The Appraisal Mechanism: Spillover Effects of All-Cash Sales on Local Housing Markets*

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Abstract

Discounted nearby all-cash sales enter the comparable set used by appraisers, depress appraised values for mortgage purchases, and cap financing, so financed deals either (i) bridge with cash, (ii) renegotiate, or (iii) fail. Based on a ring-based design using matched deed–mortgage-listing data from 2018 to 2022, I find that a one-standard-deviation increase in proximate cash activity lowers appraisals by 1.39% and sale prices by 1.38% and lengthens time-on-market by 38 days. This spillover is highly local and recent, favoring the renegotiation channel over cash-gap bridging. These effects are more pronounced for low-income, high-LTV, first-time, and minority buyers and in low-inventory neighborhoods, consistent with negotiation-driven information revelation that shifts surplus toward constrained buyers. Additional evidence links higher nearby cash activity to more HMDA "approved-but-not-accepted" outcomes, supporting a failure channel. A bargaining model with appraisal-anchored caps rationalizes the near one-for-one appraisal-to-price pass-through and maps welfare: spillovers mainly redistribute surplus in thick, high-growth markets but generate exclusion and misallocation in thin, low-growth markets.

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Introduction

In the past two decades, all-cash home purchases have increased tremendously from around 12% to over 30% in the US while the share of first-time buyers has fallen to historic lows (Figure 1). Cash buyers avoid traditional financing contingencies and often close faster, allowing them to acquire properties at an 11% discount on average (Reher and Valkanov, 2024; Han and Hong, 2024). Such discounts are typically viewed as isolated to the transaction level. However, this paper investigates an appraisal spillover mechanism through which cash sales can indirectly impact the pricing and liquidity of other homes in the vicinity. When discounted cash sales occur in a neighborhood, they could enter the set of "comparable sales" (comps) used by appraisers, dragging down appraised values for subsequent mortgage-financed transactions. An appraisal lower than the agreed price in turn limits the buyer's financing, leading to three potential outcomes: (1) the buyer injects additional cash to cover the shortfall, (2) the parties renegotiate and lower the sale price, or (3) the transaction falls through entirely. I investigates which of these outcomes dominates and to what extent discounted cash sales in a mortgage-financed property's immediate vicinity spill over to its appraisal value, transaction price, and liquidity.

The analysis centers on the appraisal process as the transmission channel. Standard practice and regulations direct appraisers to value a home using recent nearby comps and to remain neutral to the source of financing. When low-priced cash trades occur on the same block or a few streets away, those sales are likely to be selected as comps and to anchor the appraisal downward. A lower appraisal caps the lender's loan amount, potentially forcing the transaction to adjust. As a consequence, the buyer and the seller may not fully anticipate the extent to which proximate cash sales become binding reference points, making this a distinct credit-through-collateral friction rather than a mere reflection of neighborhood demand. The empirical goal is to isolate this appraisal mechanism from confounding neighborhood dynamics and assess its magnitude, heterogeneity, and welfare implications.

To do so, I assemble a national, transaction-level dataset by matching CoreLogic deeds, tax, and listings with HMDA mortgage originations. The main sample consists of more than 6.2 million arm's-length, single-family and townhome purchases from 2018–2022, spanning 2,074 counties and roughly 76,000 census tracts, with property-loan-buyer-level details and listing information observed.

To isolate the causal impact of nearby cash sales on mortgage-financed transactions, I employ a ring-based identification strategy that has been widely used in a recent empirical literature on neighborhood effects to identify a variety of spatial spillovers, such as investor and foreclosure contagion in housing markets (Bayer et al., 2021; Gupta, 2019). In specific, I measure the exposure to recent nearby cash activity in two rings for each focal mortgage-financed transaction: the count of cash sales within 0.6 miles in the prior year (inner ring) and the count within 1.2 miles (outer ring). Identification comes from comparing hyper-local exposure (inner ring) while conditioning on broader neighborhood trends (outer ring), together with rich controls for property, buyer, and loan attributes as well as including tract-by-year fixed effects to capture unobserved local housing trends. Two validation tests support the choice of 0.6 miles as an appropriate inner ring radius: (i) ring-by-ring estimates show that the average treatment effect declines with distance and is indistinguishable from zero beyond roughly 0.6 miles; and (ii) a comps-imputation exercise shows that about 93% of realistic comps fall within 0.6 miles. Furthermore, a placebo test using all-cash focal transactions (where the appraisal mechanism should not operate) yields near-zero effects at all distances, corroborating this mechanism that is embedded as a mortgage-dependent home buyer's unique financial constraint.

The baseline results show economically meaningful and significantly localized spillovers. A one–standard-deviation increase in nearby cash sales within 0.6 miles (i.e., 25 additional cash transactions out of 73 all nearby sales) reduces the appraised value of a financed home by roughly 1.39% and its final sale price by 1.38%, a near one-for-one pass-through consistent with renegotiation to the appraisal as the dominant mechanism rather than buyers bridging the gap with cash. The effect decays with distance and with time – most of the impact comes from cash comps within 0.6 miles and the past six months – and remains robust when conditioning on neighborhood-level activity in the outer ring. Including the listing price attenuates but does not eliminate the estimated effect, suggesting that an alternative listing-price anchoring channel (i.e., listing-agents incorporating the cash spillover) exists but is not the primary driver once the appraisal mechanism is accounted for. On liquidity, one additional nearby cash sale increases a subject property's time-on-market by about 1.5 days; namely, a one–standard-deviation increase adds roughly 37.5 days, indicating a more prolonged bargaining when appraisals are more likely to bind with a higher presence of nearby cash activity.

The spillover is stronger where appraisal caps are more likely to bite and where buyer outside options are weaker: among low-income, high-LTV, first-time, and minority buyers; in lower-income or more affordable neighborhoods; and in low-growth tracts. By contrast, the effect is attenuated in high-growth markets. This price compression also varies with nearby inventory: the estimated price impact is largest when nearby listings are scarce and declines as inventory grows, consistent with sellers' bargaining power eroding as buyers have more outside options. Together, these patterns point to a distributional channel: appraisal-mediated spillovers are most pronounced for financially constrained and information-disadvantaged buyers in cooler markets, while being less salient in hot neighborhoods where appraisals track rapid appreciation more closely. These results suggest that negotiations help reveal asymmetric information between the seller and the buyer, with less sophisticated, less informed, and more financially constrained buyers benefiting the most. Using the placebo effect on all-cash transactions as a proxy for pre-negotiation prices, I estimate the implied seller-to-buyer transfer in dollar values (or the seller's willingness-to-pay to avoid a failure, approximately $4,000), and document its variation across market conditions.

To test whether appraisal gaps caused by nearby discounted cash sales trigger deal failures, I assemble a national sample of unsuccessful mortgage origination records matched with cash activity at the neighborhood level. On the mortgage side, I identify applications in HMDA data that were approved but not accepted or denied for collateral reasons: cases most consistent with appraisal-stage breakdowns. Controlling for a complete set of local socioeconomic characteristics and fixed effects, I find that more local cash activity predicts a higher mortgage rejection rate at the census tract and year level, indicating that the failure channel coexists with the established renegotiation channel.

Building on the evidence so far, I develop a stylized buyer-seller bargaining model with heterogeneous neighborhoods that incorporates the renegotiation (Hypothesis 2) and failure (Hypothesis 3) channel to quantify the welfare implications of appraisal-anchored financing frictions. Nearby cash exposure lowers appraised values, tightening financing caps defined by liquid wealth and the permissible loan-to-value ratio. When this cap lies between the seller's reservation value and the frictionless price, bargaining compresses prices to the cap, producing the near one-for-one appraisal-to-price pass-through observed empirically; when it falls below the seller's reservation value, transactions fail. The model yields two neighborhood-level welfare objects: (i) price-compression transfers from sellers to buyers in successful transactions, and (ii) welfare losses from exclusion and misallocation when constrained high-valuation buyers are displaced. As a consequence, appraisal spillovers have opposite welfare effects across markets: they amplify credit frictions and suppress turnover in low-growth, high-inventory areas, but act as a mild stabilizer that contains overpaying in hot, unconstrained markets. Quantifying these differences allows me to map where appraisal-driven spillovers act as a friction versus a stabilizer in local housing markets.

Related Literature

This paper first contributes to the growing literature in housing finance examining differences between cash and mortgage-financed transactions. Recent studies document a mortgage-cash premium and attribute it to a combination of market frictions and behavioral factors embedded in search models (Reher and Valkanov, 2024; Han and Hong, 2024). I complement this literature by showing that the source of financing not only has transaction-level price impact but also has spillover effects through a mortgage-financed home buyer's financial constraint based on how appraisals work. This unique channel links micro-level negotiation advantage of cash buyers to broader implications for local house price dynamics and housing affordability. Notably different from a recent study by Chia and Ambrose (2024) identifying how tighter credit conditions depress home prices through cash discounts, the appraisal mechanism operates even without explicit credit constraints: cash sales in the vicinity alone can compress prices and increase the time-on-market of a mortgage-financed home by depressing future appraisals.

This paper also adds to the broader economic literature studying the role of financing frictions in local house price discovery. I uncover a unique credit friction operating through the appraisal process by showing that appraisal-based loan caps can transmit price pressure from cash sales to financed sales. Classic theories have long established that borrower constraints can amplify market volatility. For instance, Stein (1995) models how down-payment requirements tie purchasing power to existing equity, amplifying price and volume fluctuations over the housing cycle. Supporting this mechanism, Genesove and Mayer (2001) provide empirical evidence that sellers with low equity (i.e., tighter liquidity constraints) set higher list prices and experience longer time on market, implying distortion due to credit frictions. Behavioral biases further amplify these frictions, such as Landvoigt et al. (2015), Kaplan et al. (2020), and Guren (2018). In contrast to these studies on broader credit conditions or sellers' equity constraints, I highlight a new channel through which financial constraints affect price formation and transaction outcomes: even well-intentioned lending standards (i.e., appraisal limits) can locally suppress prices and liquidity, an underexplored complement to the classic credit-constraint narratives.

Existing real estate literature on residential appraisals documents appraisal distortions driven by incentive conflicts and regulatory regimes (Agarwal et al., 2020) and provides evidence that idiosyncratic low appraisals anchor bilateral renegotiation (Fout et al., 2022). Empirically, more than half of the low-appraisal cases enter the seller-buyer renegotiation and result in a depressed close price. My empirical results – depressed appraisals and prices with a longer time on market – support the bilateral renegotiation channel by exploring an understudied cause for a low appraisal: nearby discounted cash sales entering the set of comparable properties used by the appraiser.

The resulting transfer from the seller to the buyer also speaks to the literature on housing negotiations. Existing studies emphasize how information and financing shape prices and surplus splits: agents with better information and lower holding costs hold out longer and sell for more (Levitt and Syverson, 2008); shifts in who is informed (sellers vs. buyers) move prices through asymmetric information (Kurlat and Stroebel, 2015); classic evidence on listing strategies links asking prices to time on market and outcomes (Genesove and Mayer, 2001; Knight, 2002); and financing contingencies matter: cash trades buy certainty and a discount, while low appraisals in financed deals anchor renegotiation (Reher and Valkanov, 2024; Fout et al., 2022). My contribution is to show that bargaining outcomes are also shaped by a third-party valuation shock originating outside the bargaining parties: discounted nearby cash sales enter appraisers' comp sets, pushing down appraised values and thereby imposing a hard financing cap for mortgage buyers. By linking neighborhood comp-driven appraisal shocks to bilateral bargaining, this paper links information frictions with financing frictions and clarifies who gains and who loses from appraisal-anchored negotiations across market conditions, a margin that prior work has not investigated.

1 The Appraisal Mechanism

In this section, I introduce the institutional details on residential appraisals and discuss three competing hypotheses implied by the appraisal mechanism through an example.

The Financing-Neutrality of Residential Appraisals

A residential appraisal is expected to provide an impartial assessment of a property's value and is typically required by a lender during the mortgage approval process. A central tenet of federal regulations, industry guidelines, and professional standards is that the source or type of financing must not influence the appraisal's outcome. In practice, this means that an appraiser's estimate of market value should remain consistent regardless of whether a purchase is financed by a loan (e.g., conventional, FHA, or VA), or completed with cash.

Both housing and banking regulatory frameworks adopt a market value definition that presumes a fair, arm's-length transaction, free of special financing or sales incentives. For instance, Fannie Mae's Selling Guide[1] defines market value as "the most probable price that a property should bring in a competitive and open market... assuming the price is not affected by undue stimulus," further specifying that "payment is made in terms of cash... or financial arrangements comparable thereto; and the price represents the normal consideration for the property sold unaffected by special or creative financing or sales concessions granted by anyone associated with the sale." This guidance reinforces that financing terms, such as interest rate buydowns or seller concessions, should neither inflate nor deflate the appraised value.

The FDIC follows similar standards, requiring that the agreed-upon sale price reflect normal consideration without creative or non-market financing[2]. Appraisers are instructed to treat each sale as if conducted with cash or its equivalent to avoid distortions introduced by atypical financing. The agency further mandates that appraisal reports include a certification stating that "the appraisal assignment was not based on a requested minimum valuation, a specific valuation, or the approval of a loan." In other words, an appraiser must not allow loan type or financing terms to influence their valuation approach or conclusion.

[1] https://selling-guide.fanniemae.com/

[2] See Code of Federal Regulations at: https://www.ecfr.gov/current/title-12/chapter-III/subchapter-B/part-323/subpart-A/section-323.2.

Comparable Sales (Comps)

To perform a home evaluation, an appraiser usually selects similar properties that are transacted nearby and recently. For geographic proximity, a comparable is ideally within 0.3-0.5 mile in urban/suburban areas – the closer the better. In rural or unique markets, one may expand the search radius if necessary, explaining the rationale. For temporal proximity, an appraiser usually selects recent sales within 90–180 days; however, older comps may be used in slow markets. Naturally, comps are also selected based on how similar they are to the target property in terms of lot size, square footage, age, number of bedrooms, conditions, etc.

In residential appraisals conducted for mortgage lending purposes in the U.S., the minimum number of comparable sales is three. The standard number of comparable sales can lie between 3 to 6. Quoting institutional standards, Fannie Mae and Freddie Mac require that appraisers provide at least three settled (closed) comparable sales in the appraisal report[3]. Under Fannie Mae Selling Guide B4-1.3-08, "The appraiser must analyze and report at least three closed comparable sales that are the most recent and the most similar to the subject property." Similarly, FHA has the same minimum requirement: "The appraiser must provide a minimum of three comparable sales to support the value of the property," quoting HUD Handbook 4000.1, II.D.4.c.

In practice, despite regulatory requirements and industry standards, appraisers retain considerable discretion in selecting comparable sales, which can significantly influence the final appraised value. As a result, the extent to which appraisers consistently adhere to these guidelines remains an open and empirical question[4].

