Mortgage Choices and Housing Speculation*

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Abstract

We develop a model that allows for a speculative bubble in housing as an equilibrium phenomenon, i.e. when prices exceed the fundamental value of housing. When a bubble arises, it leads to the use of mortgages with backloaded payments, with or without the presence of other incentives to backload. Using data from US cities between 2000–2008 we find that the extensive use of interest-only (IO) mortgages with backloaded payments is essentially limited to housing markets with boom-bust episodes. Failure to observe the use of these contracts in such cities would cast doubt on the claim that houses in these cities were overvalued. While this does not prove houses were overvalued, given other reasons could explain IO use, we argue that the use of IOs in these cities cannot be fully explained by either income growth or because housing was becoming less affordable, and that the use of IOs led house price appreciation rather than emerged in response to it. We also find that the use of IOs is not merely reflecting growth in subprime loans, securitization, or high leverage. These findings offer support to the view that houses were overvalued in some cities during the 2000-2008 period.

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1 Introduction

The recent financial crisis has re-focused attention on the housing market and its apparent vulnerability to large price swings. As evident from the U.S. experience, such cycles can severely disrupt financial markets and adversely affect real economic activity. Economists and policymakers have therefore sought to understand when and why boom-bust cycles can arise in the housing market. Are such price movements driven by fundamentals, or do they reflect speculation in which prices increasingly drift away from the expected value of the services the underlying assets provide? Are there any indicators that can predict when such boom-bust episodes might occur if policymakers wish to intervene before they develop?

This paper examines whether mortgage data can help address these questions. Our focus on the mortgage market is motivated by research that suggests credit markets can play a key role in allowing for speculative bubbles, *e.g.* Allen and Gorton (1993), Allen and Gale (2000), and Barlevy (2011). These papers show that if traders purchase assets with borrowed funds, they may be willing to pay more for a risky asset than its expected payout given they can default if their purchase turns unprofitable. Lenders would ordinarily refuse to finance such purchases that come at their expense. But if lenders cannot distinguish speculators from profitable borrowers, they may end up financing speculators after all.

If credit plays a role in allowing for speculative bubbles, it stands to reason that credit market data may be useful for understanding such episodes. For example, if borrowers bid up house prices above their underlying value because they can default if prices collapse, one might expect boom-bust cycles to be more likely when borrowers can use greater leverage. Indeed, previous work by Lamont and Stein (1999) has found that house prices tend to be more volatile in cities where a larger proportion of mortgages are highly leveraged.\footnote{More precisely, Lamont and Stein (1999) show that house prices respond more to income shocks in cities with a larger share of mortgages whose loan-to-value ratio exceeds 80%. Their analysis is motivated by the work of Stein (1995). In his model, house prices reflect fundamentals. Down-payment constraints impede the efficient allocation of houses and make the fundamentals more volatile, similarly to Kiyotaki and Moore (1997). This hypothesis is distinct but not mutually exclusive of the forces we study.}

While previous work has focused on leverage, here we focus on the path of payments stipulated in mortgage contracts. Our motivation comes from Barlevy (2011), who argues that when bubbles arise because agents can buy assets with borrowed funds, lenders have an incentive to design particular repayment schedules on loans to speculators. We build on this insight and argue that when houses are overvalued, lenders and speculators can both be made better off using contracts with backloaded payments, *i.e.* where the initial payments are low but later payments are onerously high. The purpose of this backloading is to get...
borrowers to commit to repay their debt early when their payments rise and they must sell or refinance, in exchange for low initial payments. The reason both parties can be made better off this way is the asset is overvalued. Together the borrower and lender are no better off buying it, and once it is purchased they would be collectively better off selling it. It follows that the existence of a bubble should lead to the emergence of backloaded payments even when there is no other reason to use them. This suggests that failure to see the use of backloaded payments could, in principle, provide evidence that houses are properly valued. At the same time observing the use of such contracts does not necessarily imply houses are overvalued because there are other reasons to backload payments.

These considerations lead us to explore the use of mortgages with backloaded payments in the recent boom-bust episode in housing. As is well known, this period involved significant use of backloaded mortgages known as interest-only (IO), which require borrowers to only pay interest until some pre-specified date and only then pay back principal. We find that use of IO mortgages was highly concentrated in those cities that experienced a rapid run-up in house prices.

As an example, consider the two extreme cases of Phoenix, AZ and Laredo, TX. Laredo is a low income border city in a state with little regulation and ample space to build, so there is little scope for large house price appreciation. Although Phoenix also has ample open space, it ranks relatively high on the regulation index complied by Gyourko, Saiz, and Summers (2008), which may prevent supply from similarly reining in house price growth. Figure 1 shows the Federal Housing Finance Agency (FHFA) house price index for these two cities, deflated by the Consumer Price Index. Real house prices in Laredo grew roughly 2.5% per year between 2000 and 2008 and in Phoenix grew much faster, averaging 9.5% per year between 2001 and 2006 and rising 36% in 2005 alone, only to revert to 2001-levels by 2010. The fact that cities with geographical or regulatory restrictions on housing supply have more volatile housing prices is already well known, e.g., Krugman (2005) and Glaeser, Gyourko, and Saiz (2008). Less known and also shown in Figure 1 is that home buyers in the two cities relied on different types of mortgages. At the peak, over 40% of all new mortgages for purchase in Phoenix were IO, but no more than 2% in any given quarter in Laredo. More generally, we find that IOs were largely confined to cities with restrictions on housing supply, with higher IO use in cities where house prices grew more rapidly.

\(^2\) The same intuition implies the two parties would be even better off if the lender paid speculators not to buy the asset. In practice, though, it will be hard to pay people not to borrow without drawing in agents who have no intention to borrow in the first place.

\(^3\) The correlation between house price appreciation and the use of backloaded contracts has been previously noted in policy circles. See, for example, the Congressional testimony of Thompson (2006).
While the use of IOs in cities with boom-bust episodes is consistent with houses being overvalued in these cities, it can also be consistent with other explanations. For example, cities with boom-bust episodes may have experienced rapid income growth, leading liquidity-constrained households in those cities to seek mortgages with payments pushed off into the future. Alternatively, in cities where house prices increased rapidly, borrowers may have flocked to IOs simply because these were the only mortgages they could afford. Indeed, IOs were frequently advertised as affordability products during this time.

We argue that these particular explanations cannot fully account for the pattern of IO use we find. First, controlling for income growth or industrial composition within cities does not eliminate the strong association between IO use and house price appreciation. Essentially, there are too many cities with high income growth or booming industries where IOs were used sparingly and house prices did not surge. Conversely there are quite a few cities where IOs were used heavily but growth was not unusually high. Likewise, we argue that the use of IOs cannot be fully explained as a response to houses becoming unaffordable. Controlling for the level of house prices, both in absolute terms and relative to income, does not explain away the correlation we document. Nor do we find that an increase in house prices was followed by greater IO use. To the contrary, the use of IOs anticipates price increases in cities with heavy IO usage. This pattern can be seen in Panel A of Figure 1. The use of IOs in Phoenix began in early 2004, while house prices only took off in late 2004.

In sum, we find that in cities where house prices boomed and crashed, house purchases were frequently financed using backloaded mortgages, even before the big run-up in house prices. Our model provides one explanation for why: when houses are overvalued, lenders and borrowers both find such mortgages appealing. This does not deny that IOs also appealed to non-speculators, *e.g.* liquidity-constrained borrowers. Indeed, the fact that IOs actively traded in the secondary market suggests these contracts were not viewed as exclusively used for speculation. Nor does our model deny other potential explanations for the pattern we document, such as that some development led lenders to offer IOs, drawing in more buyers and fanning house price appreciation. However, we do show that the use of IOs is not merely reflecting growth in subprime loans, securitization, or high leverage. An important challenge for such alternative explanations, which our theory can address, is to explain why lenders would offer backloaded mortgages rather than other affordability products such as longer-

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4 The notion that IOs appeal to speculators and not just liquidity-constrained borrowers did appear to be recognized even before house prices declined. For example, Thompson (2006) notes in Congressional testimony that backloaded mortgages were not only used for affordability reasons but that “Investors also used nontraditional mortgage products as a way to purchase properties with lower upfront and monthly payments.” The Williams (2006) GAO report also notes that some borrowers who used alternative mortgage products bought homes for investment purposes, and expresses concern that they were more likely to default.
term mortgages. Backloaded mortgages are more affordable for borrowers in the short run but less affordable in the long run, leaving the lender exposed to larger losses from default while increasing the odds of eventual default.

We view the contribution of our paper as twofold. First, we document new facts about the recent boom-bust cycle in the housing market that any theory for this episode ought to explain, namely that rising house prices coincided with the use of backloaded mortgages, and that the use of these contracts anticipated rather than followed the rise in prices. Second, our paper suggests a new approach for exploring the occurrence of speculative bubbles that does not involve estimating the fundamental value of an asset and comparing it to its price. Instead, our approach looks at auxiliary behavior exhibited in choices of debt contracts that ideally should only be observed if and only if there was a bubble. While there are reasons to observe IOs even when there is no bubble, we can try to test these alternative explanations. In practice, showing that alternative explanations cannot fully account for a particular behavior such as contract choice may be easier than verifying the necessary restrictions on the stochastic process for future dividends required to infer an asset’s fundamental value.

The paper is organized as follows. In the next section, we discuss the theoretical environment that motivates our focus on backloaded payments. Section 3 describes our data and Section 4 documents the cross-sectional relationship between house price appreciation and mortgage choices. Section 5 shows that in cities where IO contracts were common, their use anticipated rather than followed house price appreciation. In Section 6 we confirm our model’s implication that IOs are more likely to be repaid early, and those that survived until prices fell were more likely to be defaulted on. Section 7 concludes.

2 Theory

Our model of speculative bubbles in the housing market builds on the risk-shifting models of Allen and Gorton (1993), Allen and Gale (2000), and Barlevy (2011). We first describe the economic environment that underlies our analysis. Afterwards we characterize equilibrium prices and explain why under under some circumstances a speculative bubble will arise in our model. Next, we show that when there is no other reason to backload mortgage payments absent a speculative bubble, the presence of a bubble implies such contracts will be used. We end with a brief discussion of how to incorporate an incentive to backload payments into our model even when house prices reflect their fundamental value.
2.1 Economic Environment

All agents are infinitely-lived, discount the future at rate $\beta$, and have preferences over a representative consumption good and housing services given by

$$\sum_{t=1}^{\infty} \beta^t (c_t + \nu I_t)$$

where $c_t$ denotes consumption at date $t$ which is the numeraire, $I_t$ is an indicator equal to 1 if the individual occupies a house at date $t$, and $\nu$ denotes the utility value of housing services and varies across types in a way we specify below. The representative agent maximizes its preferences, given an exogenous income stream and the remaining structure of the model described below, subject to its budget constraint.

Agents differ in how much they value home ownership and this preference is private information. We assume there are just two types, but this is not essential. High types strongly prefer owning to renting, e.g. because they can customize the house to their personal tastes. These agents value housing services at $\nu = (\beta^{-1} - 1) d$ if they rent and $\nu = (\beta^{-1} - 1) D$ by owning, where $D > d$. Low types derive no added benefit to owning over renting. They value housing services at $\nu = (\beta^{-1} - 1) d$ units of consumption, whether they own the house they occupy or not, and hence would pay up to $d$ to buy a house they can begin occupying next period. High types are natural owners who would hold on to their homes even if house prices fall, while low types are ordinarily indifferent between owning and renting. We assume agents can occupy only one house, although they may own multiple houses and rent some out. In addition, once high types customize their “dream” house, they cannot derive the same high flow elsewhere. This ensures that if house prices fall, high types who borrowed to buy their house will not default and move to a cheaper house.\(^5\)

We analyze a single city in isolation where there is free entry of lenders that can access funds at the risk free rate. The initial mass of houses in this city at date 0 is normalized to 1, but could in principle grow over time. This housing stock can be purchased by a number of potential homeowners, which can grow over time. Agents who do not buy a house can either rent in the city or move on to another city. The way houses are allocated before trade takes place at date 0 is irrelevant for equilibrium outcomes, so we do not specify it. We also assume an unlimited number of low types who are willing to rent a house in this city for $(\beta^{-1} - 1) d$ per period. That is, not all renters need to be potential homeowners, and homeowners can always count on finding someone to whom they can rent.

\(^5\)In practice, high types who value owning may be reluctant to default and move for other reasons, most notably because default would hurt their credit score and make it difficult for them to buy a new home.
To introduce dynamics, we need to let either the number of buyers or the number of houses vary over time. For simplicity, we assume the number of houses is fixed so that housing supply is completely inelastic. As we remark below, in the extreme case where housing supply is perfectly elastic because the cost of a new house is constant (and equal to $d$ to ensure builders cannot make infinite profits), bubbles will not arise. For intermediate cases where supply within each period is upward sloping, it is more difficult for bubbles to arise, since an overvalued asset encourages builders to create more houses and sell them at a profit. However, bubbles still can potentially arise in this case.

With a fixed number of houses, any dynamics will be driven by changes in the number or composition of buyers over time. We assume that at date 0, the number of high types falls short of the number of houses. Let $\phi_0 \in (0, 1]$ denote the mass of houses occupied by low-types or renters at date 0. We then let a random number of new potential buyers arrive each period, starting at date 0. We view this shock as the result of financial innovation that lets agents previously shut out of credit markets to now buy housing.\textsuperscript{6} However, the shock can equally be viewed as a migration wave. New potential buyers include high and low types. Since the number of potential buyers is random, agents will be uncertain whether there will ultimately be more high types or houses.

New potential buyers arrive gradually, so uncertainty as to whether there will be more high types or houses can persist. Specifically, new potential buyers arrive sequentially in cohorts of constant size $n$ until some random date $T$ that is distributed geometrically, i.e. $\Pr(T = t) = (1 - q)^{t-1} q$ for $0 < q < 1$ and $t = 1, 2, \ldots$ A known constant fraction $\phi$ of each arriving cohort are low types. Agents do not know when potential buyers will stop arriving until $T+1$, the first date in which no new buyers arrive. Up until $T+1$, the probability that new potential buyers will stop arriving next period is $q$.

To motivate a demand for credit we assume new buyers have limited resources with which to pay a downpayment, which for convenience we set to zero. Our assumption is in line with interpreting new arrivals as agents with limited credit access. The combination of uncertainty and leverage is what allows bubbles to arise, since agents who can default do not care about the down-side risk from buying assets.

