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

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Abstract

This paper examines the impact of growing all-cash home purchases on local home appraisals and transaction prices. Using micro data from 2018–2022 and a ring-based spatial design, I identify a new appraisal channel through which discounted cash sales can depress prices of nearby mortgage-financed homes. This spillover is stronger in low-growth, more affluent neighborhoods, whereas it is muted or offset in high-growth, less advantaged areas where it signals heightened housing demand. To validate the mechanism, I propose a novel algorithm that manually constructs comparable sales and show that appraisers predominantly rely on very local sales as comps, supporting the identification assumptions. A stylized model rationalizes these findings and indicates that these spillovers can reduce welfare by excluding mortgage-dependent buyers and eroding housing wealth in low-demand markets, but may improve affordability by lowering entry prices in hot markets.

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Introduction

In the past two decades, the share of all-cash home purchases in the U.S. has increased substantially—from approximately 12% to over 30% (Figure 1). While institutional and professional buyers[1] have consistently relied heavily on cash, individual buyers who historically account for over 90% of all housing transactions have also steadily increased their use of cash over time (Appendix Figure A1). Despite this notable rise, the effects of growing cash activity on local house price formation and the underlying mechanisms remain poorly understood.

A growing body of literature has documented an average price differential of approximately 11% between mortgage-financed and all-cash home purchases, commonly referred to as the "cash-mortgage discount" (Reher and Valkanov, 2024; Han and Hong, 2024). Contrary to the frictionless benchmark assumption in Modigliani and Miller (1958), the housing market is characterized by substantial transaction frictions. Sellers often prefer cash offers—even at a discount—due to reduced risks of financing contingencies, delays, and appraisal-related uncertainty. Empirical evidence further suggests that this discount is especially pronounced for lower-priced, distressed, foreclosed, or poor-quality properties, particularly in small or struggling markets and during downturns (Chia and Ambrose, 2024; Seo et al., 2021; Asabere et al., 2015; Aroul and Hansz, 2023).

In this paper, I examine the *economic consequences* of a rising share of hyper-local cash purchases. I conceptually propose and empirically test an *appraisal mechanism* through which the local prevalence of cash buyers can *depress* house prices, even after accounting for property-level selection and unobserved local market trends (e.g., housing demand).

Institutionally, mortgage lenders typically hire an external appraiser to assess the fair market value of a home before approving a loan. By regulatory and professional standards, appraisers are prohibited from considering the buyer's financing method when assigning value. Crucially, residential appraisals are based primarily on recent comparable sales ("comps"). These institutional details are discussed in Section 1.

This appraisal process introduces a potential channel through which cash buyers affect prices. First, a higher local incidence of low-priced cash transactions depresses the comps used in appraisals. Next, these lower comps lead to reduced appraised values for future

[1] The definition and categorization of institutional buyers follow Gorback et al. (2025), including long-term rentals (LTRs), iBuyers, builders, flippers, etc.

mortgage-financed sales. As a consequence, lower appraisals constrain the loan amount a buyer can obtain unless they provide a larger down payment. Finally, in the absence of sufficient unconstrained buyers, sellers may reduce their asking prices to match the appraisal, thereby anchoring transaction prices to these lower valuations. While a high cash share may also signal strong local housing demand, identifying the appraisal mechanism requires controlling for this and other confounding factors.

To isolate this mechanism, I adopt a ring-based spatial research design that leverages hyper-local variation in exposure to cash purchases, similar to the spirit of Bayer et al. (2021) and Gupta (2019). For each mortgage-financed transaction, I define three concentric rings—inner, middle, and outer—representing increasing geographic radii. I construct the share of all-cash transactions within each ring and examine their effects on the focal property's appraised and transaction values, while controlling for property characteristics and tract-by-year fixed effects to absorb unobserved, time-varying neighborhood-level shocks.

The identification assumption is that the spillover effect of nearby cash purchases on the focal property can be isolated by controlling for broader market activity, such that the inner ring has similar endogeneity to the outer rings. To validate this assumption, I propose a novel algorithm that manually constructs comparable sales for each focal transaction, following industry standards. I show that these imputed comps are significantly closer, more recent, and more similar to the focal property than other nearby sales within a 1-mile radius. Notably, over 95% of imputed comps are located within 0.5 miles — this suggests that appraisers seldom need to search beyond the inner ring and supports the internal validity of the ring-based approach.

The baseline results are consistent with the appraisal mechanism: homes in close proximity to recent cash sales exhibit lower appraised values, which translate into reduced transaction prices. These effects are robust when controlling for property characteristics and tract-by-year fixed effects. While still statistically and economically meaningful, the negative impact attenuates as the inner ring expands from 0.1, 0.15, and up to 0.4 miles, beyond which the estimates lose statistical significance. Meanwhile, I find an always robust and strong positive association between cash share in the outer ring and both appraisals and prices, consistent with the idea that broader cash activity reflects heightened housing demand. This "bidding war" effect slightly grows with the radius, gradually offsetting the appraisal mechanism, which operates most strongly in a hyper-local context.

Interestingly, the negative effects of nearby cash sales on appraisals and prices are most pronounced in more affluent neighborhoods with low house price growth between 2018 and 2022. In contrast, the bidding-war mechanism dominates in less advantaged neighborhoods with above-median house price growth, particularly when the radius exceeds 0.3 miles. This is consistent with the empirical finding that neighborhoods with more lower-income subprime borrowers may experience a larger house price increase during a housing boom as in Mian and Sufi (2010).

To rationalize these findings, I incorporate this appraisal constraint in a stylized housing choice model. Allowing for heterogeneity across neighborhood types, the model highlights context-dependent welfare implications. In affluent, low-growth neighborhoods, cash-induced appraisal declines reduce welfare by excluding mortgage-dependent buyers and limiting opportunities for wealth accumulation. In contrast, in high-growth, relatively disadvantaged areas, such spillovers may not be detrimental—and can even enhance affordability by lowering entry prices for prospective buyers.

Related Literature

This paper is motivated by a growing strand of literature in housing finance that examines differences between cash and mortgage-financed home purchases. Recent studies document a mortgage-cash price differential (commonly referred to as the "cash-mortgage discount") and attribute it to a combination of market frictions and behavioral factors, often embedded in search-based models (Reher and Valkanov, 2024; Han and Hong, 2024). My analysis complements this literature by showing that the prevalence of cash buyers affects not only the prices of individual transactions but also generates *spillover effects* on nearby mortgage-financed sales by depressing their appraised values. In other words, this paper identifies a mechanism through which the "cash discount" propagates across the local market: a higher share of nearby cash transactions can lower the benchmark for local pricing via reduced comps, thereby forcing subsequent mortgage-financed transactions to close at lower prices than they otherwise would. This new channel links the micro-level negotiation advantage of cash buyers to broader implications for local house price dynamics and housing affordability.

A particularly relevant study by Chia and Ambrose (2024) documents how a declining supply of small-dollar mortgages leads to lower home prices *through increased cash discounts*.

They provide the first causal evidence that tighter credit conditions magnify cash discounts, disproportionately reducing prices in low-income neighborhoods. In contrast, the mechanism proposed in this paper can operate even without explicit credit constraints—cash buyers alone can depress house prices simply by influencing future appraisals.

This paper also relates to the broader literature in urban and housing economics that emphasizes the role of financing frictions in local house price formation. 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. Empirical work supports this mechanism: Genesove and Mayer (2001) find 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. These frictions are further compounded by behavioral biases. For example, loss-averse sellers show downward price stickiness during market downturns. More recent structural studies incorporate buyer heterogeneity and highlight how credit access shapes the cross-section of house prices. Landvoigt et al. (2015), for example, calibrate a model for the San Diego market and show that expanded credit to marginal borrowers was a key driver of price appreciation in lower-end segments. Similarly, Kaplan et al. (2020) argue that the recent housing boom and bust were fueled by the entry and subsequent withdrawal of subprime credit. I build on this broader literature by highlighting an appraisal-induced constraint and showing how the interaction between comparable sales and mortgage underwriting can impact prices, especially in lower-demand, low-growth neighborhoods.

The appraisal-based channel also relates to research on informational frictions and the persistence of house price momentum. Guren (2018) find that sellers extrapolate asking prices from recent nearby sales, generating positive autocorrelation in prices over time. Such "strategic complementarities" suggest that even small frictions in value updating can lead to large momentum effects. The appraisal mechanism operates similarly: appraisers propagate past sales into present valuations through comparables, contributing to market inertia. Unlike seller heuristics, however, this appraisal channel is institutionalized as an underwriting rule that mechanically anchors prices. Both forces—backward-looking pricing by sellers and appraisal-driven pricing by lenders—introduce rigidity into housing markets, diverging from frictionless asset pricing. My contribution is to identify a specific institutional source of price stickiness, namely appraisal conventions, and to show how this mechanism shapes neighborhood-level price formation. In doing so, I complement recent segmented search models (e.g., Piazzesi et al. (2020)), which suggests that constrained and unconstrained buyers operate in distinct submarkets. In my setting, this segmentation emerges endogenously: when appraisals bind, mortgage-dependent buyers are excluded from the bidding process, leaving homes to be acquired by cash buyers and potentially reinforcing low-price equilibria.

Finally, this paper is closely related to Aldana and Zhu (2025), who document how the influx of cash buyers acts as a negative demand shock for mortgage-dependent borrowers and lenders. They find that an increased local share of cash purchases leads smaller mortgage lenders (e.g., community banks) to reallocate their portfolios toward non-residential loans, often becoming overexposed in those sectors. In contrast, larger banks can smooth local demand shocks by pooling across geographies. These findings suggest that shifts in buyer composition due to rising cash activity can also have implications for financial intermediation and local credit stability, complimentary to the scope of this paper.

1 The Appraisal Mechanism

1.1 The Financing-Neutrality of Residential Appraisals

A residential appraisal is *supposed 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*[2]. In practice, this means that an appraiser's estimate of market value should remain consistent regardless of whether a purchase is financed by a conventional loan, an FHA-insured loan, a VA loan, 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[3] 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[4]. 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.

[2]Anecdotally, *commercial* real estate appraisers often incorporate the source of financing into their evaluations, such as applying discounts to all-cash acquisitions of income-producing properties like shopping malls.

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

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

In cases where a comparable sale includes *non-market* financing or incentives, appraisers are required to adjust the observed sale price to reflect a cash-equivalent value. Fannie Mae explicitly states that "adjustments to the comparables must be made for special or creative financing or sales concessions," instructing appraisers to apply adjustments that "approximate the market's reaction" rather than using a mechanical formula. The overarching goal is to ensure that the appraised value reflects the property's intrinsic worth, independent of how the transaction is financed. This financing-neutral approach safeguards lenders and investors by offering a credible assessment of collateral value and ensures fairness for buyers and sellers by grounding appraisals in genuine market dynamics rather than temporary financial incentives.

1.2 Comparable Sales

Residential appraisers mainly rely on comparable sales to perform home evaluations, together with the cost approach[5]. Appraisers usually select comparables based on proximity, time of sale, similarity in property characteristics, etc. For geographic proximity, a comparable is ideally within 1 mile in urban/suburban areas - the closer the better. In rural or unique markets, appraisers may expand the search radius if necessary, explaining the rationale. For temporal proximity, appraisers usually select 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 (typically on the Uniform Residential Appraisal Report, Form 1004). 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

[5] Addtionally, unlike residential, commercial real estate appraisers mostly use the income approach by discounting all future expected cash flows of an income-producing property to arrive at its fair market value.

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 empirical question[6].

1.3 Spillover Effects of Cash Buyers via The Appraisal Mechanism

Here I illustrate the appraisal mechanism through which cash buyers—conditional on other factors such as housing demand—can exert downward pressure on house prices, particularly in distressed or credit-constrained markets.

It is well established that cash buyers frequently purchase homes at discounted prices, often because sellers are willing to accept lower offers in exchange for the speed and certainty associated with cash transactions. As a result, a higher prevalence of cash sales at reduced prices can *depress the recent comparable sales* (comps) used in future appraisals. If a sufficient number of nearby comps reflect cut-rate cash transactions, subsequent mortgage-financed home sales are likely to receive lower appraised values.

