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House-Price Expectations, Alternative Mortgage Products, and Default[*]

by

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Abstract

Rapid house-price depreciation and rising unemployment were the main drivers of the huge increase in mortgage default during the downturn years of 2007 to 2010. However, mortgage default was also associated with an increased reliance on alternative mortgage products such as pay-option and interest-only adjustable rate mortgages (ARMs), which allow the borrower to defer principal amortization. The goal of this paper is to better understand the forces that spurred use of alternative mortgages during the housing boom and the resulting impact on default patterns, relying on a unifying conceptual framework to guide the empirical work. The conceptual framework allows borrowers to choose the extent of mortgage "backloading," the postponement of loan repayment through various mechanisms that constitutes a main feature of alternative mortgages. The model shows that, when future house-price expectations become more favorable, reducing default concerns, mortgage choices shift toward alternative products. This prediction is confirmed by empirical evidence showing that an increase in past house-price appreciation, which captures more favorable expectations for the future, raises the market share of alternative mortgages. In addition, using a proportional-hazard default model, the paper tests the fundamental presumption that backloaded mortgages are more likely to default, finding support for this view.

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House-Price Expectations, Alternative Mortgage Products, and Default

1. Introduction

Rapid house-price depreciation and rising unemployment were the macroeconomic drivers of the huge increase in mortgage default during the downturn years of 2007 to 2010. However, mortgage default was also associated with an increased reliance on alternative mortgage products (AMPs). These AMPs include pay-option adjustable-rate mortgages (option ARMs), which are ARMs that allow negative amortization, and interest-only (IO) mortgages (usually ARMs), which defer principal amortization for an initial period of five to 10 years. Being characterized by deferral (or "backloading") of mortgage costs, AMPs had substantially worse repayment performance than standard fixed-rate mortgages (FRMs) during the downturn.

In previous work (Brueckner, Calem, and Nakamura (2012), hereafter BCN), we analyzed the genesis of another important factor leading to the surge in defaults during the housing downturn: the relaxation of underwriting standards associated with subprime lending. The theoretical model in that paper showed how more-favorable expectations regarding future house-price appreciation can spur relaxation of underwriting standards by easing concerns about potential default, and the paper's empirical results supported this prediction.

While AMPs were widely viewed as lacking the credit risks of subprime loans, the present paper extends BCN's argument to explain the growing use of these products over the boom period. We argue that, when rapid house-price appreciation is expected, the higher default risk inherent in AMPs due to payment backloading is mitigated, encouraging their use. As in the prior paper, we provide theoretical and empirical analysis supporting this view. Together, the papers demonstrate that, once the housing bubble gained momentum, the favorable price expectations it generated fed the decline of underwriting standards and the use of AMPs, setting the stage for a surge in defaults once prices started to fall.

Our conceptual framework extends the model of BCN, which explains loosened underwriting as a consequence of evolving price expectations. We modify this framework to allow borrowers to choose the extent of mortgage backloading, the postponement of loan repayment through various mechanisms that constitutes a main feature of AMPs. By postponing mortgage payments, greater backloading is more likely to generate negative equity when house prices fall, making default risk higher for AMPs.[1] However, as house-price expectations become more favorable, with future price gains perceived as more likely by both borrowers and lenders, the riskiness of AMPs lessens, spurring their use.[2]

This argument is consistent with empirical evidence that we develop in two directions. We first examine the connection between the market share of AMPs and house-price appreciation. We find that, irrespective of whether the loans are retained on bank balance sheets or packaged into Agency or non-Agency securities, growth of alternative mortgages is positively associated with prior appreciation in house prices and other favorable economic indicators, similar to the association between high-risk subprime lending and house-price growth observed by BCN. In the areas with the steepest rises in house prices, alternative mortgages are favored over traditional FRMs and ARMs, and this finding appears robust to controlling for housing affordability, which is another force that may have spurred the use of AMPs.[3]

Next, in order to test the underlying presumption that alternative mortgages are more likely to default, we examine repayment performance during the downturn across the spectrum of mortgage contracts.[4] We find substantially higher default rates for the alternative products, again irrespective of whether the mortgages are retained on bank balance sheets or packaged into securities. Results from a multivariate Cox proportional-hazard model demonstrate that these differences exist even after controlling for the effects of the initial rise and subsequent fall in house prices, for regional differences in unemployment, and for standard credit-quality measures such as FICO score and interest-rate spread. These results confirm that backloaded mortgages are riskier, being more prone to default than traditional contracts. Moreover, the poorer performance of AMPs relative to other mortgages was evident to a similar degree among both

[1]In our stylized, two-period setting, the higher default risk of AMPs is a direct consequence of the impact of back-loading on the potential for negative equity. However, since the decision to backload depends on an expectation that the future value of the home will suffice to repay the mortgage, the model implies that a reversal of these expectations (arising from a decline in house prices) would provide an additional incentive to exit the contract through default. Note that the higher default risk of AMPs in our model is not a consequence of the payment shock associated with the reset into an amortizing mortgage. Thus, the model is consistent with the relatively high default rates observed for AMPs during the recent downturn, which occurred well prior to their reset dates.

[2] Unlike in Keys et al. (2009), for example, this argument does not depend on agency problems, which cause lenders to be indifferent to the likelihood of repayment of the credit instrument.

[3] Although affordability may have been a factor causing borrowers to choose AMPs, these were not “affordability products” in the sense of being targeted to low- or moderate-income households. For instance, the average loan size of interest-only and option ARM mortgages in our sample is substantially higher than that of FRMs within the same county and quarter; the median ratio of AMP to FRM loan size across counties and quarters is about 1.3.

[4] Our empirical analysis focuses on the prime and near-prime market segments, reflecting the composition of our sample.

portfolio mortgages and (private or public) securitized mortgages. Thus, the role of agency issues tied to securitization in spurring risky mortgage lending appears weak.

The paper contributes to the large prior literature on mortgage choice, which is extensively referenced in Brueckner (2000) and in the recent paper by Chiang and Sa-Aadu (2013). Much of that literature focuses on the choice between fixed and adjustable-rate mortgages, recognizing that borrower interest-rate risk is absent with FRMs but present with ARMs. Our framework, by contrast, ignores the fact that AMPs usually involve interest-rate risk, focusing instead on the backloading feature of these contracts.

Chiang and Sa-Aadu (2013) share some aspects of the present focus by using simulation methods to analyze the choice of alternative mortgages. Other previous papers that analyze mortgage choice in a model that includes default include Posey and Yavas (2001) and Campbell and Cocco (2003), which focus on the choice between traditional fixed and adjustable-rate mortgages, as well as LaCour-Little and Yang (2010). Like the present paper, LaCour-Little and Yang (2010) develop a model of alternative mortgage products while presenting an empirical analysis of contract choice that includes a connection to prior house-price appreciation. To a more limited extent, they also analyze default performance. Despite the broad similarities to this paper, we use different theoretical and empirical models, employ a more broadly representative data set, and provide more detailed analysis of repayment performance.[5]

Our empirical findings are consistent with LaCour-Little and Yang's evidence that favorable house-price expectations helped drive the rise in AMPs, and we identify other factors that spurred the use of these contracts. Whereas their evidence is primarily limited to Bear Stearns securitizations, our substantially larger data set permits us to evaluate the empirical importance of prior price appreciation in contract choice for a large portion of the overall U.S. housing market, including loans held in bank portfolios. Indeed, a substantial volume of AMPs was present in bank portfolios at the onset of the financial crisis, and these loans played an important role in bank losses during the crisis. At the end of 2010, according to Inside Mortgage

[5]The theoretical framework in LaCour-Little and Yang (2010) is relatively complex and incorporates both income shocks (payment-driven default risk) and house-price shocks (equity-driven default risk), thus requiring numerical analysis. It portrays reduction in default risk associated with adverse income shocks as the primary incentive for choosing an interest-only loan. Thus, the model implies (somewhat counterintuitively and in contrast to the empirical results in our paper) that higher expected income growth makes an AMP less attractive. In contrast, default risk in our model is solely equity driven, and the model remains agnostic on the relationship of AMP choice to expected income growth.

Finance (2013), U.S. banks and thrifts held $1.8 trillion in mortgage loans on their portfolios, of which nearly 13 percent were in default at the time.

Our empirical work on default shows that AMPs had higher default rates than other types of contracts with comparable measured credit quality, while pointing out that bank portfolios of AMPs performed, broadly speaking, as badly as securitized AMPs. The empirical analysis of default in LaCour-Little and Yang (2010), by contrast, is mainly devoted to analyzing default risk conditional on the choice of an AMP, not to comparing default risk between AMPs and other types of contracts. In addition, their data are limited to 2007 and earlier, prior to the peak years of the mortgage crisis, whereas our analysis of repayment performance extends through the first quarter of 2012.

Another related paper is that of Cocco (2013), who uses British data to show that AMP borrowers expected higher future income growth than users of traditional mortgages, a finding that parallels some findings of LaCour-Little and Yang (2010). In addition, Barlevy and Fisher (2011) examine backloaded mortgages from a different perspective, arguing that lenders preferred to make these mortgages to encourage prepayment.

The paper is organized as follows. Section 2 presents the simple theoretical framework that formalizes the notion of backloading, demonstrating the link between favorable house-price expectations and backloading of mortgage repayments through use of AMPs. Section 3 demonstrates empirically the link between expected house-price appreciation and reliance on AMPs. Section 4 presents the default analysis, and section 5 offers conclusions.

2. Model

In this section, the model of Brueckner (2000) is adapted to analyze the effect of house-price expectations on the choice of alternative mortgages by borrowers. Brueckner's earlier model analyzed only the choice of loan size in the presence of borrower default, but the framework can be recast to study the choice of mortgage backloading, the key feature of alternative contracts, in a setting with default.

