WORKING PAPER

The NWIMBY Effect (No WalMart In My Backyard): Big Box Stores and Residential Property Values

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Abstract: Recent Wal-Mart openings have been accompanied by public demonstrations against the company's presence in the community, asserting (among other things) that their presence is deleterious to residential property values. This study empirically evaluates that claim, analyzing the spatial correlation between Wal-Mart locations and residential property values, while comparing Wal-Mart with other big-box retailers for a frame of reference and controlling for other important aspects of a home's market value. We recognize that market value may represent a trade-off between price and patience, so perform a similar analysis using a property's days on the market to evaluate any big-box effect. Finally, we interpret the resulting effects in two ways, from both the resident's and retailer's point of view, casting new light on the NWIMBY effect.

Keywords:

JEL codes: N9 --- Regional and Urban History
R1 --- Urban, Rural and Regional Economics

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I. Introduction

Recent Wal-Mart openings have been accompanied by public demonstrations against the company's presence in the community, asserting (among other things) that their presence is deleterious to residential property values. Consider the following review of the film "Wal-Mart: The High Cost of Low Price":

> At the start of intrepid muckraker Robert Greenwald's awareness-building documentary, Wal-Mart CEO Lee Scott addresses an ecstatic crowd of employees to announce yet another year of unparalleled growth for the world's largest store. And though this success also makes Wal-Mart a bigger target of envy and bad feelings, he exhorts the crowd to stay the course: Wal-Mart is vital to families struggling to get by on a budget; to the suppliers who depend on Wal-Mart to sell their goods; and to the "associates" who depend on Wal-Mart for a paycheck. But is it possible that rather than serve these dependents, Wal-Mart is actually destroying them? How can a store that drives down property values and kills off mom-and-pop businesses that can't afford to compete with Wal-Mart's high-volume, low-price strategy be good for a community?

However, despite the availability of tools to measure this effect, the authors are unaware of any previous study that has attempted to empirically relate Wal-Mart locations to home prices.

This study evaluates the claim, and goes much further. We evaluate the spatial correlation between Wal-Mart locations and residential property values, also comparing Wal-Mart with other big-box retailers for a frame of reference and controlling for other important aspects of a home's market value. We recognize that market value may represent a trade-off between price and patience, and perform a similar analysis using a property's days on the market to evaluate any big-box effect. Finally, we interpret the resulting effects in two ways, from both the resident's and retailer's point of view, casting new light on the NWIMBY effect.

In section II of the paper, we review the literature on property valuation and the spatial impact of construction events. Section III describes our data set, designed for compatibility with the literature, and Section IV explains the model we constructed. In Section V we present the regression analyses using retail prices and ‚days of market' as dependent variables. The final section concludes with interpretation of the results and implications for policy and further research.

II. Literature

There is a robust literature on property valuation, and we cannot hope to review it thoroughly here. Instead, we focus on the issues of model and explanatory variable selection. One obvious characteristic of a property that contributes to its valuation is the amount of area included. The literature is quite clear that more area is unambiguously associated with higher property valuations (Friedman, 1975; Brueckner and Colwell, 1983; Blamire and Barnsley, 1996; Clapp, 2003; Sirmans et al., 2006). Clearly, the zoning type of the property is also essential to a fair comparison of values (Brigham 1965; Lafferty and Frech, 1978; Van Cao and Cory, 1982; Cervero and Duncan, 2004; Spikowski 2006; Haughwout et al., 2008). For residential properties, various measures of area such as bedrooms (Garrod and Willis, 1992) and bathrooms (Clapp, 2003; Sirmans et al., 2006) are often highly correlated with lot area, unanimously showing positive impacts on property value.

Time is important in several ways. First, the age of the property at date of valuation is frequently included as an explanatory variable as well, often in nonlinear fashion to accommodate consumer preferences for new construction or historical homes relative to middle-aged residences (Clapp, 2003; Byrne, 2006). In addition, the date of sale obviously matters, whether directly (Garrod and Willis, 1992; Clapp and Giacotto, 1992) or indirectly via standardization against assessed values as they change over time (Cypher and Hansz, 2003; Hess and Almeida, 2007).

Finally, there is clear evidence that proximity to landmark neighborhood institutions has an effect on proximate property values. These have been calculated for desirable institutions such as parks (Hendon, 1971; Jackson, 2009) but are most often calculated for potentially negative pollution effects from transportation or energy sector installations (Poon, 1978; Nelson, 1982; Pennington and Ward, 1988). At the extreme, there is a body of work that examines the housing price responses to hazardous waste locations or Superfund sites (Boyle and Kiel, 2001; Kiel and Williams, 2005; Kiel, 2006; Gayer and Viscusi, 2002). Occasionally, a study will consider the impact of an institution with potential for either positive or negative impact, such as a sports stadium (Tu, 2005). In this line of the literature, there is also some evidence that residential proximity to differently zoned communities (e.g. mixed use or

commercial) has an impact on residential property values as well (Van Cao and Cory, 1982; Cervero and Duncan, 2004; Spikowski 2006; Haughwout et al., 2008).