This dynamic can create a financing constraint for mortgage-dependent buyers: lower appraisals reduce the maximum loan amount a lender is willing to approve, unless the buyer is able to make a larger down payment. In markets where unconstrained (cash) buyers are scarce, sellers may be compelled to reduce asking prices to meet appraisal thresholds, thereby anchoring sale prices to the artificially low appraised values and reinforcing downward price momentum.

A further consequence of this mechanism is that buyers facing appraisal shortfalls may resort to riskier forms of financing, such as loans with higher loan-to-value ratios, adjustable rates, piggyback structures, or otherwise unfavorable terms[7].

This appraisal mechanism is likely to be more pronounced in lower-priced or credit-constrained neighborhoods, where even modest appraisal gaps can jeopardize financing and where distressed sellers are more inclined to accept discounted cash offers. Supporting this

[6] 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.

[7] However, this scenario can happen only if the seller is unwilling to drop the price.

dynamic, Chia and Ambrose (2024) document that in disadvantaged communities, a decline in the availability of small-dollar mortgages led to a rise in cash purchases and a corresponding decline in house prices—consistent with cash buyers stepping in and transacting at lower valuations.

1.3.1 An Example of The Appraisal Mechanism

Consider a neighborhood in a low-income, credit-constrained ZIP code where the *typical home value* is $150,000. Historically, appraisals are anchored to three nearby comparable sales ("comps") within the past three months.

Step 1: Discounted Cash Sales Pull Down Comps And Appraisals

Suppose a distressed seller accepts a *cash offer at* $135,000 (a 10% discount) due to the speed and certainty of closing. Over a short period, **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:

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

An appraiser, aiming to remain consistent with recent market evidence, values the next property at $140,000—$10,000 below what a mortgage-dependent buyer might otherwise offer.

Step 2: Lower Appraisals Place Pressure on Mortgage Buyers

A home is pending at $150,000, but 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:

$$\text{Required Down Payment} = 150{,}000 - 112{,}000 = 38{,}000$$

In credit-constrained markets, such a shortfall is often unaffordable. The buyer either renegotiates the purchase price, turns to a riskier loan product, or exits the deal.

Step 3: Downstream Effects

This mismatch creates several ripple effects:

- Sellers often lower prices to align with appraisals, especially when cash-rich buyers are scarce.
- Buyers unable to cover shortfalls may resort to higher LTV loans, adjustable-rate mortgages, or piggyback loans—exposing them to more risk.
- Repeated discounted cash comps reinforce lower appraisals, potentially triggering a localized price decline.

Step 4: Amplification in Credit-Starved Areas

This mechanism can be particularly pronounced in disadvantaged or credit-scarce neighborhoods, where small price shortfalls can derail deals and sellers are more willing to take quick, lower cash offers.

1.4 Cash Buyers as A Signal of High Demand

It is important to note that cash buyers do not always portend price declines. Instead, a high cash-buyer presence can be a symptom of a hot market rather than a weak one. For instance, in booming housing markets or desirable neighborhoods, buyers with ample liquidity might use cash to win bidding wars. In such cases, cash offers may actually drive prices up (or at least keep them high) because these buyers are 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. In other words, when demand is strong, sellers gain little by accepting a lower cash price; financed buyers often match or exceed cash offers. Indeed, nationally, mortgage buyers have been observed to pay more than cash buyers on average (an 8–11% premium), which suggests that in many cases cash buyers are not depressing prices but rather that financed buyers stretch to compete.

Thus, we must consider that the effect of cash buyers could be context-dependent instead of applying to all areas or scenarios. In order to empirically identify the new appraisal mechanism through which cash buyers can depress prices, it is crucial to *control for demand.*

2 Data

In this section, I introduce the process that constructs the main sample and describe how to measure the exposure to nearby cash buyers of each focal property in preparation for the ring-based research design.

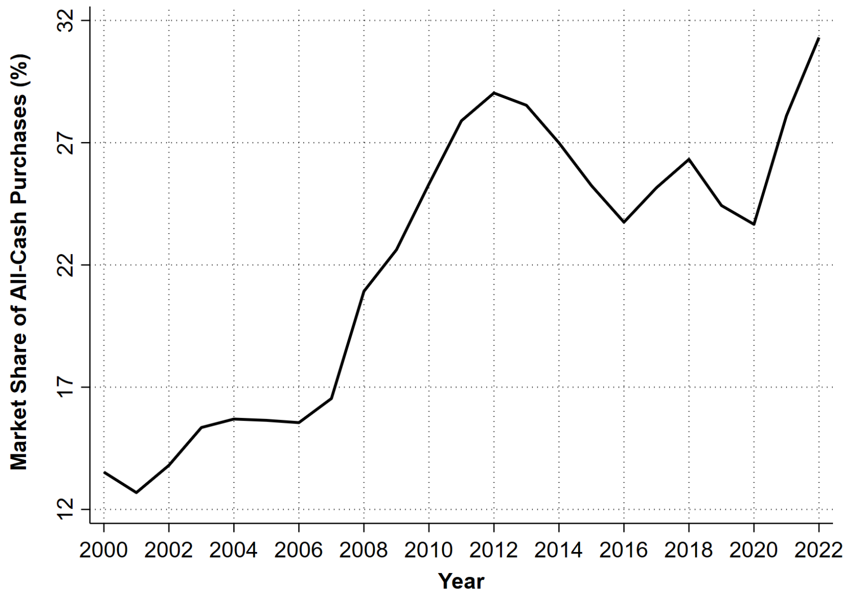
2.1 Primary Sample Overview

To construct the primary dataset, I first match deed records from CoreLogic with loan applications from the Home Mortgage Disclosure Act (HMDA), administered by the Consumer Financial Protection Bureau (CFPB), at the property transaction level. Appendix Section B provides details on the matching process. The final matched sample consists of over 7.9 million residential transactions from 2018 to 2022, which is the only period during which appraisal values are reported. The appraisal values ("property_value") are 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. The values are and rounded to $5,000[8]. The final analysis sample includes only arms-length transactions involving individual buyers and excludes intra-family transfers and investor purchases. In total, the dataset spans 2,074 counties, approximately 76,000 census tracts, and covers more than 90% of the U.S. population.

Including investor purchases in the sample does not materially affect the estimation results. Indeed, individual buyers account for more than 85% of all housing transactions and are likely the primary driver of cash buyer activity in local housing markets. I exclude investor transactions to provide a cleaner identification of the appraisal mechanism, as institutional buyers may affect housing markets through their own unique channels and incentives (e.g., see Gorback et al. (2025)).

[8] More detailed information can be found in https://ffiec.cfpb.gov/documentation/publications/loan-level-datasets/lar-data-fields.

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

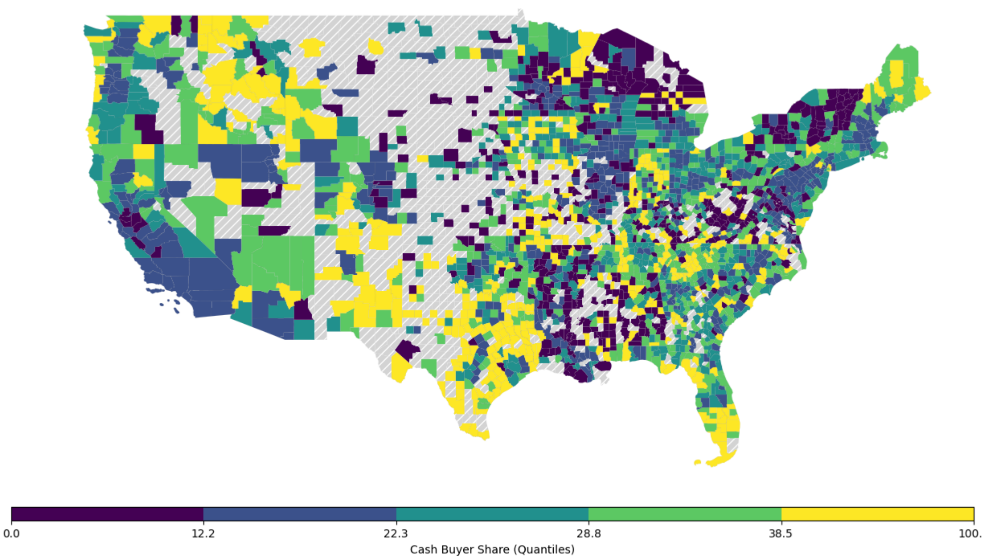


Notes: This figure plots the annual national market share of all-cash home purchases during 2000-2022. Only arms-length transactions by individual home buyers are included.

2.2 Variations of All-Cash Purchase Market Share

I document substantial temporal and cross-sectional variation in the market share of all-cash home purchases over a longer horizon during 2000–2022. As illustrated in Figure 1, the national share of all-cash transactions has steadily increased over the past two decades. This trend aligns with findings from Han and Hong (2024) and Reher and Valkanov (2024), notwithstanding minor differences in sample construction. Figure 2 highlights considerable heterogeneity in cash purchase shares across counties in 2020, measured by quantiles. This spatial variation suggests that cash buyers may systematically sort into specific markets or property types, reinforcing the importance of incorporating both neighborhood- and property-level controls in the subsequent empirical strategy.

Figure 2: Cash Purchase Share Quantiles by County in 2020



Notes: This figure shows the heat map for the cash purchase market share quantiles cross all 2,076 counties in the U.S. The grey areas indicate counties with missing data. Only arms-length transactions by individual home buyers are included.

3 Estimating Spillovers of Cash Buyers

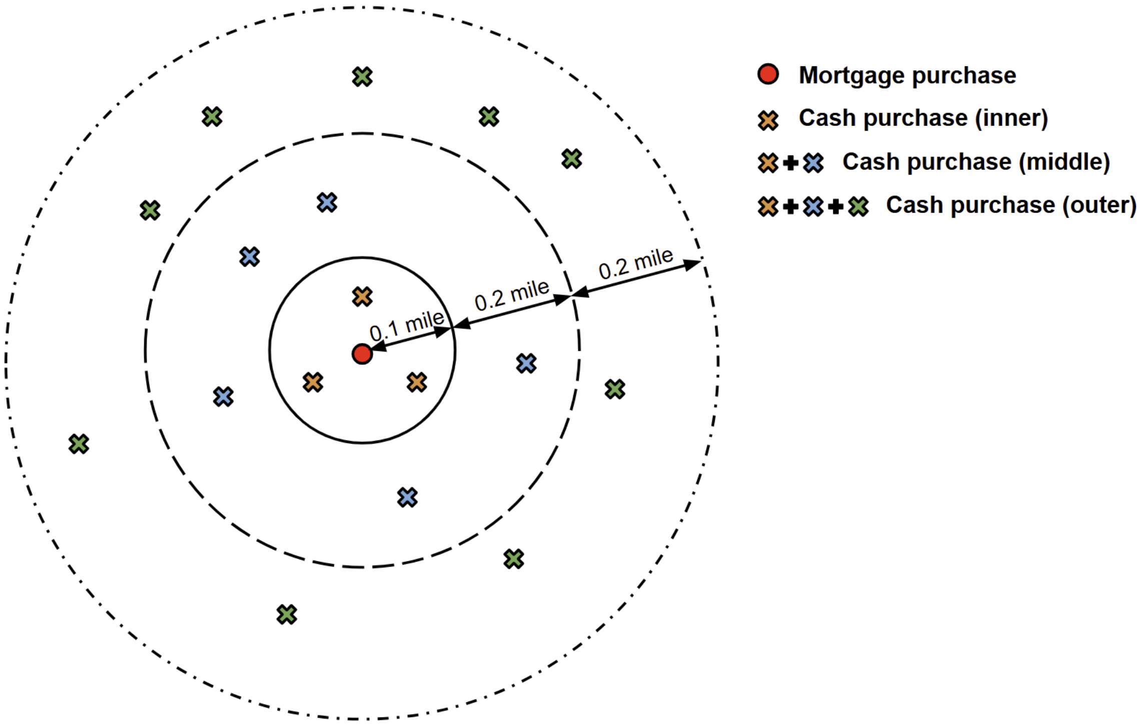
3.1 Ring-Based Research Design

The primary objective of this analysis is to identify the causal effects of all-cash home purchases on both appraisal values and transaction prices of nearby mortgage-financed home sales. The central hypothesis is that the appraisal mechanism leads to lower appraised values and transaction prices for mortgage-dependent buyers when the local market share of nearby cash purchases is high, controlling for everything else.