An Example

Consider a mortgage-financed home transaction in a neighborhood where the typical home value is \$150,000. With an 80% loan-to-value (LTV) ratio, a buyer needs to put \$30,000 down. Suppose this property sees an increase in nearby cash sales, with sellers

[3] The Uniform Residential Appraisal Report, Form 1004

[4] Relatedly, there have been legal issues surrounding appraisal gaps in the U.S. have centered on allegations of racial bias, discriminatory undervaluation, and regulatory scrutiny of appraisal practices. See, for example, https://www.justice.gov/archives/opa/pr/justice-department-sues-rocket-mortgage-appraisal-management-company-and-appraiser-race.

accepting discounted cash offers at \$135,000 for the speed and certainty. More surrounding cash sales increase the likelihood for the appraiser to include cash-purchased properties as comparables. Assume that two out of three comps used by appraisers are such cash sales at \$135,000, while the third comp is a conventional sale at \$150,000. The resulting average of the three comps becomes:

$$\text{Average Comp Price} = \frac{135{,}000 + 135{,}000 + 150{,}000}{3} = 140{,}000$$

While this home is pending at \$150,000, the appraisal comes in at \$140,000. Suppose the lender requires an 80% loan-to-value (LTV) ratio. Then the maximum loan amount becomes:

$$\text{Loan Cap} = 0.80 \times 140{,}000 = 112{,}000$$

To close at the agreed price, the buyer must now bring \$38,000, which is \$8,000 higher than the originally required down payment.

Competing Hypotheses

Consider three potential outcomes following the chain of events above:

- Hypothesis 1 (H1): To close at the agreed price, the buyer puts an extra \$8,000 down payment so that the deal goes through. The actual transaction price of this property is not affected, while its appraisal value is lower.

- Hypothesis 2 (H2): If the buyer is not able to put more cash down, the seller and the buyer may start negotiating the price down, leading to lower transaction price anchored towards the appraisal value.

- Hypothesis 3 (H3): If the negotiation is not successful, the buyer will walk away from the deal, resulting in a failed transaction.

Based on a sample of successful transactions and listings, I formally investigate H1 and H2 by estimating the spillover effects of nearby cash sales on the appraisal value, transaction price, and time-on-market of a subject mortgage-financed transaction. To test H3, I collect a sample of failed mortgage applications and property listings, match them with nearby comparable sales, and check whether having more nearby cash sales would predict a higher failure rate.

Cash Bidding Wars as A Signal of High Demand

One might be concerned that cash buyers do not always portend price declines; instead, a high cash presence can be a symptom of a hot housing market. For instance, in booming housing markets or desirable neighborhoods, some buyers with ample liquidity (e.g., out-of-town individual investors) might use cash to win bidding wars. In such cases, cash offers may actually be correlated with higher prices, at least unconditionally, because these buyers might be willing to pay a premium for a quick, guaranteed close.

Existing studies find that the typical price discount for cash purchases shrinks during housing booms and in liquid markets (Han and Hong, 2024; Aroul and Hansz, 2023; Seo et al., 2021). Thus, one might also hypothesize that the spillover effect of cash sales vary across market conditions. In order to isolate this appraisal mechanism, it is crucial to control for demand, among other endogenous factors.

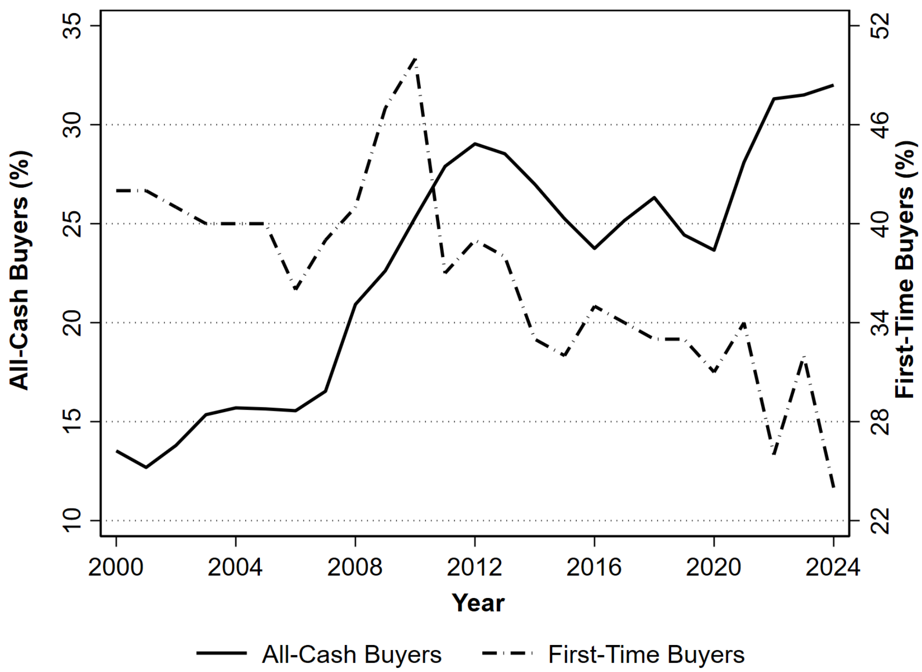
2 Data

In this section, I introduce how I construct the main sample and the exposure to nearby cash sales for each focal mortgage-financed property in preparation for the ring-based research design.

2.1 Primary Sample Overview

To construct the primary dataset, I match deeds, tax assessment records, and listings (MLS) from CoreLogic with loan origination records from the Home Mortgage Disclosure Act (HMDA) hosted by the Consumer Financial Protection Bureau (CFPB), at the property transaction level. Appendix Section A documents the matching process in detail. I only include arms-length transactions involving individual buyers, excluding foreclosures, intra-family transfers, and investor purchases. I also drop records with an extremely high or low transaction price, appraisal value, similar to Reher and Valkanov (2024), as well as extreme

Figure 1: National Cash Purchase Share (2000-2022)



Notes: This figure plots the annual national market share of all-cash home purchases during 2000-2022. Only arms-length transactions by individual home buyers are included.

property, loan, and buyer characteristics. The final matched sample consists of over 6.2 million[5] residential mortgage-financed transactions of single-family and town homes from 2018 to 2022, the only period during which appraisal values are reported. In total, the dataset spans 2,074 counties, approximately 76,000 census tracts, and covers more than 90% of the U.S. population. The appraisal value of a property[6] ("property_value") is reported as the value of the property provided by appraisers, in the case of a loan application, to secure the covered loan, which the lender relies on to make the credit decision.

Including investor purchases in the sample does not meaningfully affect the estimation results. Individual buyers account for more than 85% of all housing transactions and act as the primary driver in local housing markets. I exclude investor transactions to provide a cleaner identification of the appraisal mechanism, as institutional buyers may affect housing

[5]This larger merged sample includes records with partially missing tax or listing formation.

[6]The values are rounded to the nearest $5,000. More detailed information can be found in https://ffiec.cfpb.gov/documentation/publications/loan-level-datasets/lar-data-fields.

markets through their own unique channels and incentives, potentially confounding identification[7] (e.g., see Gorback et al. (2025)).

Figure 1 shows the how the market share of all-cash home transactions has increased from 12% to 32% in the past two decades, while the share of first-time home buyers has tumbled to a historic low around 24%. This trend aligns with findings from Han and Hong (2024) and Reher and Valkanov (2024), notwithstanding minor differences in sample construction. Appendix Table D1 shows the summary statistics of the primary sample. An average home transacts at $307,654 while appraised at $308,224, built 33 years ago, with around 3 bedrooms and 2 bathrooms. An average home buyer has a reported annual income of $99,000 and purchases a home with an 85% LTV.

2.2 Exposure to Nearby Cash Sales

Having constructed the primary sample, I quantify the exposure of each mortgage-financed transaction to its nearby all-cash sales. For each focal transaction, I calculate the accumulate count of nearby cash sales as well as all transactions for each ring with varying radii across 0.1, 0.2, ..., up to 1.2 miles. I stop searching for nearby properties beyond 1.2 miles due to computational capacity. Also, choosing 1.2 miles may well satisfy the hyper-local nature crucial to my research design, as implied by Bayer et al. (2021)[8]. Table 1 shows the summary statistics of the exposure of each focal transaction to nearby cash sales across all distances. For instance, the 0.6-mile radius has 17 all-cash sales with 73 transactions in total. The level of exposure rises mechanically with the expanding radius, and the outer rings are inclusive of the inner ring exposure, so that any exposure within 0.1 mile, for example, is also within 0.3 and 0.5 miles.

3 Research Design and Identification

The primary goal of this analysis is to identify the causal impact of nearby all-cash sales on the outcomes of a focal mortgage-financed home. Specifically, I seek to examine whether having more nearby cash sales can depress a subject home's appraisal value (through lower

[7]For example, it is possible that a mortgage-financed buyer would not like to buy a home close to an investor-owned rental property, endogenously driving down prices.

[8]Bayer et al. (2021) use 0.1, 0.3, and 0.5 miles for the inner, middle, and outer ring radius, respectively.

Table 1: Exposure to Nearby Cash Sales

	Panel A: Number of Cash Sales		Panel B: Number of Housing Transactions	
Distance (miles)	**Mean**	**SD**	**Mean**	**SD**
0.1	2	4	6	7
0.2	4	7	15	21
0.3	7	11	26	34
0.4	10	15	39	46
0.5	14	20	54	60
0.6	17	25	73	77
0.7	22	31	93	96
0.8	26	38	115	118
0.9	31	44	139	139
1.0	37	52	164	162
1.1	43	60	192	191
1.2	49	69	221	218
No. Observations			6,216,851	

Notes: This table presents the exposure of each focal mortgage-financed transaction to its nearby cash sales. For each ring with varying radii across 0.1, 0.2, ..., up to 1.2 miles, I calculate the accumulative count of nearby cash sales and the number of all housing transactions. The outer rings are inclusive of the inner ring exposure, so that any exposure within 0.1 mile, for example, is also within 0.3 and 0.5 miles.

comps) and, consequently, influence its transaction price and liquidity.

3.1 Ring-Based Research Design

The main challenges with identifying spillover effects along these lines are that (i) cash buyers are not randomly assigned to neighborhoods or surrounding a financed transaction and (ii) unobserved neighborhood-level factors simultaneously influence both cash buyer activity and housing outcomes. To deal with these issues, I adopt a ring-based research design that has been used extensively in the recent literature on neighborhood effects, local spillovers, and spatial contagion, such as Bayer et al. (2021) and Gupta (2019). The idea is to examine the influence of hyper-local cash buyer activity (e.g., on a focal property's own block) while controlling for comparable activity on other nearby blocks. In practice, I will measure the spillover effect of nearby cash sales within a radius of 0.6 mile, while conditioning on activity in a wider band (i.e., 1.2 miles). Additional nonparametric controls for time period and broader geographic definitions can also be included. Figure 2 illustrates the specific ring design with an inner ring of 0.6 mile and an outer ring of 1.2 miles that encompasses all cash purchases within both rings. Section 3.2.3 will discuss the tests to validate the choice of inner and outer ring radii. The baseline regression specification is

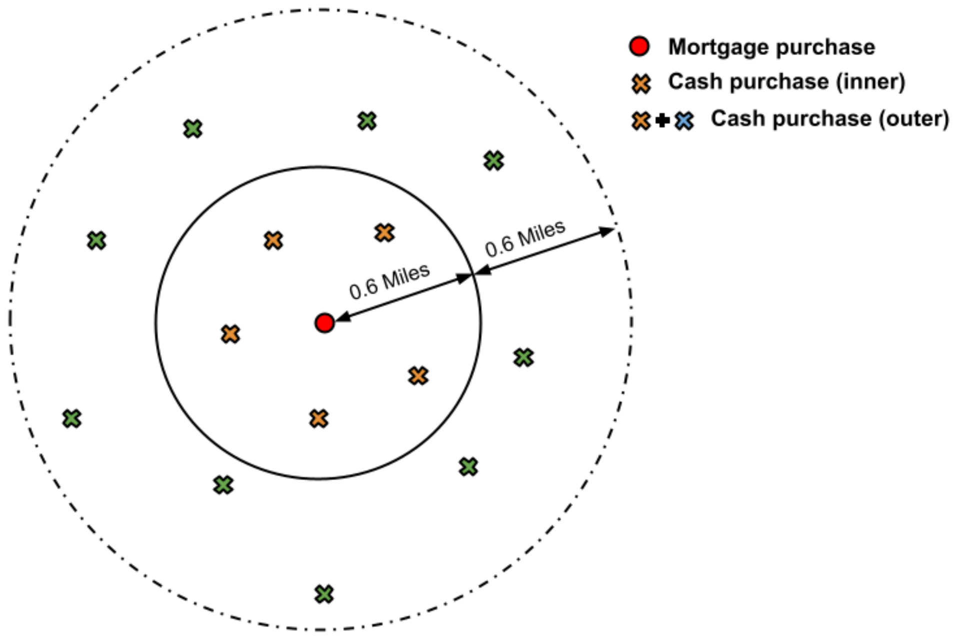
$$log(Y_{i,t}) \;=\; \beta_1\,\mathrm{C}^{\text{inner}}_{t-s:t} + \;\beta_2\,\mathrm{C}^{\text{outer}}_{t-s:t} + \;\gamma X_i \;+\; \delta_{c(i),t} \;+\; \varepsilon_{i,t} \tag{1}$$

where i indexes each focal transaction and t denotes the transaction date. The dependent variable $Y_{i,t}$ refers to the appraisal value recorded in the mortgage application or the actual transaction price of the property recorded in the deed. The main explanatory variables of interest are the exposure to nearby cash sales in the inner ring, $\mathrm{C}^{\text{inner}}_{t-s:t}$, and the same measure in the outer ring, $\mathrm{C}^{\text{outer}}_{t-s:t}$. As described above, each of these is measured as the cumulative count in a recent time period, $t-s:t$, and within the 0.6-mile or 1.2-mile ring. I start with a one-year lag, so that $s = 11$ (months), as appraisers do not typically search for comps beyond one year. This research design is to measure the effect of exposure at the inner ring distance, 0.6 miles, controlling for exposure at the wider disc. Note that the outer disc is inclusive of the inner ring exposure. Thus, the coefficient β_1 measures the additional effects of the exposure occuring within the inner ring and above the effect of exposure occuring within the entire outer ring. There is both spatial and temporal variation in the level of nearby cash activity. Intuitively, I can identify an effect by comparing two exposed mortgage-financed homes, one with neighbor cash sales and one without, or by comparing the housing outcome of the same exposed property when there has been recent cash activity to a period when there was not.

