Cash is King? Understanding Financing Risk in Housing Markets*

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Abstract

In Los Angeles, the fraction of all-cash home purchases quintupled during the last decade, with the growth being more pronounced among experienced buyers, flippers, and out-of-state buyers. Exploiting these variations, we quantify a new source of housing market frictions: *financing risk*, referring to delays and uncertainties that a seller faces in closing a transaction with a mortgage offer. Using the transaction level data, we find that an all-cash purchase is associated with a 33% shorter time to close and a 5% discount in the sales price. The estimates are robust to controlling for unobserved house and buyer attributes through a rich interaction of fixed effects as well as an instrumental variable strategy. We further find that the estimated cash discount is larger among more experienced buyers and smaller among out-of-state buyers, suggesting the importance of an informational advantage when a buyer bargains over a cash offer.

Keywords: cash, mortgage, time to close, financing risk, bargaining

JEL classification: D12, D83, G21, L85, R30

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1 Introduction

The recent decade has witnessed a steady increase in all-cash home purchases, which skyrocketed to make up nearly one-third of all home purchases in 2021.[1] While cash purchases are dominant for institutional buyers (Lambie-Hanson, Li, and Slonkosky, 2022), their fraction among individual buyers has quintupled in recent years, reaching nearly 20% of non-foreclosure transactions in Los Angeles (Figure 1). This rising trend has been mirrored in many metropolitan areas in the U.S. (Figure 2) and is likely to continue.[2] Despite the fact that cash transactions comprise about one-third of the housing market, little attention has been devoted to understanding cash purchases, contrary to the substantial literature that examines the implications of mortgage payments and related policies (Amromin et al. 2018; Gabriel et al. 2021; Hilber and Turner, 2014; Purnanandam, 2011).

Compared to a mortgage offer, a cash offer reduces *financing risk* – delays and uncertainties that a seller faces in closing a transaction when taking a mortgage offer. In a competitive market without financing risk, a seller should take the highest offer he receives, regardless of whether the offer is made with all-cash or mortgage. In reality, stringent policies for income and assets documentation for a mortgage approval can be translated into substantial costs in the closing process, which significantly delays or even entirely stalls the transaction. According to the National Association of Realtors (2016), after a seller accepted an offer from a buyer, 33% of housing transaction contracts were settled with delay, and 6% of them were terminated. In particular, "issues related to obtaining financing" accounted for 37% of the delayed transactions and 14% of the terminated transactions, suggesting the importance of financing risk. Hence, an offer could win over other offers not only through the best price but also through the fewest contingencies. An all-cash offer is the cleanest offer that a seller could obtain. Thus the speed and the discount associated with an all-cash offer relative to a mortgage offer should reflect the degree of financing risk.

In this paper, we aim to quantify financing risk by comparing all-cash house transactions

[1] "Share of homes bought with all cash hits 30% for first time since 2014" (*Redfin News*, July 15, 2021).

[2] In recent years, companies such as FlyHomes, Ribbon, and Orchard started to help homebuyers make cash offers. They buy the house with cash on behalf of the buyer who is prescreened and will pay back with a loan. See, e.g., "Seattle homebuying startup Flyhomes draws $150 million in new funding" (*The Seattle Times*, Jun 10, 2021), "In a hot market, you can buy a home with cash – even if you don't have a lot of it" (*NPR*, December 18. 2021).

with mortgage transactions in terms of the *speed of closing* and the *sales price*, using detailed housing transaction data. Among cash buyers, we further compare the estimated price discount obtained by more informed buyers with that of the less informed. Doing so allows us to examine how financing risk interacts with buyers' information, given that cash provides a powerful advantage in the bargaining process.[3]

Despite the popular belief that cash purchases speed up transactions, the evidence is scarce given the difficulty of finding readily available and high-quality data on how long it takes to close a transaction. Turning to the cash effect on the sale price, a central challenge is possible clientele effects and unobserved heterogeneity. For instance, cash buyers may self-select into homes that have unobserved poor qualities, as mortgage applications on these houses are unlikely to be approved. This leads to an overestimation of the cash discount. On the other hand, cash buyers may also represent wealthy people who have a higher willingness to pay for homes with unobserved luxury features, resulting in an underestimation of the cash discount.

To address these challenges, we estimate the effects of cash financing on both sales price and closing speed by drawing on 979,268 non-foreclosure residential house transactions with individual buyers in Los Angeles county between 2002-2016, provided by CoreLogic. The data have several advantages. First, they contain detailed transaction-level information on home purchases, including house characteristics, buyer attributes, and financing. Importantly, our data include information on the time to close, which we call the *time-to-record*.[4] This allows us to estimate the delays associated with the mortgage approval process, which is novel to the literature and provides a necessary basis for understanding the cash discount. Moreover, while the unobserved buyer attributes may result in a spurious correlation between the sales price and the decision to purchase with cash, such correlation is unlikely to concern the time-to-record since the latter is rarely a bargaining outcome. Second, by observing the same house or the same buyer in different transactions, we can further control for time-invariant unobserved heterogeneity specific to houses or buyers. The data also contain

[3]See, e.g., "Want That House? You'd Better Pay in Cash" (*Wall Street Journal*, December 5, 2017).

[4]The time-to-record is measured by the number of days between the agreement date – when a buyer and a seller agree to transact – and the recording date – when the transaction is legally recorded. In particular, the recording date is also the closing date in California. Hence, the time-to-record measures the time to close in our data.

useful information to identify different types of buyers, thereby helping us understand who are likely to be cash buyers and how bargaining with cash varies with the home purchase experience. Finally, the sample spans a boom, a bust and a recovery, thus permitting us to explore variation in cash financing at different stages of the housing market cycle.

To estimate the causal effects of cash financing, we compare the closing speed and sales price for the same house bought by buyers with different financing options and for properties bought with different financing options by the same buyer, thereby alleviating the self-selection concern and avoiding unobserved heterogeneity that may confound the estimates. Moreover, including the property tax assessment value allows us to additionally control for house attributes that are observed by consumers but not by researchers. We also use census tract fixed effects interacted with year and month to control for time-varying market conditions at the neighborhood level.

With this very rich set of controls and fixed effects at our disposal, we further strengthen our identification of the cash discount by using an instrument variable strategy. Following Bayer, Mangum, and Roberts (2021), we use buyer names to track the same individual who bought different homes at different times in Los Angeles. We find that buyers who have previously bought homes with cash are more likely to pay by cash again in their next home purchase. Controlling for buyers' wealth and previous home purchase experience, we use a buyer's prior cash purchase indicator as an instrument for her decision on whether to purchase the current house with cash, which allows us to establish the causal effects of the cash purchase on the sale price.

Several patterns emerge from our estimation. First, cash purchasers are not evenly distributed among buyers; rather, experienced buyers, out-of-state buyers, flippers, and Chinese buyers are more likely to pay with cash. The rapid growth in all-cash home transactions and their concentration among certain types of buyers contrast the housing market experience during the pre-crisis period. Second, an all-cash purchase reduces the time-to-record by about 33% and reduces the sales price by 5%, consistent with the hypothesis that cash offers reduce the delays and uncertainties that arise from the mortgage approval process.

We further explore heterogeneity in a cash discount stemming from two aspects of buyers' information: a buyer's previous home purchase experience and the geographic proximity where the buyer previously lived. The estimated cash effect on time-to-record does not vary with these information proxies, suggesting that the way we measure information is unrelated to the size of financing risk itself. This allows us to relate the cash advantage in bargaining to the buyer's information. We find that both experience and proximity matter: among local buyers, the cash discount obtained by experienced buyers doubles that from inexperienced ones; but unlike local home buyers, out-of-state buyers do not obtain a significant cash discount.

Our findings give a new meaning to the conventional wisdom that cash is king in the context of housing markets, in that cash buyers can pay a lower price by eliminating financing risk associated with a mortgage offer. Quantifying financing risk has profound implications for house price formation. In existing bargaining and auction models for housing (e.g. Albrecht et al. 2007; Carrillo, 2012), potential buyers compete only on price. Such models do not incorporate the realistic fact that buyers compete for a house along two dimensions – the price they are willing to offer and the contingencies attached to an offer. In the mortgage brokerage market, Woodward and Hall (2010) show that there is substantial room for cash payment (upfront fees) to affect the bargaining outcome on brokerage fees. In the housing market, understanding such cash discount is even more important, as the market is dominated by amateur buyers and sellers, and bargaining is important for price determination (Harding, Rosenthal, and Sirmans, 2003).

Our newly gained evidence on the cash purchases also contributes to a small but important literature on all-cash purchases by homebuyers (Asabere et al., 1992, for Upper Darby, Pennsylvania; Hansz and Hayunga, 2016, for Pinehurst, North Carolina; Reher and Valkanov, 2022, based on Zillow repeat sales in the U.S.) and by iBuyers (Buchak et al. 2021). Focusing on Los Angeles, one of the most expensive housing markets, our work complements existing studies in two ways. First, we provide novel evidence about the ability of cash buyers to close a transaction quickly. This is an important measure as it offers an explicit notion of trading delays and thus provides a basis for a cash discount. Second, we use more detailed information on different types of buyers to study the heterogeneous effects of cash financing. Our results on how the cash discount varies with buyers' information further add to the recent work on out-of-town home buyers (Chinco and Mayer, 2016; DeFusco, et. al., 2018; Favilukis and Van Nieuwerburgh, 2018).

More broadly, how collateralized borrowing affects the asset price dynamics has been a repeated theme in asset pricing literature. It has been examined in the context of a variety of markets, including stocks (Garbade, 1982), corporate asset sales (Shleifer and Vishny,1992), and land (Kiyotaki and Moore, 1995). Compared to other financial markets, housing market has been particularly relevant because many buyers have to finance their home purchase with mortgages. However, with the increasing prevalence of all-cash purchases in the recent years, a relevant question is how the cash purchase affects local house price dynamics and monetary policies. A preliminary exploration of our sample data shows that the magnitude of price reaction to a local demand shock decreases with the fraction of cash buyers, consistent with the notion that cash buyers mitigate the impact of an initial shock to local house price because their housing demand is a strictly decreasing function of house price (Stein, 1995).[5] In a similar vein, the increasing prevalence of cash financing may also mitigate the monetary policy transmission, given that the operation of such policies often relies on mortgage payments (Agarwal el al. 2022; Berger et al. 2021; Di Maggio et al. 2017). Lacking suitable detailed mortgage data, we leave examining market level implications of cash financing for future research.

The structure of the paper is as follows. Section 2 describes our data and presents the key patterns related to cash financing. Section 3 discusses the role of financing risk in housing markets and describes our empirical strategies. Section 4 reports the estimation results on the determinants of cash purchases and the degree of financing risk, as well as heterogeneous effects of cash financing across different types of buyers. Section 5 concludes.