There are two main challenges with identifying this mechanism: (i) cash purchases are not randomly distributed across neighborhoods and even across properties, and (ii) unobserved neighborhood-level factors, such as local housing demand, may simultaneously influence both the incidence of cash purchases and housing outcomes, potentially confounding the estimated effects.

To address these concerns, I adopt a ring-based spatial identification strategy, following

Figure 3: Ring Analysis



Notes: This figure shows how the inner, middle, outer rings are designed around the focal mortgage purchase represented by the red circle. The inner ring encompasses all cash purchases within, say, a 0.1-mile radius while the middle ring encompasses both cash transactions contained in the inner ring and those in the donut-shaped area between the range of 0.1 mile and 0.3 mile. Similarly, the outer ring includes all transactions within its 0.5-mile radius.

the approach used by Bayer et al. (2021) and Gupta (2019), who study investor activity and foreclosure spillovers, respectively. These studies build on a broader literature examining neighborhood effects and local contagion. The core idea is to compare the influence of hyper-local housing activity (e.g., cash purchases within one's own block) to nearby but slightly more distant areas. In this setting, I estimate the effect of cash buyer activity within concentric rings of 0.1, 0.15, ..., and up to 0.4 mile, while controlling for comparable activity in broader bands (e.g., 0.3, 0.5, ..., and up to 1 mile). The specification also includes property- and neighborhood-level controls to further isolate the appraisal channel. A visual representation of the ring design is provided in Figure 3.

The rationale for this design is that the focal mortgaged property is much more likely to be affected by depressed appraisal values through comps derived from nearby cash transactions in the immediate vicinity (inner ring) than the broader market conditions that is instead captured by cash transactions in the middle and outer ring. This spatial differencing approach is intended to isolate the causal effect of nearby cash purchases by differencing out broader neighborhood-level shocks or trends common to all rings. Section 4 provides a detailed examination on the internal validity of this approach.

The baseline transaction-level regression specification is

$$Y_{i,t} \;=\; \beta_1\,\text{CashShare}^{(\text{inner})}_{i,t-1} \;+\; \beta_2\,\text{CashShare}^{(\text{middle})}_{i,t-1} + \beta_3\,\text{CashShare}^{(\text{outer})}_{i,t-1} \;+\; \gamma X_i \;+\; \delta_{c(i),t} \;+\; \varepsilon_{i,t}. \quad (1)$$

where i indexes properties and t denotes the transaction date. The dependent variable $Y_{i,t}$ refers to either the appraisal value recorded in the mortgage application or the actual transaction price of the property. The three key explanatory variables capture the market share of cash purchases within specific geographic bands around each focal mortgage-financed transaction, based on transactions that occurred in the 12 months prior to date t. Specifically, these variables measure the prevalence of cash purchases within the inner, middle, and outer rings. Their formal definitions are provided below[9].

$$\text{CashShare}^{(\text{inner})}_{i,t-1} \;=\; \frac{\text{Number of cash transactions within 0.1 mile of property } i \text{ in the past year of } t-1}{\text{Number of all transactions within 0.1 mile of property } i \text{ in the past year of } t-1} \quad (2)$$

$$\text{CashShare}^{(\text{middle})}_{i,t-1} \;=\; \frac{\text{Number of cash transactions within 0.3 mile of property } i \text{ in the past year of } t-1}{\text{Number of all transactions within 0.3 mile of property } i \text{ in the past year of } t-1} \quad (3)$$

$$\text{CashShare}^{(\text{outer})}_{i,t-1} \;=\; \frac{\text{Number of cash transactions within 0.5 mile of property } i \text{ in the past year of } t-1}{\text{Number of all transactions within 0.5 mile of property } i \text{ in the past year of } t-1} \quad (4)$$

[9] The choice of radius can be varied without meaningfully affecting the regression results. However, the ring sizes have to remain sufficiently narrow to preserve the hyper-local identification necessary to isolate the appraisal mechanism. Expanding the inner ring from 0.1, 0.15, 0.2, up until 0.4 mile has modest effects on the estimated coefficients, as discussed in Section 3.3.

The inner-ring cash share serves as a proxy for the local prevalence (or treatment intensity) of cash purchases in the immediate vicinity of property i. In contrast, the middle and outer ring measures function as controls to account for broader neighborhood-level housing trends. Notably, both the middle and outer rings include *all transactions within the inner ring*. The vector X_i captures time-invariant property characteristics to address potential selection at the property level. The fixed effects $\delta_{c(i),t}$ represent tract-by-year controls, which absorb unobserved shocks specific to each census tract in a given year. These controls help isolate the effect of local cash transactions by netting out time-variant neighborhood-level unobservables that could otherwise confound identification, such as shifts in housing demand. For instance, a high concentration of cash buyers may reflect intense bidding wars rather than the appraisal mechanism of interest. Intuitively, the coefficient β_1 aims to capture the average spillover effect of nearby cash purchases on the focal property, while β_2 and β_3 are supposed to absorb the influence of cash transactions in the broader surrounding area and any associated housing market trends.

Table 1 reports summary statistics for the estimation sample, which includes 7,954,675 mortgage-financed transactions matched between CoreLogic and HMDA from 2018 to 2022. On average, although appraisal values slightly exceed actual transaction prices, both in mean and standard deviation, the difference is not statistically significant. The table also shows how exposure to cash transactions and the number of nearby transactions increase with ring size. For example, the smallest ring (0.1 mile) has a mean cash purchase share of 20% and includes roughly 8 transactions on average. Expanding the radius to 0.15 mile increases the exposure to 23% and adds about 6 more transactions. At a 0.6-mile radius, the exposure converges to 26%, with a substantial increase in the number of included transactions (up to 96). Because each marginal expansion increases the area of the ring substantially, particularly the donut-shaped part of the outer-ring, the number of captured transactions rises disproportionately.

3.2 Baseline Results

Table 2 presents estimates from equation 1, using 0.1, 0.3, and 0.5 miles as the radii for the inner, middle, and outer rings, respectively. All specifications include tract-by-year fixed effects to account for unobserved, time-varying neighborhood-level factors such

Table 1: Estimation Sample Summary Statistics (2018–2022)

Panel A: Number of Mortgage-Financed Transactions		
	7,954,675	
Panel B: Outcome Variables		
	Mean	**SD**
Transaction Prices	343,830	293,197
Appraisal Prices	349,123	308,489
Panel C: Exposure to Cash Purchases		
Distance (miles)	**Mean**	**SD**
0.1	0.20	0.18
0.15	0.23	0.17
0.2	0.24	0.15
0.3	0.25	0.14
0.4	0.25	0.12
0.5	0.26	0.11
0.6	0.26	0.10
Panel D: Number of Housing Transactions		
Distance (miles)	**Mean**	**SD**
0.1	8.07	9.35
0.15	14.11	15.17
0.2	19.18	17.99
0.3	38.15	35.11
0.4	52.72	46.74
0.5	80.95	66.58
0.6	95.68	79.82

Notes: This table reports the main summary statistics for the estimation sample, including the number of CoreLogic-HMDA matched housing transactions, the main outcome variables, and the exposure to cash purchases and the number of housing transactions in each ring across different ranges.

as local economic shocks, gentrification, fluctuations in mortgage credit supply, or shifts in housing demand. Standard errors are clustered at the census tract level to accommodate arbitrary spatial and temporal correlation in the residuals within tracts. This clustering is particularly important given that housing transactions within a neighborhood are likely to be correlated due to shared amenities, school quality, or appraisal practices that may systematically influence pricing and valuation outcomes.

Column (1) reports a statistically significant and negative coefficient on the inner-ring cash share, while the coefficient on the outer-ring share is positive. A 100-percentage-point increase in the share of nearby all-cash purchases within the immediate vicinity (i.e., the inner ring) is associated with a $29,680 decrease in the appraised value of a mortgage-financed home. Interpreted proportionally, a one-standard-deviation increase in inner-ring cash share (0.18 within a 0.1-mile radius) corresponds to an estimated $5,342 reduction in appraised value (-29,680 $\times$ 0.18). This result provides suggestive evidence for the appraisal mechanism: nearby cash purchases, often occurring at discounted prices, can depress the comparable sales used in subsequent appraisals, thereby lowering the appraised values of surrounding mortgage-financed transactions. The positive coefficient on the outer-ring cash shares (17,648) suggests that these more distant nearby transactions may reflect broader local housing demand and are less likely to be used as direct comparables.

However, moving from Column (1) to Column (2), the estimated coefficient on the inner-ring cash share declines by nearly half after controlling for property characteristics, indicating substantial selection at the property level. For instance, newer and larger single-family homes (the benchmark property type), as well as those with more bedrooms, are associated with higher appraised values. After accounting for this selection, the estimated spillover effect of a 100-percentage-point increase in inner-ring cash share is a $16,232 reduction in appraisal value. Translating this into standard deviation units, a one-standard-deviation increase in inner-ring cash share (0.18) is associated with a $2,921 decrease in appraisal value, which is statistically significant. Consistent with Column (1), the coefficient on the cash share in the outer ring grows larger and remains statistically significant, suggesting that a higher prevalence of cash purchases in the broader neighborhood reflects stronger underlying housing demand. For example, a 100-percentage-point increase in cash share within the 0.5-mile radius is associated with an average increase of $28,604 in appraisal value.

Do these estimated appraisal spillovers translate into lower transaction prices for homes in

Table 2: Main Regression Results

	(1)	(2)	(3)	(4)
	Appraisal Values		*Transaction Prices*	
Inner Share	-29,680***	-16,232***	-29,680***	-16,233***
	(2,203)	(2,256)	(2,203)	(1,203)
Middle Share	-12,819	1,447	-10,583***	3,865
	(6,085)	(6,158)	(2,146)	(2,350)
Outer Share	17,648***	28,604***	18,635***	29,663***
	(8,902)	(8,849)	(3,962)	(3,872)
Property Category - Condo		-187,242***		-190,080***
		(7,271)		(6,636)
Property Category - Duplex		60,646***		51,686***
		(7,297)		(4,593)
Building Age		-1,511***		-1,521***
		(39)		(29)
Land Sqft		0.223**		0.210**
		(0.180)		(0.151)
No. Bed		9,384**		9,062**
		(4,070)		(3,924)
Observations	7,363,648	7,363,648	7,363,648	7,363,648
Tract-by-Year FE	Y	Y	Y	Y
R-squared	0.146	0.147	0.757	0.763

Notes: This table shows the regression results estimated for equation 1 with 0.1, 0.3, and 0.5 mile for the inner, middle, and outer ring respectively. 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

the inner ring? Columns (3) and (4) confirm this conjecture, showing highly similar patterns when the dependent variable is the actual transaction price. Specifically, a 100-percentage-point increase in the inner-ring cash share leads to a \$16,233 decline in transaction price, or approximately \$2,922 for a one-standard-deviation increase, virtually identical to the effect on appraisals. The influence of property-level selection follows the same pattern as observed in Column (2), reinforcing the robustness of the estimated spillover effects.