We impose several assumptions that govern credit arrangements. First, we assume the fraction of low types $\phi$ is small, which ensures that equilibrium interest rates will be close to the risk-free rate given most borrowers are high types who intend to keep their homes and repay their debt. Second, we allow lenders to offer only non-recourse fixed interest rate mortgage contracts. A fixed rate mortgage contract obligates the borrower to pay a constant

\textsuperscript{6}For evidence on the expansion of credit in the period we consider, see Mian and Sufi (2009).
rate on any outstanding principal and stipulates a sequence of payments. If an agent fails to make a payment, he is found in default and ownership of the house transfers to the lender. Non-recourse means that once a lender takes possession of a house, he cannot go after the borrower’s other income sources. For now we assume both types of potential buyers receive a constant income flow, $\omega$. This is not an innocuous assumption since it implies there is no inherent advantage to backloading mortgage payments, as there might be if income grew over time. Since our purpose is to highlight the connection between overvaluation and backloading, we initially focus on the case where there is no other inherent reason to backload payments. We discuss allowing for other income profiles in Section 2.4 below.

Finally, we assume that between dates 1 and $T$, only those who just arrived can buy houses, i.e. agents cannot delay their purchases. Allowing agents to delay significantly complicates the analysis, but would not change our main result that new potential buyers are willing to overpay for houses, in a sense we make precise now.

### 2.2 Equilibrium House Prices

We now characterize equilibrium house prices with and without uncertainty in the number of new arrivals to the city. For the case with uncertainty we define a speculative bubble and show that one can arise in our model.

To understand equilibrium prices under uncertainty it is help to first consider the case without uncertainty where the number of both potential buyers and houses are constant. Since houses can always be rented out at $(\beta^1 - 1) d$ per period, there would be excess demand for houses if the price of a house were below $d$. The price that actually clears the market depends on how the number of houses compares with the number of high type buyers. If there are more houses than high types, all high types will own the houses they live in, but some houses will be occupied by low-type owners or renters. House prices will then equal $d$ because they can be no lower and by a standard argument cannot exceed $d$ without violating some agent’s transversality condition. If there are more high types than houses, all houses will be owned by high types who occupy their own homes. The equilibrium price of houses cannot fall below $D$, and the transversality condition implies it will not exceed $D$. Notice that the equilibrium price corresponds to the value the marginal buyer assigns to a house,

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7 For a discussion on recourse in the U.S., see Ghent and Kudlyak (2009). They argue that even in states that allow for recourse, lenders often find it unprofitable to go after other sources of income.

8 In particular, if the price exceeded $d$, no one will hold houses not occupied by high types unless they expect to sell these houses at even higher prices in the future. This implies there cannot be any finite date beyond which house prices always grow by less than $\beta^{-1} - 1$. But this violates the transversality condition, which holds that the value of any asset at date $t$ discounted to the present tends to 0 as $t \to \infty$. 

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which is identical to the value of relaxing the constraint on the number of houses in the city.

Non-trivial price dynamics emerge when the number of buyers is random and there is uncertainty whether the number of high types will ultimately exceed the fixed supply of houses. Define $t^*$ as the smallest integer strictly greater than $\phi_0/[n(1 - \phi)]$, the ratio of initial houses not already occupied by high types to the number of high types who arrive each period. After $t^*$ periods, all uncertainty about the housing market is resolved; if buyers stop arriving before date $t^*$, i.e. if $T < t^*$, there will be fewer high types than houses, while if buyers continue to arrive through $t^*$, i.e. $T \geq t^*$, there will be more high types than houses.

From date $t^*$ on, the equilibrium price can be determined in the same way as when the number of houses and potential buyers are constant. That is, house prices from date $t^*$ on equal $d$ if buyers stop arriving before this date and $D$ otherwise. Likewise, if buyers stop arriving on or before date $t^*$, i.e. if $T < t^*$, then the equilibrium price from date $T + 1$ on must equal $d$, since from that point on it becomes clear that there will be more houses than high types. The only prices left to solve for are those prior to min $(t^*, T + 1)$, i.e. when the number of high types is still less than the number of houses but new cohorts keep arriving.

Before solving for these prices we introduce a benchmark to compare prices against. Specifically, we define the fundamental value of housing as the value to society from an additional house in the city, i.e. the value of relaxing the constraint on the number of houses. We choose this definition because house prices must equal this value to align incentives and ensure construction of the socially efficient number of homes. As we noted above, when both the number of houses and potential buyers are constant, house prices equal this value.

Consider the fundamental value prior to date $t^*$. Since there is an unlimited number of renters, an additional house can always be used to deliver at least $(\beta^{-1} - 1)d$ in housing services per period. But in any period with more high types than houses, allocating an additional house to a high type can generate $(\beta^{-1} - 1)D$ worth of housing services. Since there are more houses than high types before $t^*$ by definition, the flow value in these periods is $(\beta^{-1} - 1)d$. After $t^*$, the flow value will be either permanently high or low, depending on whether enough high types arrived to exhaust the stock of housing. Since $p_t$ is equal to the $\phi_0$/[n(1 - \phi)]

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A more common definition for the fundamental value of an asset is the value of holding it indefinitely, taking into account the issues in Allen, Morris, and Postlewaite (1993) when different agents value the asset differently. As long as the set of rental contracts is rich enough that home owners can rent out houses to high types in a way that lets them derive a high service flow, e.g. a perpetual lease where the renter cannot be evicted as long as he meets his payments, this definition yields the same fundamental value as ours.
value of housing to the marginal buyer at date \( t^* \), the fundamental value is just

\[
f_t = \left[ \sum_{s=t+1}^{t^*} \beta^{s-t} (\beta^{-1} - 1) d \right] + \beta^{t^*-t} E_t[p_{t^*}]. \tag{1}
\]

At date 0, the fundamental value will exceed \( d \). Until date \( t^* \), \( f_t \) will keep growing if potential buyers arrive and will fall to \( d \) if they do not. If potential buyers keep arriving through date \( t^* \), the fundamental value will rise to \( D \) and stay at that value.\(^{10}\) Intuitively, if potential buyers keep arriving through date \( t^* \), a marginal house will become more valuable, since it can now be allocated to a high type. Each period beforehand in which another cohort arrives, the scenario that there will eventually be more high types than houses remains possible. Since date \( t^* \) is now one period closer, the fundamentals rise because of discounting. In addition, each arrival makes the event that high types ultimately outnumber houses more likely, so \( E_t[p_{t^*}] \) rises. At the same time, if no potential buyers arrive, the value of a marginal house will fall to \( d \).\(^{11}\) The fundamental value of the asset thus exhibits a boom-bust pattern; it can grow faster than the discount rate, but it may also collapse. The reason is that relevant information about the social value of an additional asset is gradually revealed.\(^{12}\) In principle, then, a boom-bust episode in house prices can be consistent with the price of housing properly reflecting the social value of an additional housing unit at all dates.

We define a **bubble** as a situation where the price of an asset differs from its fundamental value. While this definition is standard, it is worth emphasizing that it is distinct from the way the term **bubble** is sometimes used to refer to a boom-bust cycle. The notion of a bubble we use is meant to capture the idea that house prices fail to properly reflect their intrinsic worth, which is arguably more relevant for policy and welfare than whether prices rise and fall. In particular, an increase in the fundamental value of housing in our model signals that housing is more likely to become scarcer in the future. If housing supply is upward sloping within a period, it will be optimal to produce some additional units today for the event that more high types arrive. But a bubble in which houses are overvalued only encourages overbuilding relative to the social optimum. For policy purposes, then, it may be important to determine whether a boom-bust is associated with a bubble as we define it.\(^{13}\)

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\(^{10}\)The fact that the value remains at \( D \) forever is not essential. Our results only require uncertainty about prices at date \( t^* \). In principle, we could allow supply constraints to be temporary, so new construction would eventually drive the value of an additional house down to \( d \).

\(^{11}\)This process for fundamentals is similar to Zeira (1999). He assumes dividends keep growing until a random date, while we assume dividends can jump up at a known date with some probability. In both cases, positive news – dividends will keep growing, or the jump remains possible – raise the fundamental value, while negative news – dividends will stop growing, or the jump will not occur – lower it.

\(^{12}\)Burnside, Eichenbaum, and Rebelo (2010) offer an alternative theory of boom-bust cycles in housing that relies on the slow transmission of information as opposed to slow revelation.

\(^{13}\)While we define a bubble as a deviation between the price of housing and its *social* value, other definitions
Finally, we define *speculation* as in Harrison and Kreps (1978): speculation occurs when agents who buy an asset value the right to resell it. This definition is meant to capture the notion that agents buy an asset not just for the dividends it generates, but also because they expect that selling the asset in the future will be more profitable than holding it. This notion is distinct from that of a bubble. For example, an asset can exhibit a bubble even when agents have no intent to resell it. Indeed, Allen and Gale (2000) develop a static model in which there is no second period to resell the asset, yet an asset with a risky payoff can still trade above its fundamental value because borrowers can default if the realized dividend is low. Conversely, in our model agents can engage in speculation even if asset prices properly reflect the social value of an additional house. That is, even if house prices were always equal to the fundamental value in (1), agents could earn expected profits by borrowing to buy a house, then selling it to a high type one period later if they can and defaulting otherwise. A *speculative bubble* describes a situation in which the price of an asset exceeds its fundamental value and agents use that asset for speculation.

Under certain conditions a speculative bubble so defined arises in our model. Here we only sketch the argument. The formal analysis for this and the other propositions below is in Appendix A. First, in equilibrium both types will want to buy houses. High types want to occupy a home, while low types can profit by buying a house to sell to a high type and defaulting if no high types arrive.\(^ \text{14} \) Lenders are happy to lend to high types, but not to anyone engaged in speculation. Since lenders cannot tell types apart, they end up lending to both, but only enough to buy one house which the borrower must occupy.\(^ \text{15} \) Hence, only low types speculate in equilibrium.

In some cases, this speculative activity will cause house prices to exceed the fundamental value \( f_t \). This is because as long as a borrower owes more than \( d \), he would be better off holding on to his house for one more period to see if more potential buyers arrive than selling his property for \( f_t \). If potential buyers fail to arrive so that the price falls to \( d \), he would still have been proposed. For example, He, Wright, and Zhu (2011) develop a model with a scarcity of liquid assets that housing can alleviate. They describe a situation where house prices exceed the value of housing services, by an amount equal to the liquidity services housing provides in equilibrium. But such a bubble does not lead to oversupply of housing, nor does it encourage backloaded payment contracts.

\(^ {14} \)Such a strategy will be profitable given we assume default is costless. More generally, we can allow some cost to default if it is not too big. For example, default would be costly if there was any down payment. Alternatively, default can make it difficult to borrow or rent given the custom of some landlords run credit checks on potential tenants. In practice these costs do not appear to have completely deterred voluntary default once house prices fell.

\(^ {15} \)The fact that borrowers can only buy one house is not essential, nor is it essential that agents occupy the property they speculate on. If we added agents who can profit from managing multiple investment properties, the model would admit speculation on properties that borrowers do not occupy. However, it is important that agents be somewhat constrained so that the first cohort cannot buy up all \( \phi_0 \) houses.
benefit by defaulting and repaying his lender only \(d\) instead of what he truly owes. Since in equilibrium high types will end up with houses, all low types must eventually sell their houses if enough new buyers arrive. To get a low type who owes more than \(d\) to sell, then, the price would have to rise above \(f_t\) to induce him to give up his option to default. Hence, as long as the constant income \(\omega\) is not too large so they are unable to pay down their debts quickly, a bubble will necessarily emerge. Formally, if \(\phi\) and \(n\) are both sufficiently small, we obtain the following result.

**Proposition 1:** If each cohort of potential borrowers earn sufficiently low income, the equilibrium price \(p_t > f_t\) for \(t < \min(t^*, T + 1)\). Moreover, the bubble term \(b_t = p_t - f_t\) evolves according to

\[
\begin{align*}
    b_t &= \begin{cases} 
        (1 + g_t) b_{t-1} & \text{with probability } 1 - q \\
        0 & \text{with probability } q
    \end{cases}
\end{align*}
\]

where the growth rate of the bubble \(g_t > 0\).

The bubble in our model resembles the stochastically bursting bubble in Blanchard and Watson (1982). However, there are important differences. First, in their framework the bubble grows at a rate that only depends on \(q\) and is thus constant over time. In our model, the growth rate also depends on the option value to default for the marginal seller, and is thus time-varying. Second, their model is consistent with multiple equilibria, and says nothing about when bubbles arise or collapse. In our model the price is generically unique, and a bubble bursts because of a specific event, i.e. the failure of new buyers to arrive.

Note that our model does *not* imply every boom-bust represents a bubble. If income were sufficiently high so borrowers could repay their debts quickly, low types would still speculate, buying houses upon arrival and selling them at higher prices if new high types arrive. However, along the equilibrium path, by the time low types end up selling the houses they bought, they would owe less than \(d\) and no longer value default. The price would then equal \(f_t\), and the boom-bust would simply reflect the possibility of future housing scarcity.

In sum, uncertainty about the housing market, combined with conditions that leave agents indebted for long periods, allow speculative bubbles to arise. The constrained supply of housing underlies the uncertainty in our model, since it implies there may or may not be more high types than houses at some point. If instead supply were perfectly elastic (new housing units can be produced at a constant cost, equal to \(d\) for positive and and finite supply), arriving high types can always be accommodated by new construction. In that case, the price of housing would always equal \(d\), low types cannot profit from speculation, and a bubble would not arise. We return to the connection between supply and the possibility of price booms and busts in our empirical work.
2.3 Mortgage Contract Choice

So far, we have established the existence of a speculative bubble without specifying the exact nature of equilibrium loan contracts. This does not mean that contracts and house prices are independent; the two are jointly determined in our model. But since borrowers cannot pay more than their income, there is a natural limit on how quickly the borrower can repay his debt. As long as agents have large outstanding debt, the option to default if house prices fall remains valuable, leading house prices to rise above their fundamental value. Since the conditions for whether a bubble arises can be established independently of the exact equilibrium contract, we can use the model to explore what contracts would emerge when a bubble can arise and when it cannot.

Our main result is that the existence of a bubble leads to the use of mortgage with backloaded payments. Since by design there is no other reason to backload payments in our model, we get a particularly striking result: Contracts with backloaded contracts emerge if and only if there is a bubble, and only speculators use such contracts. As we discuss in Section 2.4, once we enrich the model so that there are other reasons to backload payments, such contracts still emerge if there is a bubble, but they can also emerge when prices reflect fundamentals.