2 Data

This section first describes our main dataset, and then examines the trends in all-cash purchases of real estate properties. Lastly, we compare cash transactions with mortgage

[5]In Online Appendix, we show that, all else equal, in areas with a 10-percentage-point lower fraction of cash buyers, it takes one extra year for the local house price to revert back to half of its long run mean. Controlling for local market conditions, in markets with a low fraction of cash buyers, not only prices react quite quickly to an income shock but also the magnitude of the reaction is so large that it entails a substantial overshooting of prices relative to their new long-run level. The price reaction in markets with a high fraction of cash buyers is much more modest.

transactions, and document stylized facts about all-cash purchase.

2.1 Data Description

The primary source of our data is CoreLogic. We obtain the data for Los Angeles county from 1999 to 2017. The CoreLogic data are constructed from deeds in the county recorder's office as well as tax assessments by county assessors. The dataset includes deed data – containing records of all deed transfers such as sales of properties – and tax data – containing house characteristics from the property assessment in 2017. The deed data include detailed information about each transaction, including sale amount, mortgage amount, property type, the location information of the property, and the names of buyers and sellers. The tax data include detailed information on house characteristics, but one caveat is that only the information from the most recent tax assessments is available. Because most house characteristics do not change over time, however, house characteristics from the tax data are used for each property in the deed data after matching the tax data and the deed data based on assessor's parcel identification number.

We focus on Los Angeles County for a number of reasons. First, it is the most populous county in the US. Second, the trend in the share of all-cash sales from our Los Angeles sample is comparable to that from the National Association of Realtors (NAR) realtor confidence index surveys that cover the entire US.[6] Third, a majority of observations in CoreLogic data for Los Angeles county do not have missing values for our key variables (e.g. cash dummy, sales price, or time-to-record), which is not the case in many other counties. In particular, time-to-record cannot be constructed from the sale date and the recording date in states where the closing precedes the recording of the deed (see footnote 13 in Section 2.3).

We use only arm's length transactions. This means that we do not use non-arm's length transactions (e.g. between family members) or deed transfers involving non-transactions such as foreclosure transfers of properties between financial institutions. Our analysis also focuses on residential properties that consist of single family homes, duplexes, and residential

[6] According to the NAR (2016, 2021) based on NAR realtor confidence index surveys, the fraction of all-cash home sales was 0.2 in 2009, 0.31 in 2013, 0.23 in 2016, and 0.24 in 2021. In our sample, the fraction is 0.1 in 2009, 0.19 in 2013, and 0.12 in 2016. Thus, both our sample and NAR surveys show similar changes over time, despite the difference in their levels. This difference may be due to the restrictions we impose on our sample (e.g. excluding foreclosure sales and institutional buyers).

condominiums. Though it would be also interesting to examine other types of properties such as commercial properties, typical buyers of these other properties are not individual home buyers.

We exclude two types of sales from our sample: those by institutional buyers and foreclosure sales. Both types of sales are featured by a high fraction of cash purchases. We exclude institutional buyers because they are investors with different objectives, financial portfolios, and tax brackets from individual buyers. We exclude foreclosed sales for two reasons. First, properties at foreclosure auctions must be purchased with cash, and hence an all-cash purchase is by requirement rather than by choice. Second, foreclosure properties are sold by banks, and therefore the discount associated with cash cannot speak for the financing risks that individual sellers face.

We further drop missing observations and outliers.[7] In addition, our final sample does not include earlier years in our data because one of our key variables is constructed using the same buyer's previous transactions. Previous transactions are unlikely to be observed for buyers who purchased houses in earlier years in our data, say in 2000, even if they had bought homes before. For this reason, our sample starts from 2002.

2.2 The Fraction of All-Cash Purchase

The CoreLogic data contain information on whether a transaction was carried out by all-cash or mortgage. Using this information, we define cash to be an indicator for all-cash purchases.[8] We further distinguish among four types of home buyers: "experienced" buyers, flipper buyers, Chinese buyers, and out-of-town buyers. Experienced buyer indicates those who purchased any real estate property in Los Angeles County in the past (during our sample period). Following Bayer, Mangum, and Roberts (2021), we use owner names to match buyers across different transactions. This allows us to identify buyers with prior

[7] Some observations do not contain sales prices or house characteristics. For some observations, only the partial amount of sales price is recorded, or the same property is sold on the same date using multiple transactions, likely involving multiple buyers, multiple sellers, or multiple deeds for the same property. All these observations are not included in our sample.

[8] Our data also include sale amounts and mortgage amounts, and so we create a separate indicator variable for mortgage amounts equal to zero. We find that both variables for cash purchase are almost identical.

purchases.[9] Flipper buyer is the buyer who sold the house within two years after purchasing the house. Chinese buyer means that the home buyer's last name is in the list of Chinese last names that we have complied.[10] Out-of-state buyers are defined to be those whose mailing address is outside California at the time of the transaction. Note that these four types of buyers are not mutually exclusive. For experienced buyers, we further consider "downsized" buyers whose previous houses had more bedrooms, more bathrooms, and larger building square footage than the current houses that they purchased.

Table 1 shows the fraction of all-cash purchases among different buyer groups. Two striking patterns emerge from this table. First, there has been an unprecedented rapid growth in all-cash transactions during the last decade for all individual buyers (column 1). This pattern is also visualized in Figure 1. The percentage of all-cash purchases in Los Angeles was less than 4% in the early 2000s and reached 2.2% in 2006, but increased to 9.9% in 2009, reaching 19% in 2013. The rapid growth in all-cash transactions is not unique to Los Angeles. Figure 2 also shows a similar pattern for several other cities, where we plot the fraction of cash purchases, using the Integrated Public Use Micro Samples (Ruggles et al. 2017) for the American Community Survey (ACS).[11] Based on the Zillow house transaction data, we also find that the fraction of all-cash purchases increased from 7.1% to 21.3% in New York City and from 7.2% to 17% in Seattle from 2004 to 2013.[12]

Second, while a similar pattern is observed for experienced buyers and downsized buyers (columns 2-3), the growth in all-cash transactions is particularly pronounced among flippers (from 4.5% to 44.7%), Chinese buyers (from 6.8% to 36.2%), out-of-state buyers (from 14.5%

[9] The matching is not perfect because we cannot separate different individuals with the same name. However, this is less problematic when we restrict the sample to one metropolitan area as in Bayer et al. (2021), rather than much larger geographical areas. In addition, we exclude those who purchased different properties on the same date since they are unlikely to be bought by the same individual.

[10] We are motivated to consider Chinese buyers because according to NAR (2015), the bulk of purchases by international clients were all-cash, and international clients from China purchased $28.6 billion worth of properties in 2015, exceeding all other international buyers. However, our data does not allow us to separate Chinese foreign buyers from Chinese local residents, so we do not interpret Chinese buyers as foreign buyers per se. Nevertheless, even Chinese local buyers may access the capital from China through family and business connections. Hence, they can still reflect capital connections from the Chinese market.

[11] For each MSA in the ACS, we use only households who moved to the current house last year and owned the house and impute the fraction of cash buyers, assuming that they are those who owned the house without any mortgage. Though the ACS provides useful estimates across different cities, one caveat is that it lacks transaction-level information, and so we cannot identify non-arm's length transactions or foreclosure sales, implying that the fraction of cash buyers from the ACS is likely overestimated.

[12] We thank Camilo Acosta-Mejia for sharing this information from the Zillow data.

to 42.1%) from 2004 to 2013 (columns 4-6). These different groups of buyers are likely to have different knowledge about local housing markets, and we expect more informed cash buyers obtain a larger discount given their informational advantage during the bargaining process, which we test in the subsequent analysis.

2.3 Cash vs. Mortgage Transactions

Table 2 reports the mean values of key variables for all transactions (column 1), all-cash transactions (column 2), and mortgage transactions (column 3). Several interesting patterns emerge from the comparison of cash vs. mortgage transactions. First, cash transactions lead to much quicker closing than mortgage transactions, as shown in the first row. Time-to-record is the number of days between the sale date and the recording date. In California, the closing of escrow occurs on the recording date when the deed and other documents are recorded at the county recorder's office, and the property is officially transferred. Note that the sale date here is the date when a transaction agreement is made between a buyer and a seller.[13] When an offer is subject to financing, it could take a significant amount of time for the bank to approve the mortgage application and transfer the funds to the seller, and a transaction could fall apart when the financing conditions are not met. The difference in time-to-record between cash transactions and mortgage transactions reflects the delay and risk that a seller faces when accepting a conditional offer subject to financing. Consistent with this, we find that on average, time-to-record is about 25 days for all-cash transactions but 36 days for mortgage transactions. In the subsequent analysis, we will further strengthen this result by controlling for observed and unobserved house heterogeneity and market conditions.

Second, the average sales prices are similar between cash and mortgage transactions. However, this does not mean that the relationship between cash purchase and sales prices is insignificant because cash transactions do not necessarily involve similar properties as mortgage transactions. The table also shows that compared to homes bought with mortgage, homes purchased with all-cash are slightly newer and larger in terms of square footage and

[13] In states where the closing precedes the recording of the deed, the sale date in the CoreLogic data could be the "closing date" when the property is officially transferred, rather than the "contract date" when both a seller and a buyer sign the sale contract. In California, however, the recording date is typically the date of transfer, that is, the closing date. As a result, the sale date in our data is not the closing date, but the contract date.

the number of bathrooms, but they are also smaller in terms of the number of bedrooms and total rooms on average. In addition, though single family homes account for the majority of residential properties in our sample, they account for relatively less cash transactions than mortgage transactions. Therefore, the discount associated with financing risk cannot be identified without controlling for significant heterogeneity in house characteristics and potentially in local market conditions. This concern will be addressed by our approach described in Section 3.3.

Third, cash transactions bring in different types of buyers relative to mortgage transactions. The bottom rows of Table 2 present the fraction of different buyer groups. Among all-cash homebuyers, about 37% are experienced, about 15% are flippers, about 25% are Chinese; and about 2% are out-of-state buyers. Compared to mortgage transactions, all-cash transactions are twice more likely to involve flippers, three times more likely to include Chinese buyers, five times more likely to bring in out-of-state buyers, and one-fifth times more likely to involve experienced buyers. For experienced buyers, we further separate buyers with only one house purchase experience in LA County in the past – single purchase experience – from those with two or more previous transactions in the past – multiple purchase experience. Cash transactions are slightly more likely to include the former type of experienced buyers, while they are almost a half times more likely to involve the latter type of experienced buyers. Note that one key difference between these different types of buyers lies in their information about local housing markets. We will explore the role of the information difference in their bargaining over financial frictions in the subsequent empirical analysis.