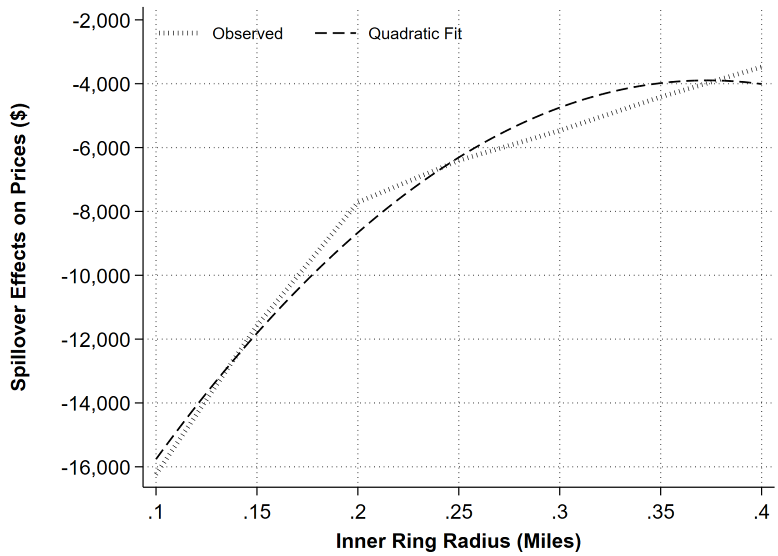
3.3 The Impact of Ring Expansion

It is natural to ask whether the baseline results are sensitive to changes in the radius definitions used to construct the spatial rings, especially the inner ring. Figure 4 plots the estimated spillover effects of cash purchases on the mortgage-financed properties in the *inner ring* across a range of radii, including 0.1, 0.15, 0.2, ..., and up to 0.4 mile while adjusting the middle and outer ring expanded accordingly[10]. To compare across different settings easily, I simply report the estimated effect of a 100-percentage-point increase in inner-ring cash purchase share on the appraisal or sale price of an average focal property

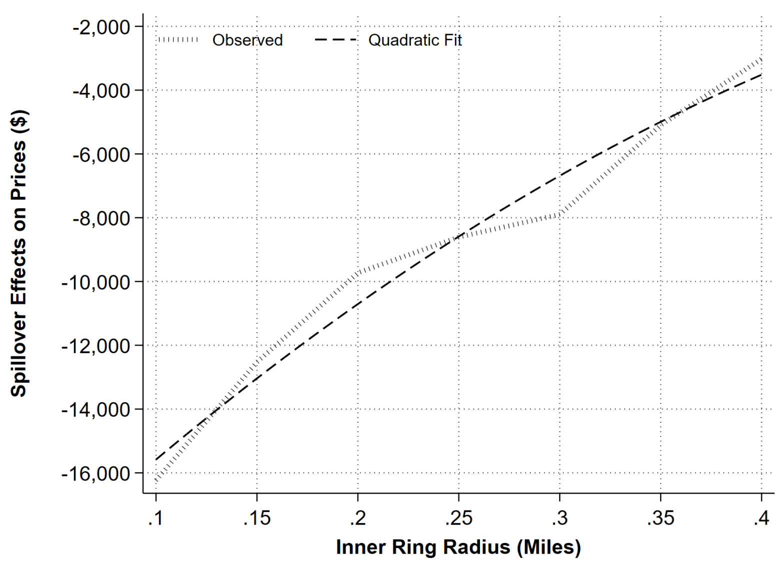
Panel A displays the estimated effects on appraisal values (all negative), which exhibit a slightly increasing trend as the inner ring expands. In other words, the absolute value of the negative effect becomes smaller. The concave shape of the fitted quadratic line suggests a convergence of the spillover effects as the radius increases. For example, the estimated effect declines in magnitude from approximately \$12,000 at a 0.15-mile radius to around \$4,000 at 0.4 miles. To translate, the impact of a one-standard-deviation increase in the inner ring on local appraisals ranges from \$2,880, \$1,300, and down to around only \$500 as both the coefficient estimate and the standard deviation declines as the inner ring expands from 0.1 to 0.4 mile. Panel B shows a similar upward trend in the effect on transaction prices, though with a less pronounced curvature. Appendix Tables C1, C2, and C3 report detailed regression results for inner-ring radii of 0.15, 0.2, and 0.3 miles, respectively. Although the estimated effects remain negative across all specifications, they start to lose statistical significance as the inner ring expands beyond 0.4 miles.

These attenuated effects seem to reflect that, as the spatial definition of "hyper-locality" broadens, the estimated coefficients increasingly capture general correlations between cash buyer activity and local housing demand, rather than the narrowly defined appraisal spillover channel that manifests well in a very small geographic area. This suggests a tradeoff: maintaining the hyper-local nature of the identification strategy is essential for isolating the appraisal mechanism, but expanding the radius too far risks confounding the mechanism with broader market dynamics, even after controlling for unobservables at the tract-year level.

[10]For example, a 0.4-mile inner radius correpsonds to a 0.6-mile middle ring and a 0.8-mile outer ring.



(A) Panel A: Spillover Effects on Appraisal Values



(B) Panel B: Spillover Effects on Transaction Prices

Figure 4: Spillover Effects with Expanded Inner Ring Radii

Notes: This table shows the estimated spillover effects of nearby cash purchases on the focal mortgage-financed homes in the inner ring. All specifications used in the baseline results apply.

3.4 Heteogeneity

The average negative effects may mask important heterogeneity across neighborhoods that depend on local market conditions, such as housing demand, credit access, and other socioeconomic and demographic characteristics. In particular, neighborhoods with different housing demand and, consequently, differential house price growth trends may react differently to a prevalence of cash buyers. For example, more credit-constrained or disadvantaged areas (often characterized by lower incomes and higher subprime borrowing) might have distinct effects of cash purchases compared to wealthier, less credit-constrained neighborhoods. Supporting this intuition, Mian and Sufi (2010) shows that, during the 2000s housing boom, areas with a high share of subprime borrowers experienced much greater house price appreciation during the boom than more affluent "prime" areas, even though incomes in those subprime neighborhoods were not growing. As the credit supply and housing demand shocks can diverge tremendously across neighborhoods, I will show whether the impact of cash buyers likewise differs in high-growth vs. low-growth areas.

Heterogeneous Effects across Neighborhoods

I categorize neighborhoods based on their house price growth rates during 2017-2022. I compute the average house price growth for each census tract, and split tracts into "high-growth" vs. "low-growth" categories depending on whether their five-year average exceeds the national median. The five-year average during the analysis sample from 2018-2022 captures a sustained trend in local housing markets rather than noisy year-to-year swings, providing a simple way to proxy for underlying demand conditions. A tract with high five-year price growth likely had a hot market with strong demand, whereas a low-growth tract had a cooler market.

This classification is grounded in recent literature using standard hedonic regressions to construct local housing price indices (HPIs), such as Baum-Snow and Han (2024). Following a similar approach, I build my own HPIs for each tract and each year during 2000-2022 and validate them by benchmarking against established price indices from FHFA and Zillow. Intuitively, the resulting HPIs capture the unobserved local housing price trend that varies across neighborhoods and years after controlling for housing quality. Table 3 documents the summary statistics of estimated HPIs during 2018-2022, a booming housing market with

Table 3: 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 hedonic regressions 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.

an average five-year growth rate around 9% and a notable 15.8% increase in 2021. All construction details, including the hedonic regression and HPI validation, are documented in Appendix Section D. Using these tract-level HPIs, I calculate each tract's average annual house price growth over five years, and then label tracts as low-growth if their five-year average is below the median, or high-growth if above.

The regression specification accounting for the neighborhood heterogeneity is:

$$\begin{aligned} Y_{i,t} \;=\; & \beta_1 \,\mathrm{CashShare}^{(\mathrm{inner})}_{i,t-1} \;+\; \theta\, \mathrm{CashShare}^{(\mathrm{inner})}_{i,t-1} \times \mathrm{LowGrowth}^{(18\text{–}22)}_{c(i)} \\ & +\; \beta_2\, \mathrm{CashShare}^{(\mathrm{middle})}_{i,t-1} \;+\; \beta_3\, \mathrm{CashShare}^{(\mathrm{outer})}_{i,t-1} \;+\; \gamma X_i \;+\; \mu_{c(i)} \;+\; \lambda_t \;+\; \varepsilon_{i,t} \end{aligned} \tag{5}$$

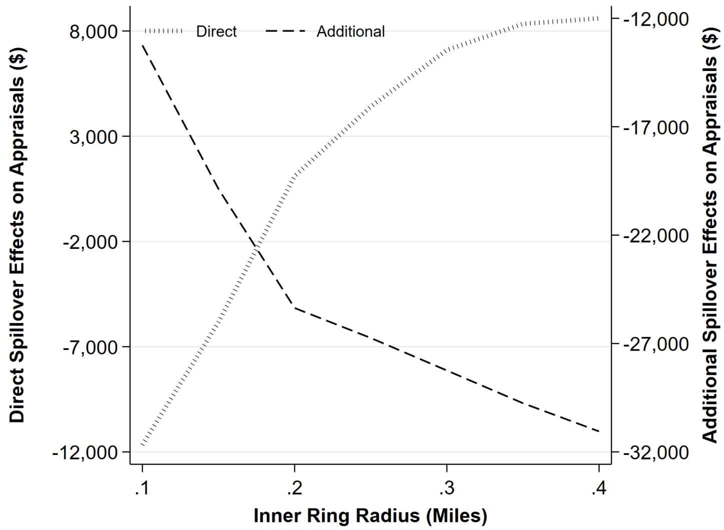
where i indexes properties and t denotes the transaction date, similar to the baseline Equation 1. To examine how the spillover effects might differ between high-growth and low-growth tracts, I extend the baseline specification by introducing an interaction between inner-ring cash share and the low-growth dummy. The term $\mathrm{CashShare}^{(\mathrm{inner})}_{i,t-1} \times \mathrm{LowGrowth}^{(18\text{–}22)}_{c(i)}$ allows the coefficient on the proportion of nearby cash purchases to vary depending on the tract's growth category. Different from the baseline, however, tract fixed effects ($\mu_{c(i)}$) and year fixed effects (λ_t) are included separately here and replace the tract-by-year dummies in the baseline. While the model still controls for all time-invariant tract attributes and for any year-specific shocks common to all tracts, this change will make sure that the interaction terms can paly a role by entering *only through the interaction term*, which does vary at the tract-year level since $\text{CashShare}^{(\text{inner})}_{i,t-1}$ varies by property and time.

This new setting yields two key coefficients of interest. The direct effect, β_1, is the coefficient on the inner-ring cash share itself and analogous to the spillover effect in the baseline, in which a high-growth neighborhood is the benchmark. It measures how an increase in cash buyer prevalence in the surrounding area impacts house prices in *high-growth* tracts. The additional effect, θ, measures the difference in the cash spillover effect for low-growth tracts compared to high-growth tracts. In other words, it is the *extra impact* associated with being a *low-growth* neighborhood. For a low-growth tract, the total spillover effect of cash purchases would be the sum of the direct effect and this additional effect.

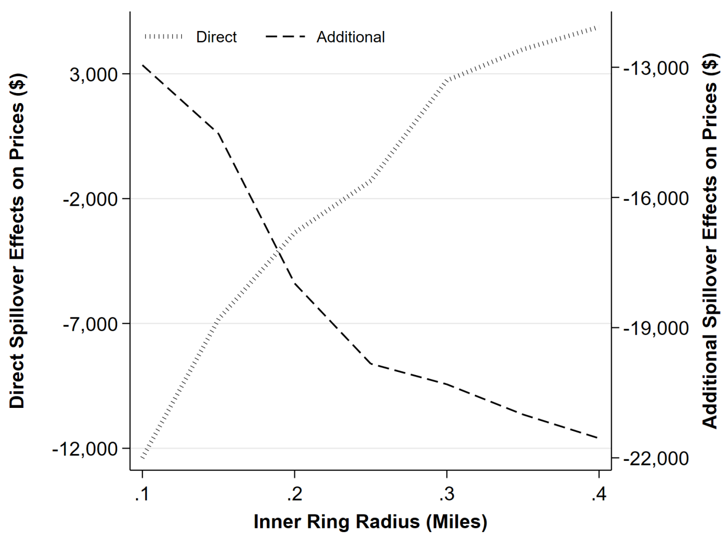
Figure 5 documents how the heterogeneous effects on appraisal values and transaction prices vary as the inner ring radius expands from 0.1, 0.15, ..., up to 0.4 mile. Overall, the additional effects in low-growth tracts are consistently negative and grow in magnitude with inner-ring distance. In comparison, the direct effects in high-growth tracts are relatively smaller in magnitude and even turn positive as the ring expands. The detailed estimation results (e.g., for ring radius 0.3/0.5/0.7 mile) are documented in Appendix Section E.

