	***	Casper, WY	-2.79	
Atlantic City, NJ	5.62	***	Cedar Rapids, IA	12.35	***
Auburn, AL	13.04	***	Champaign, IL	14.29	***
Augusta, GA	7.14	**	Charleston, SC	9.08	***
Austin, TX	19.36	***	Charleston, WV	4.10	**
Bakersfield, CA	4.23	***	Charlotte, NC	15.87	***
Baltimore, MD	2.14		Charlottesville, VA	8.71	***
Bangor, ME	6.38	***	Chattanooga, TN	13.93	***
Barnstable, MA	3.73	*	Cheyenne, WY	17.98	***
Baton Rouge, LA	11.01	***	Chicago, IL	4.68	***
Battle Creek, MI	3.94	***	Chico, CA	5.28	***
Bay City, MI	4.28	**	Cincinnati, OH	10.73	***
Beaumont, TX	5.07		Clarksville, TN	14.19	**
Bellingham, WA	9.58	***	Cleveland, OH	6.18	***
Bend, OR	11.49	**	Cleveland, TN	9.67	**
Billings, MT	6.62	***	Coeur d'Alene, ID	8.69	**
Binghamton, NY	1.48	***	College Station, TX	5.94	
Birmingham, AL	9.62	***	Colorado Springs, CO	20.24	***
Bismarck, ND	12.68		Columbia, MO	31.58	***
Blacksburg, VA	9.17	***	Columbia, SC	8.47	**
Bloomington, IL	16.40	***	Columbus, GA	5.49	***
Bloomington, IN	20.09	***	Columbus, IN	9.24	***

* indicates a p-value ≤ 0.1
** indicates a p-value ≤ 0.05
*** indicates a p-value ≤ 0.01

MSA	Elasticity Estimate		MSA	Elasticity Estimate	
Columbus, OH	13.44	***	Gainesville, GA	13.34	***
Corpus Christi, TX	10.05	***	Glens Falls, NY	6.76	***
Corvallis, OR	1.37		Goldsboro, NC	9.13	***
Cumberland, MD	1.27		Grand Forks, ND	10.24	***
Dallas, TX	30.75	***	Grand Junction, CO	9.10	***
Dalton, GA	10.06	***	Grand Rapids, MI	10.00	***
Danville, IL	1.21		Great Falls, MT	5.19	***
Davenport, IA	4.52	***	Greeley, CO	31.60	***
Dayton, OH	9.37		Green Bay, WI	9.75	***
Daytona Beach, FL	25.68	***	Greensboro, NC	30.62	***
Decatur, AL	5.63	**	Greenville, NC	32.46	***
Decatur, IL	8.62	***	Greenville, SC	8.54	*
Deltona, FL	5.78	**	Hagerstown, MD	8.90	***
Denver, CO	15.77	***	Hanford, CA	3.31	***
Des Moines, IA	12.16	***	Harrisburg, PA	4.13	**
Detroit, MI	4.31	***	Harrisonburg, VA	8.65	***
Dothan, AL	3.35	*	Hartford, CT	2.99	***
Dover, DE	10.69	***	Hattiesburg, MS	9.06	***
Dubuque, IA	2.69		Hickory, NC	13.45	***
Duluth, MN	5.17	***	Hinesville, GA	3.01	*
Durham, NC	11.68		Honolulu, HI	1.14	**
Eau Claire, WI	16.98	***	Hot Springs, AR	2.22	**
El Centro, CA	6.40	***	Houma, LA	5.45	**
El Paso, TX	2.14	*	Houston, TX	19.00	***
Elizabethtown, KY	22.56	***	Huntington, WV	5.10	***
Elkhart, IN	13.01	***	Huntsville, AL	19.53	***
Elmira, NY	0.58		Idaho Falls, ID	15.57	**
Erie, PA	7.63	***	Indianapolis, IN	11.60	***
Eugene, OR	5.97	***	Iowa City, IA	27.48	***
Evansville, IN	10.21	***	Ithaca, NY	2.52	*
Fairbanks, AK	7.41	**	Jackson, MI	7.52	***
Fargo, ND	20.07	***	Jackson, MS	15.96	***
Farmington, NM	2.61	***	Jackson, TN	15.99	***
Fayetteville, AR	19.89	***	Jacksonville, FL	10.58	***
Fayetteville, NC	4.75		Jacksonville, NC	-1.94	
Flagstaff, AZ	4.60	**	Janesville, WI	10.40	***
Flint, MI	4.59	***	Jefferson City, MO	8.53	**
Florence, AL	2.17		Johnson City, TN	7.05	
Florence, SC	7.49	*	Johnstown, PA	4.81	**
Fond du Lac, WI	8.56	**	Jonesboro, AR	-4.39	
Fort Collins, CO	19.00	***	Joplin, MO	10.10	***
Fort Smith, AR	5.16	***	Kalamazoo, MI	6.29	***
Fort Walton Beach, FL	11.38	**	Kankakee, IL	11.37	***
Fort Wayne, IN	10.55	***	Kansas City, MO	13.34	***
Fresno, CA	2.41	**	Killeen, TX	18.76	***
Gadsden, AL	5.70	***	Kingsport, TN	9.38	***
Gainesville, FL	7.01	***	Kingston, NY	3.65	***