3.2 Identifying Assumptions and Internal Validity

Similar to Bayer et al. (2021), there are two key identifying assumptions underlying this ring-based spatial approach. The first is that the sorting of nearby cash sales is quasi-random in a hyper-locality. It is okay that all-cash home buyers select into certain properties and broader neighborhoods; however, they may have limited ability to cherry-pick micro-locations. In other words, the occurrence of a cash sale in a property's immediate vicinity is limited by some search frictions (e.g., timing and listing availability) rather than a reflection of some unobserved desirability of that exact block. The smaller blocks within in a relatively bigger neighborhood (e.g., a census tract) should see similar properties that appeal similarly

Figure 2: Ring Analysis



Notes: This figure shows how the inner and outer rings are designed around the focal mortgage purchase represented by the red circle. The inner ring encompasses all cash purchases within a 0.6-mile radius while the outer ring encompasses both cash transactions contained in the inner ring and those in the donut-shaped area between the range of 0.6 and 1.2 miles.

to cash buyers. In my context, the directly testable assumption is that the selection of cash sales into properties or blocks does not vary significantly across the geographic scale within a broader neighborhood (e.g., within 2 miles). The second identifying assumption is that neighborhood interactions are stronger at hyper-local geographies – a necessary condition for detecting nonzero effects from the inner ring exposure. The effects measured will contrast the response of a focal home to cash activity within 0.6 miles with that just a bit farther away, so that the estimated effects would be zero if we only see uniform neighborhood interactions with in the 1.2 mile ring. Economic theories do not define the scale at which such interactions truly take place. The selection of radii is intended to be a comparison between a city block's distance to a set of farther blocks. To the extent that interactions also operate at a broader geographic scale, perhaps at a lower intensity, this analysis may understate the full size and scope of these neighborhood interactions.

In the following sections, I will examine these two identifying assumptions through a series of tests, investigate the appropriate choice of the inner ring radius, and conduct a placebo test by using only all-cash transactions as the focal subject properties.

3.2.1 Testing for Cash Selection across Geographic Scale

To examine how the degree of cash activity sorting changes with geographic proximity, I compare a cash-purchased home's attribute x_i with the mean of those attributes within successive annuli (i.e., the donut-shaped areas) of width d, $\bar{x}_{i,rd,(r+1)d}$ for d = 0.1 mile and r = 1, 2, ..., 20. For example, if X is a property attribute and d is an increment of one-tenth mile, $\bar{x}_{(2)0.1,(2+1)0.1}$ is the mean attribute in an annulus whose inner radius is 0.2 miles and outer radius is 0.3 miles. I then take the average absolute value of the differences between x_i and $\bar{x}_{i,rd,(r+1)d}$ over the sample for 20 (r = 1, ..., 20) bins of 0.1 mile rings (d = 0.1 miles). To decide which property attributes to use in the above procedure, the following regression estimates the revealed preferences of cash buyers at the property level:

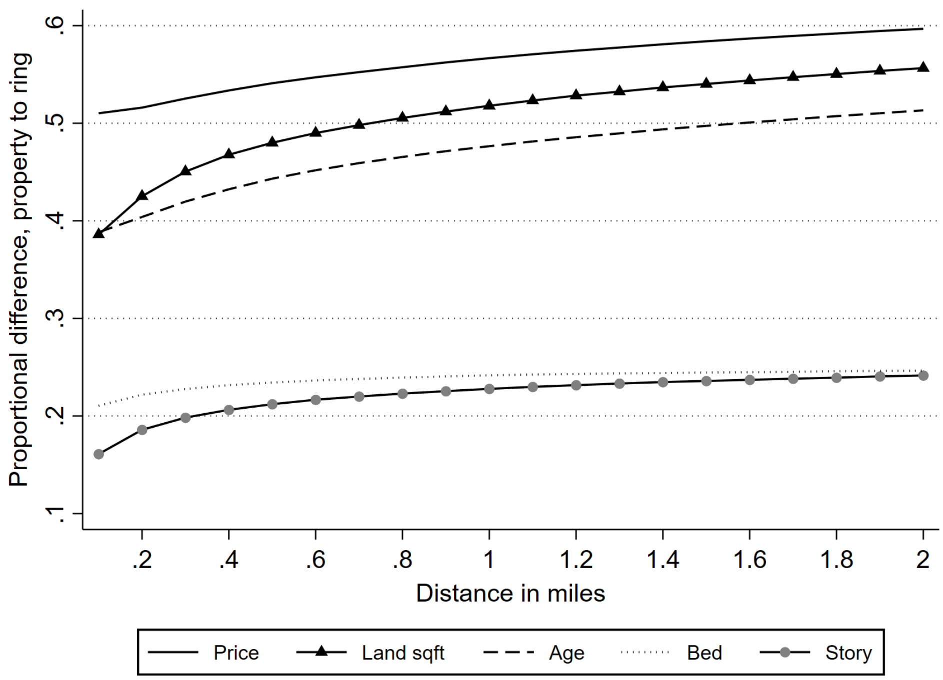
$$Cash_{i,t} \;=\; \beta \, log(P_{i,t}) \;+\; \sum_{k=1}^{N} \gamma_k X_{i,k} \;+\; \delta_{c(i),t} \;+\; \varepsilon_{i,t} \tag{2}$$

where $Cash_{i,t}$ is an indicator if a transaction i on date t is purchased with all cash, $log(P_{i,t})$ is the log transaction price, $X_{i,k}$ includes a suite of property attributes standardized with zero mean and unit one as the standard deviation, and the tract-by-year fixed effects, $\delta_{c(i),t}$. By rearranging Equation 2, the equation below estimates the mortgage cash premium through the loading on the cash indicator, ζ:

$$log(P_{i,t}) \;=\; \zeta \, Cash_{i,t} \;+\; \sum_{k=1}^{N} \gamma_k X_{i,k} \;+\; \delta_{c(i),t} \;+\; \varepsilon_{i,t} \tag{3}$$

In Appendix Table D2, Column (1) documents that cash buyers prefer cheaper, younger homes with fewer bedrooms, larger living space, and more land and parking space, while controlling for unobserved local housing trend at the neighborhood level. Column (2) replicates the 11% mortgage-cash premium, as documented by Reher and Valkanov (2024), validating my sample construction.

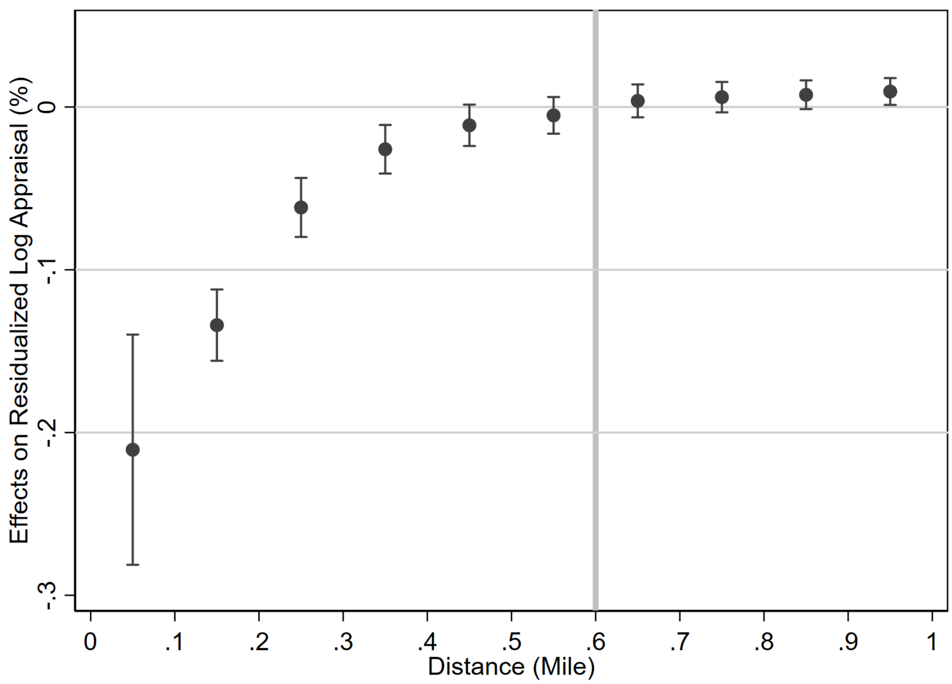
Figure 3: Cash Selection across Geographic Scale



Notes: This figure shows how the proportional difference in property characteristics between a focal cash sale and its nearby cash sales change across 0-0.1, 0.1-0.2, ..., to 1.9-2 mile donut-shaped rings. The key predictors (i.e., price, land square footage, building age, number of beds and stories) increase only gradually along the geographic scale.

Figure 3 reports the proportional differences between a focal cash-purchased home's and its neighbors' attributes as a function of the distance between the focal property and the neighbors. The figure reveals that for key cash purchase predictors – price, land square footage, property age, number of bedrooms, and number of stories – this difference increases quite gradually with distance. That is, the preferred property characteristics are only slightly less similar to their neighbors 0.1-0.2 miles away relative to neighbors within 0.1 miles, and again slightly less to those 0.2-0.3 miles away, and so on. Though cash sales systematically sort into select property characteristics, this sorting does not vary significantly across micro-locations within a neighborhood, suggesting hyper-local quasi-randomness of cash activity.

Figure 4: Treatment Effects on Residualized Log Prices as a Function of Distance



Notes: This figure plots the average treatment effects of nearby cash sales on the focal mortgage-financed property in each concentric 0.1-mile wide ring.

3.2.2 Testing for Stronger Hyper-local Neighborhood Interactions

Next, I investigate whether neighborhood interactions are more likely to take place at hyper-local geographies. The most direct test is to estimate the average treatment effect of nearby cash sales on a focal property's outcomes in each concentric ring (i.e., 0-0.1, 0.1-0.2, ..., 0.9-1 miles) and observe how the effect would vary in distance. To estimate the spillover (β_1 in Equation 1) for each concentric ring, I first residualize the outcome variable (e.g., appraisal value or transaction price) on all controls and then regress the estimated residuals on the explanatory variable, the cumulative count of nearby cash sales. Thus, I isolate the differential impact of each concentric ring across 0-0.1, 0.1-0.2, ..., up to 0.9-1 miles.

Figure 4 plots the average treatment effects of nearby cash sales on the focal property's appraised value for the ten 0.1-mile-wide rings from 0 to 1 mile away. To interpret the effects of the 0-0.1-mile ring, for example, one additional cash sale decreases the subject property's appraisal value by around 0.21%. Similarly, an increase of one cash sale in the 0.1-0.2-mile ring decreases the appraisal value by 0.13%, and so forth. These spillover effects are highly localized in that they decay to be statistically not different from zero for cash activity further than 0.6 miles from the focal property.

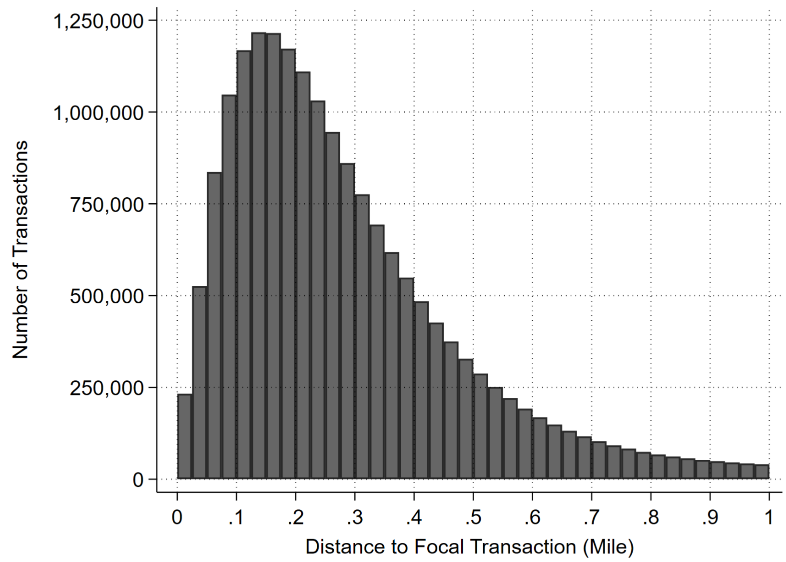
Simulating Comparable Sales

In the second complementary test, examine how appraisers choose comparable sales in reality, particularly whether appraisers predominantly draw similar transactions from the immediate vicinity so that they would have little reason to go outside the inner ring. Due to the lack of available data on comps, I manually construct comps for each transaction following the industry standard by Zillow.

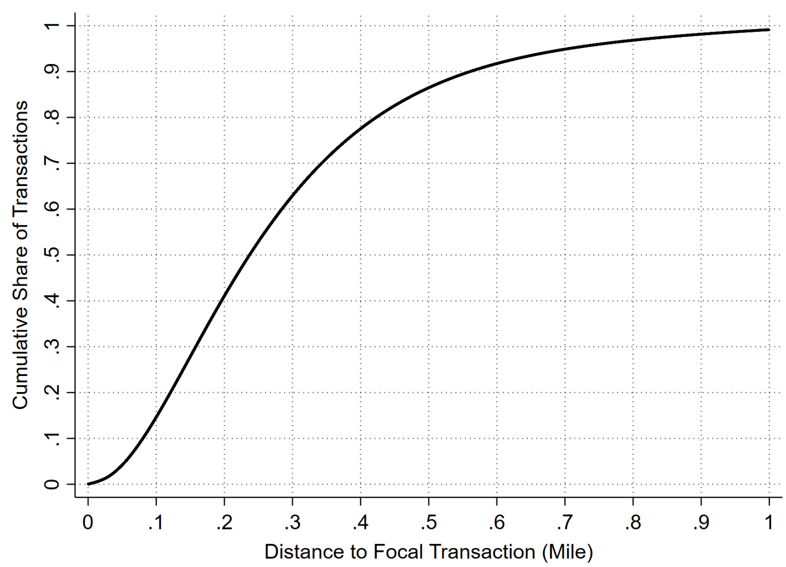
Zillow recommends that the comparable sales (not listings or pending sales) should ideally be within the same neighborhood or within about 0.25–0.5 mile of the subject home, and have sold in the past 3–6 months. This ensures that the comps reflect the same local market conditions and seasonal trends as the subject. If the immediate vicinity lacks sufficient comps, the search radius can be expanded outward (e.g. up to 1 mile) or the look-back period extended up to 6–12 months (or more in slower markets) to obtain enough data. The goal is to stay as close as possible in location and time so that the market-level differences are minimal[9].

In addition to location and time, physical property attributes are carefully matched. Comps should be close in size (e.g., living area within 300 square feet of the subject) with the same number of bedrooms and bathrooms, and a similar age and condition to the subject home. For example, a 4-bed/3-bath house with 2,500 square feet. built in 2005 should be compared to homes of roughly 4-bed/3-bath and 2,200–2,800 square feet. built around the same year. Major differences in features such as an extra garage, a swimming pool, a finished basement, or recent renovations should be accounted for, either by choosing comps that also share those features or by making value adjustments. Also, note that property type must be the same – a single-family home is not directly comparable to a condo or townhouse in valuation. Moreover, factors like lot size, views, and location amenities (waterfront, school district, walkability) are considered so that the comps capture the subject's desirability. By controlling for these criteria, the selected comps provide a fair benchmark for the subject property's market value.

[9] For example, see details at https://www.zillow.com/learn/real-estate-comps/.



