Searching for Goldilocks: The Distance-Based Capitalization Effects of Local Public Services

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Abstract

This paper empirically models the effect of distance on residential property values of three different types of services, fire, police, and emergency medical services. Interesting economic tradeoffs emerge as service station proximity provides both amenity and disamenity effects. Using over three million home sales from the state of Florida along with two different measures of distance, this study provides evidence of non-linear capitalization effects on local housing values. A difference-in-difference model utilizing new facility construction provides corroborating evidence of these findings.

JEL: *H41, R21, R31*

Keywords: *capitalization, housing, hedonic modeling, public goods*

1. INTRODUCTION

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 determining 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, cap-

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

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

italization 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]

The remainder of the paper is organized as follows. Section one will explore prior research on spatial based capitalization effects. Sections three and four describe the data and methodology. Results are reported in Section five and Section six concludes.

2. 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 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

[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).

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-Letrémy 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.

3. 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.[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 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 3 contains a list of included counties. 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 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] [Figure 1, 2, and 3 about here] 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

[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.

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

[9]See Figures 1, 2, and 3 respectively.

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 (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

[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.

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 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.

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:

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

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 characteris-

[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.

tics such as living space, age, and lot size[12] 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 (i.e. controlling for response time), all households should receive the same approximate station-level of service.[13] 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

[12]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.

[13]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.

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 allows 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[14]. 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:

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

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.

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

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.[15] 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. This method uses only data on newly constructed facilities to analyze how home prices *change* when new stations are constructed.[16] 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.[17] [Figure 4 about here] 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

[15]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.

[16]There were 176 EMS, 145 police, and 464 fire stations built between 1995 and 2010.

[17]See Figure 4 for an illustration of these two groups.

be used is as follows:

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

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 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.

5. RESULTS

Table 3 presents the estimated results for model (1) using both Euclidean and Network distance measures.[18] 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 sta-

[18]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.

tion 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 3 may at first glance appear to be small 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 5 visually illustrates the implied effects of distance from service stations. [Figure 5 about here] 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%.[19] 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 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).

[19] 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 regardless of disamenities.

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 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 5 and 6 present the results from taking models (1) and (2) and splitting them up into urban and rural samples.[20] 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 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

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

signs. However, while in rural areas a similar case occurs with volunteer fire departments, both the police 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 7 and 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 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 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.[21] 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

[21] 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.

dropped by 50%.[22] 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 10, 11, and 12. It should be noted however, that outside of the three variables in 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.[23]. Both non-matched and matched versions of the DID have been provided.

Table 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 original fire station found their housing values to fall.[24] 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

[22]See Table 9 for an overview of these distances.

[23]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.

[24]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.

a change in housing values. Importantly, the use of the CEM methodology corroborates these findings.

For hospitals, Table 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 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 5 through 9. Indeed, this finding may indicate why the police station results for rural areas in Table 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.

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.

Table 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

Table 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	

Table 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.

Table 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 Voluntee$r$	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 Othe$r$	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 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 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.

Table 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.

Table 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.

Table 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)

Table 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 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 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.

Table 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 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.

Table 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.