MSA	Elasticity Estimate		MSA	Elasticity Estimate	
Knoxville, TN	11.24	***	Modesto, CA	4.00	**
Kokomo, IN	11.78	***	Monroe, LA	6.45	
La Crosse, WI	12.17	***	Monroe, MI	7.48	**
Lafayette, IN	27.07	***	Montgomery, AL	5.70	**
Lafayette, LA	12.42	***	Morgantown, WV	-4.39	*
Lake Charles, LA	2.11		Morristown, TN	8.15	***
Lake Havasu City, AZ	1.10		Mount Vernon, WA	6.93	***
Lakeland, FL	9.64	***	Muncie, IN	8.61	***
Lancaster, PA	5.19	**	Muskegon, MI	6.27	***
Lansing, MI	6.26	***	Myrtle Beach, SC	32.69	***
Laredo, TX	12.99	***	Napa, CA	3.46	***
Las Cruces, NM	9.86	***	Naples, FL	10.67	**
Las Vegas, NV	9.25	***	Nashville, TN	19.69	***
Lawrence, KS	20.47	***	New Haven, CT	1.27	***
Lawton, OK	8.38	**	New Orleans, LA	5.77	***
Lebanon, PA	9.09	***	New York, NY	1.63	***
Lewiston, ID	7.64	***	Niles, MI	9.25	***
Lewiston, ME	4.30	***	Norwich, CT	4.78	***
Lexington, KY	21.91	***	Ocala, FL	13.00	***
Lima, OH	8.77	***	Ocean City, NJ	18.35	***
Lincoln, NE	15.99	***	Odessa, TX	-0.21	
Little Rock, AR	4.31		Ogden, UT	4.80	
Logan, UT	4.74		Oklahoma City, OK	13.49	***
Longview, TX	-1.07		Olympia, WA	9.00	***
Longview, WA	5.00	***	Omaha, NE	6.57	**
Los Angeles, CA	2.89	**	Orlando, FL	9.41	***
Louisville, KY	12.14	***	Oshkosh, WI	13.45	***
Lubbock, TX	31.50	***	Owensboro, KY	17.00	**
Lynchburg, VA	8.92	***	Oxnard, CA	2.54	***
Macon, GA	16.77	***	Palm Bay, FL	7.12	***
Madera, CA	5.84	***	Panama City, FL	17.07	***
Madison, WI	14.30	***	Parkersburg, WV	2.90	*
Manchester, NH	3.50	**	Pensacola, FL	5.31	***
Manhattan, KS	23.39		Peoria, IL	5.06	***
Mankato, MN	-11.75		Phoenix, AZ	8.30	***
Mansfield, OH	8.29	***	Pine Bluff, AR	2.04	
McAllen, TX	21.74	***	Pittsburgh, PA	2.72	***
Medford, OR	6.49	***	Pittsfield, MA	3.25	***
Memphis, TN	7.76	***	Pocatello, ID	7.79	***
Merced, CA	4.17	***	Port St. Lucie, FL	12.83	***
Miami, FL	3.70	***	Portland, ME	5.98	***
Michigan City, IN	5.96	*	Portland, OR	6.28	***
Midland, TX	0.86		Prescott, AZ	10.17	**
Milwaukee, WI	6.31	***	Providence, RI	2.14	***
Minneapolis, MN	8.21	***	Provo, UT	8.12	***
Missoula, MT	6.58	**	Pueblo, CO	17.49	***
Mobile, AL	6.32	**	Punta Gorda, FL	14.33	***

