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ROBERT LEE TROSPER III
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THREE ESSAYS IN LOCAL PUBLIC FINANCE

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BY

Dr. Gregory Burge, Chair

Dr. Kevin Grier

Dr. Alexander Holmes

Dr. Dawn Jourdan

Dr. Cynthia Rogers

DEDICATED

to

Laura Dronyk-Trosper

In the boat of life we find ourselves in, you are my wind above and rudder below.

and

Jetsy Trosper

Life may not always be easy, but nobody can contend your courage and strength.

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Table of Contents

List of Tables

List of Figures

Abstract

"All politics is local."- Tip O'Neill

This dissertation targets three questions relating to local public finance. Given the importance of local public finance on the average person's everyday life (consider the state of local roads and schools), understanding economic elements associated with local revenue generation are integral to our knowledge of how municipalities can affect their local fiscal situation. To this end, three essays are provided here to consider two major topics; capitalization effects, and local budget composition issues.

The first two chapters discuss how local public services, in particular fire stations, police stations, and hospitals, can impact the value of nearby land. In particular, the first chapter concentrates on how single family home values will, on average, decrease in value if they are located too close to these emergency service stations, but can also decrease in value if they are located too distantly. Understanding these effects and modeling them are the targets of the first essay.

Incorporating similar ideas, the second chapter utilizes the same stations, but now tackles the question of how these services can affect non-residential structures such as office buildings, retail centers, and manufacturing plants. Of interest here is the large heterogeneity of land use, leading to concerns over prior research and its tendency to aggregate land uses when considering these capitalization effects.

The final chapter utilizes fiscal override and budget data to analyze how changes in local budget composition can be driven by fiscal overrides in revenue constrained municipalities. When communities are fiscally constrained in their ability to raise own-source revenue, local budget officials may be incentivized to use voter approved fiscal overrides and local budget fungibility to drive expenditures into different portions of the budget. Findings suggest that local budget composition tends to favor certain kinds of spending, such as public works, over other types such as education.

Keywords: *Local public finance, capitalization, hedonic regressions, local budgets*

Chapter 1

Searching for Goldilocks

Economists have long been interested in understanding how public services are capitalized into property values. This paper enhances an understanding of capitalization effects from three largely ignored types of public services; fire, police, and emergency medical services (EMS). To examine these effects, a database of over 3 million home sales throughout the state of Florida is utilized. The data covers an 18 year period from 1994 to 2011. Using Geographical Information System (GIS) software, a variety of distance measures are calculated for each residential parcel.

Economic theory suggests that the value of a property depends in part on the services and amenities that are available to its tenants (Oates, 1969). Oates' work established critical linkages between service provision and property values. For example, residents that value open space may prefer (and thus be willing to pay for) land adjacent to parks or preserved land. Previous work has also suggested that residents may value locations near schools or transportation hubs. These amenity effects translate into higher housing values for those areas with better access to such services. Evidence also suggests that these premia dissipate with distance as the quality of service provision falls.

Fire, police, and EMS services are also generally accepted as valuable public amenities, and as such, they should exhibit similar spatial positive capitalization effects. However, these services generate an inherent economic tension. On one hand, locating near a fire station ensures a faster response time and in turn, reduced fire-related losses. Insurance companies have long been known to provide cheaper insurance for properties with nearby fire stations, lowering an important cost to homeowners (Brueckner, 1981). Similarly, police and medical services' locations can determine their response time to crimes or health emergencies emergencies.[1] In essence, the quality of service such public goods provide is a function of the distance required to respond to emergency situations. Hence, services such as these contain a strong spatial component. However, there are also disamenities associated with close proximity to service stations. These services may generate increased traffic congestion, noise and air pollution, and often times are clad with unappealing faades. Such undesirable characteristics should be negatively capitalized into nearby housing values (Van Praag and Baarsma, 2005) and (McMillen, 2004). Given the opposing directions of these competing economic effects, one would expect the creation of something akin to a "Goldilock's Zone" wherein the property valuation is maximized with respect to each service location.[2]

The impact of the proximity of these three public services on home prices using hedonic regression techniques will be considered herein. Of particular interest is the nature of the spatial component of service valuation. As such, the analysis will explore the relationship between housing and service proximity. Analyses for other public services commonly use straight-line distance calculations between points as the measure of proximity. An additional nuance here investigates whether there exists a difference between using straight-line distance and actual driving distance. Drive distance analysis using a network analysis should better capture the response times that are critical in determin-

[1]See Blackwell and Kaufman (2002) and Pons et al. (2005)

[2]For a more technical discussion of these effects see Appendix A.

ing emergency service provision. Finally, a difference-in-difference (DID) model identifying effects based solely on the construction of 785 new service facilities during the sample period will be conducted.

Several interesting results have been identified. Aggregate measures of each of the three major types of services are found to have a 'hill' shape with respect to distance. In other words, housing prices tend to be positively correlated with station distance out to a specific distance. In each case, capitalization effects become negatively correlated with station distance beyond this inflection points. These results are relatively robust to several measures of distance and parcel choice. Additionally, the difference-in-difference analysis largely corroborates the general regression findings. Finally, the methodology and measurements established here can be utilized to investigate other economic questions.[3]

1.1 Literature Review

Capitalization effects have traditionally focused on three types of publicly provided amenities; education[4] , open-space[5], and transportation[6]. The prior research provides a series of perspectives on how to consider the impact of emergency service access. The following examples of the literature are representative of prior research in the capitalization field, but by no means is an exhaustive list.

Much literature has been written on the effects of transportation and nearby

[3] One such possibility may be studies on airports. Closer locations may benefit from having quick access to the airport, but closer proximity will increase noise pollution from overhead air traffic.

[4] See also Kain and Quigley (1970), Bogart and Cromwell. (1997), and Cheshire and Sheppard (2004)

[5] See also Correll, Lillydahl and Singell (1978), Irwin and Bockstael (2001), and Walsh (2007).

[6] See also Bollinger and Ihlanfeldt (1997) and Ihlanfeldt (2001).

housing prices. Early work by Spengler (1930) demonstrated the positive effects that transportation access has on residential property values. Using New York real estate data, Spengler found that an increased distance from transportation access was correlated with lower property values. Bollinger and Ihlanfeldt (1997) showed the effects of Atlanta's MARTA rail expansion on population and employment growth. The authors found positive benefits related to station construction. One difference between their research and the work presented here is the unit of analysis. While Bollinger and Ihlanfeldt used census tract level data for their study, parcel level data is used here, providing a finder level of detail. This paper also contributes to the capitalization literature by considering a different set of services.

As noted by Ihlanfeldt (2001), there have been relatively few studies accounting for the negative externalities associated with extremely close service location, as most studies only estimate a single averaged effect over all 'nearby' parcels of land. This led to a number of conflicting results, as locations with negative spillover effects likely offset the expected positive effects from locating at a slightly further distance away from the service. His contribution recognized that having a metro rail station in the immediate vicinity provided positive benefits to residents, but also generated negative spillovers through noise, pollution, and possibly increased crime rates. Using a hedonic regression, he found that housing prices within a quarter mile of a station were 19% lower than those more than three miles away. However, housing prices between one and three miles from the station were significantly higher compared to the nearest and most distant groups. Hence, this study provides initial evidence of a "Goldilock's": phenomenon for public transportation services. On the other hand, Redfearn (2009) shows evidence against capitalization effects of light rail transportation.

One of the primary subjects of study in the literature has been the capitalization effects of educational services. Chin and Foong (2006) used four years of home sales in Singapore to evaluate the effects of schools on nearby housing values. Recognizing that distance is not the only way to measure service accessibility, the authors create a measurement of school accessibility by utilizing testing scores and open admission slots. They find that schools with higher test scores as well as better access tend to raise higher housing values in local neighborhoods. Weimer and Wolkoff (2001) also demonstrate the positive effect that school quality has on local housing prices. They exploit the fact that public school districts and elementary school enrollment areas do not perfectly overlap, allowing identification within hedonic regression using 1997 sales data in Monroe County, New York. Similarly, they find that high quality schools lead to higher housing prices.

Open-space amenity valuations have been researched as well. Shultz and King (2001) use census block level data to derive residential valuations of open space in Tucson, Arizona. They find a positive and significant effect of locating near open-space amenities, even at the census block level. Irwin (2002) adds to the literature by identifying that valuations of open space may differ based on the type of open space (i.e. whether it is zoned park, undeveloped land, or protected forestland) in Maryland. Her study uncovers a significant and positive valuation placed on permanently preserved land compared to land that may be developed in the future. Anderson and West (2006) question whether high density or high income locations provide a different valuation of open space than other neighborhoods. Their results suggest that there may be asymmetric capitalization effects leading the authors to note that "...a metropolitan area's average value may substantially overestimate or underestimate the value of open space in particular neighborhoods."

Another contribution to this literature comes from Matthew's (2006) thesis on the effect of commercial and retail locations on neighboring residential property values. He uses hedonic regressions combined with a novel system of identifying neighborhood layouts to derive the distances over which disamenity effects may be present from the commercial structures. Matthews found negative capitalization effects out to 250 feet, with generally positive effect from 250 to 1,000 feet. His work also addresses the possibility of non-linear spatial effects on property values. Grislain-Letrmy and Katossky (2014) demonstrates the negative effect of disamenities on local housing. They analyze homes in three French cities, finding reduced home values when people are exposed to nearby hazardous industrial facilities.

This study enhances the literature in several ways. First, it uses parcel-level data instead of the more aggregated data seen in most prior studies. Second, it considers three important services not previously given attention. Third, the length and breadth of the data set enables a refined difference-in-difference identification strategy keying on new facility construction, and advantage that is rarely present in previous studies.

The work presented here will add to the existing literature by focusing on two additional considerations; the use of parcel-level data and the inclusion of three types of services not examined in the past. Each of these inclusions will help address some of the gaps that exist in the service capitalization literature.

Table 1.1: Select summary statistics using Euclidean distance measures.

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Sales Price ($)	3309888	198127	244894	10004	14500000
Living Area (sq. ft)	3309888	2066	906.81	101	45068
Lot Size (sq. m)	3309888	1312	3920	100	2199091
Age (years)	3309888	19.05	17.99	1	111
In City (dummy)	3309888	0.46	0.50	0	1
Elementary Distance (m)	3309888	1574	1699	0.69	36721
Distance to CBD (m)	3309888	19984	12792	0	60530
Euclidean Hospital Distance (m)	3309888	7228	5813	25.55	63160
Euclidean Fire Distance (m)	3309888	2438	1683	0.47	25376
Euclidean Police Distance (m)	3309888	4221	3391	2.78	44638
Network Hospital Distance (m)	3273202	9755	7325	12.02	91623
Network Fire Distance (m)	3273202	3615	2447	0.07	40448
Network Police Distance (m)	3273202	5922	4504	0.54	60136

1.2 Data

The data used for this analysis comes from four main sources; the Florida Department of Revenue (FLDOR), the Florida Division of Emergency Management (FLDEM), the University of Florida GeoPlan Center (UFGC), and the U.S. Census Bureau. The breadth of the data includes the entire state of Florida, and much of it comes at the parcel level. The data covers the 18 year period between 1994 and 2011. Selected summary statistics of the data using Euclidean and Network distance measures are presented in Table 1.1.[7]

The Florida DOR, in conjunction with the DeVoe Moore Center at Florida State University, provided tax roll data at the parcel level for each of the 18 sample years. This database contains information on every parcel in the state of Florida. Information on sales price and date, building age, land use classification, number of living units, and interior living space are all included in the dataset. The DOR also provided GIS data on the location of each parcel. Using ESRI's ArcGIS program, it is possible to generate lot sizes and various

[7]The discrepancy in observation numbers comes from the inability of the GIS program to calculate distances for the Network analysis if there are no nearby roads. Thus, a small number of largely rural parcels with no road access according to information provided by the U.S. Census Bureau were removed from the Network analysis.

distance measures using this data. Each parcel's unique parcel ID was used to merge the GIS location data with the tax roll data. Due to historical parcel ID changes, eight counties[8] are not retained in the dataset. Table 1.2 contains a list of included counties.

Table 1.2: List of included Florida Counties.

County	County	County
Alachua	Glades	Okeechobee
Baker	Gulf	Orange
Bay	Hamilton	Osceola
Bradford	Hardee	Palm Beach
Brevard	Hendry	Pasco
Broward	Hernando	Pinellas
Calhoun	Indian River	Polk
Charlotte	Jackson	Putnam
Citrus	Jefferson	Saint Johns
Clay	Lafayette	Saint Lucie
Collier	Lake	Sarasota
Columbia	Lee	Seminole
Dade	Leon	Sumter
Desoto	Madison	Suwannee
Dixie	Manatee	Taylor
Duval	Marion	Union
Flagler	Martin	Wakulla
Franklin	Monroe	Walton
Gadsden	Nassau	Washington
Gilchrist	Okaloosa	

An important note is that historical GIS data is not available regarding parcel locations over the period of study. As such, parcels that did not exist as of 2011 are not included in the analysis. Given the relative stability of parcel existence (only merging or demolition/reconstruction with land use change is likely to remove parcels from the database), this restriction affected less than 3% of the parcels originally contained in the tax rolls. Data for emergency

[8]These are; Escambia, Highlands, Hillsborough, Holmes, Levy, Liberty, Santa Rosa and Volusia.

service stations comes from the FLDEM. They have furnished a database with the GIS location information for 1,917 fire stations, 992 police stations, and 483 hospitals.[9] The data include information on the type of station, its location, and in the case of the hospital data, number of beds and hospital operation type (i.e. public, private, or not-for-profit). Hospitals are the least common and most concentrated in urban areas. Many rural counties have only a single hospital facility to serve their region. The geographic coverage of fire and police stations is far more extensive. Fire stations especially are widely scattered and numerous compared to EMS. All three services display agglomeration tendencies in urban areas, thus indicating the importance of controlling for central business district effects.

As one might expect, not all fire stations, police stations, or hospitals are the same. As in many states with both urban and rural populations, publicly funded fire stations and volunteer fire departments are each utilized. The state has 1,592 staffed fire stations primarily in urban areas. The 298 volunteer fire departments are mainly located in more rural locations. One might expect the capitalization effects of being near a (likely better funded) professional fire station to differ from a volunteer fire department. Similarly, police substations are likely to have a different effect compared to sheriff's departments (which are likely smaller and have fewer resources) or headquarters buildings. As such, two of the three main categories of services were split into subgroups to look for potentially differential effects. Fire stations were split into standard publicly funded fire stations and volunteer departments. The police stations were split into four major categories; police substations, headquarters buildings, sheriff offices, and state or federal buildings such as Alcohol, Tobacco, and Firearms

[9] See Figures 1.1, 1.2, and 1.3 respectively.

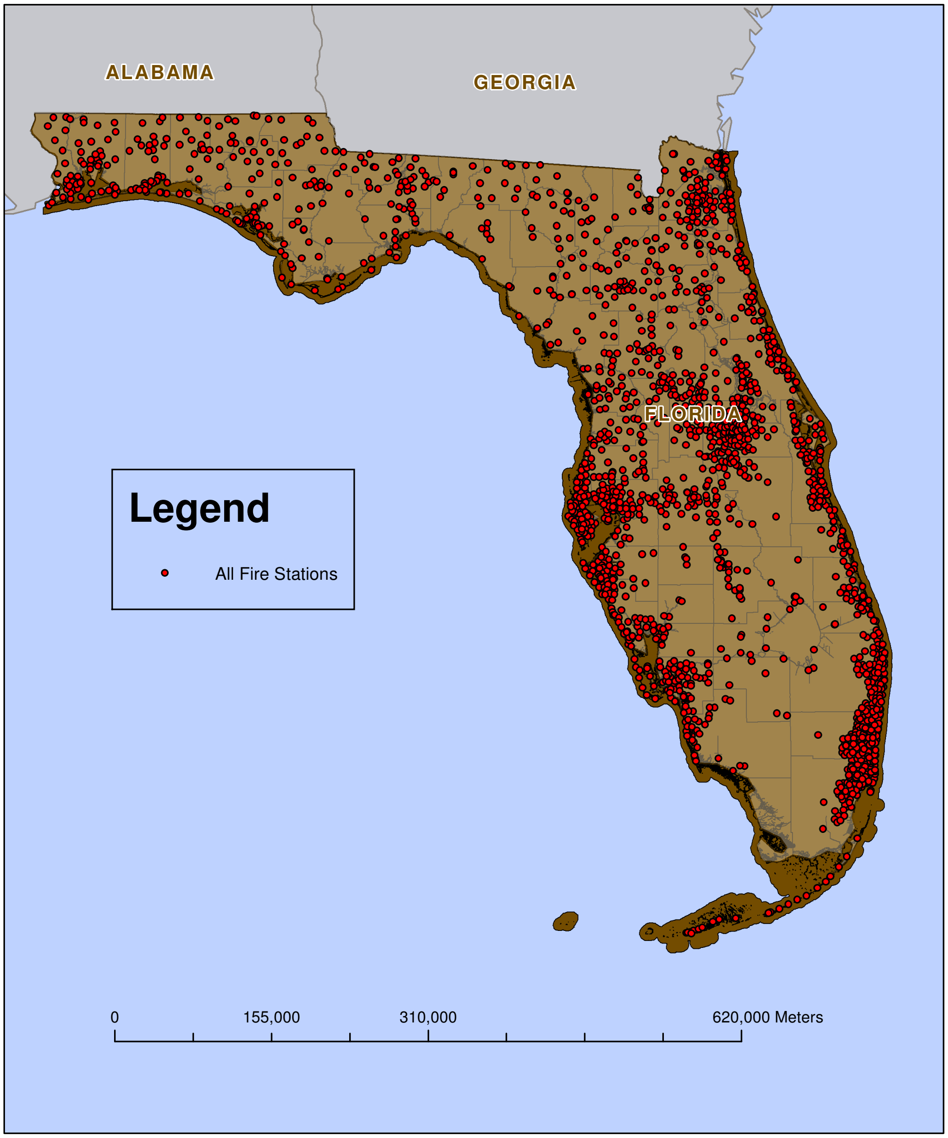

Figure 1.1: Location of all fire station types.

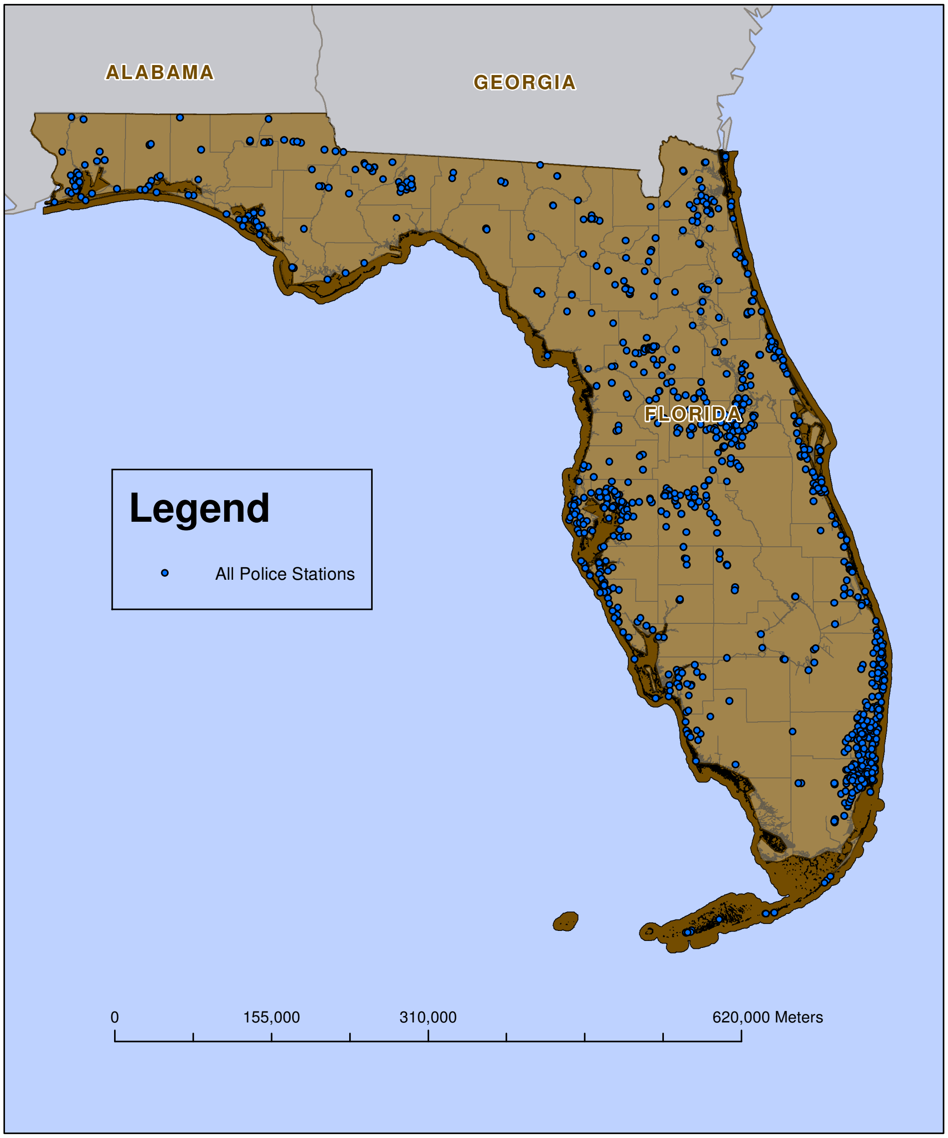

Figure 1.2: Location of all police station types.