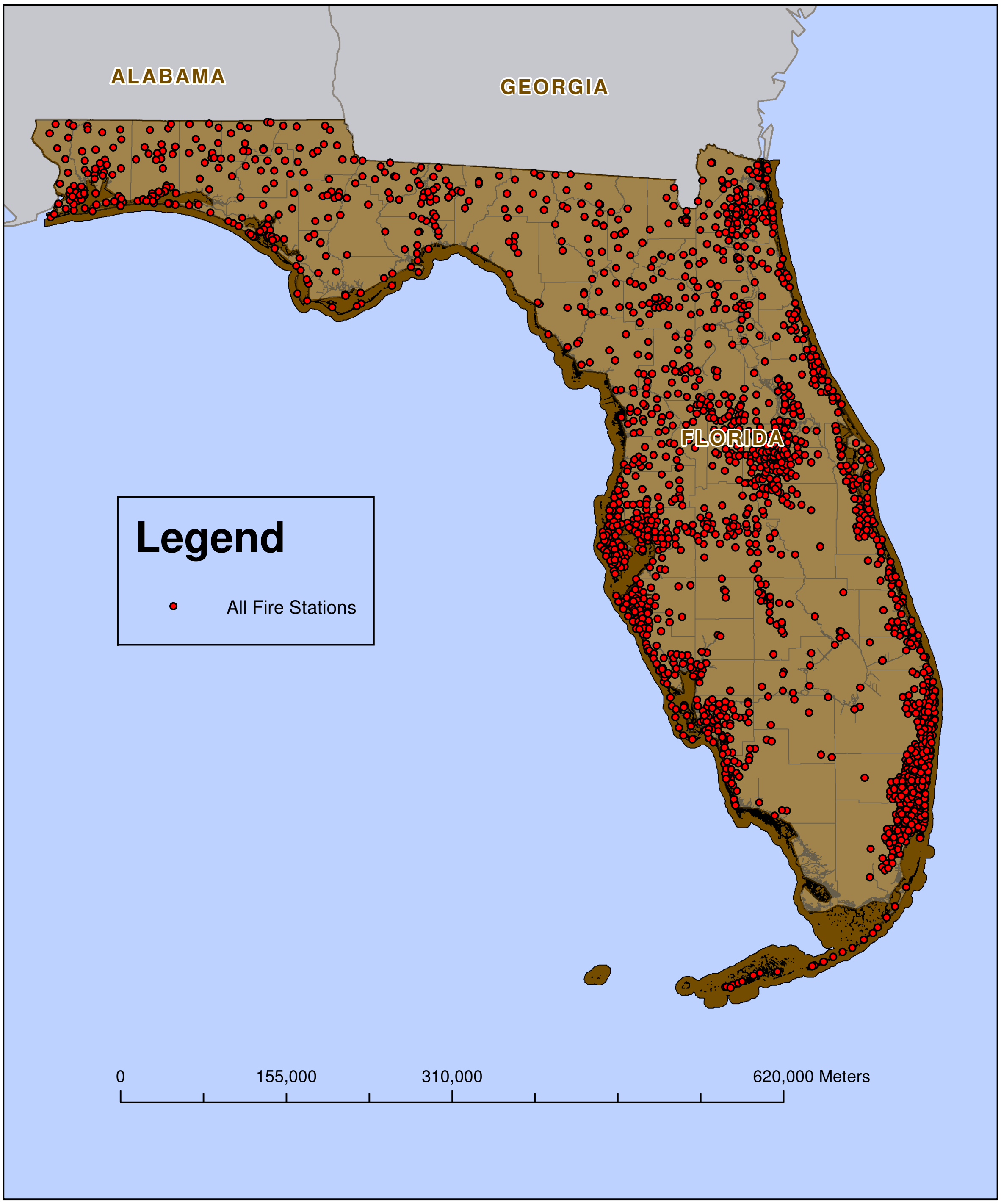

Figure 1: Location of all fire station types.