(A) Histogram of Imputed Comps



(B) Histogram of Other Nearby Transactions

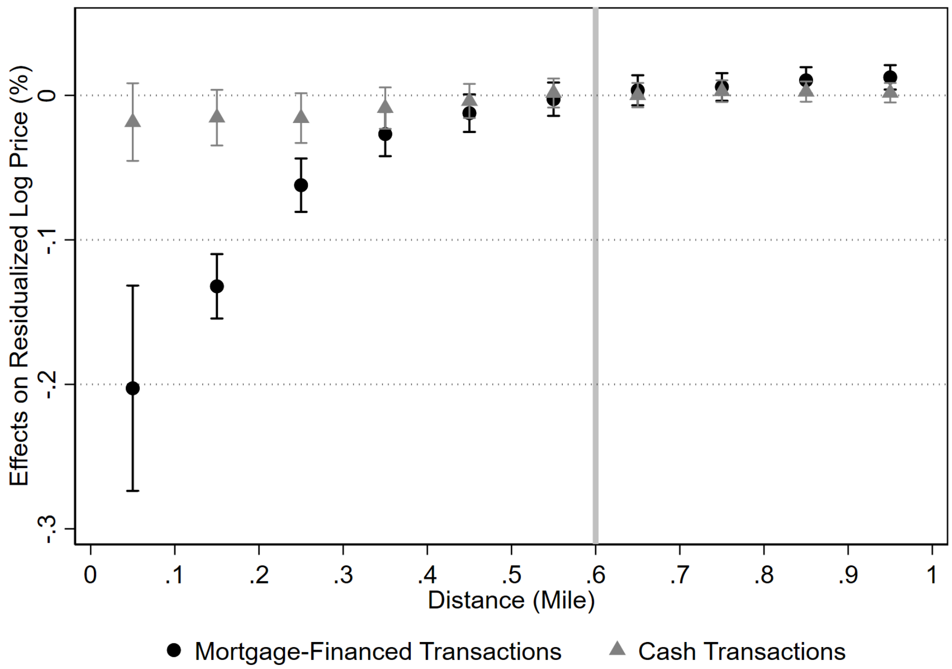
Figure 5: Panel A plots the histogram of the number of imputed comps across distances between 0 to 1 mile. Panel B plots the cumulative share of imputed comps against different radii from 0 to 1 mile. The algorithm to impute comps are documented in Appendix Section B in detail.

Closely following the industry standard, I create an algorithm to manually construct comparable sales for each transaction using detailed CoreLogic deeds and MLS data, with details documented in Appendix Section B. For each applicable subject property, I manage to select 3 or 4 comps from all nearby properties that are transacted in the past 12 months within 1 mile. Appendix Table D3 compares the property characteristics of the imputed comps with other nearby transactions that are not selected as comps. Confirming the efficacy of this algo, the selected comps are far more similar in all dimensions as well as geographically and temporally closer to the subject property. Panel 5A in Figure 11 displays the number of imputed comps in 0.25-mile bands across distances from 0 to 1 mile. The nearby neighborhoods within 0.1-0.25 miles consist of the highest density of comps with more than one million comps selected for each band. Panel 5B plots the cumulative share of imputed comps against distances to the focal property. 92.8% of all imputed comps are within the 0.6-mile radius, indicating a high likelihood that the appraisers choose comps in the immediate vicinity of a subject home if they follow what my algo simulates, echoing the decaying effects.

3.2.3 Choosing The Inner and Outer Ring Radius

Figure 4 suggests that the appropriate choice of the inner ring be 0.6 mile, which would suffice to capture all spillover effects from nearby cash sales while the effects beyond 0.6 mile are negligible. This intuition is also confirmed by Panel 5B in Figure 11 – the vast majority of simulated comps are within the 0.6 radius, indicating that it is unnecessary for appraisers to search for comps beyond 0.6 mile. The choice of the outer ring radius (1.2 miles) is bounded by the computational burden that increases exponentially as the ring expands. As some densely populated census tracts can be as small as or overlap with the 1.2-mile radius, they may (at least partially) absorb the broader effects of nearby cash activity captured by the outer ring. Ex ante, I am agnostic to whether the outer ring can materially capture any broader spillover effects after conditioning on the tract-by-year fixed effects, so I include it following the standard ring-analysis setting.

Figure 6: Placebo Test Using Only Cash Sales



Notes: This figure plots the pseudo-average treatment effects of nearby cash sales on the focal all-cash sales (in grey and diamonds) in each concentric 0.1-mile wide ring, estimated using Equation 1. These effects are plotted against the average treatment effects on focal mortgaged sales (in black and dots) taken directly from Figure 4.

3.2.4 Placebo Test Using Only Cash Sales

The appraisal mechanism is effectively a financial constraint of mortgage-financed home buyers and should not apply to all-cash buyers. I re-estimate Equation 1 by using all-cash sales[10], instead of mortgage-financed sales, as the focal property transactions. Figure 6 plots the pseudo-average treatment effects of nearby cash sales on focal all-cash sales in each concentric 0.1-mile wide ring, together with the decaying average treatment effects on focal mortgage-financed sales taken from Figure 4. The cash spillover on focal all-cash sales is significantly smaller than that on the mortgage-financed sales, suggesting that the appraisal mechanism only applies to mortgage-financed home buyers who are required to apply for a

[10]To be consistent,I use a sub-sample taken from a broader sample encompassing both cash and mortgaged sales used in estimating Equation 3.

mortgage and may face the low appraisals. In contrast, home buyers with cash can bypass all traditional financial constraints, transact with speed and certainty, and consequently unaffected by nearby cash activity through how appraisals work.

4 Baseline Results

Having established internal validity, I now formally estimate Equation 1. Table 2 reports the full regression results for a focal property's appraisal value and transaction price. All specifications use the same sample to ensure that the coefficient estimates are directly comparable across columns. Standard errors are conservatively clustered at the tract and year levels to allow for within-year correlation across tracts.

Column (1) includes all buyer and loan controls as well as tract-by-year fixed effects, but excludes property characteristics. The coefficient on the main explanatory variable, the number of cash sales within 0.6 miles, is estimated at -0.1356% and is statistically significant, which translates into a 3.38% decrease in the appraisal value when nearby cash sales increase by one standard deviation (i.e., 25 cash sales out of 73 total home sales within 0.6 miles). In Column (2), after adding property characteristics, the estimated effect attenuates to -1.55%, consistent with the notion that appraisals primarily reflect property-specific attributes and that cash activity tends to sort along those features, as discussed in Section 3.2.1.

The coefficient on the 1.2-mile ring is small and statistically insignificant, suggesting that spillover effects are highly localized. Together with the sharp spatial decay illustrated in Figure 4, these results indicate that the impact of nearby cash activity diminishes rapidly beyond 0.6 miles. I retain the outer ring in subsequent specifications, however, as I remain ex ante agnostic about the appropriate spatial boundary and seek consistency with the standard multi-ring empirical framework.

In Column (3), I further include two additional explanatory variables: the cumulative number of nearby mortgage-financed sales within the inner ring and the corresponding measure for the outer ring. Because mortgage-financed transactions are not typically discounted in the same way as cash sales, nearby mortgage-financed sales should not directly affect a focal mortgage-financed property, unless there exist unobserved factors that simultaneously influence both the local volume of sales and the focal property's appraisal value or transaction price. Consistent with this expectation, adding these two variables does not meaningfully

Table 2: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Appraisal Values				*Transaction Prices*			
Regression coefficients (%)								
No. Cash Sales								
within 0.6 miles	-0.1356***	-0.0619***	-0.0714***	-0.0558***	-0.1355***	-0.0619***	-0.0710***	-0.0555***
	(0.0146)	(0.0085)	(0.0092)	(0.0077)	(0.0145)	(0.0086)	(0.0090)	(0.0075)
within 1.2 miles	0.0265**	0.0184*	0.0188	0.0146	0.0268**	0.0184*	0.0166	0.0124
	(0.0086)	(0.0078)	(0.0105)	(0.0084)	(0.0080)	(0.0080)	(0.0106)	(0.0085)
No. Mortgage Sales								
within 0.6 miles			0.0077**	0.0076***			0.0075**	0.0074***
			(0.0017)	(0.0014)			(0.0017)	(0.0014)
within 1.2 miles			-0.0014	-0.0012			-0.0004	-0.0003
			(0.0020)	(0.0015)			(0.0020)	(0.0015)
List price				0.5917***				0.5900***
				(0.0040)				(0.0036)
Constant	12.5793***	11.9753***	11.9741***	4.6383***	12.5786***	11.9856***	11.9836***	4.6689***
	(0.0055)	(0.0078)	(0.0070)	(0.0526)	(0.0055)	(0.0084)	(0.0075)	(0.0487)
Average treatment effects								
No. cash sales within 0.6 miles								
Increase by one SD	-3.38%	-1.55%	-1.93%	-1.39%	-3.37%	-1.55%	-1.91%	-1.38%
Increase from Q1 to Q3	-2.71%	-1.24%	-1.54%	-1.12%	-2.70%	-1.24%	-1.52%	-1.11%
Property characteristics		Y	Y	Y		Y	Y	Y
Buyer age	Y	Y	Y	Y	Y	Y	Y	Y
Buyer race	Y	Y	Y	Y	Y	Y	Y	Y
Loan type	Y	Y	Y	Y	Y	Y	Y	Y
Tract-by-year FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.7140	0.8180	0.8180	0.8450	0.7050	0.8080	0.8080	0.8340
Observations	3,532,462	3,532,462	3,532,462	3,532,462	3,532,462	3,532,462	3,532,462	3,532,462

Notes: This table shows the baseline results estimated from Equation 1 with 0.6 and 1.2 miles for the inner and outer ring respectively. All specifications include tract-by-year fixed effects. All standard errors are clustered at the tract and year level with robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

alter the magnitude of the estimated effect on nearby cash sales.

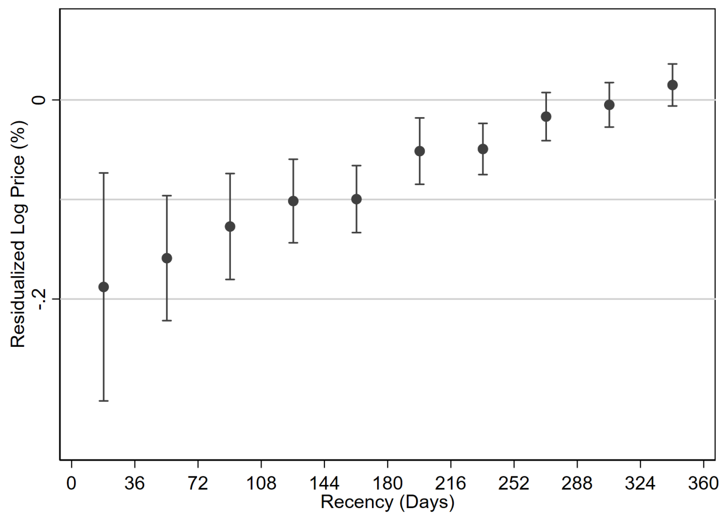
The coefficient on inner-ring mortgage sales is statistically significant but substantially smaller in magnitude than that of inner-ring cash sales. In contrast, the coefficient on outer-ring mortgage sales is negligible and statistically insignificant. These results indicate that, unlike nearby cash transactions, nearby mortgage-financed transactions exert little to no influence on the valuation of the focal property. Any residual association does not appear to undermine the appraisal mechanism identified in this study.

An alternative channel for the price-depressing effect of nearby cash sales is listing agent anchoring. The seller agents setting a home's listing price may preemptively lower the asking price if they observe many nearby cash sales, anticipating those sales could signal lower market values and appraisal issues, and anchor the transaction price to a lower level. Ex ante, it is not unambiguous to what extent listing agents incorporate the impact of nearby cash sales into pricing. Column (4) adds in an additional variable: the initial listing price for each transaction. There is clear sign of the listing agent anchoring channel in that this variable significantly predicts the appraisal value, and that the coefficient estimate on the inner ring cash measure also drops by 22%; plus, the constant estimate shrinks by 60%, suggesting that the listing price tremendously anchors the appraisal value. Controlling for the listing agent anchoring effect, the main coefficient estimate of interest (-0.0558%) in Column (4) now isolates the cash spillover from all other controls and confounding channels. To interpret, a one standard deviation increase in inner ring cash sales (i.e., 25 cash sales out of 73 total home sales) causes the appraisal value of the focal property to decrease by 1.39%.

Moving to the results on prices from Column (5) to (8), I find a very similar pattern. Considering Column (8), directly comparable to Column (4), a one standard deviation increase in inner ring cash sales indicates a 1.38% decrease in the focal property's transaction price. In other words, the impact of nearby cash activity on the appraisal and the price is almost one-for-one. This result supports Hypothesis 2 in Section 1: facing a lower appraisal due to discounted nearby cash sales, the buyer does not put more cash down, so the seller and the buyer enter negotiations that eventually drive the transaction price to the compressed appraisal value. Effectively, the negotiation process results in a transfer from the seller to the buyer by pushing the transaction price closer to the reservation price of the seller and farther away from the buyer's. Arguably, this resulting transfer also proxies the seller's willingness to pay (WTP) in order to avoid a transaction failure and thus may vary across market conditions (e.g., hot and cold markets), neighborhoods, and for different buyers. I discuss this transfer in detail and quantify its dollar values in Section 6.

Alternatively, Appendix Table D5 presents the estimation results for Equation 1 using the nearby cash market share (instead of the count) as the main explanatory variable. The overall output is very similar to the above baseline results.

Figure 7: Treatment Effects on Residualized Log Prices as a Function of Recency



Notes: This figure plots the average treatment effects of nearby cash sales on the focal mortgage-financed property across ten equally-split bins with different recency.

Decaying Effects in Recency

As appraisers also anecdotally choose temporally closer comparable sales, now I investigate the differential impact of nearby cash sales transacted in different time spans on a focal property. Specifically, I create ten different recency groups, count the cumulative cash sales transacted in the past 0-36, 36-72, ..., 324-360 days prior to each focal property's transaction date, and estimate the impact of each group similar to Figure 4. Figure 7 plots the average treatment effects across the ten equally-split bins. The effects decrease significantly as the the average number of days increases and fade away around 300 days. The most pronounced effects come from those nearby cash sales transacted within the past 180 days, consistent with how appraisers typically choose comps: conditioning on nearby properties with similar attributes, they typically choose those sold in the past 3 to 6 months.