The model has two periods, 0 and 1. At the beginning of period 0, the borrower purchases a house of value P_0 with a 100 percent mortgage (this no-down-payment assumption is used only for convenience). At the end of the period, the borrower makes his first mortgage payment, denoted M_0. In period 1, the mortgage contract requires a second payment, denoted M (for simplicity, period-1 values are not subscripted). Mortgage backloading corresponds to a shift in the payment burden toward period 1, with a decrease in M_0 and an increase in M.

The value of the purchased house changes stochastically between the periods, and if the value drops sufficiently, then default is the right decision for the borrower. To write the borrower's default rule, let P denote the period-1 house value and C denote "default costs." These costs include the cost from impairment of the borrower's credit rating following default, the moving costs that must be incurred following foreclosure, and any other costs of failing to honor the mortgage contract. Default is optimal when $P - M \leq -C$, or when housing equity $P - M$ is negative and larger in absolute value than default costs. Rearranging this condition, the default rule can be written as

$$P \leq M - C, \tag{1}$$

where $M - C$ is the "default" price, the house price below which default occurs. With backloading raising the value of *M*, the default rule in (1) is more easily satisfied for a backloaded mortgage since the default price is then higher. Therefore, backloading raises the riskiness of a mortgage by making default more likely. The riskiness of a loan also depends on the default costs *C* of the borrower. When *C* is low, the borrower defaults more easily, with (1) more easily satisifed for a given *M*, so that low-*C* individuals are risky borrowers. Note that while the default rule in (1) emphasizes equity (relative to default costs) as the driving force, the rule allows trigger events to play a role in default.[6]

Using this rule, Brueckner (2000) assumed that heterogeneous default costs are private information to borrowers and analyzed the resulting distortion of the mortgage market equilibrium. Brueckner, Calem and Nakamura (2012), by contrast, assumed that C is observable to lenders (being captured by the borrower's credit rating) and portrayed subprime lending as a reduction in the minimum C (or credit rating) required to obtain a loan. Although default costs are not central to the current analysis, this observability assumption will be maintained.

[6]A trigger event could affect the value of *C*, thereby generating default without a change in *P*. For example, moving costs would normally be an element of *C*, since a move is necessary following default and eviction. But if the borrower loses his or her job, then a move is necessary regardless of whether or not default occurs, and moving costs no longer are an element of *C*. With *C* then falling, the default condition (1) may now hold with *P* unchanged, leading to default. Stated differently, the need to move may have restrained default for a borrower with negative equity, but a job loss (which necessitates a move in any case) makes negative equity more prominent in the default decision.

Expectations about period-1 house prices, which shape perceptions of the likelihood of default, govern the writing of mortgage contracts in period 0. These house-price expectations, which are assumed to be common across borrowers and mortgage lenders, are summarized in the density function $f(P,\delta)$, where δ is a shift parameter that moves the density to the right, in the direction of higher P values. The cumulative distribution function is given by $F(P,\delta)=\int_0^P f(P',\delta)dP'$, and it is assumed that δ shifts this function in the sense of first-order stochastic dominance. In other words, $F_\delta(P,\delta)\le 0$ is assumed to hold, where the subscript denotes partial derivative, indicating that an increase in δ reduces (or leaves unchanged) the probability that P lies below any particular value. The purpose of the analysis is to determine the effect of an increase in δ on the choices of M_0 and M.

To answer this question, we specify the borrower utility and lender profit functions and characterize borrower indifference curves and the lender zero-profit locus in (M,M_0) space. The chosen mortgage contract corresponds to a point of tangency between an indifference curve and the zero-profit locus, and we analyze the effect of a higher δ on the location of this tangency.

Letting η denote the lender's discount factor, the present value of profit is written

$$\pi \equiv -P_0 + M_0 + \eta\left[\int_0^{M-C} Pf(P,\delta)dP + \int_{M-C}^{\infty} Mf(P,\delta)dP\right]. \tag{2}$$

To understand (2), observe that the lender makes a loan outlay of P_0 at the beginning of period 0, receiving the first payment of M_0 at the end of the period. In period 1, the lender receives the contracted payment M if P is above the default price $M-C$, which induces the borrower to repay the loan. Otherwise, the lender receives the house value P instead of M, capturing it via foreclosure and resale of the house (foreclosure costs are, for convenience, assumed to be zero). The term in brackets is thus the lender's expected period-1 revenue in the presence of potential default.

Setting π in (2) equal to zero gives the lender's zero-profit locus, the collection of (M,M_0) pairs that yield zero discounted profit. The slope of this locus is found by totally differentiating the resulting equation. Leibniz's rule, along with (1), yields π_M, the derivative of π with respect to M:

(3) $\pi_M / \eta = \; f(M-C,\delta)[(M-C)-M] + \int_{M-C}^{\infty} f(P,\delta)dP = -Cf(M-C,\delta) + [1-F(M-C,\delta)]$.

This expression is ambiguous in sign, reflecting two opposing forces: A higher M raises the return to the lender when default does not occur (positive second term inside the brackets) while making default more likely (negative first term).

To facilitate the analysis, we make the natural assumption that the first term is dominant over the relevant range of M, so that the lender's return is increasing in M ($\pi_M > 0$).[7] If we use the π_M expression in (3) and note that $\pi_{M_0} = 1$, the slope of the zero-profit locus (equal to $-\pi_M/\pi_{M_0}$) is given by

(4) $$\frac{\partial M_0}{\partial M_{|\pi}} = -\,\eta[1 - F(M-C,\delta) - Cf(M-C,\delta)] < 0.$$

indicating that the zero-profit locus is downward sloping and confirming the expected trade-off between M and M_0. This trade-off emerges unambiguously if the distribution of P is uniform with support $[\underline{P}+\delta, \overline{P}+\delta]$, as shown in the appendix. Although the curvature of the zero-profit locus is ambiguous in general, the appendix also shows that the locus is convex in the uniform case, as shown in Figure 1 (in other words, (4) becomes less negative as M increases, moving down the locus).

Borrowers are assumed to be risk neutral, with utility given by the present value of wealth. Letting the discount factor (which could differ across borrowers) be denoted by θ and letting Y denote the expected present value of income, utility is equal to[8]

(5) $$u = Y - M_0 + \theta\left[-\int_0^{M-C} Cf(P)dp + \int_{M-C}^{\infty}(P-M)f(P)dP\right].$$

Note that the borrower loses C when default occurs but that the increment to wealth when the mortgage is repaid equals the borrower's equity in the house, $P - M$. Setting u equal to a constant and totally differentiating the resulting equation with respect to M using Leibniz's rule, the terms involving the limits of integration all cancel, so that $u_M = -\int_{M-C}^{\infty} f(P)dP$. With $u_{M_0} = -1$, the slope of an indifference curve $(-u_M/u_{M_0})$ is then given by

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[7] As noted below, borrower utility u is declining in M. Hence, if $\pi_M \le 0$ were to hold, then both the borrower and lender would be better off reducing M, so that its optimal value is zero, implying that no mortgage is written.

[8] Note that Y does not include income from house price appreciation, which is captured in the last term of (5).

(6) $$\frac{\partial M_0}{\partial M}_{|u} = -\theta[1 - F(M - C, \delta)] < 0.$$

Indifference curves are thus unambiguously downward-sloping, and since (6) is increasing in *M*, the curves are convex. Note also that the curves are vertical parallel, having the same slope along any vertical line (where M is held constant).

Since lower indifference curves (with lower values of M_0 for given M) have higher utilities, the borrower's preferred mortgage corresponds to the point on the zero-profit locus that lies on the lowest indifference curve. If the zero-profit locus is more convex than the indifference curves, such a point will lie at a tangency between the locus and an indifference curve, assuming an interior solution. Such an outcome, which is illustrated in Figure 1, is the one of interest and will be the focus of the ensuing analysis.[9]

Assuming that the relative convexity condition is satisfied, the tangency condition that determines the preferred mortgage sets (4) and (6) equal, which implies

(7) $$\Omega \equiv -(\eta - \theta)[1 - F(M - C, \delta)] + \eta C f(M - C, \delta) = 0.$$

As seen in the appendix, solving (7) in the uniform case and gives the following optimal value for *M*:

(8) $$M^* = \overline{P} + \delta - \frac{\theta C}{\eta - \theta}.$$

Therefore, the optimal M equals the maximum house value minus a positive constant times default costs C, which is observable to the lender and thus reflected in the mortgage terms offered to the borrower.[10] The solution for M_0 is given in the appendix.

The solution in (8) shows the effect on the optimal mortgage contract of a shift in house-price expectations. In the uniform case, a favorable shift in expectations corresponds to an

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[9] A corner solution is also possible. In particular, the slope formulas in the appendix show that if $\eta \leq \theta$, so that the lender's discount factor is less than or equal to that of the borrower, then the indifference curves are steeper than the locus. The preferred mortgage then lies at the upper endpoint of the zero-profit locus, where $M_0 = P_0$ and $M = 0$. In this case, the borrower buys the house outright, without using a mortgage. To focus on cases where a mortgage is used, we thus restrict our attention to borrowers for whom $\theta < \eta$.