As shown in Table 1, an increase in cash transactions is more significant among flippers, Chinese buyers, and out-of-state buyers. Table 3, however, shows that the fraction of these buyers have changed differently over time. While the fraction of flippers is rather decreasing over time,[14] more Chinese buyers and out-of-state buyers have purchased houses in Los Angeles over time. The fraction of the latter types of buyers increased from 6.9% to 12.3% for Chinese buyers, and from 0.2% to 0.9% for out-of-state buyers between 2002 and 2016.[15]

[14]The fraction of flippers is particularly lower during the housing market crisis. However, during this period, flippers and investors are likely to have purchased more foreclosed properties that are excluded from our sample.

[15]Buyers typically use their new house address as their mailing address in the deed record, in which case we cannot identify their previous location even if they have moved from other states. For this reason, our

The difference in these patterns can reflect different housing market conditions over time as well as buyer heterogeneity that may not be related to financing risk. For this reason, we also control for different buyer types and even employ buyer fixed effects.

Note that we cannot identify experienced buyers if their previous purchase occurred only before our sample period. This issue is particularly severe at the beginning of our sample period, during which the fraction of experienced buyers may be too small. However, column 1 of Table 3 shows that experienced buyers account for about 30% of buyers, and their percentage fluctuated moderately over time. For this reason, we do not believe that this issue is critical, especially given that we do not use earlier years of our data from 1999 to 2001.[16]

3 Empirical Framework

This section begins by discussing the role of financing risk and information bias in real estate transactions. We then present our empirical approach to quantify these sources of frictions.

3.1 Financing Risk

By financing risk, we mean the delay and risk associated with getting mortgage loans approved. A typical sales agreement contains numerous contingency clauses related to the acquisition of mortgage financing. The process of securing mortgage loans is complicated and lengthy, and mortgage applications can be disapproved even after buyers and sellers agree on their sales. According to the National Association of Realtors (2016) based on NAR realtor confidence index surveys, after a transaction agreement was made, only 61% of the contracts were settled on time, 33% were not settled on time and 6% were terminated. In particular, "issues related to obtain financing" accounted for 14% of the terminated transactions and 37% of the delayed transactions.[17] This suggests that there are two layers of costs

measure of out-of-state buyers is likely to underestimate the true fraction of out-of-state buyers.

[16]Our measure of flippers also entails a similar but rather opposite issue, in that we may not be able to identify flipper buyers if they sold their houses within two years but after our sample period. To address this issue, we exclude 2017 from our final sample. We also estimate our regressions excluding 2016, but the results are very similar with or without 2016. Hence, we decided to include 2016 for our final sample.

[17]Other common reasons include "appraisal issues" (19% of delayed transactions and 14% of terminated transactions) and "home inspection" (13% of delayed transactions and 23% of terminated transactions). All these reasons are more likely to occur to mortgage financing than all-cash offers.

associated with a mortgage offer. First, a mortgage offer may not be approved by the bank, resulting in a transaction to be terminated. In this case, one would expect an all-cash offer to receive a discount that compensates the seller by removing uncertainties associated with mortgage approvals. The price after adjusting for the cash discount thus represents a seller's "certainty-equivalent" price of a risky sale that might fall apart if the mortgage financing does not go through.

In addition to the risk compensation, the cash discount also reflects the opportunity cost associated with waiting for all the contingency conditions to be met and mortgages to be approved. As seen in Table 2, all-cash transactions are associated with a significantly shorter time for a sales agreement to turn into the closing of escrow. Thus, even if a mortgage offer does not present any termination risk, an all-cash offer would still look more appealing to a seller because it avoids the cost of waiting for the payment to be fully received. In this sense, the cash discount represents a present value premium from a seller's perspective.

Based on the discussion above, we build two measures of financing risk: the time saved in closing a transaction and the price discount associated with a cash offer relative to a mortgage offer for identical homes. While the former is not a bargaining outcome, the magnitude of the cash discount depends on buyers' bargaining power. To examine this, we focus on another important friction in the housing market: *information bias.* The basic rationale is that buyers with more complete information about local housing markets should be able to gain a larger discount when they present an all-cash offer. For example, experienced buyers should have better knowledge about the housing market and real estate transactions, compared to first-time home buyers. Among experienced buyers, those who have bought houses multiple times should be more informed than those who have bought only once before. Among first-time home buyers, local buyers should be more informed than out-of-state buyers.

3.2 Econometric Model

To investigate the extent of financing risk, we consider the following regression:

$$\ln y_{jilt} = \beta_{it}\mathsf{cash}_{jilt} + X_j\alpha + G_{it}\gamma + \xi_j + \lambda_i + \theta_{lt} + \epsilon_{jilt} \tag{1}$$

where y_{jilt} is the outcome variable – either time-to-record or real sales price (in 2010 dollar) – of house j and buyer i in location l in time t, cash_{jilt} is the dummy for an all-cash purchase, G_{it} is a vector of dummy variables for types of buyers described below, X_j is a vector of house characteristics, $(\beta_{it}, \alpha, \gamma)$ is a vector of coefficients corresponding to cash_{jilt}, G_{it}, and X_j; ξ_j is unobserved house characteristics, λ_i is unobserved individual buyer characteristic, θ_{lt} is location-time fixed effects, and ϵ_{jilt} is an idiosyncratic error term. As discussed in Section 2.3, an all-cash purchase is more likely to occur among experienced buyers, flippers, Chinese buyers and out-of-state buyers. Because the outcome variable can also differ across these buyers, we include dummy variables for these buyer groups in G_{it}.

The previous section shows that the coefficient on cash_{jilt} in (1) captures the time saved in closing a transaction and the price discount due to an all-cash offer, thus likely reflecting financing risk. In particular, it suggests that the degree of cash discount associated with the financing risk varies with a buyer's bargaining power, which depends on the information that the buyer has about local housing markets and real estate transactions. Hence, following the patterns from Section 2.3, we further consider heterogeneous cash discounts that can vary across different groups of buyers. Specifically, we consider the following specification for the coefficient on cash_{jilt}:

$$\beta_{it} = \beta_0 + \beta_1 \mathsf{experienced}_{it} + \beta_2 \mathsf{flipper}_{it} + \beta_3 \mathsf{Chinese}_i + \beta_4 \mathsf{out\text{-}of\text{-}state}_{it} \tag{2}$$

In our estimation, we first consider the specification with β_0 only, and then extend the model to include the interaction terms with β_k $(k > 0)$ as well. While the cash discount may reflect both financing risk and information bias, shorter time-to-record associated with all-cash purchase is unlikely to reflect information bias. This can be tested from the coefficients on the interaction terms for all-cash and different groups of buyers as in (2).

3.3 Identification Strategies

The main challenge in estimating financing risk is that the dummy variable for an all-cash purchase is not exogenously determined and is likely correlated with unobservables in (1). Let u_{jilt} denote the error term combining all unobservables, that is, $u_{jilt} = \xi_j + \lambda_i + \theta_{lt} + \epsilon_{jilt}$. The error term u_{jilt} is then likely to be correlated with cash_{jilt} because an all-cash purchase might be more likely for houses with particular characteristics, some types of buyers, or certain neighborhoods. To address this correlation, we consider the following two sets of control variables.

First, we include very rich house characteristics in X_j, such as property sizes, the number of different kinds of rooms, [18] and information on assessed values. In particular, the assessed home value contains information about a specific house that is observable to assessors but not to the econometrician, and therefore provides a good control for unobserved house conditions.[19] Second, we include several dummy variables for different buyer groups in G_{it}, as discussed in the previous section. Some buyers may have a higher willingness to pay for the same property than other buyers, or some buyers may be better at bargaining, regardless of using cash. To the extent these buyers are more likely to purchase houses with all-cash, the error term may be correlated with the cash dummy if we do not include G_{it}.

Despite a number of variables included in control variables, they may not be sufficient to control for unobserved characteristics in house, buyer, and neighborhood, denoted by ξ_j, λ_i, and θ_{lt}. As a result, we further consider four sets of fixed effects as follows. First, we use house fixed effects for properties with multiple transactions during our sample period. This allows us to control for unobserved house characteristics not captured in X_j. Second, we also use buyer fixed effects for buyers who purchased houses in LA County multiple times during our sample period, which can account for any correlation between the cash dummy and λ_i.

Third, we include year×month fixed effects to control for time-varying market conditions in LA County in general. Fourth, we use census tract×year×month fixed effects. A census tract typically contains 1,200 to 8,000 people, and tract×year×month fixed effects can thus control for time-varying market conditions at the neighborhood level. However, it is difficult to include house fixed effects, together with tract×year×month fixed effects, since there are over 2000 census tracts in LA County and 180 months during our sample period. To control

[18]Specifically, we include the size of land; square footage information of the property; various building information, such as effective year built; #bedrooms; #rooms; #bathrooms; types of air conditioning; construction types of the property; types of the exterior walls; #fireplace; types of foundation; #parking spaces; parking types; heating types; pool; #stories; types of roof covering; roof types; kinds of view from building; location types of the parcel; types of building style.

[19]Assessed values include the logarithm of the property's land value as well as improvement.

for time-varying local market conditions together with house fixed effects, we additionally consider two control variables. Given that our key dependent variables are sales price and time-to-record, we include tract-level quarterly median price and time-to-record with house fixed effects.

These control variables and fixed effects allow us to control for potential correlations between the cash dummy and u_{jilt}, thereby identifying the cash discount associated with financing risk. Nevertheless, we further consider an instrument variable to strengthen our identification of the cash discount particularly in the regression of sales prices. Given that most variables are correlated with sales prices, it is difficult to find an instrument that is correlated with cash_{jilt} but not correlated with the sales price through u_{jilt}. One potential instrument for cash_{jilt}, however, is $\mathsf{cash}_{j'il't'}$, that is, the previous all-cash purchase decision of buyer i of house j in location l when the same buyer i bought her previous house j' in location l' in time t' ($l' \neq l$, $t' < t$). Home buyers who have previously bought with all-cash are more likely to buy their current home with all-cash due to either habit persistence or limited benefits from using a mortgage. For example, investors with multiple properties cannot claim mortgage interest deductions, in which case she may prefer all-cash to mortgage as long as she has sufficient cash holdings.

On the other hand, the buyer's prior cash purchase, $\mathsf{cash}_{j'il't'}$, is unlikely to be related to the sales price of house j in location l and time t, to the extent that her previous house j' is located in a different neighborhood ($l' \neq l$) and purchased in a different period ($t' \neq t$). One potential concern, nonetheless, is that $\mathsf{cash}_{j'il't'}$ might reflect buyer i's wealth that is likely correlated with $p_{j'il't'}$, the sales price of buyer i's previous house, while the buyer's wealth or her prior sales price might be related to the sales price of house j. We address this concern by including $\ln p_{j'il't'}$ in both the first stage regression of cash_{jilt} and the second stage regression of sales prices. One limitation of our instrument is that we cannot use observations with first-time home buyers because we do not observe their previous transactions. This also implies that $\mathsf{experienced}_{it}$ cannot be included in our instrumental variable regression since it is always 1.