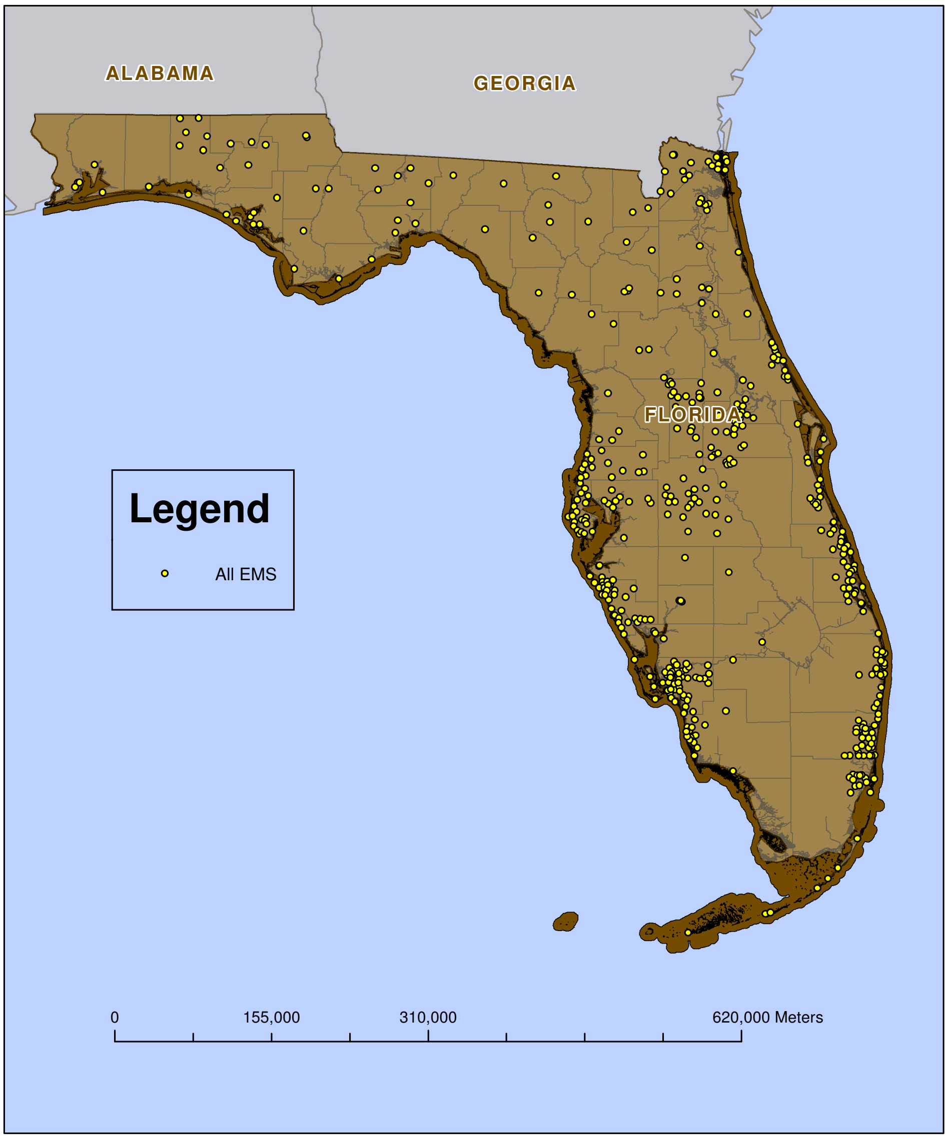

Figure 1.3: Location of all emergency medical facilities.

(ATF), Department of Fish & Wildlife (DFW), secret service, highway patrol, and customs agencies. Distances from each subtype of station were calculated for all parcels (providing 7 different distance measures) as well as a distance measure to the nearest station of the three major types regardless of the subtype (providing another 3 distance measures).

GIS coastline data was also provided through the UFGC. However, due to computational constraints, exact distance measures are not feasible.[10] Instead, a dummy variable system has been used to create categories or bins of distance. Measures were taken within 5, 25, 50, 100, 200, 500, 1000, and 2000 meters. Parcels were placed into one of these bins. Those not within 2,000 meters of the coast were given their own bin as well.

As Kain and Quigley (1970) noted, housing values tend to increase at a non-linear rate when approaching central business districts of large metropolitan areas. To control for this tendency, parcel distance to central business districts (CBD) was gathered from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD). The LEHD was used to identify the highest employment centers in each of the Census designated Metropolitan Statistical Area (MSA). The distance for each parcel was then calculated to find the distance to CBD measure.

The UFGC provided a database on 7,423 schools in Florida which includes pupil-teacher ratios, grade coverage, ownership type, reduced or free lunch enrollments, and school location. In order to account for school effects, two measures will be used, one for school quality, and a second for distance to the school. As noted by Weimer and Wolkoff (2001) and others, elementary school

[10] More specifically, the coastal GIS maps are extraordinarily detailed. However, the more detailed a map is, the longer it takes to calculate the required distance measures. By reducing the number of vertex points in the coastal map, the calculations could have been performed more quickly. Unfortunately, this also causes inaccuracy in the reported measures.

performance tends to be highly correlated with other local school performance measures, (i.e. upper grade outcomes) as well. As such, to account for local schools, each residential parcel will have a distance measure calculated for the nearest elementary school.[11] Individual school quality will be controlled for using a set of school-specific dummy variables. Given that the quality of education that a student receives will, on average, be the same across all students in the school's catchment zone, school-specific dummy variables should capture any variation in school quality from one elementary school to the next.

1.3 Theory

Importantly, there are reasons to believe the identified economic tension of amenity versus disamenity effects may not have equivalent magnitudes at various distance measures. For negative capitalization effects, there are two main contributing factors; noise pollution and traffic congestion. Both of these components generate effects displaying a dependence on distance. The effect of sound attenuation (a change in amplitude or α) can be described by Stokes' Law of Sound Attenuation (Stokes, 1845):[12]

$$\alpha = \frac{2\eta\omega^2}{3\rho V^3}$$

Where η is the viscosity coefficient of the medium, ω is the frequency of the sound, ρ is the density of the medium, and V is the speed of sound through air.

[11] Exact school catchment zones in a usable GIS format were unable to be obtained for the entire state, although some counties were available. Fortunately, most parcels are in the same catchment zone as the nearest elementary school, so these distance measures also provide a way of uncovering to which elementary school a parcel is most likely attached.

[12] The amplitude of a given soundwave is directly related to the intensity of the sound.

Given the assumption that the atmosphere will be fairly homogeneous between the point of origination (the emergency vehicle's siren), and the point of hearing (the observed parcel), α will become a constant value irrespective of a sound's distance traveled. The attenuation rate can then be plugged into the formula for sound propagation through a homogeneous medium:

$$A(d) = A_0 e^{-\alpha d} \quad \text{with } \alpha, d, A_0, > 0$$

Thus the first order partial derivative with respect to distance of A(d) is:

$$\frac{\partial A(d)}{\partial d} < 0$$

And the second order is:

$$\frac{\partial^2 A(d)}{\partial d^2} > 0$$

A(d) represents the amplitude of a sound wave at d distance from the source of origination with initial amplitude A_0. As can be seen, for any marginal increase in distance the amplitude of an originating sound will decline non-linearly with respect to distance traveled. The amplitude will eventually approach 0 given a long enough traveling distance.[13] Given that human hearing has a lower threshold, there exists a distance from which a human would be unable to hear any sound waves of a given initial amplitude from the point of origination. At

[13]Mathematically, the amplitude has a horizontal asymptote along the X-axis. However, since the transmission of a sound wave requires the transferring of energy from one set of air molecules to another, the loss of energy from this transmission will eventually result in the air molecule's movements being effectively indistinguishable from background movement. This may most easily be imagined by dropping a stone into a lake. The waves will diminish in height as they propagate through the water. Eventually the wave heights will become indistinguishable from the natural tendency of the water's surface to move.

this point, the assumption is made that if the human ear can no longer hear the noise, then the effect on utility would be neutral, i.e. 0.

The utility (U) derived from a location's noise profile will then be a function of the following variables:[14]

$$U(d, A_0, \eta, \omega, \rho, V, \alpha) = c\frac{1}{A(d)}$$

If we assume that noise is an economically undesirable trait of a given location, then the associated utility will follow an inverse function to A(d):

$$\frac{\partial U}{\partial d} > 0$$

Provided that the amplitude of sound waves exhibits a tendency to decline at a diminishing rate, the related utility should follow a similar tendency, thus the second order condition will be negative:

$$\frac{\partial^2 U}{\partial d^2} < 0$$

The negative capitalization effects from traffic will largely be dependent upon the likelihood of encountering a road or intersection with an oncoming emergency vehicle. Since a station's non-trivial effect on nearby traffic is through drivers requiring to give way for emergency vehicles with sirens active, consideration must be made for how often this is likely to occur to a driver. Assuming that the majority of emergency vehicles are leaving directly from the station, then the most highly traveled location for a station will be the immediate vicin-

[14]Since A(d) is an economic 'bad ', an individual's utility will increase as perceived noise levels decrease, thus leading to the inclusion of A(d) as an inverse component in the utility function.

ity, with farther locations receiving relatively less emergency traffic.[15]

To illustrate this relationship, consider a circle of radius r centered around an emergency facility. This circle encompasses all roads inside its area. As the circle's radius increases, more roads and intersections fall into its area. With more roads and intersections residing inside the circle, the likelihood of any random driver encountering an emergency vehicle will fall. This occurs due to the following relationship; that as the radius of an imaginary circle around a facility increases, the volume (A) of the circle increases at a faster rate than the circumference (C):

$$\frac{\partial A}{\partial r} > \frac{\partial C}{\partial r}$$

Given this relationship, for any increase in distance from a facility, there will be a disproportionate increase in roads and intersections within the provided distance. Akin to noise capitalization effects, traffic congestion problems will fall off at a non-linear rate as one moves further away from a facility. Similarly, provided that an individual's utility will increase as congestion becomes less of a problem, then the highest negative capitalization effects from traffic should be in the immediate vicinity of an emergency station followed by a non-linear drop off.

While this explains the non-linear negative effects of noise and traffic, the non-linearity of response times should be discussed as well. Consider the marginal effects of an increase in response time given a change in distance from a station. The expectation is that response time should increase for any given change in distance r. Therefore, the change in response time (R) will have a positive

[15] It should be mentioned that for fire stations this assumption will tend to hold, but for ambulances and police cars the probability of being dispatched directly from the station will be less than 1. However, in an emergency call, the most likely final destination for the police or medical services is in fact to return to the station.

correlation with increasing distance:

$$\frac{\partial R}{\partial r} > 0$$

Once an emergency vehicle is traveling at its maximum safe speed, there is no possibility to accelerate further. As such, at further distances, the marginal response time cannot be reduced by increasing vehicle speeds. Thus, the second order derivative of response time should approach zero (i.e. the increase in response time of traveling an extra meter at a distance of 10,000 meters should be very close to the change in response time at a distance of 20,000 meters.):

$$\frac{\partial^2 R}{\partial r^2} \approx 0, \text{ for } r \gg 0$$

This indicates that it would be highly unlikely for both the positive (relatively less non-linear) and negative (relatively more non-linear) capitalization effects to perfectly balance. Since these effects are not expected to balance out, it is only necessary to establish a prediction of which effects will dominate at any points to develop a testable hypothesis. It is expected that at small values of r, the negative effects of noise and traffic will dominate the positive effects of response time due largely in part to the concentration of disamenity effects in the vicinity of the facilities in question. As r increases, the disamenity effects will diminish toward 0. Once the disamenity effects reach zero, the associated impact on utility will also reach zero. Any subsequential increases in r will only have an impact on the utility levels associated with service provision levels. These two combined effects will generate a sort of 'hill' in housing prices with the foot of the hill affiliated with housing adjacent to the service station.

1.4 Methodology

The model used here follows from the rich literature on hedonic regression analysis. While the data on sales is extremely large, due to the fairly low turnover rate, the number of observations for any single parcel remains relatively limited. Often a parcel is only seen as having one sale, with some parcels seeing two or three sales over the full 18 year panel. As such, this analysis will use all the sales in a single pooled OLS regression, using time dummies to control for market price fluctuations unrelated to the variables of interest. The model is as follows:

$$log(Price_{i,t}) = D_i + S_i + H_i + DH_i + U_i + V_t + \epsilon_i \tag{1}$$

Where $Price_{i,t}$ is the sales price house i at time t, and D_i is the vector of distance measurements of interest. H_i includes housing specific characteristics such as living space, age, and lot size[16] S_i represents service station characteristics. Variables in the DH_i term include the measures of distance for the nearest elementary schools, distances to the CBD (including CBD square and cubed distances) indicators for extreme proximity to service stations, and the set of coastal distance dummies. U_i includes a set of geographical dummy variables, and V_t is a vector of time dummy variables.

An important note should be made regarding S_i. As expected, every fire station, police station or hospital has its own individual capabilities and training, resulting in station specific performance characteristics. The quality of service that an individual may receive can be thought of as being split into two components; station provision and response time. Independent of the location

[16]Prior literature has established the usage of housing characteristics while also including their squared components. As such, this paper will include the squared values of housing-specific control variables.

(i.e. controlling for response time), all households should receive the same approximate station-level of service.[17] However, the overall quality of service is dependent upon response time. Since an individual will receive the same level of service *once the emergency vehicle or service arrives*, any differences in service quality inside a station's zone can be attributed to the difference in response time. One advantage of the methodology utilized here is that it aggregates unobservable station characteristics into a set of station specific dummy variables. Each station has a dummy variable indicating its subtype (i.e. volunteer fire station vs. a professional fire station) as well as a station specific dummy variable for each station. The second dummy variable should control for aspects of station quality that are independent of response time.

The vector of interest, D_i, contains variables indicating distance to the nearest fire station, police station, and hospital. The distance measures come from two different methods. Euclidean distance is the straight-line distance from one point to another. This is measured by calculating the distance from the nearest point of each parcel's polygon to the location given by the public service database. To account for expected non-linearities, squared and cubed distances are also included. The square must be included since the underlying economic theory dictates the estimation of a model that allows for an inflection. Given that at closer distances, the economic tension expected to occur may cause a different curvature effect from locations further away (which should only be influence by response time effects given that traffic and noise congestion issues should be trivial in nature), the cubic distance term is also included. This al-

[17] While there may be differences between two fire stations (e.g. one may have a workers with more training or better equipment), there should be little difference in service *within* a single fire station's zone. Regardless of whether a location is in the immediate vicinity of a station or at its extreme response range, upon arriving at the scene, each location will still receive the same crew with the same equipment.

lows the model to reveal non-symmetric effects over the distance measure if one exists in the underlying data generating process.

The second measurement approach is known as a network analysis. Using this method, it is possible to find the road-based travel distance between parcels. It is useful to consider this alternative methodology as it provides a more accurate description of the service connection between each parcel and its nearest service station. The coefficients on this set of variables can be used to estimate of the non-linear spatial effect of service capitalization, similar to the standard Euclidean distance measures.

To account for other important but unobserved price determinants associated with public services, two geographical dummy variables are used; county specific and city specific variables[18]. Time variable dummies include yearly (for yearly housing trends as one would expect given the recent housing bubble) and monthly measurements. Monthly measures are important to include given the well known seasonality components of both construction and home sales (i.e. both construction and sales tend to increase in warmer months, and fall in cooler months). Additionally, a variable for the interaction of county dummies with yearly dummies is included to account for county-specific unobserved effects on a yearly basis.

When considering effects of the different subtypes of stations, a variation of the main model is used. To allow each subtype of station to have its own individual effect, a series of interaction variables is included as follows:

$$(2) \qquad log(Price_{i,t}) = D_i + T_i + (D_i * T_i) + H_i + DH_i + U_i + V_t + \epsilon_i$$

[18]There will be 59 dummies for each county in the sample, and 364 for each city limit provided by the UFGC.

Where the addition of $D_i{}^*T_i$ represents the interaction term between station type (T_i) and the individual subtype distance characteristics (D_i). This variable will allow the the estimated slope effects to differ across each station type.

Due potential differences across environments, MSA specific versions of models (1) and (2) will also be investigated. This may be an important consideration given that tenants in urban areas may have difference preferences for services than those in more rural areas. To account for this possibility, a version of the models will be split into two subsamples based on whether the parcel can be found in municipal jurisdiction.

There may be an issue of endogeneity regarding station location decisions. One would expect that a local government's choice of where to locate the public services under consideration is not random.[19] The direction of this effect though is not known *a priori*. On the one hand, local governments may try to locate service stations near transportation hubs and densely developed locations. These effects might tend to bias nearby housing values upward. If present, such effects would result in a dampening effect on the present analyses, suggesting the likelihood for lower-bound estimates in the regressions. However, local governments may also be interested in reducing construction costs by building in areas containing cheaper land, thus reducing construction costs. As such, nearby housing values could be biased downward. This endogeneity problem should affect only the initial choice of station location.

As both a robustness check and as an effort to address this possible endogeneity problem, a difference-in-difference (DID) analysis is also conducted.

[19] It should also be noted that there may be a political capital story involved as well. Higher valued homes may have the political will and capability to 'push' station construction to a more preferred distance. Note however, that this assumes that households display their preferences for station distance through the expenditure of political capital. This would tend to corroborate the proposed non-linear effects, otherwise households would not spend their time and/or money lobbying for alternative construction sites.

This method uses only data on newly constructed facilities to analyze how home prices *change* when new stations are constructed.[20] The DID analysis compares the price of two groups of homes; a control group of homes that maintain their distance from the nearest station throughout the sample period, and a treatment group that initially experiences the same distance as the control group, but have their distance reduced through the construction of a closer facility.[21]

This method provides additional insight as to the likely pathway of housing capitalization effects. Significant results here would indicate that other significant findings are not likely from a spurious effect relating to municipal location choices. The DID model to be used is as follows:

$$(3) \qquad log(Price_{i,t}) = Treatment_i + State_i + (Treatment_i * State_i) + O_i + \epsilon_i$$

Where *Treatment* is a dummy variable indicating whether the parcel was treated (i.e. a station was built more closely that 'moved' the parcel from a further distance to a closer location), while *State* indicates whether the observed sale occurred before or after the treatment. The variable of interest will be the coefficient for ($Treatment_i$*$State_i$). A significant value here would demonstrate that the construction of a new facility altered local housing values; something that should not occur if the capitalization results in (1) and (2) are a spurious consequence of urban landform rather than the hypothesized station effects. O_i contains a vector of the same control variables included in models (1) and (2).

Given the tendency for human error in originally generating the tax rolls, several filters were applied to the data to remove likely errata. Obvious errors included homes that were sold in non-existent months, single family homes with

[20]There were 176 EMS, 145 police, and 464 fire stations built between 1995 and 2010.
[21]See Figure 1.4 for an illustration of these two groups.