Model choice within the literature has largely chosen one of three paths: hedonics, semiparametrics or repeated sales models. Hedonics have been vastly more frequent (see Boyle and Kiel, 2001 for a review), although semiparametric approaches (e.g. Clapp 2003) have leveraged the hedonic model to improve on their ability to reflect unmeasurable neighborhood effects. Repeated sales models rely on a subset of observations for properties which have been valued more than once, therefore abstracting away from the hedonic treatment of property characteristics as an implicit fixed effect of the property in order to focus on changes in valuation over time (e.g. Case and Mayer, 1996).

III. Data Description

This study focuses on single-family home sales within a two-mile radius of 13 big-box stores in El Paso County, Colorado between 1994 and 2005. The stores include five Wal-Mart stores, three Kmart stores, three Target stores, and two Best Buy stores.

A. Opening Date Data

The opening dates for the 13 big-box stores located within the city of Colorado Springs, Colorado were collected from the El Paso County Planning Department and confirmed with the national headquarters of the retail chains and local phonebooks. Opening dates were used to determine how many *open* big-box stores were within a two-mile radius of each property and which *open* big-box store was closest to the sold property, on the date of sale. Of the 13 big-box stores considered, six stores opened within the time period studied, between 1994 and 2005. Given this, homes within the two-mile radius of these stores may be located within two miles of an increasing number of big-box stores over time. For example, a specific property might be located within half a mile of a single big-box store when sold in 1996, but then located within a two-mile radius of three stores in 2002 following the opening of two new big-box stores. The opening dates allow us to accurately calculate the number of *open* big-box stores within a two-mile radius of a specific property, *at the moment of sale*.

B. Property Data

Data were gathered from the Pikes Peak Multiple Listing Service, recording information from every single-family property sold in El Paso County, Colorado between January 1, 1994 and December 31, 2005.[1] For all properties sold, we collected data on MLS number, address, property type, number of bedrooms, number of bathrooms, number of cars in garage, finished square feet, total square feet, year built, list price, sales price, loan type, and the number of days on market. We focused on homes that were sold rather than properties that were listed, withdrawn, expired or cancelled because of the market valuation information contained in the transaction price. In addition the study is limited to single-family residential properties. Commercial data were eliminated because of inconsistencies with many variables, including the number of rooms and bathrooms. In addition, single family residential properties provided us with the greatest accuracy in matching the property location in the mapping software that provided the distance to the nearest big-box stores. This provided a total of 102,017 sales of single -family properties between January 1st, 1994 and December 31st, 2005.

Several additional explanations are warranted. Bedrooms, bathrooms and total square footage were highly correlated, so the study utilizes only total square footage. This is a particularly appropriate choice given the ages of many of the properties in our sample, dating from the late 1800s when large numbers of bedrooms and bathrooms were less common, even in expansive homes. We had hoped to include information on the school district and crime rates associated with each property, but this information was unfortunately not available. Finally, the regressions incorporate a time trend, instead of year dummies, to capture the appreciation of property over time.

For each of the 13 big-box stores located within the county, distances (measured in feet) were calculated to each property located within a two-mile radius. Those calculations were provided by the El Paso County Assessor's Office in Colorado Springs, Colorado.

[1] We are grateful to Nate Banet of Flying Horse Realty, Colorado Springs, for providing us access to the Pikes Peak MLS system. This allowed us to gather the most accurate and complete data set available. These data were gathered between June 22 and June 26, 2009.

C. Cleaning and Matching

In order to maximize the number of property sales in our data, we took great efforts to clean the data prior to matching the distance data from the Assessor's Office to property data from the MLS. While the addresses from the Assessor's Office were standardized and consistent across properties, the MLS data were entered by different realtors and did not adhere to a uniform format. For example, numerically designated streets would appear as both "First Street" and "1st Street". Simple misspellings were also a significant obstacle to matching the distance information to the sales data.

Ultimately we were able to match more than 54,000 observations. We believe that there are three primary factors that prevented the matching of a larger number of observations: (1) properties located more than two miles from all big-box stores, (2) errors within the MLS data, misspellings or other formatting mistakes that we were unable to correct, or (3) sales that were not included in the Assessors Office data. In addition, 45 observations were dropped due to obvious typos in the date of sale (the number of days on market was negative). Several thousand observations were also dropped for which the sale took place before the opening of any store within a two-mile radius.

Table 1 contains a description of each of the variables used in the study. Table 2 describes the summary statistics for each of the variables.