Conditional on finding evidence for financing risk, we are interested in testing the information bias in the housing markets by estimating how different buyers bargain over financing risk given their different knowledge about local housing markets. To do so, we also estimate the cash discount for different types of buyers. For the experienced buyers in particular, we construct two additional dummy variables – single purchase experience for the buyer who bought only one house in LA County in the past, and multiple purchase experience for the buyer who bought two or more houses in LA County in the past.

Note that we do not attempt to quantify all the information bias associated with a specific buyer group. Our focus is rather on how these different groups of buyers bargain differently over the financing risk that they eliminate by making an all-cash offer given their relative information advantage. This helps us avoid some potential endogeneity concerns that would arise from a setting where the buyer demographics alone are used to test information bias. For example, some Chinese buyers are relatively wealthy and hence buy more expensive homes; alternatively, out-of-state buyers are not locally employed and may not have sufficient income to afford an expensive home in LA. In our setting, these effects are absorbed by the coefficients on these variables alone. In other words, we are less concerned about the presence of unobservables that could affect house prices and buyer demographics simultaneously. Rather, we would be concerned if, conditional on eliminating financing risk, some unobservables affect how different buyer groups bargain over this advantage not through information bias. In this sense, our focus on the interactions between the cash dummy and different buyer groups allows us to obtain a cleaner estimate of information advantage in house bargaining.

4 Estimation Results

This section begins by exploring factors that lead to all-cash purchase. We then quantify the delay and premium associated with a non-cash purchase for observationally identical homes and buyers, and further examine how they vary across different price segments and buyer information, using the approach described in Section 3.

4.1 Cash Purchase Decision

Table 4 reports the results from the regressions where the dependent variable is an indicator for an all-cash purchase. In the table, columns 1 and 4 control for house characteristics and assessed values. To control for unobserved house characteristics, columns 2-3 also include house fixed effects but restrict the sample to only observations with repeated transactions of the same property. Columns 2-4 include year×month fixed effects to control for time-varying factors. To further control for time-varying neighborhood conditions, column 1 includes census tract×year×month fixed effects, and columns 3-4 include the quarterly median price and time-to-record at the census tract level.

We find that cash buyers span many categories, from downsizing boomers, flippers and wealthy Chinese buyers to people moving from out of state. Four patterns emerge from this table. First, all else being equal, experienced buyers are more likely to purchase a home with all-cash than inexperienced buyers. This effect is particularly strong when the buyers are downsizing their home, consistent with the conjecture that when people trade down on the housing ladder, the wealth they have accumulated from the previous home makes it easier for them to afford the next home with all-cash. Second, on average, flippers are about 7% more likely to purchase a home with all-cash. An all-cash purchase makes it easier for flippers to sell their real estate holding in a short horizon. In addition, flippers do not enjoy mortgage interest deduction benefits if they do not buy the house as a primary residence.

Third, Chinese buyers are about 8% more likely to purchase houses with all-cash than non-Chinese buyers. While we treat Chinese buyers as an ethnically different group, we do not interpret them as foreign investors.[20] Nevertheless, buyers with typical Chinese last names are more likely to access the capital from the Chinese market through family and business connections. Thus a strong link between cash purchases and Chinese buyers could reflect both cultural behavior and capital connections from the overseas market. Fourth, we find that out-of-state buyers are about 18% more likely to use all-cash than buyers from California. Note that the fraction of out-of-state buyers in LA County during our sample period is only about 0.6%, which partly explains the large coefficient estimate on out-of-state.

Column 4 in Table 4 further includes buyer's prior cash – a dummy variable indicating whether a buyer has previously bought a home with all-cash – as well as the value of the

[20] Note that most Chinese buyers in our data have local mailing addresses at the time of the home purchase. This does not necessarily mean that they are not from China, because most buyers use their new house address as their mailing address in the deed even though they might have moved from other states or other countries. However, we cannot identify where they have moved from, and many Chinese buyers are indeed local residents in LA. For this reason, we do not consider Chinese buyers as foreign investors.

previous home of the same buyer. As expected, the coefficient on the previous cash purchase dummy is significantly positive, reflecting a strong habit persistence in home financing. Given that those who purchased previous houses with all-cash are also very likely to purchase their houses with all-cash, a buyer's prior cash can be a potential instrument for the cash dummy.

Taken together, these findings highlight four groups of all-cash homebuyers: experienced buyers, flippers, Chinese buyers and out-of-town buyers. Compared to an average local home buyer, they all differ in an important dimension: information about local housing markets. For this reason, we will explore how the capitalization of financing risk varies across these buyers.

4.2 Quantifying Financing Risk in Home Purchase

In this section, we quantify the degree of financial friction by estimating the closing speed and the discount associated with all-cash offers versus mortgage offers for identical homes. We begin with time-to-record, which indicates the number of days it takes to record a transaction in the county recorder's office after a transaction agreement is made. This reflects the time spent on a variety of activities, including clearing all the contingencies on the offer, getting the mortgage application approved and preparing for legal documents. Compared to the sales price, the reduction in time-to-record associated with cash purchase presents a cleaner measure of financing risk. In particular, since the time it takes to record a transaction is not an outcome of negotiations between a buyer and a seller, it is less likely to be affected by unobserved house or buyer characteristics. Moreover, a potential reverse causality issue discussed below concerns sales prices rather than time-to-record.

In Table 5, we regress the logarithm of time-to-record on an indicator for cash purchase. In column 1, we control for observed house characteristics and assessed home value. In column 2, we include buyer group dummies to control for observed buyer heterogeneity. In columns 1-2, we also include tract$\times$year$\times$month fixed effects to control for tract-level time-varying unobservables that might influence cash purchase decisions as well as time-to-record. In column 3, we restrict the sample to repeated homebuyers and include buyer fixed effects to control for unobserved buyer characteristics. In column 4, we restrict the sample to repeated sales and include house fixed effects. However, both buyer fixed effects and house fixed effects reduce the sample size and make it difficult to include tract×year×month fixed effects together. Hence, column 5 additionally includes tract-level quarterly median price and time-to-record to control for time-varying neighborhood conditions.

The estimated cash coefficient ranges from −0.332 to −0.369, which is remarkably consistent across different specifications. In particular, neither controlling for buyer fixed effects nor controlling for house fixed effects changes the cash coefficient substantially, consistent with the notion that the time measure suffers less from the unobserved buyer or house heterogeneity. Based on column 5, we find that, compared with a mortgage offer, an all-cash purchase cuts the time-to-record by one-third, which is capitalized into a price discount estimated below.

We now turn to sales price. In Table 6, we regress the logarithm of real sales price on an indicator for cash purchase. In column 1 where we control for observed house characteristics, assessed home value, and tract-level monthly fixed effects, the estimated cash coefficient is −0.048, indicating that, all else equal, an all-cash buyer pays 4.8% less for observationally identical homes purchased with mortgages.

A standard concern here is that the coefficient on the cash dummy can be biased in both directions. It can be biased downward if poor quality houses are less likely to get financed by mortgage loans, in which case the estimate of −0.048 could reflect a correlation between unobserved house characteristics and the likelihood of getting financed and thus cannot be used to establish the existence of financial friction. It can also be biased upward if rich people have a taste for better homes, in which case the estimated cash coefficient would be contaminated by the positive correlation between unobserved buyers' wealth/taste and unobserved house conditions, and therefore −0.048 provides only a lower bound for financial risk. Below we will explore a rich set of fixed effects specifications and an instrumental variable strategy to address the issue of reverse causality – the hypothesis that sales prices reflect unobserved house characteristics that also attract all-cash offers.

Columns 2-5 of Table 6 repeat the same specifications in columns 2-5 of Table 5, except for the dependent variable. Column 2 controls for observed buyer heterogeneity as well as tract-level time-varying unobservables that might influence cash purchase decisions and house prices. Column 3 controls for unobserved buyer characteristics, while columns 4-5 include house fixed effects to alleviate the concern that unobserved house characteristics might affect both cash purchase decisions and house prices. Column 5 additionally includes tract-level quarterly variables to control for time-varying neighborhood conditions.

The table shows that the estimated cash discount is about 5%, though it varies moderately across different columns. The specifications with a rich set of house and buyer demographics, combined with house- and buyer-fixed effects provide assurance for the estimated cash discount. Nevertheless, one may still be concerned that these approaches do not fully address the aforementioned reverse causality. For example, some time-varying unobserved house characteristics might enter both cash decisions and house prices. To deal with this final concern, we use buyer's prior cash, namely, a dummy variable that indicates whether the buyer used cash in the prior purchase, to instrument the cash dummy for the current transaction. The rationale is that a buyer who purchased a home with all-cash before is more likely to purchase a home with all-cash again, either due to habit persistence or accumulated wealth.

A legitimate concern is that buyer's prior cash might be correlated with sales prices through the buyer's wealth and preference. To address this concern, we control for the house price in the buyer's prior purchase, and further restrict the sample to repeated buyers whose previous house was located at least 10 miles from the current house and purchased more than one year ago. Thus, the underlying identification assumption is that, once we control for various factors, whether a buyer purchased a home with all-cash before is correlated with her current decision to use all-cash, but independent of the house price in the current purchase, given that her wealth is proxied by home price in her prior purchase, and the previous transaction occurred in a different neighborhood and time from the current transaction. As shown in column 4 of Table 4, our instrument is very strongly correlated with the cash dummy, indicating that whether a buyer purchases a home with all-cash is indeed related to her previous payment choice.[21]

[21] One more concern with our instrument is that we identify the buyer's prior purchase based on her name, but this approach is not perfect as mentioned in footnote 9. That is, the buyer's prior cash dummy could reflect the cash purchase of a different buyer with the same name. However, this issue may weaken the correlation between the cash dummy and our instrument, but does not result in any correlation between the instrument and the error term. Given that the instrument is strongly correlated with the cash dummy as shown in Table 4, this issue is unlikely to invalidate our instrument.

One limitation with our instrumental variable approach is that the sample size is reduced substantially, which prevents us from further including house fixed effects. Nevertheless, we rely on a rich set of observed house characteristics, assessed home values, as well as year×month fixed effects, census tract fixed effects, and the tract-level monthly median price to control for house-specific factors, time-varying factors specific to LA County, and time-varying neighborhood-specific conditions. Column 6 presents the result from the instrumental variable approach. We find that the coefficient estimate is -0.06, which is close to the cash estimate in other columns of Table 6.

To sum up, the estimated coefficient on the cash dummy ranges between -0.043 and -0.06. Across all specifications, the estimate is statistically significant at the 1% level. Given that the estimates are fairly robust and that unobserved house heterogeneity is most concerning, we choose to use the house fixed effect specification (column 5) as the baseline in the subsequent analysis. As shown in Table 5, column 5 not only yields the highest R^2 but also maintains a decent sample size, particularly compared to columns 3 and 6. Based on column 5, we find that an all-cash purchase is associated with a 5% price discount. This means that by eliminating additional time and risk involved in obtaining financing, a cash offer can outperform up to a 5% higher offer with mortgages, suggesting substantial financing risk associated with the latter.