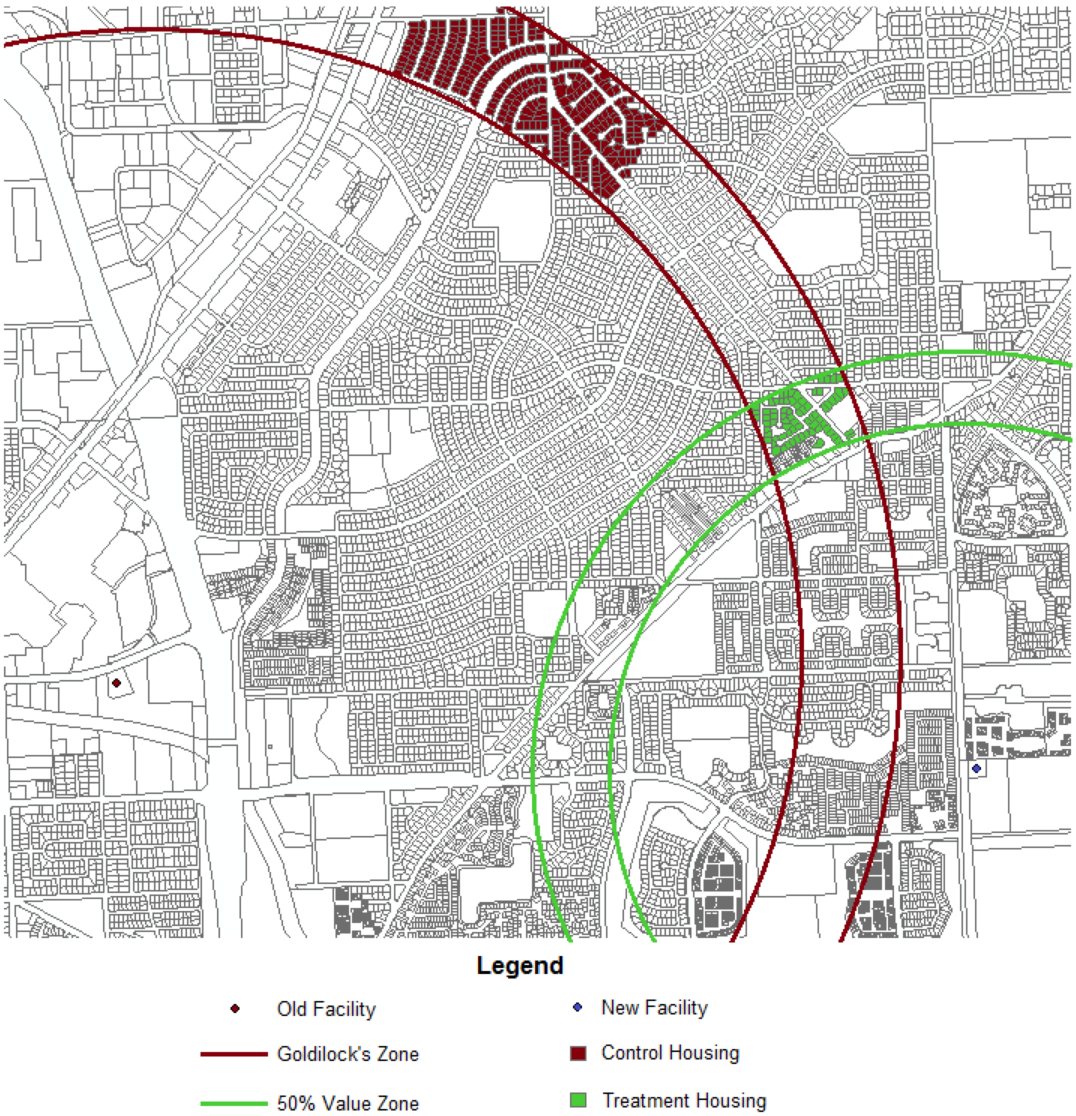

Figure 1.4: Illustration of control and treatment for DID regression groups.

living spaces less than 100 or greater than 50,000 square feet, lot sizes less than 100 square meters, and sales prices less than $1,000 or great than $15,000,000. Two sets of outliers were also removed as the underlying data generating process for them might be different than the bulk of the sample. Any homes built prior to 1900 were removed as well as homes in the 99th and 100th percentile of distance from the nearest CBD. These filters ultimately removed less than 6% of qualified home sales.

1.5 Results

Table 3 presents the estimated results for model (1) using both Euclidean and Network distance measures.[22] Both provide evidence in support of the expected relationship between service provision and home values. While the estimated magnitudes differ between the three different service categories, they all follow the same general pattern. As distance from the service station increases, on average, housing values tend to increase as disamenity effects diminish at a faster pace than the loss of the amenity of service provision. However, this effect is non-linear in nature and provided a large enough distance from the nearest station; housing values begin to level off and eventually decline. This was expected given the assumption that the utility loss from the disamenity effects eventually reach zero.

The magnitudes shown in Table 1.3 may at first glance appear to be small

[22] In general, every model version has high r^2 and expected results on the control variables. Lot size, living area, and coasts are both valuable to homeowners, but lot size and living area tend to see diminishing returns. Older homes are more likely to be worth less, though again, there is a diminishing effect of age on home values. These are similar in nature to prior research.

Table 1.3: Comparing Euclidean and Network distance results using model (1).

	Euclidean Model		Network Model	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Hospital Distance	2.29e-6***	4.82e-7	6.17e-6***	3.23e-7
Hospital Distance^2	-3.78e-10***	3.32e-11	-2.07e-10***	1.36e-11
Hospital Distance^3	8.99e-15***	6.42e-16	1.46e-15***	1.58e-16
Fire Distance	2.4e-5***	6.63e-7	2.23e-5***	4.82e-7
Fire Distance^2	-3.05e-9***	1.24e-10	-1.52e-9***	6.32e-11
Fire Distance^3	9.42e-14***	5.22e-15	2.94e-14***	1.94e-15
Police Distance	1.53e-5***	5.49e-7	1.86e-5***	4.27e-7
Police Distance^2	-1.53e-9***	5.99e-11	-1.07e-9***	3.73e-11
Police Distance^3	2.40e-14***	1.70e-15	1.79e-14***	8.61e-16
Total Living Area	5.1e-4***	4.94e-7	5.06e-4***	4.99e-7
Total Living Area^2	-2.16e-8***	6.08e-10	-2.14e-8***	6.14e-11
Lot Size	1.22e-5***	6.52e-8	1.2e-5***	6.56e-8
Lot Size^2	-6.98e-12***	6.69e-14	-6.82e-12***	6.69e-14
Age	-0.006***	3.47e-5	-0.006***	3.49e-5
Age^2	3.49e-5***	4.56e-7	3.23e-5***	4.58e-7
Elementary Distance	1.63e-5***	2.71e-7	1.19e-5***	2.7e-7
CBD Distance	8.98e-6***	7.86e-7	1.76e-6**	7.69e-7
CBD Distance^2	-4.05e-10***	3.22e-11	-2.32e-10***	3.18e-11
CBD Distance^3	4.91e-15***	3.82e-16	3.52e-15***	3.79e-16
Coast 5m	0.537***	0.002	0.531***	0.002
Coast 25m	0.485***	0.002	0.477***	0.002
Coast 50m	0.243***	0.003	0.233***	0.003
Coast 100m	0.117***	0.002	0.112***	0.002
Coast 200m	0.07***	0.002	0.065***	0.002
Coast 500m	0.031***	0.002	0.03***	0.001
Coast 1000m	-0.007***	0.001	-0.002	0.001
Coast 2000m	-0.015***	0.001	-0.009***	0.001
Observations	3309888		3273202	
R^2	0.821		0.821	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)
† All regressions include county, city, and time dummies.

in magnitude (especially the square and cubic coefficients). However, recall these effects are per meter variables. Given the average distance from each station type, most housing units experience a non-trivial effect. Figure 1.5 visually illustrates the implied effects of distance from service stations. Fire stations demonstrate that, all else equal, a house bordering a fire station will be approximately 5.7% less valuable than a home located approximately 2.2 miles away (the aforementioned Goldilock's Zone). Similarly, police stations tend to generate a 4% differential in house prices while hospitals generate a much smaller maximum differential at just .38%.[23]

[23] The distance measures start at 250 meters due to the use of a dummy variable to control for homes very close to facilities. When within 250 meters of a fire station, housing prices drop by another 1.5%, and 2.2% when near police stations. Hospitals however exhibit a positive proximity valuation of 4%, likely indicating the high value placed on the low response time

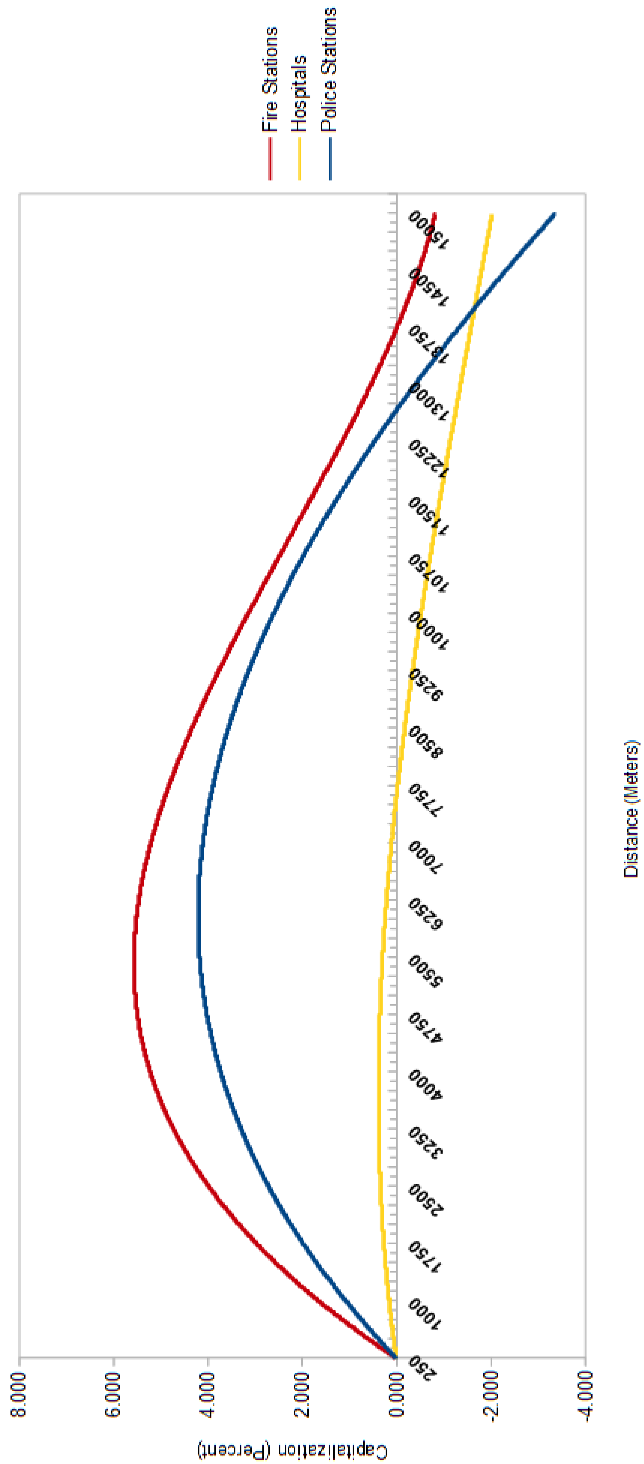

Figure 1.5: Capitalization effects based on Euclidean distance measures.

This likely indicates that the utility loss from a marginal change in response time for hospitals is much larger than for other service types. Such an effect may be expected if consumers value the service a hospital provides more than police or fire stations. Given that an emergency visit to a hospital is more likely to be a life-threatening situation compared to a fire or police response. Another possibility might lie with a differentiation regarding how hospitals provide their service. For fire and police stations, the emergency service is provided upon arriving at the home. However, while ambulances provide some level of service upon arriving at the home, most of a hospital's service provision occurs after the ambulance delivers the patient to the hospital - effectively doubling the response time for hospitals at any specific distance.

Table 1.4 compares the results for both measurement methods for each of the seven different subtypes of stations. Since each parcel has distance measures for each subtype, a special note should be made of the methodology utilized for model (2). For any home, only one distance measure was used for each subtype (i.e. three total, one each for fire, police, and hospital). All other distances were set to zero. As an example, take a home with a fire station 1,000 meters away and a volunteer fire department 10,000 meters away. That home's distance measure would be 1,000 for staffed fire stations and zero for volunteer fire departments. This prevents the home's distance measure to the volunteer fire department from creating untoward effects on the calculated volunteer coefficients. However, this distance measure of zero still has implications in that a measurement of zero has a specific meaning (i.e. bordering) when considering distance measures. Thus, an additional dummy variable was constructed for each subtype designated by a 1 if the distance measure is zero. Including

regardless of disamenities.

these dummies should help control for distance measures that are included in the regression, but that shouldn't be altering any coefficients given that this analysis is limited to only nearest station results. After controlling for these effects, the results are found to validate the proposed hypothesis once again. The coefficients associated with each subtype demonstrate increasing housing values at near distance measures followed by an inversion at farther distances. While the magnitudes may differ across each station subtype, they still each create the expected pattern of curvature as expected.

Given the differences between rural and urban service provision and relative distances, it is a logical step to split the sample into two groups to test whether the prior results are generally robust. Tables 1.5 and 1.6 present the results from taking models (1) and (2) and splitting them up into urban and rural samples.[24] Regardless of urban or rural classification, when considering the broadest definition of each service type, the results are found to be consistent with expectations. Each type's coefficients generate the now familiar 'hill' shape of housing values. In the case of urban hospitals, the level distance measurement is found to be statistically insignificant, but the squared term has become positive and the cubic term has become negative, thus still generating the expected housing value curvature.

Similarly, as shown in Table 1.6, when using the different subtype distance measurements, the results generally hold true. For urban locations, hospitals share a similar result wherein the level measure is not statistically different from zero, but the squared and cubic terms still have the expected signs. All other subtypes in urban areas are found to have the predicted signs. However, while in rural areas a similar case occurs with volunteer fire departments, both the police

[24]The urban designation what provided to any parcel within one of the 364 cities' municipal boundaries. All other parcels were classified as rural.

Table 1.4: Comparing Euclidean and Network distance results using model (2).

	Euclidean Model		Network Model	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Hospital Distance	2.42e-6***	4.84e-7	7.09e-6***	3.23e-7
Hospital Distance^2	-3.77e-10***	3.33e-11	-2.37e-10***	1.37e-11
Hospital Distance^3	8.89e-15***	6.45e-16	1.71e-15***	1.58e-16
Fire Stations	2.49e-5***	6.85e-7	2.2e-5***	5.09e-7
Fire Stations^2	-3.33e-9***	1.29e-10	-1.45e-9***	6.81e-11
Fire Stations^3	1.03e-13***	5.37e-15	2.76e-14***	2.13e-15
Fire Volunteer	2.5e-5***	2.76e-6	3.87e-5***	1.9e-6
Fire Volunteer^2	-2.11e-9***	5.08e-10	-2.92e-9***	2.28e-10
Fire Volunteer^3	1.03e-13**	5.37-15	6.33e-14***	7.71e-15
Police HQ	3.47e-6***	1.03e-6	1.1e-5***	6.9e-7
Police HQ^2	-5.65e-10***	1.22e-10	-6.72e-10***	5.93e-11
Police HQ^3	8.36e-15***	3.92e-15	1.26e-14***	1.36e-15
Police Sheriff	2.27e-5***	8.08e-7	1.9e-5***	5.53e-7
Police Sheriff^2	-2.42e-9***	9.74e-11	-1.04e-9***	4.72e-11
Police Sheriff^3	5.44e-14***	3.21e-15	1.75e-14***	1.09e-15
Police Substation	2.84e-5***	1.4e-6	1.81e-5***	1.13e-6
Police Substation^2	-2.79e-9***	1.83e-10	-7.43e-10***	1.17e-10
Police Substation^3	4.34e-14***	6.27e-15	1.24e-14***	2.97e-15
Police Other	6.61e-6***	1.20e-6	1.14-e-5***	9.48e-7
Police Other^2	-7.03e-10***	1.20e-10	-8.07e-9***	8.13e-11
Police Other^3	3.04e-15***	1.20e-15	-1.39e-14***	1.77e-15
Total Living Area	5.1e-4***	4.94e-7	5.07e-4***	4.99e-7
Total Living Area^2	-2.15e-8***	6.08e-11	-2.14e-8***	6.15e-11
Lot Size	1.22e-5***	6.52e-8	1.2e-5***	6.56e-8
Lot Size^2	-6.98e-12***	6.69e-14	-6.83e-12***	6.69e-14
Age	-0.006***	3.47e-5	-0.006***	3.49e-5
Age^2	3.49e-5***	4.56e-7	3.23e-5***	4.58e-7
Elementary Distance	1.65e-5***	2.72e-7	1.21e-5***	2.69e-7
CBD Distance	8.725e-6***	7.87e-7	9.46e-7	7.71e-7
CBD Distance^2	-3.97e-10***	3.23e-11	-2e-10***	3.18e-11
CBD Distance^3	4.86e-15***	3.83e-16	3.25e-15***	3.81e-16
Coast 5m	0.537***	0.002	0.531***	0.002
Coast 25m	0.484***	0.002	0.478***	0.002
Coast 50m	0.243***	0.003	0.234***	0.003
Coast 100m	0.117***	0.002	0.113***	0.002
Coast 200m	0.07***	0.002	0.066***	0.002
Coast 500m	0.031***	0.001	0.03***	0.001
Coast 1000m	-0.008***	0.001	-0.02	0.001
Coast 2000m	-0.016***	0.001	-0.009***	0.001
Observations	3309888		3273202	
R^2	0.821		0.821	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)

† All regressions include county, city, and time dummies.

Table 1.5: Urban vs. rural effects using model (1) with Euclidean distance measures.

	Urban		Rural	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Hospital Distance	-5.02e-7	8.12e-7	2.64e-6***	6.76e-7
Hospital Distance^2	1.76e-10**	7.00e-11	-4.7e-10***	4.38e-11
Hospital Distance^3	-3.27e-15**	1.48e-15	1.09e-14***	8.04e-16
Fire Distance	2.01e-5***	1.53e-6	2.43e-5***	8.86e-7
Fire Distance^2	-2.62e-9***	4.61e-10	-2.83e-9***	1.57e-10
Fire Distance^3	4.73e-14	3.75e-14	8.45e-14***	6.21e-15
Police Distance	2.47e-5***	1.15e-6	1.54e-5***	7.68e-7
Police Distance^2	-3.73e-9***	2.01e-10	-1.47e-9***	7.64e-11
Police Distance^3	1.49e-13***	9.43e-15	2.14e-14***	2e-15
Total Living Area	5.27e-4***	7.66e-7	4.91e-4***	6.63e-7
Total Living Area^2	-2.52e-8***	1e-10	-1.93e-8***	7.76e-11
Lot Size	2.25e-5***	1.77e-7	1.1e-5***	7.4e-8
Lot Size^2	-1.59e-11***	1.84e-13	-6.10e-12***	7.5e-14
Age	-0.007***	4.59e-5	-0.003***	6e-5
Age^2	4.89e-5***	5.38e-7	-4.19e-5***	1.06e-6
Elementary Distance	1.89e-5***	5.04e-7	1.39e-5***	3.45e-7
CBD Distance	1.07e-5***	1.27e-6	9.86e-6***	1.12e-6
CBD Distance^2	-3.88e-10***	6.30e-11	-4.45e-10***	4.29e-11
CBD Distance^3	4.31e-15***	9.04e-16	5.4e-15***	4.85e-16
Coast 5m	0.531***	0.003	0.544***	0.003
Coast 25m	0.472***	0.003	0.497***	0.004
Coast 50m	0.2***	0.003	0.294***	0.004
Coast 100m	0.119***	0.002	0.11***	0.003
Coast 200m	0.086***	0.002	0.049***	0.003
Coast 500m	0.041***	0.002	0.02***	0.002
Coast 1000m	-0.001	0.002	-0.013***	0.002
Coast 2000m	-0.011***	0.001	-0.019***	0.002
Observations	15128558		1797033	
R^2	0.857		0.794	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)

† All regressions include county, city, and time dummies.

Table 1.6: Urban vs. rural effects using model (2) with Euclidean distance measures.

	Urban		Rural	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Hospital Distance	-3.75e-8	8.16e-7	2.87e-6***	6.79e-7
Hospital Distance^2	1.40e-10**	7.05e-11	-4.67e-10***	4.4e-11
Hospital Distance^3	-2.9e-15*	1.49e-15	1.07e-14***	8.08e-16
Fire Stations	2.02e-5***	1.57e-6	2.54e-5***	9.18e-7
Fire Stations^2	-2.9e-9***	4.77e-10	-3.16e-9***	1.63e-10
Fire Stations^3	7.83e-14*	3.96e-14	9.4e-14***	6.4e-15
Fire Volunteer	6.91e-5***	6.77e-6	3.16e-6	3.45e-6
Fire Volunteer^2	-1.12e-8***	1.81e-9	2.03e-9***	6.23e-10
Fire Volunteer^3	4.35e-13***	1.34e-13	-1.16e-13***	3.03e-14
Police HQ	1.36e-5***	1.92e-6	-2.44e-6	1.97e-6
Police HQ^2	-2.40e-9***	3.92e-10	6.92e-11	1.9e-10
Police HQ^3	7.78e-14***	2.21e-14	-1.03e-14**	5.22e-15
Police Sheriff	2.35e-5***	1.99e-6	2.25e-5***	1.01e-6
Police Sheriff^2	-2.55e-9***	3.2e-10	-2.41e-9***	1.16e-10
Police Sheriff^3	8.6e-14***	1.39e-14	5.4e-14***	3.66e-15
Police Substation	5.7e-5***	2.43e-6	2.93e-5***	2.44e-6
Police Substation^2	-1.01e-8***	4.59e-9	-2.15e-9***	2.76e-10
Police Substation^3	4.54e-13***	2.35e-14	1.61e-14***	8.6e-15
Police Other	1.68e-5***	2.75e-6	1.77e-6	1.74e-6
Police Other^2	-1.93e-9***	4.84e-10	-6.16e-10**	1.57e-10
Police Other^3	9.54e-14***	2.15e-14	3.44e-14	3.44e-15
Total Living Area	5.26e-4***	7.66e-7	4.91e-4***	6.63e-7
Total Living Area^2	-2.52e-8***	1.e-10	-1.93e-8***	7.76e-11
Lot Size	2.25e-5***	1.77e-7	1.1e-5***	7.4e-8
Lot Size^2	-1.59e-11***	1.84e-13	-6.1e-12***	7.5e-14
Age	-0.007***	4.59e-5	-0.003***	6e-5
Age^2	4.89e-5***	5.39e-7	-4.2e-5***	1.06e-6
Elementary Distance	1.91e-5***	5.09e-7	1.42e-5***	3.46e-7
CBD Distance	1.01e-5***	1.27e-6	9.01e-6	1.12e-6
CBD Distance^2	-3.74e-10***	6.33e-11	-4.08e-10***	4.3e-11
CBD Distance^3	4.31e-15***	9.07e-16	4.98e-15***	4.86e-16
Coast 5m	0.531***	0.003	0.543***	0.003
Coast 25m	0.472***	0.003	0.496***	0.004
Coast 50m	0.2***	0.003	0.294***	0.004
Coast 100m	0.119***	0.002	0.109***	0.003
Coast 200m	0.085***	0.002	0.048***	0.003
Coast 500m	0.04***	0.002	0.019***	0.002
Coast 1000m	-0.002	0.002	-0.014***	0.002
Coast 2000m	-0.012***	0.001	-0.02***	0.002
Observations	1512855		1797033	
R^2	0.857		0.794	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)

† All regressions include county, city, and time dummies.

headquarters and police other categories only have statistical significance on one variable (the cubic and square term respectively). These results run counter to the hypothesis. Despite this, there may be an explanation. Relatively few police headquarters and other police structures in rural areas combined with larger average distance measures and sparse sales may lead to the reported statistical insignificance. There may also be concerns over the choice of defining urban and rural areas as strictly a jurisdictional divide. As evidenced by Jacksonville, the city's jurisdictional limits include nearly the entire county's land area, resulting in a number of parcels that observers may think of as rural being included in the urban designation. In either case, it must be cautioned, that these results likely hold in urban areas, but there may be more hesitation about the generality of these results as they might pertain to rural areas.