Effects on Time-on-Market

Next, I study the spillover effects on the liquidity of a subject property, as the appraisal constraint is more likely to bind with more nearby discounted cash sales compressing the appraisal value, potentially making a home harder to sell and staying on the market for a

Table 3: Effects on Time on Market

	(1)	(2)	(3)	(4)
	Days on Market			
No. Cash Sales				
within 0.6 miles	5.56***	1.56**	1.50***	1.46**
	(0.25)	(0.26)	(0.26)	(0.26)
within 1.2 miles	-0.03**	-0.01*	-0.01**	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
List price	1.59***	21.54**	21.94***	21.87**
	(0.06)	(0.24)	(0.25)	(0.25)
Tract-by-year FE		Y	Y	Y
Property characteristics			Y	Y
Buyer/Loan Controls				Y
R-squared	0.001	0.567	0.567	0.567
Observations	3,467,928	3,467,928	3,467,928	3,467,928

Notes: This table shows the estimated results on days on market of each focal transaction, similar to Equation 1. All specifications include tract-by-year fixed effects. All standard errors are clustered at the tract level. with robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

longer time. I re-estimate Equation 1 using days on market of each focal property as an alternative outcome. Figure 3 presents the estimation results. Without including any controls in Column (1), the coefficient of the main explanatory variable is 5.56. This coefficient shrinks dramatically when including the tract-by-year fixed effects and becomes stable as I include other controls, such as property characteristics, buyer attributes, and loan features. Column (4) isolates the cash spillover on liquidity: one more nearby cash sale increases TOM by 1.5 days, or an equivalently 38-day increase if the nearby cash sales increase by one standard deviation. This indicates that nearby discounted cash sales impose a downward spillover effect on a focal property's liquidity. Because the appraisal constraint is more likely to bind due to more nearby cash sales, the seller and the buyer spend more time negotiating. A longer negotiation is potentially good for the buyer as more asymmetric information can potentially be revealed so that the sale price is pushed closer to the seller's reservation value. Section 5.2 investigates the information revelation mechanism in detail.

Consider the coefficients of other controls in Table 3. Nearby cash sales in the broader

1.2-mile outer ring do not have meaningful impact on a focal property's TOM, similar to the baseline results in the sense that this impact is highly concentrated in the immediate vicinity. Notably, a higher initial listing price is significantly correlated with a longer TOM. This result is strongly supported by housing literature on seller behavior: setting an asking price well above market value typically backfires, resulting in the property sitting on the market longer and eventually selling at a discount (e.g., Genesove and Mayer (2001) and Knight (2002)).

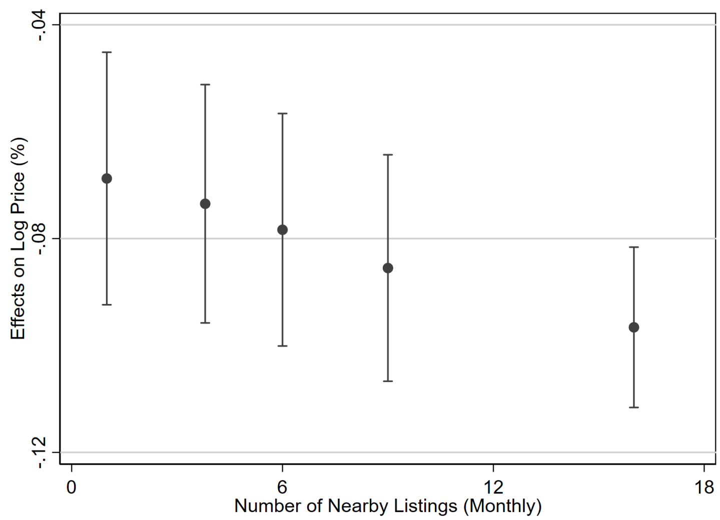
5 Heterogeneity and Potential Mechanisms

As discussed, the baseline results support Hypothesis 2 (H2): a successful renegotiation between the seller and the buyer drives the eventual transaction price to the depressed appraisal value. Naturally, the extent to which negotiations drive down prices would depend on a variety of factors, such as the relative bargaining power between the seller and the buyer, the buyer's financial literacy, the role of asymmetric information, etc. In this section, I investigate these potential mechanisms by examining how the spillover effects vary across different market conditions, neighborhoods, and buyers.

5.1 Seller Bargaining Power

As noted by the baseline results, the depressing spillover effects on the focal property can be viewed as the seller's willingness to pay in order to avoid a transaction failure. Naturally, the seller's bargaining power relative to the buyer may vary across housing markets with different inventory that differentially favor the seller or the buyer. To measure local inventory near each focal property, I calculate the number of listings during the property's transaction month and within its 1-mile radius. This measure can proxy the contemporaneous and nearby housing inventory around a focal property. Next, I divide all transactions into five groups based on the listing count and interact this new categorical group variable with the inner ring cash count, the main explanatory variable in Equation 1. Figure 8 shows the average treatment effects for these five inventory groups. The effect is most pronounced for transactions with fewer than 6 nearby monthly listings. Furthermore, it decreases by around 50% as the number of nearby listings increases from 1 to 16, indicating that the

Figure 8: High vs. Low-Inventory Markets



Notes: This figure plots the differential impact of nearby cash sales on the high- and low-inventory markets. All transactions are equally split into five groups based on the count of nearby listings.

seller's ability to negotiate to her own advantage is more limited when there is more nearby inventory. Indeed, the buyer will have better outside options when there are more available listings nearby so that she can negotiate more and obtain a lower transaction price.

5.2 Information Revelation

Negotiations can potentially help with the revelation of asymmetric information as well as financial illiteracy. In this section, I will investigate the information revelation channel by examining how the cash spillover varies across neighborhoods of different affordability, household income, and minority shares and, at a more granular level, across buyers of different attributes. Ex ante, it is unclear whether the negotiation process helps reveal asymmetric information (e.g., of the property or the seller's reservation value) so that relatively disadvantaged buyers benefit more by obtaining a lower price ex post. On the other hand, it might also be true that the seller would negotiate more with those less sophisticated, poorly informed, or more financially constrained buyers and obtain a more favorable (though still compressed) price that is closer to her reservation value.

Heterogeneity across Neighborhoods

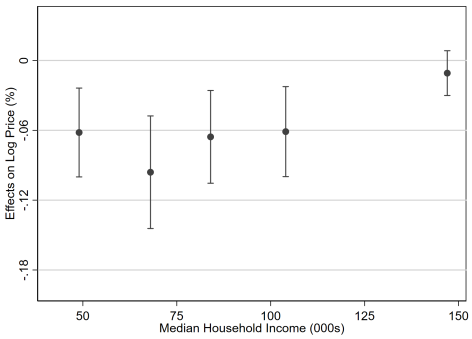
Figure 9 presents the heterogeneous impact of nearby cash sales across four different neighborhood characteristics: median household income, income-to-price ratio, minority population, and average price growth. For each attribute, respectively, I create a categorical variable by splitting all census tracts into multiple groups and interact it with the main explanatory variable (i.e., the cumulative cash count in the inner ring) in Equation 1.

Panel 9A shows that the most pronounced effects come from neighborhoods with an annual median household income lower than $100,000, indicating that home buyers in relatively poorer neighborhoods benefit the most. In contrast, this impact becomes negligible for relatively affluent neighborhoods where a median household earns higher than $150,000, supporting the information revelation channel. In Panel 9B, I measure the affordability of a neighborhood using the ratio between its median household income and median home value. The negotiation is more advantageous for the buyer in more affordable neighborhoods, especially those with an income-to-price ratio higher than 0.35. Arguably, there are less sophisticated buyers and older and potentially more heterogeneously homes in those more affordable areas. As a result, negotiation reveals more useful information and benefits these neighborhoods. Panel 9C shows that the effects are also stronger in neighborhoods with a larger minority population, particularly those with more than 40% of their population being non-white[11]. While minority home buyers are known to be relatively less advantaged in credit access, liquidity, and information, they benefit the most from the spillover effects of nearby cash sales through negotiation, at least those who successfully navigate through this friction.

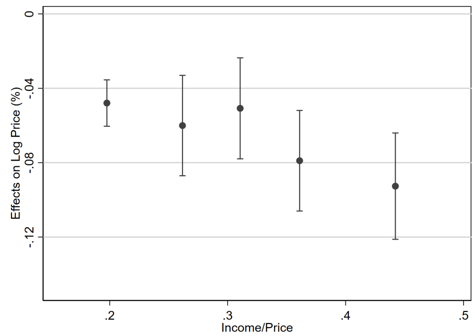
In Panel 9D, I investigate whether the impact differs in high-growth and slowly growing markets. I categorize neighborhoods based on their house price growth during 2018-2022 by splitting tracts into "high-growth" vs. "low-growth" categories depending on whether the five-year average exceeds the national median. I expect the five-year average to capture a sustained local housing trend and proxy for the underlying demand conditions. Appendix Section C documents how I estimate the quality-adjusted local house price growth in detail, including the hedonic regression to construct the tract-year-level house price indices (HPIs), the validation, and relevant summary statistics. Generally, a high-growth tract is likely to

[11] HMDA race categories ("derived_race") include American Indian or Alaska Native, Asian, Black or African American, Native Hawaiian or Other Pacific Islander, White, 2 or more minority races.

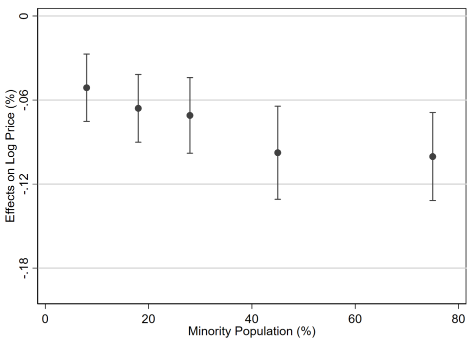
Figure 9: Heterogeneity across Neighborhoods



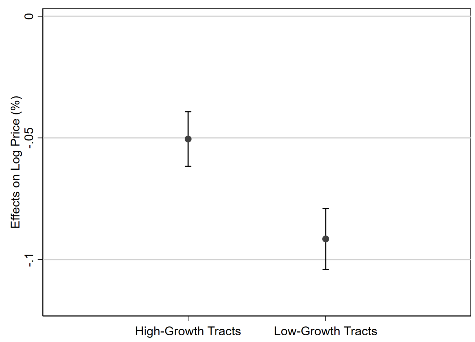
(A) Income



(B) Affordability



(C) Minority Population



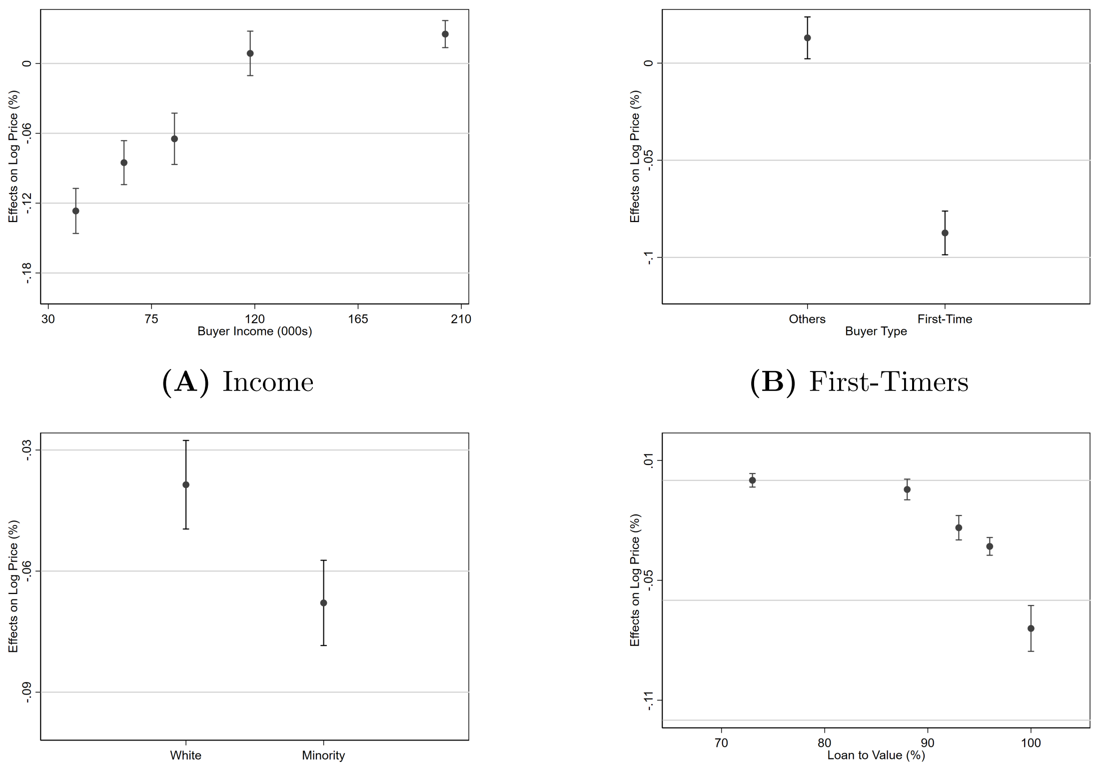
(D) Price Growth

Notes: These figures show the differential impact of nearby cash sales on a mortgage-financed home by neighborhood heterogeneity.

have a hot market with strong demand, whereas a low-growth tract has a relatively cooler market. I find that the price-depressing impact is more pronounced in low-growth tracts than that in those growing rapidly. Indeed, in slowly moving markets with lower demand, there would be fewer cash bidding wars that support prices instead of anchoring them down.

Taken together, the cash spillover is stronger in low-income, more affordable, low-growth neighborhoods with a higher minority population share, suggesting that the negotiate process predominantly benefits the potentially disadvantaged buyers instead of favoring the seller.

Figure 10: Heterogeneity across Home Buyers



(A) Income

(B) First-Timers

(C) Minority

(D) Leverage

Notes: These figures show the differential impact of nearby cash sales on a mortgage-financed home by neighborhood heterogeneity.

Heterogeneity across Buyers

Figure 10 presents the differential impact of nearby cash sales across different buyer attributes, allowing more granular variations at the transaction level, including the buyer's reported income, first-time home buyer status, race, and leverage. Overall, the buyer-level heterogeneity is consistent with and is even more pronounced than the neighborhood-level evidence.

Panel 10A plots the differential impact on the transaction price for five different income groups. It is striking that this impact is only pronounced for those with an annual income lower than \$90.000. Those earning \$120,000 higher do not see any economically meaningful impact. Appendix Figure E1A presents very similar heterogeneous pattern on appraisals.

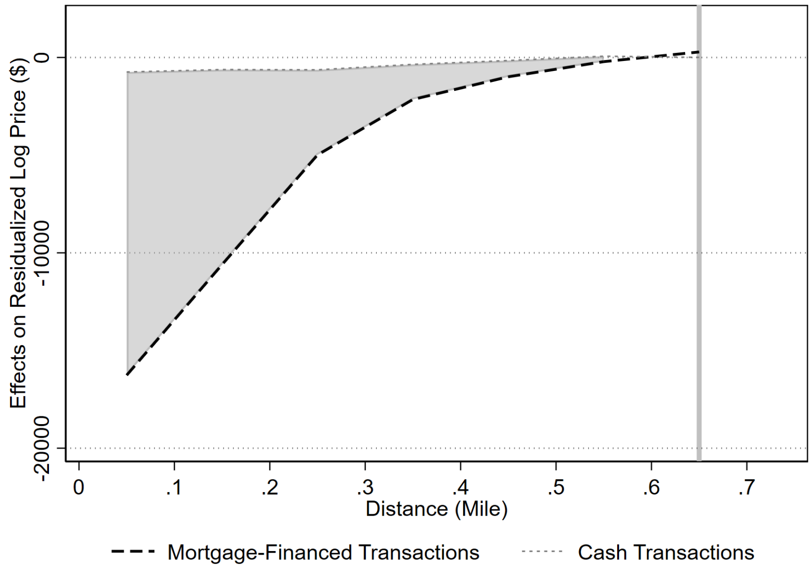
This result suggests that it is mostly the low-income buyers who face low appraisals and, fortunately, are able to benefit from the negotiation process through information revelation. In contrast, high-income buyers either do not often encounter the low-appraisal scenario or they already incorporate the appraisal constraint into the bargaining process so that the impact on both the appraisal and the transaction price turn out to be negligible. High-income buyers may be better at identifying listings that are less likely to be constrained by low appraisals due to reasons such as seller-agent anchoring that already incorporates nearby cash sales into the listing price and compresses the close price (at least partially), or an initially low listing price due to risk aversion or seller pessimism ex ante.