4.3 Heterogeneous Cash Discounts Across Housing Price Segments

The previous section shows that all-cash offers can significantly reduce both time-to-record and sales price, indicating a sizable extent of financing risk faced by sellers when they take a conditional offer subject to financing. In this section, we further explore potentially heterogeneous effects of all-cash offers in time-to-record and sales price. To the extent that house bargaining focuses on sales prices rather than time-to-record, the cash discount in sales price may vary particularly across different price levels, but this may not be the case for time-to-record. A natural way to estimate such heterogeneous effects is quantile regression but our identification of the cash discount requires controlling for various fixed effects, while incorporating such fixed effects in a quantile regression is not practically feasible. For this reason, we instead consider different price segments and separately estimate the cash discount for each segment. Specifically, we divide all census tracts in the sample into four groups based on the tract-level median price, with each group corresponding to a quantile in the median price.[22]

Panel A of Table 7 presents the results. As a benchmark, column 1 in Table 7 replicates the house fixed effects specification as shown in column 5 of Table 5. Columns 2-5 use the same specification and present the cash coefficient for each price segment. Columns 2-5 show that the cash effect on time-to-record does not differ in a significant way across housing price segments, which is consistent with our notion of house bargaining that involves sales prices rather than time-to-record.

In Panel B of Table 7, we estimate a similar regression using the log of the sales price as the dependent variable. Comparing columns 2-5, we find that the magnitude of the estimated cash coefficient decreases monotonically as we move up the price segments. In particular, using all-cash is associated with a 7.7% discount in the bottom quartile, a 6.5% discount in the second to the bottom quartile, a 4.5% discount in the second to the top quartile and a 3% in the top quartile. Therefore, it is plausible that bargaining over financing risk may result in a smaller cash discount for more expensive houses in terms of the percentage, though the dollar amount of the cash discount may still be larger for more expensive houses.

4.4 Information Bias

So far we have established solid evidence for the existence of financing risk in the housing markets. The extent to which the elimination of financing risk can be capitalized into the transaction price depends on buyers' bargaining power relative to sellers, which in turn depends on information buyers have about local housing markets. More informed buyers obtain a larger surplus during the bargaining process and hence expect a larger discount associated with an all-cash purchase. In this subsection we test the presence of information bias by estimating how the discount associated with a full-cash purchase varies with buyers' information set.

Throughout Table 8, we rely on the house fixed effects to address the concerns with

[22] Alternatively, we could divide price segments directly based on sales prices, but this will put different transactions of the same house into different price segments if prices have changed significantly over time.

unobserved house heterogeneity so that we can focus on the difference in cash discount that results from the difference in buyers' information about local housing markets. Specifically, we extend column 5 of Tables 5 and 6 to incorporate two aspects of buyers' information set: previous experience, measured by single purchase experience and multiple purchase experience; and geographic proximity, measured by out-of-town. In the table, column 1 presents the results for the sales price, while column 2 reports the results for time-to-record.

Column 1 of Table 8 reveals that, in general, more informed buyers obtain a larger surplus during the bargaining process and hence pay a lower price for hedonically identical homes. The degree of cash discount increases monotonically with the intensity of the experience, with multiple purchase experience in the local area almost doubling the cash discount that she obtains. In addition, distance matters. Compared to local cash buyers, out-of-state cash buyers do not obtain a noticeable discount from an all-cash purchase, consistent with the recent literature on out-of-town homebuyers (Chinco and Mayer, 2016). Note that some out-of-state buyers might not be identified in our data and instead could be included in local buyers, suggesting potential attenuation bias in the coefficient estimate on cash$\times$out-of-state, in which case the role of information bias captured from this coefficient might be underestimated.[23]

In addition, the coefficient on cash$\times$Chinese is positive and significant, implying that, if anything, Chinese buyers tend to pay more when they purchase a home with all-cash. This could be due to a behavioral explanation that Chinese buyers may be less aggressive in bargaining. Another possibility is that some Chinese buyers receive the capital from their connections in China. In light of the growing economy and the accompanying risk in China during the recent period, buyers from China may treat real estate in LA as a safe haven for storing their financial assets. Compared with local residents, these buyers have greater access to cash financing but a relative disadvantage at the information gathering stage (e.g. geographical distance) and the bargaining stage (i.e., language barriers). As a result, they get a smaller discount from a cash-purchase conditional on housing unit location and quality.

[23]Recall that we define out-of-state buyers to be those who used out-of-state address as their mailing address at the time of purchase. However, most buyers in our data used their new house address as their mailing address. Though some of them may have moved from other states, we cannot identify these out-of-state buyers.

We also find that all else equal, an all-cash buyer obtains a 3.9% discount in a bust versus a 2.3% discount in a boom.[24] Intuitively, a bust is associated with a buyer's market where sellers are desperate to sell and buyers have more room to bargain when submitting a cash offer. Lastly, we find that flippers obtain twice more discount on an all-cash purchase compared to non-flippers. Part of their bargaining advantage could be attributed to their experience as 43.3% of flippers are also experienced homebuyers. In addition, the idiosyncratic match value from a house matters less for flippers than for a potential homebuyer, which makes the former more patient in bargaining.

In column 2 of Table 8, we estimate the effects of financing risk and information bias on the log of time-to-record. Consistent with Table 5 and Panel B of Table 7, we find that an all-cash purchase reduces the time-to-record by about one-third. In particular, this effect does not vary across different states of a housing cycle. Moreover, the information variables proxied by buyer demographics have no significant effects in the regression of time-to-record. This further suggests that the information variables we have exploited affect house prices only through their impact on buyers' bargaining power, not through amplifying or weakening the financing risk itself.

5 Conclusion

In this paper, we focus on the interaction of two important sources of frictions in housing markets: financing risk and information bias. Using transaction-level data from the Los Angeles housing market, we first document the rapid growth in all-cash transactions, particularly among experienced buyers, flippers and out-of-state buyers, which contrasts the housing market experience during the pre-crisis period. We then find that all-cash purchase is associated with a 33% shorter time to close a transaction and a 5% discount in the sales price. These estimates are robust even when we control for unobserved house characteristics and time-varying local market unobservables, using various fixed effects, or when we use instrumental variables to address potential endogeneity due to reverse causality. We further explore heterogeneity in time delay and cash discounts among different price segments and

[24]To determine the bust period, we rely on Case-Shiller Los Angeles Home Price Index, and define bust to be the dummy for the housing market downturn period in Los Angeles from September 2007 to March 2012.

buyer groups, and find that the estimated cash discount increases with experience and proximity of home buyers, suggesting the importance of information advantage when a buyer bargains over a cash offer.

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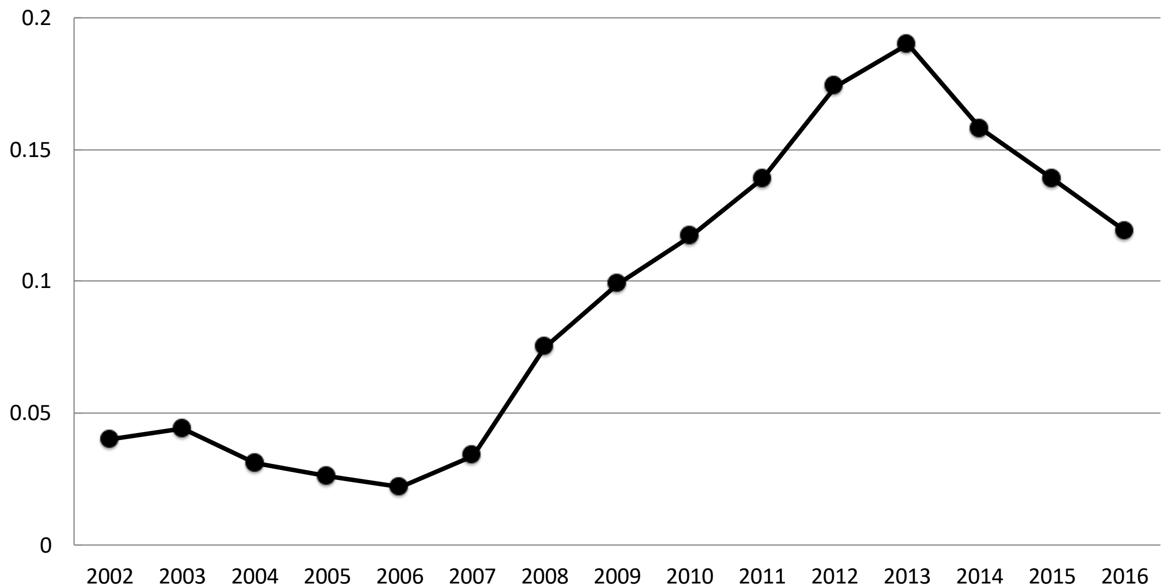
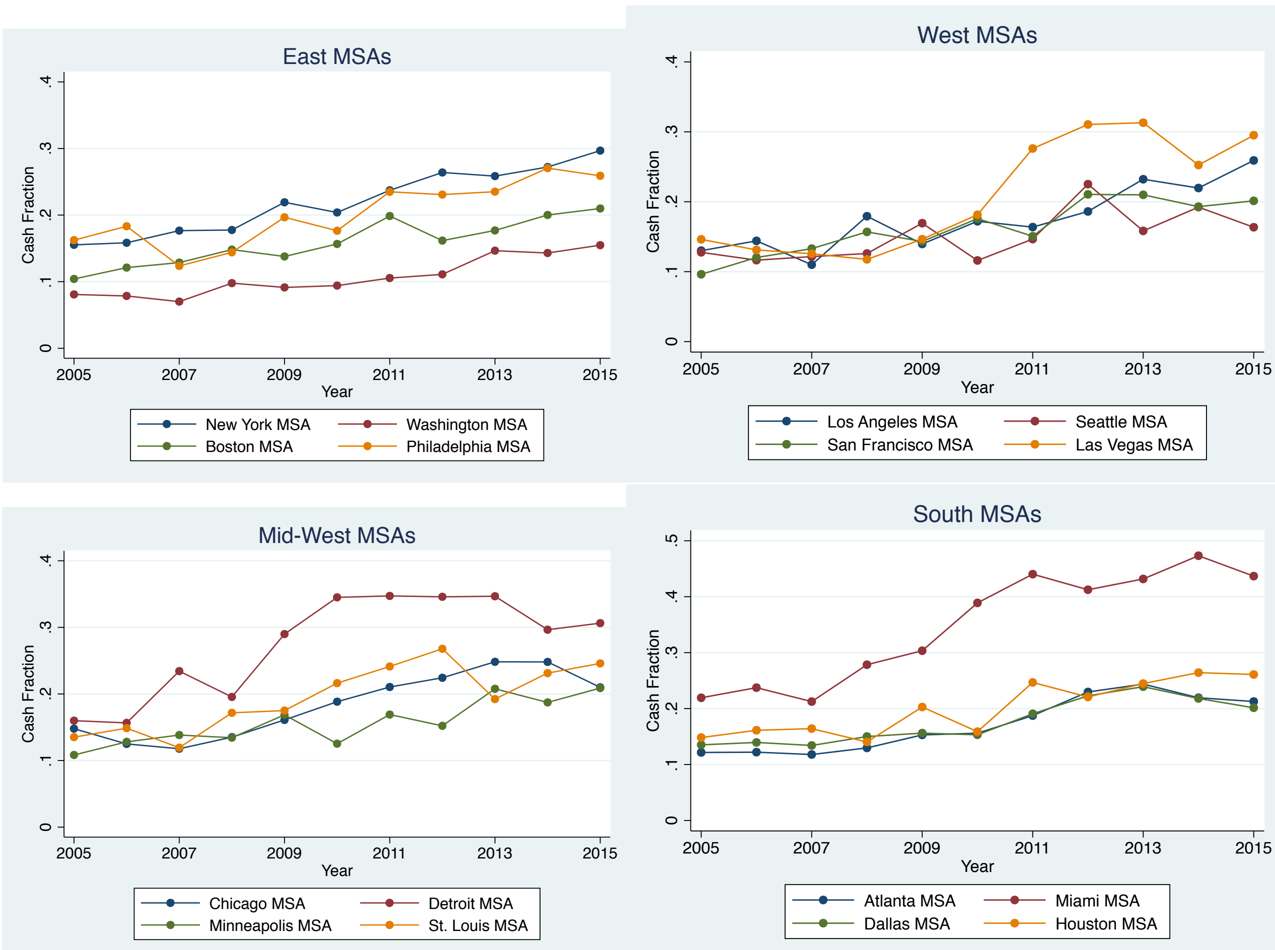
Figure 1: Yearly Fraction of All-Cash Purchase in Los Angeles[a]