[10] It can be verified from the appendix formulas that the relative convexity condition holds in the uniform case, so that the tangency point given by (7) is a utility maximum. In particular, it is easily seen that the indifference curve slope in (*a*2) is less (more) negative than the zero-profit locus slope in (*a*1) as $M < (>) M^*$, confirming the pattern shown in Figure 1.

increase in δ, which shifts P's uniform distribution to the right. The effect of a higher δ can be seen directly in (8), which shows that M^* rises as δ increases. As seen in the appendix solution, M_0^* correspondingly falls as δ increases. Therefore, a favorable expectations shift leads the borrower to choose a mortgage that is more backloaded, with a higher M and lower M_0. With backloading a main feature of alternative mortgage products, the prediction is that more-favorable price expectations increase the use of AMPs.[11]

To investigate the effect of a higher δ in the general case, without imposing a distributional assumption, (7) is totally differentiated with respect to M and δ. The relative convexity condition requires $\Omega_M > 0$, but satisfaction of this inequality is not guaranteed in general and must be assumed. Carrying out the differentiation of (7) yields

(9) $$\frac{\partial M}{\partial \delta} = -\frac{\Omega_\delta}{\Omega_M} = -\frac{(\eta-\theta)F_\delta(M-C,\delta) + \eta C f_\delta(M-C,\delta)}{\Omega_M}.$$

From above, the stochastic dominance assumption implies $F_\delta < 0$. If $f_\delta(M-C,\delta) \le 0$ holds as well, so that the height of the density is non-increasing in δ at the default price $M-C$, then (9) is positive. M then rises with a favorable expectations shift ($\partial M / \partial \delta > 0$), just as in the uniform case, and it can be shown that M_0 falls.[12] Summarizing yields:

> **Proposition.** *When the house-price distribution is uniform, a favorable shift in the distribution raises the extent to which the optimal mortgage is backloaded. Thus, a favorable expectations shift increases the use of alternative mortgage products. The same conclusion holds in general if the relative convexity condition is satisfied and if the expectations shift reduces (or leaves constant) the height of the house-price density at the default price.*

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[11]If the zero-profit locus is concave, a corner solution with $M_0 = 0$ is likely to arise. In this case, the expectations shift would not change the nature of the mortgage contract (which would still be fully backloaded); it would only change the magnitude of *M*.

[12]Performing integration by parts on the first integral, the bracketed term in (2) reduces to $-CF(M-C,\delta) - \int_{\underline{P}}^{M-C} F(P,\delta)dP + M$. The derivative of this expression with respect to δ is

$$-CF_\delta(M-C,\delta) - \int_{\underline{P}}^{M-C} F_\delta(P,\delta)dP + [1 - F(M-C,\delta) - Cf(M-C,\delta)]\frac{\partial M}{\partial \delta},$$

which is positive when the zero-profit locus is downward sloping (see (4)). With the bracketed expression in (2) thus rising with δ, M_0 must fall.

Thus, as a favorable shift in price expectations reduces anticipated default by making condition (1) less likely to hold, borrowers opt for an offsetting change in the pattern of mortgage payments. An increase in M , which reverses the effect of the shift by raising the likelihood of default, becomes optimal. In effect, the borrower responds to the more-favorable price environment by opting for a riskier mortgage.

More technically, it can be shown that the zero-profit locus shifts downward as δ increases under the stochastic dominance assumption. In addition, it can be seen from (5) and (8) in the uniform case that the indifference-curve family and the zero-profit locus both become steeper at any given M as δ increases. The reason is that the resulting lower chance of default means that an increase in M is more beneficial to the lender (more harmful to the borrower), requiring a larger offsetting movement in M_0. However, because $\eta > \theta$ holds, the zero-profit locus steepens by more than the indifference curves, making it steeper than the curve intersecting it at the old value of M . But as can be seen from the slope expressions, moving to a larger M reduces the steepness of the indifference curves and the locus; once M has risen by the amount δ (see (8)), both slopes are back at their original values and thus again equal, restoring the tangency. Therefore, M must rise, moving the mortgage contract down the new zero-profit locus until a tangency is reached.

The model has been developed assuming a 100-percent mortgage, but the effect of a lower required LTV is easily analyzed. In (5), the down payment αP_0 would be subtracted from income along with M_0, where α is one minus the required LTV ratio, while P_0 in (2) is replaced by $(1-\alpha)P_0$. Since the tangency condition (7) is not affected by these changes, M is independent of LTV, with the only effect of a larger down payment being a reduction in M_0 in one-for-one fashion.[13] Thus, by reducing M_0 while leaving M unchanged, a lower required LTV effectively increases the backloading of the mortgage.

A related point applies to an increase in P_0 with LTV held fixed. Assuming that the distribution of P also shifts to the right ($\overline{P} + \delta$ increases by an amount equal to the change in P_0), then M^* fromfrom (8) increases one-for-one as well. But the appendix solution for M*

[13] This conclusion can be derived from the appendix solution for M_0 with P_0 replaced by $(1-\alpha)P_0$.

shows that the same distributional shift raises M_0^* by $1-\eta$ times the amount of the shift; that is, less than one-for-one. Thus, M_0^* rises by less than M^*, so that mortgage backloading increases. Therefore, when housing affordability falls (with future price expectations adjusted accordingly), the optimal mortgage becomes more backloaded, an effect that is similar to but distinct from the effect of more-favorable price expectations holding P_0 constant. This effect of reduced housing affordability in spurring the use of AMPs is noted in the literature (see, for example, LaCour-Little and Yang (2010)).

Note also that in the model, non-housing income Y has no effect on M_0^* or M^* and, thus, no impact on backloading. This outcome is a consequence of the model's assumption that borrower utility is linear. While linearity makes the analysis tractable, it eliminates any incentive to smooth consumption across periods. In a more general framework where such an incentive is present, higher income will have an effect on backloading, but the direction will depend on the period in which the income increase occurs. Finally, while an increase in the default-cost parameter C reduces M^* from (8), the appendix shows that the effect on M_0^* is ambiguous. Therefore, the model yields no clear prediction about the effect of default costs on backloading.

3. Empirical Evidence on the Use of Alternative Mortgage Products

3.1. Data and variables

In the empirical work, we analyze panel data on the market share of newly originated ARMs and AMPs by county and quarter of origination, over the 2004-2007 period. The panel data set is constructed from widely used, loan-level data collected by the vendor Loan Processing Systems (LPS) from the largest mortgage servicing companies. Attention is restricted to conventional, first-lien mortgage contracts, with FHA and other government-insured mortgages excluded from the estimation sample. The underlying loan-level data contain more than 20 million mortgages (compared with the 97,000 loans in LaCour-Little and Yang (2010)). These data are used to create 18,823 county-quarter observations.

Because our data set comes from the largest mortgage servicers, it tends to represent the loans of the lenders with contractual relationships with those servicers. This pattern is advantageous in terms of detecting selection issues (lenders' decisions as to whether to hold loans in portfolio or to sell them). However, the data tend to underrepresent subprime mortgage servicers, with mortgages identified (by the servicer) as subprime comprising only 3.6 percent of our sample.

As noted in the introduction, we conduct the empirical analysis on a sample pooling all investor types and then separately for subsamples of mortgages retained on bank balance sheets (almost 2 million loans), mortgages sold to Fannie Mae and Freddie Mac and packaged into Agency securities (public securitized; 12.9 million loans), and mortgages placed into private (non-Agency) mortgage-backed securities (private securitized; 5.7 million loans). The data are segmented in this way because mortgage contracts might differ systematically along unobserved dimensions based on whether they were originated for a bank's own portfolio or for public or private securitization.

We estimate a set of regression equations relating the market share of each product type to recent house-price appreciation (a proxy for expected future house-price changes) and control variables, including other indicators of economic conditions. These indicators include the log of state per capita income and the regional consumer confidence index of the Conference Board, measured as of the prior quarter. Economic conditions in the market could affect the AMP share by altering expectations of house price or income growth. These panel regressions include both county and year-quarter fixed effects.

We estimate equations for both overall (home purchase plus refinancing) market shares, as well as equations for refinance-only shares. The refinance-only analysis is intended to isolate the effect of house price expectations on contract choice from the impact of affordability. Since the house is already owned, the contract chosen under refinancing will be largely unaffected by affordability considerations, with past price appreciation then capturing the pure effect of price expectations uncontaminated by any influence effect of past appreciation on current prices and thus affordability.[14]

Our measure of house-price inflation over the prior year uses county-level data from First American CoreLogic for all single-family combined (attached and detached) units.[15] The variable equals the four-quarter percentage change in the index, lagged four quarters (that is, the

[14] Affordability may continue to be a factor in refinance contract choice to the extent that borrowers choose to refinance under their original contract type, which may have been chosen on the basis of affordability.

[15] We also ran regressions excluding both attached units and distressed sales and found only small differences; these regressions are available upon request.

percentage change in the index between eight and four quarters prior to the current quarter).[16] A higher percentage change is assumed to generate a price-expectations shift like that portrayed in the theoretical model.

Two borrower leverage measures are included to capture the LTV effect in the theoretical model and to also serve as proxies for housing affordability. Reduced housing affordability is expected to spur use of high LTV (or second-lien) loans as home purchase borrowers seek to amass the funds required for the purchase. The two leverage variables are the median LTV of first-lien mortgages and the percentage of first-lien home purchase loans accompanied by a second lien, by county and quarter. We also explored using a more-direct affordability measure (a county house-price-to-income ratio), but since this measure involves the price and income variables already imbedded in the model, its performance was not satisfactory.

The required LTV ratio in the theoretical model has a direct and negative effect on backloading. As a proxy for reduced affordability (in terms of the model, an increase in P_0), greater borrower leverage is expected to increase backloading and thus the AMP market share, given the previous discussion. Therefore, the predicted sign of regression coefficients on the leverage variables, being the composite of the affordability and direct effects, is ambiguous. But if the affordability effect dominates, we would expect to see the emergence of positive coefficients. Note in addition that LTV may be associated with the size of the borrower's discount factor θ, a low value of which favors both backloading as well as high leverage. Therefore, including LTV in the regression may help control for the backloading effects of variation in θ within the population. The predicted sign from this channel is again positive.

Median LTV is calculated directly from the LPS loan-level data, and it is measured separately for loans in the three investor categories, for each county and quarter. Second-lien percentage by county and quarter is obtained from Home Mortgage Disclosure Act data and is not investor-specific.[17] The latter variable is not available for all counties, leading to a modest

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[16] Price endogeneity was a serious issue in our previous paper, given that weakened underwriting standards (subprime lending) increased the pool of mortgage borrowers, with a consequent effect on the demand for housing and thus prices. Since the present focus is instead on the market shares of different types of mortgage contracts, which presumably have a smaller impact on demand and thus on prices, endogeneity is less of a concern. Therefore, lagging our prior appreciation measure by one year is a sufficient precaution.