Consider the spillover effects on appraisals documented in Panel A. At the very local level (0.1-mile inner ring), the direct effect[11] is about -\$12,000, implying a downward pressure from cash purchases on nearby mortgaged transactions with a relatively smaller magnitude compared to the baseline estimate of around -\$16,000. The additional effect is also about -\$12,000 - there is an additional downward impact on the appraisal value of a mortgaged transaction if the target property is located in a low-price-growth neighborhood while the combined total effect is around -\$24,000. At a 0.2-mile inner ring, the combined effects are around –\$27,000, attributed mostly to the additional effect (–\$25,000) whereas the direct effect is only –\$2,000 for high-growth areas. A divergence appears from here: nearby cash purchases drag down appraisals significantly only in low-growth tracts and do not have huge impact in the high-growth neighborhoods. At 0.3 mile, the direct effect becomes +\$7,000 for high-growth neighborhoods, while the additional effect grows to –\$30,000. So a low-growth tract sees a net impact of roughly –\$23,000 (\$7,000 –\$30,000). High-growth areas at this radius actually experience positive effects on prices (\$7,000 higher) with more cash buyers nearby, whereas low-growth areas experience a \$23,000 lower price due to the same cash

[11] For the ease of interpretation, only consider the impact of a 100-percentage-point increase in inner-ring cash share in this section.



(A) Panel A: Heterogeneous Effects on Appraisal Values



(B) Panel B: Heterogeneous Effects on Transaction Prices

Figure 5: Direct and Additional Spillover Effects

Notes: This table shows the heterogeneous spillover effects of nearby cash purchases on the focal mortgage-financed homes in the inner ring. The dotted line plots the direct effects against the inner ring radius in miles, similar to Figure 4. The dash line captures the additional effects of cash purchases conditional on a property located within a low-growth neighborhood.

buyer presence. This pattern solidifies beyond 0.3 mile - at 0.4 mile, the direct effect is around +\$8,000 and the additional effect around –\$32,000. To interpret, the estimated coefficient on the standalone inner-ring cash share term seems to be dominated by the bidding-war effect in the high-growth neighborhoods. As suggested by (Mian and Sufi, 2010), neighborhoods with more lower-income subprime borrowers may experience a larger house price increase during a housing boom - cash offers have tremendous comparative advantage to outbid mortgage-financed offers. The positive relationship between appraisals and nearby cash share may be a symptom of cash bidding wars. In contrast, the net negative effects mainly come from those low-growth tracts where the appraisal mechanism dominates instead. The heterogeneity implies that the average effect estimated in the baseline masked two opposing tendencies in hot and cooler markets.

Panel B in Figure 5 shows heterogeneous effects on transaction prices - a pattern that is very similar to appraisals. The effects on appraisals translate into a smoother and similarly upward-trending direct spillover effects and slightly attenuated downward-sloping additional effects on prices when plotted against inner-ring radii. The combined effects on prices (around -\$25,000) also remain stable as the inner ring expands.

Opposing Spillover Effects and Neighborhood Characteristics

What differentiates these high-growth and low-growth tracts and potentially explains the opposing spillover effects between the two groups? Perhaps counter-intuitively, the high-growth tracts in 2018-2022 sample tend to be those with more socio-economic disadvantages, while the low-growth tracts are more affluent. Table 4 reveals statistically significant differences in neighborhood characteristics between the two groups. In terms of socio-economic characteristics, high-growth tracts have lower median household incomes, median home values, average rents than low-growth tracts. They also have a smaller share of college-educated residents and a lower proportion of residents of Asian ethnicity, on average. These indicators suggest that the high-growth neighborhoods are relatively less affluent. Focusing on signs of distress or disadvantage, high-growth areas exhibit higher unemployment rates and higher poverty rates, as well as a greater fraction of homes that are vacant. Demographically, they have a higher proportion of Black and Hispanic residents compared to low-growth tracts. Also, the housing stock in high-growth tracts tends to be newer on average, implying more recent development or turnover. In contrast, the low-growth tracts (with a smaller

Table 4: Comparison of Neighborhood Characteristics by Tract-Level HPI Growth

	Low-Growth Tracts		***High-Growth Tracts***		
	Mean	**SD**	**Mean**	**SD**	**Difference**
Median Rent	1,125	597	1,070	503	-55***
Median Home Value	341,510	287,462	293,872	227,797	-47,637***
Median Household Income	85,796	41,572	73,613	33,858	-12,182***
Unemployment Rate	0.05	0.04	0.06	0.05	0.01***
College	0.36	0.20	0.29	0.18	-0.06***
Poverty	0.12	0.10	0.14	0.11	0.02***
Median Age	41	8	40	9	-1.23***
Vacancy	0.10	0.10	0.11	0.11	0.01***
New Homes	0.07	0.10	0.09	0.12	0.01***
Black	0.11	0.19	0.15	0.22	0.03***
Asian	0.05	0.10	0.04	0.08	-0.02***
Hispanic	0.11	0.16	0.15	0.19	0.04***
Single Family Homes	0.64	0.26	0.64	0.26	-0.00
New Homes			33,233		

Notes: This table compares neighborhood characteristics between two equally sized groups of census tracts: those with low and high average house price index (HPI) growth. For example, tracts in the low-growth group are defined as having below-median average HPI growth from 2018 to 2022. For each neighborhood characteristic, the table reports the mean and standard deviation for both groups, along with the difference in means. Statistical significance of the differences is given by t-tests. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

price growth) are generally higher-income, higher-value areas with more educated and non-minority residents, lower unemployment and poverty, and older housing stock. These observations align with the early-2000s housing boom, where previously credit-constrained or disadvantaged neighborhoods saw an influx of mortgage credit and buyer demand, leading to rapid price appreciation.

The initial and perhaps more intuitive expectation was that the depressing spillover effects of cash purchases might be more pronounced in more credit-constrained or disadvantaged neighborhoods – for instance, if buyers in those areas have trouble obtaining financing, a cash buyer could potentially come in with a low offer and set a low benchmark price, unrestrained by appraisal limits. Moreover, sellers in distressed areas might accept "cash discounts" due to fewer financing options. Indeed, on average across the U.S., all-cash buyers pay about 10% less than buyers using mortgages, reflecting the leverage cash buyers have in negotiations (Reher and Valkanov, 2024). Such a discount, if prevalent in a neighborhood, could pull down comparable sale prices and appraisals for subsequent transactions, leading to broader price declines. One might therefore think that in poorer, credit-starved neighborhoods, cash purchases would depress prices more via this appraisal channel.

However, the empirical results in this section show the opposite pattern: the negative spillovers are actually more pronounced in the more affluent, low-growth neighborhoods, and are muted or even reversed in the less advantaged, high-growth neighborhoods. The evidence suggests a key reason for this reversal is differences in housing demand and competition (i.e., "hotness" of the market) between the two types of neighborhoods. The high-growth tracts – though socio-economically less advantaged – were experiencing strong housing demand and price momentum, likely due in part to the credit-fueled boom as discussed above. In such hot markets, housing transactions often involved bidding wars or rapidly rising price trends. Cash buyers in these areas were likely participating in competitive bidding rather than opportunistically low-balling sellers. In fact, a cash offer in a frenzied market might need to come in at a premium to win against other offers, or at least at the market price – meaning there is little or no "discount" on cash sales in these high-growth tracts[12]. As a result, having more cash buyers present is more a symptom of a heated market (where many buyers, including investors, are scrambling to buy), and their purchases do not actually

[12] It is potentially interesting to investigate whether the discount defined in the literature still pertains even for properties involved in cash bidding war.

undercut prices. If anything, cash buyers in hot markets might help sustain the price boom by quickly absorbing inventory. Thus, the spillover effect in high-growth neighborhoods appears slightly positive or essentially zero, as any potential negative appraisal effect is overwhelmed by the strong upward market pressure.

In contrast, the low-growth neighborhoods had weaker demand and little price growth in that period. These are more affluent markets that perhaps did not benefit from or were not targets of the subprime credit expansion, and thus saw relatively less housing activity. In these cooler markets, a cash buyer faces far less competition and can negotiate more aggressively on price. Sellers, valuing the certainty and speed of an all-cash deal while avoiding the risk of mortgage delays or denials, may accept notably lower prices from cash buyers. This implies that in those low-growth tracts, cash purchases likely occurred at a discount relative to what a financed buyer might pay. Such discounted sales then become comparable sales for the neighborhood, pulling down appraisals and future listing prices. With fewer other sales to offset them (since demand is weak), these low-priced comps exert a significant negative spillover on surrounding property values. The further the radius is extended, the more of these discounted cash transactions might be included in the "inner ring," which could explain why the estimated negative effect grows larger with distance in low-growth areas. A wider area captures more depressed comps and hence amplifies the downward pressure on the given home's price.

4 Internal Validity

Following industry standards and regulatory guidance (see details in Section 1.2), appraisers are generally expected to select at least three recent transactions involving similar properties located within one mile (typically within the same census block or tract), and sold within the past three to six months (extendable up to twelve months in slower markets). However, the extent to which appraisers consistently adhere to these guidelines in practice remains an open empirical question.

The identification strategy employed in this paper implicitly assumes that *the inner ring shares similar endogeneity with the outer rings*, such that the broader influence of nearby cash purchases on appraisals and prices is appropriately absorbed by the controls in the wider areas. One potential concern is that cash sales may systematically occur in micro-areas experiencing localized market declines, precisely where the focal mortgage-financed transaction takes place. Unfortunately, no publicly available dataset provides appraiser-chosen comparable sales matched to actual deed records at the transaction level, making it difficult to directly examine this simultaneity.

To proxy the comp selection process, I *manually construct comparable sales* for each focal property using Zillow's industry-standard methodology. If these manually identified comps are predominantly drawn from the immediate vicinity (i.e., the inner ring), it would indicate that appraisers are unlikely to search beyond the inner ring in most cases, thereby alleviating concerns about differential selection across rings.

As a quick validity check, the feasibility of this exercise relies on whether the inner ring contains a sufficiently large pool of recent transactions from which appraisers can select comparable properties. Table 1 shows that the 0.1-mile inner ring includes, on average, about 8 recent sales within the prior year—a modest number. However, this figure increases substantially as the radius expands, reaching approximately 81 transactions at 0.5 mile and 96 at 0.6 mile. These numbers suggest that the transaction base within the inner ring is generally adequate to support a realistic manual comp selection process.

4.1 Zillow's Comparable Sales Methodology

Ideally, 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 market differences are minimal[13].

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 of the home. For example, a 4-bed/3-bath house with 2,500 square feet. built in 2005 should be compared

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

to homes of roughly 4-bed/3-bath and 2,200–2,800 square feet. built in the same. Major differences in features (e.g. 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. Zillow also notes 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.

4.2 Manually Constructing Comparable Sales

Mimicking the industry standard, here I operationalize the steps of manually constructing 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:

$$S(i,j) = \sum_{k=1}^{K} w_k \cdot \frac{|x_{k,i} - x_{k,j}|}{\Delta_k} \tag{6}$$

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:

$$P_{i,j,t} = \sum_{k=1}^{K} \beta_{i,k} \frac{|\mathrm{X}_{i,t,k}|}{\Delta_k} + \alpha_{j,t} + \phi_m + \varepsilon_{i,t}, \tag{7}$$

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 $1/\text{dist}(i, j)$ (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*.

4.3 Ring Distribution of Imputed Comps

Constructed following the procedures in Section 4.2, the resulting dataset includes all pairwise combinations between focal mortgage-financed transactions and both their manually imputed comparables and other nearby transactions[14] during 2017–2022. Table 5 summarizes key statistics for this dataset, which contains 609,622,168 unique two-way pairwise combinations[15] and 3,816,516 unique focal mortgage-financed transactions. This sample constitutes just over 60% of the full regression dataset, as only focal transactions with non-missing similarity scores are retained[16].

[14] These are nearby transactions within a 1-mile radius that were initially considered as potential comparables but were not ultimately selected as comps through the procedures in Section 4.2.