[a]Source: CoreLogic. The figure plots the fraction of all-cash purchases among arm's length transactions of individual buyers who purchased residential properties in Los Angeles county. The sample excludes non-arm's length transactions as well as sales of foreclosed properties.

Figure 2: Cash Fractions in Some MSAs[a]



[a]Source: American Community Survey (ACS). Each figure plots MSA-level cash fractions in each region. The cash fraction is the fraction of households without any mortgage among all households who owned houses and moved to the current house last year. The ACS does not collect any information on the household's transaction to purchase the current house. As a result, the fraction is among all transactions, including arm's length transactions and non-arm's length transactions, as well as sales of foreclosed properties.

Table 1: Fraction of Cash Purchase Among Each Buyer Group[a]

Year	All Individual (1)	Experienced (2)	Downsized (3)	Flipper (4)	Chinese (5)	Out-of-state (6)
2002	0.040	0.048	0.058	0.070	0.078	0.181
2003	0.044	0.046	0.054	0.063	0.091	0.174
2004	0.031	0.032	0.041	0.045	0.068	0.145
2005	0.026	0.025	0.032	0.039	0.053	0.100
2006	0.022	0.022	0.030	0.028	0.055	0.210
2007	0.034	0.033	0.038	0.043	0.071	0.174
2008	0.075	0.076	0.097	0.166	0.131	0.335
2009	0.099	0.117	0.137	0.367	0.194	0.356
2010	0.117	0.141	0.173	0.427	0.235	0.414
2011	0.139	0.169	0.201	0.369	0.294	0.402
2012	0.174	0.213	0.241	0.430	0.330	0.422
2013	0.190	0.232	0.274	0.447	0.362	0.421
2014	0.158	0.183	0.211	0.346	0.357	0.372
2015	0.139	0.165	0.196	0.336	0.309	0.403
2016	0.119	0.143	0.169	0.373	0.288	0.378
total	0.080	0.096	0.114	0.132	0.210	0.324
observations	979268	306488	119662	91320	92543	5395

[a]The table reports the fraction of transactions for which purchased properties are paid by only cash. The sample includes individual buyers in arms-length transactions of residential properties, excluding sales of foreclosed properties. Column 1 reports the fraction of cash transactions among all individual buyers. Columns 2-6 report the fraction of cash transactions among different buyer groups defined as follows: experienced buyer indicates buyers who purchased any house in Los Angeles county in the past (starting from 1999); downsized buyer is the buyer whose previous house has more bedrooms, more bathrooms, and larger building square footage than the current house (since downsized buyers must have purchased houses before, they are also experienced buyers); flipper buyer is the buyer who sold the house within two years after purchasing the house; Chinese buyer means that the last name of the house owner belongs to the list of Chinese last names; out-of-state buyer is defined to be 1 if the state of the owner's mailing address is outside California at the time of the transaction.

Table 2: Summary Statistics for Cash vs. Mortgage Transactions[a]

	All (1)	Cash (2)	Mortgage (3)
time-to-record (#days)	35.56	25.34	36.46
sales price (in 2010 dollar)	$488,552	$485,042	$488,859
building square footage	1611.10	1636.90	1608.84
effective year built	1968.42	1971.29	1968.17
#bedrooms	2.99	2.89	3.00
#total rooms	3.23	2.91	3.26
#bathrooms	2.20	2.27	2.19
#parking spaces	1.07	0.98	1.08
single family house	0.69	0.59	0.70
duplex	0.07	0.08	0.07
condo	0.24	0.34	0.23
experienced buyer	0.313	0.374	0.308
experienced: single purchase experience	0.153	0.163	0.152
experienced: multiple purchase experience	0.160	0.211	0.156
downsized	0.122	0.173	0.118
flipper	0.093	0.153	0.088
Chinese	0.095	0.247	0.081
out-of-state	0.006	0.022	0.004
observations	979268	78713	900555

[a]The table reports the mean values of transaction-specific variables and house characteristics, as well as dummies for buyer types. Column 2 reports the mean of each variable among all-cash transactions, whereas column 3 reports the mean among mortgage transactions. Time-to-record is the number of days from the agreement date to the recording date when the deed and other recordable documents are recorded at the county recorder's office – in California, the closing of escrow occurs on the recording date. Sales price is real transaction price, deflated by Consumer Price Index. Effective year built is the first year when the building was assessed with its current components. Experienced, downsized, flipper, Chinese, and out-of-state buyers are defined in Table 1's footnote. Experienced: single purchase experience is the dummy for the buyer who bought only one house in LA County in the past, while experienced: multiple purchase experience is the dummy for whether buyers bought two or more houses in LA County in the past.

Table 3: Fraction of Each Buyer Group[a]

Year	Experienced (1)	Flipper (2)	Chinese (3)	Out-of-state (4)
2002	0.207	0.112	0.069	0.002
2003	0.262	0.142	0.070	0.002
2004	0.305	0.154	0.062	0.003
2005	0.357	0.132	0.061	0.003
2006	0.380	0.111	0.048	0.003
2007	0.334	0.079	0.077	0.006
2008	0.272	0.036	0.118	0.007
2009	0.250	0.024	0.137	0.005
2010	0.276	0.032	0.131	0.005
2011	0.295	0.048	0.125	0.008
2012	0.317	0.067	0.137	0.009
2013	0.348	0.077	0.154	0.011
2014	0.360	0.069	0.138	0.009
2015	0.367	0.066	0.123	0.009
2016	0.367	0.035	0.123	0.009
total	0.313	0.093	0.095	0.006
observations	979268	979268	979268	979268

[a]The table reports the fraction of each buyer group among all individual buyers of residential properties in arms-length transactions, excluding sales of foreclosed properties. Experienced, flipper Chinese, and out-of-state buyers are defined in Table 1's footnote. To identify experienced buyers and flipper buyers, we additionally use the data for 1999-2001, and 2017, but these additional years are not used in the estimation.

Table 4: Cash Purchase Regressions[a]

	dependent variable: dummy for cash purchase			
	(1)	(2)	(3)	(4)
experienced	0.006**	0.014**	0.014**	
	(0.001)	(0.002)	(0.002)	
downsized	0.024**	0.025**	0.026**	0.007**
	(0.002)	(0.003)	(0.003)	(0.002)
flipper	0.066**	0.077**	0.078**	0.091**
	(0.002)	(0.002)	(0.002)	(0.004)
Chinese	0.076**	0.087**	0.086**	0.081**
	(0.003)	(0.005)	(0.004)	(0.004)
out-of-state	0.176**	0.184**	0.184**	0.199**
	(0.009)	(0.014)	(0.014)	(0.025)
buyer's prior cash				0.148**
				(0.005)
ln(buyer's prior purchase price)				0.019**
				(0.002)
house characteristics	yes	no	no	yes
assessed values	yes	no	no	yes
year×month fixed effects	no	yes	yes	yes
tract×year×month fixed effects	yes	no	no	no
census tract quarterly median price	no	no	yes	yes
census tract quarterly median time-to-record	no	no	yes	yes
house fixed effects	no	yes	yes	no
observations	979268	500215	500215	98169
adjusted R^2	0.153	0.104	0.106	0.109

[a]The dependent variable is the dummy for whether properties are purchased by all-cash. Columns 2-3 include only observations with repeated transactions of the same property. Column 4 reports the first stage instrumental variable regression that uses only observations for buyers who purchased their previous houses at least one year ago and whose previous house was located at least 10 miles away from their current houses. Experienced, flipper Chinese, and out-of-state buyers are defined in Table 1's footnote. Buyer's prior cash is the dummy for all-cash purchase in the buyer's previous transaction, and buyer's prior purchase price is the real sales price (in 2010 dollar) in the buyer's previous transaction. Assessed values include the logarithm of the property's land value as well as improvement, all assessed in 2017. House characteristics include the followings: property type dummies; the size of land; building square footage; various building information, such as effective year built; #bedrooms; #bathrooms; types of air conditioning; construction types; types of the exterior walls; #fireplace; types of foundation; #parking spaces; parking types; heating types; pool; #stories; types of roof covering; roof types; kinds of view from building; location types of the parcel; types of building style. To compute census tract quarterly median prices (or time-to-record), we use all arms-length transactions in each census tract (including sales of foreclosed properties) and compute the median for each year and quarter. We then include the logarithm of monthly values. Robust standard errors clustered at the census tract level are in parentheses. + denotes significance at a 10% level, * denotes significance at a 5% level, and ** denotes significance at a 1% level.