Panel 10B, 10C, and 10D echo the results above: first-time home buyers, non-white minority buyers, and those using a high leverage ($\geq 90\%$) see a disproportionately larger discount in the final appraisal and transaction price. While these buyers are the main beneficiaries of the cash spillover, other buyers do not see an economically meaningful impact. In sum, these results show that more disadvantaged buyers (e.g., first-time minority buyers with lower income and higher leverage) benefit the most from the discounted appraisal through the information revelation process during negotiations.

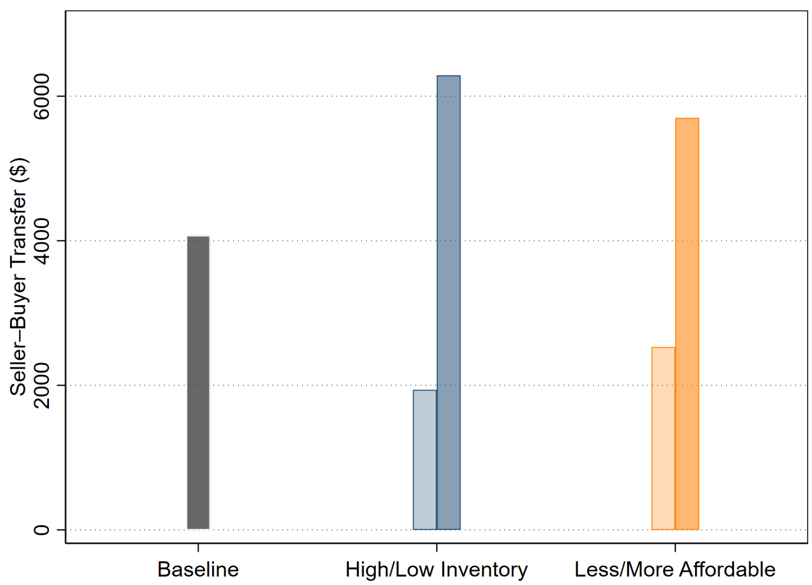
6 Quantifying The Seller-Buyer Transfer

As discussed, the baseline results support the seller-buyer negotiation hypothesis that results in a sale price anchored to the depressed appraisal value. The degree to which the final price is compressed can proxy the seller's willingness-to-pay, or a transfer to the buyer, to avoid a failed transaction or a longer time on market. However, while I observe the post-negotiation price effect, the pre-negotiation price is not observable. To proxy the counterfactual of what happens to a mortgage-financed property absent nearby cash activity to gauge the pre-negotiation price effect, I re-estimate the placebo (or pseudo) effect of nearby cash sales on a focal cash sale in dollar values as in Figure 6.

Figure 11A plots the transfer between the seller and the buyer by the gray area, measured by the the differential impact (in \$) of nearby cash relative to a focal mortgage-financed transaction and on a focal all-cash transaction, across different radii. For example, an increase of one nearby cash sale in the 0-0.1-mile concentric ring would depress the final sale price by around \$16,000, whereas the pseudo effect on a focal cash sale is less than \$1,000.



(A) Spillover vs. Placebo Effects in Dollars



(B) The Seller-Buyer Transfer

Figure 11: Panel A plots the transfer between the seller and the buyer in the gray area, proxied by the the differential impact (in $) of nearby cash relative to a focal mortgage-financed transaction and on a focal all-cash transaction, across different radii.

Both of these two effects decay drastically up to the 0.6-0.7-mile ring band where they are not significantly different from zero. There are two benefits of estimating the transfer this way: (i) the impact on a focal cash sale is effectively negligible compared to the true spillover on a focal mortgaged sale, corroborating that the appraisal constraint is the unique force in play that only affects a mortgage-financed home buyer; (ii) using the effect on a focal cash sale, though much smaller, can account for the neglected unobserved hyper-local trend that impacts both nearby cash activity and the outcome of all transactions in a micro-location[12]. Note that the average number of cash sales in the closer concentric ring is much smaller (e.g., on average, there are only two cash sales in the 0-0.1-mile ring), while this number goes up exponentially in the further rings. Thus, I aggregate the accumulative difference in effect (the gray area) between the mortgage-financed sales and the cash sales using analytical weights based on the number of nearby cash transactions in each concentric ring. Figure 11B plots this aggregated transfer – the seller facing the cash spillover would be willing to lower the initial ask price by $4,000 to avoid a potential failure compared to a seller absent any nearby cash sales. To explore heterogeneity, I split all mortgage-financed transactions into two groups based on nearby inventory or income-to-price ratio, respectively. Echoing the results in Section 5.2, this transfer is larger when there is more nearby inventory such that buyers have more outside options or in more affordable markets where there may be less sophisticated buyers and more heterogeneous homes.

7 Investigating Hypothesis 3: Mortgage Failure

So far, I have examined Hypothesis 1 and 2 using a sample of successful transactions and provided robust evidence for the second channel: the seller-buyer negotiation puts the sale price down to the depressed appraisal value. In this section, I formally examine the third hypothesis by assembling a sample of failed mortgage origination records: if the negotiation is not successful, the buyer would walk away from the deal, resulting in a failed transaction.

For the failed mortgage records, I select those with "application approved but not accepted", a particular category among all actions that can be taken for each mortgage application. This is the most consistent category for a transaction that fails after a low appraisal

[12] In Figure 3, for example, although the cash sorting only increases slightly across small geographic scales, its existence might still undercut an accurate estimation of the true spillover effects.

and unsuccessful renegotiation for a few reasons: (i) the lender did approve the loan conditional on collateral value, which turned out insufficient, (ii) the buyer and seller could not resolve the gap, and (iii) the borrower therefore did not proceed to closing and did not accept the loan. A smaller share of such cases may appear to be "application denied by financial institution" if the lender's underwriting system treats the low appraisal as a denial reason (e.g., "collateral not sufficient" or "property value declined"). Between 2018 and 2022, there are 1,057,340 failed home purchase loan applications that fall into these two categories. The ideal empirical design would assess whether greater nearby cash activity predicts a higher likelihood of mortgage application failure, closely following the ring-based specification in Equation 1. However, this approach is not feasible because rejected loans in the HMDA dataset cannot be linked to the CoreLogic data, which only record successfully originated mortgages. Consequently, I shift to analyzing the relationship between the local mortgage rejection rate and the market share of all-cash home purchases at the census tract level. The following regression is estimated at the tract-year level:

$$\text{RejectionRate}_{c,t} \;=\; \beta_1\, \text{CashShare}_{c,t} + \;\gamma X_{c,2020} \;+\; \delta_{county\times t} \;+\; \zeta_c \;+\; \varepsilon_{c,t} \tag{4}$$

where $\text{RejectionRate}_{c,t}$ denotes the share of "approved but not accepted" loans in tract c at time t, $\text{CashShare}_{c,t}$ measures the share of all-cash home purchases in tract c at time t, and $X_{c,2020}$ represents a vector of 2020 neighborhood characteristics for tract c. These include median home value, median gross rent, median household income, racial composition, poverty rate, unemployment rate, homeownership rate, vacancy rate, and the share of single-family homes. Together, these controls account for the observed housing market structure and the socio-economic composition of the local neighborhood.

I further include county-by-year fixed effects, $\delta_{county\times t}$, and tract fixed effects, ζ_c, to absorb any shocks common to all tracts within the same county-year. The coefficient of interest, β_1, captures how a tract's mortgage rejection rate changes with variation in its cash purchase activity relative to other tracts in the same county-year, after controlling for each tract's average level. All standard errors are clustered at the tract level.

Table 4 presents the estimation results for Equation 4. The results in Column (1) indicate a positive and statistically significant relationship between a tract's mortgage rejection rate (measured as the share of "approved but not accepted" loans) and its share of all-cash home purchases when comparing tracts within the same county-year. Column (2) reports

Table 4: Effects on Mortgage Failure

	(1)	(2)	(3)	(4)
	Approved but Not Accepted Rate			
Regression coefficients				
Cash Share	0.037***	0.041***	0.027***	0.022***
	(0.001)	(0.001)	(0.001)	(0.002)
Constant	0.019***	0.018***	0.032***	0.024***
	(0.000)	(0.000)	(0.002)	(0.000)
Summary Statistics				
Dep. Var Mean	0.035			
Dep. Var SD	0.027			
Ind. Var Mean	0.289			
Ind. Var SD	0.268			
County FE	Y			
Year FE	Y			
County-Year FE		Y	Y	Y
Tract Controls			Y	
Tract FE				Y
R-squared	0.151	0.190	0.222	0.596
Observations	216,453	216,453	216,453	216,453

Notes: This table shows the estimation results for Equation 4, where the dependent variable is the share of "approved but not accepted" mortgages of a tract and the independent variable is its cash purchase share. All standard errors are clustered at the tract level. with robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

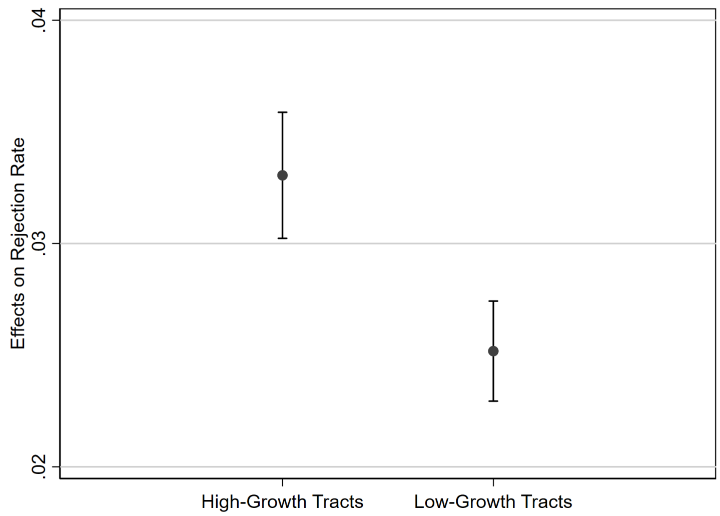
a similar coefficient on tract-level cash share after controlling for county-by-year fixed effects. In Column (3), where I further include the full set of neighborhood characteristics, the magnitude of the coefficient declines by roughly one third, suggesting that part of the variation is explained by local housing and socioeconomic conditions. Column (4) presents the most restrictive specification, adding tract fixed effects to account for all time-invariant neighborhood attributes.

The coefficient on cash purchase share remains positive and significant at 0.022, implying that a 100 percentage point increase in a tract's cash purchase share is associated with a 2.2 percentage point increase in its mortgage rejection rate. This corresponds to a 62.9% increase relative to the average rejection rate of 3.5%. More realistically, a one standard deviation increase in cash share (26.8 percentage points) predicts a 0.59 percentage point rise in the rejection rate, or a 16.8% increase relative to the mean. These results support Hypothesis 3, consistent with the mechanism that unsuccessful negotiations following low appraisals lead buyers to withdraw from transactions, resulting in failed mortgage applications. Although the volume of failed applications is much smaller than that of successful ones (over six million), the evidence suggests that this failure margin represents a meaningful channel, or at least a consequential byproduct, of local cash-sale spillovers.

Heterogeneity: High- vs. Low-Growth Neighborhoods

Next, I examine whether the effect on mortgage failure rates varies across neighborhoods with different housing market dynamics, following the same design that investigates neighborhood heterogeneity as Figure 9D. Figure 12 presents the heterogeneous effects across two equally sized groups split by local price growth. The results indicate that a 100 percentage point increase in a tract's cash purchase share is associated with an 0.03 percentage point increase in the mortgage rejection rate in low-growth tracts, which is 31% higher than the corresponding effect in high-growth tracts. This asymmetry is consistent with stronger appraisal-based financing constraints in low-growth, low-demand neighborhoods, where buyers are more liquidity constrained and more sensitive to downward appraisal revisions triggered by discounted nearby cash transactions. As a result, the buyer is more likely to walk away from the constrained deal and less likely to have a successful negotiation with the seller, resulting in a higher likelihood of an unsuccessful mortgage. In contrast, in high-growth neighborhoods characterized by stronger demand and a larger share of unconstrained or equity-rich buyers, appraisals are less likely to bind and may even serve as a mild screening mechanism that improves match quality. Consequently, the welfare implications of this failure channel highlight a trade-off: while appraisal frictions can help contain overvaluation pressures in growing markets, they may simultaneously exclude marginal buyers and exacerbate credit access disparities in weaker housing markets.

Figure 12: Hypothesis 3: High vs. Low-growth Neighborhoods



Notes: This figure plots the differential conditional correlation between a tract's cash purchase share and its rejection rate across high-growth and low-growth markets, estimated by Equation 4, similar to Figure 9D.

8 Welfare Implications

In this section, I investigate the welfare implications based on all previously established empirical evidence and a bargaining model featuring a key tradeoff: the exclusion of home buyers due to spillover-induced transaction failure vs. the lower cost of ownership that benefits those who take advantage of the information revelation through negotiations.

Model Set-Up

I study a one–neighborhood, one–period environment with a single representative house offered for sale. A set of potential buyers $i = 1, \dots, K$ draw idiosyncratic valuations v_i from a continuous distribution F_v with common support. There are two types of buyers: a fraction $\mu \in (0, 1]$ are unconstrained (U) and can pay up to their valuation: they face no financing cap; the remaining fraction $1 - \mu$ are mortgage-constrained (M) and have liquid wealth $W_i \geq 0$ (cash available for down payment) and a loan capacity limited by the appraised value of the house. The seller has reservation value R. Let $P^\star$ denote the frictionless benchmark price that would obtain absent appraisal-based financing frictions.

Appraisal channel. Let s denote the exposure to nearby cash transactions (e.g., the standardized count within 0.6 miles in the recent window implied by Table 1). The appraised value used by the lender is anchored to nearby comparables and is modeled as

$$A(s) \;=\; \big(1-\alpha s\big)\, P^{\star}, \qquad \alpha>0, \tag{5}$$

so that a one–standard-deviation increase in s reduces the appraisal by α percent of $P^{\star}$ (e.g., empirically, $\alpha \approx 0.014$ in the baseline).