[17] We rely on estimates of the incidence of piggyback home purchase loans developed by staff at the Federal Reserve Board. A junior-lien loan was identified as a piggyback to a reported first-lien loan if both loans (1) were conventional loans involving property in the same census tract, (2) were originated by the same lender with approximately the same dates of loan application and closing, and (3) had the same owner-occupancy status and

reduction in sample size for the regressions containing it. For the refinance-only regressions, median LTV is measured specifically for first-lien refinance loans. In these regressions (which hold affordability constant), the two LTV variables control for the direct LTV effect implied by the model and any residual impact of affordability (whereby borrowers may choose to refinance under their original contract type, which may have been chosen on the basis of affordability), as well as controlling for variation in borrower discount factors.

The regressions also include the mean FICO score in the county and quarter (measured separately for loans under the three investor categories), in order to capture the model's default-cost parameter *C*. For the refinance-only regressions, mean FICO was measured specifically for refinance loan originations. Although the theory yields no prediction about the direction of the FICO score's effect on backloading, the theory indicates that credit score nevertheless belongs in the model.

Table 1 reports sample means for regression variables from the county-quarter data (home purchase and refinance). While the pooled data show an AMP share of 9.4 percent, the share across the investor categories varies from a low of 3.8 among public securitized loans to a high of 27.3 percent among bank portfolio loans (private securitized loans have an intermediate share of 20.8 percent). Among AMPs, interest-only ARMs dominate option ARMs among both types of securitized loans, with the reverse relationship holding for bank portfolio loans. The mean FICO scores are similar among bank portfolio and private securitized loans, but notably higher among public securitized loans. Median LTV is similar across investor categories, lying just below 80 percent, while about 10 percent of loans have a second lien.

3.2. Regression results for the full sample

Market-share equations are estimated individually for each of the following product categories: interest-only ARMs, option ARMs, and a composite category of one-, two-, and three-year ARMs. The latter category (which represents more-standard ARM contracts) is included for comparison purposes.[18] In addition, an all-AMPs regression combining the two AMP products is estimated. Although interest-only FRMs were another type of alternative mortgage product originated during this period, they were relatively uncommon and hence not

identical borrower income, race or ethnicity, and sex. See Avery, Brevoort, and Canner (2008) for further discussion of piggyback junior lien identification in HMDA data.

[18] These are ARMs which have an initial, fixed rate period of 2 and 3 years, respectively, after which they are subject to annual rate adjustments for their remaining term (typically 28 and 27 years; hence, they are commonly referred to as 2/28 and 3/27 ARMs.)

conducive to panel-data analysis. Note that the remainder of the market consists of standard FRMs combined with 5-, 7-, and 10-year ARMs.[19]

Estimation results for the full sample (home purchase plus refinance) are reported in Table 2, with panel *a* showing pooled results for all mortgages regardless of investor type, and panels *b*, *c*, and *d* containing results for the three investor categories. Note that, with the exception of the FICO and LTV variables, which are specific to the investor type, the values of the explanatory variables in panels *b, c,* and *d* are the same for each regression.[20] The panels differ in the values of the dependent market-share variables for the various loan products, which differ across investor types.

Each panel shows results for two specifications, with the first (shown in the first four columns) using median LTV as the only housing-affordability proxy and the second (shown in the last four columns) adding the percent of loans with a second lien as an additional affordability proxy. Within each block of a particular panel of the table, the first regression uses the combined AMP market share (the combined share of interest-only ARMs and option ARMs) as dependent variable, while the second and third regressions use the shares of these two contracts separately. For comparison purposes, the last column in the block uses the share of standard (non-alternative) 1-, 2-, and 3-year ARM contracts as a dependent variable.

The pooled regression results are consistent with the theoretical prediction that more-favorable house-price expectations encourage use of contracts with a greater degree of payment backloading. In particular, the results indicate that the aggregate market share of AMPs, as well as the individual market shares of interest-only and option ARMs, increase with expected house-price appreciation, as proxied by past appreciation. Exactly the same pattern emerges for both the public- and private-securitized subsamples, although in the bank-portfolio subsample, the effect of past price appreciation on the interest-only ARM share is insignificant. All these results are qualitatively the same regardless of whether the second-lien percentage is added as an affordability variable.

Although the model predicts no effect of consumer income on mortgage backloading (because it contains no incentive for intertemporal consumption smoothing), the empirical results show that the overall and individual AMP market shares rise with income. A higher level of the

[19] These are ARMs that have an initial, fixed rate period of 5, 7, and 10 years.

[20] While the variable values are the same, the slight differences in Table 1 in the means of these variables across investor types are due to different sample sizes.

consumer confidence index also tends to raise these market shares, although some regressions show insignificant coefficients for the index and one has a significantly negative index coefficient.[21] The mean FICO score has an inconsistent affect on the AMP shares, with a higher mean score raising the interest-only ARM share in many regressions while often simultaneously reducing the option ARM share. Recall that the theory did not generate a clear-cut prediction regarding the effect of this variable.

Turning to the affordability proxies, the coefficients of median LTV and the percent of loans with a second lien are almost uniformly positive and significant in the pooled regressions, with the exception of one insignificant coefficient. In the investor subsamples, the affordability-proxy coefficients are either significantly positive or insignificant (all coefficients are significant in the private securitized subsample). Recall that, when it is viewed as an affordability proxy, the effect of consumer leverage (LTV and second liens) on backloading is positive while its direct backloading effect is negative. The positive coefficients from Table 2 thus appear to indicate that the affordability effect dominates, with increases in the leverage variables leading to a higher market share of AMPs rather than a lower share.

The regressions in Table 2 explaining the market share of standard ARM contracts show different patterns than the AMP regressions. The pooled regressions show a negative effect of past price appreciation on the ARM market share, an effect that appears driven by private securitized loans (the only investor category with a significantly negative coefficient). Income and consumer confidence have inconsistent effects on the ARM share, while a higher mean FICO score reduces the share. Higher values of the leverage variables reduce the ARM share in the pooled regressions, the reverse of the AMP findings, but the coefficients in the remaining panels of the table are often positive and significant.

Overall, the results in Table 2 are quite supportive of the empirical hypothesis linking favorable house-price expectations to greater use of alternative mortgage products, with faster past house-price appreciation raising AMP market shares. Because of the presence of the various other control variables in the regressions, it is likely that this estimated effect indeed

[21] These observed relationships (to income and consumer confidence) seem intuitive in that favorable economic conditions may generate optimism about rising incomes, which in turn may help to motivate backloading.

captures the hypothesized link rather than some other force connecting AMP usage to prior price appreciation.[22]

3.3. The AMP market share among refinance loans

While we have relied on the leverage variables as affordability proxies to control for a potential effect of housing affordability on AMP usage, an additional step is to restrict the sample to loans used for refinancing. As described earlier, focusing on refinance mortgages should isolate the effect of house price expectations from the impact of affordability, given that the borrower already owns the home.

As can be seen from Table 3, refinancing and purchase loans account for roughly equal loan volumes within in each investor category.[23] However, because the AMP share is low for public securitized loans and because the number of bank portfolio loans is absolutely small, most of the refinancing loans are in the private-securitized category. The results in Table 4, which show the AMP refinancing market-share regressions for the pooled data, are thus driven by private-securitized loans.

As can be seen, the refinancing regression results are qualitatively similar to the all-loan pooled results from Table 2a. Past house-price appreciation raises the all-AMP market share and the individual shares of interest-only and option ARMs. Higher levels of income and consumer confidence index raise the AMP shares, as do higher values of the leverage variables. The effect of the mean FICO score is inconsistent across regressions, as in Table 2a. These results conclusively show that the regression results in Table 2 do not reflect a failure to adequately control for housing affordability.

[22]It could be argued that the two leverage variables should be treated as endogenous since they are jointly determined with the choice of mortgage type and thus potentially correlated with the regression error term. However, it is unclear what the direction of this correlation might be. In other words, is a county whose unobservables favor a large AMP share (leading to a large error value) likely to have a low or high median LTV or percentage of second-lien loans? Given the absence of a clear answer to this question (and thus a clear direction of bias), we treat the leverage variables as exogenous in the estimation. We also note that the estimated relationships between the AMP shares and house-price appreciation are robust to excluding the LTV measures.

[23] Due to presence of a modest number of loans with unknown purpose, the sum of refinancing and purchase loans is somewhat smaller than the totals shown in Table 1.

4. Empirical Evidence on Mortgage Default by Contract Type

4.1. Data and variables

In this section, we test the fundamental presumption of the conceptual framework, namely, that backloaded mortgages are more likely to default. To do so, we examine the repayment performance through March 2012 of all conventional mortgages originated in the 2004-07 period and contained in the LPS database.

We estimate a loan-level, proportional-hazard model of default, which is defined as the first incidence of the loan becoming 60 days past due. The model relates default to mortgage contract type and a variety of control variables. Again, we conduct the empirical analysis separately for mortgages retained on bank balance sheets, mortgages sold to Fannie Mae and Freddie Mac (packaged into Agency securities), and mortgages placed into private mortgage-backed securities, along with an analysis pooling the three investor types.

This empirical analysis was conducted with a 10 percent random sample of the underlying data set, yielding over 1.6 million observations.. Ten percent of the loans are private securitized, 66 percent public securitized, and 24 percent held in bank portfolios.