Table 1: Description of Variables

Variable	Description (units of measurement)
cdom	Number of days on market until sale (days)
salesprice	Sales price ($)
Sqft_w	Total square feet if property is closest to a Wal-Mart store, zero otherwise (ft)
Sqft_t	Total square feet if property is closest to a Target store, zero otherwise (ft)
Sqft_k	Total square feet if property is closest to a Kmart store, zero otherwise (ft)
Sqft_b	Total square feet if property is closest to a Best Buy store, zero otherwise (ft)
age_w	Age of house at time of sale, if property is closest to a Wal-Mart store, zero otherwise (yrs)
age_t	Age of house at time of sale, if property is closest to a Target store, zero otherwise (yrs)
age_k	Age of house at time of sale, if property is closest to a Kmart store, zero otherwise (yrs)
age_b	Age of house at time of sale, if property is closest to a Best Buy store, zero otherwise (yrs)
age^2_w	Square of age_w (yrs^2)
age^2_t	Square of age_t (yrs^2)
age^2_k	Square of age_k (yrs^2)
age^2_b	Square of age_b (yrs^2)
Zone_w	Dummy variable set to one if property is closest to Wal-Mart store, zero otherwise
Zone_t	Dummy variable set to one if property is closest to Target store, zero otherwise
Zone_k	Dummy variable set to one if property is closest to Kmart store, zero otherwise
Zone_b	Dummy variable set to one if property is closest to Best Buy store, zero otherwise
Distance_w	Distance to closest store if closest big-box store is a Wal-Mart, zero otherwise (ft)
$Distance^2\_w$	Square of wsaledistance (ft^2)
Circles_w	Number of stores within 2 mile radius of property if closest is a Wal-Mart, zero otherwise
Distance_t	Distance to closest store if closest big-box store is a Target, zero otherwise (ft)
$Distance^2\_t$	Square of tsaledistance (ft^2)
Circles_t	Number of stores within 2 mile radius of property if closest is a Target, zero otherwise
Distance_k	Distance to closest store if closest big-box store is a Kmart, zero otherwise (ft)
$Distance^2\_k$	Square of ksaledistance (ft^2)
Circles_k	Number of stores within 2 mile radius of property if closest is a Kmart, zero otherwise
Distance_b	Distance to closest store if closest big-box store is a Best Buy, zero otherwise (ft)
$Distance^2\_b$	Square of bsaledistance (ft^2)
Circles_b	Number of stores within 2 mile radius of property if closest is a Best Buy, zero otherwise
year dummies	Dummy variables for the year in which the property was sold, 1994-2005, zero otherwise

Table 2: Summary of Variables

Variable	Observations	Mean	Standard Dev.	Min	Maximum
cdom	41977	47.01	56.57	0	1304.00
salesprice	41977	163074.20	86473.95	0	3059564.00
Sqft_w	41977	568.59	1032.36	0	14492.00
Sqft_t	41977	678.17	1092.15	0	15800.00
Sqft_k	41977	698.45	1098.17	0	13597.00
Sqft_b	41977	133.31	575.28	0	7031.00
age_w	41885	11.91	24.84	0	134.00
age_t	41885	6.94	12.42	0	115.00
age_k	41885	8.72	18.52	0	127.00
age_b	41885	1.04	5.01	0	43.00
age^2_w	41885	758.94	2140.21	0	17956.00
age^2_t	41885	202.47	489.12	0	13225.00
age^2_k	41885	419.16	1476.62	0	16129.00
age^2_b	41885	26.23	144.69	0	1849.00
Zone_w	41977	0.28	0.45	0	1.00
Zone_t	41977	0.33	0.47	0	1.00
Zone_k	41977	0.34	0.47	0	1.00
Zone_b	41977	0.06	0.23	0	1.00
Distance_w	41977	2027.93	3504.14	0	11501.63
$Distance^2\_w$	41977	16400000.00	31800000.00	0	132000000.00
Circles_w	41977	0.42	0.76	0	5.00
Distance_t	41977	2238.80	3517.97	0	11100.55
$Distance^2\_t$	41977	17400000.00	31200000.00	0	123000000.00
Circles_t	41977	0.48	0.81	0	4.00
Distance_k	41977	2357.09	3590.74	0	11145.08
$Distance^2\_k$	41977	18400000.00	32100000.00	0	124000000.00
Circles_k	41977	0.52	0.87	0	4.00
Distance_b	41977	397.76	1726.80	0	11166.97
$Distance^2\_b$	41977	3139969.00	14900000.00	0	125000000.00
Circles_b	41977	0.14	0.64	0	4.00

IV. Model

In terms of modeling, the literature is largely bifurcated between hedonic and semi-parametric estimation on one hand versus repeated sales models on the other. We adopt a hedonic approach here, in order to answer our simple question: are Wal-Mart (or other big-box store) locations associated with lower values on adjacent residential properties? We leave for future researchers the equally intriguing questions to be answered by repeated sales models. Given our data, which extend only two miles from a

retail store epicenter in thirteen circles, we assume as negligible the neighborhood effects so adeptly captured by semi-parametric approaches, and return to the simple hedonic approach.

