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Sample Selection Approaches to Estimating House Price Cash Differentials

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Abstract We extend the literature on house price cash differentials in important ways. First, our paper is the first to employ methods to correct for sample selection bias, using both switching regression and propensity score matching of cash vs. non-cash transactions. We use selection models to produce price counterfactuals for cash and noncash buyers. We also include both average treatment effect and a propensity score weighted selection models. From the selection models, we find that previous studies likely overstate the cash discount. Results from counterfactual tests examining cash discounts suggest amplified cash discounts in areas with close proximity to an environmental hazard; and also a pricing differential based on CBG level income, with purchasers in high income areas more likely to pay a cash premium compared to market participants in areas with comparably lower income, where a cash discount is detected. These results provide useful insights for market participants including real estate appraisers, brokers, and buyers and sellers of real estate.

Keywords Housing · Cash discount · Environmental economics · Sample selection · Valuation

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Introduction

The financing of housing purchases in the United States has experienced substantial changes over the last few years, especially since the financial crisis of 2007–2009. In October of 2008, approximately 15 % of Realtor® transacted house sales were cash transactions, whereas in April of 2013 the percentage had increased to 31 % (Realtors® 2013).[1] Although investors are more likely to purchase with cash, the recent trend in cash transactions has been the result of an increasing proportion of current homeowners electing all cash transactions (Inside Mortgage Finance 2013). A variety of factors might explain this differential, notably changing lending criteria, shortened waiting period for cash-out-refinances, and consumer sentiment. Mortgage origination costs have also increased recently, perhaps further encouraging cash transactions (Schmit 2013).[2] Even though the importance of cash-only housing transactions relative to conventional financing purchases has changed, research in this area is limited.

A monetary discount might motivate a cash transaction, as the use of cash might benefit the seller. First, with a cash purchaser, uncertainty about a buyer's mortgage eligibility is eliminated, and second a reduced time to contract closing may result from not having the need to secure financing as financing issues are the most common cause in delays (Inside Mortgage Finance 2014). As a result, cash buyers typically are able to make purchases at a discount to those that need external financing. According to a recent survey by Inside Mortgage Finance, the increase in cash buyers is compressing house values, as these purchasers receive the well-known cash discount (Housing Predictor 2012). Given this sentiment, and the increased occurrence of cash transactions, further examination of the cash differential is a pertinent topic.

The choice of funding a house purchase is not random, but subject to systematic confounding factors, potentially biasing effect estimates. Cash-only buyers make a choice to use cash instead of other financing options when purchasing a house, so buyer characteristics along with other market characteristics shape this decision. Controlling for these differential characteristics could yield a better approximation of the true cash discount. We therefore focus on models controlling for differences between cash only transactions (and their buyers) from housing sales utilizing mortgage financing. As such, we recognize the potential for self–selection bias and use propensity score matching (PSM) and Heckman Sample Selection models (Heckman 1979) to control for this potential bias. As part of the process we estimate a probit model to support the matching process, which helps us better understand the impact of exogenous housing, neighborhood, and demographic factors on the likelihood of purchasing a house with cash.

Next we consider the influence of environmental and income characteristics on the observed cash differential, recognizing potential for a non-static effect. Extrapolating from the ample mortgage default literature, an increased discount is representative of the purchaser giving up the option of mortgage default and therefore we expect a cash

[1] Realtor® also reports that most international buyers purchase properties with cash, given their limited access to conventional financing options.

[2] In a recent interview with USA Today, Guy Cecala, publisher of Inside Mortgage Finance suggested that the main catalyst for the increasing closing costs are origination fees having increased by 8 % in the past year. Additionally, he remarked that rising mortgage rates often result in lenders making less profit on their loans, often they mitigate this potential loss with higher closing fees." *Source:* "*Mortgage closing costs are on the way up,*" *USA Today (Aug. 5, 2013).*

discount to be inversely related to distance to an environmental disamenity since markets near disamenities are likely thinner than those further away (Hite 1998). As such, we expect comparatively large cash discounts on houses in close proximity to an environmental disamenity.

The possible cash differential with regards to levels of purchaser and seller financial constraints, respectively, is also examined. If higher (lower) income on average points towards a less (more) financially constrained buyer, an application of the Black-Scholes pricing formula would suggests that a less constrained purchaser would be willing to pay a premium for a house call option relative to a buyer with larger financial constraints (Hung and So 2012), resulting in a higher transacted price. Consistent with previous research, we expect the relative cash discount to decrease as transaction price increases.

In controlling for self-selection bias, we extend the literature on the estimation and determinants of cash-only housing transactions. By implementing PSM and Heckman Sample Selection approaches to correct for potential selectivity bias, we present more robust estimates and standard errors, and provide useful insight into the determinants of cash only transactions. We also implement controls to evaluate the effects of environmental and income characteristics on the observed cash differential. These findings help us quantify the cash differential, providing useful insights for real estate appraisers, brokers, and buyers and sellers of real estate.

Literature Review

Few studies have controlled for self-selecting behavior between cash-only housing transactions and mortgage housing transactions. Rather, the focus in this area of research has been the magnitude of the discount obtained from purchasing a house with cash versus mortgage financing options. In a review of the literature on hedonic price models, Sirmans and Macpherson (2003) finds that in a sample of 82 studies, only 4 of them control for cash-only sales. Of the studies controlling for cash transactions, all of them find a statistically significant discount for cash-only transactions, which is consistent with expectations.

Asabere et al. (1992) is the first paper providing a formal theoretical framework for the existence of a discount for cash-only housing transactions, also providing the first empirical evidence. They contend that cash-only transactions are attractive in that they carry fewer uncertainties over housing transactions involving a mortgage. For example, there is always some uncertainty regarding the financing provision and appraised value. Further, cash-only transactions typically take fewer days to close (Asabere et al. 1992), reducing uncertainty during the contract period. Empirically, they find that out of a sample of 319 “row” housing transactions in Delaware County, Pennsylvania, between 1989 and 1991, the cash-only housing purchases carry a 13.4 % price discount (Asabere et al. 1992).

Lusht and Hansz (1994) find a 16.5 % discount for cash-only transactions in a sample of 200 “row” housing transactions in Lehigh County, Pennsylvania, in 1989. They also find that 1) the size of the premium is indifferent to transaction-specific variables; and 2) differences in the opportunity costs of waiting for a sale to be finalized do not have a statistically significant impact on housing prices.

More recently, Aroul and Hansz (2011) find a 13.5 % discount for cash-only transactions in Clovis, California, from 2008 through 2010. Their research focus was not on cash-only transactions, but used this information as a control dummy variable in a hedonic pricing model. In another study contradicting the prior body of research, Hansz and Hayunga (2012), find that cash buyers in some residential areas pay a premium and suggest that financing be added to future house pricing models.