The unit of observation for the hazard model estimation is loan account and month. Each account's payment status is tracked each month, until a termination occurs due to 60-day delinquency, prepayment, or end of the sample period. Prepayments are treated as censored observations, like loans surviving to the end of the period. The delinquency hazard equations take the "proportional hazard" form:

(14) $$h(t \mid X) = \eta(t) \exp(\beta_1 X_1 + \cdots + \beta_p X_p) .$$

The hazard rate $h(t|x)$ in (14) is the rate of delinquency at time t conditional on an account surviving until t and conditional on a vector of covariates X. Its relation to the cumulative survival probability $S(t|X)$ is $h(t \mid X) = d \log S(t \mid X) / dt$.

Under the proportional-hazard formulation in (14), the hazard rate consists of a baseline hazard rate $\eta(t)$ that depends only on the survival time and is multiplied by a function of the covariates. The advantage of this approach is that it does not impose any restrictions on baseline hazard rates. Moreover, estimates of the coefficients β_1 through β_p can be obtained by maximizing the partial likelihood function without any need to estimate the baseline hazard rates.[24] This approach is taken since we are concerned not with the baseline hazard but with testing relationships between the hazard rate and economic covariates.

We control for unobserved factors associated with different origination channels, using indicators for the retail (bank) and nonretail (wholesale or broker) origination channels, respectively, and interactions of these indicators with contract type. We also control for the deterioration in underwriting standards during 2005 through 2007, as demonstrated in prior studies, by including dummy variables for each of these origination vintages. In addition, we control for the origination FICO score; if this score is missing from the data (the case for about 25 percent of observations), it is set equal to zero and an indicator variable for missing FICO is set equal to 1 (and zero otherwise).

Factors associated with the credit quality of the loan for which we cannot control directly (due to missing or incomplete data) may be reflected in the pricing of the loan. We include the spread at origination—the difference between the note rate and a comparable Treasury rate—at the time of origination, as a proxy for such factors.[25]

Spreads are affected by anticipated prepayment speeds and the expected life of the mortgage. For this or other reasons, the spread relationship to credit quality may vary systematically between ARM and FRM mortgages. Moreover, many ARMs (including AMPs) were originated with teaser interest rates—tempoarily reduced interest rates designated to reset to a level more reflective of the loan's credit quality at the expiration of the initial "teaser" period. Therefore, we include a dummy variable identifying ARMs originated with a teaser rate, along with three spread-at-origination variables: spread interacted with an indicator for ARM with teaser rate; spread interacted with an indicator for ARM without a teaser rate; and spread interacted with an indicator for FRM.[26]

We also control for economic conditions affecting the default probability by including the contemporaneous loan-to-value ratio, as measured by updating the origination loan-to-value ratio using the county CoreLogic house-price index. In addition, we control for local house-price appreciation and employment conditions. Specifically, we include the county-level annual house

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[24] See Allison (1995).

[25] For 1-year, 2/28, and 3/27 ARMs we employ the 3-month Treasury rate as the base rate for calculating the spread. For FRMs and ARMs with an initial fixed rate period longer than 3 years, we employ the 10-year Treasury rate as the base rate.

[26] We cannot directly identify loans with teaser interest rates; as an approximation, we equate teaser rate with a spread of less than 50 basis points.

price lagged four quarters (as in the other empirical model), along with the county-level unemployment rate change from the prior quarter. General financial market and macroeconomic conditions that influence default along with the competing risk of prepayment are captured by a yield curve measure (gap between 10-year and three-month Treasury rates).[27]

Additional control variables include property and occupancy type; a jumbo-loan indicator and its interactions with origination vintage (except in the public securitized model); and a servicer-reported subprime loan indicator (only in the private securitized model; it was found to be non-predictive for the other investor categories, which have relatively few indicated subprime loans). Summary statistics for the hazard model variables are presented in Table 5.

While it is important to control for macroeconomic factors and general risk factors, we believe it is less important to control for risk measures that might correlate with backloading such as presence of a "piggyback" second lien, low or no documentation of income, or "cash out" at origination.[28] We can view the results as reflecting the overall contribution of backloading to delinquency risk, including the interest rate and principal repayment structure as well as associated factors.

4.2. Estimation results

Results are presented in Table 6, using as the baseline mortgage category five-, seven- or 10-year ARMs. The results strongly support the hypothesis that the backloading of mortgage payments inherent in ARMs and AMPs was associated with an elevated default likelihood during the housing market downturn. The estimated coefficients on each of the alternative product-type indicators (interest only and option ARM) for each origination channel and investor type are positive and statistically significant. In addition, these contracts mostly have an estimated hazard ratio at least 40 percent higher than those of the baseline category. Moreover, AMPs exhibit significantly higher default likelihoods than all other product categories with the exception of the 2- or 3-year ARMs, which were less common than AMPs, and some categories associated with an insignificant share of loans (such as one-year ARMs within bank portfolios).[29] Generally, the

[27] Changes in the yield curve could be viewed as influenced by the monetary policy response to mortgage market and other macroeconomic conditions, raising endogeneity concerns, but dropping this measure does not materially affect the coefficients (results are available upon request).

[28] Presence of a second lien is not reported, and loan purpose (whether cash out) is imperfectly reported in the data. Documentation type, also imperfectly reported, may also be viewed as potentially related to backloading, as low-documentation borrowers often overstated their income in order to obtain a larger mortgage than they could afford to repay should expectations of rising incomes and home prices fail to materialize.

[29] The 2/28 and 3/27 ARMs typically were associated with subprime borrowers and offered a large initial "teaser"

nonretail channel is seen to have a higher default frequency than the retail channel, consistent with potential agency issues tied to broker or wholesale channels and also with findings from some prior studies.[30]

Among the other important covariates, a higher FICO score reduces the default hazard, as does a steepening of the yield curve; investor loans and loans on two-to-four-unit properties are quicker to default; and the hazard is raised by a higher unemployment rate and a higher LTV (the default category is above 150 percent). Larger non-teaser spreads are associated with increased default risk, while teaser spreads exhibit the reverse relationship. As expected, faster prior house-price appreciation lowers the default hazard.

The Table 6 estimates pertain to the period of the Great Recession, one in which home prices fell by an unusual amount. Is the poor default performance of AMPs simply a consequence of the extraordinary house price declines and high unemployment rates seen during this period? To consider this question, we also estimated hazard models only through December 2007, before the onset of the worst of the house price declines and the unemployment rate increases and the date that the NBER calls the business cycle peak. Through the end of 2007, home prices, according to our CoreLogic data, had fallen by just 10.8 percent from their peak in March 2006. When we do so, we find similar relative performance across product types. In particular, the coefficients on the AMPs dummies have mostly the same signs as those in Table 6, are highly statistically and economically significant, but are not as large. Thus, the poor performance of AMPs does not depend on the unusual characteristics of the Great Recession.

4.3. Additional results on securitization

Our final question is whether the AMPs that were off-loaded from lender portfolios through securitization tended to be riskier than other products off-loaded through securitization.[31] To answer this question, we establish the relative riskiness within each product and origination channel group of loans in bank portfolios compared with those in public or private securitization.

This is accomplished by appending product and investor type interaction terms to the pooled default hazard model of Table 6. Mortgages are distinguished by investor type *i* (bank

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discount relative to the post-reset, risk-based margin, a form of backloading.

[30] See, for example, Jiang, Nelson, and Vytlacil (2009).

[31] See Ashcroft and Schuermann (2008) for a discussion of the adverse-selection problems that could have led to such an outcome.

portfolio, *B*; private securitized, *P*; and public (agency) securitized, *A*), by mortgage type *j* (fixed rate, option ARM, interest-only ARM, etc.), and by channel type *k* (retail, other). The dummy variable for holder type *i* is δ_i, the dummy for mortgage type *j* is δ_j, the dummy for channel type *k* is δ_k, and additional covariates are X_l.

We then can rewrite (14) as

(15) $$h(t \mid X) = \eta(t)\exp(\sum_i \alpha_i \delta_i + \sum_i \sum_j \sum_k \lambda_{ijk} \delta_i \delta_j \delta_k + \sum_l \rho_l X_l).$$

Note from the second summation in (15) that mortgage-type/channel effect is allowed to vary by investor type. The total impact of a given holder-mortgage-channel combination on the mortgage's average default hazard is $\alpha_i + \lambda_{ijk}$. If the default hazard of bank portfolio mortgages of type *j* in channel *k* were less than that of private securitized loans of the same mortgage and channel type, the inequality $\alpha_B + \lambda_{Bjk} < \alpha_P + \lambda_{Pjk}$ would hold.

Table 7 shows the coefficient estimates for bank portfolio loans along with private- and public-securitized loans (which come from a single hazard estimation). In the first three columns, the first row shows the α_P and α_B coefficients, with public-securitized loans being the baseline (α_A is set equal to zero). The remaining elements in the first three columns are the λ_{ijk} coefficients. The hazard equation also includes the other covariates from the pooled model of Table 6, but their coefficients (being quantitatively similar to those in Table 6) are omitted.

Columns 4 and 5 show the significance tests on the differences $\alpha_B + \lambda_{Bjk} - (\alpha_P + \lambda_{Pjk})$ and $\alpha_B + \lambda_{Bjk} - (\alpha_A + \lambda_{Ajk})$. These tests indicate whether the bank portfolio hazard is significantly different from the private- and public-securitized hazards, respectively.

Results are mixed. In most cases, portfolio loans have a lower default hazard than private securitized loans, but in some categories this pattern is reversed. Similarly, in most cases portfolio loans have a higher default hazard than public-securitized loans, but the reverse is also observed. AMPs do not appear to be exceptional in this context. In particular, they mostly have a lower default likelihood than private or public securitized AMPs, but to a degree no greater than that observed for the non-AMP categories.