We propose two models in line with the literature, one treating sales price as the dependent variable, while the other treats the property's days on the market before sale as the dependent variable. As both dependent variables are limited to non-negative values, each equation is estimated independently as a Tobit with variances White-corrected to eliminate concerns about heteroskedasticity. All variables pass standard tests for pair-wise correlation.

The equations estimated are:

$$days\ on\ market = \sum_{i=1995}^{2005} \alpha_i Year_i + \sum_{j=1}^{4} \beta_{j,zone} Zone + \sum_{j=1}^{4} [\beta_{j,Sqft} Sqft + \beta_{j,Age} Age + \beta_{j,Age2} Age^2 + \beta_{j,circles} Circles + \beta_{j,distance} Distance + \beta_{j,distance2} Distance^2] + \varepsilon$$

$$sales\ price = \sum_{i=1995}^{2005} \alpha_i Year_i + \sum_{j=1}^{4} \beta_{j,zone} Zone + \sum_{j=1}^{4} [\beta_{j,Sqft} Sqft + \beta_{j,Age} Age + \beta_{j,Age2} Age^2 + \beta_{j,circles} Circles + \beta_{j,distance} Distance + \beta_{j,distance2} Distance^2] + \varepsilon$$

where $Year_i$ is dummy variable for each year;

$Zone_j$ is a dummy variable indicating which of the four types of big-box stores the property is closest to at the time of sale;

Sqft is the number of square feet, improved or unimproved, encompassed in the residence;

Age is the age in years of the residence at time of sale;

Circles is the number of circles, of radius two miles around retail outlets, the property appears in at the time of sale;

and *Distance* is the distance in feet to the closest retail outlet.

Notice that we permit the annual dummy variables to vary individually by year, rather than constraining them to follow a common time trend. However, we constrain them across the entire population rather than permitting them to vary by neighborhood, a choice necessitated for numerical reasons in the estimation.

Estimation permits all other coefficients to vary by type of retail outlet, j = Wal-Mart, Target, Kmart or Best Buy. Structural break tests on preliminary regressions that constrained other coefficients across types of retail outlet summarily rejected equality.

V. Analysis

Tobit regressions using both sales price and current days on market as the dependent variables both confirm similar results, as shown in Table 3.

Considering the first columns of Table 3, many of the results align with what would be expected. An increase in square footage increases the number of days a property will be on the market. The effect is largest for properties located within a two-mile radius of Best Buy and smallest for Target. In terms of age, new homes and vintage homes sell more quickly. Properties spent an increasing number of days on the market between 1995 and 1999, and again between 2002 and 2005. With the exception of properties for which the closest big-box store is a Kmart, the larger the number of big-box stores within a two-mile radius, the more days a property will remain on the market. Finally, there is a nonlinear relationship between distance and days on market. There is a tradeoff between the convenience of a close store, and the nuisance of the light and traffic pollution.

The right columns of Table 3 confirm similar results for property sales prices. An increase in square footage increases the sales price of properties near all types of big-box stores. The greatest effect is seen for properties located within a two-mile radius of Wal-Mart, with the smallest effect in place for stores near Kmart. As above, new homes and vintage homes are more desirable and thus sell for higher prices. Sales prices are shown to increase over time, rising at an increasing rate. For properties for which the closest big-box store is a Kmart or a Best Buy, the larger the number of big-box stores in a two mile