Financing caps. A constrained buyer i can borrow up to a fraction $\lambda \in (0,1)$ of the appraised value $A(s)$ and can add her liquid wealth W_i to meet the price. Her maximum feasible payment is

$$\mathrm{cap}_i(s) \;=\; W_i \;+\; \lambda\, A(s). \tag{6}$$

Unconstrained buyers face no cap. For any buyer i, the effective amount she can commit to pay is $\min\{\mathrm{cap}_i(s),\, v_i\}$.

Allocation and pricing with appraisal renegotiation. Define the neighborhood's optimal effective payment

$$C_{\max}(s) \;=\; \max_{i=1,\ldots,K}\; \min\{\mathrm{cap}_i(s),\, v_i\}. \tag{7}$$

The transaction price implements the three hypotheses:

$$P(s) \;=\; \begin{cases} P^{\star}, & \text{if } C_{\max}(s) \ge P^{\star} \quad \text{(H1: no binding cap);} \\ C_{\max}(s), & \text{if } R \le C_{\max}(s) < P^{\star} \quad \text{(H2: renegotiation/price compression);} \\ \varnothing \text{ (fail)}, & \text{if } C_{\max}(s) < R \quad \text{(H3: exclusion/failure).} \end{cases} \tag{8}$$

When the best buyer is constrained and her cap binds below $P^{\star}$ but above R, the contract price is renegotiated down to the cap, $P(s) = C_{\max}(s)$, delivering the near one-for-one appraisal–to–price pass-through documented empirically. If no buyer can meet R, the sale fails.

Welfare objects. Let v_{win} denote the valuation of the winning buyer when a sale occurs. Buyer surplus is $v_{\text{win}} - P(s)$, seller surplus is $P(s) - R$, and total surplus is

$$W^N(s) \;=\; \begin{cases} v_{\text{win}} - R, & \text{if a sale occurs;} \\ 0, & \text{if the sale fails.} \end{cases} \tag{9}$$

Two additional diagnostics are useful. First, *price compression* (a transfer from seller to buyer) when a binding cap bites is

$$\text{Compression}(s) \;=\; P^\star - P(s) \;=\; \big[P^\star - C_{\max}(s)\big]_+. \tag{10}$$

Second, *misallocation* arises when the highest-valuation buyer (with value $v_{(1)}$) does not win due to caps; the associated loss is

$$\text{Misalloc. loss}(s) \;=\; v_{(1)} - v_{\text{win}} \;\geq 0. \tag{11}$$

Case 1: Low-Growth, Low-Demand Neighborhoods

In low-growth neighborhoods, demand is thin (small K), unconstrained buyers are scarce (low μ), and constrained buyers have limited liquid wealth (low W_i). Inventory is relatively ample and comparable sales are less frequent, so recent nearby sales receive higher weight in appraisals; effectively, the mapping $s \mapsto A(s)$ in (5) is more sensitive. From (6)–(7), a higher s lowers $A(s)$ and thus $\text{cap}_i(s)$ for constrained buyers, reducing $C_{\max}(s)$. It follows from (8) that the probability mass shifts away from the region $C_{\max}(s) \geq P^\star$ (no compression) and toward the regions with $R \leq C_{\max}(s) < P^\star$ (renegotiation to the cap, generating larger Compression(s)) or $C_{\max}(s) < R$ (failure). As caps bind more often, misallocation in (11) rises because high-valuation constrained buyers lose to lower-valuation unconstrained buyers or the sale fails altogether. Neighborhood welfare in (9) declines with s due to both a higher incidence of failure and greater misallocation, even though winners enjoy larger transfers in (10).

Case 2: High-Growth, High-Demand Neighborhoods

In high-growth neighborhoods, demand is higher (large K), unconstrained buyers are prevalent (high μ), and constrained buyers have greater ability to bridge appraisal gaps (higher W_i). Frequent transactions make appraisals track fundamentals more closely, so $A(s)$ is less sensitive to s. Consequently, $C_{\max}(s) \geq P^{\star}$ holds with high probability; the transaction price remains near $P^{\star}$, price compression is limited, and failures are rare. In this case, allocation is closer to efficient in the sense that the highest-valuation buyer typically wins, limiting misallocation. Therefore, the total surplus is close to the frictionless benchmark, with any small compression modestly reducing prices for buyers who transact without meaningfully excluding others.

Discussion: Linking to Traditional Financial Constraints

The appraisal constraint is closely related to traditional financial constraints well-studied by existing models; however, it is notably unique. To reiterate, I introduce a third-party, local valuation shock that endogenously sets financing caps via appraisals anchored to nearby comps. Unlike Shleifer and Vishny (1992), where fire-sale discounts arise because potential buyers are themselves liquidity constrained, here the cap $A(s)$ is produced by the valuation technology, creating spatial spillover. Relative to Stein (1995) and Ortalo-Magne and Rady (2006), which emphasize constraints through down-payment or life-cycle channels, the appraisal mechanism can bind even when buyer wealth is sufficient ex ante: if appraisals fall with s, the mortgage limit prevents paying the frictionless price, $P^{\star}$. In spirit with Che and Gale (1998), efficiency can fail because the budget-constrained (i.e., appraisal-capped) highest-valuation buyer may not win; however, in my setting, the budget is endogenously determined by neighborhood comparables rather than by exogenous credit supply. While Genesove and Mayer (1994) emphasize seller behavior that prolongs time-on-market with loss aversion, the near one-for-one appraisal-to-price pass-through arises from hard caps, causing price compression without assuming the seller's risk preference. Finally, relative to Bian et al. (2018) that embed mortgage constraints in bargaining, I add a key neighborhood-level state variable s that generates a unique welfare tradeoff (i.e., price compression vs. exclusion or misallocation) and therefore link micro bargaining outcomes to spatial welfare implications, a way other models do not.

9 Conclusion

This paper studies how rising all-cash activity spills over to nearby mortgage-financed transactions through the appraisal process. Because appraisers select recent, proximate comparable sales, discounted cash trades mechanically enter the comp set, depress appraised values, and cap loan size for financed buyers. Using a ring design that contrasts exposure within 0.6 miles to activity out to 1.2 miles on 6.2 million transactions from 2018 to 2022, I find that a one–standard-deviation increase in nearby cash sales reduces appraisals by 1.39% and sale prices by 1.38%, and lengthens time-on-market by about 38 days; effects are highly local and recent, robust to rich controls and the listing-price anchoring channel, and materially larger than any outer-ring effect. Supporting the renegotiation channel, prices pass through appraisal changes nearly one-for-one, while a placebo using cash focal sales shows near-zero sensitivity, isolating an appraisal-mediated, credit-through-collateral channel.

The spillover is heterogeneous across different neighborhoods, market conditions, and buyer chareacteristics. It is strongest for low-income, high-LTV, first-time, and minority buyers, in more affordable and low-growth neighborhoods, and when nearby inventory is scarce, patterns consistent with bargaining that reveals information and shifts surplus toward financially constrained buyers who face binding appraisal caps. Additional evidence shows that the incidence of failed mortgages rises with more cash activity at the neighborhood level. This finding corroborates Hypothesis 3, indicating that appraisal gaps can cause some financed transactions to collapse, thereby creating an additional channel through which local cash sales dampen mortgage-financed market activity.

A bargaining model shows how welfare varies across neighborhoods. When caps bind above the seller's reservation value, bargaining compresses price to the cap and generate seller-to-buyer transfers. When caps bind below the value, trades fail, creating exclusion and misallocation. Consequently, appraisal spillovers act as a friction in low-growth markets, suppress liquidity, and displace high-valuation constrained buyers; in contrast, this friction can act as a mild stabilizer in high-demand, high-growth markets. These findings suggest that lenders, appraisers, and investors should incorporate local cash activity as a meaningful externality in collateral and home evaluation. Also, policymakers may encourage policies to alleviate or internalize this externality (e.g., encouraging alternative evaluation methods) so that mortgage-reliant buyers would not be systematically excluded due to this constraint.

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APPENDIX

A Merging CoreLogic Deed Records and HMDA Loan Applications

My procedure of matching CoreLogic and HMDA (2007-2022) closely follows the methodology adopted by Mateen et al. (2023).

A.1 Processing HMDA Data

The HMDA data used in this paper is comprised of two components: (1) Loan Application Registration (LAR) contains borrower, loan, and property information. Each observation is a unique loan application record. (2) Transmittal Sheets (TS) includes lender names – an important merging key to identify the same lender that exists in both CoreLogic deed records and HMDA.

When cleaning LAR, I only keep originated loans and drop denied ones, loans with missing loan amount, and refinance or home improvement loans. For TS, I harmonize lender names by converting them into lower cases, standardizing frequently seen abbreviations (e.g., " bk" into " bank"), dropping redundant strings (e.g., " corp"), and removing punctuations and spaces. Following these steps, to streamline the name cleaning and subsequent matching process, I only keep the first seven letters and the first five letters of each lender name.

The final step is to link lender names with borrower characteristics by matching cleaned LAR and TS data. The merging keys include the activity year, lender unique identifier " respondent id" (by 2018) or " lei" (after 2018). The merged data set contains more than 55 million mortgage origination and deed records, including detailed borrower, lender, loan, and property information.

A.2 Matching HMDA and CoreLogic at The Transaction level

I mainly follow four steps to match each loan origination record from HMDA with each deed record from CoreLogic. The following steps are repeated for each year, state, and county.

Step 1: Merge two data sets based on the cleaned 7-digit lender names and mortgage amount in thousands. This will result in a roughly merged data set with many duplicates, since the merge does not restrict to the same census tract.

Step 2: Take the minimum of the two distances: the distance between CoreLogic tract and HMDA raw tract and that between CoreLogic tract and HMDA tract in 2010 vintage. Only keep the matched records from Step 1 with a distance that is smaller or equal to 0.02 mile. Save all successfully matched records in this step.

Step 3: For the remaining records that are not yet successfully matched, repeat Step 1 and 2 using the 5-digit lender names and the mortgage amount in thousands. Keep successful matches and use the 7-digit lender names and mortgage amount in tens of thousands to match the remaining records. Repeat this for the remaining records using the 5-digit lender names and mortgage amount in tens of thousands. Finally, use the 7-digit lender names and truncated mortgage amount in tens of thousands and then the 5-digit lender names and the truncated mortgage amount in tens of thousands.

Step 4: Mark observations that still have zero successful matches as "unmerged" and record the number of rounds in which each CoreLogic deed record is matched with at least one HMDA loan origination.

B An Algorithm to Construct Comparable Sales

Mimicking the industry standard, I create an algorithm to manually construct comparable sales using detailed CoreLogic deeds and MLS data.

Temporal and Geographic Filtering

For a given focal property i, the first step is to narrow down the universe of past sales to a manageable set of potential comparables. I retain only historical transactions j that are close in both time and location to property i. In practice, this means limiting to sales that occurred within the previous *12 months* of i's transaction date and within a *1-mile* radius of i's location. Formally, let t_k denote the sale date of property k and $\text{dist}(i, j)$ denote the distance between properties i and j; then j is included as a candidate if $|t_j - t_i| \leq 12$ months and $\text{dist}(i, j) \leq 1$ mile. This filtering ensures that the initial pool of potential comparables shares a similar market environment and neighborhood context with the subject property i.

Computing Similarity Scores

Next, for each candidate property j in the filtered set, we compute a similarity score $S(i, j)$ that captures how comparable property j is to the subject property i based on their attributes. The similarity score is defined as a weighted sum of normalized differences across key property features. Let $x_{k,i}$ be the value of feature k for property i. We define the score as:

$$S(i, j) = \sum_{k=1}^{K} w_k \cdot \frac{|x_{k,i} - x_{k,j}|}{\Delta_k} \tag{12}$$

where the summation is over all relevant features k. In this formulation, Δ_k is the standard deviation of that feature in the sample, a normalization factor for feature k, which ensures that differences in each attribute are measured on a comparable scale. The weight w_k reflects the relative importance of feature k in determining property values, with larger weights assigned to attributes deemed more influential; here, $\sum_k w_k = 1$ for interpretability. The set of features used in the similarity metric spans both continuous variables and categorical indicators. Continuous features include characteristics such as living area square footage, lot size, building age, and the number of bedrooms and bathrooms. For these, the term $|x_{k,i} - x_{k,j}|/\Delta_k$ represents the absolute difference between i and j in that characteristic, scaled by Δ_k (e.g., a difference of 500 square feet might be normalized by a standard deviation of square footage in the area). Categorical or binary features include property type (e.g., single-family vs. condominium), the presence of amenities like a swimming pool or fireplace, parking availability, number of stories, architectural style, and the heating/cooling system. For such features, the "difference" can be represented by an indicator function: for example, $|x_{k,i} - x_{k,j}|$ would effectively equal 0 if both properties share the same property type or amenity and 1 if they differ. In this way, a term like $w_k|x_{k,i} - x_{k,j}|/\Delta_k$ for a binary feature becomes w_k if property i and j differ on that attribute and 0 if they are the same (we can set $\Delta_k = 1$ for indicator variables for simplicity). By construction, a *lower* similarity score $S(i, j)$ indicates that property j is *more similar* to the subject i across the full range of characteristics.

For each property, I construct two similarity scores, one using equal weights ($w_k = 1/K$) for all features and the other score using the weights $\hat{w_k}$ calibrated to reflect each feature's importance in predicting transaction values so that each those features with larger (normalized) impacts on sale price receive higher weights. The formal estimation equation is:

$$P_{i,j,t} = \sum_{k=1}^{K} \beta_{i,k} \frac{|\mathrm{X}_{i,t,k}|}{\Delta_k} + \alpha_{j,t} + \phi_m + \varepsilon_{i,t}, \tag{13}$$

where $P_{i,j,t}$ is the price of property i, in census tract j, in year t, $\mathrm{X}_{i,t,k}$ are property characteristics (each feature X_k scaled by its standdard deviation Δ_k), $\alpha_{j,t}$ is a census tract-by-year fixed effect, and ϕ_m is a month indicator to control for seasonality in housing market cycles.

Selecting Final Comps

Finally, select the top three comparables for property i by choosing the three candidate sales j with the lowest similarity scores $S(i, j)$ (namely, the three most similar properties according to our metric). These three properties constitute the final set of comps to proxy an appraiser's choice of the three best comparables for a subject property. In the event of ties or very close scores (e.g., top ten candidates scoring from 0.10 to 0.15), assign additional scores to the comps that are geographically closer to the subject property and more recent in time. The adjusted score slightly rewards proximity and more recent deals and breaks ties by favoring the property with a larger $1/\mathrm{dist}(i, j)$ (smaller distance) or by favoring a property with a smaller $|t_i - t_j|$ (more recent). In practice, if two candidate comparables have nearly identical $S(i, j)$, the one located closer to i or sold more recently would be chosen. This ensures that the final comparables not only have very similar property characteristics to the subject but also reflect the same local market and time period *as closely as possible.*

C Hedonic Regressions and Local House Price Indices

Following the standard setting[13], the hedonic regression specification is:

$$\log(P_{i,j,t}) = \sum_{\tau \in [1,N]} \beta_{i,\tau} \mathrm{X}_{i,t,\tau} + \alpha_{j,t} + \phi_m + \varepsilon_{i,t}, \tag{14}$$

where $P_{i,j,t}$ is the price of unit i, in census tract j, in year t. $\mathrm{X}_{i,t,\tau}$ includes a suite of property characteristics including square footage, acreage, bedrooms, bathrooms, total rooms, and whether the unit has a garage or carport. $\alpha_{j,t}$ is a census tract-by-year fixed effect, from which we construct our local HPI, and ϕ_m is a month indicator to control for seasonality in housing market cycles. This regression is run for 2,074 counties separately.