MSA	Elasticity Estimate		MSA	Elasticity Estimate	
Racine, WI	6.48	***	Springfield, MO	18.26	***
Raleigh, NC	20.99	***	St. Cloud, MN	13.42	***
Rapid City, SD	11.44	*	St. George, UT	10.20	
Reading, PA	4.39	***	St. Joseph, MO	3.57	**
Redding, CA	4.54	***	St. Louis, MO	7.93	***
Reno, NV	7.52	***	State College, PA	6.68	
Richland, WA	14.06	**	Stockton, CA	3.63	***
Richmond, VA	7.48	***	Sumter, SC	6.41	**
Riverside, CA	5.63	**	Syracuse, NY	3.83	***
Roanoke, VA	7.22	***	Tallahassee, FL	9.60	***
Rochester, MN	17.02	***	Tampa, FL	6.02	***
Rochester, NY	4.12	***	Terre Haute, IN	7.42	***
Rockford, IL	9.33	***	Texarkana, TX	6.91	
Rocky Mount, NC	11.78	***	Toledo, OH	4.76	***
Rome, GA	11.83	***	Topeka, KS	13.04	***
Sacramento, CA	5.42	***	Trenton, NJ	3.73	***
Saginaw, MI	5.91	***	Tucson, AZ	5.64	*
Salem, OR	7.24	***	Tulsa, OK	11.59	***
Salinas, CA	1.67	**	Tuscaloosa, AL	16.70	***
Salisbury, MD	10.07	***	Tyler, TX	8.74	***
Salt Lake City, UT	4.41	**	Utica, NY	1.64	***
San Angelo, TX	1.93		Valdosta, GA	11.10	***
San Antonio, TX	13.35	***	Vallejo, CA	3.42	**
San Diego, CA	3.62		Victoria, TX	-4.94	
San Francisco, CA	1.94		Vineland, NJ	3.15	***
San Jose, CA	1.13	*	Virginia Beach, VA	2.92	***
San Luis Obispo, CA	6.44	***	Visalia, CA	3.23	***
Santa Barbara, CA	1.86	***	Waco, TX	10.26	**
Santa Cruz, CA	1.99	**	Warner Robins, GA	26.98	***
Santa Fe, NM	4.13	**	Washington, DC	3.84	***
Santa Rosa, CA	3.40	*	Waterloo, IA	0.33	
Sarasota, FL	11.20	***	Wausau, WI	17.70	***
Savannah, GA	10.37	***	Weirton, WV	1.87	
Scranton, PA	3.47	***	Wenatchee, WA	6.88	***
Seattle, WA	3.53	*	Wheeling, WV	2.21	**
Sebastian, FL	11.51	***	Wichita Falls, TX	9.06	**
Sheboygan, WI	11.44	***	Wichita, KS	12.57	***
Sherman, TX	6.10		Williamsport, PA	-0.13	
Shreveport, LA	7.75	**	Winchester, VA	8.31	***
Sioux City, IA	8.63	***	Winston, NC	23.43	***
Sioux Falls, SD	30.46	***	Worcester, MA	3.24	***
South Bend, IN	10.08	***	Yakima, WA	5.01	***
Spartanburg, SC	20.04	**	York, PA	7.52	***
Spokane, WA	5.96	***	Youngstown, OH	6.31	***
Springfield, IL	15.60	**	Yuba City, CA	8.35	***
Springfield, MA	3.43	***	Yuma, AZ	5.65	***

Appendix B

Optimal and Actual Shares of Open Space by MSA

MSA	Optimal [a]	Actual [b]	Low [c]	High [d]	Significance [e]
Abilene, TX	-5.8%		11.9%	-2.3%	
Akron, OH	0.9%	22.2%	0.8%	1.1%	***
Albany, NY	2.6%		1.8%	5.1%	***
Albany, GA	1.4%		1.0%	2.9%	***
Albuquerque, NM	1.1%	28.1%	0.6%	10.2%	**
Alexandria, LA	2.3%		1.2%	-696.6%	**
Allentown, PA	1.9%		1.2%	3.7%	***
Altoona, PA	2.6%		1.0%	-5.5%	
Amarillo, TX	-8.3%		1.1%	-0.9%	
Ames, IA	0.2%		0.2%	0.5%	***
Anchorage, AK	1.0%	39.9%	0.5%	14.8%	**
Ann Arbor, MI	0.8%		0.5%	2.3%	***
Appleton, WI	0.4%		0.3%	1.0%	***
Asheville, NC	0.9%		0.6%	1.4%	***
Athens, GA	0.4%		0.3%	1.1%	***
Atlanta, GA	0.4%	4.6%	0.3%	0.7%	***
Atlantic City, NJ	1.7%		1.4%	2.0%	***
Auburn, AL	0.6%		0.5%	1.1%	***
Augusta, GA	1.3%		0.6%	44.4%	**
Austin, TX	0.4%	18.0%	0.3%	0.9%	***
Bakersfield, CA	2.4%	11.6%	1.7%	3.7%	***
Baltimore, MD	6.5%	9.5%	1.6%	-3.1%	
Bangor, ME	1.4%		0.9%	4.2%	***
Barnstable, MA	2.8%		1.2%	-9.7%	*
Baton Rouge, LA	0.8%	2.8%	0.6%	1.2%	***
Battle Creek, MI	2.6%		1.7%	5.6%	***
Bay City, MI	2.3%		1.2%	19.6%	**
Beaumont, TX	1.9%		0.7%	-3.3%	
Bellingham, WA	0.9%		0.6%	1.8%	***
Bend, OR	0.7%		0.4%	2.1%	***
Billings, MT	1.4%		0.8%	3.9%	***
Biloxi, MS	0.9%		0.6%	1.6%	***
Binghamton, NY	14.1%		5.4%	-23.5%	***
Birmingham, AL	0.9%	3.7%	0.7%	1.3%	***

[a] Value-maximizing share of open space; calculated using the following values: $\varepsilon_S^{H^d} = 0.05, \lambda = 1, \mu = 0.68, \varepsilon_r^{H^d} = 0.56$

[b] Observed share of park space as listed in Trust for Public Land (2011) (if available)

[c] Value-maximizing share of open space as calculated by the upper limit of the 95% confidence interval of the housing supply elasticity estimate

[d] Value-maximizing share of open space as calculated by the lower limit of the 95% confidence interval of the housing supply elasticity estimate

[d] Statistical significance of the housing supply elasticity estimate used to calculate the value-maximizing share of open space