Our study extends the literature, as previous studies control for cash-only transactions by assuming an exogenous indicator variable in a traditionally specified hedonic pricing model. A limitation to these models is that they disregard potential selectivity bias. Recognizing that cash-only buyers make a choice to use cash rather than mortgage financing when purchasing a house, and that systematic differences in buyer characteristics along with market characteristics guide this decision, self-selection bias is likely to be a problem if a cash-only dummy variable is used. Our study is the first to address this issue. This study also differs in that we examine the influence of environmental issues, and income on the observed cash differential; it is possible that some cash buyers may be purchasing investment houses to rent, and therefore are not sensitive to environmental quality. It is also possible that savvy investment buyers use knowledge of a disamenity to bid down house prices (Hite 1998). The probit model that predicts the likelihood of a cash transaction also provides useful information regarding the determinants of cash transactions.

Data

The data set used in the analysis consists of 9716 housing transactions located in 556 Census block groups (CBG) in Franklin County, Ohio occurring in 2000; we included only those transactions that are in cities and townships located completely within the Franklin County border lines. A total of 646 or approximately 6.7 % of the transactions are identified as cash-only, which we verified against Franklin County Auditor's Records to make sure that they did not show a mortgage. We did not include transactions that were located in cities that share several county lines (for example, Canal Winchester between Franklin County and Fairfield County). Figure 1 presents a spatial map of our sample identifying cash and non-cash transactions; from the map, it appears that cash transactions are not concentrated in particular areas of the county suggesting that they are not systematically associated with any particular housing type.

Following the traditional hedonic price literature, we included three types of housing characteristics in the hedonic price models: individual housing characteristics, neighborhood demographic characteristics, and neighborhood environmental characteristics. Tables 1 and 2 contain variable descriptions, sources, and descriptive statistics by transaction type. The average house price for mortgage transactions is approximately $143,772 with an average size of 1621 square feet, 1.81 bathrooms, and 6.30 rooms. Cash-only transactions sell at a discount relative to mortgage transactions, and tend to be marginally smaller in size. The average house price for cash-only transactions is approximately $140,400 (a 2.4 % unadjusted discount) with an average size of 1600 square feet, 1.81 bathrooms, and 6.16 rooms. Although the price difference appears at first glance to be related to fewer square feet for cash transactions, the price per square foot is also lower than for non-cash transaction.

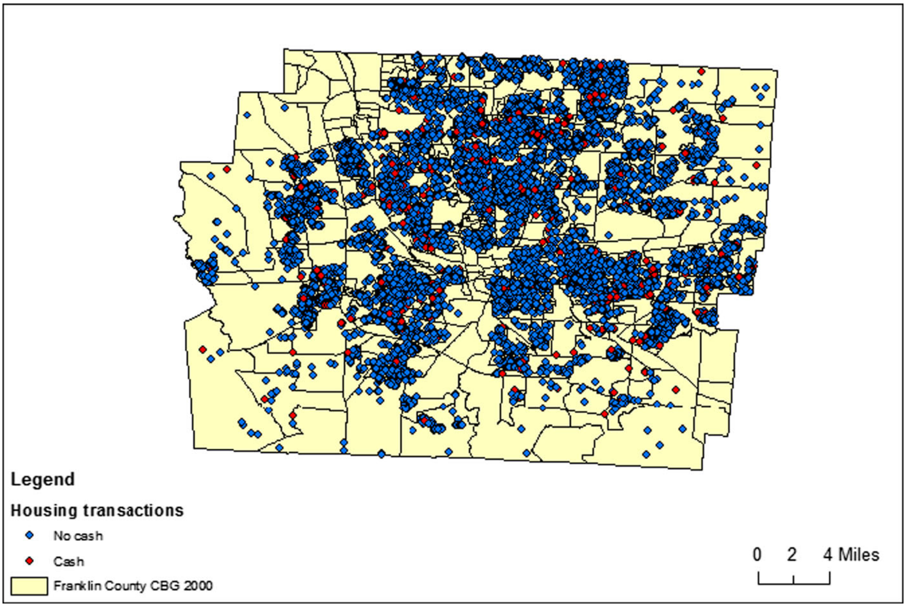

Fig. 1 Cash and non cash transactions

Individual housing characteristic variables are obtained from First American Real Estate Solutions; each transaction is geocoded and matched to U.S. Census demographic, school quality, and environmental information. Demographic information and crime statistics come from the GeoLytics Census CD 2000 Long Form (Release 2.0), the environmental data are from the Ohio Environmental Protection Agency, and data regarding school quality are from the Ohio Department of Education.

Methodology

Sample Selection Model

The central hypothesis of this paper is that housing sales transacted with cash have a significant, non-trivial discount relative to non-cash housing transactions. This implies behavior driving individuals to select whether to use cash or other financing options when buying a house. If we observe a cash transaction, we hypothesize that the buyer expects to receive a discount from the reduced risk involved in the transaction. Sellers would also agree to this not only for risk abatement, but also to have an opportunity to invest sales proceeds sooner, thus accruing added interest.

Our secondary hypotheses are as follows:

1) The rate of cash discount may be affected by proximity to environmental disamenities; our expectation is that discounts would be higher near disamenities. That is, markets are thinner near disamenities, and thus cash buyers could secure a larger discount because of increased bargaining power; and
2) the rate of cash discount may be affected by buyers' financial constraints.