Table 3: Tobit regression results

Variable	Days on market as dependent variable			Sales price as dependent variable		
	Coefficient	**t stat**		**Coefficient**	**t stat**	
totalsqft_w	8.94×10^{-3}	(6.79)	***	82.06	21.23	***
totalsqft_t	7.09×10^{-3}	(8.32)	***	69.61	27.61	***
totalsqft_k	1.07×10^{-2}	(8.01)	***	56.57	51.93	***
totalsqft_b	1.55×10^{-2}	(7.20)	***	58.73	30.27	***
age_w	-1.08×10^{-2}	(0.13)		-437.72	-3.69	***
age_t	-1.14	(7.33)	***	-1878.54	-8.94	***
age_k	-0.39	(4.97)	***	-537.17	-9.06	***
age_b	-1.46	(2.56)	***	-3004.56	-9.33	***
age_w2	1.41×10^{-3}	(2.03)	**	4.25	5.33	***
age_t2	1.76×10^{-2}	(5.77)	***	39.21	6.91	***
age_k2	3.56×10^{-3}	(4.89)	***	9.35	14.62	***
age_b2	3.58×10^{-2}	(2.52)	***	75.75	8.91	***
year1995	8.14	(5.19)	***	7341.68	9.05	***
year1996	7.37	(5.39)	***	16152.74	19.75	***
year1997	14.87	(10.17)	***	19608.04	21.14	***
year1998	15.80	(10.88)	***	24321.88	28.19	***
year1999	15.18	(9.17)	***	32888.33	33.39	***
year2000	6.56	(4.69)	***	43761.16	43.19	***
year2001	-1.85	(1.44)	**	60737.52	51.84	***
year2002	3.11	(2.34)	***	65834.83	59.27	***
year2003	11.18	(7.94)	***	70122.35	56.40	***
year2004	10.33	(7.71)	***	73934.31	66.50	***
year2005	24.05	(16.00)	***	86208.68	70.11	***
saletype_w	13.70	(2.63)	***	-49695.00	-4.41	***
saletype_t	38.86	(9.38)	***	-7013.84	-1.03	
saletype_k	23.13	(5.03)	***	203.94	0.06	
saletype_b	6.45	(0.56)		23540.55	3.22	***
wsaledistance	-6.33×10^{-4}	(0.55)		2.27	2.02	**
wsaledist2	2.55×10^{-8}	(0.29)		-3.32×10^{-5}	-0.37	
wsalenumber	2.24	(2.24)	**	-5906.66	-4.37	***
tsaledistance	-1.58×10^{-3}	(1.55)		-2.40	-2.90	***
tsaledist2	1.38×10^{-7}	(1.73)		1.98×10^{-4}	3.05	***
tsalenumber	0.12	(0.20)		-2728.55	-5.35	***
ksaledistance	-5.80×10^{-3}	(0.62)		-1.22	-2.00	**
ksaledist2	1.80×10^{-8}	(0.25)		1.75×10^{-4}	3.61	***
ksalenumber	-2.12	(3.45)	***	987.49	2.50	**
bsaledistance	-2.63×10^{-4}	(0.09)		-10.02	-6.87	***
bsaledist2	5.92×10^{-8}	(0.24)		8.88×10^{-4}	7.63	***
bsalenumber	0.91	(0.67)		6160.06	8.10	***
Observations	41885			41930		
F-statistic	833.00			24776.71		

radius, the higher the sales price. The reverse is true for properties for which the closest big-box store is a Wal-Mart or Target. Finally, there is a nonlinear relationship between distance and sales price. In this case however, the relationship is the reverse for Wal-Mart relative to other types of stores. The coefficient on distance is positive for Wal-Mart and negative for all others, while the coefficient for distance squared is negative for Wal-Mart and positive for all other types of big-box stores.

A. Breakeven Calculation

The results of the regressions can be used to calculate the breakeven value for each type of big-box store. In essence this calculation describes the tradeoff between the convenience of being located close to a big-box store, against the disadvantage of the additional lights and traffic that are associated with proximity to such a store, controlling for other property characteristics.

The breakeven value has been calculated for both sales price and the number of days on market. The breakeven value, for a specific store type, is the sum of seven factors: (1) the premium/penalty of being within a two-mile radius of this type of store, (2) the benefit/cost per foot of distance separating the store from the property, multiplied by the mean distance between the store and properties located within the two-mile radius, (3) the benefit/cost of distance squared, multiplied by the mean of the squared distance between the store and properties located within the two-mile radius, (4) the premium/penalty of being within a two-mile radius of additional big-box stores, multiplied by the mean number of big-box stores located within two-miles of each property near a specific type of store, (5) the incremental benefit per square foot, multiplied by the mean number of square feet for properties within a two-mile radius of a specific type of store, (6) the incremental loss in value for each year of the property's age, multiplied by the mean age of properties located within a two-mile radius of a specific store type, and (7) the benefit of age squared, multiplied by the mean of age squared of properties located within a two-mile radius of a specific store type.

Figure 1 (below) plots the breakeven value for sales price, describing the relationship between sales price and a property's distance from the location of the specific big-box store (Kmart, Wal-Mart, Target or Best Buy). The calculation indicates that there is a $7000 penalty for properties located within

two-miles of a Wal-Mart store, and the value of the property increases with increasing distance from the Wal-Mart store. The interpretation of the calculation for the other types of big-box stores is more nuanced. In the case of Kmart, Target and Best Buy stores, there is a premium (between $29,107 and $39,222) for properties located within the two-mile radius of these types of stores. However, this premium falls as one moves further away from the store, only to increase after some critical distance (between 3400 and 6000 feet). This may indicate that benefits of being located close to the store outweigh the inconvenience of the traffic for properties more closely located. Beyond some critical distance the disadvantage of traffic disappears and greater travel distance is a disadvantage.