* indicates a p-value ≤ 0.1

** indicates a p-value ≤ 0.05

*** indicates a p-value ≤ 0.01

MSA	Optimal	Actual	Low	High	Significance
Birmingham, AL	0.9%	3.7%	0.7%	1.3%	***
Bismarck, ND	0.7%		0.4%	2.3%	***
Blacksburg, VA	0.9%		0.7%	1.4%	***
Bloomington, IL	0.5%		0.4%	0.9%	***
Bloomington, IN	0.4%		0.3%	0.9%	***
Boise City, ID	1.0%	6.9%	0.5%	-31.3%	*
Boston, MA	26.9%	15.8%	9.0%	-27.4%	***
Boulder, CO	0.6%		0.4%	0.9%	***
Bowling Green, KY	0.3%		0.2%	0.9%	**
Bremerton, WA	3.0%		2.0%	6.3%	***
Bridgeport, CT	-33.5%		5.1%	-3.9%	
Brownsville, TX	0.3%		0.2%	0.4%	***
Brunswick, GA	1.1%		0.7%	2.2%	***
Buffalo, NY	31.2%	8.3%	3.7%	-4.8%	
Burlington, NC	0.2%		0.2%	0.3%	***
Burlington, VT	5.1%		2.0%	-9.6%	*
Canton, OH	1.9%		1.4%	3.0%	***
Cape Coral, FL	0.5%		0.3%	1.1%	**
Cape Girardeau, MO	1.0%		0.4%	-3.3%	
Casper, WY	-2.1%		1.4%	-0.6%	
Cedar Rapids, IA	0.7%		0.5%	1.3%	***
Champaign, IL	0.6%		0.4%	1.1%	***
Charleston, SC	1.0%		0.6%	2.1%	***
Charleston, WV	2.5%		1.6%	5.0%	***
Charlotte, NC	0.5%	5.5%	0.3%	1.3%	***
Charlottesville, VA	1.0%		0.7%	2.0%	***
Chattanooga, TN	0.6%		0.5%	0.7%	***
Cheyenne, WY	0.5%		0.3%	0.8%	***
Chicago, IL	2.1%	8.2%	1.5%	3.7%	***
Chico, CA	1.8%		1.4%	2.6%	***
Cincinnati, OH	0.8%	13.7%	0.6%	1.1%	***
Clarksville, TN	0.6%		0.4%	1.6%	***
Cleveland, OH	1.5%	6.3%	1.2%	2.0%	***
Cleveland, TN	0.9%		0.6%	1.8%	***
Coeur d'Alene, ID	1.0%		0.6%	3.7%	**
College Station, TX	1.6%		0.3%	-0.4%	
Colorado Springs, CO	0.4%	10.0%	0.2%	1.2%	***
Columbia, MO	0.3%		0.2%	0.4%	***
Columbia, SC	1.0%		0.5%	-3.7%	*
Columbus, GA	1.7%		1.2%	2.8%	***
Columbus, IN	0.9%		0.8%	1.2%	***
Columbus, OH	0.6%	8.4%	0.4%	1.5%	***
Corpus Christi, TX	0.9%	2.2%	0.6%	1.4%	***
Corvallis, OR	17.4%		1.1%	-1.3%	
Cumberland, MD	22.8%		3.6%	-5.3%	
Dallas, TX	0.3%	13.4%	0.1%	1.2%	**
Dalton, GA	0.9%		0.7%	1.2%	***
Danville, IL	27.3%		7.1%	-14.7%	**
Davenport	2.2%		1.4%	5.0%	***