Various factors may influence the decision whether to securitize a mortgage, including incentives related to private information, and it is not the purpose of this paper to delve into why private securitized loans appear to have generally performed more poorly. The estimation results suggest, however, that banks did not off-load the riskiest AMP loans through securitization more systematically compared with other products. Thus, it appears that adverse selection with respect to loan sales did not play a major role in specifically encouraging AMP lending activity.[32] Rather, it appears that expectations of continuing house-price inflation may have led lenders to believe that these products had lower risk than proved to be the case.[33]

5. Conclusion

While the work of Brueckner, Calem, and Nakamura (2012) studied the link between subprime lending and house-price expectations, this paper studies the related link between price expectations and the use of alternative mortgage products. These contracts, which involve backloading of mortgage payments, are risky, being more likely to generate negative borrower equity when house prices fall, thus encouraging default. The paper argues that, as expectations become more favorable, with future price gains perceived as more likely, the riskiness of alternative contracts lessens, encouraging their use.

This hypothesis has been tested using county-level data, relying (like BCN) on past house-price appreciation as a proxy for price expectations. The results confirm the main prediction, showing that rapid past price appreciation generates a higher market share for AMPs. In addition, the paper confirms the underlying presumption regarding the riskiness of alternative products by showing, through use of a proportional-hazard model, that default is more likely to occur under these contracts. Moreover, both sets of results are consistent across the three major classifications of mortgage holder: bank portfolio, Agency, and private securitized.

The paper thus contributes to the large and growing literature on the U.S. housing crisis. It extends BCN's argument that more favorable price expecations fed market developments that

[32]Of course, the analysis does not rule out adverse selection with respect to contract choice by borrowers as a contributing factor to higher default rates among AMP borrowers.

[33]Finally, we note that higher conditional default rates or hazard rates for a given contract type do not necessarily generate higher cumulative default rates, to the extent that the contract type is associated with faster prepayment that leaves behind a smaller but riskier pool. However, a separate hazard analysis of prepayment (available upon request) indicates that prepayment rates of interest-only and option-ARM mortgages were no faster than more traditional products, particularly after 2007 when mortgage delinquency was rising. Moreover, delinquency was largely occurring within the population of homeowners whose homes were "underwater,", while prepayment was occurring in the population of homeowners with equity in their properties, minimizing the "competing risk" (survivor bias) impact of prepayment on default, controlling for factors affecting the amount of equity. This delinking of prepayment and default during the crisis period was reflected in strong negative correlation of cumulative prepayment and delinquency rates across states (details available upon request).

worsened the eventual downturn. While BCN's focus was on the relaxed underwriting standards associated with subprime lending, the current paper has studied the adoption of alternative mortgage products as another response to shifting price expectations. This work adds a new perspective to research on the housing crisis, contributing to a deeper understanding of this important economic event.

Appendix

If the distribution of P is uniform with support $[\underline{P}+\delta, \overline{P}+\delta]$, then the density is $1/(\overline{P}-\underline{P})$ over this range. As a result, $F(M-C,\delta)=(M-C-(\underline{P}+\delta))/(\overline{P}-\underline{P})$, and (4) reduces to

$$(a1) \qquad \frac{\partial M_0}{\partial M}\bigg|_{\pi} = -\eta\,\frac{(\overline{P}+\delta-M)}{(\overline{P}-\underline{P})} < 0,$$

where the inequality follows because $M<\overline{P}+\delta$, with M being smaller than the largest possible P (otherwise default would be certain). Although the curvature of the zero-profit locus is ambiguous in general, inspection of (a1) shows that the locus is convex in the uniform case.

In the uniform case, the indifference-curve slope from (6) is given by

$$(a2) \qquad \frac{\partial M_0}{\partial M}\bigg|_{u} = -\theta\,\frac{\overline{P}+\delta-(M-C)}{\overline{P}-\underline{P}}.$$

Equating (*a1*) and (*a2*) to solve for the tangency yields

$$(a3) \qquad -(\eta-\theta)\frac{\overline{P}+\delta-(M-C)}{\overline{P}-\underline{P}}+\eta\,\frac{C}{\overline{P}-\underline{P}}=0,$$

and solving for M gives (8) in the text.

In the uniform case, the optimal value of M_0 can be derived by substituting (7) into the zero-profit condition and solving. The optimal value (assumed to be positive) is

$$(a4) \qquad M_0^* = P_0-\eta\left[\frac{\overline{P}+\underline{P}}{2}+\delta+\left(1-\left[\frac{\theta}{\eta-\theta}\right]^2\right)\frac{C^2}{2(\overline{P}-\underline{P})}\right].$$

Note from (8) and (a4) that an increase in the borrower's discount factor θ, which indicates a greater preference for future contributions to wealth, reduces M^* and raises M_0^*, as intuition would suggest. An increase in default costs reduces M^*, but M_0 could rise or fall with C, depending on the size of θ relative to η. If $\theta<\eta/2$, then the term multiplying C in (a4) is positive and a higher C reduces M_0, so that a less-risky borrower receives a mortgage with lower payments in both periods. If $\eta>\theta>\eta/2$, however, then C's coefficient is negative, and a higher C raises M_0. The less-risky borrower's lower M is then accompanied by a higher M_0.

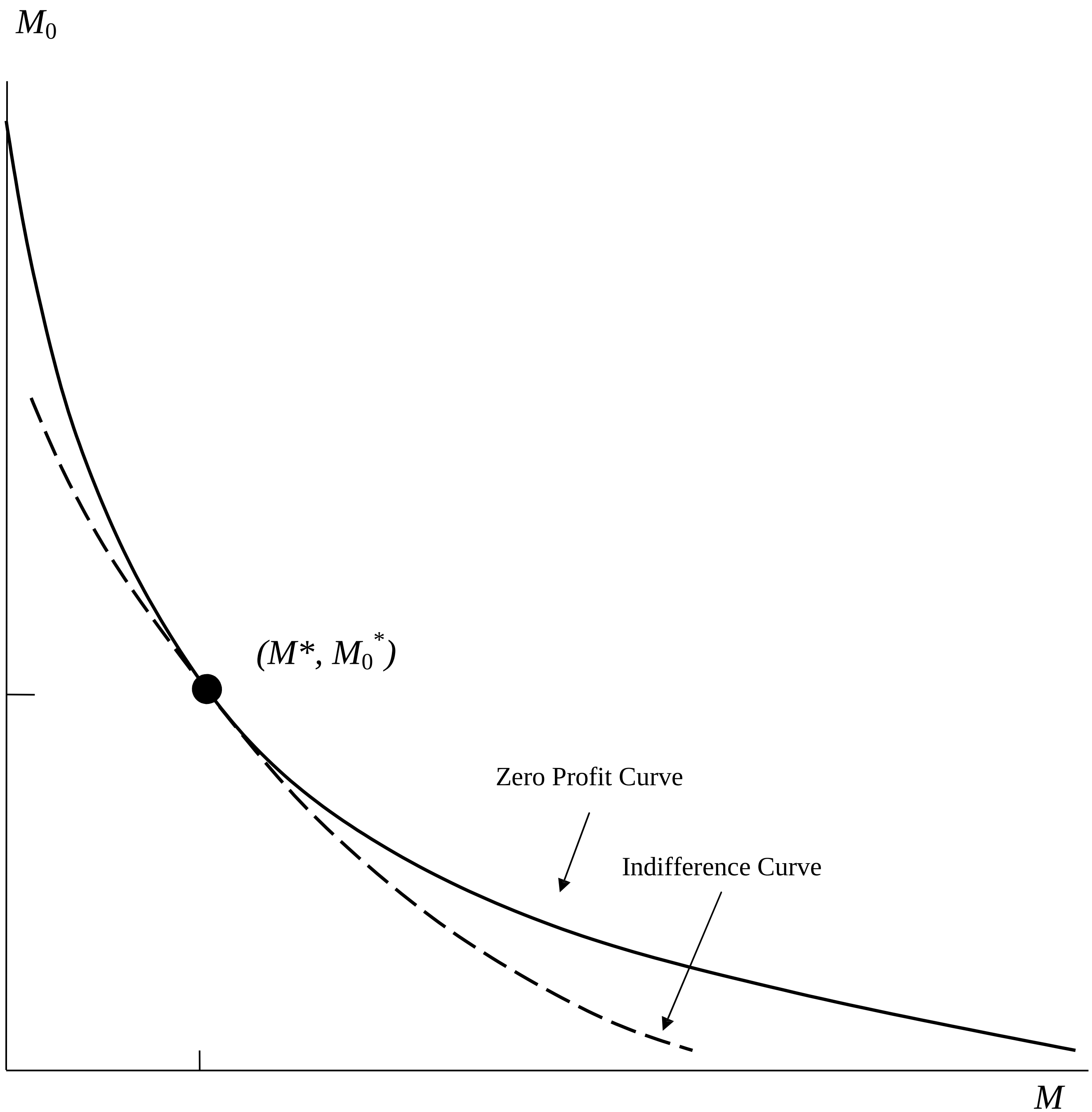

Figure 1: Optimal Mortgage Contract

Table 1: Summary Statistics

1a. Pooled

(20,537,054 loans)

Summary Statistics: County-Quarter Panel			
	Mean	SD	N
Share of all AMPs	0.094	0.107	18825
Share of Interest-Only ARM	0.055	0.067	18825
Share of Option ARM	0.038	0.052	18825
Share of 1- 2- or 3- year ARM	0.044	0.037	18825
Prior year HPI change	0.074	0.063	18825
Log of real per capita personal income	10.451	0.127	18825
Consumer confidence index	99.207	18.694	18825
Mean FICO score	715.082	15.101	18824
Median LTV	77.246	4.076	18825
Share of loans with 2nd lien	0.105	0.066	15061

1b. Bank Portfolio

(1,961,898 loans)