Table 1 Variables definition and source

Variable name	Description	Sources
tranamt	House sale transaction amount in U.S. dollars.	First American Real Estate Solutions
cash	1 for house sales with cash; 0 otherwise	Own calculations
agehouse	Age of house, where 2000 is the base year 22	First American Real Estate Solutions
rooms	Number of rooms in house	First American Real Estate Solutions
baths	Total number of bathrooms in the house (sum of full bathrooms and partial bathrooms)	First American Real Estate Solutions
building_sqmt	building size in square meters	First American Real Estate Solutions
lotsize_sqmt	lot size in square meters	First American Real Estate Solutions
avg_room_sz	(building_sqmt/rooms)	Own calculations
air	1 for houses with air conditioning, 0 otherwise	First American Real Estate Solutions
dgarage	1 for houses with garage(s), 0 otherwise	First American Real Estate Solutions
duration	Number of days of house duration	Own calculations
mindist	Distance from each house to nearest environmental hazard in miles	Own calculations from various sources, primarily TRI On-site and Off-site Reported Releases
inchet_cbg	Coefficient of variation for household income in census block group	GeoLytics CensusCD 2000 Long Form Release 2.0
percapinc_cbg	Per capita income in dollars in census block group	GeoLytics CensusCD 2000 Long Form Release 2.0
commute_cbg	Average commute time in minutes for persons 16 years and over not working at home in census block group who were both employed and at work during the reference week	GeoLytics CensusCD 2000 Long Form Release 2.0
ownerocc_cbg	Percent of occupied housing units in census block group that are occupied by owners rather than renters	GeoLytics CensusCD 2000 Long Form Release 2.0
pct9all00	Percent of 9th grade students in school district who passed all five sections (citizenship, reading, writing, math, science) of Ohio proficiency test in 2000–01 school year	Ohio Department of Education, Division of Information Management Services
pctvacant_cbg	Percent of housing units in census block group that are vacant	GeoLytics CensusCD 2000 Long Form Release 2.0
offensecap	Grand total of actual offenses in police district per thousands of persons in police district	GeoLytics CrimeReportsCD 1.0 of 2000
unemp_cbg	Percentage of labor force in census block that is unemployed; labor force is sum of employed plus unemployed persons age 16 and over	GeoLytics CensusCD 2000 Long Form Release 2.0
density_cbg	Number of persons per square mile in block group	GeoLytics CensusCD 2000 Long Form Release 2.0
volume_buyer	House buyers who buy more than 4 houses in a year	Own calculations

This table contains a description and the source for sample data analyzed in this study. The individual housing characteristic variables were obtained from First American Real Estate Solutions. Each transaction was geocoded and matched to U.S. Census demographic, school quality, and environmental information. The demographic information and crime statistics are from the GeoLytics Census CD 2000 Long Form (Release 2.0), the environmental data is from the Ohio Environmental Protection Agency, and data regarding school quality is from the Ohio Department of Education

Table 2 Descriptive statistics

Variable name	Full sample (N=9716)		Non-cash (N=9070)		Cash (N=646)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
tranamt	143,548.00	105,415.1	143,772.30	103,467.80	140,399.90	129,761.20
cash	0.07	0.25	–	–	–	–
agehouse	34.41	29.62	34.48	29.86	33.38	25.98
rooms	6.28	1.33	6.30	1.33	6.16	1.27
baths	1.81	0.71	1.81	0.71	1.81	0.72
building_sqmt	150.48	61.55	150.61	61.13	148.67	67.29
lotsize_sqmt	1032.65	2005.17	1020.64	1989.56	1201.30	2207.63
air	0.78	0.41	0.78	0.41	0.79	0.41
avg_room_sz	23.46	5.85	23.45	5.74	23.65	7.19
dgarage	0.64	0.48	0.64	0.48	0.64	0.48
duration	2302.10	1934.33	2292.28	1909.43	2439.97	2252.27
mindist	1.27	0.76	1.27	0.76	1.30	0.75
percapinc_cbg	25,194.08	10,631.79	25,152.85	10,612.85	25,772.92	10,886.23
inchet_cbg	0.65	0.15	0.65	0.16	0.64	0.13
commute_cbg	23.63	2.91	23.64	2.91	23.65	3.02
owneroccc_cbg	71.98	22.00	71.85	22.08	73.91	20.82
pct9all00	60.39	19.77	60.39	19.76	60.41	19.92
offensecap	91.85	67.71	91.75	67.06	93.39	76.24
unemp_cbg	3.65	3.55	3.68	3.58	3.28	3.10
pctvacant_cbg	5.17	4.82	5.18	4.81	4.95	4.92
density_cbg	4520.49	2891.44	4531.61	2903.35	4364.25	2716.05
volume_buyer	0.005	0.07	0.004	0.06	0.02	0.13

The data consists of 9716 housing transactions located in 556 Census block groups (CBG) in Franklin County, Ohio occurring in 2000; we included only transactions that are in cities and townships located completely within the Franklin County border lines. A total of 646 or approximately 6.7 % of the transactions are identified as cash-only, which we verified with Franklin County Auditor Records

Following Rosen's (1974) hedonic framework we incorporate the cash discount into the buyer's utility maximization problem as:

$$Max\ U = u(Z, X,\ DSC; \delta)\ \text{s.t.}\ Y = (P(Z)(1-DSC)) + X \tag{1}$$

where Z is a vector of housing attributes, δ is a vector of buyer's characteristics, Y is income, DSC denotes a discount percentage that occurs with an all-cash transaction, and X is a composite, numeraire good. If DSC is large enough so that $U_{Cash} > U_{Non\text{-}cash}$, and a buyer has the ability to pay, then they would buy a house with all-cash instead of other financing. Furthermore, utility is an increasing function of the size of the discount, that is, $\frac{\partial U}{\partial DSC} > 0$.

Because individuals self-select into making cash purchases based partially on unobserved factors, we require the effect of cash buyers on transaction prices to be modeled using a sample selection model. In the model, we first form the sample selection mechanism. We assume that observed choice of using cash occurs when

$U_{Cash} > U_{Non\text{-}cash}$, holds; that is, buyers receive higher utility as a result of lower costs resulting from the cash discount, which is statistically related to variables observable in the data. Thus, the selection model is as follows:

$$\begin{array}{l} C_i^* \;=\; Z_i\eta \,-\, \nu_i \\ C_i = 1 \;\text{iff}\; C_i^* > 0 \\ C_i = 0, \;\; \text{otherwise} \end{array} \tag{2}$$

where C_i^* is an unobservable level of utility that an individual receives from buying a property with cash, Z_i is a vector of demographic, income, and other variables that explain using cash to buy a property, η_i represents the parameter vector, and ν_i represents the error term.

Next, the hedonic housing price models are as follows:

$$P_{Ci} = X_{Ci}\alpha_C + \lambda_{iC} + \varepsilon_{Ci} \tag{3}$$

$$P_{NCi} = X_{NCi}\alpha_{NC} + \lambda_{iNC} + \varepsilon_{NCi} \tag{4}$$

where P_{Ci} is the log price obtained when buying a property with cash, P_{NCi} is the price obtained when buying a property without cash, X_C and X_{NC} are vectors of housing characteristics, $\lambda_{iC} = \frac{\phi(\eta Z_i)}{\varphi(\eta Z_i)}$ and $\lambda_{iNC} = 1 - \frac{\phi(\eta Z_i)}{\varphi(\eta Z_i)}$ are the selection correction terms, and $(\varepsilon_C, \varepsilon_{NC}, \nu)' \sim N(0, \sum)$. The observed housing price P_i is then defined as:[3]

$$P_i = P_{Ci} \;\text{iff}\; C_i = 1 \tag{5}$$

$$P_i = P_{NCi} \;\text{iff}\; C_i = 0_3 \tag{6}$$

It is important to keep in mind that parameters estimates from Eqs. (3) and (4) represent the percentage contribution each characteristic makes to the overall house price for linear covariates, and represent elasticities for log transformed covariates; we expect that parameter estimates should differ between the two equations under the hypothesis of self-selection. That is, we expect cash buyers to have different returns to characteristics than noncash buyers.