Table 5: Time-to-Record Regressions[a]

	dependent variable: ln(time-to-record)				
	(1)	(2)	(3)	(4)	(5)
cash	-0.369**	-0.364**	-0.337**	-0.369**	-0.332**
	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
house characteristics	yes	yes	yes	no	no
assessed values	yes	yes	yes	no	no
tract×year×month	yes	yes	no	no	no
year×month	no	no	yes	yes	yes
buyer group dummies	no	yes	yes	yes	yes
buyer fixed effects	no	no	yes	no	no
house fixed effects	no	no	no	yes	yes
tract quarterly median price	no	no	no	no	yes
tract quarterly median record-time	no	no	no	no	yes
observations	979268	979268	338550	500215	500215
adjusted R^2	0.126	0.126	0.089	0.087	0.159

[a]The dependent variable is the logarithm of time-to-record + 1, where time-to-record means the number of days from the agreement date to the recording date when the deed and other recordable documents are recorded at the county recorder's office – in California, the closing of escrow occurs on the recording date. Column 3 includes only buyers with two or more transactions. Columns 4-5 include only properties with repeated transactions. The footnote in Table 4 provides the list of variables included in house characteristics and assessed values. Buyer group dummies include the dummy variables for experienced, downsized, flipper, Chinese, and out-of-state. Tract-level quarterly median prices and tract-level quarterly median time-to-record are computed by using all arms-length transactions in each census tract in each year and quarter. Robust standard errors clustered at the census tract level are in parentheses. + denotes significance at a 10% level, * denotes significance at a 5% level, and ** denotes significance at a 1% level.

Table 6: Sales Price Regressions[a]

	dependent variable: ln(sales price)					
	(1)	(2)	(3)	(4)	(5)	(6)
cash	-0.048**	-0.043**	-0.055**	-0.050**	-0.051**	-0.060**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.016)
house characteristics	yes	yes	yes	no	no	yes
assessed values	yes	yes	yes	no	no	yes
tract×year×month	yes	yes	no	no	no	no
year×month	no	no	yes	yes	yes	yes
tract fixed effect	no	no	no	no	no	yes
buyer group dummies	no	yes	yes	yes	yes	yes
buyer fixed effects	no	no	yes	no	no	no
house fixed effects	no	no	no	yes	yes	no
tract quarterly median price	no	no	no	no	yes	yes
tract quarterly median record-time	no	no	no	no	yes	yes
buyer's prior purchase price	no	no	no	no	no	yes
IV estimation						yes
observations	979268	979268	338550	500215	500215	98169
adjusted R^2	0.881	0.883	0.818	0.891	0.904	0.868

[a]The dependent variable is the logarithm of real sales price (in 2010 dollar). Columns 3 includes only buyers with two or more transactions. Columns 4-5 include only properties with repeated transactions. The footnote in Table 4 provides the list of variables included in house characteristics and assessed values. Buyer group dummies include the dummy variables for experienced, downsized, flipper, Chinese, and out-of-state. Tract qtr. med. price is tract-level quarterly median prices, and tract qtr. med. record-time is tract-level quarterly median time-to-record. Both median values are computed by using all arms-length transactions in each census tract in each year and quarter. Column 6 reports the instrumental variable regression that uses only observations for buyers who purchased their previous houses at least one year ago and whose previous house was located at least 10 miles away from their current houses. The instrument is the dummy for all-cash purchases in the buyer's previous transaction, while the buyer's prior purchase price is included as an additional control variable. The first regression results are reported in column 4 of Table 4. Robust standard errors clustered at the census tract level are in parentheses. + denotes significance at a 10% level, * denotes significance at a 5% level, and ** denotes significance at a 1% level.

Table 7: Regressions of Time-to-Record and Sales Price by Census Tract-level Price[a]

	All (1)	low (2)	middle low (3)	middle high (4)	high (5)
	A. dependent variable: ln(time-to-record)				
cash	-0.332**	-0.357**	-0.321**	-0.331**	-0.331**
	(0.008)	(0.018)	(0.016)	(0.016)	(0.014)
year×month fixed effects	yes	yes	yes	yes	yes
tract quarterly median price	yes	yes	yes	yes	yes
tract quarterly median time-to-record	yes	yes	yes	yes	yes
buyer group dummies	yes	yes	yes	yes	yes
house fixed effects	yes	yes	yes	yes	yes
observations	500215	126661	130134	121785	121635
adjusted R^2	0.159	0.154	0.160	0.166	0.134
	B. dependent variable: ln(sales price)				
cash	-0.051**	-0.077**	-0.065**	-0.045**	-0.030**
	(0.002)	(0.005)	(0.004)	(0.005)	(0.004)
year×month fixed effects	yes	yes	yes	yes	yes
tract quarterly median price	yes	yes	yes	yes	yes
tract quarterly median time-to-record	yes	yes	yes	yes	yes
buyer group dummies	yes	yes	yes	yes	yes
house fixed effects	yes	yes	yes	yes	yes
observations	500215	126661	130134	121785	121635
adjusted R^2	0.904	0.868	0.860	0.853	0.861

[a]Column 1 is the same as in column 5 of Tables 5-6. For columns 2-5, we divide census tracts into four groups based on tract-level median prices, and each group is included in each column: the low group includes properties located in census tracts with tract-level median prices lower than the first quartile of sales price; the middle low includes those with tract-level median prices between the first and second quartiles; the middle high includes those between the second and third quartiles; the high group includes those higher than the third quartile. The sample includes only properties with repeated transactions. In Panel A, the dependent variable is the logarithm of time-to-record + 1, where time-to-record means the number of days from the agreement date to the recording date. In Panel B, the dependent variable is the logarithm of real sales price (in 2010 dollar). Robust standard errors clustered at the census tract level are in parentheses. + denotes significance at a 10% level, * denotes significance at a 5% level, and ** denotes significance at a 1% level.

Table 8: Information Heterogeneity in Cash Payment Effects[a]

	dependent variable: ln(sales price)	dependent variable: ln(time-to-record)
	(1)	(2)
cash	-0.023**	-0.307**
	(0.003)	(0.012)
cash × single purchase experience	-0.022**	-0.016
	(0.004)	(0.020)
cash × multiple purchase experience	-0.052**	-0.026
	(0.004)	(0.018)
cash × out-of-state	0.025*	0.006
	(0.010)	(0.049)
cash × Chinese	0.046**	-0.027
	(0.005)	(0.018)
cash × bust	-0.016**	-0.025
	(0.004)	(0.018)
cash × flipper	-0.071**	-0.023
	(0.004)	(0.017)
year×month fixed effects	yes	yes
tract quarterly median price	yes	yes
tract quarterly median time-to-record	yes	yes
buyer group dummies	yes	yes
house fixed effects	yes	yes
observations	500215	500215
adjusted R^2	0.905	0.159

[a]In column 1, the dependent variable is the logarithm of real sales price (in 2010 dollar). In column 2, the dependent variable is the logarithm of time-to-record + 1, where time-to-record means the number of days from the agreement date to the recording date. The sample includes only properties with repeated transactions. Bust is the dummy for the housing market downturn period in LA County from September 2007 to March 2012. Buyer group dummies include the dummy variables for single purchase experience, multiple purchase experience, flipper, Chinese, out-of-state, and downsized. Single purchase experience is the dummy for the buyer who bought only one house in LA County in the past, while multiple purchase experience is the dummy for whether buyers bought two or more houses in LA county in the past. Robust standard errors clustered at the census tract level are in parentheses. + denotes significance at a 10% level, * denotes significance at a 5% level, and ** denotes significance at a 1% level.

Online Appendix to

"Cash is King? Understanding Financing Risk in Housing Markets"

A Potential Implications on House Price Volatility

Focusing on Los Angeles, we have found substantial effects of an all-cash payment on the individual transaction price and the speed of closing a sale. In this appendix, we extend the analysis to the market-level and examine the relationship between the fraction of cash buyers and local house price volatility. To this end, we expand the sample to 212 metropolitan areas, using the Integrated Public Use Micro Samples (Ruggles et al. 2017) for the American Community Survey (ACS) between 2005 and 2015,[A1] from which we impute the MSA-level fraction of cash buyers.[A2]

Though the ACS is useful to examine variations in cash purchase across many cities, it lacks transaction-level information. In particular, we cannot identify non-arm's length transactions or foreclosure sales, but these transactions do not typically involve mortgage, suggesting that the fraction of cash buyers from the ACS is likely overestimated. In addition, the ACS only provides housing values assessed by home owners, but these values are not only subjective, but also top-coded. For this reason, we cannot use the ACS data to examine the relationship between sales prices and all-cash purchase. Hence, our aggregate analysis in this appendix uses quarterly MSA-level housing price indexes from the Federal Housing Finance Agency (FHFA) based on transaction prices.

We begin by estimating the following GARCH(1,1) for each MSA, using quarterly MSA-level housing price indexes from the Federal Housing Finance Agency (FHFA).

$$r_{m,t} \sim N(0, \sigma^2_{m,t}), \quad \sigma^2_{m,t} = \omega_m + \alpha_m r^2_{m,t-1} + \beta_m \sigma^2_{m,t-1},$$

where $r_{m,t}$ is annual rates of changes in the log of FHFA price indexes for MSA m, computed by comparing the current quarter to the same quarter of the previous year. In a stationary GARCH process, the volatility returns back to its mean at the long-term horizon, and it is a rate regulated by $\alpha_m + \beta_m$. In particular, the half-life of the volatility shocks, defined

[A1] MSA codes are not available in the ACS before 2005. In addition, some MSAs are not observed in all years from 2005 to 2015, or contain a small number of households who moved to the current house last year and owned the house. Excluding these MSAs results in 212 MSAs for our ACS sample.

[A2] For each MSA, we count the number of households who moved to the current house last year and owned the house without any mortgage, which is mostly likely to happen if the house is purchased with all-cash. We compute the fraction of cash purchase in each MSA by dividing the number of these cash buyers by the number of all households who moved to the current house last year and owned the house in each MSA.

by $L_m^{\text{half}} = \ln(1/2)/\ln(\alpha_m + \beta_m)$, measures the average time periods for the volatility to return back to its mean value in a long run horizon. We estimate this model separately for each MSA. We were able to estimate GARCH model for 186 MSAs. For most of these MSAs, $\alpha_m + \beta_m < 1$, confirming the finding from the literature that house price follows a mean-reversion process in the long run (Glaeser et al., 2014).

Across MSAs, we compute the correlation between the GARCH $\alpha_m + \beta_m$ estimate and the fraction of cash purchase. We find that the Spearman's rank correlation coefficient is -0.132, suggesting that markets with a higher fraction of cash buyers experience less volatile house price movements. In addition, regressing L_m^{half} on the fraction of cash buyers yields the coefficient of -44.2, which implies that when the fraction of cash buyers decreases by 10 percentage points, it takes about 4.4 quarters, or about an extra year for the local housing market to revert back to half of its mean. Recall that Table 8 indicates that a bust presents an attractive opportunity for informed cash buyers to purchase houses, which increases housing demand and helps local house markets recover faster.