We first need to specify the contracts agents can write. As noted earlier, we restrict lenders to non-recourse mortgage contracts a fixed interest rate and repayment schedule. Failure to make a payment transfers ownership of the house to the lender and frees the borrower of all obligations. In principle, the payments could be contingent on the relevant state of the world, which here would be the state of the housing market as summarized by $\mathcal{T}$ as well as whether the borrower sells his house. For our purposes, we need to assume lenders do not offer only contingent contracts to the exclusion of all others, since contingent contracts may allow lenders to avoid speculators altogether. For example, lenders could stipulate mortgage payments that rise with $\mathcal{T}$ or if the borrower ever sells his house. These stipulations would not matter to high types who plan to occupy the house forever and only care about their expected repayment, but they can make speculation unprofitable given it involves selling a house to new buyers if they arrive. In practice, lenders routinely offer non-contingent mortgages, presumably for reasons not captured in our model.\footnote{For example, it may be costly to condition contracts on the state of the housing market, which is why equity-like mortgages are rare. Contracts that penalize borrowers for selling the house are more common, typically in the form of a prepayment penalty. But most mortgages do not involve these penalties, presumably because some good borrowers value moving and catering to such borrowers is profitable.} As long as lenders find it profitable to offer contracts that also make it profitable to speculate, these contracts would attract speculators even if lenders also offered contingent contracts.
We therefore ignore contingent contracts in what follows. Lenders choose a fixed interest rate, \( r \), and a sequence of state uncontingent payments \( \{m_\tau\}_{\tau=1}^T \) where \( T \) is the term on mortgage to maximize returns subject to the constraint that returns are at least as large as the opportunity cost of funds, the risk free rate. Under these conditions we establish the following result in Appendix A:

**Proposition 2:** If \( p_t > f_t \), an optimal contract between a lender and a speculator signed at date \( t < t^* - 1 \) structures payments to ensure the borrower will sell the house before date \( t^* \).

To gain insight into how the presence of a speculative bubble affects the terms of contracts in equilibrium, observe that the borrower and lender are never collectively better off from having bought an overvalued asset. This is because the borrower and lender together have no debt obligation against the asset, and so they will value the asset in the same way as a low type owner who already owns a house. But in an equilibrium with a speculative bubble, such owners are always willing to sell their houses. Hence, the borrower and lender will be weakly better off not buying an overvalued asset in the first place, and once they own it they will be better off selling it.

To see what Proposition 2 implies for contracts, first consider the case where borrowers cannot refinance. We consider the refinancing case below and show that contracts with backloaded payments will be used as well. Without refinancing, the only way for a lender to induce an early sale is to stipulate a high payment the borrower cannot afford, *e.g.* with a balloon mortgage that requires the entire balance be repaid before the full term of the mortgage. High types would find balloon mortgages unappealing, since they would prefer to stay in their house indefinitely. Wanting to attract high types, lenders offer them mortgages with payments that never exceed the borrower’s income. As long as the latter contracts are offered, the contract offered to speculators must be at least as attractive. In particular, early payments must be lower than under the contract offered to high types to compensate speculators for committing to sell the asset early. Later payments will be higher than under the contract offered to attract high types. This implies the payments targeted to low types rise with \( \tau \).

To further simplify we let lenders choose from only two repayment schedules, as well as the interest rate to charge – one schedule with constant payments and one with an interest-only (IO) feature in which the borrower only pays interest for the first \( T_0 \) periods, and then
repays as under a traditional mortgage with term $T - T_0$:

$$m_\tau = \begin{cases} 
  rL & \text{if } \tau = 1, \ldots, T_0 \\
  \frac{r(1 + r)^{T - T_0}}{(1 + r)^{T - T_0} - 1}L & \text{if } \tau = T_0 + 1, \ldots, T 
\end{cases}$$

Although our theory naturally suggests using a balloon payment to achieve the optimal contract, such mortgages were not especially popular in the past decade. One reason might be that the way balloon mortgages were structured fails to sufficiently reward borrowers for committing to sell early; they typically offered only a slightly discounted interest rate over mortgages with otherwise identical terms, so payments were lower than traditional mortgages but not substantially. The far more common backloaded mortgage product instead was the IO mortgage. Such a contract could be optimal even without a balloon if the jump in payments once the IO feature expires is sufficiently large. In practice the rise in payment was often unaffordable for borrowers. In line with this, we restrict lenders to IO contracts and assume borrowers cannot meet the first payment at date $T_0$. Allowing lenders to also offer traditional mortgages is natural given our assumption that borrowers’ income is constant. In equilibrium, lenders will want to offer high types mortgages that are as unattractive to speculators as possible; otherwise, a lender could skim off high type borrowers. But the least attractive contract for speculators is the one that imposes the fastest repayment possible. Such a contract would set payments equal to income. Therefore with constant income, the payment in the mortgage targeted to high types must be constant.

Under these assumptions on the set of admissible mortgage contracts, we can show that if both lenders and borrowers prefer some IO contract to a fixed payment mortgage with the same interest rate, then in equilibrium lenders will offer both fixed and IO mortgages. High types choose the fixed mortgage and low types choose IOs. IOs will carry higher rates.\(^{17}\)

The fact that the equilibrium is separating may seem surprising: Why don’t lenders offer only the mortgages that high type borrowers take? The answer is that in equilibrium, low types are indifferent between the two mortgages and would be willing to take either. In equilibrium lenders must expect speculators to accept fixed-rate contracts with positive probability if only offered those, or else all lenders would offer only the fixed-rate contract, which low types would take if that was the only contract available. Hence, lenders don’t expect they can avoid speculators by only offering mortgages with constant payments.

We now turn to the case where borrowers can refinance. Refinancing imposes additional constraints on the lender’s problem. Suppose lenders try to offer the same contracts as when there is no refinancing. If the two types continued to choose separate contracts, they would reveal their types. Low types would then be unable to refinance, while high types could get new loans at risk-free rates. This would be a problem for lenders, since they need the remaining flow of profits from high types to cover the losses on low types. In addition, if choosing the contract targeted to high types allows a borrower to refinance, low types may have incentive to pretend to be high types. But lenders can avoid this by charging a higher interest rate to high types. After one period, high types can and will refinance to loans at the risk-free rate, but the original lender will have already booked all the profits he needs from high types to cover losses on low types. At the same time, low types would find the prospect of taking this contract and then refinancing less appealing than the contract offered to high types where there is no refinancing, since frontloading interest charges makes speculation less profitable.

Refinancing thus does not preclude lenders from offering mortgages with backloaded payments. Rather, refinancing helps lenders; it allows high types to more easily distinguish themselves by accepting a higher up-front interest rate they later refinance, a feature low types dislike. However, low types can still earn profits by pretending to be high types, so refinancing does not preclude speculation. In equilibrium low types continue to receive a backloaded contract although possibly at different terms than when refinancing is not allowed.

Earlier we argued that when incomes are constant there is no reason to backload payments in our model absent a bubble. The next proposition shows this formally.

**Proposition 3:** Suppose \( p_\tau = f_\tau \) for all dates \( \tau \). Then the sum of the expected utility of the borrower and lender is constant, so if a mortgage contract makes one party better off relative to some benchmark contract, it must make the other party worse off.

Intuitively, since the borrower and lender are no longer jointly worse off from buying the asset, there is no scope for gains from forcing an earlier sale as there is when the asset is overvalued. Note that Proposition 3 does not tell us what mortgages we should observe when there is no bubble. However, when housing supply is constrained so that \( f_t \) exhibits a boom-bust pattern, the model predicts all borrowers will take the fixed payment mortgage.

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18This discussion reveals that restricting lenders to a single interest rate is not innocuous, since a declining path for interest rates could be used to frontload charges and make speculation less profitable. We rule out such contracts for the same reason we rule out contingent payment contracts, namely that mortgages with deterministically declining interest rates are rarely offered in practice.
The reason is that high types will prefer these contracts to an IO contract that forces them to sell their house. Lenders will therefore offer fixed-rate contracts to draw these types. As for low types, lenders either prefer to offer them fixed rates contracts, so only fixed rates contracts will be offered, or they prefer to offer them IOs, but by Proposition 3 low types must prefer fixed-rate contracts and would choose those. Either way, a boom-bust that reflects fundamentals will not be associated with the use of backloaded payments.

2.4 Introducing Additional Types of Potential Buyers

Our analysis so far shows that when there is no inherent reason to backload payments, a bubble will give rise to such contracts. In reality, there are multiple reasons to rely on backloaded payments. Indeed, IOs were routinely traded in the secondary market, suggesting traders did not expect negative returns from holding such mortgages. Similarly, borrowers who took out IOs were often able to refinance. A realistic model of the housing market would thus require introducing these alternative reasons for backloading. However, adding these reasons would not change our basic point that overvaluation offers an independent reason why contracts should feature backloaded payments in equilibrium.

For example, suppose we introduced high type potential buyers who value housing services but whose income rises over time. In particular, suppose their income is less than $\omega$ for the first few periods after arrival, but earn considerably more thereafter. As with the other types, suppose these potential buyers cannot delay their purchases. In this case, high types with flat income profiles would continue to receive fixed payment mortgages that stipulate debt be repaid as quickly as possible. Low types and high types with rising income will receive backloaded contracts. Whether they end up with the same contract depends on the income process of liquidity constrained high types. Hence, backloaded contracts will be used, regardless of whether house prices reflect fundamentals. Moreover, some backloaded contracts can trade in the secondary market, and those who take out these contracts might be able to refinance their loans. The key implication we take from the model is not that IOs uniquely identify a speculative bubble or are used exclusively by speculators, but that they will appeal to speculators during a bubble. As such, interpreting the use of these contracts as evidence of speculation requires showing that other explanations cannot fully account for the use of such contracts.

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19 As a caveat, those who purchased these mortgages were often leveraged themselves, and so may have willing to buy them even if expected returns were negative. Landier, Sraer, and Thesmar (2011) argue that lenders gambling for resurrection had incentive to hold backloaded mortgages, including IOs.
3 Data

This section describes the data on house prices, mortgages, and city characteristics that we use to explore the implications of our model. More details are in Appendix B.

3.1 House Prices

For house prices, we mainly use the Federal Housing Finance Agency (FHFA) house price index, previously known as the OFHEO index. The FHFA house price index is compiled quarterly from house prices for mortgages purchased or securitized by Fannie Mae and Freddie Mac. Since we are interested in real house prices, we deflated the FHFA index for each city by the national Consumer Price Index. The FHFA house price index has several advantages. First, it is a repeat-sales index based on the change in price for the same home over time. This makes it robust to changes in the composition of houses sold over time. Second, the index tracks a large number of cities over a long time period. Third, the FHFA index is publicly available and widely used. However, the index also has some well-known shortcomings. For example, it excludes homes that were financed with non-conforming mortgages such as jumbo or subprime loans. Such homes are included in other price indices, e.g. the Case-Shiller index, the Zillow Home Value Index, and the CoreLogic House Price Index. The Case-Shiller index is only publicly available for 20 cities. Still, we confirmed that for these cities, the rate of price appreciation during the boom phase was similar to the FHFA index. The Zillow Home Value Index and the CoreLogic House Price Index are available for more cities, and we confirmed that using these did not change our results.\footnote{We explored two other issues concerning the FHFA index. First, the index relies on both market transactions and appraised home values from refinances. The FHFA also reports a purchase-only house price index for 25 cities based solely on transaction prices. Our price growth measures based on the two indices are almost perfectly correlated for the cities where both are reported. Second, the FHFA index uses a simple average of house price appreciation rather than weighting by house value. We therefore looked at the Conventional Mortgage House Price Index, which is essentially a value-weighted version of the FHFA index. Again, we found that our price growth measures were nearly identical to those based on the FHFA index. This is consistent with the fact that we obtain similar results for the CoreLogic house price index, which is only based on transactions prices and is value-weighted.}

To capture house price appreciation in each city with a single statistic, we first identified the peak real price between 2000q1 and 2008q4 for each city. We then computed the maximum 4-quarter log real price growth between 2000q1 and the city-specific peak. That is, we summarize the rate of price appreciation during the boom for each city as the fastest rate at which real house prices grew within a 4-quarter window. We also considered the average price appreciation between 2000q1 and the peak, and below we discuss the implications for
our results of using this measure. The reason we prefer the maximum 4-quarter growth rate is that it picks up especially rapid house price growth concentrated over a short time period. That is, given two cities with the same average growth rate, this measure ranks a city higher if house prices grow slowly at first but then surge. Maximal 4-quarter price growth seems to better identify those cities that are often singled out for the boom-bust cycle they experienced. For example, the two cities with the highest maximal 4-quarter price growth are Las Vegas and Phoenix, respectively, yet these cities rank only 53rd and 57th in terms of their average price appreciation from 2000 to their peak, respectively.

3.2 Mortgages

For mortgage data, we use the Lender Processing Services (LPS) Applied Analytics dataset, previously known as the McDash dataset. The data consists of information on mortgages from the servicers who process mortgage payments, including all 10 top mortgage servicers, and covers about 60% of the mortgage market as compared with mortgage totals reported under the Home Mortgage Disclosure Act (HMDA). However, the dataset is not meant to be a representative sample. Indeed, it underrepresents mortgages held by banks on their portfolios, since smaller and mid-size banks often service their own loans and do not report to LPS. The dataset also appears to undersample subprime mortgages, which again tend not to be serviced by those firms that report to LPS. Since our analysis uses variation across cities, this should only compromise our analysis if selection varies systematically across cities. Still, we verify that our results are robust to measures of subprime shares compiled from completely different sources, as we discuss below.

From this data, we want to construct a measure of how pervasive the type of backloaded contracts implied by the model were in each city. For this, we first need to take a stand on what mortgages should count as backloaded. There are several mortgage products that involve unambiguously backloaded payments. One such mortgage is the graduated payment mortgage, first introduced in the 1970s. As suggested by its name, this mortgage offered payments that gradually increased over the duration of the loan, often during the first five years. However, these mortgages were rarely used in the period we look at. Another backloaded contract is the balloon payment mortgage, which typically requires full repayment of the loan before the term of the mortgage. As we noted in the previous section, a balloon payment would be ideal for ensuring a speculator would repay his loan. In practice, however, these too were not very common, and we conjectured above that the interest discount on these mortgages may not have been enough to reward speculators for committing to repay early. By far the most commonly used backloaded contract during this period appears to be
the IO mortgage, in which the borrower only pays interest for some specified period and then repays both principal and interest. A related but less widely used product is the option-ARM mortgage, which for some initial period gives the borrower the option to pay both principal and interest, interest only, or even less than the required interest so the borrower increases his obligation, typically up to some maximum limit. Table 1 reports some characteristics for IO and option-ARM mortgages, as well as fixed-rate and adjustable-rate mortgages. Note that some IOs and option-ARMS are reported as far back as 2000, confirming that these mortgages were not new but rather existing products whose use suddenly took off.