Statistical Tests

We devise counterfactual tests similar to Hite (2000) and Jauregui and Hite (2010) to verify our hypothesis that cash buyers pay less for a house than would attain with other forms of financing. Parameter estimates from the model given by (3) and (4) are used to calculate empirical counterfactuals. Using the estimated parameters from Eq. (4), we calculate the prices that would be expected if the sample of cash transacted houses had the same returns to characteristics as the non-cash transacted houses, which can then be tested against the actual expected price from Eq. (4); we likewise create expected prices for noncash buyers had they received the same returns to characteristics as cash buyers. We conduct paired t-tests at various distances from the landfills to test for significant

[3] For a detailed description of models with self-selectivity, refer to Maddala (1983, pp. 257).

statistical differences in expected prices vs counterfactual prices. That is:

$$H_0 = \hat{Price}_{(C/C)} - \hat{\mathrm{Price}}_{(C/NC)} = 0 \;\text{ vs. }\; H_A = \hat{Price}_{(C/C)} - \hat{\mathrm{Price}}_{(C/NC)} \neq 0 \tag{7}$$

where $\hat{Price}_{(C/C)}$ is cash transactions assuming cash expected prices and $\hat{Price}_{(C/NC)}$ is cash transaction assuming non-cash expected prices. The counterpart hypothesis for non-cash transactions assuming cash estimates is

$$H_0 = \hat{Price}_{(NC/NC)} - \hat{\mathrm{Price}}_{(NC/C)} = 0 \;\text{ vs. }\; H_A = \hat{Price}_{(NC/NC)} - \hat{\mathrm{Price}}_{NC/C} \neq 0. \tag{8}$$

Propensity Score Matching

We also employ a propensity score matching (PSM) approach, as it has been suggested as a method for mitigating self-selection bias (Rosenbaum and Rubin 1983).[4] Matching treated with control observations based on propensity scores can reduce bias by controlling for observed heterogeneity between samples of treated (cash sales) and control (noncash sale) observations.

The PSM technique enables comparison of control and treated observations by calculating an aggregated index value (propensity score) for each observation to form observational matches based on similar index values. The efficacy of PSM is dependent on the technique's ability to compare the outcomes of treatment and control subjects with similar propensity scores and characteristics. This is known as the balancing hypothesis. The balancing hypotheses states that the propensity score and mean of each characteristic must be approximately equal. The assignment to treatment must also be unconfounded, given the propensity score.[5]

Rosenbaum and Rubin (1983) define propensity score as the conditional probability of receiving treatment based on a vector of observational characteristics, and in our analysis can be expressed as

$$p(X) \equiv \Pr\left(C = 1 \middle| X\right) = E\left(C \middle| X\right) \tag{9}$$

where, C=(0, 1) indicates either cash or noncash transactions and X is a vector of observable characteristics.

The propensity score [6] can be estimated with a standard probability model for the entire sample (Frolich 2004; Grinstein-Weiss 2012); we use a probit model expressed as

$$\Pr\left(C_i = 1 \middle| X_i\right) = \Phi\{\mathrm{h}(\mathrm{X_i})\} \tag{10}$$

where, Φ represents the normal c.d.f. and $\mathrm{h}(\mathrm{X_i})$ represents the covariates.

[4] For recent uses of PSM in the real estate domain, see, for example, Liu et al. (2013), Reichardt (2013); Nanda and Ross (2012); McMillen (2012); Holupka and Newman (2012); and Ding et al. (2011).

[5] See Becker and Ichino (2002) and Liu and Lynch (2011) for a summary of PSM.

[6] The propensity score is generally the predicted probability of an observation being either cash vs. noncash.

In a-one to-many treatment-to-control match, weights are assigned to the control matches based on closeness of propensity scores. The estimators used for matching have the same standard form

$$\left(\hat{Y}_{i0}\middle|D_i = 1\right) = \left(\Sigma_{j\epsilon\{D_j=0\}} w(ij) Y_{J0}\middle|D_j = 0, P(D = 1)\middle|X\right) \tag{11}$$

Where j is the index for a non-cash transaction that is matched based on propensity scores to a cash transaction i. Matrix $w(ij)$ consists of the j^{th} transaction weights that are matched to the i^{th} transactions. It is notable that the specific weighting format will differ between matching estimators.

The formula to calculate the average treatment effect on the treated (ATT), which compares the outcomes of the treatment group (cash transactions) with similar observations with financing, is

$$ATT = \frac{1}{N}\sum_{i=1}^{N}\left[Y_{i1} - \left(\hat{Y}_{i0}\middle|D_i = 1\right)\right] \tag{12}$$

N represents the cash transactions, Y_{i1} is the transaction price in transaction i and $(\hat{Y}_{i0}|D_i=1)$ represents the transaction price of the implemented counterfactuals for transaction i.

We use several methods to create matched datasets: Nearest Neighbor, Stratification, Radius, and Kernel Matching methods. The Nearest Neighbor method matches one observation from the treatment group to a single observation from the control group having the closest propensity score, a one-to-one match. We also use one-to-many matching methods including stratification, radius, and kernel matching. Stratification matches the observations between the groups based on average observed values within propensity score intervals. Radius matching utilizes a tolerance level on the maximum distance between propensity scores of control and treatment group outcomes. Kernel matching is a weighted average of all observations, with the weight based on the distance between propensity scores for a treatment observation and all observations in the control group, with larger weights applied to closer matches. The algorithms that use the entire data place a greater weight on control observations that are 'close' in propensity score to their matched treatment observations than those that are further away.

The use of multiple methods provides robustness to the treatment effect conclusions, although the methods are not differentiated by superiority they trade quantity for quality in observed comparisons.