Summary Statistics: County-Quarter Panel			
	Mean	SD	N
Share of all AMPs	0.273	0.269	17736
Share of Interest-Only ARM	0.103	0.150	17736
Share of Option ARM	0.170	0.206	17736
Share of 1- 2- or 3- year ARM	0.094	0.155	17736
Prior year HPI change	0.076	0.064	17736
Log of real per capita personal income	10.455	0.126	17736
Consumer confidence index	99.549	18.741	17736
Mean FICO score	699.92	37.679	17485
Median LTV	78.701	8.599	17720
Share of loans with 2nd lien	0.107	0.066	14241

1c. Public Securitized

(12,877,766 loans)

Summary Statistics: County-Quarter Panel			
	Mean	SD	N
Share of all AMPs	0.038	0.053	18824
Share of Interest-Only ARM	0.029	0.041	18824
Share of Option ARM	0.009	0.019	18824
Share of 1- 2- or 3- year ARM	0.014	0.020	18824
Prior year HPI change	0.074	0.063	18824
Log of real per capita personal income	10.451	0.127	18824
Consumer confidence index	99.205	18.694	18824
Mean FICO score	721.941	13.205	18820
Median LTV	76.194	5.677	18824
Share of loans with 2^{nd} lien	0.105	0.066	15060

1d. Private Securitized

(5,697,390 loans)

Summary Statistics: County-Quarter Panel			
	Mean	SD	N
Share of all AMPs	0.208	0.182	18445
Share of Interest-Only ARM	0.126	0.129	18445
Share of Option ARM	0.082	0.100	18445
Share of 1- 2- or 3- year ARM	0.142	0.154	18445
Prior year HPI change	0.074	0.063	18445
Log of real per capita personal income	10.452	0.127	18445
Consumer confidence index	99.280	18.673	18445
Mean FICO score	695.659	35.261	18136
Median LTV	78.478	5.187	18424
Share of loans with 2^{nd} lien	0.128	0.081	14820

Table 2: Market-Share Regressions

2a. Pooled

	Affordability proxy is median LTV				Affordability proxies are median LTV and percent of loans with 2nd lien			
	All AMP	**IO ARM**	**Option ARM**	**ARM (1-year, 2/28, or 3/27)**	**All AMP**	**IO ARM**	**Option ARM**	**ARM (1-year, 2/28, or 3/27)**
Constant	-3.589** (0.481)	-2.474** (0.363)	-1.114** (0.175)	1.069** (0.181)	-4.144** (0.436)	-2.987** (0.349)	-1.157** (0.226)	0.699** (0.220)
Prior year HPI change	0.322** (0.020)	0.155** (0.012)	0.166** (0.014)	-0.028** (0.007)	0.302** (0.018)	0.140** (0.011)	0.163** (0.013)	-0.041** (0.007)
Log of real per capita personal income	0.274** (0.046)	0.171** (0.035)	0.103** (0.017)	-0.023 (0.017)	0.374** (0.042)	0.243** (0.033)	0.130** (0.022)	0.020 (0.021)
Consumer confidence index	0.0010** (0.0001)	0.0008** (0.0001)	0.0002** (0.0000)	-0.0001 (0.0000)	0.0005** (0.0001)	0.0007** (0.0001)	-0.0001 (0.0001)	0.0001* (0.0001)
Mean FICO score	0.0003** (0.0001)	0.0005** (0.0001)	-0.0002** (0.0000)	-0.0011** (0.0001)	-0.0000 (0.0001)	0.0003** (0.0001)	-0.0004** (0.0000)	-0.0011** (0.0001)
Median LTV	0.0064** (0.0007)	0.0036** (0.0004)	0.0028** (0.0004)	-0.0006** (0.0001)	0.0004** (0.0007)	0.0019** (0.0003)	0.0013** (0.0002)	-0.0005* (0.0002)
Pct. with 2nd lien					0.176** (0.026)	0.144** (0.017)	0.032 (0.020)	-0.068** (0.009)
Number of Observations	18547	18547	18547	18547	14840	14840	14840	14840
R-Squared	0.568	0.516	0.469	0.470	0.544	0.475	0.445	0.464

Regressions are quarterly from 2003Q1 to 2007Q4 and include both quarter and county fixed effects. Asterisks (* (**)) indicate coefficient's statistical significance at the 5% (1%) level.

Table 2 (cont'd)

2b. Bank Portfolio

	Affordability proxy is median LTV				Affordability proxies are median LTV and percent of loans with 2nd lien			
	All AMP	**IO ARM**	**Option ARM**	**ARM (1-year, 2/28, or 3/27)**	**All AMP**	**IO ARM**	**Option ARM**	**ARM (1-year, 2/28, or 3/27)**
Constant	-4.949** (1.148)	-3.681** (0.806)	-1.268 (0.864)	0.446 (1.013)	-13.872** (1.600)	-8.386** (1.060)	-5.487** (1.327)	0.243 (1.168)
Prior year HPI change	0.216** (0.039)	0.018 (0.028)	0.198** (0.036)	-0.003 (0.025)	0.164** (0.043)	-0.003 (0.030)	0.167** (0.040)	-0.024 (0.025)
Log of real per capita personal income	0.450** (0.111)	0.308** (0.078)	0.142 (0.084)	0.043 (0.098)	1.333** (0.155)	0.754** (0.102)	0.579** (0.129)	0.065 (0.113)
Consumer confidence index	0.0023** (0.0003)	0.0016** (0.0002)	0.0007** (0.0002)	0.0007** (0.0002)	0.0015** (0.0004)	0.0012** (0.0002)	0.0003 (0.0004)	0.0002 (0.0003)
Mean FICO score	0.0001 (0.0001)	0.0005** (0.0000)	-0.0003** (0.0001)	-0.0012** (0.0001)	0.0001 (0.0001)	0.0006** (0.0001)	-0.0005** (0.0001)	-0.0012** (0.0001)
Median LTV	0.0002 (0.0003)	0.0007** (0.0002)	-0.0004 (0.0002)	0.0007** (0.0002)	0.0003 (0.0003)	0.0007** (0.0002)	-0.0004 (0.0003)	0.0004 (0.0002)
Pct. with 2nd lien					0.142* (0.064)	0.177** (0.041)	-0.035 (0.055)	-0.077* (0.038)
Number of Observations	17227	17227	17227	17227	13843	13843	13843	13843
R-Squared	0.441	0.248	0.322	0.223	0.375	0.162	0.285	0.234

Regressions are quarterly from 2003Q1 to 2007Q4 and include both quarter county fixed effects. Asterisks (* (**)) indicate coefficients' statistical significance at the 5% (1%) level.

Table 2 (cont'd)

2c. Public Securitized

	Affordability proxy is median LTV				Affordability proxies are median LTV and percent of loans with 2nd lien			
	All AMP	**IO ARM**	**Option ARM**	**ARM (1-year, 2/28, or 3/27)**	**All AMP**	**IO ARM**	**Option ARM**	**ARM (1-year, 2/28, or 3/27)**
Constant	-1.759** (0.335)	-1.273** (0.270)	-0.487** (0.090)	0.018 (0.100)	-2.138** (0.312)	-1.506** (0.249)	-0.632** (0.101)	-0.309* (0.142)
Prior year HPI change	0.110** (0.014)	0.076** (0.011)	0.034** (0.005)	0.015** (0.003)	0.104** (0.012)	0.068** (0.010)	0.036** (0.005)	0.012** (0.004)
Log of real per capita personal income	0.131** (0.032)	0.091** (0.026)	0.040** (0.008)	-0.000 (0.010)	0.175** (0.029)	0.119** (0.024)	0.056** (0.009)	0.034** (0.014)
Consumer confidence index	0.0007** (0.0001)	0.0005** (0.0001)	0.0002** (0.0000)	0.0001** (0.0000)	0.0006** (0.0001)	0.0004** (0.0001)	0.0002** (0.0000)	0.0001** (0.0000)
Mean FICO score	0.0004** (0.0000)	0.0003** (0.0000)	0.0001** (0.0000)	-0.0000 (0.0000)	0.0003** (0.0000)	0.0002** (0.0000)	0.0000* (0.0000)	-0.0001* (0.0000)
Median LTV	0.0012** (0.0002)	0.0011** (0.0002)	0.0001 (0.0001)	0.0003** (0.0001)	0.0010** (0.0002)	0.0009** (0.0002)	0.0001 (0.0001)	0.0003** (0.0001)
Pct. with 2nd lien					0.079** (0.014)	0.077** (0.012)	0.003 (0.005)	-0.029** (0.004)
Number of Observations	18543	18543	18543	18543	14838	14838	14838	14838
R-Squared	0.393	0.407	0.158	0.448	0.318	0.332	0.121	0.513

Regressions are quarterly from 2003Q1 to 2007Q4 and include both quarter and county fixed effects. Asterisks (* (**)) indicate coefficient's statistical significance at the 5% (1%) level.

Table 2 (cont'd)

2d. Private Securitized

	Affordability proxy is median LTV				Affordability proxies are median LTV and percent of loans with 2nd lien			
	All AMP	IO ARM	Option ARM	ARM (1-year, 2/28, or 3/27)	All AMP	IO ARM	Option ARM	ARM (1-year, 2/28, or 3/27)
Constant	-5.044** (1.064)	-3.025** (0.821)	-2.019** (0.479)	3.226** (0.685)	-5.856** (1.023)	-2.965** (0.730)	-2.891** (0.670)	2.687** (0.827)
Prior year HPI change	0.341** (0.029)	0.124** (0.021)	0.217** (0.020)	-0.160** (0.023)	0.333** (0.025)	0.100** (0.020)	0.233** (0.021)	-0.183** (0.025)
Log of real per capita personal income	0.445** (0.103)	0.234** (0.080)	0.211** (0.046)	-0.191** (0.066)	0.539** (0.099)	0.236** (0.070)	0.303** (0.065)	-0.127 (0.080)
Consumer confidence index	0.0014** (0.0002)	0.0016** (0.0002)	-0.0002 (0.0001)	-0.0005** (0.0002)	0.0008** (0.0002)	0.0015** (0.0002)	-0.0007** (0.0002)	0.0003 (0.0002)
Mean FICO score	0.0003** (0.0001)	0.0006** (0.0000)	-0.0003** (0.0001)	-0.0017** (0.0001)	0.0002** (0.0001)	0.0005** (0.0001)	-0.0003** (0.0001)	-0.0019** (0.0001)
Median LTV	0.0020** (0.0004)	0.0011** (0.0003)	0.0009** (0.0002)	0.0011** (0.0003)	0.0012** (0.0004)	0.0007* (0.0003)	0.0006** (0.0002)	0.0017** (0.0004)
Pct. with 2nd lien					0.517** (0.046)	0.363** (0.031)	0.154** (0.026)	-0.260** (0.034)
Number of Observations	17871	17871	17871	17871	14328	14328	14328	14328
R-Squared	0.390	0.271	0.339	0.452	0.386	0.300	0.293	0.381

Regressions are quarterly from 2003Q1 to 2007Q4 and include both quarter and county fixed effects. Asterisks (* (**)) indicate coefficient's statistical significance at the 5% (1%) level.