[15] Each row corresponds to a focal transaction matched with either a unique comparable sale or a unique non-comp nearby sale, resulting in a large number of pairwise observations.

[16] Some focal transactions could not be assigned a similarity score due to reasons such as missing hedonic characteristics or insufficient comparable sales within a 1-mile radius.

Table 5: Imputed Comps vs. Other Nearby Transactions

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	3.58	0.71	1	6	3,816,516
Other Nearby	156.15	136.18	1	2,373	3,816,516

Panel C: Differences from Focal Transaction

	Mean	**Std. Dev.**	**Min.**	**Max.**	**N**
Group 1: Imputed Comps					
Similarity Score	0.37	0.35	0.01	3.72	13,683,225
Distance (Mile)	0.17	0.17	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.	4,174.45	20,168.46	0	174,240.94	13,683,225
Building Sq. ft.	368.08	388.90	0	2,390.37	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	1.21	0.50	0.01	3.72	595,938,943
Distance (Mile)	0.62	0.26	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.	7,983.02	30,129.73	0	207,15.27	595,938,943
Building Sq. ft.	831.76	827.78	0	4,727.03	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 Section 4.2. 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.

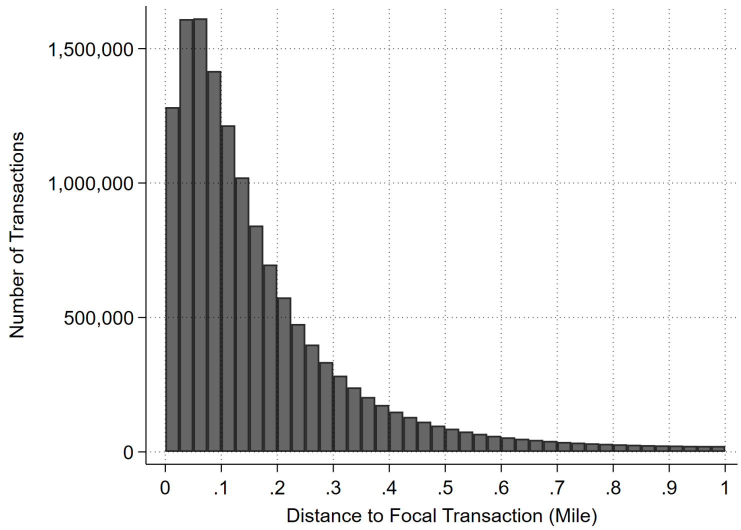
As shown in Panel B, each focal transaction is matched, on average, with 3 to 4 unique imputed comps and approximately 156 other nearby transactions within a 1-mile radius. Panel C reports the differences in property characteristics between the focal property and its matched transactions across the two groups. Compared to other nearby properties, the imputed comps are significantly more similar: they exhibit a lower average similarity score (0.37), are geographically closer (0.17 mile), and occurred more recently (178 days prior). They also align more closely with the focal property's characteristics, including building age, lot square footage, total building area, and number of bedrooms and bathrooms. In contrast, transactions not selected as comps have a higher average similarity score (1.21), are located farther away (0.62 mile on average), and transacted slightly earlier (183 days prior). These properties also differ more substantially in physical characteristics from the focal property. Taken together, these summary statistics support the credibility of the comp-selection algorithm described in Section 4.2.

Figure 6 presents histograms that visualize the distribution of matched nearby transactions by distance to the corresponding focal property across all 609,622,168 pairwise combinations. The x-axis denotes distance bins, while the y-axis counts the number of transactions located within each distance band. Note that a given transaction may appear multiple times as it can serve as a comp for several different focal transactions. For example, as shown in Panel A, over 1.6 million imputed comps fall within the 0.75 to 1-mile range from the focal property. The figure shows that imputed comps are heavily concentrated within the 0.15-mile radius, with approximately 95% located within 0.5 miles (see also Figure 7).

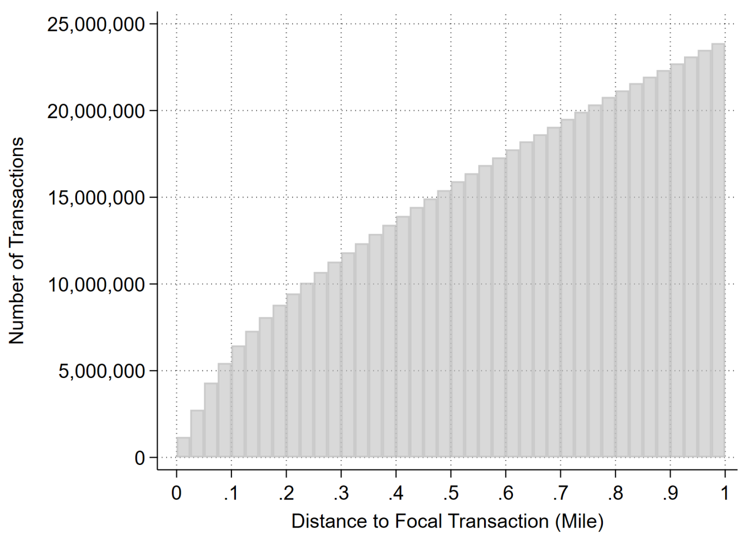
By contrast, Panel B shows that the number of other nearby transactions increases steadily with distance, consistent with the fact that the geographic area (and thus the potential pool of comparable sales) grows nonlinearly with the ring radius. This pattern supports the idea that appraisers typically do not need to search beyond the immediate vicinity to identify appropriate comps.

Supporting Evidence of Internal Validity

The empirical findings so far seem to support the internal validity of the ring-based identification strategy. As shown in Table 1, the pool of recent sales in the immediate vicinity of each property is modest but expands rapidly with distance. On average, the 0.1-mile inner ring contains about 8 sales in the past year, but this grows to roughly 81 sales by



(A) Panel A: Histogram of Imputed Comps

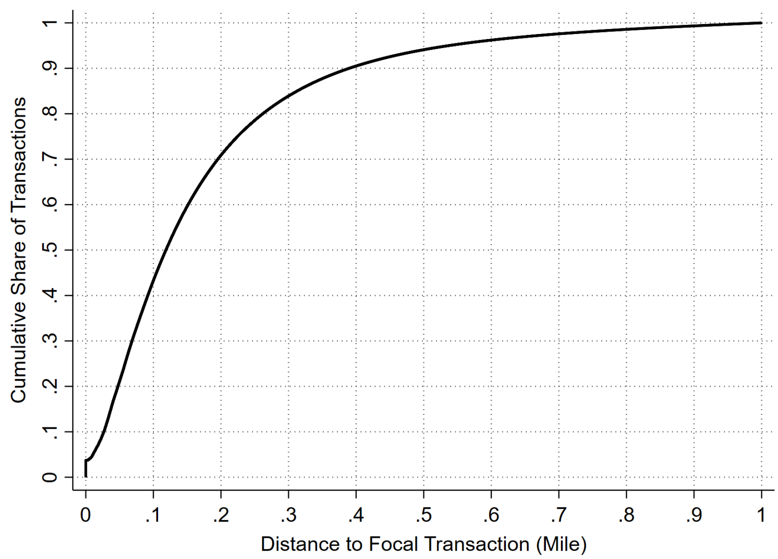


(B) Panel B: Histogram of Other Nearby Transactions

Figure 6: Selected Comps vs. Other Nearby Transactions

Notes: This figure shows the histogram of all nearby transactions' distances to their corresponding focal properties for two mutually exclusive samples: imputed comps (in dark grey) and all other nearby transactions (in light grey). The analysis sample covers all focal transactions and their nearby transactions, including imputed comps and other nearby transactions, within 1 mile during 2017-2022.

Figure 7: Cumulative Density of Imputed Comps



Notes: This figure shows the cumulative share of imputed comps along each comp's distance to its focal property. This is the cumulative density function derived from Figure 6.

a 0.5-mile radius (and about 96 by 0.6 mile). Also, to proxy how appraisers select comps in practice, the manually imputed comparables are overwhelmingly drawn from this inner area. Panel A of Figure 6 and Figure 7 show that over 95% of the identified comps lie within a 0.5-mile radius of the focal property, with a pronounced concentration in the first 0.15 mile. This suggests that appraisers may rarely need to search beyond the immediate vicinity to find suitable comps - the inner ring typically provides a sufficient base of similar sales, and only in rare cases would an appraiser expand the search to outer rings (e.g. extremely sparse transactions).

Notably, each focal property has on average only about 3–4 comparables chosen out of roughly 160 candidate sales within a one-mile radius (Panel B of Table 5), underscoring the selectivity of the simulated comp selection process. Moreover, those chosen comps are far more similar to the subject property than other nearby transactions. Panel C of Table 5 confirms that the imputed comparables have a much lower average similarity score (0.37) than non-comparable nearby sales (1.21), indicating far smaller differences in property attributes. These comps are also significantly closer in proximity (on average only 0.17 miles away, versus 0.62 miles for other nearby sales) and just as recent in time (about 178 days prior, compared to 183 days for others). Consistent with industry best practices, the selected comps align closely with the focal property's characteristics, including similar building age, lot size, living area, and number of bedrooms/bathrooms, whereas the other nearby sales differ much more on these dimensions. This evidence validates that the manual comp-imputation procedure captures similar, if not the same, comps an appraiser would choose. If sufficient similar homes have sold in the inner ring, appraisers have little need to pull comps from farther away, alleviating concerns that they systematically go outside the inner circle to find more favorable comparisons.

Taken together, the evidence so far supports the key identification assumption behind the ring-based design. Namely, the inner and outer rings are part of the same local housing market and thus experience similar underlying conditions and shocks. It is likely that the inner ring provides the most relevant price signals since nearly all (imputed) comps come from right around the property, while the wider rings capture the broader neighborhood context. Current results seem to suggest that area-wide demand trends or neighborhood effects should impact both the inner-ring area (0.1, 0.15, and up to 0.4 mile) and the surrounding rings on parallel - the broader the ring expands, the stronger the positive relationship between the outer-ring cash share and the outcomes while the weaker the negative effects of inner-ring cash sales on appraisals and prices. Controlling for influences from the wider rings in the regressions seems to effectively difference out these common shocks and broader market factors - this pattern is consistent across all baseline and heterogeneity specifications. What remains is supposed to be the *local* effect, namely the impact of having cash buyer transactions in the immediate vicinity. In summary, the evidence suggests that properties just outside the immediate vicinity serve as a valid counterfactual for those inside it, ensuring that differences in outcomes can be attributed to truly local effects rather than any broader confounding influences.

5 Depressing Prices or Signaling Demand?

One might initially expect the appraisal mechanism to operate more prominently in disadvantaged, credit-constrained neighborhoods with mortgage limits binding and conversely anticipate that bidding wars would dominate in more affluent or high-demand areas. However, the heterogeneity patterns observed in Section 3.4 suggest a different mapping: the largest bidding-war effects from cash purchases appear in high-growth neighborhoods with relatively low income levels (i.e., more disadvantaged areas), whereas the most pronounced appraisal-induced price effects occur in lower-growth, relatively affluent neighborhoods. To rationalize the empirical findings, it is useful to conceptualize the conditions under which *the appraisal-induced effects dominate* and when they are likely to be mitigated or even absent.

I model a static housing market in which sellers interact with two types of buyers (i.e., cash buyers and mortgage-financed buyers) who segment the market, following the framework of Piazzesi et al. (2020). The model illustrates how *appraisal-based financing frictions* can lead to price declines and restricted credit access, and under what circumstances such dynamics are likely to prevail.

5.1 Setup

Let there be a continuum of homogeneous houses and a continuum of buyers. A fraction μ of buyers are cash buyers, and $1 - \mu$ are mortgage buyers. *Mortgage-financed buyers* are constrained by loan-to-value limits, appraisals, and underwriting frictions. They cannot buy above a certain price if the appraisal is low, or if they can't make a large down payment. *Cash buyers*, by contrast, face no such constraints. They can bid at or above the appraisal, close quickly, and have greater flexibility. All buyers draw valuations[17] $v \in [0, \bar{v}]$ from a common distribution $F(v)$.