Results

Heckman Sample Selection Models

Table 3 presents the results for the cash and non-cash sample selection hedonic models corrected for standard errors in the second stage of the Heckman selection correction model. We include structural and neighborhood characteristics, along with the environmental variable, distance to nearest hazard. The majority of the variable estimates in

Table 3 Sample selection hedonic regression results

Variable name	Probit estimates		Cash hedonic regression		Non-cash hedonic regression	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
intercept	−1.4872***	−4.01	10.6582***	21.11	9.6100***	87.77
lnbuilding_sqm	0.1191	1.25	–		–	
rooms	−0.066***	−2.57	–		–	
inchet_cbg	−0.3015**	−2.15	–		–	
volume_buyer	0.8060***	3.91	–		–	
lnmindist	0.0219	0.74	0.0060	0.28	0.0287***	7.20
lnagehouse	0.0029	0.51	−0.0240***	−5.29	−0.0094***	−11.23
avg_room_sz	–		0.0204***	7.95	0.0293***	48.01
lnbaths	–		0.2814***	5.26	0.2197***	22.01
lnlotsize_sqm	–		0.1207***	4.15	0.0729***	12.40
air	–		0.1003***	2.50	0.0692***	9.48
dgarage	–		0.0217	0.59	−0.0150**	−2.11
lnduration	–		0.0277**	2.04	−0.0208***	−8.62
lncommute_cbg	–		−0.3093***	−2.5	−0.2970***	−13.08
lnpercapinc_cbg	–		0.6772***	11.2	0.5133***	49.68
oownerocc_cbg	–		−0.0014*	−1.74	−0.0009***	−6.09
pct9all00	–		0.0031***	3.77	0.0023***	14.51
lnoffensecap	–		0.0016	0.69	0.0010**	2.39
unemp_cbg	–		0.0088	1.56	−0.0036***	−3.93
pctvacant_cbg	–		−0.0040	−1.18	−0.0044***	−6.17
ln_density_cbg_a	–		0.0113	0.55	0.0090***	2.53
lambda	–		0.2769**	1.97	0.8952***	23.83
sigma	–		0.3393***	35.94	0.2336***	134.68
N	9716		646		9070	
Log likelihood	−2361		−218.29		318.28	
AIC	4737		474.59		−598.56	

This table presents the results for the cash and non-cash sample selection hedonic models, including the Inverse Mills Ratio coefficients

the cash and non-cash hedonic price models are consistent with economic theory; that is, economic goods, such as house size have a positive impact on house price, while economic bads, such as proximity to an environmental hazard, negatively affects house price (i.e., house price increases with increased distance to a hazard). It is interesting to note that cash buyers are insensitive to environmental hazards (elasticity = 0), while distance from an environmental hazard is highly inelastic for noncash buyers (elasticity = 0.0287).

Counterfactual T-Tests of Simulated Prices

Table 4 presents results of paired t-tests based on Eq. (7), calculated at increasing distances from environmental hazards. We estimate the expected property price of cash

Table 4 Simulated house prices for cash transactions at various distances from the closest disamenity

Distance to environmental disamenity	N	$Price_{(C/C)}$		$Price_{(C/NC)}$		Price differential	
		Mean	t-statistic	Mean	t-statistic	Mean %	t-statistic
Distance ≤ 0.25	27	$71,259.74	9.91	$82,709.26	11.08	−14.79	−9.14
0.25 ≤ Distance < 0.50	68	$111,786.22	14.3	$122,242.96	15.05	−9.29	−8.07
0.50 ≤ Distance < 0.75	76	$104,298.21	15.86	$117,203.32	17.5	−12.72	−10.96
Distance > 0.75	475	$143,430.79	25.56	$158,688.51	19.28	−8.79	−20.97

In this table, simulated house price estimates are presented from several subsamples at varying levels of distance to environmental disamenity

NC Non-cash, *C* Cash

transactions using the parameter estimates from the cash model ($P^{C|C}$) versus the mean expected price of cash transactions using parameter estimates from the noncash model ($PC^{C|NC}$)[7] to form the counterfactual test. Results indicate that for transactions less than 0.25 miles from a disamenity, buying a house with cash results in a discount of about 15 % for as compared to the counterfactual, a price differential of $11,449. This discount decreases to about 9 % as the transacted house is located greater than 0.75 miles from a disamenity.

Table 5 presents the opposite counterfactual, that is, the mean simulated property price of non-cash transactions based on location to a disamenity based on the parameter estimates from the cash model versus the mean simulated property price of non-cash transactions assuming the estimates from the non-cash model, a test of Eq. (8). Results from Table 5 indicate that a home owner buying a house with a mortgage instead of cash pays an average 15.38 % premium for a property within 0.25 miles of a disamenity. This premium decreases to 9.72 % (distance > 0.75 miles) as we move away from the disamenity. Together, Tables 4 and 5 support our hypothesis that cash buyers near disamenities receive a higher discount than noncash buyers.

Table 6 presents results of house price counterfactuals as in Table 4, but examines the transactions at various levels of income to test for the effect of financial constraints. We find a cash discount of 17.42 % in CBGs with income less than $15,000, compared with a price discount of 5.66 % in areas where per capita income is greater than $40,000. These results demonstrate the dynamic cash discount. The pricing differential observed can be attributed to the house purchaser's level of financial constraint, with purchasers enjoying low levels of financial constraints more likely to value the property higher as compared to market participants with more stringent financial constraints. A more financially constrained purchaser buys a house with a greater consumption rather than investment use, while a less financially constrained purchaser is more likely to view house ownership more like a financial asset with upside potential but

[7] $PC^{C|NC}$ represents the price a noncash buyer would pay if they had the same return to characteristics as a cash buyer.

Table 5 Simulated house prices for non-cash transactions at various distances from the closest disamenity

Distance to environmental disamenity	N	$\text{Price}_{(NC/NC)}$		$\text{Price}_{(NC/C)}$		Price differential	
		Mean	t-statistic	Mean	t-statistic	Mean %	t-statistic
Distance ≤ 0.25	339	$98,726.74	35.66	$85,656.98	30.61	15.38	28.25
0.25 ≤ Distance < 0.50	1062	$116,423.4	66.9	$104,460.2	59.71	12.47	39.18
0.50 ≤ Distance < 0.75	1124	$118,635.3	54.98	$104,155.6	50.89	14.30	45.36
Distance > 0.75	6545	$148,257.3	140.89	$136,106.8	134.84	9.72	91.05

In this table, simulated house price estimates are presented from several subsamples at varying levels of distance to environmental disamenity

NC Non-cash, *C* Cash

less sensitive to downside risk of negative price changes due to the consumption aspect of housing. Table 7 presents counterfactuals similar to Table 5, but by income, illustrating a mortgage differential that is sensitive to the income levels ranging from a premium of 22.03 % to a premium of 4.06 %. These counterfactual tests also confirm our second hypothesis.

Propensity Score Matching Results

We begin by calculating propensity scores using the same probit model as in the selection model (Table 3). The propensity scores for cash and non-cash transactions are not completely evenly distributed and have some differentials between the groups.[8] Therefore, selectively matching observations should improve the efficiency in the estimated discount for cash transactions. The region of common support, where there is overlap in the propensity score between the two samples, ranges from 0.0289 to 0.20. Table 8 presents the frequency for the estimated propensity score for all cash and non-cash transactions.