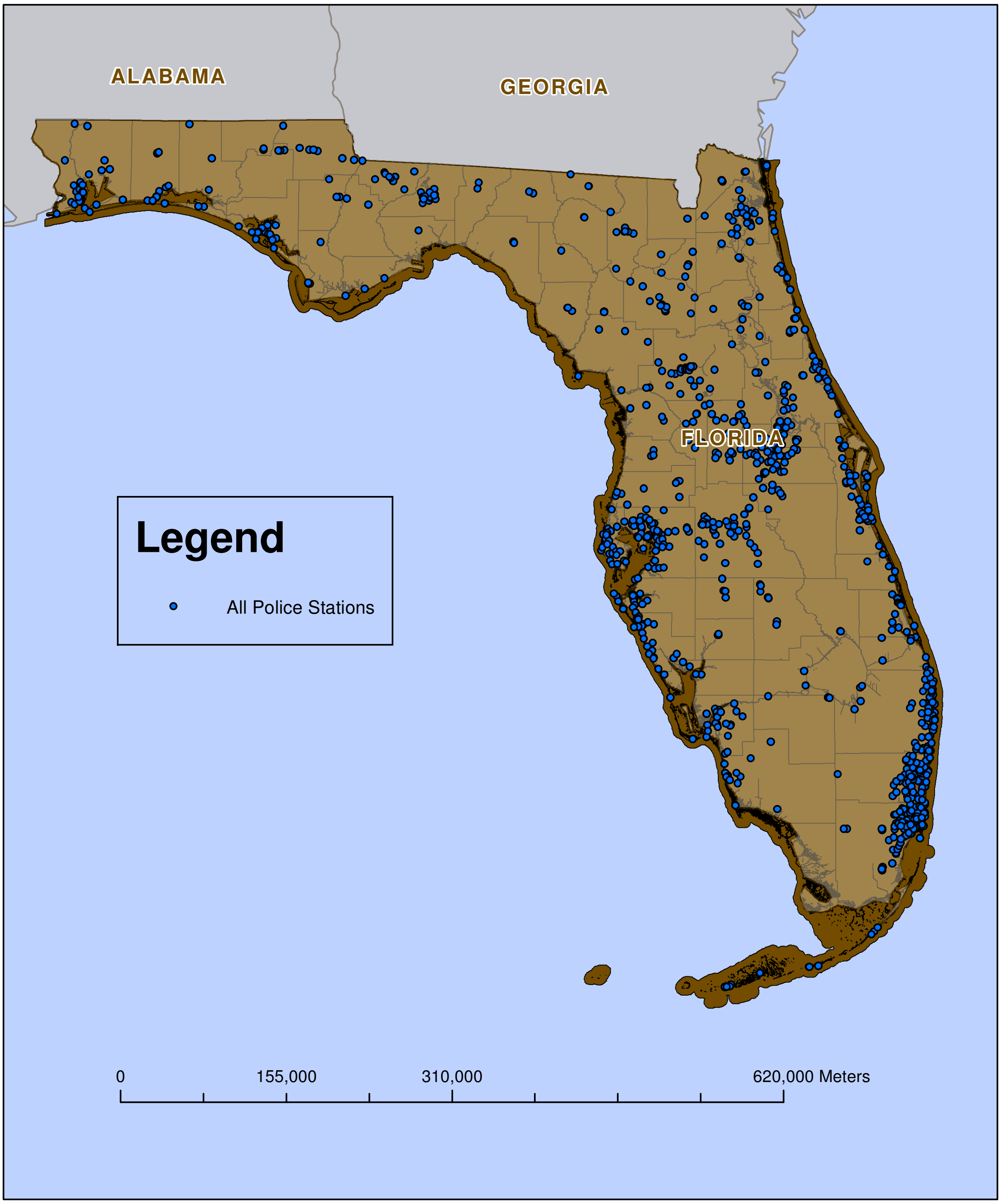

Figure 2: Location of all police station types.