From the perspective of the retailers, this information informs the location decision. When retail stores select a location for a future store, they presumably face a tradeoff between locating in a neighborhood with low property values, providing a lower purchase price for the land, and locating in an more prosperous neighborhood, providing a close set of more affluent consumers. In the context of Figure 1, a store would optimally hope to locate on the most affordable property possible, but surrounded by households of increasing affluence. Presumably this would be at, or immediately to the right of, the minimum of the store's plotted curve. It appears that Wal-Mart has been best able to maneuver this balance, locating their stores on the most affordable properties, with increasingly more valuable properties surrounding the location.

Alternatively, Figure 2 (above) plots the breakeven value for current days on market, describing the relationship between days on market and a property's distance from the location of the specific big-box store (Kmart, Wal-Mart, Target or Best Buy). The figure indicates that there is an 8 to 39 day penalty for properties located within two-miles of a big-box store. For a given distance within the two-mile radius surrounding a big-box store, properties located near Best Buy sell the fastest, followed by Wal-Mart, Kmart and Target. This ordering is invariable for any distance within the two-mile radius. For Best Buy and Target stores, there is an optimal distance for more rapid property sales. However, for Wal-Mart and Kmart, properties sell faster the further they are located from the big-box store. It is also worth

Figure 1: Breakeven Chart for Sales Price and Distance from Stores of Different Types

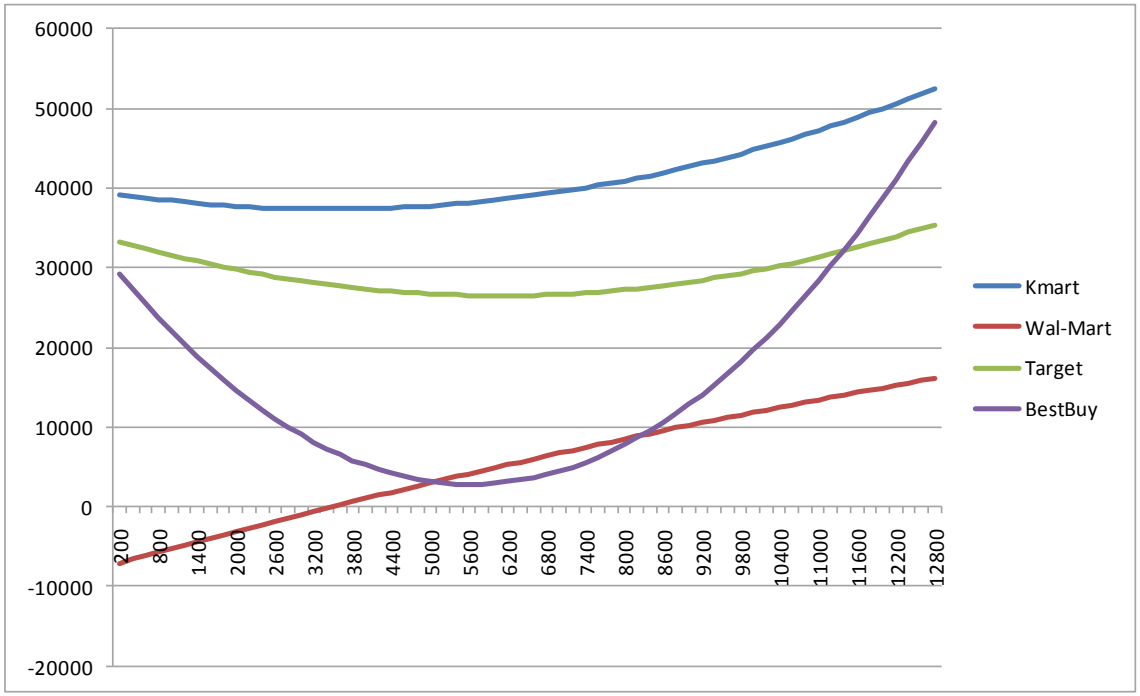
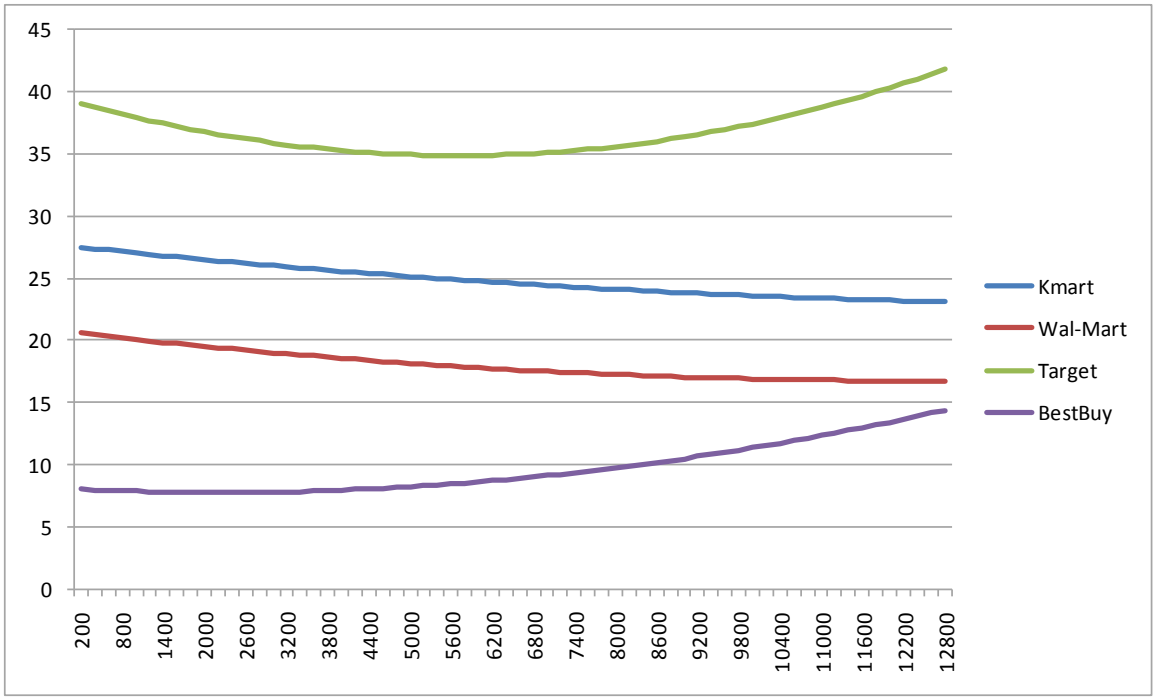