To satisfy the balancing hypothesis, the sample is divided into equally spaced propensity score intervals until within each interval the average propensity score between cash and non-cash transactions is the same. The mean of each covariate should not differ either, as within each interval the average mean of the covariates should be approximately the same. If unbalanced, the ATT can be influenced by the unbalanced covariates and a more parsimonious model is recommended (Becker and Ichino 2002). In this analysis, the balancing criteria are satisfied for all the covariates in the comprehensive model. [9]

The estimated average treatment effects (ATT), obtained from several matching algorithms are reported in Table 9, and reflect a moderate range in observed cash discounts estimates. Values range from 8.4 to a 10.1 % (average 9.0 %), are significant,

[8] The propensity score results for cash and non-cash transactions, were based on the probit results.

[9] For comparative purposes of the treatment effect, covariates in the probit model remain the same across the parceled sample analyses. All subsamples examined are not completely balanced, however the comprehensive model is balanced, and the potential trade-off resulting in differing sub-sample probit models does not exceed the benefit of model consistency.

Table 6 Simulated house prices for cash transactions at various levels of per capita income

Income	N	$Price_{(C/C)}$		$Price_{(C/NC)}$		Price differential	
		Mean	t-statistic	Mean	t-statistic	Mean %	t-statistic
Income < \$25,194	369	98,352.68	58.79	87,730.99	51.92	−11.37	−22.09
Income > \$25,194	277	211,328.62	15.77	192,090.35	22.08	−7.14	−14.68
Income < \$15,000	54	67,018.58	22.36	54,862.80	20.54	−17.42	−10.18
Income > \$40,000	62	367,967.75	6.86	327,659.6	10.46	−5.66	−3.92

In this table, simulated house price estimates are presented from several subsamples at varying levels of income

NC Non-cash, *C* Cash

and are similar to the robust regression model presented in Table 10. The range in estimates suggests they are not particularly robust to matching methodology; even so, the average discount rate is approximately 32 to 45 % less than reported in previous papers.[10] Moreover, given the distribution of the propensity scores, the nearest neighbor matching technique is our preferred method, as the distribution allows for sufficient overlap in cash and noncash scores. This maximizes the quality of our comparable observations, and also yields a substantial reduction in the discount. [11]The calculated z-score and p-values correspond to a one-tailed test. All calculated test statistics reject the null hypothesis in favor of the alternative hypothesis at a 10 % significance level. We can conclude that our coefficient estimates on cash discount are significantly smaller than estimates obtained in prior studies.

Results from the probit analysis are also used to create propensity score weights used in a regression model that includes a dummy variable for cash transactions, this allows us to compare all of our exogenous variables between the two samples for differences. The weights for cash transactions is $\frac{1}{\hat{p}}$ and that for the noncash transactions is $\frac{1}{1-\hat{p}}$, where $\hat{p}$ is the estimated probability of a cash transaction from the probit. Table 10 reports results of a baseline unweighted hedonic price model along with the propensity score weighted regression model. The control variables in both models consist of house and neighborhood characteristics. In the unweighted model, nearly all the coefficients are highly significant and follow their theoretically expected signs.

The weighted model has fewer significant variables. The cash coefficients for the two models are both significant at the 99 % level, with that the cash discount for the weighted model (−11.42 %) being slightly smaller than that for the unweighted model (−12.02 %).

[10] See Literature Review for discussion of previous findings.

[11] We performed hypothesis test on the differences in coefficients between our coefficient estimates and estimates from three previous studies mentioned in the literature review section. Tests statistics reject the null hypothesis in favor of the alternative hypothesis at a 10 % significance level, confirming that our coefficients estimates are statistically smaller than the estimates from previous studies. Calculated z-score and p-values correspond to a one-tailed test.

Table 7 Simulated house prices for non-cash transactions at various levels of per capita income

Income	N	Price$_{(NC/NC)}$		Price$_{(NC/C)}$		Price differential	
		Mean	t-statistic	Mean	t-statistic	Mean %	t-statistic
Income < $25,194	5358	$100,393.32	219.63	$87,966.94	189.92	13.66	107.42
Income > $25,194	3712	$194,744.73	123.61	$182,256.88	123.77	6.72	52.80
Income < $15,000	997	$65,258.75	122.39	$50,915.77	106.76	22.03	73.61
Income > $40,000	736	$295,942.02	55.00	$282,939.78	58.73	4.06	12.20

In this table, simulated house price estimates are presented from several subsamples at varying levels of income

NC Non-cash, *C* Cash

PSM Subsample Analysis

Based on expectations regarding potential differences in the cash discount at varying levels of, distance to an environmental hazard, and income, we examine several subsamples and estimate the discount at varying levels of these characteristics. Tables 11 and 12 present the estimates.

When examining models based on distance to environmental hazard we find that the closer a house is to an environmental hazard the larger the cash discount, as the average discount within 0.25 miles to an environmental hazard is about 35 %, and only about 8.5 % in transactions with a distance greater than 0.75 miles, as reported in Table 11. The increased discount is representative of the purchaser giving up the option of mortgage default. Therefore, the cash discount is estimated to be larger if the house is located near an environmental disamenity because of greater spatial uncertainty. Comparing these results to those from the counterfactuals in Table 4, we find a much higher rate of discount using matched outcomes. This may be due to the fact that the switching regression takes into account returns to individual characteristics, while ATT calculations do not.

The cash differential with regards to CBG level income[12] is examined, as lower (higher) income on average should point towards on average more (less) financially constrained seller and buyer. The results suggest that cash discounts are inversely connected to income, i.e., lower income (less than 15,000 per capita income) yields higher cash discounts when compared to those estimated in areas with higher income. It is notable to point out that we actually find evidence of a cash premium in high income areas (per capita income > $40,000). These results, presented in Table 12, are similar to the lowest income purchasers from the counterfactual estimates; however the similarity does not extend throughout the income distribution, as the PSM results show a dynamic cash discount and even a cash *premium* in areas with relatively high income. The pricing differential can be attributed to the house purchasers' levels of

[12] Income at the level of individual homeowners is unavailable to us.

Table 8 Balancing properties

Inferior of block of pscore	Control	Cash	Total	Percent of Total	
	0	1		Control	Cash
0.0289	390	19	409	4 %	3 %
0.05	7305	494	7799	81 %	76 %
0.075	1334	122	1456	15 %	19 %
0.1	5	0	5	0 %	0 %
0.2	25	11	36	0 %	2 %
Total	9059	646	9705	100 %	100 %

This table presents the frequency of estimated propensity scores for cash and non-cash transactions

financial constraints, as the house ownership constraint reduces the proportion invested in stocks and bonds (Kullmann and Siegel 2003), placing financial portfolio constraints (Flavin and Yamashita 2002) leading to less than optimal asset allocation from an investment prospective (see, for example, Benjamin et al. 2004). Cauley et al. (2007) contend that financially constrained house owners “require a 6 % increase in total net worth to achieve the same utility level as an individual not facing the asset allocation constraint”.