Tables 1.7 and 1.8 perform the same analyses utilizing Network distance measures instead of the standard Euclidean calculations. As before, both urban and rural areas demonstrate the expected signs and similar magnitudes as prior results have shown. While there is statistical insignificance for general fire stations at the cubic level in urban areas, the level and squared terms still create the predicted curvatures. When estimating these coefficients using station subtypes, both rural and urban areas are found to follow the principles laid out previously. Urban fire stations continue to demonstrate no asymmetric effects through the cubic coefficient, and the urban sheriff's offices also lose statistical significance on the cubic term. Each subtype those still has a positive level and negative squared term as expected.

The only unexpected result in rural areas stems from the positive squared term on police substations. These are also relatively sparsely found rural areas, however, the coefficient on the cubic term is negative, indicating that the results

Table 1.7: Urban vs. rural effects using model (1) with Network distance measures.

	Urban		Rural	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Hospital Distance	8.75e-6***	7.01e-7	4.03e-6***	4.66e-7
Hospital Distance^2	-3.82e-10***	4.73e-11	-1.63e-10***	1.83e-11
Hospital Distance^3	6.14e-15**	8.8e-16	1.07e-15***	1.92e-16
Fire Distance	1.46e-5***	1.1e-6	2.61e-5***	6.54e-7
Fire Distance^2	-1e-9***	2.23e-10	-1.58e-9***	8.17e-11
Fire Distance^3	-2.16e-15	1.24e-14	2.71e-14***	2.4e-15
Police Distance	2.21e-5***	8.95e-7	2.08e-5***	6e-7
Police Distance^2	-2.03e-9***	1.24e-10	-1.13e-9***	4.78e-11
Police Distance^3	6.42e-14***	4.81e-15	1.88e-14***	1.03e-15
Total Living Area	5.23e-4***	7.73e-7	4.85e-4***	6.68e-7
Total Living Area^2	-2.5e-8***	1.01e-10	-1.9e-8***	7.82e-11
Lot Size	2.36e-5***	1.82e-7	1.08e-5***	7.42e-8
Lot Size^2	-1.63e-11***	1.86e-13	-5.92e-12***	7.48e-14
Age	-0.007***	4.63e-5	-0.003***	6.02e-5
Age^2	4.77e-5***	5.42e-7	-4.69e-5***	1.06e-6
Elementary Distance	1.71e-5***	4.97e-7	9.17e-6***	3.42e-7
CBD Distance	-2.11e-6*	1.20e-6	8.8e-6***	1.12e-6
CBD Distance^2	2.03e-10***	6.04e-11	-5.75e-10***	4.31e-11
CBD Distance^3	-2.24e-15**	8.74e-16	7.3e-15***	4.89e-16
Coast 5m	0.523***	0.003	0.541***	0.003
Coast 25m	0.465***	0.003	0.49***	0.003
Coast 50m	0.193***	0.003	0.278***	0.004
Coast 100m	0.114***	0.002	0.108***	0.003
Coast 200m	0.079***	0.002	0.044***	0.003
Coast 500m	0.036***	0.002	0.023***	0.002
Coast 1000m	-2.26e-5	0.002	-0.002	0.002
Coast 2000m	-0.009***	0.001	-0.007***	0.002
Observations	1502792		1770410	
R^2	0.857		0.795	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)

† All regressions include county, city, and time dummies.

still expect a 'hill' shape with a steeper near slope than predicted. Given that police substations are generally highly active locations, consumer's utility may be more heavily penalized by locating near such stations. In such a case, it might be plausible for movements away from the station to generate larger utility gains than expected, especially if local consumers feel that there is little to gain from police services (i.e. rural locations might be correlated with lower levels of crime (Wells and Weisheit, 2004), thus diminishing the expected need for police).

Another possibility may be an externality-based story. For any fire truck or ambulance driving past a home, the act of driving past confers no direct benefit on the tenants. An ambulance traveling past a home does not alter the likelihood of a medical emergency in the future. Similarly, traffic from fire trucks will not change the probability of a house fire. However, Bahn (1974) and Sherman and Weisburd (1995) both provide evidence that increased police presence may have a dampening effect on local crime rates. If the mere presence of police traffic can have effect crime rates, then this may result in amenity and disamenity effects generating similar, but opposite effects. The outcome of this possibility is that it may become difficult to differentiate which economic effect is dominating, thus creating the aforementioned insignificant results.

As discussed in the prior section, the possibility exists that housing values may be a function of the underlying urban landform. If this were the case, then it could be that municipal choice of station locations may be driving the results, rather than the hypothesized service effects. A difference-in-difference analysis can be used to address this concern. If the underlying urban landform were generating these results, then the construction of a new station should have no impact on the value of homes in its service area. However, if the previous results

Table 1.8: Urban vs. rural effects using model (2) with Network distance measures.

	Urban		Rural	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Hospital Distance	1e-5***	7.03e-7	5.02e-6***	4.67e-7
Hospital Distance^2	-4.46e-10***	4.75e-11	-1.97e-10***	1.84e-11
Hospital Distance^3	7.08e-15***	8.83e-16	1.34e-15***	1.93e-16
Fire Stations	1.47e-5***	1.14e-6	2.6e-5***	6.94e-7
Fire Stations^2	-9.7e-10***	2.35e-10	-1.58e-9***	8.78e-11
Fire Stations^3	8.01e-15	1.33e-14	2.79e-14***	2.62e-15
Fire Volunteer	3.88e-5***	5.23e-6	3.73e-5***	2.35e-6
Fire Volunteer^2	-4.46e-9***	8.74e-10	-2.2e-9***	2.75e-10
Fire Volunteer^3	1.51e-13***	4.27e-14	4.12e-14***	8.64e-15
Police HQ	1.61e-5***	1.41e-6	9.94e-6***	1.22e-6
Police HQ^2	-1.36e-9***	2.15e-10	-5.83e-10***	8.82e-11
Police HQ^3	1.97e-14**	9.19e-15	1.19e-14***	1.79e-15
Police Sheriff	1.25e-5***	1.57e-6	2.19e-5***	7.15e-7
Police Sheriff^2	-5.78e-10**	2.24e-10	-1.15e-9***	5.76e-11
Police Sheriff^3	3.69e-15	9.03e-15	1.94e-14***	1.28e-15
Police Substation	2.89e-5***	1.69e-6	9.18e-6***	1.96e-6
Police Substation^2	-2.63e-9***	2.23e-10	6.75e-10***	1.82e-10
Police Substation^3	8.5e-14***	8.24e-15	-2.09e-14***	4.17e-15
Police Other	2.25e-5***	2.31e-6	9.43e-6***	1.35e-6
Police Other^2	-2.93e-9***	3.33e-10	-7.44e-10***	1.04e-10
Police Other^3	1.39e-13***	1.32e-14	1.36e-14***	2.14e-15
Total Living Area	5.24e-4***	7.73e-7	4.85e-4***	6.68e-7
Total Living Area^2	-2.5e-8***	1.01e-10	-1.9e-8***	7.82e-11
Lot Size	2.36e-5***	1.82e-7	1.08e-5***	7.42e-8
Lot Size^2	-1.63e-11***	1.86e-13	-5.94e-12***	7.48e-14
Age	-0.007***	4.63e-5	-0.003***	6.03e-5
Age^2	4.77e-5***	5.42e-7	-4.69e-5***	1.06e-6
Elementary Distance	1.81e-5***	5.01e-7	9.3e-6***	3.42e-7
CBD Distance	-2.97e-6**	1.21e-6	7.31e-6***	1.12e-6
CBD Distance^2	2.42e-10***	6.09e-11	-5.13e-10***	4.33e-11
CBD Distance^3	-2.62e-15***	8.79e-16	6.72e-15***	4.91e-16
Coast 5m	0.524***	0.003	0.5432***	0.003
Coast 25m	0.466***	0.003	0.49***	0.003
Coast 50m	0.193***	0.003	0.279***	0.004
Coast 100m	0.114***	0.002	0.109***	0.003
Coast 200m	0.08***	0.002	0.045***	0.003
Coast 500m	0.037***	0.002	0.023***	0.002
Coast 1000m	-3.79e-4	0.002	-0.002	0.002
Coast 2000m	-0.009***	0.001	-0.007***	0.002
Observations	1502792		1770410	
R^2	0.857		0.795	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)

† All regressions include county, city, and time dummies.

were the consequence of amenity and disamenity effects as predicted, then the construction of a new service station should cause housing values to change within the new station's service area.[25] To test for either of these possibilities, a comparison can be made between parcels that do not change their distance from the nearest station, and those whose distance is shortened by the construction of a new facility.

For the DID analysis, a band width and a band location must be chosen. The band locations can be generated from the prior estimation results. Specifically, the Goldilock's Zone was chosen as the starting point. As such, any parcels that already sit in the Goldilock's Zone will be compared to those that start in the same area, but have their distance to the nearest station reduced through new construction. The final destination band was calculated as the distance at which the station-specific effects on housing values had dropped by 50%.[26] An area of 500 meters was chosen (250 meters on each side of the band) around each band location to collect enough observations to run the DID without reducing the control variable count. However, this did result in low observation counts when using the Network model coefficients to calculate the band locations. To remedy this the band area was increase to a 1000 meter thickness (500 meters on each side of the chosen location band) for comparison purposes.

For a treatment analysis to be valid, both the treated and untreated groups should, on average, be statistically similar (or balanced) across each observable variable. The variable comparisons for fire stations can be found in Tables 1.10, 1.11, and 1.12. It should be noted however, that outside of the three variables in

[25]More specifically, if the underlying parcel is within the Goldilock's Zone or closer to the original station, then the construction of a newer, closer facility should on average reduce the house's value. If the parcel is further away, then a newly constructed facility would likely increase the home's price so long as the home doesn't 'jump' from the distance side of the Goldilock's Zone to the near side.

[26]See Table 1.9 for an overview of these distances.

Table 1.9: Band location choices for difference-in-difference models: Distance in meters

	Goldilock's Zone (Miles)	50 Percent Band (Miles)
Euclidean Fire	5175 (3.216)	1400 (0.87)
Network Fire	10600 (6.587)	2725 (1.693)
Euclidean Hospitals	3450 (2.144)	950 (0.59)
Network Hospitals	18525 (11.511)	5100 (3.169)
Euclidean Police	5800 (3.604)	1600 (0.944)
Network Police	12800 (7.954)	3275 (2.035)

the hospital DID, there are not statistically similar variables. At this point, the standard procedure would be to introduce a matching methodology to select a subset of the treatment analysis whose variables meet the balance requirements. Exact matching cannot be used due to a lack of perfectly similar treatment and control observations. Iacus, King and Giuseppe (2011*a*) provides a new methodology known as coarsened exact matching (CEM) to address this issue.[27]. Both non-matched and matched versions of the DID have been provided.

Table 1.10: Variable comparisons for Euclidean and Network fire models.

	500m Euclidean				1000m Network			
	Treated		Untreated		Treated		Untreated	
Variable	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error
log(Sale Price)	12.14	0.63	11.93	0.70	12.29	0.67	11.98	0.73
Living Area	2302.11	927.41	2252.87	823.18	2452.38	996.97	2296.01	859.40
Lot Size	1082.29	1903.54	2816.24	9870.28	1330.98	3491.29	5043.28	16302.60
Age	10.858	14.30	9.73	11.04	12.96	23.45	9.49	11.78
CBD Distance	17964.79	9387.53	25268.49	12411.51	20832.56	11492.77	29067.45	11967.31
Elementary Distance	1793.86	1427.01	2780.03	2609.89	2163.33	1764.62	3837.29	3337.21
In City	0.44	0.50	0.18	0.38	0.44	0.500	0.14	0.34
Observations	47099		53745		26562		11960	

* Denotes statistically indistinguishable means.

Table 1.13 presents the results of the difference-in-difference analysis for fire stations. The variable of interest, *Difference*, is both negative and statistically significant for both methods of distance measurement. This indicates that homes which were serviced by a newly constructed facility closer than their orig-

[27]See Iacus, King and Giuseppe (2011*b*) for a discussion of the statistical properties of CEM. CEM benefits from the ability to address any leftover imbalance issues by including control variables in the structural regression equation. Unfortunately, the CEM methodology is relatively data hungry making it difficult to assess the validity of smaller sample size questions. As such, the CEM methodology has only been used on the more observationally expansive Euclidean versions of the DID.

Table 1.11: Variable comparisons for Euclidean and Network hospital models.

	500m Euclidean				1000m Network			
	Treated		Untreated		Treated		Untreated	
Variable	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error
log(Sale Price)	12.37	0.88	11.84	0.75	12.09	0.68	11.87	0.80
Living Area	2008.46	1158.82	1934.88	945.62	2267.47*	892.47	2262.97*	1016.50
Lot Size	664.80	1232.74	1038.08	1720.14	1033.26	1355.04	2440.36	6065.77
Age	25.92*	20.52	26.72*	18.62	19.92	29.78	13.08	12.82
CBD Distance	14491.01	3616.08	17160.59	12441.32	23504.40	11486.47	24520.23	11717.39
Elementary Distance	972.89*	460.10	971.34*	700.19	1709.80	947.767	2912.51	2654.91
In City	0.90	0.30	0.62	0.48	0.56	0.50	0.24	0.43
Observations	3609		269506		8988		44763	

* Denotes statistically indistinguishable means.

Table 1.12: Variable comparisons for Euclidean and Network police models.

	500m Euclidean				1000m Network			
	Treated		Untreated		Treated		Untreated	
Variable	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error
log(Sale Price)	12.12	0.71	11.96	0.68	11.99	0.88	12.13	0.72
Living Area	2181.38	987.55	2275.75	859.28	2173.80	998.65	2390.965	918.33
Lot Size	1116.33	1522.93	1429.08	4598.08	1368.97	1916.78	2226.45	12655.80
Age	15.11	17.09	11.82	13.03	10.22	11.194	8.22	9.50
CBD Distance	17393.08	8573.93	22510.05	11714.70	22477.16	11580.18	27815.46	13472.40
Elementary Distance	1402.28	925.55	1801.92	1635.11	1340.19	1057.15	3268.50	2803.44
In City	0.59	0.49	0.25	0.43	0.46	0.50	0.12	0.33
Observations	16264		174529		11334		54115	

* Denotes statistically indistinguishable means.

inal fire station found their housing values to fall.[28] In this situation, it would be expected that housing values should decrease since any movement toward a station from the Goldilock's Zone will be generating greater traffic and noise disamenities while providing less utiliity from increased service provision. If the distance coefficients were merely the result of urban landforms, then the difference-in-difference should not be picking up a change in housing values. Importantly, the use of the CEM methodology corroborates these findings.

[28] Recall that included in the DID analysis are variables controlling for station type and quality. This is important, as failure to do so could mean that the measured effects were derived from a change in station-specific capability rather than distance variability.

Table 1.13: Difference-in-difference using fire distance measures.

	Non-Matched				CEM	
	Euclidean		Network		Euclidean	
Variable	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error
Difference	-0.032***	0.012	-0.109***	0.037	-0.031**	0.013
Treatment	0.039	0.025	0.123*	0.068	0.059*	0.03
State	0.003	0.009	0.018	0.034	0.017	0.011
Observations	100844		38522		83998	
R^2	0.782		0.829		0.805	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)
† All control variables used in the full sample regressions are included here.

Table 1.14: Difference-in-difference using hospital distance measures.

	Non-Matched				CEM	
	Euclidean		Network		Euclidean	
Variable	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error
Difference	-0.059**	0.027	-0.14***	0.051	-0.042*	0.021
Treatment	0.057	0.236	-0.806***	0.182	-0.011	0.207
State	-0.015*	0.008	0.016	0.022	-0.025*	0.014
Observations	273115		53751		117213	
R^2	0.878		0.82		0.92	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)
† All control variables used in the full sample regressions are included here.

For hospitals, Table 1.14 provides evidence of the expected result; negative and statistically significant effects. The construction of new hospitals has, on average, resulted in a decrease in house prices for those parcels serviced by the new stations. Using CEM continues to provide similar results as the DID analysis.

The difference-in-difference results for police stations are in Table 1.15. Unfortunately, newly constructed police stations are found to have a negative but *statistically insignificant* effect on housing values. This indicates that nonrandom station location choices may be at least partially driving the police station results found in Tables 1.5 through 1.9. Indeed, this finding may indicate why the police station results for rural areas in Table 1.7 do not completely conform to the predicted hypothesis. While this does not necessarily negate the prior findings, it does mean that there might an opening for future research to address this issue. After accounting for imbalance, the CEM method finds statistically significant results of the sign expected when considering Euclidean distance measures.

Table 1.15: Difference-in-difference using police distance measures.

	Non-Matched				CEM	
	Euclidean		Network		Euclidean	
Variable	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error
Difference	-0.001	0.013	-0.024	0.029	-0.025*	0.013
Treatment	-0.241***	0.053	-0.272	0.256	-0.429***	0.058
State	-0.005	0.006	0.027	0.02	0.002	0.01
Observations	190793		65449		93610	
R^2	0.792		0.8		0.874	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)

† All control variables used in the full sample regressions are included here.

1.6 Conclusion

While previous research into the capitalization effects of emergency public services has been elusive, this paper represents a step forward in uncovering the effect of station distance on local housing values. The work here may be useful to scholars as well as urban planners and local developers when considering new service station and housing development locations. Of particular interest may be the overall effects that station placement can have on the local property tax base. While any single individual home's price may not see intensive price changes; given the large numbers of homes that even a single facility will service, this can amount to a rather large total economic effect.

These regressions indicate that fire stations and hospitals by and large follow the hypothesized non-linear effects which will create "Goldilock's Zones". These results are supported by the difference-in-difference analyses, which provide evidence that home prices change with the construction of new facilities as opposed to being a spurious result of underlying urban landforms. While considerable evidence suggests that police stations also follow the predicted hypothesis, the difference-in-difference analysis on police stations cannot rule out the possibility of spurious results.

Additionally, by utilizing the majority of the state of Florida, the results herein should be generalizable to other locations. This is also supported by results indicating relative robustness to urban versus rural locations. Importantly, the results provided uphold the establishment of the hypothesized location based amenity-disamenity relationship. While additional research may be needed to establish the magnitudes of these relationships in other counties or states, it should be possible to identify other "Goldilock's Zones" elsewhere. The methodology here can also be generalized to investigate other locations than may generate both positive and negative economic effects such as airports, industrial plants, sports stadiums, etcetera.

For scholars and governments interested in better understanding the capitalization effects of local public services, this study indicates that service location has a meaningful effect on nearby housing values. Even homes two or three miles away from service stations have valuations that still react to the proximity of service locations. Future work on housing capitalization effects should consider these nuanced location effects. This may be particularly important when considering the extensive coverage of all three types of services. It may be interesting to explore other definitions of urban and rural areas, as well as comparing the non-linear effects across different urban boundaries. There may also be valuable future studies utilizing a third measure of service provision; true response times. These measures are slowly becoming more reliable as technology spreads deeper into public service provisioning.