Although all of these mortgages rely on backloaded payments, we focus exclusively on IOs in our empirical work. Adding graduated payment mortgages and balloons would have little effect on our results given how few such mortgages there are compared with IOs. Incorporating option-ARMs would matter more, but we chose to omit these as well in most of our analysis. We do this for two reasons. First, LPS only began to identify mortgages as IO or option-ARM from 2005 on. Mortgages that originated and terminated before January 2005 are not classified. However, we can still detect IO mortgages using the scheduled payment, since the scheduled payment for an IO equals the interest rate times the loan amount for IOs. Unfortunately, there is no analogous way to identify option-ARMs. Thus, we trust the time series on IOs more than we do the series on option-ARMs. Second, as suggested by Table 1, the two types of mortgages apparently served different purposes. In particular, option-ARMs were much more common among subprime borrowers and tended to be associated with high rates of prepayment penalties. The latter is inconsistent with the notion that backloaded contracts were designed to induce early repayment of the loan. By contrast, slightly fewer IOs were subprime than among mortgages as a whole, and the fraction of IOs with prepayment penalties is only a little higher than the fraction for all mortgages. Thus, IOs seem closer to the type of backloaded contract in our model. Amromin, Huang, and Sialm (2010) report additional evidence in support of this view. They find that IOs tended to go to borrowers with higher income and credit scores than option-ARM borrowers. That

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21 In private correspondence, Paul Willen also pointed out that option-ARM mortgages before 2003 were largely held in portfolio because these mortgages were readjusted monthly, providing a better hedge for lenders against interest-rate movements than conventional ARM mortgages. Since loans held in portfolio are underrepresented in LPS, the data is likely to misrepresent the time series pattern for these mortgages. The same point does not apply to IOs. Willen’s point is mirrored in press releases from Golden West Financial Corp, one of the leading issuers of option-ARM mortgages prior to 2003. See, for example, the note “History of the Option ARM” at http://www.goldenwestworld.com/wp-content/uploads/history-of-the-option-arm-and-structural-features-of-the-gw-option-arm3.pdf

22 Prepayment penalties come in two varieties; hard penalties, which penalize any early repayment, and soft penalties, which waive the penalty if the house is sold. Anecdotal evidence suggests that penalties on option-ARMs were increasingly shifted towards the soft variety, i.e. lenders were allowing more borrowers to sell the asset without penalty. Still, our model suggests lenders would want speculators to refinance.
said, we did repeat our analysis using the combined share of both types of mortgages, as well as for the share of IOs and option-ARMs that did not involve a prepayment penalty. The results were similar to what we found for IOs.

To capture the use of backloaded mortgages in each city, we use the share of IOs in all first-lien mortgages for purchase (as opposed to refinancing). We also considered the share of IOs weighted by loan size, but this ratio proved similar to the unweighted share.\textsuperscript{23} When we need to summarize the use of IOs with a single statistic in our cross-sectional analysis, we use the highest share of IOs in each city in any quarter over the sample period.

We constructed analogous statistics for other relevant mortgage characteristics. Specifically, the shares of first-lien for-purchase mortgages with a 30-year hybrid repayment (so-called 2/28 and 3/27 mortgages with a fixed rate for 2-3 years followed by an adjustable rate), the share of mortgages with a term of 30 years or more, the share of subprime mortgages, the share of mortgages reported as privately securitized one year after origination, and the share of mortgages by non-occupant investors.

Finally, we constructed a measure of the degree of leverage for each city. For this, we consider the combined loan-to-value (CLTV) of all loans against a given property. Unfortunately, LPS does not match liens taken against the same property. We therefore turned to the LoanPerformance ABS database on non-prime privately securitized mortgages. This data is reported by trustees of privately securitized mortgage pools rather than servicers, and does report the CLTV for each loan. Thus, we have data on total leverage for each city, but only for non-prime mortgages, which includes a mix of Alt-A mortgages for borrowers with high credit scores together with subprime mortgages for low-quality borrowers. Following Lamont and Stein (1999), we look at the share of mortgages in each city with a CLTV exceeding 80%. Our summary measure for CLTVs is the average share rather than the maximum share we use for the other mortgage characteristics.\textsuperscript{24} Table 2 reports descriptive statistics for how all these summary statistics are distributed across the cities in our sample.

3.3 Other Data

Lastly, we compiled data used in previous studies to explain house price appreciation across cities, e.g. Case and Shiller (2003), Himmelberg, Mayer, and Sinai (2005), and Glaeser et al.

\textsuperscript{23}This might seem to contradict the fact that average IO loan in Table 1 is larger than the average loan across all mortgages. But recall that IOs were more common in relatively expensive cities. Within cities, IOs do not appear to systematically involve either larger or smaller loans.

\textsuperscript{24}The reason is that this series is based on non-prime mortgages, a relatively small market in the beginning of our sample. The maximum share is thus particularly prone to outliers.
Our variables include real per capita income, unemployment, population, property tax rates, the share of undevelopable land due to water or steep land terrain as compiled by Saiz (2010), and the Wharton Residential Land Use Index from Gyourko et al. (2008).

4 Cross-Sectional Evidence

In this section, we lay out the evidence on the relationship between the use of IOs and house price changes in the cross-section of cities. In particular, we seek to establish whether rapid price appreciation was associated with high use of IO mortgages, and if so whether this association can be explained by various observed variables. Our purpose is only to document this correlation; we lay no claims to estimating any causal relationships.

4.1 House Prices, IOs, and Housing Supply

As a first step, we split the sample into cities with relatively elastic and relatively inelastic housing supply. Specifically, we classify cities as having elastic housing supply if they rank in the bottom half of all cities both in the share of undevelopable land and in their respective Wharton Regulation Index. Similarly, we identify cities in the top half of both measures as having relatively inelastic supply. Figure 2 plots our preferred measure of price appreciation against the maximal share of IOs in each city. As evident from the top panel, cities with few restrictions on supply exhibit low rates of house price appreciation, in line with earlier work by Glaeser et al. (2008). However, Figure 2 also shows that these cities tended not to use IOs. By contrast, cities with more restricted supply exhibit wider variation in both house price appreciation and IO usage, as evident from the bottom panel of the figure. However, IO use seems to go hand-in-hand with high price appreciation. Essentially, IOs were only used in cities where housing supply is inelastic, and then only if house prices grew rapidly.

4.2 Baseline Estimates

For a more rigorous analysis, we regressed the maximal rate of house price appreciation on the maximum share of IOs, using data for all of the cities in our sample, with controls for various city characteristics, including those related to supply elasticity. We report our results in Table 3. The first column shows that the positive relationship between house price appreciation and IO contracts remains when we expand our sample to all cities. The coefficient on the share of IOs is statistically significant at the 1% level. To help interpret...
the coefficient of .410, note that the difference between the largest and smallest maximal IO share in our data is equal to \(0.612 - 0.015 = 0.597\). Multiplying this by .410 implies that the maximum 4-quarter growth rate in the city with the largest share of IO mortgages should exceed the rate with the smallest share by \(\exp(0.245) = 27.8\%\). This is comparable to the difference in peak growth rates between Phoenix (36%) and Laredo (7.8%) in Figure 1.

Of course, some of the variation in house price appreciation might be due to differences in factors that naturally affect the value of housing services in a city. We therefore add a set of covariates used in previous studies to see whether IOs are used in cities with high rates of price appreciation that cannot already be explained by these covariates. The second column in Table 3 shows the explanatory role of these variables measured both in levels and in annualized changes between the beginning of our sample and the respective date at which house prices peak in each city. The change in population growth, unemployment, and property tax rates all enter significantly with the expected signs, as do the two supply variables we use. Interestingly, the \(R^2\) for these variables is not much larger than for the share of IOs by itself.

In the third column of Table 3, we use these variables as controls in regressing price growth on IO usage. The coefficient on the share of IOs is smaller than in the first column, although we cannot reject that the two coefficients are equal at the 5% level. More importantly, the coefficient remains tightly estimated and significantly different from zero. That is, the share of IOs is significantly related to the residual variation in house price appreciation that cannot be explained by the set of covariates typically used to explain house price appreciation. Note that accounting for the share of IOs renders the two supply variables we use statistically insignificant. In other words, once we know which cities relied on IOs, additional information on the elasticity of housing supply does not help to better predict which cities experience house price booms. In the last column, we add state fixed effects to focus on variation from cities in the same state. The coefficient falls to .22, but remains highly statistically significant. These findings confirm that greater use of IOs tended to be associated with larger house price appreciation.\(^{25}\)

\(^{25}\)We also added as a control the city-specific house price growth between 1985 and 1989, when national house prices also exhibited a boom-bust pattern. This variable may capture omitted variables that indicate a propensity towards boom-bust patterns. When we omit the share of IOs, this variable is indeed significant. But once we include the share of IOs, price growth during this last period turns insignificant, and the coefficient on the maximal IO share is nearly identical to that in Table 3.
4.3 Controlling for Other Mortgage Characteristics

Are IOs proxying for other mortgage characteristics? For example, if subprime borrowers could only afford IO mortgages, the use of IOs may simply reflect a high share of subprime mortgages. We now add several alternative mortgages characteristics to our baseline regression to show that IOs are not simply proxying for some other aspect of mortgage markets.

We consider several alternative mortgage characteristics. First, we consider mortgage products designed to lower lower payments for borrowers, in order to gauge whether the use of IOs is simply picking up a shift towards mortgages with lower payments. In particular, we look at the share of mortgages in each city that involve a hybrid of fixed and variable interest rates and which tended to offer lower rates compared to fixed-rate mortgages, as well as the share of long-term mortgages with terms of at least 30 years.

We also consider several variables related to explanations that have been proposed for the boom-bust cycle in the housing market. Specifically, we consider the share of subprime mortgages, the share of mortgages that were securitized soon after origination, and the share of highly leveraged mortgages (with a CLTV of at least 80%). In particular, we want to verify that our measure is not simply picking up an increase in marginal borrowers – those with low credit scores, an inability to make a 20% down payment, or whom lenders would only fund if they could sell off the loans – just because such borrowers relied on IOs.

Lastly, following work by Robinson and Todd (2010) which shows that mortgages taken by non-occupants may have affected house price appreciation, we also consider the share of mortgages which the borrower indicated he did not plan to occupy.

The effect of including additional mortgage variables can be seen in Table 4. As evident from the first row of the table, adding any one variable by itself has little impact on the coefficient on the IO share. This confirms that IOs are not merely a proxy for one of these other mortgage characteristics. When we add all of these variables, the coefficient on the share of IOs falls somewhat, but it remains statistically significant at the 1% level. Moreover, since the standard error on IO share doubles when we combine all of these alternative measures, we cannot reject that the coefficient is the same as in our benchmark specification.

Turning to the coefficients on these other variables, the share of hybrid mortgages is insignificant and negative but the share of long-term mortgages is positive and significant at the 5% level. To be clear, both variables are positive and significant when we omit the share of IOs. That is, in cities with rapid price growth, borrowers were more likely to take out hybrid and long-term mortgages, as one would expect. This is consistent with our model, which implies that as house prices rise, high type borrowers would find it more difficult to
afford homes, so we should not be surprised to see greater use of affordability products. The point of Table 4 is that the use of IOs seems to be more closely related to rapid appreciation than the use of these other types of mortgages, and adding data on the popularity of these other contracts provides little additional information for predicting house price growth.

The share of subprime mortgages is statistically significant, but its sign is the opposite of what we might expect: Cities with more subprime mortgages have lower house price appreciation.\(^\text{26}\) When we include all of our mortgage characteristics in the final column of Table 4, though, the coefficient is no longer significant. The negative coefficient seems to reflect the prevalence of subprime mortgages in low income cities, such as Detroit and Laredo, while rapid house price appreciation was mostly concentrated in medium and high income cities. However, this does not mean that the expansion of the subprime market was unimportant, either for house price growth or for the housing market more generally. Mian and Sufi (2009) find that within cities, house price appreciation tended to be concentrated in poorer areas where more low quality borrowers resided in 2000. In addition, the rise in subprime lending appears to have played an important role in the rise in home ownership and the subsequent foreclosure crisis, which is just as important of a concern for policymakers as the boom-bust cycle in housing prices.\(^\text{27}\)

The share of mortgages privately securitized one year after origination is not statistically significant once we control for the share of IOs. Again, this variable is significant when we omit the IO share, suggesting more securitization took place in cities with higher appreciation. IOs are simply a better indicator of whether a city experienced high price appreciation.

The average share of mortgages with a CLTV of over 80% enters significantly, but has a surprising sign: cities where borrowers were more leveraged experienced less house price appreciation. One potential explanation is that in cities with house price speculation, lenders knew to protect themselves by insisting borrowers own a greater equity stake. Regardless, controlling for CLTV has little effect on the coefficient on IOs.

Lastly, the share of mortgages taken out by investors does enter significantly, both by itself and when we control for all other mortgage characteristics. However, the share of

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\(^\text{26}\)Since subprime mortgages are underrepresented in LPS, we also considered alternative measures of subprime mortgages. First, we used the ratio of all mortgages included in subprime mortgage pools as reported by LoanPerformance to the total number of mortgages for each city as reported in the Home Mortgage Disclosure Act (HMDA) data. Since the vast majority of subprime mortgages were securitized, this should be a better measure of the true share of subprime mortgages in each market. We also looked at the share of loans issued by known subprime lenders as classified by HMDA. Both continue to yield a negative coefficient on the share of subprime mortgages, although in neither case is it significant.

\(^\text{27}\)The role of subprime mortgages for these patterns are explored in Chambers, Garriga, and Schlagenhauf (2009) and Corbae and Quintin (2009), respectively.
investor mortgages is essentially orthogonal to the share of IOs, as evidenced by the fact
that adding it has no effect on the coefficient on IO share.

All of the regressions in Table 4 use the maximum 4-quarter price appreciation as the
dependent variable. As we noted above, we also considered average house price appreciation
between 2000q1 and each city’s peak price. Most of the results are similar. The share of
IOs are statistically significant at the 1% level when we use this as our left-hand variable.
Adding various controls did not knock this variable out, although when we include all of the
alternative mortgage characteristics that we use in the last column of Table 4, the share of
IOs only comes in significant at the 5% level rather than the 1% level. Still, the statistic we
use to summarize prices matters. For example, the share of privately securitized mortgages
is significant at the 5% level for this measure, both by itself and when we control for all
other characteristics, which is different from what we find in Table 4.