Hung and So (2012) use a call-option concept to understand buyer reservation prices, as owning a house provides the upside potential of an investment with limited downside risk due to consumption. Applying a Black-Scholes pricing formula the authors suggests that the subjective value of a house call option is dependent on the level of buyer financial constraint - less financially constrained (e.g., higher income) purchaser would be willing to pay a premium for a house call option compared to a buyer with more financial constraints. Accordingly, house purchasers under loose financial constraints are likely to overvalue the house call option (and pay a higher price) because they give up less financial freedom in a portfolio allocation context (Hung and So 2012). This call premium would potentially result in higher house reservation prices for cash purchasers if cash purchasers are less constrained financially and the

Table 9 Average treatment effect on cash transactions (ATT)

Method	n. treat.	n. contr.	ATT	Std. Err.	t
Nearest neighbor matching	646	622	−0.084	0.03	−2.54
Radius matching	608	2938	−0.101	0.03	−3.67
Kernel matching[a]	646	9059	−0.095	0.02	−4.07
Stratification[a]	646	9059	−0.080	0.03	−2.96

[a] Bootstrapped standard errors

Table 10 Hedonic regression results versus robust hedonic regression results

Variable name	Hedonic regression		Robust hedonic regression	
	Coefficient	t-stat	Coefficient	t-stat
cash	−0.1202***	−11.79	−0.1142***	−7.98
lnagehouse	−0.0110***	−12.78	−0.0176***	−7.8
avg_room_sz	0.0248***	41.89	0.0223***	15.18
lnbaths	0.2902***	29.41	0.3111***	11.6
lnlotsize_sqm	0.0916***	15.32	0.1079***	6.34
air	0.0674***	8.94	0.0766***	3.31
dgarage	−0.0214***	−2.92	−0.0073	−0.35
lnduration	−0.0181***	−7.26	0.0006	0.08
lnmindist	0.0080**	1.99	0.0058	0.51
lncommute_cbg	−0.3196***	−13.64	−0.3444***	−5.1
lnpercapinc_cbg_a	0.5664***	53.8	0.6217***	20.49
owneroc_cbg	−0.0015***	−10.34	−0.0017***	−3.88
pct9all00	0.0021***	12.81	0.0025***	4.95
lnoffensecap	0.0009**	2.11	0.0010	0.9
unemp_cbg	0.0005	0.53	0.0049*	1.69
pctvacant_cbg	−0.0028***	−3.91	−0.0037*	−1.86
lndensity_cbg_a	0.0077**	2.08	0.0128	1.18
Constant	11.4969***	146.73	11.5307***	48.44
F(17, 9698)	2026***		287.25***	
R-squared	0.78		0.74	

This table compares the estimates from an unweighted hedonic regression with those from a propensity score weighted robust regression. The propensity score weights are used and included is an indicator variable for cash transactions. The weights for cash transactions is $1/\hat{p}$ and that for the noncash transactions is $1/\ (1-\hat{p})$, where $\hat{p}$ is the estimated probability of a cash transaction from the probit

*** Significant at the 0.01 level

** Significant at the 0.05 level

* Significant at the 0.10 level

subjective value of a house call option is dependent on the level of financial constraints. It should be noted that the use of leverage does necessarily solve the asset allocation problem; rather it increases the mortgage debt component in the portfolio (Cauley et al. 2007).

Conclusion

In estimating the differences in house prices for cash and transactions with mortgage financing, we control for the inherent selection process involved; Heckman Sample Selection Model and PSM procedures. We find that volume

Table 11 Average treatment effect on cash transactions (ATT) for various distances to an environmental disamenity

Method	n. treat.	n. contr.	ATT	Std. Err.	t
Distance to environmental disamenity < 0.25 miles					
Nearest neighbor matching	27	25	−0.329	0.141	−2.335
Radius matching	na				
Kernel matching[a]	27	322	−0.359	0.094	−3.807
Stratification[a]	27	322	−0.368	0.113	−3.267
0.25 ≤ Distance to environmental disamenity < 0.50 miles					
Nearest neighbor matching	69	62	−0.044	0.087	−0.507
Radius matching	22	23	0.007	0.119	0.062
Kernel matching[a]	69	1040	−0.045	0.070	−0.645
Stratification[a]	69	1040	−0.040	0.063	0.632
0.50 ≤ Distance to environmental disamenity < 0.75 miles					
Nearest neighbor matching	77	73	−0.021	0.104	−0.206
Radius matching	22	28	−0.150	0.164	−0.913
Kernel matching[a]	77	1048	−0.095	0.085	−1.119
Stratification	77	1048	−0.095	0.083	−1.142
Distance to environmental disamenity > 0.75 miles					
Nearest neighbor matching	475	450	−0.125	0.039	−3.182
Radius matching	411	1279	−0.075	0.034	−2.233
Kernel matching[a]	475	6520	−0.074	0.035	−2.102
Stratification[a]	475	6520	−0.064	0.028	−2.296

[a] Bootstrapped standard errors

buyers are more likely to use cash than regular house buyers, and also find that income heterogeneity and number of rooms in a house decrease the probability of a cash transaction. From the selection model, we perform counterfactual tests to examine how cash discounts behave in relation to proximity to an environmental hazard and also with respect to increasing neighborhood incomes. Consistent with our hypotheses, we find amplified cash discounts in areas with close proximity to an environmental hazard; and also a pricing differential based on CBG level income, with purchasers in high income areas more likely to pay a cash premium compared to market participants in areas with comparably lower income, where a cash discount is detected.

With PSM, we first estimate a regression using propensity score weights computed from a probit model for the entire sample (Frolich 2004; Grinstein-Weiss 2012). We find that the use of propensity score weighting attenuates the estimated cash impact, finding the weighted model predicts an average discount of about 11.4 %, while the discount in the unweighted model is about 12.0 %.