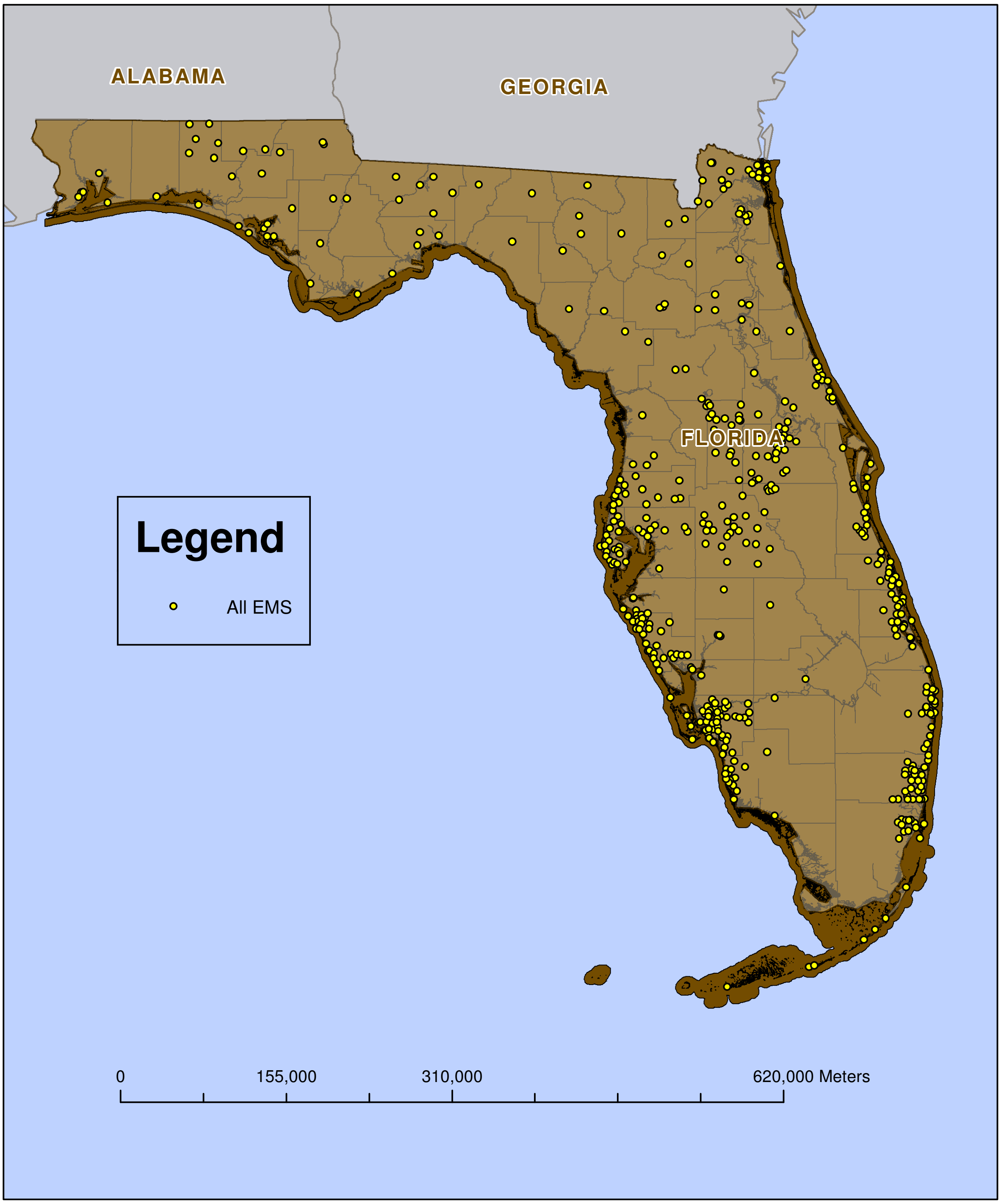

Figure 3: Location of all emergency medical facilities.