Figure E2 plots the nationally aggregated hedonic HPIs against the FHFA and Zillow HPIs. The base year is 2010 where the price level is mechanically set as 100. The tract-year-level HPIs are aggregated using the number of transactions for each tract and year as the analytical weights. FHFA HPIs are constructed using *repeat* mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975. Unlike the hedonic methodology used in this paper, the indices are constructed using repeat-sales regressions[14]. The Zillow Home Value Indices (ZHVI) are constructed using all single-family, condo, and co-op transactions and seasonally adjusted, similar to Equation 14 that includes the month indicator. I collect both indices at the tract-year-level and aggregate them to the national level in the same manner.

Overall, the hedonics-imputed house price indices ("Hedonic HPI") align well with the FHFA and Zillow HPIs, especially by 2011. Although there is a small divergence starting 2012 perhaps due to slight sample and methodological differences, the slope of Hedonic HPI maps well with the benchmark indices, especially during 2018-2022 (the main analysis sample). Table D4 documents the summary statistics of estimated HPIs during 2018-2022, a booming housing market with an average five-year growth rate around 9% and a notable 15.8% increase in 2021.

[13] For example, see Baum-Snow and Han (2024) and Gorback et al. (2025).

[14] Detailed information can be found at: https://www.fhfa.gov/data/hpi.

D Appendix Tables

Table D1: Primary Sample Summary Statistics (2018–2022)

Variable	Mean	SD	Min	P25	P50	P75	Max
Sale Amount ($)	307,654	167,512	6,351	187,000	269,900	386,765	1,300,000
Appraisal Values ($)	308,224	166,754	5,000	185,000	265,000	385,000	1,005,000
Age	33	26	0	14	31	47	122
No. Bed	3.28	1	1	3	3	3	6
No. Bath	2.30	0	1	2	2	2	5
No. Stories	1.45	0	1	1	1	2	3
Land (Sqft)	16,776	21,350	1,065	6,599	9,749	16,553	168,577
Building (Sqft)	2,377	812	825	1,877	2,377	2,592	5,773
Parking (Sqft)	481	120	193	440	481	491	1281
Basement (Sqft)	750	120	120	750	750	750	1926
Income (000s)	99	61	23	57	83	124	409
LTV (%)	85	12	37	80	92	97	102
No. Observations				6,216,851			

Notes: This table presents the summary statistics for the primary sample, including transaction, property, buyer, and loan characteristics. The primary sample only includes arms-length transactions by individual home buyers and exclude foreclosures, intra-family sales, investor purchases, and records with extreme values in property, buyer, and loan characteristics.

Table D2: Cash Sale Predictors and Mortgage-Cash Premium

	(1) Cash Indicator	(2) Log(Price)
Cash Indicator		-0.113***
		(0.001)
Log(Price) Std	-0.124***	
	(0.001)	
Age Std	-0.006***	-0.091***
	(0.000)	(0.001)
Bed Std	-0.005***	0.017***
	(0.000)	(0.000)
Building Sqft Std	0.038***	0.188***
	(0.000)	(0.001)
Land Sqft Std	0.009***	0.032***
	(0.000)	(0.000)
Stories Std	-0.015***	-0.001
	(0.000)	(0.000)
Parking Sqft Std	0.008***	0.030***
	(0.000)	(0.000)
Basemen Sqft Std	-0.003***	-0.002***
	(0.000)	(0.000)
Observations	8,303,958	8,303,958
Tract-by-Year FE	Y	Y
Other Hedonic Controls	Y	Y
R-squared	0.161	0.795

Notes: This table presents property attributes that predict cash sales and replicates the mortgage-cash premium, as documented in Reher and Valkanov (2024). Column (1) estimates Equation 2 and shows the property characteristics that predict a transaction purchased by all cash, conditional on tract-by-year fixed effects and other categorical hedonic variables. All property attributes are standardized with a zero mean and unit one as the standard deviation. Column (2) replicates the mortgage-cash premium (11.3%) by estimating Equation 3.

Table D3: Imputed Comps vs. Other Nearby Candidates

Panel A: Summary Counts	
No. Unique Pairwise Combinations	609,622,168
No. Unique Focal Transactions	3,816,516

Panel B: No. Nearby Transactions Matched Per Focal Transaction

	Mean	**Std. Dev.**	**Min.**	**Max.**	**N**
Imputed Comps	3.61	0.73	1	6	3,816,516
Other Nearby	156.11	123.57	1	2,373	3,816,516

Panel C: The Difference from Focal Transaction

	Mean	**Std. Dev.**	**Min.**	**Max.**	**N**
Group 1: Imputed Comps					
Similarity Score	0.38	0.35	0.01	3.72	13,683,225
Distance (Mile)	0.27	0.19	0	1	13,683,225
Recency (Day)	178.17	107.09	1	365	13,683,225
Building Age	5.21	9.99	0	125	13,683,225
Land Sq. ft.	4,011	19,186	0	145,547	13,683,225
Building Sq. ft.	348	396	0	2,390	13,683,225
No. Bed	0.19	1.26	0	5	13,683,225
No. Bath	0.18	0.50	0	4	13,683,225
Group 2: Other Nearby Transactions					
Similarity Score	1.19	0.50	0.01	3.72	595,938,943
Distance (Mile)	0.73	0.24	0	1	595,938,943
Recency (Day)	183.05	106.16	1	365	595,938,943
Building Age	15.24	19.09	0	125	595,938,943
Land Sq. ft.	7,583	29,128	0	189,150	595,938,943
Building Sq. ft.	831	827	0	4,727	595,938,943
No. Bed	0.72	1.90	0	5	595,938,943
No. Bath	0.73	0.94	0	4	595,938,943

Notes: This table shows the detailed summary statistics of the analysis sample resulting from the steps that manually construct comps in Appendix Section B. Panel A and Panel B show the basic summary counts for the full sample, including the number of unique observations, focal transactions, matched comps, and matched other nearby properties. Panel C presents the differences in a variety of property characteristics between a focal property and its matched transaction in each of the two groups - imputed comps and other nearby transactions that are not selected as comps.

Table D4: Summary Statistics of HPI Growth (2018-2022)

Year	**Mean**	**SD**	**P10**	**P25**	**P50**	**P75**	**P90**	**N**
2018	0.064	0.211	-0.120	-0.009	0.061	0.135	0.248	66,466
2019	0.051	0.208	-0.126	-0.021	0.048	0.122	0.238	66,466
2020	0.087	0.203	-0.084	0.016	0.083	0.156	0.268	66,466
2021	0.158	0.195	-0.021	0.079	0.154	0.232	0.341	66,466
2022	0.128	0.192	-0.059	0.049	0.128	0.210	0.314	66,466
Average	0.092	0.069	0.042	0.065	0.089	0.116	0.147	66,466

Notes: This table summarizes the house price indices (HPIs) estimated from Equation 14 and aggregated to the annual level. The last row shows the summary statistics of the five-year average price growth across all 66,466 tracts.

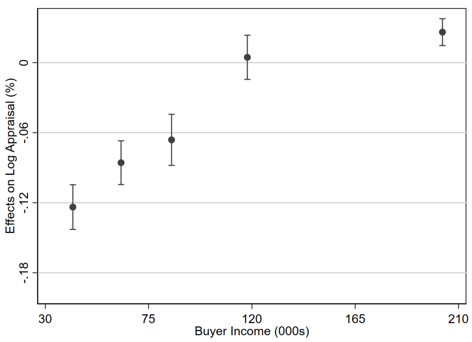
Table D5: Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Appraisal Values				*Transaction Prices*			
Regression coefficients (%)								
No. Cash Sales								
within 0.6 miles	-0.1365***	-0.1260***	-0.0662***	-0.0570***	-0.1377***	-0.1267***	-0.0662***	-0.0570***
	(0.0226)	(0.010)	(0.0064)	(0.0055)	(0.0225)	(0.0102)	(0.0067)	(0.0057)
within 1.2 miles		-0.0290	-0.0057	-0.0080		-0.0303	-0.006	-0.009
		(0.0434)	(0.039)	(0.031)		-0.0303	(0.0392)	(0.0313)
List price				0.5912***				0.5895***
				(0.004)				(0.0036)
Constant	12.6001***	12.6039***	11.9895***	4.6576***	12.5999***	12.6038***	12.0001***	4.6890***
	(0.0044)	(0.0099)	(0.0111)	(0.0542)	(0.0044)	(0.0098)	(0.0118)	(0.0504)
Average treatment effects								
No. cash sales within 0.6 miles								
Increase by one SD	-2.18%	-2.02%	-1.06%	-0.91%	-2.18%	-2.02%	-1.06%	-0.91%
Increase from Q1 to Q3	-2.59%	-2.40%	-1.26%	-1.08%	-2.59%	-2.40%	-1.26%	-1.08%
Property characteristics			Y	Y			Y	Y
Buyer age			Y	Y			Y	Y
Buyer race			Y	Y			Y	Y
Loan type			Y	Y			Y	Y
Tract-by-year FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.717	0.717	0.819	0.846	0.707	0.707	0.809	0.836
Observations	3,503,909	3,503,909	3,503,909	3,503,909	3,503,909	3,503,909	3,503,909	3,503,909

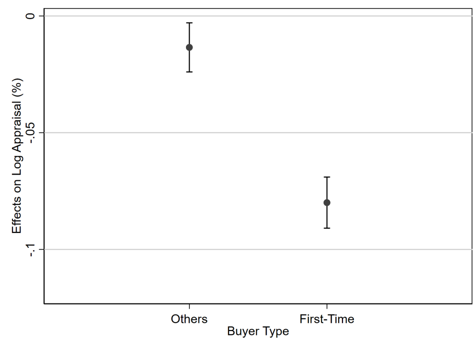
Notes: This table shows the alternative baseline results estimated from Equation 1 with 0.6 and 1.2 miles for the inner and outer ring respectively, using nearby cash market share as the main explanatory variable. All specifications include tract-by-year fixed effects. All standard errors are clustered at the tract and year level with robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

E Appendix Figures

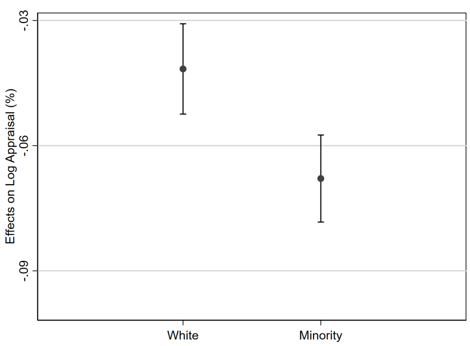
Figure E1: Heterogeneity across Home Buyers (Appraisals)



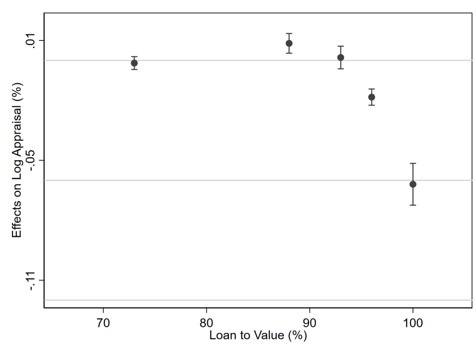
(A) Income



(B) First-Timers



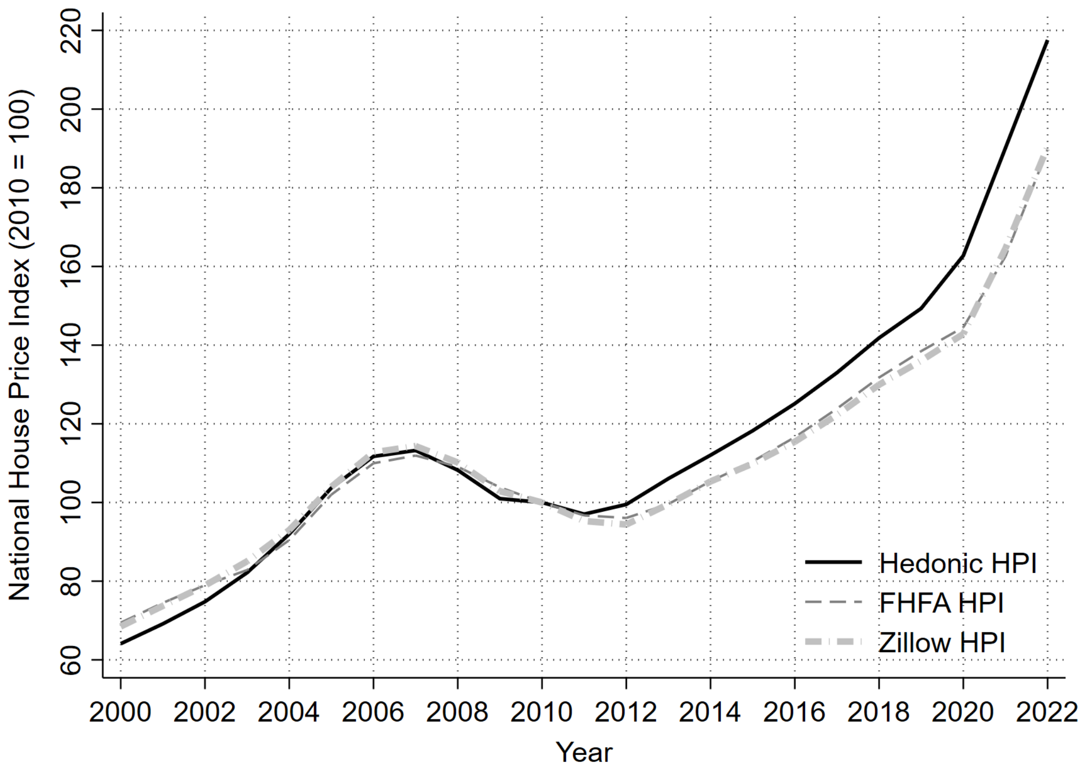
(C) Minority



(D) Leverage

Notes: These figures show the differential impact of nearby cash sales on a mortgage-financed home's appraised value by buyer-level heterogeneity, including income, race, first-timer status, and loan-to-value ratio.

Figure E2: National House Price Indices (2000-2022)



Notes: This figure plots the nationally aggregated hedonic HPIs (estimated from Equation 14) against FHFA and Zillow HPIs. The base year is 2010 where the price level is mechanically set as 100. The tract-year-level HPIs are aggregated using the number of transactions for each tract and year as the analytical weights.