Chapter 2

Non-Residential Capitalization Effects

Past research in the capitalization literature has focused on the effect of services on housing values. The majority of this work has concentrated on single-family detached housing. While there are many more single family houses than commercial properties across the United States, commercial construction is worth much more relative to its proportionate size.[1] For example, in Florida, nearly twenty times as many residential (141,014) structures were sold as compared to non-residential (7,183) structures. However, the residential land in total was only worth three times as much as the non-residential land. As such, a valuable contribution to the literature would be to similarly consider the effects of public service access on non-residential property values. Specifically, this paper will focus on fire, police, and emergency medical facilities and their effects on commercial and industrial property sales prices. In particular, the analysis will focus on how service facilities may differentially impact property values based on the designated use of the non-residential building. In addition, the analysis will include distance measures rarely used in the literature before; road-based measures (also known as a network analysis) to accompany than the more standard straight-line, Euclidean distance. The use of road-based measures allows for

[1]See U.S. Census Bureau, Statistical Abstract of the United States: 2012.

the analysis to more accurately control for the distance that emergency vehicles must cover to arrive at their destination.

The level of service that a parcel may receive can be broken down into two major components, *in situ* service and response time. *In situ* service is the level of service that a facility can directly provide to a location. This would include quality measures such as training and equipment. Interestingly, this measure of service would be expected to be constant over each station's service area. In essence, regardless of how far away a fire station is, once it arrives on location, it can provide the same level of service to a home one mile away or one ten miles away. However, response time is also an important determinant of service provision. Longer response times tend to correlate with degraded outcomes in emergency situations[2]. Similarly, the expected loss from a fire would tend to increase if the fire can burn for longer periods of time before a fire crew can arrive on site. This is why many insurance companies include distance from the nearest fire station in generating their cost structures for fire insurance (Brueckner, 1981). Thus, the three types of public goods analyzed here provide services that can be defined as a function of the response distance.

However, while these services provide valuable amenities, they also generate disamenity effects as well. Emergency vehicles en route to a dispatch call will tend to create traffic congestion on the roads they drive through as well as producing noise pollution from active sirens. As these effects are undesirable to many businesses, locations more likely to suffer from such negative effects should find their property values falling relative to locations that receive lower probabilities of these disamenity effects. These negative effects may vary from business to business, not just based on distance from the service facility, but also

[2] See Blackwell and Kaufman (2002) and Pons et al. (2005)

upon the type of business at the location. Some commercial structures such as golf courses may have intense preferences for lower noise pollution compared to industrial manufacturing plants where additional noise may be less of a concern. In such a case, it may be expected that non-residential structures preferring less noise pollution will be more adversely affected by emergency vehicle traffic, resulting in negative capitalization effects of a larger magnitude than those businesses with less intensive preferences. Similarly, some business that utilize more dangerous materials may prefer faster response times from emergency vehicles.

The following analysis provides two contributions to the literature on non-residential capitalization effects. Access to fire stations, police stations, and hospitals are found to correlate with commercial and industrial land prices. Given the value of each parcel of land, these effects are non-trivial in nature. In addition, strong heterogeneous effects are found, not just between commercial and industrial property land use designations, but also between the three different emergency services. For example, camping ground and race tracks tend to show relatively weak preferences (land prices increasing) for being located further away from fire stations and hospitals, but demonstrate much stronger preferences for being closer to police stations. On the other hand nightclubs, bars, and other adult-oriented entertainment venues tend to see their property values fall the further away they are from fire stations and hospitals, however, these same land values increase as with distance from police stations.

The paper is organized as follows. Prior research on non-residential spatial capitalization effects are covered in Section I. Information on the data utilized can be found in section II. Methodology and results are reported in Section III and Section IV respectively. Section V concludes.

2.1 Literature Review

Prior research on capitalization effects with respect to non-residential structures can be broadly linked into three categories, spacial locations[3], transportation access, and land usage. The literature on non-residential valuations is extensive. As such, the following is not an exhaustive review of prior research.

Spatial research has largely focused on the importance of location with respect to Central Business Districts (CBDs), or other large employment centers, and micro-locational effects. Downing (1973) uses data from Milwaukee, Wisconsin to analyze some of the main determinants to commercial land values. The data contained sales from over 400 businesses, and considered measures for distance to CBD, distance to the nearest shopping center, traffic levels on Main Street, and corner locations. Downing finds that for the city as a whole, nearby traffic levels were the only statistically significant and positive predictors. However, in certain sections of the city, distance to CBD and shopping center were also positively correlated with commercial land value. In an effort to determine the specific value of CBD distance on non-residential valuations, Sivitanidou (1996) considers how commercial structures (specifically office space) value access to employment centers. The study demonstrates that office-commercial land is positively correlated with CBD and large employment access. Additionally, the work provides evidence for jurisdiction-specific and crime rate effects. Importantly, crime rates are found to fall with the addition of more frequent police car sightings, indicating that business closer to police stations are likely to see positive externalities associated with increased local patrolcar presence.[4] Interestingly, Schmenner (1981) indicates that distance to the CBD matters lit-

[3]See Guntermann and Thomas (2005).
[4]See Bahn (1974).

tle for manufacturing rents. Using survey data from 535 manufacturing firms to explore the rental gradient of manufacturing plants, the study finds evidence that industry does not appear to compete for land in or near the CBD, but instead observe relatively flat rent gradients across cities.[5] This highlights the importance of considering differential effects based on land usage rather than performing an analysis that lumps all non-residential structures into one category.

More recent work on the effects of transportation access can be found in Cervero and Duncan (2002), Kim and Zhang (2005), and Debrezion, Pels and Rietveld (2007). In general, most transportation access research has found positive and significant effects on commercial land values. These range from 12% to 25% outside of CBD areas to as high as 120% in CBD areas. Kim and Zhang's work focuses on subway stations in Seoul and their effect on 731 commercial locations. As noted, their paper found large positive valuation effects for locating in and near the CBD, but also found that commercial structures were positively effected by subway access as well. Using a meta-analysis procedure Debrezion et. al. find positive values associated with commercial structures based on distance from the nearest railway station as well. Additionally, Ryan (2005) uses data from San Diego to explore the effects of light rail and highways on office and industrial firm values. Ryan's findings complement prior research demonstrating the importance of transportation access to commercial and office structures. However, the author also finds that industrial firms receive no rent premium for locating close to highways or rail stations.

Land use regulation has also been an extensive area of study. As noted by Hanushek and Quigley (1990), land use regulations targeting non-residential

[5] See also Kowalski and Paraskevopoulos (1990) and Peiser (1987) for a more in depth discussion of industrial capitalization effects.

structures have been found to correlate with increased land values. This is often argued to be a result of local zoning rules attempting to limit low income businesses or pushing for high profitability firms. Given that higher profit firms are likely to bid land values up (and therefore property values), local municipalities face fiscal incentives to actively manage land use regulations. Asabere and Huffman (1991) use data from Philadelphia to demonstrate that the act of rezoning a location for industrial use can be associated with a 58% drop in land value.

This paper contributes to the literature by investigating effects from three previously ignored types of services; fire, police, and hospital. These stations provide valuable services to their local communities, but they have seen little consideration in the literature. In addition, the literature demonstrates the importance of different types of land use on capitalization effects, indicating that firm preferences are a vital component to consider in any land value analysis. Thus, this paper not only discusses the value these locations place on service access, but also considers how assorted categories of firms may receive differential effects from service stations.

2.2 Data

To investigate the effects of fire stations, police stations, and hospitals on non-residential property, an extensive database has been collected across the state of Florida. The Florida Department of Revenue (FDOR) has provided tax rolls that contain detailed information on each parcel of land, including building characteristics such as lot size, building square footage. In addition, the tax rolls have information on the sales price, time, and land usage classification.

The database contains all arms-length transactions from 1994 until 2011. Eight counties were dropped from the analysis due to issues resulting from unique parcel ID changes during the period.[6]

The Florida Division of Emergency Management (FDEM) maintains a database of emergency services, including information on their capabilities as well as their latitudinal and longitudinal coordinates.[7] Hospitals are the least common and most concentrated in urban areas. Many rural counties have only a single hospital facility to serve their region. The geographic coverage of fire and police stations is far more extensive. Fire stations especially are widely scattered and numerous compared to EMS. All three services display agglomeration tendencies in urban areas, thus indicating the importance of controlling for central business district effects. By combining the FDOR tax rolls with data from FDEM, it becomes possible to calcaulate the Euclidean distance from each non-residential parcel in the state of Florida to nearby emergency service stations. In addition, the U.S. Census Bureau has made available Geographical Information Systems (GIS) data that plots the location of all roads in the state as of 2010. The Census Bureau data can be used to run the network analysis, providing detailed road-based distance measures for all commercial and industrial businesses.

Figure 1.1 shows the location of every fire station within the state of Florida. With almost 2,000 fire stations, large portions of the state, especially populated areas, are within close proximity of a station. Police station locations can be found in Figure 1.2. Many of the more rural areas can be seen to be serviced by just a handful of police structures, oftentimes by small sheriff offices. Urban areas are still well covered by police stations. As can be seen in Figure 1.3 how-

[6]These are; Escambia, Highlands, Hillsborough, Holmes, Levy, Liberty, Santa Rosa and Volusia.

[7]The FDEM location data covers 1,917 fire stations, 992 police stations, and 483 hospitals.

ever, the limited number of hospitals means that rural non-residential structures may find themselves a great distance from the nearest hospital. There are still relatively strong agglomerations in the larger urban areas along the coasts in the southern half of the state.

Additional control variables have been provided by the University of Florida GeoPlace Center (UFGC) and the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) databases. The UFGC provides extraordinarily detailed information on coastal data. While the literature suggests that industrial land are less likely to be effected by coastal locations, commercial and office structures may have a preference for coastal locations, particularly hotels and motels. Measurements for creating dummy variables were used for structures within 5, 25, 50, 100, 200, 500, 1000, and 2000 meters of the coast. As noted in the literature, distance from the CBD can have a large effect on commercial values, especially office buildings. Therefore, the LEHD database was used to find the highest employment centers in each of the Census designated Metropolitan Statistical Areas (MSA). Distance from the census tract with the highest employment density were used to calculate distance from the CBD.[8]

Given that not all service stations will have the same equipment and training, dummy variables are utilized to help control for station specific characteristics. However, this does not address the fact that certain groups of stations may have differential slope effects as well. Therefore, each distance measure was calculated not just to the nearest fire station, police station, and hospital; but also to each of these different types of stations as well. For example, larger urban fire stations likely have different amenity and disamenity effects on

[8] Orange County, home of Orlando, used the *second* highest employment density tract. Interestingly, Disney World contains the highest employment center in the county, but is not located in the downtown area.

Table 2.1: Select summary statistics.

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Sales Price ($)	1012531	873128	4072400	5000	448000000
Building Area (sq. ft)	1012531	14366	49526	10	5021883
Lot Size (sq. m)	1012531	8646	45620	5.3	7160417
Age (years)	1012531	27.95	17.71	1	108
In City (dummy)	1012531	0.68	0.47	0	1
Distance to CBD (m)	1012531	20810	22371	0	176898
Euclidean Hospital Distance (m)	1012531	6581	9130	4.96	96446
Euclidean Fire Distance (m)	1012531	1788	1637	0.47	24268
Euclidean Police Distance (m)	1012531	3000	4558	0.32	65565
Network Hospital Distance (m)	1012531	6768	6559	4.96	96449
Network Fire Distance (m)	1012531	2348	2065	0.06	30513
Network Police Distance (m)	1012531	3795	5170	0.67	67622

non-residential land value than the less common, typically rural volunteer fire departments. Similarly, police stations also have several categories, including police headquarters, substations, and sheriff offices. A fourth police category (labeled as ‘other’) was used to combine the largely federal stations such as Alcohol, Tobacco, and Firearms (ATF), Department of Fish & Wildlife (DFW), and customs agencies with state highway patrol facilities. Using these distance measures it is possible to investigate how different types of stations can cause differential capitalization effects on nearby non-residential structures. See Table 2.1 for select summary statistics.

2.3 Methodology

For the analysis performed here, special attention will be paid to the land use codes each parcel is designated with. These land use codes identify the category of improved structure that exists on the parcel. These codes can be fairly precise, not just differentiating between commercial and industrial property, but even to the point of noting differences between food packing plants and food processing plants. To capture the specific station effects of interest here, a cross-sectional hedonic regression analysis will be utilized. The model is as follows:

$$(1) \quad log(P_{i,t}) = D_i + L_i + S_i + X_i + U_i + V_t + \epsilon_i$$

Where P is the sales price of parcel i in year t. The variable of interest is D_i which contains a vector of distance measurements to the service station type under consideration. This variable includes the level, square, and cubic distance terms. The vector L_i indicates a set of dummy variables for defining different land use codes. X_i is a set of control variables describing the physical structure such as lot size, structure size, and age. S_i contains a set of station dummy variables for each station type to account for differential effects based on each facilities' *in situ* service quality. The variables U_i and V_t control for various geography and time, respectively. U_i contains city, county, and census tract location controls while V_t controls for sales month and year. However, firms likely have differential preferences for locating near these services. This method fails to account for the possibility that each land use type may have differential slopes for their capitalization effects.

A second method utilizes the land use codes along with a set of interaction terms to provide a more nuanced view of the effects of distance on non-residential sales prices. The following model includes the interaction terms of interest:

$$(2) \quad log(P_{i,t}) = D_i + S_i + T_i + X_i + L_i + (D_i * L_i) + (D_i * Z_i) + U_i + V_t + \epsilon_i$$

Here, the interaction term D_i*L_i is the variable of interest. It contains coefficients that allow for different effects on each land use type. 22 different land use types for commercial structures will be considered along with another 8 industrial categories. Each category will be independently interacted with the distance measures to retrieve specific distance based capitalization effects. Given that prior research has demonstrated that distance to the CBD is correlated with land prices for commercial structures, particularly office buildings, but generally or weakly correlated with industrial values, a second set of interaction terms are included in $D_i{*}Z_i$. This set interacts the land usage types with distance to CBD measurements and the coastal location dummies. This allows for differential effects amongst the different land designations. The coastal measures are included given that one might believe that hotels and motels more strongly prefer coastal locations than industries.

A third method of analysis includes a consideration of land use code changes. The tax roll data provided by the Florida DOR has data on every parcel in the state for every year. While only a portion of all parcels will be sold during any one time period, information on each parcel is still recorded over time. This creates the capability to track any sales that may have resulted in the underlying structure changing from one land use code to another. For example, a parking lot (land use code 028) may be sold to an entrepreneur interested in building a restaurant (land use code 021) on that site. If the lot sells in 1997, the tax rolls will identify the sale price, date, and the old land use code of 028. If the restaurant construction is approved by the municipality, then the next year, the land use code will change to 021. While the tax rolls only identify another sale for that parcel if the restaurant is eventually sold, these land use code changes can be a way to identify disamenity effects by land use type. In addition, these land use changes can be tracked both forward, and backward in time to better understand how land usage types may react to service station locations.

Finally, of particular interest here, is that each of these methods will include both standard Euclidean measures of distance from the stations, but also a network analysis. This addition provides for more accurate measures of response capability for emergency services. Given that emergency vehicles must use the road network to respond, straight-line measures of distance may be inaccurate for representing the ability of these stations to provide a specific level of service. This is particularly true given that road based distance measures will almost always be longer than Euclidean measures, indicating that using straight-line distances will generally under represent (and thus may bias results) response times.

2.4 Results

Table 2.2 provides a breakdown of land designations and their sales prices. While there are some designations with relatively thin sales counts such as open air entertainment (91), others contain a wealth of sales. Single story stores account for 18 percent of all sales, with non-professional services offices making up another 14 percent. In general, far more commercially designated land sold over this period than industrial land. Golf courses are the most valuable plots of land per sale, followed by tourist attractions, and malls and regional shopping centers. The least valuable land is occupied by florists and greenhouses.

The results of using model (1) with both Euclidean and Network distance measures can be found in Table 2.3. Table 2.3 shows the effect of each land designation category on land values. Given that industrial warehousing and storage is the omitted variable, most land types are more highly valued than warehousing land. Three are worth less; mixed office and retail, professional services, and produce housing. As might be expected, land designated for golf courses is highly valued, as are hotels, and malls and shopping centers. As

Table 2.2: Land usage categories and sales prices.

Commercial	Number	Average Price	Price Per ft^2
(1) Single Story Stores	184386	512986	117
(2) Mixed Store and Offices	77871	266814	126
(3) Department Store/Supermarkets	11333	1900335	115
(4) Malls and Shopping Centers	26975	3639243	97
(5) Non-Professional Service Offices	147480	1029286	207
(6) Professional Service Buildings	65946	531908	234
(7) Transportation Terminals	2785	1285756	1084
(8) Restaurants	58687	859391	234
(9) Financial and Insurance	20882	1377801	283
(10) Repair, Service, and Auto Sales	103447	553760	172
(11) Parking Lots/Mobile Home Sales	31180	1184791	6384
(12) Outlets and Produce Houses	3465	376663	61
(13) Florists and Greenhouses	1876	138614	75
(14) Open Air Entertainment	91	525774	183
(15) Enclosed Auditoriums/Theaters	969	1996806	137
(16) Nightclubs and Bars	9721	372845	113
(17) Daytime Attractions/Arenas	2483	836509	126
(18) Tourist Attractions	2033	4478406	345
(19) Camps	2475	781720	735
(20) Racing	315	903367	354
(21) Golf Courses	10639	6062071	4984
(22) Hotels or Motels	32428	2128807	147
Industrial			
(23) Light Manufacturing	60167	532046	41
(24) Heavy Manufacturing	2973	1085721	65924
(25) Lumber Yards/Sawmills	2422	485157	64
(26) Food Packing Plants	2441	530035	66
(27) Canneries/Distilleries/Wineries	617	931556	175
(28) Food Processing	1470	693930	76
(29) Mineral Processing	2288	1056428	289
(30) Warehousing and Storage	142686	685858	63

Table 2.3: Euclidean and Network distance results using Model (1).

	Euclidean Model		Network Model	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Land Use (1)	0.13***	0.004	0.13***	0.004
Land Use (2)	-0.23***	0.005	-0.23***	0.005
Land Use (3)	0.60***	0.010	0.60***	0.010
Land Use (4)	0.89***	0.007	0.89***	0.007
Land Use (5)	0.02***	0.004	0.02***	0.004
Land Use (6)	-0.02***	0.005	-0.03***	0.005
Land Use (7)	0.36***	0.021	0.28***	0.021
Land Use (8)	0.41***	0.005	0.41***	0.005
Land Use (9)	0.61***	0.008	0.06***	0.008
Land Use (10)	0.12***	0.004	0.12***	0.004
Land Use (11)	0.54***	0.007	0.54***	0.007
Land Use (12)	0.13***	0.017	0.14***	0.017
Land Use (13)	-0.27***	0.023	-0.25***	0.023
Land Use (14)	0.55***	0.103	0.56***	0.103
Land Use (15)	0.56***	0.032	0.60***	0.032
Land Use (16)	0.09***	0.011	0.09***	0.011
Land Use (17)	0.33***	0.020	0.32***	0.020
Land Use (18)	0.18***	0.023	0.20***	0.023
Land Use (19)	0.64***	0.023	0.68***	0.023
Land Use (20)	0.23***	0.058	0.22***	0.059
Land Use (21)	0.95***	0.016	0.94***	0.016
Land Use (22)	0.75***	0.007	0.74***	0.007
Land Use (23)	0.08***	0.005	0.08***	0.005
Land Use (24)	0.15***	0.019	0.14***	0.019
Land Use (25)	0.31***	0.020	0.32***	0.020
Land Use (26)	0.26***	0.021	0.26***	0.021
Land Use (27)	0.65***	0.041	0.64***	0.042
Land Use (28)	0.06**	0.026	0.06**	0.026
Land Use (29)	0.33***	0.023	0.33***	0.022
Observations	1012531		1012531	
R^2	0.586		0.595	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)

expected, building size and lot size are both positive and statistically significant, given that larger tracts of land and buildings will generally cost more. Both have decreasing returns though, as noted by the negative squared terms on each. While the literature generally finds little correlations between industrial land price and CBD distance, the statistical significance found here can be accounted for the much larger number of commercial structures compared to industrial land. As prior research has indicated, moving away from the CBD is associated with a drop in the value of land. Similarly, coastal locations are highly valuable; even for non-residential structures, but this effect falls off once a plot of land is half a mile or more inland.

Both the Euclidean and Network distance measures show similar signs on the distance variables of interest. Land values are positively correlated with hospital and fire station distance. This indicates that movement away from these stations will lead to positive capitalization effects. The negative sign on police stations shows that land values are negatively correlated with distance away from police stations. In other words, on average, non-residential structures prefer to be further away from hospitals and fire stations, but closer to police stations. Essentially, the loss of disamenity effects from noise, traffic congestion, and unsightly buildings tend to dominate the loss of amenity affects from fire stations and hospitals. Note that the negative coefficient on the square terms for hospitals and fire stations does indicate that this movement away has a diminishing effect, and eventually reverses course. This likely corresponds with the point at which the disamenity effects generated by the station have basically reached zero. However, police stations provide enough value (or conversely, they have a smaller negative 'footprint') that, all else being equal, non-residential land values will be higher near police stations. This particularly make sense if commercial or industrial structures are targeted by criminals at a relatively high rate compared to the likelihood of accidents or fire.