4.4 Alternative Explanations

The previous section demonstrates that IOs do not seem to be proxying for some other
mortgage characteristic. Still, there are other reasons why we might observe backloaded
mortgages in cities with rapid house price growth that have nothing to do with speculative
bubbles. For example, cities with faster house price appreciation may have faster income
growth, and individuals who expect their income to grow may prefer backloaded mortgages
even when assets are priced at their fundamental value. However, recall that we included
growth in per capita income in each city as one of our control variables in Table 3, establishing
that even among cities with the same realized income growth, IOs were used more where
prices rose more rapidly.\footnote{We also considered the variance of changes in real log per-capita income from 1969 to 2000, and a vector of employment shares in 2000 for 8 industries (agriculture and mining, construction, manufacturing, transportation and utilities, trade, finance and real-estate, services, and government) in the hope that this captures differences in income patterns. In both cases, the coefficient on IOs remained significant.} A more mundane explanation is that as houses become expensive, borrowers resort to more affordable mortgage products. IOs have the advantage that they offer at least temporary affordability. By this view, the use of IOs simply mirrors rapid house price appreciation rather than offering evidence of speculation. We check this by testing whether adding the level of house prices at the peak drives out the share of IOs as a predictor of appreciation. To do this, we used the median price of single family homes for each city from the National Association of Realtors in 2000q1, and then used the rate of real price appreciation in the FHFA to compute the implied price of the same home at the peak.

The first two columns in Table 5 show the effect of adding the log of the price level
at the peak when we continue to control for the same explanatory variables as in Table 4. When we include the log peak price by itself, this variable has a positive and statistically significant effect, confirming that places with greater appreciation were also more expensive. However, when we add the share of IOs, the coefficient on log peak price becomes statistically insignificant, while the coefficient on the share of IOs remains highly significant and not statistically different from the estimate we report in Table 3. We also considered the ratio of the peak price to per-capita income in the year of the peak. These estimates are reported in the third and fourth columns of Table 5, and lead to the same conclusion.

4.5 Price Declines

So far, our analysis has focused on house price appreciation. However, one could just as well ask whether the use of IOs was also associated with large subsequent collapses in house prices. To investigate this, we constructed an analogous measure of house price declines. That is, for each city we measure the largest 4-quarter decline between the city-specific peak and the end of our sample in 2008q4. In 43 cities, the highest price recorded occurred in 2008, so the period of decline was not long enough to compute a 4-quarter growth rate. Of these, in 31 cities the peak price was in 2008q4, implying there was never a bust in house prices. Among remaining cities, the largest 4-quarter price decline in 85% of the cases occurred between 2007q3 and 2008q3, even though these cities peaked at different dates, some as early as 2003. The collapse in house prices was thus highly synchronized. In what follows, we adopt the convention of using the negative of the price change.

We report our key results in Table 6. Again, IOs appear to be concentrated in cities where prices fell by a larger amount. Moreover, this result is robust to controlling for the level and changes in population, unemployment, per capita income, and property tax rates in the period after the peak, as well as to including other mortgage characteristics.

The main difference between the results for price declines and price increases is that mortgage variables that were not significant for explaining house price appreciation do appear to be important in explaining house price declines, even if they do not knock out or even significantly change the coefficient on the IO share. We suspect this is because these other variables help to predict the excess of foreclosures beyond what one would predict based on the share of IO contracts alone. As documented in Campbell, Giglio, and Pathak (2009), foreclosures are likely to drive house prices down, both because foreclosed properties sell at a steep discount and because they drive down the value of neighboring properties. Some of the differences in house price declines between otherwise similar cities do seem related to
differences in foreclosures. For example, the IO share in Washington DC and Stockton were similar, 47% and 49% respectively, and both experienced relatively similar rates of house price appreciation, with a maximum 4-quarter growth of 22.5% and 28.2%, respectively. Yet house prices fell 17.3% in Washington DC but 42.3% in Stockton over a 4-quarter period. This is consistent with differences in foreclosure rates between these two cities: Stockton had a foreclosure rate of 9.5% in 2008 according to RealtyTrac, a firm that tracks foreclosure rates, while Washington DC had a foreclosure rate of 3.0%.

As confirmation, we constructed a measure of unanticipated foreclosures for each city using the residual from regressing the maximum share of the mortgages in LPS that enter foreclosure in each city on the maximum share of IOs. When we add this residual to the list of controls, it comes in highly significant and knocks out all of the other mortgage characteristics we consider, in line with the notion that the composition of mortgages that are not associated with rapid price increases can still predict price declines is that they tend to predict unusually high foreclosure rates.

5 Time Series Evidence on Affordability

We now use panel data to address the possibility that the use of IOs in cities with rapid appreciation is due to affordability reasons. In particular, we examine whether the rise in use of IOs appears to be a response to houses becoming more expensive. Formally, we look at whether house price appreciation Granger-causes the increased use of IOs. We find it does not, and that if anything, house price appreciation leads to a decline in the use of IOs. Indeed, this can be seen in the case of Phoenix in Figure 1. This suggests affordability cannot account for all of the use of IOs, since at least some of it predates the rise in prices.

We also look at whether the use of IOs Granger-causes house price appreciation. The model suggests such a pattern could arise. In particular, since speculators take out IO loans in anticipation of possible future house price appreciation, the use of IOs can lead price appreciation if it occurs, i.e. if more buyers arrive. The share of IOs among all new purchases depends on the fraction of speculators among all borrowers, \( \phi \). In general, our model imposes no restriction on how \( \phi \) evolves over time, and so there is nothing that requires that it lead price appreciation. Still, the notion that contract choice may be a leading indicator is potentially useful in alerting policymakers to possible future price growth.

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As a robustness check, we looked whether the residual foreclosure rate predicts price growth before the peak. When we add it as a variable, it is significant at the 5% level we include it on its own but turns insignificant when we control for all of the other mortgage characteristics.
5.1 Construction of Panel Data

Our Granger causality tests are meant to determine whether in those cities where IOs were especially popular, their use was anticipated by price appreciation. In particular, as is clear from our analysis above, cities with relatively elastic supply for housing experienced both low rates of both price appreciation and usage of IOs, but some individuals took out IOs even in these cities. In the latter case, the dynamics of house prices and IOs could very well be different. This is confirmed in Figure 3, which plots the contemporaneous correlation between the change in IO use and the change in price as well as the the autocorrelation of both quarterly price changes, and changes in IO shares against the maximal IO share in the city. The figure suggests that cities with a maximal IO share of at least 40% have relatively similar dynamics, but exhibit different dynamics from other cities. For this reason, we consider cities with a maximum IO share that is at least 40%. This leaves us with a sample of 29 cities. Our results remain unchanged when we change the cutoff to 30%. When we include all cities, we find that house price growth does not Granger causes an increase in IOs but that IOs do Granger cause price growth when we allow for city fixed effects, but our model fails the specification tests for uncorrelated error terms.

We further focus on the period of rising house prices, since we are interested in whether borrowers shifted to IOs once houses became more expensive. In particular, we do not want our results to be driven by the collapse of IOs when house prices started to decline. We therefore only consider data through 2006q4, when national FHFA real house prices peaked. Our results are robust to ending the sample earlier in 2006.30

We begin with some simple correlations which show the dynamics of IO use and house price appreciation across the 29 cities with the highest IO usage. Figure 4 displays dynamic correlations between changes in the share of IOs at date t + j, $\Delta io_{t+j}$, with log changes in real house prices at date t, $\Delta p_t$, for $j = -4, -3, \ldots, 4$. The correlations are positive for $j \leq 2$, peaking at $j = -2$ and negative for $j > 2$. In other words, the increased use of IOs leads house price appreciation, the opposite of what we expect if IO use is being driven by affordability.

30There are concerns about data quality in the LPS in earlier years. We argue in Appendix B that these are not a problem for our analysis. For example, our results are robust to starting the sample in 2004q1.
5.2 Granger-Causality

We now present our formal Granger-causality tests. We estimate the two equations

\[ \Delta p_{it} = \alpha_p + \beta_p(L)\Delta p_{it-1} + \gamma_p(L)\Delta i o_{it-1} + \varepsilon_{it}^p \]  
(2)

\[ \Delta i o_{it} = \alpha_{io} + \beta_{io}(L)\Delta i o_{it-1} + \gamma_{io}(L)\Delta p_{it-1} + \varepsilon_{it}^{io} \]  
(3)

where \( \Delta i o_{it} \) and \( \Delta p_{it} \) refer to city \( i \) at date \( t \) and the \( \beta(L) \) and \( \gamma(L) \) functions are lag polynomials. For simplicity, we focus on models where the number of included lags is the same for both \( \beta(L) \) and \( \gamma(L) \). Table 7 and Table 8 report our results based on two different ways of estimating this model, depending on whether we assume (2) and (3) are homogeneous across the different cities in our sample or not.

5.2.1 OLS Estimates

If the coefficients \( \alpha, \beta(L), \) and \( \gamma(L) \) in (2) and (3) are the same for all cities, we can estimate these equations using ordinary least squares. These estimates are reported in Table 7. The first four columns show that for all lag specifications, an increase in the share of IOs does Granger-cause house price appreciation in the period we consider. More precisely, as evident from the row labeled with summations, we reject the hypothesis that the sum of the coefficients on the share of IOs is zero. In addition, the null hypothesis that all the coefficients on IOs are zero is rejected for all four specifications. The F-statistics associated with this hypothesis are in the row labeled “F-stat” with the associated p-values below.

In the opposite direction, with only one lag, there is no evidence that price growth Granger-causes increased IO use. With two and three lags, house price appreciation does appear to Granger-cause an increase in IO usage, but the sum of the coefficients is negative, implying a rise in prices causes a decline in the use of IOs. When we allow for four lags, the sum of the coefficients remains negative but is no longer significant at the 5% level. None of the specifications offer evidence that house prices leads to an increased use of IOs.

The OLS estimates are inconsistent if the residuals are serially correlated. Table 7 reports p-values for Arellano and Bond (1991) tests of the null hypothesis that the residuals exhibit no serial correlation of order one through four, \( AR(j), j = 1, 2, 3, 4 \). For conventional significance levels, these tests indicate it is not possible to reject serial correlation for some \( j \geq 2 \) for all lag specifications. That is, there is always some value at which the p-value on the hypothesis that errors are serially correlated falls below 5%. Serial correlation remains even when we increase the number of lags to six, calling into question the use of OLS.
5.2.2 GMM Estimates

One potential source of serial correlation is if the intercept terms $\alpha$ in (2) and (3) vary across cities. To accommodate city-specific constants, that is “fixed effects,” with homogeneous slope coefficients, we use the System-GMM estimator developed by Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998) and Holtz-Eakin, Newey, and Rosen (1988). System-GMM involves estimating (2) or (3) with a system of two equations. The first equation of the system involves differencing the original equation to remove the fixed effects, and using lagged values of the variables in the original estimation equation as instruments. The second is the original estimation equation using differences of the variables in the original estimation equation as instruments. In the latter case we assume that the differences are orthogonal to the fixed effects. Our GMM estimates, reported in Table 8, are based on using the third and fourth lags as instruments.\textsuperscript{31} The validity of our instruments with GMM depends on the lack of serial correlation in the estimation errors for the differenced equation of order three and higher. The Arellano and Bond tests of serial correlation now indicate that four lags are necessary for this condition to be satisfied for forecasting house price growth, but two or more lags are necessary when forecasting the change in IO use.\textsuperscript{32} Allowing for fixed effects thus appears to resolve the problem of serial correlation.

Turning to the results, the conclusions are similar to what we found using OLS. The first four columns of Table 8 continue to imply that for all lag specifications, an increase in IOs still Granger-causes house price appreciation in the period we consider. The next four columns show that there is little evidence that that house price appreciation Granger-causes the use of IOs, for all lags. With only one lag, the coefficient is essentially zero. With more lags, the sum of the coefficients on lagged prices is negative as with OLS, but is no longer significant at the 5% level. The use of IOs in these cities thus appears to arise in anticipation of future appreciation rather than in response to past appreciation.\textsuperscript{33}

\textsuperscript{31}These estimates were calculated using \texttt{xtabond2} for \texttt{STATA}, described in Roodman (2009). The standard errors are robust to arbitrary patterns of autocorrelation within cities (clustering) and include the small sample correction developed in Windmeijer (2005). We follow the convention of including orthogonality conditions that are valid at each date so even with just two lags as instruments there are a large number of orthogonality conditions. While we fail to reject the $J$-test of the over-identifying restrictions with a $p$-value of unity in all cases, the actual values of the test statistic are relatively small indicating that the non-rejection of the over-identifying restrictions is not noise driven. Evaluating expectations over cities and dates rather than over cities at each date separately dramatically reduces the number of orthogonality conditions. Our findings are robust to using a smaller number of orthogonality conditions based on this latter approach. Our findings are also robust to using a single lag and including a third lag as an instrument.

\textsuperscript{32}While we report results for various lag lengths, we explored using the lag selection criterion for dynamic panel data models in Andrews and Lu (2001). For both (2 and (3), this criterion favored a one lag model.

\textsuperscript{33}As a robustness check, we re-ran our estimates including lags of log GDP growth and the Federal Funds interest rate as additional controls, and our findings remain unchanged.
6 Mortgage Pre-payment and Default

Our theory is premised on the notion that lenders prefer IOs over traditional mortgages because they encourage speculators to re-pay their mortgages earlier. A natural check on our theory, then, is whether IOs indeed pre-paid at a faster rate than other kinds of mortgages. Of course, there may be other reasons for this pattern, e.g. borrowers who know they intend to move within a few years may select into IOs. Still, if we were to find that IOs are pre-paid at a slower rate than other mortgages, it would be evidence against our theory. Our model further predicts that when prices collapse, holders of IO mortgages will default rather than pre-pay. This suggests looking at foreclosure rates for different types of mortgages.

We focus on the same 29 cities with high IO shares that we considered in our time-series analysis in Section 5. Once again, we want to make sure that our results are not driven by other cities where the use of IOs is more influenced by other considerations. That said, we obtain similar results when we look at all cities. To minimize the impact of composition and time effects, we separate mortgages depending on when they originated. In what follows, we report results for mortgages originating in 2005q1, although mortgages originating at any quarter of 2004 and 2005 look similar. The results are different for 2003, but this may be because few IOs originated that year and so the estimates are likely to be noisy.