Supply: Let $S(P)$ be the housing supply at price P. This can be upward-sloping or fixed at $\bar{S}$.

Appraisal Rule: Appraisers set the valuation A based on recent transaction prices:

$$A = \mathcal{A}(P_{\text{recent}})$$

[17] Independent and identical distribution is necessarily needed here as this is a common value model.

For simplicity, assume $A = P_{t-1}$. In other words, A is the exogenously given appraised value of the house (determined by recent comparable sales in the neighborhood).

Financing Constraint: Mortgage buyers can borrow up to a fraction λ of the appraisal value:

$$L = \lambda A$$

They must cover the gap $P - L$ from their own liquid wealth W. Assume $W = (1 - \lambda)A$, so buyers can afford $P \leq A$.

5.2 Buyer Demand

- If $P \leq A$, both buyer types with $v \geq P$ can purchase. Demand is:

$$D(P; A) = 1 - F(P)$$

- If $P > A$, mortgage buyers are excluded, similar to Kaplan et al. (2020). Demand is:

$$D(P; A) = \mu[1 - F(P)]$$

5.3 Equilibrium

An equilibrium price P^* satisfies:

$$S(P^*) = D(P^*; A)$$

This condition balances supply with the effective demand, which depends on whether mortgage buyers are active (if $P^* \leq A$) or priced out (if $P^* > A$).

Equilibrium house prices in a neighborhood are determined by the interaction of buyer valuations and the appraisal-induced cutoff:

- In the absence of any binding constraint ($A \geq v$ or effectively no appraisal cap), standard competition would drive the price to $P^* = \bar{v}$ as both mortgage and cash buyers bid up to their valuations. This unconstrained benchmark corresponds to a scenario of abundant liquidity, in line with cases where influxes of liquid wealth fuel higher local house prices (Hartman-Glaser et al., 2023).

- However, if the appraisal value is below fundamentals ($A < v$), the financing friction comes into play. Two cases illustrate the possible outcomes:

    1. **Bidding wars:** If at least two cash buyers are actively bidding, they will compete against each other up to their valuation v. In this case, the winning bid will reach v (or arbitrarily close to it in a continuum of buyers), and the price is effectively unconstrained by A. The presence of sufficient unconstrained capital in the buyer pool allows the market to realize the full fundamental value of the house, despite the low appraisal, as cash buyers are not limited by A.

    2. **The appraisal trap:** If cash buyer presence is very limited (for example, only one or none in the bidding pool), the appraisal constraint binds and caps the price. With no competition from another cash buyer, a sole cash buyer would only need to bid slightly above the highest constrained buyer's bid (which is capped at A) to win, resulting in a sale price approximately equal to A. In the extreme case of no cash buyers, all bidders drop out once $P > A$, so the house trades at $P = A$. In either scenario, the price is pinned near the appraisal ceiling when cash-funded demand is scarce.

This equilibrium outcome implies that the neighborhood's sale price will be $P = v$ in a regime with ample cash buyers, and $P = A$ in a regime dominated by mortgage buyers who are constrained by a low appraisal. The comparative statics are intuitive: holding A fixed, a higher share μ of cash buyers makes it more likely that the price will be bid up to v, while a lower μ increases the likelihood that P stays at the constrained level A. In equilibrium, a tract with very few unconstrained buyers will experience depressed prices relative to fundamentals due to the appraisal cap, consistent with evidence that tighter credit conditions or a greater reliance on constrained financing tend to dampen housing prices (Guren et al., 2021). On the other hand, when unconstrained buyers form a large part of the market, the constraint is endogenously relaxed by competitive bidding, and the tract realizes higher prices. In other words, the "bidding war" regime will tend to emerge in neighborhoods with surging demand and ample cash buyer presence, even if those neighborhoods have lower average incomes. On the other hand, the "appraisal trap" regime prevails where unconstrained buyers are scarce, even in relatively affluent areas with limited new demand.

6 Welfare Implications

Given the finding that house prices can be depressed by nearby cash sales in a hyper-local setting, in what context are these effects good or bad? Adapting the set-up in Section 5, I examine how these spillovers from cash purchases propagate through appraisal adjustments and under what conditions they are welfare-enhancing or detrimental.

6.1 Model Framework

Consider a housing market where buyers derive utility from both housing services and non-housing consumption. Each buyer i has utility $U_i(h_i, c_i)$ defined over housing h_i and a composite non-housing consumption good c_i. We can express this separably as:

$$U_i(h_i, c_i) = u(h_i) + v(c_i),$$

where $u(\cdot)$ captures the utility from housing and $v(\cdot)$ from other consumption. For example, one convenient specification is $U_i(h, c) = \alpha \ln(h) + (1 - \alpha) \ln(c)$, where $\alpha \in (0, 1)$ reflects the importance of housing in utility.

In this context, each buyer demands at most one house (a discrete unit $h_i \in \{0, 1\}$ of a standardized home), so $u(h_i)$ can be thought of as $u(1) = u_0$ if the buyer purchases the home (of a given quality) and $u(0) = 0$ if not. The term u_0 thus represents the utility benefit (or intrinsic value) of owning that particular house. We denote by v_i the *monetary equivalent* of this housing utility for buyer i (their willingness-to-pay), i.e. v_i satisfies $u_0 = v_i$ in utility units. Each buyer also has an initial wealth or liquid assets W_i that can be used toward a down payment. Non-housing consumption c_i is then constrained by income/wealth minus housing expenditure. We assume quasi-linear preferences for tractability, so that $v(c_i)$ is roughly c_i (or linear in money), ensuring that v_i indeed measures willingness to pay in dollar terms. Under these assumptions, buyer i will choose to purchase the house if and only if it maximizes their utility, which in monetary terms requires $v_i \geq P$ (their value exceeds the price P) and that they can finance the price P given their budget constraints.

6.1.1 Financing and Appraisal Constraint

Buyers may use mortgage financing subject to an *appraisal-based constraint.* Let A_t denote the appraised value of the house at time t. If buyer i seeks a mortgage, the lender will typically lend no more than a fraction λ (loan-to-value ratio) of the *appraised value.* Thus the loan L_i must satisfy:

$$L_i \leq \lambda \cdot A_t \ ,$$

where $\lambda \in (0, 1)$ (e.g. $\lambda = 0.8$ for an 80% LTV limit). In addition, the buyer must cover the remainder of the purchase price with their own wealth as a down payment:

$$P - L_i \leq W_i \ .$$

Combining these constraints, a mortgage-dependent buyer i cannot pay a price above

$$P_{i,\max} = W_i + \lambda A_t \ ,$$

since any $P > W_i + \lambda A_t$ would require a loan exceeding the appraisal-based cap or a down payment beyond the buyer's means. In contrast, a *cash buyer* does not face the appraisal limit – effectively $\lambda = 1$ and L_i is only limited by their own funds. We assume cash buyers have sufficient liquid wealth to cover the price (or access to unsecured funds), so their only limit is their valuation v_i.

6.1.2 Appraisal Updates from Comparable Sales

The appraised value A_t is based on recent comparable sales. A tractable updating rule is:

$$A_{t+1} = (1 - \rho)A_t + \rho P_t \ ,$$

where P_t is the price of the most recent transaction and $\rho \in (0, 1]$ reflects appraisal sensitivity to new comps. This defines an *appraisal feedback loop*, where recent sales influence borrowing capacity for future buyers.

6.2 Differential Welfare Implications in Two Scenarios

Here I analyze two market environments: (1) *low-growth, low-demand neighborhoods*, and (2) *high-growth, competitive neighborhoods*. In both cases, a house is sold to the buyer with the highest *effective* willingness-to-pay, constrained by financing ability.

6.2.1 Low-Growth Neighborhoods

These areas are characterized by weak or stagnant demand and sparse transactions. With limited buyer competition, any sales that do occur—sometimes involving cash buyers—often transpire at relatively low prices, effectively serving as discounted comparables. Appraisers rely heavily on these low comps, leading to *low appraised values* A_t. Consequently, mortgage-dependent buyers face tight constraints:

$$P_i \leq W_i + \lambda A_t \ ,$$

which may be *well below* their true willingness-to-pay v_i. Hence, high-valuation buyers are *excluded* due to financing limits. When cash buyers with lower valuations v_c can bid more than P_i, they win. This leads to a *misallocation* where homes do not go to the highest-valuing buyers. It also triggers further appraisal declines:

$$P_t \downarrow \Rightarrow A_{t+1} \downarrow \Rightarrow \text{financing caps tighter} \Rightarrow P_{t+1} \downarrow \ ,$$

trapping the neighborhood in a low-price, low-equity equilibrium. Welfare is lost both due to misallocation and the exclusion of credit-constrained households. Buyers may either forgo homeownership or take on riskier financing (higher LTV, second liens), reducing utility further. Importantly, this appraisal trap dynamic can arise not only in economically distressed communities but also in any neighborhood with persistently low growth and a lack of unconstrained buyers—even a relatively affluent area will see prices capped at A_t if no one is willing or able to bid above the appraised value.

6.2.2 High-Growth Neighborhoods

Here, demand is strong, and prices are high. For example, these could be rapidly gentrifying neighborhoods that were previously lower-income but are now attracting intense competition. Frequent high-price transactions ensure that appraisals A_t keep pace with the market. Buyers (often outside investors or higher-income newcomers) typically have substantial wealth W_i or can compensate for appraisal gaps. Thus:

$$P_i \leq W_i + \lambda A_t \approx v_i \ ,$$

meaning constraints are *not binding*. Homes go to those who value them most. Cash buyers do not depress future appraisals; if anything, they raise them. The feedback loop is benign or even positive:

$$P_t \uparrow \Rightarrow A_{t+1} \uparrow \Rightarrow \text{future } P_i \uparrow \ ,$$

so welfare is near-efficient: no exclusion or misallocation occurs. Appraisal constraints do not distort outcomes.

6.3 Context-Dependent Welfare Implications

The equilibria above highlight that *context matters*. In low-growth, relatively affluent neighborhoods, price declines due to cash purchases and appraisal feedback *reduce welfare* via exclusion and reduced wealth-building. In high-demand, high-growth, relatively socioeconomically disadvantaged neighborhoods experiencing an influx of capital, cash buyer spillovers are *not harmful* and may even improve affordability by quickly bringing appraisals in line with market fundamentals.

Furthermore, exploring comparative statics over W_i, λ, or appraisal rigidity ρ can help identify thresholds where credit frictions really bite. Policies that increase W_i (e.g., down payment assistance) or relax appraisal constraints (e.g., adjusted rules for comps) may restore efficiency in low-demand markets. Detailed simulation results with above parameters calibrated to the data will be updated in the next iteration of this paper.

7 Conclusion

In this paper, I propose and empirically identify a new channel through which cash purchases exert downward pressure on nearby mortgage-financed home sales via appraisal constraints. The results highlight that *who* the buyers are—cash versus financed—can affect how local markets function through a previously underexplored mechanism.

Using a ring-based identification strategy, I show that all-cash transactions can distort local price formation through what I term the "appraisal mechanism." Properties located near recent cash sales tend to receive lower appraisals, driven by depressed comparable sales. This effect persists even after controlling for property characteristics and unobserved local housing demand and ultimately translates into lower transaction prices for nearby mortgage-financed homes. The effect is most pronounced within a 0.1-mile radius and diminishes with distance, becoming statistically insignificant beyond 0.4 miles. This pattern suggests that the appraisal mechanism operates at a hyper-local level and is overshadowed by broader demand effects as the radius expands.

Interestingly, these negative spillover effects are more pronounced in more affluent, low-growth neighborhoods, whereas the appraisal channel appears weaker in relatively disadvantaged, high-growth neighborhoods. In the latter, the prevalence of cash buyers may signal heightened demand and bidding wars, counteracting the downward appraisal pressure, especially beyond the 0.3-mile radius.

To validate the core identification assumption, I construct imputed comparables using a Zillow-style matching algorithm. These comps align closely with the focal property in terms of physical attributes and are overwhelmingly drawn from within a 0.5-mile radius. This suggests that appraisers primarily select comparables from the inner ring, reinforcing the internal validity of the empirical design.