As previously noted though, each land use designation may have its own preferences for distance from these stations. Table 2.5 provides a summary of model (2) with Euclidean distance measure to analyze how each land use category effects land prices with respect to the distance from the nearest fire station.[9] 9 of 22 commercial land designations are found to have a positive correlation between distance from the nearest fire stations and land prices. These nine categories; single story stores, malls, restaurants, produce and flora businesses, tourist attractions, racing, golf courses, and hotels, all evidence a preference for

[9]Network distance measurements using model (2) found nearly identical results.

Table 2.4: Continued Euclidean and Network distance results using Model (1).

	Euclidean Model		Network Model	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Hospital Distance	3.78e-5***	2.42e-6	3.09e-5***	2.55e-6
Hospital Distance^2	-1.60e-9***	1.13e-10	-1.81e-9***	1.68e-10
Hospital Distance^3	1.48e-14***	1.04e-15	2.22e-14***	2.42e-15
Fire Distance	1.36e-5***	3.68e-6	5.42e-6*	3.03e-6
Fire Distance^2	-3.46e-9***	7.78e-10	-1.76e-9***	4.87e-10
Fire Distance^3	1.22e-14***	3.48e-14	4.47e-14***	1.67e-14
Police Distance	-1.02e-5***	2.50e-6	-9.27e-6***	2.26e-6
Police Distance^2	-6.34e-11	2.11e-10	-1.39e-10	1.78e-10
Police Distance^3	-1.00e-15	3.07e-15	1.14e-15	2.63e-15
Building Size	1.00e-5***	3.24e-8	1.01e-5***	3.23e-8
Building Size^2	-3.07e-12***	1.49e-14	-3.07e-12***	1.48e-14
Lot Size	4.35e-6***	3.88e-8	4.37e-6***	3.92e-8
Lot Size^2	-9.75e-13***	1.69e-14	-9.70e-13***	1.60e-14
Age	-1.92e-4	1.89e-4	-1.66e-4	1.89e-4
Age^2	-8.66e-5***	2.37e-6	-8.66e-5***	2.37e-6
CBD Distance	-2.81e-6	2.02e-6	-1.05e-5***	2.66e-6
CBD Distance^2	-1.93e-10***	6.48e-11	1.46e-10**	7.07e-11
CBD Distance^3	9.04e-16**	4.16e-16	-9.13e-16**	4.38e-16
Coast 5m	0.607***	0.012	0.671***	0.013
Coast 25m	0.447***	0.015	0.494***	0.015
Coast 50m	0.333***	0.014	0.376***	0.014
Coast 100m	0.218***	0.012	0.257***	0.012
Coast 200m	0.202***	0.010	0.249***	0.011
Coast 500m	0.067***	0.009	0.106***	0.010
Coast 1000m	0.007	0.009	-0.040***	0.009
Coast 2000m	-0.018**	0.008	0.007	0.008
Observations	1012531		1012531	
R^2	0.586		0.595	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (All distances measured in meters.)

Table 2.5: Euclidean fire station distances using interaction terms.

Land Use	Fire Distance	Fire Distance^2	Fire Distance^3
(1) Single Story Stores	+*	+	-
(2) Mixed Store and Offices	-*	+*	-*
(3) Department Store/Supermarkets	-*	+	-
(4) Malls and Shopping Centers	-	+*	-*
(5) Non-Professional Service Offices	-*	+*	-*
(6) Professional Service Buildings	-*	**	-*
(7) Transportation Terminals	-*	+	-
(8) Restaurants	+*	-*	+*
(9) Financial and Insurance	-*	+*	-*
(10) Repair, Service, and Auto Sales	-*	+*	-*
(11) Parking Lots/Mobile Home Sales	-*	+	+
(12) Outlets and Produce Houses	-	+*	-*
(13) Florists and Greenhouses	+*	-*	+*
(14) Open Air Entertainment	+	-	+
(15) Enclosed Auditoriums/Theaters	+	-*	+*
(16) Nightclubs and Bars	-*	+*	-*
(17) Daytime Attractions/Arenas	-*	+	-
(18) Tourist Attractions	+*	-*	+*
(19) Camps	+	-	-
(20) Racing	+	-	+*
(21) Golf Courses	+*	-*	+*
(22) Hotels or Motels	+*	-*	+*
(23) Light Manufacturing	-	+*	-*
(24) Heavy Manufacturing	+	-*	+*
(25) Lumber Yards/Sawmills	-*	+	-*
(26) Food Packing Plants	+*	-*	+*
(27) Canneries/Distilleries/Wineries	+*	-*	+*
(28) Food Processing	+*	-*	+*
(29) Mineral Processing	+*	-*	+*
(30) Warehousing and Storage	-*	+*	-*

*: $p < 0.10$ (Full results available upon request.)

being further away from fire stations where possible. Each of the other 13 land use categories have land values that increase with proximity to a fire station, or are uncorrelated with distance.

Industrial land prices correlate positively, on average, with increasing fire station distance. Land prices increase with distance from the nearest fire station for five of the eight industrial designations; light manufacturing, food packing and processing, distilleries and wineries, and mineral processing. Only heavy manufacturing, lumber yards, and warehousing had strong preferences for locating near fire stations. These three industrial land designations possibly encompass the types of structures that house activities that may be more susceptible to fire or injury.

As can be seen, even within the broad definition of commercial or industrial land usage, there are heterogeneous effects. Even the magnitude of these capitalization effects differ from one land use category to the next. Figure 2.4 compares two somewhat similar retail buildings, restaurants versus nightclubs and bars. Nightclubs and bar are correlated with higher prices the closer they are to a fire station, however, restaurants see the value of the land increase when moving *further* away from a fire station. The average non-residential valuations with respect to fire distance from model (1) are also shown here. Restaurant capitalization effects are more closely aligned with the average non-residential structure than nightclubs and bars. Similarly, tourist attractions exhibit the largest commercial increase in land value per meter increase in distance from a fire station, while professional service buildings exhibit the largest loss in land value. Figure 2.5 provides a visual demonstration of this. Land values of tourist attractions can increase by as much as 5 percent if a neighboring fire station were moved 3,000 meters away. Conversely, moving a fire station 2,500 meters away from a professional services building may reduce the value of its land by 2 percent.

Table 2.6 provides the results of using model (2) when considering distances from the nearest hospital. A larger majority of commercial land use categories negatively associate distance away from a hospital with land prices. In particular, only parking lots, enclosed auditoriums/theaters, camping areas, and hotels have positive coefficients. These results indicate that most commercial locations tend to value land near hospitals. Logically, this make sense, particularly for any businesses that cater to hospital employees since many hospitals employ large numbers of workers.[10] Similarly, industrial valuations are largely

[10] "... 'eds and meds'are proven economic engines. They employ large workforces, occupy and manage big pieces of real estate, purchase vast quantities of goods and services..."see

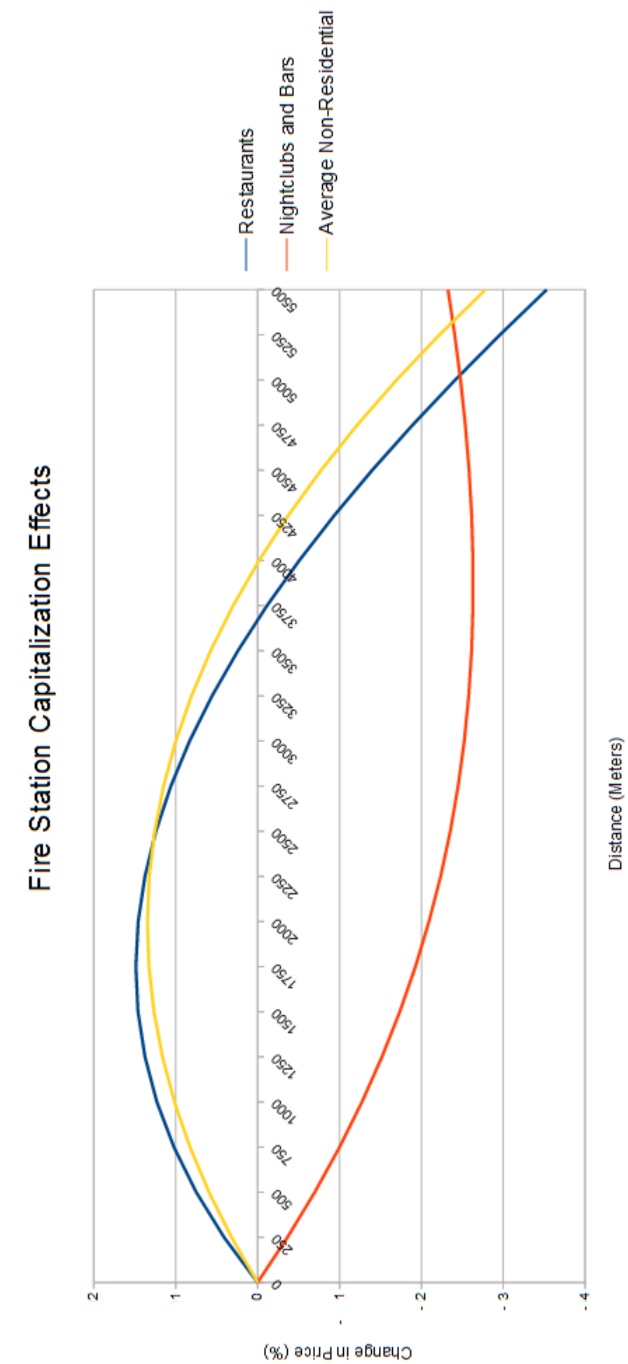

Figure 2.1: Comparison of fire station effects between Nightclubs and Restaurants.

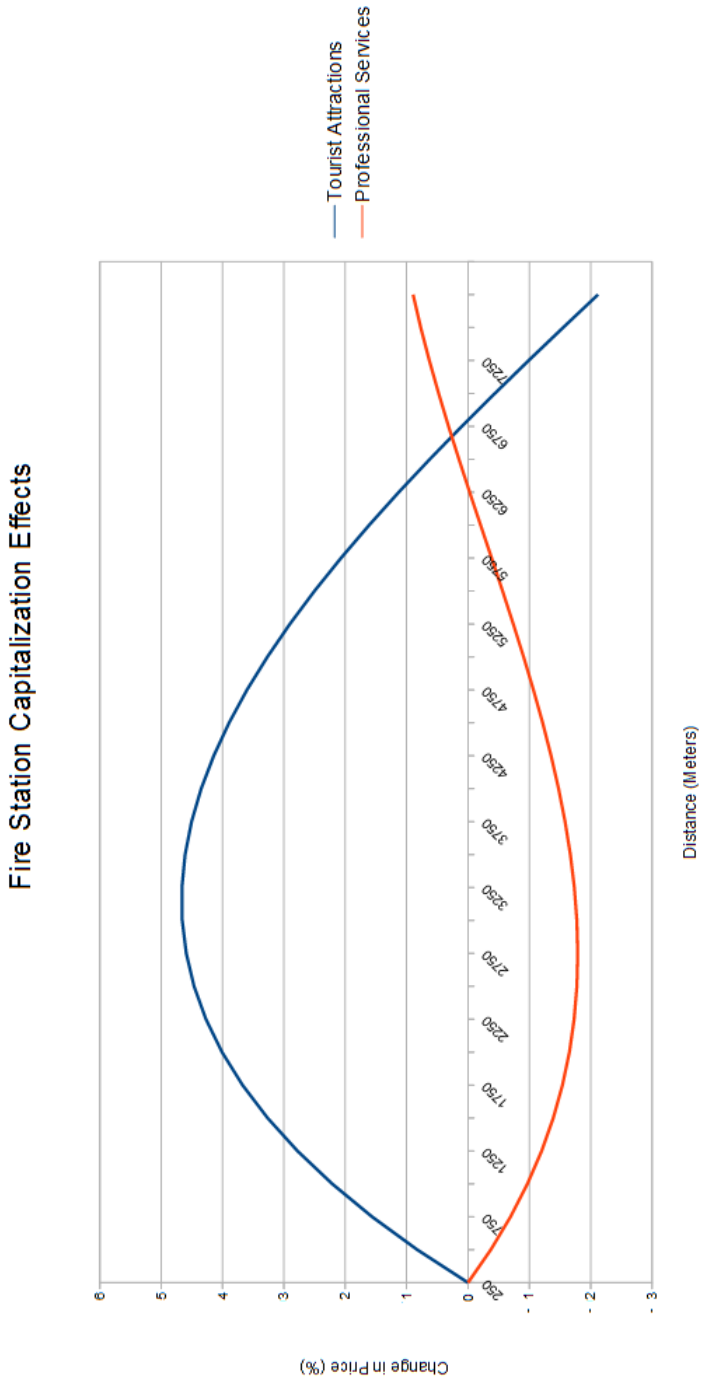

Figure 2.2: Comparison of fire station effects between Tourist Attractions and Professional Services.

Table 2.6: Euclidean Hospital distances using interaction terms.

Land Use	Hospital Distance	Hospital Distance^2	Hospital Distance^3
(1) Single Story Stores	-*	+*	-*
(2) Mixed Store and Offices	-*	+*	-*
(3) Department Store/Supermarkets	+	+	-
(4) Malls and Shopping Centers	-*	+*	-*
(5) Non-Professional Service Offices	-*	+*	-*
(6) Professional Service Buildings	-*	+*	-*
(7) Transportation Terminals	-*	+*	-*
(8) Restaurants	-	+	-
(9) Financial and Insurance	-*	+*	-*
(10) Repair, Service, and Auto Sales	-*	+*	-*
(11) Parking Lots/Mobile Home Sales	+*	-*	+*
(12) Outlets and Produce Houses	+	-	+
(13) Florists and Greenhouses	-	+	-
(14) Open Air Entertainment	-	-	-
(15) Enclosed Auditoriums/Theaters	+*	-*	+*
(16) Nightclubs and Bars	-*	+*	-*
(17) Daytime Attractions/Arenas	-*	+*	-*
(18) Tourist Attractions	-*	+*	-*
(19) Camps	+*	-*	+
(20) Racing	+	-	+
(21) Golf Courses	-	-*	+*
(22) Hotels or Motels	+*	+	-*
(23) Light Manufacturing	-*	+*	-*
(24) Heavy Manufacturing	-*	+*	-*
(25) Lumber Yards/Sawmills	-	+	-*
(26) Food Packing Plants	-*	+*	-*
(27) Canneries/Distilleries/Wineries	-**	+*	-*
(28) Food Processing	-	-	+
(29) Mineral Processing	-*	+*	-*
(30) Warehousing and Storage	-*	+*	-*

*: $p < 0.10$ (Full results available upon request.)

negatively correlated with distance away from hospitals. Only food processing plants are found to be unaffected by hospital distance. One likely explanation is that most industrial usage has little need for quiet locations, so they are relatively unconcerned by the disamenity effects from hospitals, but have strong preferences for quick responses in the case of industrial accidents. Of the three types of services, hospitals provide the lowest heterogeneity amongst the land usage classifications. In addition, the magnitudes of the associated capitalization effects are smaller than for either fire stations or police stations.

Finally, Table 2.7 shows the capitalization effects of police stations using model (2). Although the dispersion of negative and positive signs is greater than hospitals, and more akin to fire stations, a few specific types of land des-

Anchors Lift All Boats, Land Lines (2015).

Table 2.7: Euclidean police station distances using interaction terms.

Land Use	Police Distance	Police Distance^2	Police Distance^3
(1) Single Story Stores	+	-	-
(2) Mixed Store and Offices	-*	+*	-*
(3) Department Store/Supermarkets	+*	-*	+*
(4) Malls and Shopping Centers	-*	-	+*
(5) Non-Professional Service Offices	-*	+*	-*
(6) Professional Service Buildings	-*	+*	-*
(7) Transportation Terminals	+	-*	-*
(8) Restaurants	-*	-	+
(9) Financial and Insurance	-*	+	+
(10) Repair, Service, and Auto Sales	-*	+	+
(11) Parking Lots/Mobile Home Sales	-	-	+
(12) Outlets and Produce Houses	-*	+	-
(13) Florists and Greenhouses	-*	+*	-*
(14) Open Air Entertainment	+	-	+
(15) Enclosed Auditoriums/Theaters	+*	-*	+
(16) Nightclubs and Bars	+*	-*	+*
(17) Daytime Attractions/Arenas	+*	-	+
(18) Tourist Attractions	+*	-*	+*
(19) Camps	-*	+*	-*
(20) Racing	-*	+*	-*
(21) Golf Courses	+*	+	-*
(22) Hotels or Motels	-*	+	+
(23) Light Manufacturing	-*	-*	+*
(24) Heavy Manufacturing	-*	+*	-*
(25) Lumber Yards/Sawmills	+*	-*	+*
(26) Food Packing Plants	-*	+*	-
(27) Canneries/Distilleries/Wineries	+	-	+
(28) Food Processing	+*	-*	+*
(29) Mineral Processing	+	-	+
(30) Warehousing and Storage	-*	+*	-*

*: $p < 0.10$ (Full results available upon request.)

ignations deserve mention. Nightclubs and bars prefer the presence of hospitals and fire stations, but generally would like to avoid proximity to police stations. In particular, worries over drunk driving or public intoxication may drive adult-oriented nightlife away from businesses near police stations. A similar, but opposite effect occurs with warehousing and storage land. Warehousing generally prefers the police stations, but does not value fire or hospital access. Hotels and motels derive higher capitalization effects in proximity to police stations as well, but prefer to avoid fire stations or hospitals.

2.5 Conclusion

While land use designations have been broadly considered in the capitalization literature, the research presented here demonstrates the importance of considering disaggregated measures of land use. In particular, even within broad categories of commercial or industrial land usage, there are examples of both positive and negative capitalization effects to the same service. Understanding and account for this heterogeneity is important for analyzing how non-residential structures respond to service access. These capitalization effects are not only heterogeneous in magnitude, but in sign as well.

Consider the case of golf courses. While one might imagine that golf courses in general would be worth less in high traffic, high noise locations, this does not tell the whole story. This train of thought is true for the disamenities associated with police and fire stations, but not for hospitals.[11] Any analysis considering commercial capitalization effects that does not disaggregate land usage may find their coefficients being effects by the inclusion of heterogeneous preferences.

Additionally, while not all commercial or industrial parcels will capitalize emergency service access into land values, many of them do. These effect can range from minor 1 percent price changes, to much more significant 5 or more percent changes in land value with the construction of a new service station. Given the high value associated with each non-residential parcel, these changes are not trivial in nature. As such, the evidence provided here indicates that when considering the construction of a new fire station or police station, local municipalities should consider the businesses that will be effected. A new station will likely create both winners and losers, so taking these effects into account

[11] Perhaps the many lightning strikes that Florida receives ensures the value of having a hospital near a golf course.

are particularly important for municipalities concerned over revenue generation.

Chapter 3

Fiscal Overrides and Local Budget Composition

As municipalities across the United States struggle with raising revenues to meet continued budgetary obligations, it becomes more important to understand how municipalities react when dealing with fiscal constraint. California's Proposition 13, passed in 1978, limited *ad valorem* taxes on property to 1 percent of the property's cash value. The passage of this law, for good or ill, has led to a number of consequences in the state[1]. Four decades after Proposition 13, states are still enacting or editing similar laws (as recently as 2010 and 2012 in New Jersey and Oklahoma respectively). These laws are generally meant to force local governments to reduce or streamline service provision and to provide fiscal reprieve to fixed income homeowners for whom increasing property tax rates may result in being priced out of their homes (Ladd and Wilson, 1982).

The research presented here attempts to understand how local municipalities will respond when in the presence of fiscal limitations. This becomes even more important given recent political pressures to reduce government size and taxes while maintaining service provision levels. Fallout from the recent recession has even led to revenue and expenditure reductions in some locations (Congressional Budget Office, 2010).

[1]See Rosen (1982) Rosen (1982) and Sexton, Sheffrin, and O'Sullivan (1999) Sexton, Sheffrin and O'Sullivan (1999).

Using data from Massachusetts' Proposition 2 $\frac{1}{2}$ and information on votes to increase property tax revenues at the local level, it becomes possible to investigate how local budget composition changes in the presence of fiscal constraint. Specifically, a regression discontinuity design utilizing ballot initiatives that just barely pass versus those that barely fail can be exploited to analyze whether (and how) municipalities react to fiscal limitations. Part of Massachusetts' property tax cap law also provides for more than one method to override levy limits, allowing researchers to uncover whether certain types of overrides may generate differential responses in local budget composition.

Additionally, one issue with investigating the response of municipal budgets to fiscal constraint is that difficulties arise in states where the constraint is provided at a parcel level, because identifying whether a municipality is truly fiscally constrained can be problematic. For example, as millage rates are endogenously chosen, two municipalities may have the same revenue and expenditure levels, but one may be content with its current budget choices, but the other is not. This preference may not be readily visibly from budget or millage rate choices. However, Massachusetts' program enables the identification of these fiscally constrained municipalities through their choice of holding fiscal override votes. If a jurisdiction is fiscally constrained, then it is will be more likely to hold a vote overriding levy limits. Municipalities that are not fiscally constrained should be expected not to hold revenue increasing votes. Therefore confidence can be higher that fiscally constrained municipalities have been identified when restricting the analysis to those locales attempting to override their levy limits[2].