More broadly speaking, cash buyers play a stabilizing role in housing markets because their housing demand is a strictly decreasing function of house price. This is not necessarily the case for buyers who borrow/sell against their existing homes to purchase another home. As shown in Stein (1995), for marginally constrained mortgage buyers, housing demand is a strictly increasing function of house price. A fall (increase) in house price leads to reduced (enhanced) housing demand because it impairs (improves) their ability to borrow again their existing home. This amplifies the price sensitivity to demand shocks. In contrast, cash buyers serve as a buffer to absorb part of these shocks. To test this idea, we investigate how the cash buyers help mitigate the price response to a demand shock.

To this end, we follow Lamont and Stein (1999), and use MSA-level panel regressions to estimate

$$\begin{aligned}\Delta \ln P_{m,t} &= \beta_0 + \beta_1 \textsf{income growth}_{m,t} + \beta_2 \textsf{cash}_{m,t-1} + \beta_3 \textsf{cash}_{m,t-1} \times \textsf{income growth}_{m,t} \\ &\quad + \beta_4 \Delta \ln P_{m,t-1} + \beta_5 \textsf{price-to-income ratio}_{m,t-1} + \delta_m + \eta_t + \epsilon_{m,t}, \qquad \text{(A1)}\end{aligned}$$

where $\Delta \ln P_{m,t} = \ln P_{m,t} - \ln P_{m,t-1}$; $P_{m,t}$ is FHFA price index for MSA m and year t, deflated by the Consumer Price Index; income growth is the difference in the log of median household

Table A1: MSA-level Regressions of House Prices on Cash Fractions

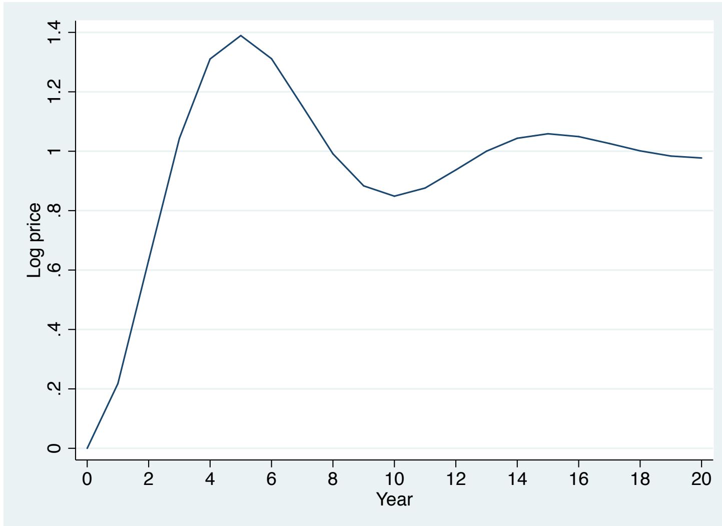
	dependent variable: change in log house price index		
	(1)	(2)	(3)
income growth	0.218**	0.237**	0.278**
	(0.018)	(0.019)	(0.028)
lagged high cash city × income growth		-0.043*	
		(0.022)	
lagged high cash city		-0.001	
		(0.002)	
lagged cash fraction × income growth			-0.228**
			(0.082)
lagged cash fraction			-0.019*
			(0.008)
lagged change in log house price index	0.688**	0.688**	0.689**
	(0.010)	(0.010)	(0.011)
lagged price-to-income ratio	-0.339**	-0.339**	-0.341**
	(0.011)	(0.011)	(0.011)
year fixed effects	yes	yes	yes
MSA fixed effects	yes	yes	yes
observations	2140	2140	2140
adjusted R^2	0.871	0.872	0.872

Notes: All variables are yearly at the MSA level. The dependent variable is the difference in the log of real house price indexes between the current year and the previous year, deflated by Consumer Price Index, where house price indexes are obtained from the Federal Housing Finance Agency. All other variables are computed from the American Community Survey. Income growth is the difference in the log median income between the current year and the previous year. Lagged cash fraction is the fraction of households without any mortgage among all households who owned houses and moved to the current house in the previous year, and lagged high cash city is equal to 1 if the lagged cash fraction is larger than the average cash fraction among all MSAs. Price-to-income ratio is the log of the ratio of house price index to median household income. Robust standard errors clustered at the MSA level in parentheses. + denotes significance at a 10% level, * denotes significance at a 5% level, and ** denotes significance at 1% level.

income; price-to-income ratio is the ratio of housing price to median household income; δ_m is MSA fixed effects, and η_t is year fixed effects. Except for $P_{m,t}$, all other variables are obtained from the ACS. For cash, we use two measures – one is the fraction of cash purchase computed for each MSA and year, and the other is high cash city which we define to be the dummy for whether the MSA's fraction of cash purchase is above the average fraction of cash purchase among all MSAs. Though we do not claim any causal effect in (A1),[A3] the

[A3]Note that MSA-level fractions of cash buyers from the ACS contain measurement errors, because they can include non-arm's length transactions and foreclosure sales from banks to individual buyers, as described above. Moreover, income growth in (A1) is not exogenous. To identify the causal effects, we would need other exogenous variables or instruments that can be applied to more wide-ranging areas.

Figure A1: Impulse Response Function: Baseline Model



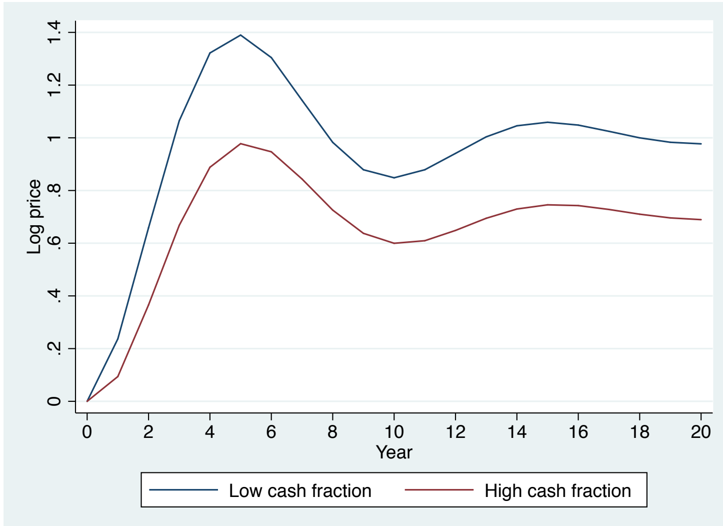
Notes: The figure plots the dynamic response of the log house price after a permanent 1% increase in median household income. The figure is based on the estimated coefficients in column 1 of Table A1.

estimates can still shed light on the implications of cash purchase on house price volatility.

Table A1 reports the results from estimating (A1), using robust standard errors clustered at the MLS level. Column 1 presents the baseline model without any cash variable. The coefficient on income growth is 0.218 and statistically significant, suggesting that contemporaneous income shocks affect housing prices. The coefficient on lagged $\Delta \ln P$ is also positive and significant, indicating that there is short-run momentum in housing prices. Lastly, the coefficient on price-to-income ratio is negative and significant, implying long-run fundamental reversion in housing price dynamics.

Using the estimated model, we further compute the impulse response function and examine dynamic response of housing prices to income shocks. Specifically, we consider a permanent 1% increase in median household income, and compute housing prices over time, where we set the initial log price and log income to be 1. We use the estimates from column 1 and plot the impulse response of housing prices in response to this income shock in Figure A1, where the y-axis is the percentage increase in housing prices relative to the initial price, that is, $(\ln P_t - \ln P_0) \times 100$. The figure shows that housing prices increase by about 0.2% in the first year, and overshoot in 3-4 years, but are eventually adjusted and have risen

Figure A2: Impulse Response Function: Low Cash vs. High Cash

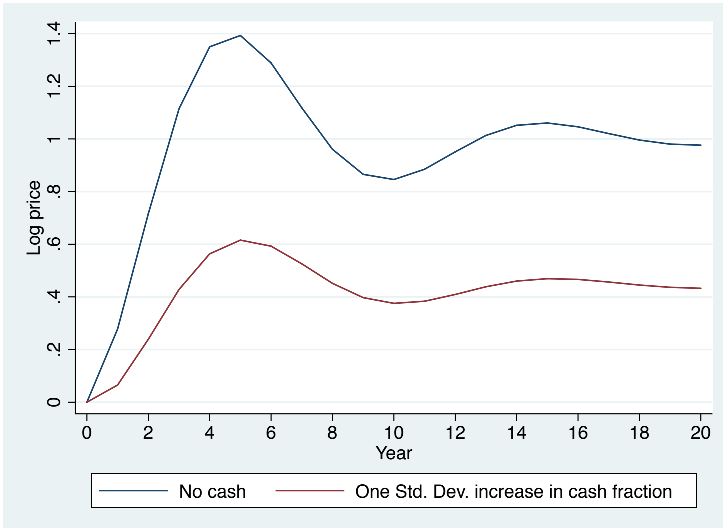


Notes: The figure plots the dynamic response of the log house price after a permanent 1% increase in median household income. The figure is based on the estimated coefficients in column 2 of Table A1.

about 1% in line with income levels. Given this baseline model, we now consider the role of cash purchase in housing price dynamics.

In column 2 of Table A1, we add high cash city, that is, the dummy for high cash cities. The coefficients on the variables used in column 1 are almost the same as before. The coefficient on the interaction between the high cash dummy and income growth is negative and significant at a 5% level. In the absence of cash purchase, income growth is likely to increase housing prices, but the presence of cash purchase seems to reduce this increase. To see this effect more clearly, we plot similar impulse response functions as in Figure A1, but consider impulse response functions separately for cities with a lower fraction of cash purchase and cities with a higher fraction of cash purchase, that is, below and above the average fraction of cash purchase. In Figure A2, the blue line for cities with a low cash fraction shows a similar impulse response function as in Figure A1. The red line for high cash fraction cities also follows a similar pattern as the blue line for low cash fraction cities. However, the red line is always below the blue line, suggesting that a higher fraction of cash purchase is likely to mitigate income shocks, and an increase in housing prices does not fully reflect income shocks.

Figure A3: Impulse Response Function: An Increase in Cash Fraction



Notes: The figure plots the dynamic response of the log house price after a permanent 1% increase in median household income. The figure is based on the estimated coefficients in column 3 of Table A1.

In the last column of Table A1, we use the fraction of cash purchase, instead of the dummy for high cash cities. The signs of cash coefficients are the same as those in column 2, but the coefficients are estimated more precisely. The estimates for income growth and cash fraction suggest that a 1% increase in income growth with no cash purchase will increase housing prices by 0.278% in one year, whereas a 1% increase in income growth together with an increase in cash fraction by a 10 percentage point – about one standard deviation – will increase housing prices by 0.065% in one year. Hence, cash purchase can weaken income shocks. Using these estimates, Figure A3 plots similar impulse response functions – one with no cash purchase, and the other with an increase in cash fraction by one standard deviation. The figure shows the significant effect of cash purchase in mitigating the impact of income shocks on housing prices.

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