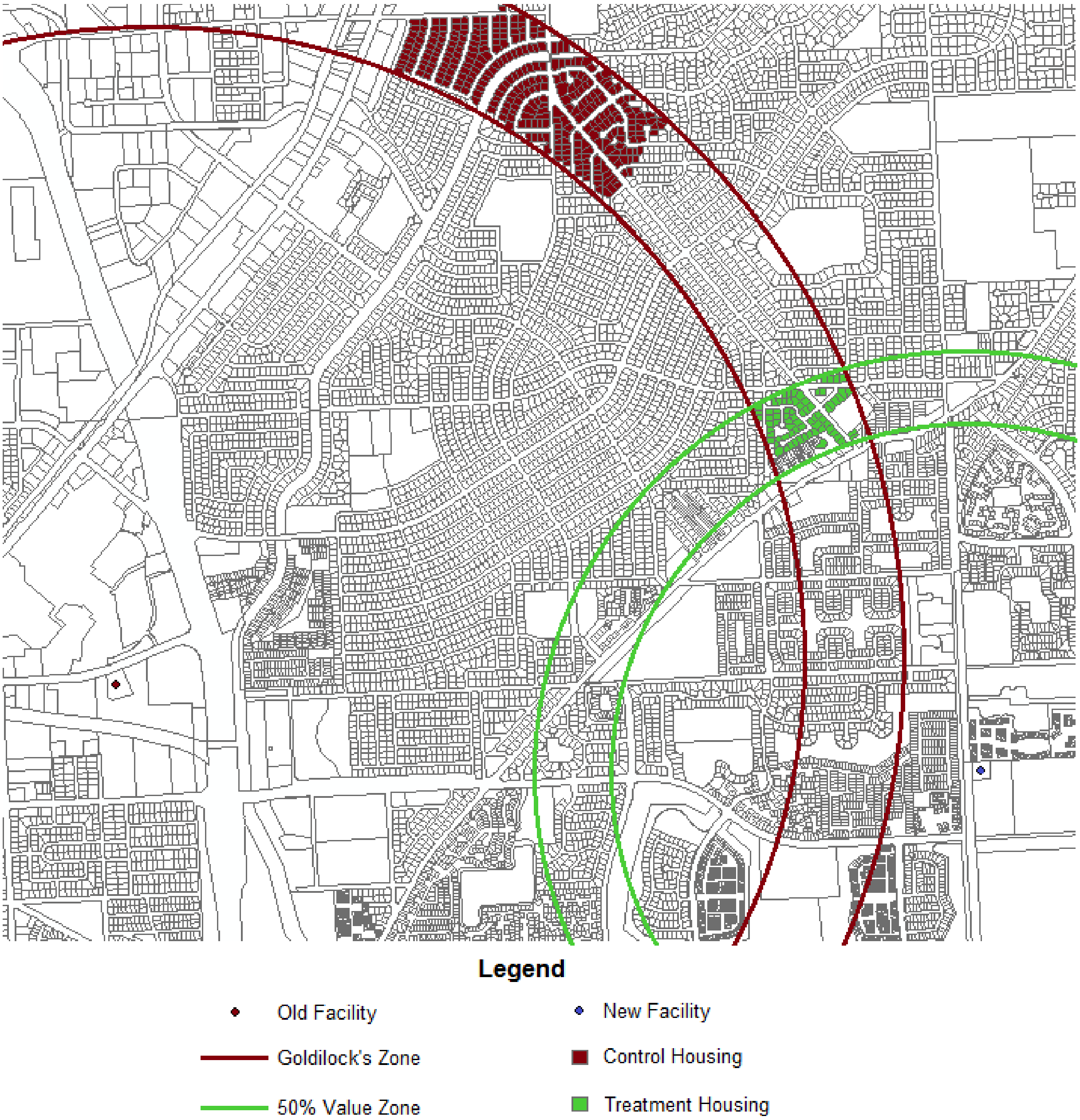

Figure 4: Illustration of control and treatment for DID regression groups.

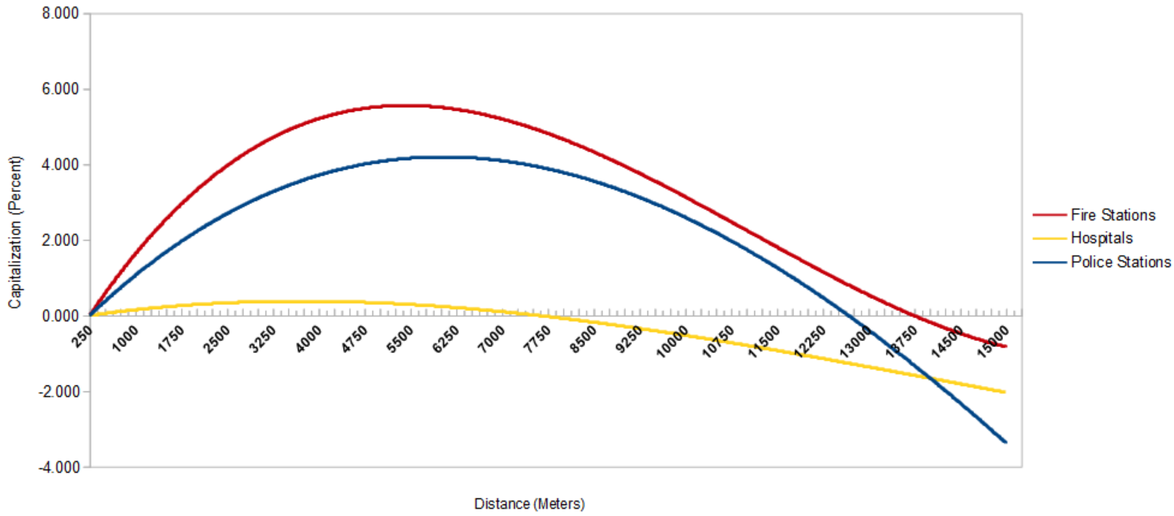

Figure 5: Capitalization effects based on Euclidean distance measures.

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Appendix A

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):[25]

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

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. 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.[26] Given that

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

[26] Mathematically, the amplitude has a horizontal asymptote along the X-axis. However,

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 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:[27]

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

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 vicinity, with farther locations receiving relatively less

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.

[27]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.

emergency traffic.[28]

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 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

[28]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.

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.