[2]Note that holding a vote is not enough to identify fiscal constraint given that some jurisdictions may choose to initiate a vote in preparation for *future* expenditures. An additional consideration therefore, is whether the municipality both initiated a vote, but also chose to raise the requested revenue at the same time and to utilize any remaining levy limit availability

Two important findings are established here. First, municipal governments will respond to fiscal constraint by altering budgetary composition. On average, municipalities that receive increased funding from overrides, but are still fiscally constrained will spend a smaller portion of their budget on education and a larger proportion on public works expenditures[3]. Also, while spending proportions change, in real expenditure terms, education remains the same while public works spending increases. Secondly, this effect is limited to only *permanent* overrides. In essence, overrides that provide more flexibility in revenue generation will tend to lead to budgets that under emphasize education as opposed to alternative override measures which may still provide increased revenue generation, but are less flexible in usage. One possible result is that fiscal constraint overrides may induce budget composition changes that are not necessarily aligned with voter preferences, but instead such budgets may emphasize more 'visible' expenditures. As such, when designing property tax caps, legislatures should pay particular attention to what override tools are provided to municipalities.

This paper is organized as follows. Section I provides a brief background of Massachusetts' property tax cap law. Section II discusses prior research into property taxes and local budgets. The methodology employed here is laid out in Section III, while Section IV discusses the results. Section V concludes.

left.

[3]Public works budgets contain expenditures on streets and highways, snow and ice, waste and sewage, and water distribution.

3.1 Background

Massachusetts' property tax law (known as Proposition 2 $\frac{1}{2}$) of 1980 enacted several limitations on local revenue generation from property taxes[4]. In particular, it created two limits; a levy limit and a levy ceiling. The levy limit sets a limit of 2.5 percent year over year growth on property taxes, while the levy ceiling limits the total amount of property taxes that may be collected to no more than 2.5 percent of all assessed real and personal property in the jurisdiction. Importantly, municipalities can choose how much of each year's increase in the levy limit they collect. If there is no perceived need to increase taxation, then a jurisdiction can choose to hold off on increasing revenue. However, the law also recognizes that municipalities may need more fiscal flexibility in some circumstances. As such, Proposition 2 $\frac{1}{2}$ includes two methods of providing jurisdictions with increased revenue options.

The most general method is known as an override. Overrides are explicitly required to have both a purpose and a specific dollar amount. They are placed on local ballots and voted upon, with a simple majority vote required to pass. An important aspect of overrides is that they are *permanent* in nature. Upon enacting an override, a municipality's levy limit is immediately raised by the aforementioned dollar value, and in subsequent years, the override amount is increased by the same 2.5 percent each year. In essence, an override enables a jurisdiction to increase their revenue generating ability as well as their future revenue generation. However, overrides have one limiting factor, they cannot increase a levy limit beyond the municipality's levy ceiling.[5]

[4]See Cutler, Elmendorf and Zeckhauser (1999) Cutler, Elmendorf and Zeckhauser (1999) for a discussion on why Massachusetts voters passed Proposition 2 $\frac{1}{2}$, and why voters might choose to override the law's revenue generation limitations.

[5]There also exists an option known as an underride in which the municipality's levy limit is reduced by the balloted amount. Only 18 overrides were voted on during the period of

On the other hand, debt and capital exclusions are able to allow local governments to raise revenues above and beyond their levy ceiling. Similar to overrides, exclusions are ballot measures that pass on simple majority votes, and are required to list their expected uses and dollar amounts (in the case of capital exclusions). They differ from overrides in that exclusions are temporary in nature. Any increase to a levy limit by exclusions will only last so long as the project is still in progress, and importantly, is not factored into the 2.5 percent annual levy limit increase. As such, exclusions are not only limited in nature (debt or capital projects only), but also in time.

Given that both forms of own-source revenue generation must state what the funds will be used for, why would there be any expectation for budget shifting that isn't already defined by the override or exclusion itself? As noted by Zampelli (1986) Zampelli (1986), Becker (1996) Becker (1996), and Fisher and Papke (2000) Fisher and Papke (2000), budget fungibility can be found in local budget choices. A decision to increase expenditures in one area of a budget does not preclude the possibility of shifting other funds away from the same area. If local budget officials choose to transfer expenditures around the budget, then they may be able to use an override or exclusion vote to raise expenditures in parts of the budget the officials would prefer. These preferred areas of the budget might include expenditures in public works or other highly 'visible' budget areas.[6] A possible reason for municipal budget composition to change may derive from budget officials wishing to increase their chances for re-election by providing expenditure increases to budget areas that can effect the largest contingent of potential voters.

analysis. They are not considered here.

[6]See the Theory section for details.

3.2 Literature Review

Prior studies have examined a few effects of fiscal constraints on local budget choices. Dye and McGuire (1997) Dye and McGuire (1997) use a property tax cap program in Illinois to analyze whether caps are effective in reducing property tax growth rates. The authors are able to utilize a differential application of the program to demonstrate that property tax caps are, in fact, an effective means of reducing property tax growth. They also note that educational expenditures tend to become restrained in capped districts, however the reduction appears to be limited to non-instructional spending.

Bradbury, Mayer, and Case (2001) Bradbury, Mayer and Case (2001) and Wallin and Zabel (2011) Wallin and Zabel (2011) discuss the effects of Proposition 2 $\frac{1}{2}$ on education expenditures, local fiscal conditions, and school segregation respectively. Bradbury, Mayer and Case (2001) utilize revenue and expenditure data from 1990 through 1994 and a large (30 percent) reduction in state aid to investigate whether the existence of fiscal constraint limited expenditures, and more significantly, if the reduction was achieved by targeting education expenditures. Their analysis also notes that municipalities that chose to cut education spending tended to see a negative impact on housing prices compared to communities that were able to avoid such expenditure reductions. This coincides with Glaeser (1996) Glaeser (1996) wherein the author argues that property taxes indicate expectations for future amenity procurement. If these property taxes are lowered, then there should be a consequential effect on housing prices, lowering them as expectations of amenities fall. Wallin and Zabel (2011) uses data from Massachusetts after passing Proposition 2 $\frac{1}{2}$ to predict whether override measures help relieve fiscal pressures. They find that local fiscal conditions, as measured by total revenues minus expenses, tend to improve with the passage of overrides. Additionally, towns with better fiscal conditions not only tended to pass overrides more often, but also voted on them more often as well. Jeffrey (2014) **?** also notes that one unintended consequence of these overrides is that they tend to increase school segregation since override votes have a tendency to pass more often in higher income towns with lower percentages of minorities.

A survey of Wisconsin municipalities by Mahar and Deller (2007) Mahar and Deller (2007) discusses the relationship between local government perceptions and reality of local fiscal stress. They note that municipalities with fiscal directors or administrators tended to respond to fiscal stress through different means (such as management improvements, and service consolidation) compared to other municipalities. The authors also include an overview of prior literature analyzing responses to fiscal stress. Buettner and Wildasin (2006) Buettner and Wildasin (2006) provides evidence that municipalities adjust to fiscal imbalances by reducing future expenditures, though the magnitude of the effect is asymmetrical on population size. Intergovernmental grants are also found to be an important source of municipal decision making, especially as local officials appear to utilize these transfers to ease fiscal adjustment periods.

This paper improves upon municipal budget research through two contributions. One, it investigates the effect of overrides on local budget composition by considering the percentage of municipal budgets enacted toward five major areas; education, health and welfare, public safety, public works, and recreation and culture[7]. Considering the impact that these expenditure decisions make on local conditions (see Oates (1969) Oates (1969)), it is important to understand

[7] On average, these five budget items account for about 75 percent of all municipal expenses.

how policies can alter these expenditure choices. During the period from 1992 until 2009, there were 6,507 votes for overrides and exclusions, of which 4,158 passed with an average value of \$249,000, indicating that these overrides are neither rare nor minor. The second major contribution is to use a regression discontinuity design to analyze how overrides effect these decisions. The usage of an RD methodology allows the analysis to be quasi-experimental in nature, which can help temper the many endogeneity problems that local budget choice can generate.

3.3 Theory

This section outlines a basic theoretical discussion of budgetary decision making in circumstances with majority rule voting and imperfect knowledge. Suppose a voter is making a decision on whether to vote for an incumbent or a challenger. If it is assumed that voters are self-interested insofar as they vote based upon their utility preferences, then it would be expected that the candidate the voter will chose can be defined as:

$$E[\mu_i(S_c)] > E[\mu_i(S_{-c})] \tag{3.1}$$

Where the expected utility from candidate c's choice of service provision level S is greater than the utility voter i expects from any and all other candidates' choices of service provision levels. If voters tend to fall along a spectrum of preferences, then there should be a set of voters for whom the the difference between their preference for the incumbent politician (I) and their second best choice (-I) is arbitrarily (ϵ) small. These voters can be defined as the marginal voters:

$$E[\mu_{mv}(S_I)] - E[\mu_{mv}(S_{-I})] = \epsilon \tag{3.2}$$

Note that ϵ can be either positive or negative depending on the marginal voter's most preferred candidate. Given that voters will vote their preferred candidate, then candidate c will receive V votes as follows:

$$V_c = \sum \nu_i \tag{3.3}$$

Where:

$$\nu_i = \begin{cases} 1 & \text{if } E[\mu_i(S_c)] > E[\mu_i(S_{-c})] \\ 0 & \text{if } E[\mu_i(S_{-c})] > E[\mu_i(S_c)] \end{cases}$$

As noted by Drazen and Eslava (2010) Drazen and Eslava (2010), local officials have incentives to alter the composition of municipal budgets to affect their final vote totals. In particular, when given a boost to revenue generation through an override or exclusion passage, local officials may want to target new expenditures toward the marginal voter groups. They would prefer to target marginal voters because such voters require a smaller change to their utility to push them from supporting one candidate to another.

If local budget officials had perfect knowledge of voter preferences, then incumbents could easily alter budgetary composition to maximize the likelihood of being re-elected by targeting expenditures toward the marginal voters. However, this assumption may be a bit strong when considering this in a more empirical fashion. With the existence of an asymmetric information problem, it becomes difficult for local officials to target expenditures toward the marginal voters. Therefore, if a candidate wishes to target as many marginal voters as possible, then modifying the budget composition to improve the utility of as many voters as possible might create the largest shift in marginal voters toward the candidate.

Consider two possible projects, α and β. For any change in expenditure to either of these projects, the utility for a voter will change as:

$$\Delta\mu_i = a\Delta S_{\alpha,i} + b\Delta S_{\beta,i} \tag{3.4}$$

Where a and b representing the preference strength for either policy choice. Conditional on an individual receiving a benefit from either policy choice, it can be seen that for any change in expenditures, an individual's utility will increase based on two factors, their marginal preference for the increase, and the magnitude of the increase. In a situation in which there is no increase in expenditures or if an individual has zero marginal preference, then utility will not change.

From the perspective of local officials without perfect knowledge, they must predict an individual's change in utility through estimation of probabilities. In particular, candidates must consider that they do not know with certainty whether an expenditure increase will even lead to a consequent increase in utility. Therefore, to make a decision between two different policies, local officials must consider the probability of a voter receiving a benefit from enacting a particular project α:

$$p_\alpha = E[Pr(k_\alpha)|\alpha = 1] \tag{3.5}$$

$$q_\alpha = E[Pr(k_\alpha)|\alpha = 0] \tag{3.6}$$

Recall that the policy decision with the greatest affect on V_c (3) will be the one that maximizes the number of marginal voters whose preferences can be flipped from the challenger or challengers to the incumbent. Local budget officials will therefore recognize that for projects α and β, the expected change in utility for a marginal voter will be proportional to the probability of the voter being effected by either of these projects:

$$E[\Delta\mu_{mv}] \propto Pr_\alpha(a\Delta S_{\alpha,mv}) + Pr_\beta(b\Delta S_{\beta,mv}) \tag{3.7}$$

While the candidate has no power (or may even have no knowledge) over deciding a or b for a marginal voter, the candidate can however choose projects with a higher probability *Pr(k)*. The advantage of this can be seen by considering two competing policy decisions. Assuming that expenditures on each project are the same and that returns to scale are similar across the two projects then the effect of a change in expenditures from period 0 to period 1 will be:[8]

$$\Delta\mu_{mv} = p_\alpha[a(E_{\alpha,1} - E_{\alpha,0})] + p_\beta[a(E_{\beta,1} - E_{\beta,0})] \tag{3.8}$$

[8]Obviously, if there are services that are facing increasing or decreasing returns to scale, then this might alter the outcome slightly. However, it should be noted that this should only alter the *mixture* of policy choices, not necessarily the underlying idea of targeting at many marginal voters as possible. One would expect that services with decreasing returns to scale will need a larger probability of effect or greater expected marginal preference boost to be considered as a first best choice. Increasing returns to scale for a service would make it easier for a local budget official to decide to implement said policy.

If the local budget official wants to decide the breakeven point for making the choice between the two possibilities, then (8) can be rearranged as:

$$\Delta\mu_{mv} = \Delta\mu_{\alpha,mv} + \Delta\mu_{\beta,mv} \tag{3.9}$$

$$\Delta\mu_{\alpha,mv} = p_\alpha[a(E_{\alpha,1} - E_{\alpha,0})] \tag{3.10}$$

$$\Delta\mu_{\beta,mv} = p_\beta[a(E_{\beta,1} - E_{\beta,0})] \tag{3.11}$$

Solving for (9) gives:

$$\frac{p_\alpha a}{p_\beta b} = 1 \tag{3.12}$$

(12) demonstrates how important the expected probability can be in determining a first best choice for the policy maker. For a first best choice, let the left hand side be greater than 1. This will occur in circumstances in which the probability of policy α is high compared to policy β. As can be seen both a and b are also determinants of the first best choice. However, the policy maker may not have full knowledge of voter preference strengths until after the election. If the candidate has strong *a priori* beliefs that $\beta \gg \alpha$, then policy β may be a better choice. All things being equal however, for any two generic policy choices, one with a larger p will be preferable.

In this case, what can be determined about likely policy decisions for a candidate in a re-election cycle? If the policy maker wants to target as many marginal voters as possible, then they would prefer to implement policies with a higher p. Policies that are in effect more visible or that potential voters have more contact with would likely generate higher p values. This may lead to local officials deciding to emphasize budget movements toward public works projects.

Increased expenditures on road maintenance and lighting are more likely to positively effect a marginal voter than education expenditures for which there may be segments of the population that generate little to no utility gains from expenditure increases[9]. This gives rise to the basis behind the results found in this paper. In essence, for communities that pass overrides, local budget officials face an incentive to increase expenditures on public works (a plausibly high p valued policy) rather than education. Choosing certain policies may be even more highly incentivized if local officials wish to appear as though they are 'accomplishing' something (i.e. disguising themselves as *people* type politicians noted by Drazen and Eslava).

This however isn't the entire story. As noted previously, only in the case of permanent overrides is this effect captured in the data. Therefore, in the case of temporary capital exclusion votes, why might officials no longer have an incentive to alter budget composition? Recall in (2) and (3) that marginal voters will choose their vote based upon whether they expect to receive more utility from one candidate versus another. For the analysis so far there has been no mention of the loss in utility that an increase in tax rates would bring. In the case of an override situation, this tax increase occurs regardless of the winner of a subsequent election. As such, the distribution of voters should not change since the tax increase is independent of whether an individual voter prefers the incumbent or the challenger.

Upon passing a capital exclusion, the tax increase is recognized by voters as being temporary in nature. For incumbent policy makers, it now becomes

[9]One may imagine older voters or middle-aged commuters preferring increased road maintenance and street lighting compared to education expenditures. This many not always be the case. For example, given that local officials may face a populace that has intense preferences for education expenditures, then the marginal voter may be more likely to be swayed by budget compositions with increased emphasis on education. It is important to understand that *on average* higher p policies are probably more likely to be preferable.

a more risky proposition to choose to alter budget compositions in response to the temporary increase. This is because voters may recognize that voting for the challenger may result in higher utility levels due to the return of lower tax rates after the capital exclusion period is over. In order to effectively target marginal voters, the policy makers must not only consider whether a policy will have a high p, but also whether it would generate enough utility to overcome the voter's preference for lower tax rates under a different regime. Thus, local budget officials may recognize that altering budget compositions can create more harm than good for their re-election chances, resulting in a decision to not change local budget compositions.

3.4 Methodology

Given the following model:

(1) $Y_i = \theta\gamma_i + \beta X_i + \epsilon_i$

Where X is a vector of covariates and γ is our variable of interest, in this case, a binary variable indicating passage of an override[10]. A typical linear regression would return a biased coefficient (θ) on γ as city specific characteristics are likely to be correlated with both γ and the error term, ϵ. This creates difficulty in establishing a statistically pleasing relationship between γ and Y.

However, prior work has demonstrated the value of using an RD design when utilizing treatment data[11]. While the passage of a ballot initiative is certainly nonrandom in nature, if one limits the analysis to only those contests that

[10] The variable determining the passage of an override, voter share, is sometimes referred to as the 'forcing variable'. Forcing variables are generally continuous in nature, and can be used to identify how close a ballot measure came to passage or failure.

[11] See Thistlewaite and Campbell (1960) Thistlewaite and Campbell (1960), Angrist and Lavy (1999) Angrist and Lavy (1999), and Lee and Lemieux (2010) Lee and Lemieux (2010).

are sufficiently close to the passage mark, the investigation begins to approach a randomized experiment. This can provide a valuable means to establish a causal relationship between γ and Y in (1). In essence, if the treatment effect is distributed randomly amongst the sample, then this effectively generates two groups, those with an override passage (the treatment group), and those without an override passage (the control group). It then becomes possible to compare these two groups to uncover whether treatment has an effect (also known as treatment on the treated or TOT) on municipal budget composition.

Of course, there are no free statistical lunches. RD methods must meet certain criteria to be a valid approximation of a randomized experiment. The caveats to RD usage fall into two categories; discontinuity validation and group differences. For discontinuity validation, individuals must not be able to alter the variable determining treatment assignment (in this case, vote share), and there must not be discrete jumps in voter share within close proximity of the discontinuity. General practice when considering ballot measures with an RD design, is to ensure that individual power to determine voting outcomes is relatively small by removing smaller voting populaces[12]. Smaller voting pools tend to lead to instances in which it becomes more likely that one or two voters can influence the assignment of treatment.

Discrete changes in voter share near the discontinuity of interest may indicate a situation in which endogenous sorting may bias results. So long as any discrete jumps in the forcing variable are far enough away from the discontinuity, then RD designs can still approximate a randomized experiment. A histogram can indicate whether any discrete jumps lie near the discontinuity

[12]See Cellini, Ferreira, and Rothstein (2010) Cellini, Ferreira and Rothstein (2010). For the following analysis, any municipality with fewer than 100 votes has been removed from the dataset. This filter reduces the ballot county by 219 total votes or 3 percent of all override and exclusion votes.

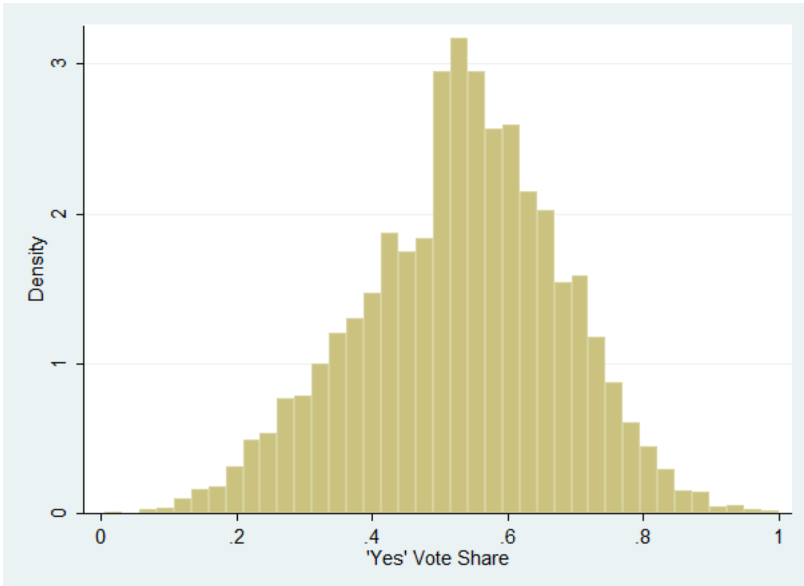

Figure 3.1: Histogram of all override types as a percent of voter share.

point. As demonstrated by Figure 3.1; the votes under consideration in this paper appear to have a discrete jump problem, with a large drop off near the 50 percent voter share mark.

However, by breaking down the votes into debt exclusion votes (Figure 3.2) and all other votes (Figure 3.3), it can be seen that the discrete jump problem is a result of debt exclusion votes, and not a product of the ballot measures in general. By limiting the analysis to overrides and capital exclusion votes, one may be reasonably certain that there are no discrete jumps in the immediate vicinity of the discontinuity.