Table 12 Average treatment effect on cash transactions (ATT) for various levels of per capita income

Method	n. treat.	n. contr.	ATT	Std. Err.	t
Income < 5194 US dollars (mean value)					
Nearest neighbor matching	369	354	−0.119	0.033	−3.645
Radius matching	303	789	−0.127	0.030	−4.232
Kernel matching[a]	369	5262	−0.137	0.025	−5.558
Stratification[a]	369	5262	−0.122	0.026	−4.754
Income > 25,194 US dollars					
Nearest neighbor matching	277	263	−0.054	0.047	−1.156
Radius matching	191	343	−0.014	0.047	−0.306
Kernel matching[a]	277	3710	−0.062	0.035	−1.775
Stratification[a]	277	3710	−0.054	0.035	−1.538
Income < 15,000 US dollars					
Nearest neighbor matching	54	53	−0.126	0.074	−1.690
Radius matching	20	26	−0.267	0.112	−2.388
Kernel matching[a]	54	942	−0.150	0.049	−3.033
Stratification[a]	53	943	−0.158	0.054	−2.918
Income > 40,000 US dollars					
Nearest neighbor matching	61	58	0.053	0.102	0.519
Radius matching	6	6	0.340	0.245	1.388
Kernel matching[a]	61	725	0.131	0.068	1.915
Stratification[a]	60	726	0.058	0.062	0.929

[a] Bootstrapped standard errors

We then estimate the ATT for cash transactions, and find a cash discount of 9 % on average, representing a statistically different 32 to 45 % reduction in the previously reported discounts. Parsing our sample based on distance to nearest environmental hazard, and per capita income helps us to understand some of the variance in the observed discount.

Collectively, these results provide insight into buyer behavior and the expected discount (premium) for cash housing purchases, and provide useful insights for market participants including real estate appraisers, brokers, and buyers and sellers of real estate. Generally, purchasers funding the transaction with cash receive a discount after controlling for potential differences in the covariates due to selectivity bias, however this discount is dynamic and in some areas the cash differential could be positive.

Areas for further research include extending the data time frame to include the post-recession period. It would be interesting to see if both determinants of a cash transaction and amount of the differential have changed with the recent increased rate of cash purchasers. The question of generalizing the observed cash differential throughout a real estate cycle is an area that could benefit from future studies. Further exploration of cash premiums in areas with high income could be of benefit given our limited sample size in this market segment.

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References

Aroul, R. R., & Hansz, A. (2011). The role of dual-pane windows and improvement age in explaining residential property values. *Journal of Sustainable Real Estate, 3*(1), 142–161.

Asabere, P. K., Huffman, F. E., & Mehdian, S. (1992). The price effects of cash versus mortgage transactions. *Journal of the American Real Estate and Urban Economics Association, 20*(1), 141–150.

Becker, S., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal, 2*(4), 358–377.

Benjamin, J. D., Chinloy, P., & Jud, G. D. (2004). Why do households concentrate their wealth in housing? *Journal of Real Estate Research, 26*(4), 329–343.

Cauley, S. D., Pavlov, A. D., & Schwartz, E. S. (2007). Homeownership as a constraint on asset allocation. *Journal of Real Estate Finance and Economics, 34*, 283–311.

Ding, L., et al. (2011). Risky borrowers or risky mortgages disaggregating effects using propensity score models. *Journal of Real Estate Research, 33*(2), 245–277.

Flavin, M., & Yamashita, T. (2002). Owner-occupied housing and the composition of the household portfolio. *American Economic Review, 92*(1), 345–362.

Frolich, M. (2004). Finite-sample properties of propensity-score matching and weighting estimators. *The Review of Economics and Statistics, 86*(1), 77–90.

Grinstein-Weiss, M. (2012). Homeownership, neighbourhood characteristics and children's positive behaviours among low- and moderate-income households. *Urban Studies, 49*(16), 3545–3563. **Available from: EconLit, Ipswich, MA. Accessed December 1, 2013**.

Hansz, J. A., & Hayunga, D. K. (2012). A cash premium in residential real property transaction prices. Working paper.

Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica, 47*(1), 153–161.

Hite, D. (1998). Information and bargaining in markets for environmental quality. *Land Economics, 74*(3), 303–316.

Hite, D. (2000). A random utility model of environmental equity. *Growth and Change, 31*(1), 40–58.

Holupka, S., & Newman, S. J. (2012). The effects of homeownership on children's outcomes: real effects or self-selection? *Real Estate Economics, 40*(3), 566–602.

Housing Predictor. Cash buyers pushing home prices lower. http://www.housingpredictor.com/cash-buyers-pushing-prices-lower/. (Jan. 24, 2012).

Hung, M., & So, L. (2012). How much extra premium does a loss-averse owner-occupied home buyer pay for his house? *Journal of Real Estate Finance and Economics, 45*(3), 705–722.

Inside Mortgage Finance (2013). Buyers increasingly using cash to purchase homes, some then get a mortgage as a refi. http://www.insidemortgagefinance.com/housing_pulse/findings.html.

Inside Mortgage Finance (2014). Delays in closing are common on purchase mortgages with private MI, FHA loans. http://www.insidemortgagefinance.com/housing_pulse/findings.html.

Jauregui, A., & Hite, D. (2010). The impact of real estate agents on house prices near environmental disamenities. *Housing Policy Debate, 20*(1), 295–316.

Kullmann, C., & Siegel, S. (2003). Real estate and its role in household portfolio choice. Manuscript, University of British Columbia.

Liu, Y., Gallimore, P., Wiley, J. A. (2013). Nonlocal office investors: anchored by their markets and impaired by their distance. *Journal of Real Estate Finance and Economics*, 1–21 10.1007/s11146-013-9446-8.

Liu, X., & Lynch, L. (2011). Do agricultural land preservation programs reduce farmland loss? Evidence from a propensity score matching estimator. *Land Economics, 87*(2), 183–201.

Lusht, K. M., & Hansz, J. A. (1994). Some further evidence on the price of mortgage contingency clauses. *The Journal of Real Estate Research, 9*(2), 213–217.

Maddala, G. S. (1983). Limited-dependent and qualitative variables in econometrics. Cambridge: Cambridge University Press.

McMillen, D. P. (2012). Repeat sales as a matching estimator. *Real Estate Economics, 40*(4), 745–773.

Nanda, A., & Ross, S. L. (2012). The impact of property condition disclosure laws on housing prices: evidence from an event study using propensity scores. *Journal of Real Estate Finance and Economics, 45*(1), 88–109.

National Association of Realtors® (2013). Realtors® confidence index report and market outlook. http://www.realtor.org/.

Reichardt, A. (2013). Operating expenses and the rent premium of energy star and LEED certified buildings in the central and eastern US. *Journal of Real Estate Finance and Economics, 49*(3), 413–433.

Rosen, S. (1974). Hedonic prices and implicit prices: Product differentiation in pure competition. *Journal of Political Economy, 82*(1), 34–35.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.

Sirmans, G. S., & Macpherson, D. A. (2003). The composition of hedonic pricing models: a review of the literature. National Association of Realtors®.

Schmit, J. (2013, August 5). Mortgage closing costs are on the way up. *USA Today*, p. 1. Retrieved from http://m.usatoday.com.akadns.net/article/money/2618783.