We estimate pre-payment and foreclosure rates using the Kaplan-Meier estimator. More precisely, denote the times we can track each mortgage by \( t_i, i = 1, 2, \ldots, N \) and \( N \) is the total number of mortgages. Corresponding to each value for \( t_i \) is the number of mortgages that we could have observed pre-paying (foreclosing) at this date, namely all the mortgages that survived to date \( t_{i-1} \) and for which data is still available at date \( t_i \). Denote this number by \( n_i \). Let \( d_i \) denote the number of mortgages that pre-paid (foreclosed) at date \( t_i \). The Kaplan-Meier estimator for pre-payment (foreclosure) is given by

\[
\hat{S}(t) = \prod_{t_i \leq t} \frac{n_i - d_i}{n_i}
\]

That is, \( \hat{S}(t) \) denotes the fraction of mortgages that have not prepaid (foreclosed) after \( t \) periods. We report the statistic \( 1 - \hat{S}(t) \), which corresponds to the fraction of mortgages that pre-paid (foreclosed) by date \( t \). Note that the Kaplan-Meier estimator addresses right-censoring, which is important since pre-payment right censors the propensity for mortgages to default, and default right censors the propensity for mortgages to pre-pay. Given the large number of mortgages in the 29 cities that originate in 2005q1, we omit standard errors.

Figure 5 shows pre-payment and foreclosure rates for IO and non-backloaded mortgages. By “non-backloaded” we mean all mortgages that are neither IOs nor option-ARMs. We
confirm that IOs were indeed more likely to pre-pay than non-backloaded mortgages. To get some sense of magnitudes, we estimate that after 8 quarters, 40% of IOs have pre-paid while less than 30% of non-backloaded mortgages are pre-paid.

Turning to defaults, the fraction of mortgages that enter foreclosure is the same for both IOs and non-backloaded mortgages until 2007q1, the quarter after the aggregate FHFA house price index begins to fall. At this date, the propensity of IOs to enter foreclosure begins to rise faster than for non-backloaded mortgages, in line with the model’s prediction that speculators who would have chosen IOs default when prices begin to fall. This is so even though many of these mortgages are still in the interest-only period. Comparing pre-payment and foreclosures reveals that when the gap in foreclosure rates between IOs and non-backloaded mortgages opens up, the tendency for IOs to pre-pay early reverses. Although we do not report the results, we confirm that the survival probabilities for the two types of mortgages are statistically different using the log rank test of equality.

7 Conclusion

In this paper we argue that when there is a speculative bubble and lenders cannot distinguish speculators from profitable borrowers a priori, both lenders and speculators will prefer mortgages with backloaded payments over traditional mortgages. This insight motivates our analysis of house prices and mortgages for a sample of US cities over the period 2000-2008. Our main findings are that IO use is a strong indicator of rapid price appreciation and subsequent depreciation, that they do not seem to proxy for other types of mortgages, and that the use of IOs leads rather than lags house price appreciation, suggesting they cannot be entirely attributed to affordability. We also confirm that IOs were more likely to be pre-paid than traditional mortgages early on, but once prices fell were more likely to enter foreclosure.

At a minimum, these facts can inform the search for an explanation for the recent boom-bust pattern in house prices. That is, any credible theory should also explain the tendency for home buyers to rely on certain types of mortgages to finance these purchases, why these mortgages were so rarely used except in certain cities when house prices in these cities rose dramatically even though these products were already in existence, and why the use of these mortgages anticipated the rise in prices. We argue these facts may be indicative of a speculative bubble in housing. In particular, we present a model where backloaded contracts should be observed if a speculative bubble arises but not otherwise.34 To be sure, our model

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34Interestingly, Minsky (1982) also argued that a telltale sign of speculation was that borrowers only cover the interest obligation on their loans. However, his argument relied on a rather different intuition that had
ignores reasons for why backloaded mortgages might be observed even when there is no speculative bubble, e.g. they may be favored by individuals who anticipate future income growth or by individuals who cannot afford houses. However, accounting for income growth as well as determinants of income growth seems not to affect the results, nor does it seem that affordability can full account for the popularity of these contracts in the cities where they were used most heavily. There may very well be other explanations for the popularity of backloaded mortgages. But we view exploring these alternatives as a more productive way to settle the question of whether house prices were overvalued than trying to directly estimate the fundamental value of housing.

Finally, we should emphasize that our findings do not imply that backloaded mortgages caused a bubble in housing, nor do they imply that regulators should have disallowed these contracts. In fact, our model predicts a speculative bubble would occur even if lenders could only offer traditional mortgages, and that backloaded mortgages actually keep overvaluation in check by encouraging speculators to unload the houses they bought. Our analysis also ignores positive aspects of backloaded mortgages such as their benefits for liquidity-constrained households, and these must be taken into account in formulating policy. Finally, a potential argument for allowing backloaded contracts is that they may be the “canary in the coal mine” for anticipating price movements. That said, our analysis does not predict the exact form of backloaded contract one should look for, and once policymakers condition their actions on the choice of contracts, this may affect the incentives for lenders and borrowers to choose these contracts in the first place.

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nothing to do with the backloading of payments. Nor did Minsky explain why lenders should not be alarmed by the rise in such borrowing, other than arguing that they too might be swept up in some general euphoria.
Appendix A  Proofs of Theoretical Results

Proof of Proposition 1: We first argue that there exists some date $\tau < t^*$ for which $p_\tau > f_\tau$ if buyers keep arriving through date $\tau$. We then show that this implies $p_t > f_t$ for all $t < \min(t^*, T + 1)$. Lastly, we argue that the bubble must grow at a positive rate.

For the first step, note first that $p_t \leq f_t$ for all dates $t < \min(t^*, T + 1)$. For suppose $p_t < f_t$. Then it would be possible to earn positive expected profits by buying a house and renting it out until date $t^*$, then selling it if buyers kept arriving through $t^*$ and selling it otherwise. Lenders would be willing to finance people to purchase houses for this purpose or to buy houses themselves, implying excess demand for houses.

It is also the case that $p_t < D$ for all dates $t < \min(t^*, T + 1)$. By the same transversality condition argument as in the case where the number of buyers is constant, $p_t \leq D$ for all dates $t$. If the price were ever equal to $D$ at some date $t < \min(t^*, T + 1)$, all non-high type occupants would sell, since there is positive probability the price will fall to $d$ but no probability the price will ever be higher. But since only new potential buyers can purchase houses, this would imply excess supply four houses.

Since $p_t < D$, it follows that for small $\phi$, all high types would want to buy a house. Specifically, continuity of the zero-profit condition for lenders implies the interest rate on a loan will be close to the risk free rate for $\phi$ close to zero. At the risk free rate, high types would certainly want to buy a house. Likewise, for small $\phi$, low types can earn positive expected profits from buying a house, since they can always profit from waiting one period and selling it if more potential buyers arrive and defaulting otherwise. Hence, for $t < \min(t^*, T + 1)$ both types will buy a house in equilibrium.

Let $t^{**}$ denote the smallest integer strictly greater than $\phi_0/n$. Given that both types buy houses upon arrival in equilibrium, by date $t^{**}$ some low type who arrived after date 0 would have to sell his house for the market to clear. Note that $t^{**} \leq t^*$. In what follows we ignore integer constraints and proceed as if $t^{**} < t^*$, which we can do for sufficiently small $n$.

Suppose all agents who arrive after date 0 still owe least $d$ to their respective lenders by date $t^{**}$. Since $p_t \geq f_t > d$, agents must have borrowed more than $d$ to begin with. Hence, this assumption amounts to the restriction that the income each cohort earns is sufficiently small that agents cannot pay down their debt too quickly. Note that this may require letting income $\omega$ rise over time to ensure early cohorts have a large debt outstanding while later cohorts can still promise to repay their debt in finite time. We have avoided imposing this assumption explicitly to avoid complicating notation.

If buyers arrive after $t^{**}$, someone other than the original owners of the $\phi_0$ houses would have to sell by date $t^{**}$ for the market to clear. But by assumption, all of them owe more than $d$ on their house. This implies that if $p_t = f_t$, they would be better off waiting than selling the house. To see this, let $L$ denote the amount they owe on the house at date $t$. Selling at date $t$ yields $p_t - L = f_t - L$. Waiting one period to sell if more buyers arrive yields an expected profit of $(\beta^{-1} - 1)(d - m_t + \beta(1 - q)(p_{t+1} - (1 + r)(L - m_t)))$ where in a slight abuse of notation $m_t$ is the mortgage payment required under the contract for date $t$. If $\phi$ is small, $r$ will be close to the risk-free rate $\beta^{-1} - 1$, and so $-m_t - \beta(1 + r)(L - m_t)$ will
be close to $L$. But
\[
(\beta^{-1} - 1) d + \beta (1 - q) (p_{t+1} - L) \geq (\beta^{-1} - 1) d + \beta (1 - q) (f_{t+1} - L)
\]
\[
> (\beta^{-1} - 1) d + \beta (1 - q) (f_{t+1} - L) + \beta q (d - L)
\]
\[
= f_t - L
\]

This implies no low type would sell at $p_t = f_t$, so the market clearing price must strictly exceed $f_t$ at some date $\tau \leq t^*$ if potential buyers keep arriving.

We now argue the existence of date $\tau$ implies a bubble will exist for all dates $t < \min(t^*, T + 1)$. First, consider any date $t < \tau$. Suppose $p_t = f_t$. Then no agent would agree to sell the asset at date $\tau$, since it is better to wait to sell the asset at date $\tau$ if buyers keep arriving. That is, $p_\tau > f_\tau$ implies
\[
E_t \left[ \sum_{s = t}^{\tau} \beta^s (\beta^{-1} - 1) d + p_\tau \right] > E_t \left[ \sum_{s = t}^{\tau} \beta^s (\beta^{-1} - 1) d + f_\tau \right]
\]
But the RHS is just $f_t$. Hence, it is better to collect dividends until $\tau$ and then sell the asset than to sell it at $t$. So no agents sell. But if $p_t = f_t$, all new arrivals at date $t$ would want to to buy the asset, which cannot be an equilibrium.

Next, consider $t > \tau$. The argument is by induction. First, at date $t = \tau + 1$, if $p_t = f_t$, then any agent who bought a house before date $\tau$ would prefer to sell the asset at date $\tau$ than to wait and sell at date $\tau + 1$ if $T > t + 1$. So none of these agents plan to sell at date $t + 1$ if $T > t + 1$. But if $p_t = f_t$, new buyers will wish to buy a house if $T > t + 1$. Supply must therefore come from low types who bought the house at date $\tau$. But they would demand a price above $f_t$ to sell since they are giving up the option to wait and default, so $p_t > f_t$. The same argument can now be applied to later dates. Hence, $p_t > f_t$ for all $t < \min(t^*, T + 1)$.

Finally, we show that the bubble grows at a positive rate. Given that only $n$ houses are bought each period, at each date $t < \min(t^*, T + 1)$ there must be some low types who opt to hold on to their houses. To see this, observe that some low types who hold the house in period $t$ must anticipate selling the house at date $t + 1$ if new buyers arrive in order that the market clear. Hence, they must prefer waiting to $t + 1$ than selling at $t$. If they sell at $t$, they will receive $p_t - L$, where $L$ denotes the amount they owe against the house (and which may equal 0). Selling at date $t + 1$ yields an expected payoff of
\[
(\beta^{-1} - 1) d - m_t + \beta (1 - q) (p_{t+1} - (1 + r) (L - m_t)) + \beta q (d - (1 + r) (L - m_t)) D_{t+1}
\]
where $m_t$ denotes the required payment (which for an agent who owns the asset outright will be 0) and $D_{t+1} = 1$ if $d > (1 + r) (L - m_t)$ and 0 otherwise, i.e. $D_{t+1} = 1$ if the house is worth more than the agent’s outstanding debt so the agent will prefer not to default.

Substituting in $p_t = f_t + b_t$, the fact that the payoff above exceeds $p_t - L$ implies
\[
\beta (1 - q) b_{t+1} \geq b_t + \theta + \chi
\]
where
\[
\theta = f_t - (\beta^{-1} - 1) d - \beta (1 - q) f_{t+1} - \beta q d D_{t+1} \geq 0
\]
where the inequality follows from the recursive representation for $f_t$, and

$$\chi = \beta(1 + r)(L - m_t)(1 - q + q\mathbb{D}_{t+1}) - (L - m_t)$$

$$\geq \beta(1 + r)(L - m_t) - (L - m_t) > 0$$

where the last inequality relies on the fact that the loan rate will be higher than the risk free rate for $\phi > 0$. Since $\theta$ and $\chi$ are positive, it follows that $\beta(1 - q)b_{t+1} \geq b_t$, and so

$$b_{t+1} \geq (\beta(1 - q))^{-1}b_t > b_t$$

from which it follows that the bubble grows as long as new cohorts arrive.

**Proof of Proposition 2:** Between them, a lender and low type agent value the asset the same as an agent who has no debt obligation against the asset. However, the standard unravelling argument for bubbles applies. In particular, at date $t^*$ the bubble term will be zero and $p_t = f_t$. Hence, at date $t^* - 1$, selling the asset will raise joint surplus. More generally, given the equilibrium characterized in the proof of Proposition 1, it will be optimal to sell the asset by date $t^{**}$, since from this point on original owners who have no debt against the asset strictly prefer to sell the asset given some agent who owes a positive amount is indifferent. But for a bubble to exist, leveraged agents will either want to hold the asset or be indifferent to selling at this date.

**Equilibrium contracting when there is a bubble.** We now argue that if at the equilibrium interest rate on the traditional mortgage, there exists an IO mortgage that low type borrowers and lenders both prefer, then (1) both traditional and IO mortgages will be offered in equilibrium, with low-types choosing the IO contract and high types choosing the traditional mortgage; (2) When there is no refinancing, IO contracts will carry a higher interest charge in equilibrium. The argument for how to deal with the possibility of refinancing is discussed in the text.

We first consider the case where agents cannot refinance. First, we argue that low-types must receive IO contracts in equilibrium. For suppose not, i.e. they receive a traditional mortgage contract with interest rate $r^*$. We first argue that $r^*$ must exceed $\beta^{-1} - 1$ to ensure non-negative profits. In particular, the interest rate on any loan must be at least $\beta^{-1} - 1$, or else the lender would never offer it. If the traditional mortgage involved a rate $\beta^{-1} - 1$, high types would at most repay at the risk free interest rate, so lenders will earn no profits from high types. But given expected profits from lending to low types at a rate $r^* = \beta^{-1} - 1$ are negative since they will default with positive probability, lenders will not be able to earn positive profits. Hence, $r^* > \beta^{-1} - 1$.