To evaluate the effect of overrides on local budget composition, two RD models will be utilized. In both, the sample will be constrained to those municipalities that are already extremely close to the levy limit to ensure conditions of fiscal constraint[13]. The first will consist of a local linear regression model.

[13]This is a necessary condition to enforce fiscal constraint. In cases where municipalities have flexibility in their expenditure choices by being under the levy limit, then local budget officials may no longer have an incentive to alter budget composition since they can easily

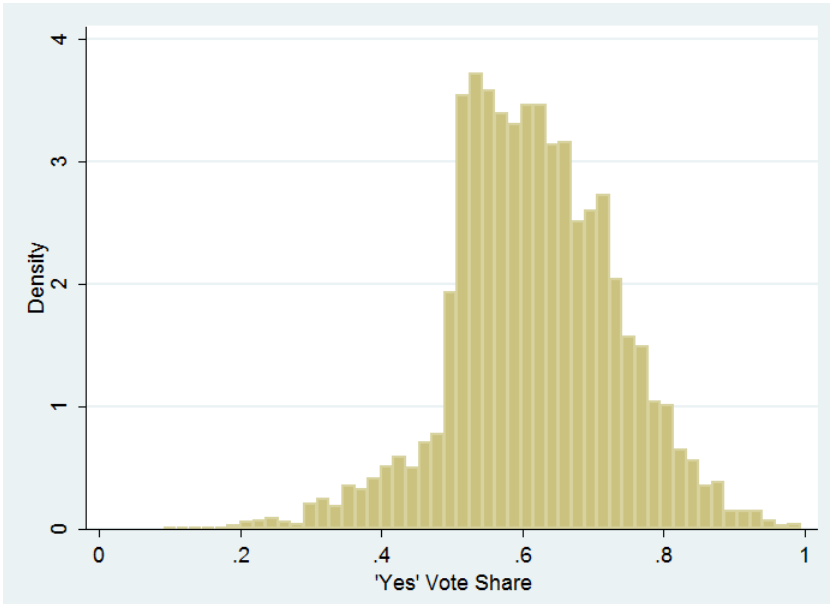

Figure 3.2: Histogram of debt exclusions as a percent of voter share.

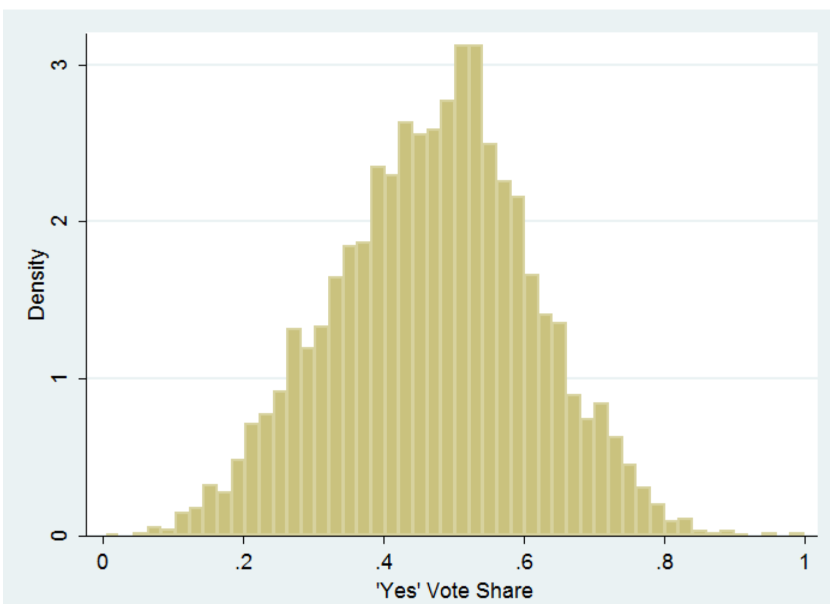

Figure 3.3: Histogram of all both overrides and capital exclusions as a percent of voter share.

This model will only use observations from within the immediate vicinity of the discontinuity using a bandwidth chosen by minimizing the mean squared error. Imbens and Kalyanaraman (2012) Imbens and Kalyanaraman (2012) discusses this methodology further. The local linear method is modeled as follows:

(2) $Y_i = \theta\gamma_i + \epsilon_i$

Where γ is a dummy variable denoting treatment assignment. θ provides the effect of the treatment on the treated. In this case, θ will show how the passage of an override or capital exclusion alters local budget composition. As per (Lee and Lemieux, 2010), multiple models can help demonstrate robustness and provide more evidence of the final results. To this end, a polynomial RD method will be utilized as well. In this form, the sample will not be filtered, and will include both observations near the discontinuity, but also those further away.

(3) $Y_i = \theta\gamma_i + \beta_1\Gamma^2 + ... + \beta_n\Gamma^n + \epsilon_i$

Where Γ represents a continuous form of the assignment variable (i.e. voter share). The inclusion of an nth degree polynomial can help soak up variation away from the discontinuity. A polynomial RD method can provide a more powerful test than a local linear analysis since it is able to utilize more observations, but there may be concerns of bias even with a higher degree polynomial. Thus, both (2) and (3) are included in the final results to provide corroborating evidence of the effects of overrides on budget choices.

increase expenditures as needed. Indeed, analyses allowing for the inclusion of non-fiscally constrained municipalities find no statistically significant effects. Thus, the sample is limited to communities with no more than 1.5 percent of their maximum levy limit left.

Table 3.1: Select summary statistics.

	All Votes		5 Percent Bandwidth	
Variable	Pass	Fail	Pass	Fail
Population	7772.8*	9258.8*	9572.5	9270.6
	(10974.00)	(13167.3)	(16383.5)	(13722.7)
Override or Exclusion Value	258368.1	242002.8	388605.7	295787.0
	(628684.8)	(638294.1)	(960733.3)	(743075.0)
Unemployment	0.033*	0.037*	0.034	0.036
	(0.025)	(0.021)	(0.024)	(0.025)
Lagged Education Share	0.491*	0.514*	0.506	0.518
	(0.118)	(0.106)	(0.114)	(0.111)
Lagged Public Works Share	0.095	0.098	0.092	0.092
	(0.063)	(0.059)	(0.053)	(0.056)
Lagged Public Safety Share	0.113	0.112	0.110	0.107
	(0.043)	(0.046)	(0.044)	(0.046)
Lagged Health and Welfare Share	0.014*	0.013*	0.013	0.013
	(0.011)	(0.009)	(0.011)	(0.010)
Lagged Recreation and Culture Share	0.026*	0.019*	0.022	0.020
	(0.016)	(0.013)	(0.015)	(0.012)
Lagged General Expenditures Share	0.071*	0.066*	0.069	0.067
	(0.029)	(0.030)	(0.031)	(0.031)
Observations	1944	2587	356	309

*: Statistically different means at $\alpha = .1$ (Standard deviation in parentheses.)
The observation counts listed are for budget observation numbers. There was a small number of extra observations available for non budget variables.

3.5 Results

With an RD method, the treated and untreated groups must be statistically indistinguishable prior to treatment, otherwise our results would likely be biased. Table 3.1 provides an overview of select variables. As one would expect, several variables, including population size, unemployment rate, and budget shares for education, health and welfare, and recreation and culture are statistically different when conditioning strictly upon vote passage or failure. This simply demonstrates that these variables likely effect ballot initiative outcomes. However, upon conditioning not just on vote passage, but also on being relatively near the discontinuity point, it can be seen that group differences become statistically indistinct. The 5 percent bandwidth demonstrates that no variables pass a differences in means test. Such an effect should be expected given that the theory behind RD methodology implies that groups should be indistinguishable when only considering close votes.

Table 3.2: Budgetary response to ballot initiative success.

Variable	Education	Public Works	Public Safety	Health and Welfare	Recreation and Culture
Win 50% Bandwidth	-0.074**	0.019**	0.013	0.001	-0.000
	(0.030)	(0.008)	(0.013)	(0.004)	(0.003)
Win 100% Bandwidth	-0.052**	0.014**	0.011	0.001	0.001
	(0.022)	(0.006)	(0.009)	(0.002)	(0.002)
Win 200% Bandwidth	-0.032**	0.013**	0.004	0.001	0.001
	(0.017)	(0.005)	(0.007)	(0.002)	(0.001)
Base Bandwidth (%)	0.109	0.182	0.099	0.107	0.130

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (Standard deviation in parentheses.)

The RD methodology is first used on five individual measures of municipal budget expenditure shares; education, public works, public safety, health and welfare, and recreation and culture. These results for three bandwidth measures are shown in Table 3.2.[14] While there appears to be no statistically significant change in public safety, health and welfare, or recreation and culture expenditures, there is a statistically significant and negative effect on the budget share of education expenditures and a positive effect on the public works expenditure share. This is indicates that the passage of an override or capital exclusion vote appears to reduce the share of expenditures devoted to education while raising the share devoted to street, roads, and other public works projects, while having little effect on other portions of the local budget.

These results suggest that education expenditure shares are falling by approximately 5 percent while public works spending is increasing by about 1.5 percent when a fiscal override or exclusion vote passes. This corresponds well with the theory that under conditions of fiscal constraint, local budget officials are choosing to increase expenditures in a more visible section of the municipal budget when given an increase in revenues. Importantly, as each vote is required to have a listed usage on the ballot, there are more educational votes

[14]The different bandwidth measure are shown to demonstrate the robustness of the results. As the chosen bandwidth shrinks, it tends to reduce bias and increase variance (Imbens and Kalyanaraman, 2012).

(20.2 percent) than public works votes (10.4 percent)[15]. With twice as many educational votes occurring, this indicates that the findings are not likely to be an artifact of simply having large numbers of public works votes tilting budget shares.

Concentrating on just education and public works expenditures, these effects can then be broken down by override votes and capital exclusion votes. The share of education expenditures is statistically significant and negatively correlated with override passage as shown in Table 3.3, while the share of public works spending is positively correlated with ballot passage. These findings corroborate the overall effects found previously. However, as Table 3.4 provides, exclusion votes are not statistically significantly correlated with budget share changes[16]. In other words, budget officials appear to alter budget composition when given permanent increases in revenue generation, but do not change their behavior when considering temporary votes. This is robust to when using either a local linear RD method or a high-order polynomial method.

Figure 3.4 provides a graphical representation of the override votes and their subsequent effect on educational expenditures shares. The graphed lines shown are the kernel-weighted polynomial regressions split between those overrides that failed and those that passed. The discrete jump at 50 percent voter share demonstrates the RD effect as expected, with those voting in the negative having, on average, higher shares of education spending. Similarly, Figure 3.5 shows

[15]Unfortunately, the exact budgeted area an initiative will fall under is not ascribed by Proposition 2 $\frac{1}{2}$. Instead, the law requires that a description of the expected usage is to be provided on the ballot. This makes it a somewhat arbitrary exercise in determining whether a specific measure's funding would be in one budget area versus another. To this end, certain key words were used to help define where an initiative's expenditures would likely fall. For example, the words 'education' 'elementary' 'school' and 'high school' were used to identify educational expenditures. Similar methodology was used to identify votes corresponding to the five categories of interest.

[16]All five areas of municipal budgets were tested. None were found to be statistically correlated with exclusion vote passage.

Table 3.3: Budgetary response to override votes.

	Education		Public Works	
Variable	RD	Polynomial	RD	Polynomial
Win	-0.059**	-0.043**	0.019**	0.018**
	(0.027)	(0.022)	(0.007)	(0.008)
Win 50% Bandwidth	-0.081**		0.027***	
	(0.037)		(0.009)	
Win 200% Bandwidth	-0.041**		0.018***	
	(0.021)		(0.006)	
Base Bandwidth	0.071		0.141	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (Standard deviation in parentheses.)

Table 3.4: Budgetary response to exclusion votes.

	Education		Public Works	
Variable	RD	Polynomial	RD	Polynomial
Win	-0.025	-0.048	-0.018	-0.017
	(0.057)	(0.048)	(0.016)	(0.019)
Win 50% Bandwidth	-0.016		-0.024	
	(0.037)		(0.020)	
Win 200% Bandwidth	0.001		-0.023	
	(0.042)		(0.014)	
Base Bandwidth	0.109		0.365	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (Standard deviation in parentheses.)

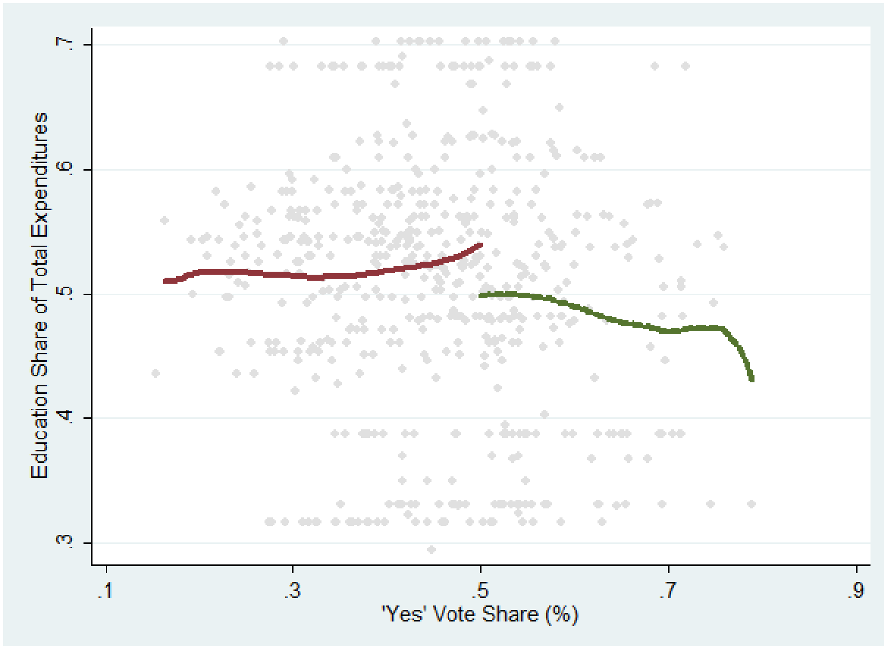

Figure 3.4: Educational expenditures compared to voter share.

how the share of public works expenditures follows a similar, but inverted relationship, with negative votes correlated with lower expenditure shares of public works. Again, the discontinuity can be easily seen here.

However, while these results indicate that permanent increases to local levy limits tend to result in budget composition changes, it does raise the question of whether total expenditures are also being affected. If budget officials are concerned about demonstrating their usage of override funds, then it would seem unlikely that they should be willing to reduce real (dollar) expenditures in education. Such a choice by local officials may be negatively perceived by the local populace, whereas an increase in real expenditures to other portions of the budget will reduce the share being spent on education, but may not necessarily lead to a reduction in real educational expenditures.

To test whether officials are cutting educational budgets and not just shifting expenditure shares, model (2) can be used with Y_i representing the per

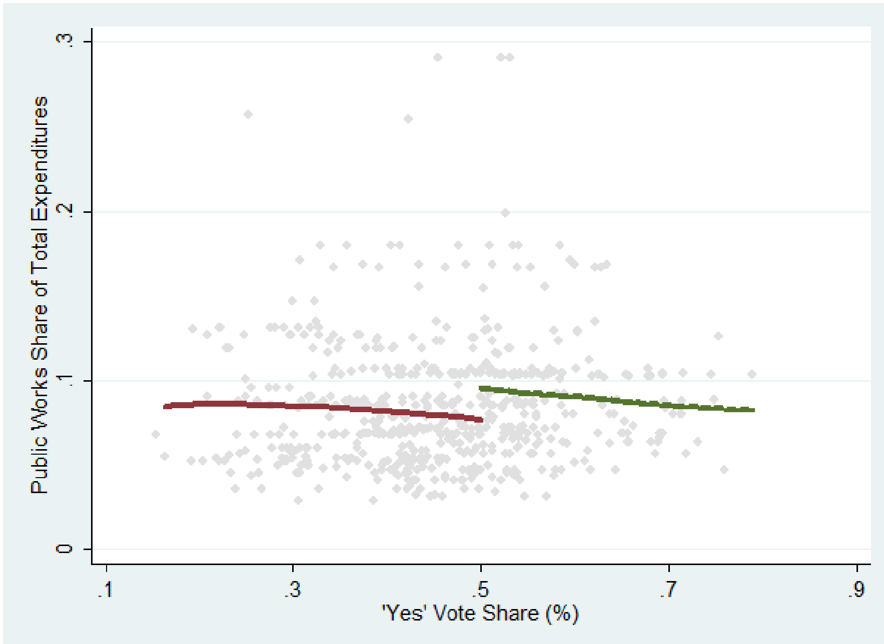

Figure 3.5: Public works expenditures compared to voter share.

capita expenditures for the two areas of interest; education and public works. Statistically insignificant results for education might indicate that local officials are largely attempting to target marginal voters and thus, attempting to avoid reducing utility levels for any group of citizens beyond the reduction already incurred by the passage of the override. Public works per capita spending should be positively correlated with override wins, indicating that budget share movement is less likely the result of a true reduction in expenditures, and more the result of where officials prefer to spend funds given at least some amount of budget fungibility.

Table 3.5 presents the results of using model (2) with per capita expenditures as the outcome variable. Regardless of bandwidth size, per capita education expenditures are positive, but statistically insignificant. This indicates that municipalities may be reducing the share of educational spending in their budgets, they don't appear to be reducing real expenditure amounts. Per capita public

Table 3.5: Per capita spending for override votes.

	Education		Public Works	
Variable	RD	Polynomial	RD	Polynomial
Win	58.778	33.867	65.668***	50.600**
	(92.798)	(77.174)	(24.667)	(20.973)
Win 50% Bandwidth	64.486		66.836**	
	(125.469)		(24.154)	
Win 200% Bandwidth	45.415		50.046**	
	(71.370)		(22.048)	
Base Bandwidth	0.108		0.098	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (Standard deviation in parentheses.)

works spending though, is statistically significant and positively correlated with override passage. On average, an override passage will lead to an increase of $66 in per capita public works spending. When considering both education and public works spending, it would appear that municipalities are increasing public works expenditures upon passing overrides, but that this increase is only limited insofar as educational expenditures do not fall in real terms.

As a final robustness check, a similar method is used to examine capital exclusion votes. Given previous results providing no statistical evidence for budget response to exclusion vote passage, it should be expected that per capita spending would also return statistically insignificant results. These results can be found in Table 3.6. As expected, neither education or public works expenditures on a per capita basis are statistically correlated with capital exclusion passage. This provides more evidence that permanent increases in revenue appear to alter municipal budget composition, but temporary increases do not.

3.6 Conclusion

By utilizing data from Massachusetts' Proposition 2 $\frac{1}{2}$, the analysis here demonstrates that fiscally constrained municipalities will react to revenue increases

Table 3.6: Per capita spending for exclusion votes.

	Education		Public Works	
Variable	RD	Polynomial	RD	Polynomial
Win	229.177	125.362	-15.590	38.555
	(413.673)	(240.132)	(97.477)	(68.233)
Win 50% Bandwidth	400.115		43.594	
	(650.857)		(163.883)	
Win 200% Bandwidth	59.862		-48.117	
	(259.936)		(66.412)	
Base Bandwidth	0.102		0.137	

*: $p < 0.10$ **: $p < 0.05$ ***: $p < 0.01$ (Standard deviation in parentheses.)

through altering budget composition. Specifically, the share of educational expenditures will tend to fall, while the share of public works spending will tend to rise. The effect is not necessarily small, as an increase in the share of expenditures by just 1.5 percent in Massachusetts is equivalent to a change of nearly $200,000. Importantly though, this composition change does not appear to come at the cost of real expenditures, as educational spending does not appear to fall in real terms, while public works expenditures increase in per capita measures. Also, these effects occur only when considering permanent increases in revenue generation rather than temporary measures.

Additionally, this analysis raises some concerns over budget fungibility in the face of voter approved expenditures. Given that there are nearly twice as many education overrides and exclusions than there are public works votes, it seems a bit surprising to find a negative correlation between vote passage and the share of educational expenditures. In other words, while by no means definitive, the results shown demonstrate that even when voters approve additional education expenditures, they may not be receiving the full (or even close to) the amount that would have been listed on the ballot initiative. These findings indicate that budget officials may not be providing the levels of expenditure that voters indicate they would prefer.

Understanding how municipalities respond under fiscal constraint is important given the continued pressure in many locations across the country to keep revenues low, thus possibly altering budget composition choices. With the relatively ubiquitous nature of property tax caps, these results demonstrate the importance of legislatively provided options for jurisdictions. Providing municipalities with permanent means of raising revenue beyond imposed levy limits may tend to lead toward lower educational expenditures shares. This in turn could have impacts at the state level as one might imagine municipalities requesting educational grants to cover share reductions in education. Based upon the findings here, several avenues of additional research into budget fungibility in own source revenue or state grant response to municipal fiscal constraints can be explored. This paper provides economists with a better understanding of how municipalities may respond to fiscal constraint, something which has been difficult to analyze in the past given problems in identifying fiscally constrained municipalities and methodological concerns from estimating endogenously driven revenue increases.

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