MSA	Optimal	Actual	Low	High	Significance
Dayton, OH	0.9%		0.5%	-75.1%	**
Daytona Beach, FL	0.3%		0.2%	0.5%	***
Decatur, AL	1.7%		1.1%	3.6%	***
Decatur, IL	1.0%		0.7%	2.3%	***
Deltona, FL	1.6%		0.9%	5.5%	**
Denver, CO	0.5%	6.0%	0.4%	0.8%	***
Des Moines, IA	0.7%		0.5%	1.3%	***
Detroit, MI	2.3%	6.7%	1.8%	3.3%	***
Dothan, AL	3.2%		1.2%	-5.4%	
Dover, DE	0.8%		0.6%	1.4%	***
Dubuque, IA	4.4%		0.7%	-1.1%	
Duluth, MN	1.8%		1.1%	6.3%	***
Durham, NC	0.7%	4.1%	0.4%	-12.0%	*
Eau Claire, WI	0.5%		0.4%	0.6%	***
El Centro, CA	1.4%		0.9%	3.3%	***
El Paso, TX	6.4%	18.4%	2.7%	-17.7%	**
Elizabethtown, KY	0.4%		0.3%	0.5%	***
Elkhart, IN	0.6%		0.5%	0.9%	***
Elmira, NY	-22.5%		3.6%	-2.7%	
Erie, PA	1.2%		0.9%	1.7%	***
Eugene, OR	1.5%		1.1%	2.9%	***
Evansville, IN	0.8%		0.6%	1.7%	***
Fairbanks, AK	1.2%		0.8%	2.1%	***
Fargo, ND	0.4%		0.2%	1.1%	***
Farmington, NM	4.6%		3.2%	8.3%	***
Fayetteville, AR	0.4%		0.3%	0.6%	***
Fayetteville, NC	2.0%		0.5%	-0.8%	
Flagstaff, AZ	2.1%		1.1%	19.0%	**
Flint, MI	2.1%		1.4%	4.2%	***
Florence, SC	1.2%		0.7%	3.4%	***
Fond du Lac, WI	1.0%		0.6%	2.9%	**
Fort Collins, CO	0.4%		0.3%	0.9%	***
Fort Smith, AR	1.8%		1.2%	4.3%	***
Fort Wayne, IN	0.8%	4.7%	0.5%	1.7%	***
Fresno, CA	5.2%	2.3%	2.6%	-135.1%	***
Gadsden, AL	1.6%		1.2%	2.7%	***
Gainesville, FL	1.3%		0.8%	3.5%	***
Gainesville, GA	0.6%		0.4%	1.1%	***
Glens Falls, NY	1.3%		0.9%	2.4%	***
Goldsboro, NC	1.0%		0.7%	1.5%	***
Grand Forks, ND	0.8%		0.5%	2.1%	***
Grand Junction, CO	1.0%		0.6%	1.9%	***
Grand Rapids, MI	0.9%		0.6%	1.5%	***
Great Falls, MT	1.8%		1.1%	6.1%	***
Greeley, CO	0.3%		0.2%	0.4%	***
Green Bay, WI	0.9%		0.5%	3.4%	***
Greensboro, NC	0.3%	9.3%	0.2%	0.4%	***
Greenville, NC	0.2%		0.2%	0.3%	***
Greenville, SC	1.0%		0.4%	-1.7%	
Hagerstown, MD	1.0%		0.6%	2.2%	***
Hanford, CA	3.3%		2.2%	6.3%	***

MSA	Optimal	Actual	Low	High	Significance
Harrisburg, PA	2.4%		1.0%	-5.7%	*
Harrisonburg, VA	1.0%		0.6%	2.3%	***
Hartford, CT	3.8%		2.0%	33.4%	***
Hattiesburg, MS	1.0%		0.6%	3.6%	***
Hickory, NC	0.6%		0.5%	0.9%	***
Hinesville, GA	3.7%		2.0%	23.5%	**
Honolulu, HI	35.9%	1.6%	5.9%	-8.7%	*
Hot Springs, AR	6.0%		3.1%	120.8%	***
Houma, LA	1.7%		0.9%	-94.8%	**
Houston, TX	0.4%	13.4%	0.3%	1.0%	***
Huntington, WV	1.9%		1.1%	8.4%	***
Huntsville, AL	0.4%		0.3%	1.1%	***
Idaho Falls, ID	0.5%		0.3%	1.1%	***
Indianapolis, IN	0.7%	4.8%	0.4%	4.0%	**
Iowa City, IA	0.3%		0.2%	0.4%	***
Ithaca, NY	4.9%		2.0%	-11.6%	*
Jackson, MI	1.2%		0.9%	1.7%	***
Jackson, MS	0.5%		0.4%	0.8%	***
Jackson, TN	0.5%		0.3%	1.0%	***
Jacksonville, FL	0.8%	8.2%	0.6%	1.2%	***
Jacksonville, NC	-2.7%		1.3%	-0.7%	
Janesville, WI	0.8%		0.7%	1.0%	***
Jefferson City, MO	1.0%		0.6%	2.8%	**
Johnson City, TN	1.3%		0.5%	-3.7%	
Johnstown, PA	2.0%		0.8%	-5.1%	
Jonesboro, AR	-1.5%		0.5%	-0.3%	
Joplin, MO	0.9%		0.7%	1.2%	***
Kalamazoo, MI	1.5%		0.8%	5.7%	***
Kankakee, IL	0.7%		0.6%	1.2%	***
Kansas City, MO	0.6%	8.6%	0.4%	1.3%	***
Killeen, TX	0.4%		0.3%	1.2%	***
Kingsport, TN	0.9%		0.7%	1.4%	***
Kingston, NY	2.9%		2.1%	4.4%	***
Knoxville, TN	0.8%		0.5%	2.2%	***
Kokomo, IN	0.7%		0.6%	1.0%	***
La Crosse, WI	0.7%		0.6%	0.9%	***
Lafayette, IN	0.3%		0.2%	0.5%	***
Lafayette, LA	0.7%		0.4%	1.5%	***
Lake Charles, LA	6.6%		1.2%	-2.0%	
Lake Havasu City, AZ	44.2%		4.3%	-5.3%	
Lakeland, FL	0.9%		0.6%	1.9%	***
Lancaster, PA	1.8%		0.8%	-10.6%	*
Lansing, MI	1.5%		1.1%	2.2%	***
Laredo, TX	0.6%	3.1%	0.4%	1.7%	***
Las Cruces, NM	0.9%		0.6%	2.0%	***
Las Vegas, NV	0.9%	4.2%	0.6%	1.9%	***
Lawrence, KS	0.4%		0.3%	0.9%	***
Lawton, OK	1.0%		0.5%	-11.7%	*
Lebanon, PA	1.0%		0.6%	2.0%	***
Lewiston, ME	2.3%		1.3%	9.5%	***
Lexington, KY	0.4%	3.3%	0.3%	0.6%	***