Figure 2: Breakeven Chart for Days on Market and Distance from Stores of Different Types



noting that the plots for Wal-Mart and Kmart, the two most similar stores, also most closely track one another.

A comparison of Figures 1 and 2 fails to provide the expected correlation. Presumably there is a tradeoff between a high sales price and the time that a property remains on the market, but the tradeoff is not evident in the two graphs. With the exception of Wal-Mart, the ordering of the big-box stores does not correlate across the two graphs to illustrate the price-time tradeoff over distance. In the case of Wal-Mart, the greater the distance to the store, the faster the property sells *and* the fewer days the property remains on the market.

VI. Conclusion

Our study finds that proximity to one or more big box stores delays home sales and diminishes home property values in that area. Proximity to a big box store also amplifies the previously observed relationship between square footage and time on market. That is, properties with relatively large square footage located near a big box store remain on the market significantly longer than their smaller counterparts located farther from big box sites. Within some critical distance, however, the data indicate that the convenience of being close to a big box store may outweigh the negative effects on pricing, at least for some homeowners.

Beyond implications for homeowners, our study also informs retailers about optimal locations, and provides rationale for the presence of big box stores in areas of affordable housing and properties of increasing value around the store. Essentially, this location strategy is the same for home property owners, the main difference in the context of this study being that homeowners do not influence the values of surrounding homes to the extent that a big box stores do.

This study does not offer evidence on the causal effect of big box stores on residential property values, so does not judge the validity of the claims by demonstrators that Wal-Mart lowers their home values. However, this study does offer clear evidence of a potential counter-argument: of all big box stores in the study, Wal-Mart is the most successful at identifying lower value neighborhoods in which to locate. There is at least the possibility that demonstrators have their causality argument backwards. We

leave that test, presumably using a repeated sales model with sales that span the opening of a store, to future study.

Further research on this topic could focus on the relationship between big box stores and home property values outside El Paso County, to determine whether these trends generalize outside of this particular region. Also, since the data suggested that K-Mart produced different effects on home property values than the other box stores in the analysis, another opportunity for further research would be an analysis of the different effects on home property values caused by different box stores in the vicinity.

Appendices

Table A1: Breakeven Calculation for Current Days on Market
(highlighted boxes indicated minimum values)