Finally, I develop a stylized housing choice model with appraisal-based borrowing constraints to interpret the welfare implications of these spillovers. In low-growth, relatively affluent neighborhoods, cash buyer spillovers reduce welfare by excluding mortgage-dependent buyers and eroding housing wealth. In contrast, in high-growth, less advantaged areas experiencing capital inflows or bidding wars, such spillovers may improve affordability by bringing appraisals closer to market fundamentals.

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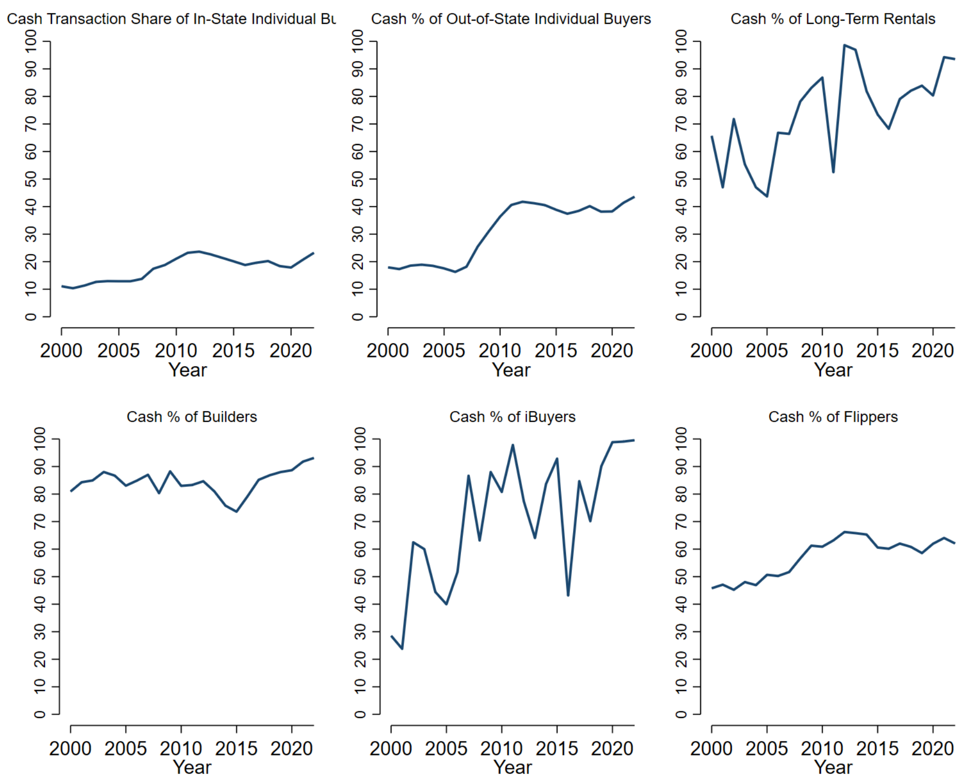
APPENDIX

A Cash Purchase Share of Various Types of Home Buyers

Figure A1: Cash Purchase Share of Different Home Buyers



Notes: This figure shows the share of cash transactions for six types of buyers in the U.S. housing market from 2000 to 2022. The definition and categorization of institutional investors (i.e., LTRs, iBuyers, builders) and flippers closely follow Gorback et al. (2025). Each subplot shows the percentage of transactions done with all cash within a buyer type over time.

B 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).

B.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.

B.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.

C Estimation Results with Expanded Rings

Table C1: Results with Expanded Rings (0.15/0.3/0.5 Mile)

	(1)	(2)	(3)	(4)
	Appraisal Values		*Transaction Prices*	
Inner Share	-25,143***	-11,579*	-28,357***	-12,525***
	(3,088)	(3,558)	(1,395)	(2,112)
Middle Share	-9,324	3,140	-6,935***	5,598**
	(5,882)	(5,938)	(2,114)	(2,291)
Outer Share	19,663**	31,861***	18,491***	30,476***
	(8,869)	(8,799)	(3,960)	(3,852)
Property Category - Condo		-170,046***		-172,696***
		(11,896)		(10,785)
Property Category - Duplex		76,331***		49,451***
		(12,038)		(4,346)
Building Age		-1,346***		-1,322***
		(112)		(96)
Land Sqft		0.223**		0.210**
		(0.180)		(0.151)
No. Bed		7,348**		7,609**
		(3,134)		(3,389)
Observations	7,363,648	7,363,648	7,363,648	7,363,648
Tract-by-Year FE	Y	Y	Y	Y
R-squared	0.149	0.150	0.757	0.767

Notes: This table shows the regression results estimated for equation 1 with 0.15, 0.3, and 0.5 mile for the inner, middle, and outer ring respectively. 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

Table C2: Results with Expanded Rings (0.2/0.4/0.6 Mile)

	(1)	(2)	(3)	(4)
	Appraisal Values		*Transaction Prices*	
Inner Share	-25,745***	-7,714**	-27,992***	-9,728***
	(3,981)	(3,138)	(1,562)	(1,837)
Middle Share	-13,071**	-3,122	-6,640***	3,426
	(6,636)	(6,662)	(2,319)	(2,432)
Outer Share	24,782***	32,878***	22,630***	30,773***
	(9,523)	(9,482)	(4,687)	(4,644)
Property Category - Condo		-188,169***		-190,927***
		(7,295)		(6,649)
Property Category - Duplex		60,200***		51,299***
		(7,293)		(4,600)
Building Age		-1,505***		-1,517***
		(39)		(25)
Land Sqft		0.163*		0.190**
		(0.145)		(0.151)
No. Bed		9,428**		9,105**
		(4,086)		(3,938)
Observations	7,363,648	7,363,648	7,363,648	7,363,648
Tract-by-Year FE	Y	Y	Y	Y
R-squared	0.145	0.146	0.756	0.762

Notes: This table shows the regression results estimated for equation 1 with 0.2, 0.4, and 0.6 mile for the inner, middle, and outer ring respectively. 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

Table C3: Results with Expanded Rings (0.3/0.5/0.7 Mile)

	(1)	(2)	(3)	(4)
	Appraisal Values		*Transaction Prices*	
Inner Share	-29,864***	-7,899*	-27,711***	-5,467**
	(6,417)	(4,541)	(2,281)	(2,636)
Middle Share	7,938	13,932	4,875	10,925***
	(11,277)	(10,264)	(3,854)	(3,792)
Outer Share	8,856*	14,868**	16,999***	23,017***
	(7,003)	(7,981)	(3,082)	(3,056)
Property Category - Condo		-188,349***		-191,213***
		(7,240)		(6,602)
Property Category - Duplex		60,016***		51,055***
		(7,290)		(4,602)
Building Age		1,503***		1,513***
		(39)		(24)
Land Sqft		0.121		0.150***
		(0.098)		(0.065)
No. Bed		9,457**		9,128**
		(4,095)		(3,945)
Observations	7,363,648	7,363,648	7,363,648	7,363,648
Tract-by-Year FE	Y	Y	Y	Y
R-squared	0.145	0.146	0.756	0.762

Notes: This table shows the regression results estimated for equation 1 with 0.3, 0.5, and 0.7 mile for the inner, middle, and outer ring respectively. 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

D Hedonic Regressions and Local House Price Indices

Following the standard setting, the hedonic regression specification is:

$$\log(P_{i,j,t}) = \sum_{\tau \in [1,N]} \beta_{i,\tau} \mathrm{X}_{i,t,\tau} + \alpha_{j,t} + \phi_m + \varepsilon_{i,t}, \tag{8}$$

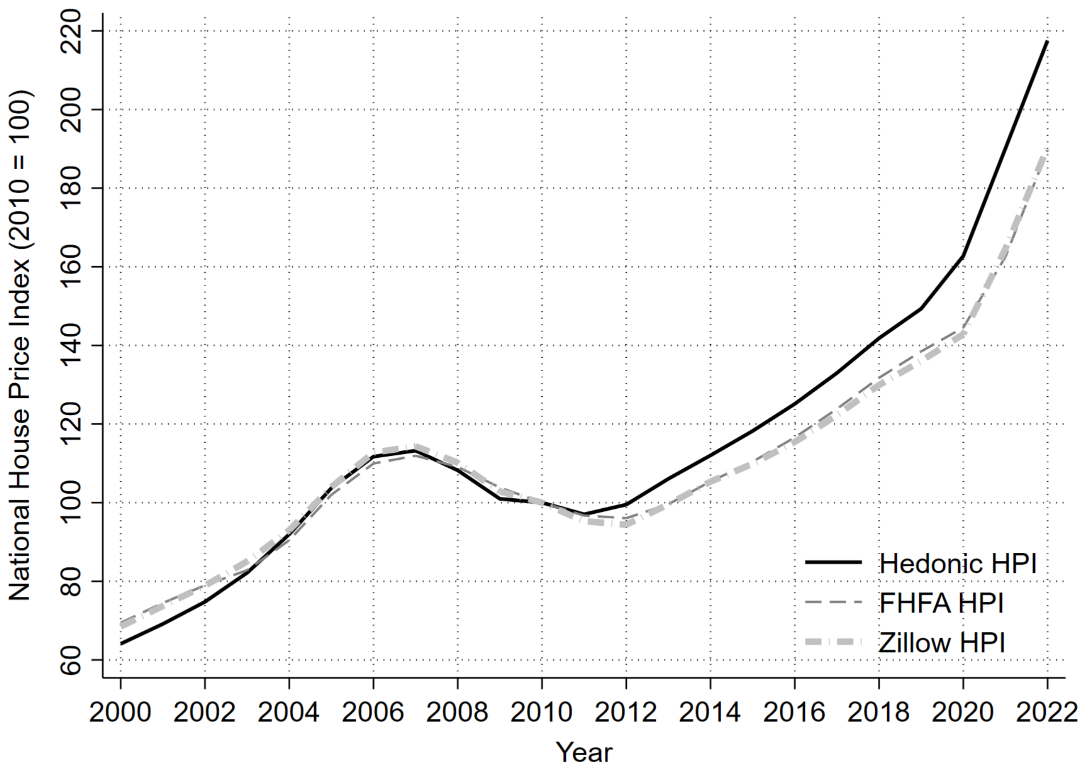
where $P_{i,j,t}$ is the price of unit i, in census tract j, in year t. $\mathrm{X}_{i,t,\tau}$ includes a suite of property characteristics including square footage, acreage, bedrooms, bathrooms, total rooms, and whether the unit has a garage or carport. $\alpha_{j,t}$ is a census tract-by-year fixed 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 D2 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[18]. The Zillow Home Value Indices (ZHVI) are constructed using all single-family, condo, and co-op transactions and seasonally adjusted, similar to Equation 8 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).

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

Figure D2: Cash Purchase Share of Different Home Buyers



Notes: This figure plots the nationally aggregated hedonic HPIs 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.

E Heterogeneous Effects

Table E4: Heterogeneous Effects (with 0.3/0.5/0.7-Mile Radius)

	(1) *Appraisal Values*	(3) *Transaction Prices*
Inner Share	7,493***	2,745***
	(2,160)	(1301)
Inner Share $\times Low\_Growth$	-27,500***	-20,306***
	(2,535)	(3,148)
Middle Share	9,378	7,947***
	(10,597)	(2,273)
Outer Share	29,249***	28,629***
	(10,940)	(3,031)
Property Category - Condo	-185,651***	-187,360***
	(5,214)	(4,243)
Property Category - Duplex	85,714***	52,817***
	(15,395)	(4,583)
Building Age	1,558***	1,511***
	(40)	(20)
Land Sqft	0.127*	0.150***
	(0.073)	(0.092)
No. Bed	7,303**	7,651**
	(2,949)	(3,239)
Observations	7,044,913	7,044,913
Tract FE	Y	Y
Tract-Year FE	Y	Y
R-squared	0.206	0.781

Notes: This table shows the detailed heterogeneous effects estimated for equation 5 with 0.3, 0.5, and 0.7 mile for the inner, middle, and outer ring respectively. 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