Now, consider a lender who offers the same set of contracts as those offered in equilibrium, but also offers an IO contract with the same interest rate $r^*$ as charged on the traditional rate in equilibrium. High types will not choose this contract, since when $r^* > \beta^{-1} - 1$, the present discounted value is lower under the traditional contract, and the IO contract would force them to give up the house at some date. Hence, these types will stick with whatever contract they were originally choosing in equilibrium. However, by assumption, both borrowers and lenders are better off under the IO contract. Since lenders earn zero
profits in equilibrium, this implies a lender can earn strictly positive profits by offering a traditional mortgage together with an IO mortgage both at the same rate $r^*$ as in equilibrium. Hence, the original contracting arrangement could not have been an equilibrium.

Next, we argue that high types will end up with a traditional mortgage in equilibrium. For suppose in equilibrium all borrowers took the IO mortgage with interest rate $\hat{r}^*$. Consider a lender who offers a traditional mortgage at rate $\hat{r}^*$. The rate on traditional mortgages in equilibrium must have been higher than $\hat{r}^*$, or else high types would have already chosen it, since high types prefer a traditional mortgage to an IO mortgage when at an interest rate above the risk-free rate, which must be the case in equilibrium. Since by assumption low types prefer IO over the traditional mortgage at the equilibrium rate, and since low types will find IO contracts even more attractive at lower rates, they must also prefer the IO mortgage at rate $r^*$. Thus, a lender offering a traditional mortgage with rate $\hat{r}^*$ will not attract low types, but will attract high types. Since lending to high types at an interest rate that exceeds the discount rate yields positive profits, such a lender will earn a strictly positive profit. But then the original contracts could not have been an equilibrium.

Both contracts will therefore be offered in equilibrium. We now argue that in equilibrium, low types must be indifferent between the types of mortgages contracts in equilibrium. For suppose not, i.e. low-types strictly prefer the IO contract. Consider a lender who offers only the traditional mortgage contract offered in equilibrium, but lowers the interest rate by $\varepsilon$. Given low-types strictly prefer the IO contract, there exists an $\varepsilon$ such that they would still prefer the IO contract. High types will prefer this contract. But there exists an $\varepsilon$ small enough that the lender offering this contract and attracting only the safe borrowers will earn a strict profit.

Finally, since low types prefer the IO contract with rate $r^*$ to the traditional mortgage contract with rate $r^*$, the only way to ensure they are indifferent between the two contracts is to charge a lower rate on the traditional mortgage in order to make it more attractive. Hence, the equilibrium rate on the traditional mortgage contract will be lower than on the IO contract.

When agents can refinance, the contracts offered high types will continue to stipulate the fastest repayment path possible, i.e. $m_\tau = \omega$. Otherwise, a lender will be able to require a slightly higher repayment and attract only high types. In addition, the interest rate charged to high types must be such that a single interest payment is enough to cover the expected loss on low types. If the interest rate were any higher, it would be possible to undercut this lender and earn strictly positive profits by poaching his borrowers. If the interest rate were lower, a lender could charge the higher rate. Even if borrowers could refinance to the risk free rate and rapid repayment, this would only be attractive to high types. Hence, high types would flock to this, expecting to be refinanced to a risk-free rate loan (with a shorter term) in the next period. The same argument for why low types will not receive the same contract as high types if both prefer a backloaded contract applies.

Determining the value of a contract to both borrowers and lenders. Let $V_\tau$ denote the expected value to a low type who still owns the house $\tau$ periods after buying it and before knowing whether new buyers will arrive that period. Under the fixed-rate mortgage, the speculator can either sell the house and pay back $(1+r)L_{\tau-1}$; pay $m_\tau$ and
retain ownership of the house; or default. The payoffs to the three options are \((\beta^{-1} - 1) d + p_t - (1 + r) L_t, (\beta^{-1} - 1) d + \beta V_{t+1} - m_t, \) and 0, respectively. Let \(\tau^*\) denote the number of periods between when the contract originated and \(t^*\). Assuming \(L_{t^*+1} > d/\beta\) so agents owe more \(d\) for at least \(t^*\) periods, the optimal strategy at date \(\tau^*\) is to sell the asset if new buyers arrive at \(\tau^*\) and default if they don’t. Hence,

\[
V_{\tau^*} = (1 - q) \left[ (\beta^{-1} - 1) d + D - (1 + r) L_{\tau^* - 1} \right]
\]

For \(\tau < \tau^*\), \(V_t\) is defined recursively as

\[
V_t = (1 - q) \max \left[ (\beta^{-1} - 1) d + p_t - (1 + r) L_{t - 1}, (\beta^{-1} - 1) d + \beta V_{t+1} - m_t, 0 \right] \tag{5}
\]

Under the IO contract, the speculator would have to either sell or default at date \(T_0 + 1\). If \(T_0 + 1 < \tau^*\), the boundary condition (4) will be replaced with

\[
V_{T_0 + 1} = (1 - q) \max \left[ (\beta^{-1} - 1) d + p_{T_0 + 1} - (1 + \hat{r}) L_{T_0}, 0 \right] \tag{6}
\]

At earlier dates, \(V_t\) can be again defined recursively using (5) with \(r = \hat{r}\). Computing back to date \(\tau = 1\) reveals which contract borrowers would prefer when they take out the loan.

We can similarly compute the revenue \(\Pi_t\) a lender expects to earn \(\tau\) periods into the loan, before knowing if buyers will arrive at date \(\tau\). Since at \(\tau^*\) the borrower would default if no buyers arrive and will repay his loan otherwise, we have

\[
\Pi_{\tau^*} = qd/\beta + (1 - q) (1 + r) L_{\tau^* - 1}
\]

For \(\tau < \tau^*\), the value \(\Pi_t\) is given by

\[
\Pi_t = qd/\beta + (1 - q) \pi_t
\]

where \(\pi_t\) depends on what the borrower does. If he sells the house, \(\pi_t = (1 + r) L_{t - 1}\). If he remains current on his payments, \(\pi_t = m_t + \beta \Pi_{t+1}\). If he defaults, \(\pi_t = [(\beta^{-1} - 1) d + p_t]\).

Expected profits when the loan is originated are thus \(\beta \Pi_1 = L\).

**Proof of Proposition 3:** We now show that if \(p_t = f_t\) for all \(t\), then \(V_t + \Pi_t = (\beta^{-1} - 1) d + E_{t-1} \{f_t\}\) for any contract \(\{m_t\}_{\tau=0}^{T}\).

Using the definition of \(V_t + \Pi_t\) shows that if the borrower either sells the asset or defaults, this sum will equal \((\beta^{-1} - 1) d + E_{t-1} \{f_t\}\). We therefore only need to check what happens if the borrower keeps making payments. In that case, the sum of the two terms is given by

\[
V_t + \Pi_t = (\beta^{-1} - 1) d + \beta (V_{t+1} + \Pi_{t+1})
\]

We will consider two separate cases, \(f_t = d\) for all dates and \(f_t\) given by (1). In the first case, note that at \(\tau = T + 1\), all debt would have been retired. Hence, \(V_{T+1} = (\beta^{-1} - 1) d + d\) and \(\Pi_{T+1} = 0\). It follows that

\[
V_{T+1} + \Pi_{T+1} = (\beta^{-1} - 1) d + d
\]

\[
= (\beta^{-1} - 1) d + E_{T-1} \{f_T\}
\]

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Next, suppose \( V_s + \Pi_s = (\beta^{-1} - 1) d + E_{s-1} [f_s] \) for \( s = \tau + 1, \ldots, T + 1 \). Then at date \( \tau \),

\[
V_\tau + \Pi_\tau = (\beta^{-1} - 1) d + \beta ((\beta^{-1} - 1) d + E_\tau [f_{\tau + 1}])
\]

\[
= (\beta^{-1} - 1) d + \beta ((\beta^{-1} - 1) d + d)
\]

\[
= (\beta^{-1} - 1) d + E_{\tau - 1} [f_\tau]
\]

This establishes the claim for \( f_\tau = d \).

Next, let

\[
f_\tau = \sum_{s=\tau+1}^{\tau^*} \beta^{s-\tau} (\beta^{-1} - 1) d + \beta^{\tau^*-\tau} E_\tau [p_{\tau^*}],
\]

where \( p_{\tau^*} \) is equal to \( D \) with probability \( 1 - q \) and \( d \) with probability \( q \). At date \( \tau^* \), since all uncertainty is resolved, the borrower will weakly prefer to sell the asset and strictly prefer to sell the asset if \( r > \beta^{-1} - 1 \). Regardless of whether the borrower defaults or sells the asset, we have

\[
V_{\tau^*} + \Pi_{\tau^*} = (\beta^{-1} - 1) d + E_{\tau^* - 1} [p_{\tau^*}]
\]

\[
= (\beta^{-1} - 1) d + E_{\tau^* - 1} [f_{\tau^*}]
\]

Finally, suppose \( V_s + \Pi_s = (\beta^{-1} - 1) d + E_{s-1} [f_s] \) for \( s = \tau + 1, \ldots, T + 1 \). Then at date \( \tau \), we have

\[
V_\tau + \Pi_\tau = (\beta^{-1} - 1) d + \beta E_{\tau - 1} ((\beta^{-1} - 1) d + E_\tau [f_{\tau + 1}])
\]

However, from the definition of \( f_\tau \), we have

\[
f_\tau = \sum_{s=\tau+1}^{\tau^*} \beta^{s-\tau} (\beta^{-1} - 1) d + \beta^{\tau^*-\tau} E_\tau [p_{\tau^*}]
\]

\[
= \beta (\beta^{-1} - 1) d + \beta \left[ \sum_{s=\tau+2}^{\tau^*} \beta^{s-\tau-1} (\beta^{-1} - 1) d + \beta^{\tau^*-\tau-1} E_\tau [p_{\tau^*}] \right]
\]

\[
= \beta E_{\tau - 1} \left[ (\beta^{-1} - 1) d + \sum_{s=\tau+2}^{\tau^*} \beta^{s-\tau-1} (\beta^{-1} - 1) d + \beta^{\tau^*-\tau-1} E_{\tau + 1} [p_{\tau^*}] \right]
\]

\[
= \beta E_{\tau - 1} \left[ (\beta^{-1} - 1) d + E_\tau [f_{\tau + 1}] \right]
\]

This allows us to rewrite the sum \( V_\tau + \Pi_\tau \) as

\[
V_\tau + \Pi_\tau = (\beta^{-1} - 1) d + E_{\tau - 1} [f_\tau]
\]

which establishes the claim. 

**Appendix B Data**

This appendix provides a detailed description of our data construction.
B1 House Price Data

Our primary data source for house prices is the Federal Housing Finance Agency (FHFA) house price index for Core-based Statistical Areas (CBSAs) as defined by the Office of Management and Budget. If a CBSA has a population greater than 2.5 million, the CBSA is divided into Metropolitan Divisions.\textsuperscript{35} For these CBSAs, FHFA reports data for each Division rather than the CBSA as a whole. We follow this convention throughout, using Metropolitan Divisions in lieu of the CBSA where applicable.

For robustness, we also used CBSA-level prices from the CoreLogic House Price Index and the Zillow Home Value Index. CoreLogic reports prices at the same CBSA level as FHFA. Zillow was available to us at the CBSA level as well, but for fewer cities. For each series, we construct our price variables as follows.

First, we convert house prices into a real index by dividing each price series by the Consumer Price Index for urban consumers as reported by the Bureau of Labor Statistics. Due to limitations on mortgage data, we restrict our attention to the period between 2000q1 and 2008q4. For each city, we identify the quarter during this period in which the real price reaches its peak. Let $p_t$ denote the price in a given city at date $t$. The quarter in which price peaks is given by

$$t^* = \arg \max_t \{p_t\}_{t=2000q1}^{2008q4}$$

We measure real house price appreciation in each city as the highest 4-quarter growth in real house prices between $t = 1$ and $t^*$, i.e.

$$\text{Max4QGrowth} = \max \{\ln \left( \frac{p_t}{p_{t-4}} \right)\}_{t=2001q1}^{t^*}$$

Since $t^* \geq 2001q1$ in all cities in our sample, i.e. the peak occurs at least a year after the start of our sample, our measure is defined for all cities.

In addition to the maximum rate of appreciation, we also calculate average annualized real house price appreciation prior to peak for each city as follows:

$$\text{MeanGrowth} = \frac{4}{t^* - 2000q1} \ln \frac{p_{t^*}}{p_{2000q1}}$$

Similarly, we calculate the largest 4-quarter decline following the peak analogously for the period between $t^*$ and $T$:

$$\text{Max4QDecline} = \max \{\ln \left( \frac{p_{t-4}}{p_t} \right)\}_{t=t^*+4}^{2008q4}$$

Since in some cities $t^* \geq T - 4$, we can only define this measure for a subset of cities.

\textsuperscript{35}The Metropolitan Divisions are: Boston-Cambridge-Quincy, MA-NH; Chicago-Naperville-Joliet, IL-IN-WI; Dallas-Fort Worth- Arlington, TX; Detroit-Warren-Livonia, MI; Los Angeles-Long Beach-Santa Ana, CA; Miami-Fort Lauderdale-Miami Beach, FL; New York-Northern New Jersey-Long Island, NY-NJ-PA; Philadelphia-Camden-Wilmington, PA-NJ-DE-MD; San Francisco-Oakland-Fremont, CA; Seattle-Tacoma-Bellevue, WA; and Washington-Arlington-Alexandria, DC-VA-MD-WV.
For data on price levels, which we use in Table 5, we took the median price of single family homes sales in each CBSA in 2000q1 as reported by the National Association of Realtors. Denote this price as $P_{2000q1}^{NAR}$. We then use each CBSA’s appreciation rate in the FHFA index to arrive at the price of the same median home at the peak date $t^*$. That is, the peak price in each city is given by $P_{t^*} = P_{1}^{NAR} \times (p_{t^*}/p_{1})$.

**B2 Mortgage Data**

Our mortgage data is primarily drawn from Lender Processing Services (LPS) mortgage performance data, formerly known McDash. However, we also constructed some of our variables from other datasets, and we report our construction of these variables as well.

**B2.1 LPS Mortgage Data**

The LPS data is reported at a monthly frequency. From these monthly reports we construct a single “static” file that includes a single record on each loan ever observed.