MSA	Optimal	Actual	Low	High	Significance
Lima, OH	1.0%		0.8%	1.3%	***
Lincoln, NE	0.5%	13.1%	0.4%	1.0%	***
Little Rock	2.3%		0.7%	-1.8%	
Logan, UT	2.0%		0.7%	-2.3%	
Longview, TX	-3.9%		3.8%	-1.3%	
Longview, WA	1.9%		1.4%	3.0%	***
Los Angeles, CA	9.2%	8.0%	4.0%	-30.8%	***
Louisville, KY	0.7%	6.5%	0.5%	1.0%	***
Lubbock, TX	0.3%	3.0%	0.1%	2.4%	**
Lynchburg, VA	1.0%		0.8%	1.3%	***
Macon, GA	0.5%		0.4%	0.8%	***
Madera, CA	1.6%		1.0%	3.9%	***
Madison, WI	0.6%	12.1%	0.4%	0.8%	***
Manchester, NH	3.0%		1.6%	59.0%	**
Manhattan, KS	0.3%		0.2%	0.6%	
Mankato, MN	-0.6%		4.9%	-0.3%	
Mansfield, OH	1.1%		0.7%	1.8%	***
McAllen, TX	0.4%		0.2%	1.0%	***
Medford, OR	1.4%		0.9%	2.9%	***
Memphis, TN	1.1%	5.1%	0.5%	-4.6%	*
Merced, CA	2.4%		1.4%	7.2%	***
Miami, FL	2.8%	1.4%	1.7%	7.6%	***
Michigan City, IN	1.6%		0.7%	-13.0%	*
Midland, TX	-127.3%		4.7%	-4.3%	
Milwaukee, WI	1.5%	9.8%	1.0%	2.4%	***
Minneapolis, MN	1.1%	11.7%	0.8%	1.9%	***
Missoula, MT	1.4%		0.8%	5.1%	***
Mobile, AL	1.4%		0.7%	-9.5%	*
Modesto, CA	2.5%		1.6%	6.1%	***
Monroe, LA	1.4%		0.6%	-7.1%	*
Monroe, MI	1.2%		0.7%	4.6%	**
Montgomery, AL	1.6%		1.0%	4.9%	***
Morgantown, WV	-1.5%		-10.0%	-0.8%	*
Morristown, TN	1.1%		0.8%	1.6%	***
Mount Vernon, WA	1.3%		1.0%	1.8%	***
Muncie, IN	1.0%		0.7%	1.7%	***
Muskegon, MI	1.5%		0.9%	3.3%	***
Myrtle Beach, SC	0.2%		0.2%	0.4%	***
Napa, CA	3.1%		1.8%	9.9%	***
Naples, FL	0.8%		0.4%	5.8%	**
Nashville, TN	0.4%	3.4%	0.3%	0.6%	***
New Haven, CT	22.7%		7.3%	-20.3%	***
New Orleans, LA	1.6%	25.8%	1.1%	2.7%	***
New York, NY	11.1%	19.5%	4.4%	-21.4%	***
Niles, MI	0.9%		0.7%	1.6%	***
Norwich, CT	2.0%		1.5%	3.0%	***
Ocala, FL	0.6%		0.5%	1.0%	***
Ocean City, NJ	0.4%		0.4%	0.5%	***
Odessa, TX	-6.9%		1.9%	-1.2%	
Ogden, UT	2.0%		0.8%	-3.0%	
Oklahoma City, OK	0.6%	5.6%	0.3%	5.0%	**