Distance	Kmart	Wal-Mart	Target	Best Buy	Distance	Kmart	Wal-Mart	Target	Best Buy
200	27.47	20.55	39.08	8.00	6600	24.54	17.61	34.98	8.89
400	27.36	20.43	38.78	7.95	6800	24.48	17.55	35.03	9.00
600	27.24	20.31	38.49	7.91	7000	24.41	17.50	35.10	9.11
800	27.13	20.19	38.21	7.87	7200	24.35	17.44	35.17	9.22
1000	27.02	20.07	37.95	7.84	7400	24.28	17.39	35.26	9.34
1200	26.92	19.95	37.69	7.82	7600	24.22	17.34	35.36	9.47
1400	26.81	19.84	37.45	7.80	7800	24.16	17.29	35.47	9.60
1600	26.70	19.73	37.21	7.78	8000	24.10	17.24	35.59	9.73
1800	26.60	19.62	36.99	7.77	8200	24.04	17.20	35.72	9.87
2000	26.50	19.51	36.78	7.76	8400	23.99	17.16	35.86	10.02
2200	26.40	19.41	36.58	7.76	8600	23.93	17.12	36.01	10.16
2400	26.30	19.31	36.39	7.76	8800	23.88	17.08	36.18	10.32
2600	26.20	19.20	36.22	7.76	9000	23.83	17.04	36.35	10.48
2800	26.10	19.10	36.05	7.78	9200	23.78	17.01	36.54	10.64
3000	26.01	19.01	35.89	7.79	9400	23.73	16.98	36.74	10.81
3200	25.92	18.91	35.75	7.81	9600	23.68	16.95	36.95	10.98
3400	25.82	18.82	35.61	7.84	9800	23.63	16.92	37.17	11.16
3600	25.73	18.73	35.49	7.87	10000	23.59	16.90	37.40	11.34
3800	25.64	18.64	35.38	7.90	10200	23.55	16.87	37.64	11.52
4000	25.56	18.55	35.28	7.94	10400	23.50	16.85	37.89	11.72
4200	25.47	18.47	35.19	7.99	10600	23.46	16.83	38.16	11.91
4400	25.38	18.39	35.11	8.04	10800	23.42	16.81	38.43	12.11
4600	25.30	18.30	35.04	8.09	11000	23.39	16.80	38.72	12.32
4800	25.22	18.23	34.99	8.15	11200	23.35	16.78	39.01	12.53
5000	25.14	18.15	34.94	8.21	11400	23.32	16.77	39.32	12.74
5200	25.06	18.07	34.91	8.28	11600	23.28	16.76	39.64	12.96
5400	24.98	18.00	34.88	8.35	11800	23.25	16.76	39.97	13.19
5600	24.90	17.93	34.87	8.43	12000	23.22	16.75	40.31	13.42
5800	24.83	17.86	34.87	8.51	12200	23.19	16.75	40.66	13.65
6000	24.76	17.80	34.88	8.60	12400	23.17	16.75	41.03	13.89
6200	24.68	17.73	34.90	8.69	12600	23.14	16.75	41.40	14.13
6400	24.61	17.67	34.93	8.79	12800	23.12	16.75	41.79	14.38

Table A2: Breakeven Calculation for Sales Price
(highlighted boxes indicated minimum values)

Distance	Kmart	Wal-Mart	Target	Best Buy	Distance	Kmart	Wal-Mart	Target	Best Buy
200	39222	-7080	33313	29107	6600	39038	5989	26546	3629
400	39000	-6631	32857	27210	6800	39263	6354	26595	4005
600	38792	-6184	32416	25385	7000	39501	6716	26660	4451
800	38597	-5740	31991	23630	7200	39754	7075	26741	4968
1000	38417	-5298	31582	21946	7400	40021	7432	26838	5557
1200	38250	-4859	31189	20333	7600	40302	7786	26950	6216
1400	38098	-4423	30812	18791	7800	40596	8137	27079	6947
1600	37959	-3989	30450	17321	8000	40905	8485	27223	7748
1800	37835	-3558	30104	15921	8200	41228	8831	27382	8621
2000	37724	-3130	29775	14592	8400	41564	9175	27558	9564
2200	37627	-2704	29460	13334	8600	41915	9516	27749	10579
2400	37545	-2281	29162	12148	8800	42280	9854	27957	11664
2600	37476	-1861	28879	11032	9000	42658	10189	28180	12821
2800	37421	-1443	28613	9987	9200	43051	10522	28419	14048
3000	37381	-1028	28362	9014	9400	43457	10852	28673	15347
3200	37354	-615	28127	8111	9600	43878	11179	28944	16716
3400	37341	-206	27907	7279	9800	44312	11504	29230	18157
3600	37342	201	27704	6518	10000	44761	11826	29532	19669
3800	37358	606	27516	5829	10200	45223	12145	29850	21251
4000	37387	1008	27344	5210	10400	45700	12462	30183	22905
4200	37430	1407	27188	4662	10600	46190	12776	30533	24629
4400	37487	1803	27047	4186	10800	46694	13088	30898	26425
4600	37558	2197	26923	3780	11000	47213	13397	31279	28292
4800	37643	2588	26814	3445	11200	47745	13703	31676	30229
5000	37742	2977	26721	3182	11400	48291	14006	32089	32238
5200	37855	3363	26644	2989	11600	48851	14307	32517	34317
5400	37982	3746	26583	2868	11800	49426	14605	32961	36468
5600	38123	4126	26537	2817	12000	50014	14901	33421	38690
5800	38278	4504	26507	2837	12200	50616	15194	33897	40982
6000	38447	4879	26493	2929	12400	51232	15484	34389	43346
6200	38630	5252	26495	3091	12600	51862	15772	34896	45781
6400	38827	5622	26513	3325	12800	52507	16057	35419	48286

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