An issue with LPS is that different servicers begin to report data to LPS at different dates. When a servicer joins, they typically only report on their outstanding loans. Mortgages that originated before the servicer reported to LPS are then disclosed if they survive into the reporting period. This generates potentially serious survivorship bias. Some have argued that because of this, only data from 2005 on should be trusted, since at least one big servicer provided data in early 2005. For our purposes, this would throw out the most relevant period in which IOs and prices were rising. An alternative approach argues for only including mortgages that are reported in LPS shortly after their origination date, and throwing out any mortgage the servicer reports but which we know was originated some time ago. This would preserve mortgages issued before 2005 by servicers who had already contracted with LPS. This approach is used, for example, by Foote, Gerardi, Goette, and Willen (2010). A problem with this resolution is that it may lead to biases due to heterogeneity across services. As mentioned by Williams (2006), p11, IOs were highly concentrated, with a small number of lenders accounting for the bulk of such mortgages. If such servicers happened to report late to LPS, which appears to be the case, restricting attention to mortgages that are reported soon after origination would make it seem as if IOs surged late, when these servicers first reported to LPS rather than when these services first began to issue IOs. For this reason, we chose to include all mortgages in LPS, regardless of whether they were originated before the servicer began to report to LPS.

To get a sense of how much this suffers from survivorship bias, we compared mortgage counts in LPS to those reported under the Home Mortgage Disclosure Act (HMDA), which we discuss below, which is reported to regulators in real time and thus not exhibit survivorship bias. Up until early 2003, there is clear upward trend, suggesting earlier data increasingly undercounts mortgages. But there are no clear trends from that point on, and the share of all for-purchase mortgages in LPS to all mortgages in HMDA in 2003q1 (62%) is no different from 2010q4 (61%). This is consistent with the fact that interest rates bottomed out in 2003, so the refinance rate should have been lower, and that turnover in houses was lower earlier...
on. We also considered evidence on IOs in particular. For this, we looked at the number of IOs in the LoanPerformance (LP) data on mortgages in private-label mortgages pools of nonprime mortgages. Again, the latter should not be subject to the same survivorship bias. When we compare the number of IOs in LP to the number of IOs that were privately securitized within 1 year, the ratio of IO mortgages that were privately securitized reported in LPS to the number of IO mortgages reported in LP exhibits no trend starting from mid 2003, averaging around 60%. This suggests our time series should not be severely distorted by survivorship bias from 2003 on. In the paper, we report panel regressions that run from 2000q1 to 2006q4 (see Tables 7 and 8). However, since IOs only start in 2003, our results are driven by later data. We confirm this by running the same regressions for data starting in 2003q1 and 2004q1 instead of 2000q1, and find the results to be nearly identical. In addition, since backloaded mortgages are more likely to prepay (see Figure 5), survivorship bias will cause our series on the use of such mortgage to lag true usage earlier in our sample, and as such to make it more likely to lag house price growth, biasing against our finding.

As our first step, we obtained counts of the total number of first-lien, for-purchase mortgages originating in each CBSA each quarter. One issue is that if a mortgage was transferred between servicers in LPS, we may end up counting the same loan twice. To avoid this, we matched all loans on zip code, origination amount, appraisal amount, interest type, subprime status, level of documentation, the identity of the private mortgage insurance provider if relevant, payment frequency, indexed interest rate, balloon payment indicator, term, indicators for VA or FHA loans, margin rate, and an indicator of whether the loan was for purchase or refinance – treating missing and unknown values as wildcards. Loans that matched were treated as duplicates, and we kept only one record in such cases. Mortgages are reported by zip code. We aggregate these codes to the CBSA level, where for zip codes that do not fall entirely within a single CBSA we assigned all mortgages for that zip code to the CBSA with the largest share of houses for that zip code.

We then obtained counts by CBSA of mortgages originating each quarter that meet various criteria, allowing us to compute shares. To identify IO mortgages, we use the IO flag (IO_FLG) reported by LPS, which in turn is based on payment frequency type (PMT_FREQ_TYPE). Since LPS only started classifying loans as IO in 2005, for mortgages that originated and terminated before 2005, we looked at whether the initial scheduled payment in the first month (MTH_PI_PAY_AMT) was equal to the interest rate on the mortgage that month (CUR_INT_RATE) times the initial amount of the loan (ORIG_AMT). Using mortgages that survive past 2005 revealed that in a small but non-negligible number of IOs, the scheduled payment was not equal to but exactly twice the monthly interest rate times the initial loan amount, perhaps because of a quirk in the reporting convention of some servicers. Experimenting with the post-2005 data led us to classify as IOs those mortgages where the ratio of the scheduled payment to the interest rate times original loan amount was in either [0.985, 1.0006] or [1.97, 2.0012]. This approach correctly identified 98.5% of IOs while falsely identifying about 1.5% of non-IOs as IO in the post-2005 period.

Other mortgage shares are constructed as follows. Hybrid mortgages are all 30-year adjustable rate mortgages whose first adjustment in rates (FIRST_RATE_NM0N) is scheduled either 24 or 36 months after origination. The share of long-term mortgages is the share of
mortgages with an amortization term (TERM_NMON) of 360 months or longer. Subprime mortgages are mortgages whose mortgage type (MORT_TYPE) is coded as Grade ‘B’ or ‘C’, following Foote et al. (2010). Privately securitized mortgages are mortgages who remain active for at least 12 months and whose investor status (INVESTOR_TYPE), which is reported each month, corresponds to a privately securitized mortgage pool exactly 12 months after origination. For mortgages that do not last 12 months, we use the last investor reported. Mortgages purchases as an investment property are those for which the occupancy status (OCCUPANCY_TYPE) is given by “Non-owner/Investment.”

In addition, we compute a foreclosure rate for each CBSA as the ratio of all mortgages that report being in foreclosure for the first time each quarter to the total stock of first-lien for purchase mortgages that are reported by LPS in that quarter.

For all of these variables, we measure of the propensity to use a particular mortgage product (or to enter foreclosure) by taking the maximum share of that mortgage type among all first-lien for-purchase mortgages in each CBSA between 2000q1 and 2008q4.

B2.2 Other Mortgage Data

We used two other sources of mortgage data to supplement the LPS. The first is the LoanPerformance (LP) data on mortgages in private-label mortgage pools of nonprime mortgages, meaning Alt-A and subprime mortgages. The second is Home Mortgage Disclosure Act (HMDA) data on mortgage applications.

Unlike the LPS dataset, the LP data matches all liens against a property and reports the combined loan-to-value (CLTV) ratio for each property. We computed the share of first-lien for-purchase mortgages reported in LP in each CBSA in each quarter with a CLTV greater than 80%. Our measure for the propensity towards leverage in each city is the average of this share between 2000q1 and 2008q4 rather than the maximum, since both in the beginning and the end of the period the number of mortgages in LP is small.

We also used LP to construct an alternative measure of subprime mortgage shares. In particular, we counted the total number of first-lien for-purchase mortgages in all private-label nonprime mortgage pools and subprime mortgage pools, respectively. We then aggregated this measure up to the CBSA level using translation tables from Geocorr2K. To convert this into a share, we divide by the total number of first-lien for purchase mortgages reported for each county and quarter under HMDA. In particular, we generated these counts by county, and then aggregated to the CBSA level using translation tables from Geocorr2K.

In addition, we tabulated the number of mortgages issued by known subprime lenders as identified in the HUD Subprime and Manufactured Home Lender List, divided by the total number of mortgages reported under HMDA in each CBSA.

B3 Other Data

Lastly, we compiled additional control variables for CBSAs from various sources. Where necessary, we used translation tables from MABLE/Geocorr2K, the Geographic Correspond-
dence Engine based on the 2000 Census from the Missouri Census Data Center, to convert data to the CBSA level. For each variable, we calculated both the average level and the average change between 2000q1 and the quarter in which real houses peak in that CBSA (or year in which the peak occurs for annual variables). We used these as controls for regressions involving price appreciation between 2000q1 and the city-specific price peak. For regressions involving price depreciation between the city-specific price peak and 2008q4, we calculate the same two averages for these periods.

Population for each CBSA comes from the Census Bureau’s Current Population Reports, P-60, at an annual frequency. All of our averages use log average annual population.

Real per capita personal income for each CBSA comes from the Bureau of Economic Analysis at an annual frequency. All of our averages use log real per capita income.

Unemployment rates for each CBSA come from the Bureau of Labor Statistics (BLS), and are available at a monthly frequency. We aggregate up to a quarterly frequency by averaging the months in each quarter and then compute quarterly averages.

Property tax rates for each CBSA are constructed from data in the American Community Survey (ACS) from the US Census Bureau, using an extract request from IPUMS USA (available at http://usa.ipums.org). In particular, we took data on annual property taxes paid (PROPTX99) and house value (VALUEH). Since PROPTX99 is a categorical variable, we set the tax amount to the midpoint of each respective range. Thus, a tax in the range of $7,001-$8,000 is coded as $7,500. Anything above $10,000 is coded as $10,000. For each household, we estimate the tax rate as the ratio of taxes paid divided by the value of the house. We then compute the median tax rate across all households in the survey in each CBSA in each year. Focusing on the median mitigates the top-coding in taxes paid. Since the ACS has its own definition of metro areas, we need to use the IPUMS metro area-to-MSA/PMSA translation table and then use a MSA/PMSA-to-CBSA table from GEOCORR2K. We also weight households by household weight (HHWT).

Our measure of regulation is the Wharton Residential Land Use Regulation Index from Gyourko, Saiz, and Summers (2008), who summarize the stringency of the local regulatory environment in each community.

Our share of the undevelopable area in each CBSA comes from Saïz (2010).
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Figure 1: House Prices and Mortgage Use in Phoenix, AZ and Laredo, TX

A. Phoenix, AZ

B. Laredo, TX

Note: Blue solid lines – Real Price, Red dashed lines – IO Share.
Figure 2: Maximum 4 Quarter Appreciation versus Maximum IO Share

Note: Circles indicate relative size of city. Red lines correspond to OLS regression lines.
Figure 3: Distinct Dynamics Among Cities with Large IO Shares

Note: Displayed are correlations and autocorrelations for $\Delta io_{it}$ and $\Delta p_{it}$ for the full sample of cities over the period 2000q1 to 2006q4.
Figure 4: Correlations between $\Delta io_{t+j}$ and $\Delta p_t$

Note: Sample restricted to those cities with maximum IO share of .4 and higher. Red lines correspond to the IO share cut-off of .4.
Figure 5: Pre-Payment and Default of Mortgages Originated in 2005q1

Note: Blue solid lines – IO Mortgages, Red dashed lines – Non-backloaded Mortgages.
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<th>Type</th>
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<th>Investor</th>
<th>Long Term</th>
<th>Priv. Sec.</th>
<th>Subprime</th>
<th>Pre Pay</th>
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Note: Entries are percent of indicated type of mortgage except for “Mean Amount” which is in units of thousands of current dollars.
Table 2: Summary Statistics for Price and Mortgage Variables

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Table 3: Baseline Models of Maximum 4 Quarter Price Appreciation in Boom Phase

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Note: OLS regressions of Maximum 4 Quarter Price Appreciation on indicated variables, weighted by number of mortgages. Most variables are mean values from 2000q1 to quarter of peak real house price. Property taxes are for 2000 and the change between 2000 and the year of the peak price. The Regulation variable is the Wharton Regulation Index and the Undevelopable Land variable is from Saiz (2010). ***, **, and * denote significance at the 1, 5 and 10 percent levels respectively.
Table 4: Controlling for Additional Mortgage Characteristics

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Note: OLS regressions of Maximum 4 Quarter Price Appreciation on indicated variables plus all explanatory variables in column (3) of Table 3, weighted by number of mortgages. ***, **, and * denote significance at the 1, 5 and 10 percent levels respectively.
Table 5: Controlling for Additional City Characteristics

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Note: OLS regressions of Maximum 4 Quarter Price Appreciation on indicated variables plus all explanatory variables in column (3) of Table 3, weighted by number of mortgages. ***, **, and * denote significance at the 1, 5 and 10 percent levels respectively. Employment shares by industry is included where indicated.
Table 6: Controlling for Additional Mortgage Characteristics With Price Declines

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Note: OLS regressions of Maximum 4 Quarter Price Declines on indicated variables plus all explanatory variables in column (3) of Table 3, weighted by number of mortgages. ***, **, and * denote significance at the 1, 5 and 10 percent levels respectively.
Table 7: Granger-Causality Based on OLS Regressions

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Note: OLS regressions of log price growth or change in IO share on indicated variables (without weights). ***, **, and * denote significance at the 1, 5 and 10 percent levels respectively. \(\sum x\) denotes sum of coefficients associated with variable \(x\). “AR(j)” indicates the \(p\)-value of the Arellano and Bond (1991) test for serial correlation in the residuals of order \(j\). “F Statistic” is the test statistic for the null that the non-regressor lag coefficients are all zero with the \(p\)-value below.
Table 8: Granger-Causality Based on System-GMM

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<th>$\Delta io_t$</th>
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</table>

$\sum \Delta p$  

|       | .45 (.04)**            | .02 (.08)              |
|       | .46 (.06)**            | -.26 (.12)*            |
|       | .65 (.07)**            | -.30 (.21)             |
|       | .44 (.16)**            | -.56 (.46)             |

$\sum \Delta io$  

|       | .21 (.03)**            | .63 (.04)**            |
|       | .26 (.03)**            | .54 (.07)**            |
|       | .21 (.04)**            | .63 (.08)**            |
|       | .24 (.05)**            | .55 (.14)**            |

J-stat  

dof  

|       | 28.54 28.7 27.71 27.76 | 28.68 28.52 27.66 26.15 |
|       | 140 138 134 126        | 140 138 134 126        |

AR(1)  

|       | 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 |
|       | 0.00 0.00 0.00 0.00 |

AR(2)  

|       | 0.53 0.007 0.32 0.57 | 0.002 0.12 0.61 0.81 |
|       | 0.00 0.00 0.00 0.00 |

AR(3)  

|       | 0.00 0.00 0.00 0.00 | 0.10 0.40 0.99 0.94 |
|       | 0.00 0.00 0.00 0.00 |

AR(4)  

|       | 0.00 0.00 0.00 0.00 | 0.61 0.80 0.77 0.68 |
|       | 0.00 0.00 0.00 0.00 |

F Statistic  

|       | 64.58 53.76 35.69 12.61 | 0.05 6.32 1.67 1.28 |
|       | 0.00 0.00 0.00 0.00 |

P-value  

|       | 0.00 0.00 0.00 0.00 | 0.83 0.01 0.20 0.30 |
|       | 0.00 0.00 0.00 0.00 |

Observations  

|       | 754 725 696 667 | 754 725 696 667 |

Note: System-GMM estimates of log price growth or change in IO share on indicated variables (without weights). ***, **, and * denote significance at the 1, 5 and 10 percent levels respectively. See Table 7 for descriptions of “$\sum x$,” “AR(j)” and “F-statistic”. “J-stat” indicates Hansen-Sargan test statistic for the over-identifying restrictions, where “dof” is the degrees of freedom of the test. In all cases the p-value is 1.