MSA	Optimal	Actual	Low	High	Significance
Olympia, WA	1.0%		0.9%	1.1%	***
Omaha, NE	1.4%	12.9%	0.6%	-8.6%	*
Orlando, FL	0.9%	4.9%	0.6%	2.3%	***
Oshkosh, WI	0.6%		0.5%	1.0%	***
Owensboro, KY	0.5%		0.3%	1.8%	**
Oxnard, CA	4.8%		2.7%	20.9%	***
Palm Bay, FL	1.3%		0.8%	3.2%	***
Panama City, FL	0.5%		0.3%	0.9%	***
Parkersburg, WV	4.0%		1.7%	-11.4%	**
Pensacola, FL	1.8%		0.8%	-17.1%	**
Peoria, IL	1.9%		1.2%	4.3%	***
Phoenix, AZ	1.1%	14.8%	0.6%	7.2%	**
Pine Bluff, AR	7.0%		2.4%	-7.2%	*
Pittsburgh, PA	4.3%	8.8%	1.9%	-18.2%	**
Pittsfield, MA	3.4%		1.9%	15.5%	***
Pocatello, ID	1.1%		0.6%	7.2%	**
Port St. Lucie, FL	0.7%		0.4%	1.3%	***
Portland, ME	1.5%		0.9%	5.9%	**
Portland, OR	1.5%	16.1%	0.9%	4.3%	***
Prescott, AZ	0.8%		0.5%	2.5%	**
Providence, RI	6.5%		3.4%	69.1%	***
Provo, UT	1.1%		0.7%	2.9%	***
Pueblo, CO	0.5%		0.3%	0.7%	***
Punta Gorda, FL	0.6%		0.4%	1.1%	***
Racine, WI	1.4%		1.0%	2.3%	***
Raleigh, NC	0.4%	4.1%	0.2%	0.9%	***
Rapid City, SD	0.7%		0.4%	-16.3%	*
Reading, PA	2.3%		1.1%	-55.1%	**
Redding, CA	2.2%		1.6%	3.4%	***
Reno, NV	1.2%	5.5%	0.8%	2.1%	***
Richland, WA	0.6%		0.4%	1.3%	***
Richmond, VA	1.2%		0.7%	5.2%	***
Riverside, CA	1.7%	9.6%	1.1%	3.0%	***
Roanoke, VA	1.2%		0.8%	3.0%	***
Rochester, MN	0.5%		0.4%	0.8%	***
Rochester, NY	2.4%	6.7%	1.2%	402.2%	**
Rockford, IL	0.9%		0.7%	1.3%	***
Rocky Mount, NC	0.7%		0.5%	1.1%	***
Rome, GA	0.7%		0.5%	1.1%	***
Sacramento, CA	1.7%	8.2%	1.1%	4.9%	***
Saginaw, MI	1.6%		1.1%	2.9%	***
Salem, OR	1.2%		0.8%	2.3%	***
Salinas, CA	10.5%		4.3%	-23.5%	***
Salisbury, MD	0.9%		0.7%	1.0%	***
Salt Lake City, UT	2.2%		1.1%	-18.0%	**
San Angelo, TX	7.8%		1.3%	-1.8%	
San Antonio, TX	0.6%	8.9%	0.4%	1.1%	***
San Diego, CA	2.9%	22.8%	1.4%	-26.5%	**
San Francisco, CA	7.7%	18.0%	1.6%	-2.8%	
San Jose, CA	37.6%	14.3%	5.3%	-7.4%	*
San Luis Obispo, CA	1.4%		1.1%	1.9%	***

MSA	Optimal	Actual	Low	High	Significance
Santa Cruz, CA	7.3%		2.8%	-11.6%	**
Santa Fe, NM	2.4%		1.3%	31.7%	**
Santa Rosa, CA	3.2%		1.4%	-11.8%	**
Savannah, GA	0.8%		0.6%	1.3%	***
Scranton, PA	3.1%		1.7%	21.0%	***
Seattle, WA	3.0%	10.2%	1.2%	-6.7%	*
Sebastian, FL	0.7%		0.5%	1.2%	***
Sheboygan, WI	0.7%		0.6%	0.9%	***
Sherman, TX	1.5%		0.7%	-6.4%	*
Shreveport, LA	1.1%		0.6%	66.5%	**
Sioux City, IA	1.0%		0.5%	7.8%	**
Sioux Falls, SD	0.3%		0.2%	0.3%	***
South Bend, IN	0.9%		0.6%	1.3%	***
Spartanburg, SC	0.4%		0.3%	0.8%	***
Spokane, WA	1.6%		0.9%	4.4%	***
Springfield, IL	0.5%		0.3%	2.7%	**
Springfield, MA	3.1%		1.9%	8.0%	***
Springfield, MO	0.5%		0.3%	0.7%	***
St. Cloud, MN	0.6%		0.5%	0.8%	***
St. George, UT	0.8%		0.5%	5.8%	**
St. Joseph, MO	3.0%		1.8%	8.3%	***
St. Louis, MO	1.1%	8.8%	0.9%	1.7%	***
State College, PA	1.4%		0.6%	-3.9%	
Stockton, CA	2.9%	1.9%	2.0%	5.4%	***
Sumter, SC	1.4%		0.7%	-946.4%	**
Syracuse, NY	2.7%		1.7%	6.7%	***
Tallahassee, FL	0.9%		0.7%	1.3%	***
Tampa, FL	1.5%	4.7%	1.0%	3.3%	***
Terre Haute, IN	1.2%		1.0%	1.6%	***
Texarkana, TX	1.3%		0.6%	-3.5%	
Toledo, OH	2.0%		1.5%	3.4%	***
Topeka, KS	0.6%		0.5%	1.0%	***
Trenton, NJ	2.8%		1.4%	37.8%	***
Tucson, AZ	1.7%	3.1%	0.8%	-10.5%	*
Tulsa, OK	0.7%	6.3%	0.4%	4.5%	**
Tuscaloosa, AL	0.5%		0.3%	1.3%	***
Tyler, TX	1.0%		0.7%	2.1%	***
Utica, NY	10.9%		4.4%	-22.5%	***
Valdosta, GA	0.8%		0.5%	1.3%	***
Vallejo, CA	3.1%		1.9%	8.4%	***
Victoria, TX	-1.3%		2.1%	-0.5%	
Vineland, NJ	3.5%		2.4%	6.7%	***
Virginia Beach, VA	3.9%	21.2%	2.1%	23.5%	**
Visalia, CA	3.4%		2.2%	6.9%	***
Waco, TX	0.8%		0.5%	5.6%	**
Warner Robins, GA	0.3%		0.2%	0.5%	***
Washington, DC	2.7%	19.0%	1.4%	28.1%	**
Waterloo, IA	-13.2%		1.9%	-1.5%	
Wausau, WI	0.5%		0.4%	0.6%	***
Weirton, WV	8.3%		2.6%	-6.7%	
Wenatchee, WA	1.3%		0.9%	2.6%	***

MSA	Optimal	Actual	Low	High	Significance
Wheeling, WV	6.1%		3.3%	32.0%	***
Wichita Falls, TX	1.0%		0.7%	1.8%	***
Wichita, KS	0.7%	5.1%	0.4%	1.7%	***
Williamsport, PA	-7.4%		2.2%	-1.4%	
Winchester, VA	1.1%		0.8%	1.8%	***
Winston, NC	0.3%	5.0%	0.3%	0.5%	***
Worcester, MA	3.4%		1.9%	18.9%	***
Yakima, WA	1.9%		1.3%	3.4%	***
York, PA	1.2%		0.8%	2.4%	***
Youngstown, OH	1.4%		1.2%	1.9%	***
Yuba City, CA	1.1%		0.6%	3.8%	***
Yuma, AZ	1.7%		0.8%	80.4%	**

Appendix C

Supplemental Maps

Figure C.A: Statistically Significant Estimates of Housing Supply Elasticity

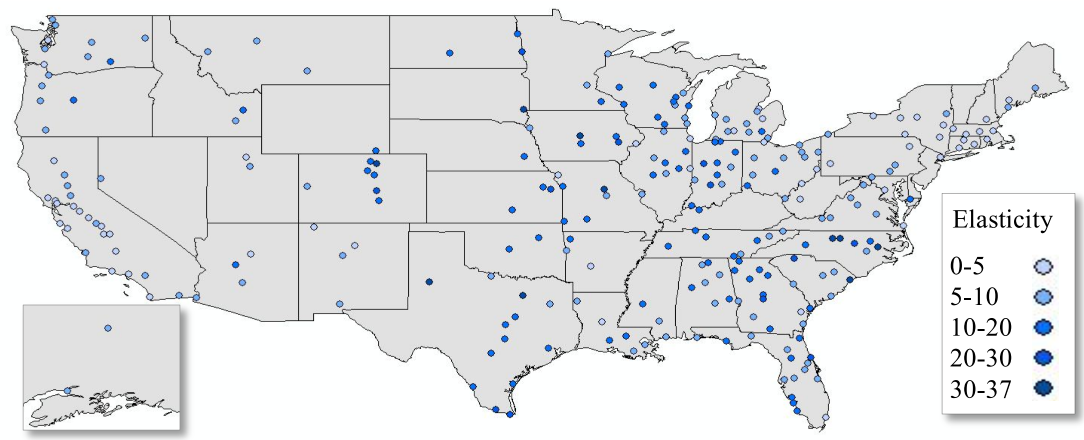

Figure C.B: Difference Between the Optimal and Observed Share of Open Space

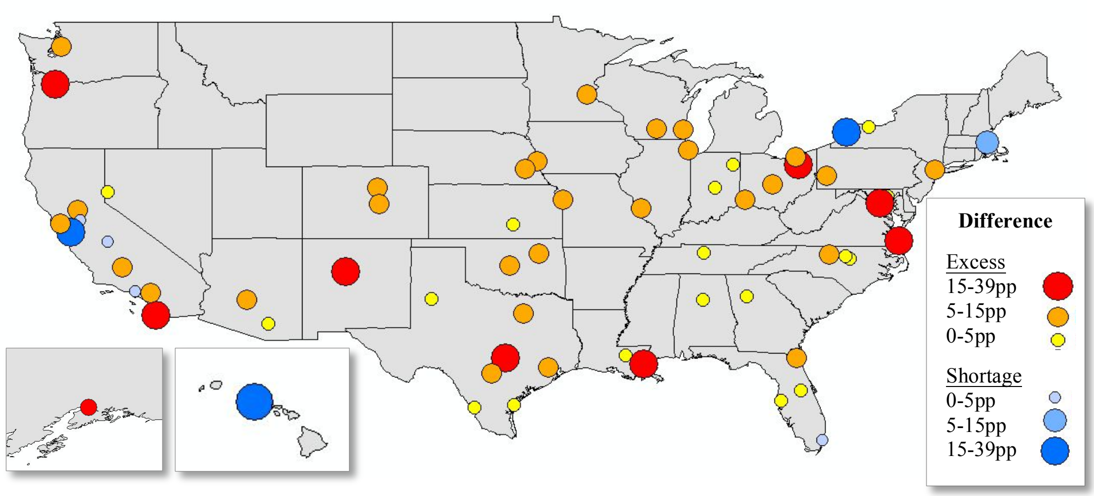

Figure C.C: Difference Between the Observed Share of Open Space and the Confidence Interval of the Optimal Share Estimate