Table 3: Refinancing vs. Purchase Loans

Pooled

	County-Quarters	Mean Percent AMP
Refinancing loans	18,792	8.37%
Purchase Loans	18,805	9.77%

Bank Portfolio

	County-Quarters	Mean Percent AMP
Refinancing loans	15,043	32.98%
Purchase loans	16,125	27.51%

Public Securitized

	County-Quarters	Mean Percent AMP
Refinancing loans	18,769	3.39%
Purchase loans	18,796	4.35%

Private Securitized

	County-Quarters	Mean Percent AMP
Refinancing loans	17,128	19.27%
Purchase loans	17,679	20.31%

Table 4: Market-Share Regressions for Refinancing Loans

Pooled Data

	Affordability proxy is median LTV				Affordability proxies are median LTV and percent of loans with 2nd lien			
	All AMP	**IO ARM**	**Option ARM**	**ARM (1-year, 2/28, or 3/27)**	**All AMP**	**IO ARM**	**Option ARM**	**ARM (1-year, 2/28, or 3/27)**
Constant	-3.158** (0.492)	-1.912** (0.387)	-1.247** (0.210)	0.453 (0.281)	-4.988** (0.547)	-2.990** (0.419)	-1.997** (0.332)	0.249 (0.331)
Prior year HPI change	0.144** (0.020)	0.106** (0.015)	0.038** (0.010)	-0.010 (0.010)	0.134** (0.018)	0.107** (0.014)	0.028** (0.010)	-0.026* (0.011)
Log of real per capita personal income	0.261** (0.047)	0.149** (0.037)	0.112** (0.020)	0.009 (0.027)	0.455** (0.052)	0.261** (0.040)	0.194** (0.032)	0.028 (0.032)
Consumer confidence index	0.0009** (0.0001)	0.0006** (0.0001)	0.0003** (0.0001)	-0.0001 (0.0001)	0.0007** (0.0001)	0.0006** (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)
Mean FICO score	0.0002** (0.0001)	0.0029** (0.0001)	-0.0001 (0.0000)	-0.0007** (0.0001)	0.0001 (0.0001)	0.0002** (0.0000)	-0.0001** (0.0000)	-0.0008** (0.0001)
Median LTV	0.0030** (0.0003)	0.0014** (0.0002)	0.0015** (0.0002)	0.0005** (0.0002)	0.0021** (0.0002)	0.0010** (0.0002)	0.0011** (0.0002)	0.0008** (0.0002)
Pct. with 2nd lien					0.192** (0.028)	0.115** (0.021)	0.077** (0.019)	-0.087** (0.015)
Number of Observations	18483	18483	18483	18483	14781	14781	14781	14781
R-Squared	0.366	0.375	0.247	0.239	0.249	0.281	0.188	0.258

Regressions are quarterly from 2003Q1 to 2007Q4 and include both quarter and county fixed effects. Asterisks (* (**)) indicate coefficient's statistical significance at the 5% (1%) level.

Table 5: Summary Statistics for Default Data Set

	Private Securitized		Public Securitized		Bank Portfolio	
Variables	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Vintage 2005	0.323	0.468	0.200	0.400	0.220	0.414
Vintage 2006	0.278	0.448	0.182	0.385	0.179	0.383
Vintage 2007	0.102	0.303	0.215	0.411	0.249	0.432
Other ARM nonretail channel	0.023	0.149	0.018	0.132	0.073	0.260
FRM retail channel	0.179	0.384	0.423	0.494	0.289	0.453
FRM nonretail channel	0.219	0.414	0.438	0.496	0.120	0.325
Option ARM retail channel	0.043	0.204	0.008	0.088	0.069	0.254
Option ARM nonretail channel	0.151	0.358	0.008	0.091	0.163	0.369
Interest-only ARM retail	0.076	0.265	0.018	0.134	0.057	0.232
Interest-only ARM nonretail channel	0.108	0.311	0.021	0.143	0.088	0.283
Interest-only FRM retail	0.010	0.098	0.006	0.075	0.004	0.064
Interest-only FRM nonretail channel	0.035	0.185	0.012	0.109	0.005	0.068
1-year ARM retail channel	0.010	0.101	0.007	0.082	0.007	0.083
1-year ARM nonretail channel	0.019	0.137	0.001	0.026	0.003	0.052
2- or 3- year ARM retail channel	0.028	0.164	0.004	0.064	0.022	0.148
2- or 3- year ARM nonretail channel	0.062	0.241	0.004	0.066	0.031	0.174
Origination FICO score	623.5	231.7	623.0	257.0	647.5	211.0
Dummy variable for missing FICO	0.114	0.318	0.140	0.347	0.089	0.285
Indicator variable for jumbo loan	0.345	0.475			0.262	0.440
Indicator for original term to maturity < 30 years	0.074	0.261	0.213	0.409	0.135	0.342
Indicator for 2-to-4-unit property	0.036	0.186	0.021	0.142	0.021	0.143
Indicator for unknown occupancy status	0.079	0.270	0.068	0.251	0.062	0.241
Indicator for second home	0.030	0.169	0.033	0.178	0.036	0.186
Indicator for investor property	0.107	0.309	0.054	0.227	0.084	0.278
Subprime loan indicator (self-reported by servicer)	0.106	0.308				
Indicator for teaser rate	0.350	0.477	0.058	0.234	0.357	0.479
Yield curve measure (gap between 10- and 3-month Treasury rates)	1.897	1.129	2.127	0.972	1.943	1.082
Average spread between note rate and 3-month Treasury rate interacted with ARM indicator	2.660	1.934	2.859	1.318	2.367	2.060
Average spread between note rate and 3-month Treasury rate interacted with ARM and teaser rate indicators	-0.170	0.650	0.005	0.076	-0.203	0.710
Average spread between note rate and 10-year Treasury rate	0.786	1.080	1.407	0.754	0.747	1.103

interacted with FRM indicator						
Change in county unemployment rate over prior 12 months	0.062	0.277	0.062	0.292	0.068	0.294
Indicator for undated LTV<50 percent	0.083	0.276	0.152	0.359	0.135	0.341
Indicator for undated LTV 50-60 percent	0.078	0.268	0.099	0.299	0.082	0.275
Indicator for undated LTV 60-70 percent	0.115	0.319	0.121	0.326	0.110	0.312
Indicator for undated LTV 70-80 percent	0.135	0.342	0.138	0.345	0.118	0.323
Indicator for undated LTV 80-90 percent	0.126	0.332	0.135	0.341	0.111	0.314
Indicator for undated LTV 90-100 percent	0.098	0.297	0.099	0.299	0.094	0.292
Indicator for undated LTV 100-110 percent	0.086	0.281	0.077	0.266	0.088	0.283
Indicator for undated LTV 110-130 percent	0.127	0.333	0.093	0.290	0.127	0.333
Indicator for undated LTV 130-150 percent	0.071	0.256	0.048	0.213	0.070	0.254
Log of annualized change in county HPI through previous quarter	-0.014	0.032	-0.011	0.030	-0.015	0.031
Number of observations	401,017		1,100,972		151,058	

Table 6: Proportional Hazard Model of Default (60-day delinquency)

	Private Securitized	Public Securitized	Portfolio
<u>Variables</u>	**Parameter (SE)** **Hazard Ratio**	**Parameter (SE)** **Hazard Ratio**	**Parameter (SE)** **Hazard Ratio**
Vintage 2005	1.408*** (0.022) 4.087	1.400*** (0.019) 4.054	1.486*** (0.038) 4.418
Vintage 2006	2.324*** (0.023) 10.215	2.540*** (0.021) 12.685	2.618*** (0.040) 13.714
Vintage 2007	2.874*** (0.026) 17.711	3.406*** (0.022) 30.158	3.503*** (0.041) 33.218
ARM non-retail channel	0.290*** (0.042) 1.336	-0.020 (0.033) 0.981	0.160** (0.061) 1.173
FRM retail channel	-0.392*** (0.034) 0.676	-0.593*** (0.023) 0.662	-0.212*** (0.049) 0.809
FRM non-retail channel	-0.120*** (0.033) 0.887	-0.412*** (0.023) 0.662	0.182*** (0.050) 1.199
Option ARM retail channel	0.518*** (0.035) 1.678	0.265*** (0.034) 1.304	0.749*** (0.051) 2.115
Option ARM non-retail channel	0.669*** (0.032) 1.953	0.452*** (0.029) 1.572	1.016*** (0.047) 2.763
Interest Only ARM retail channel	0.361*** (0.033) 1.434	0.546*** (0.025) 1.726	0.383*** (0.053) 1.467
Interest Only ARM non-retail channel	0.700*** (0.032) 2.014	0.435*** (0.025) 1.545	0.597*** (0.050) 1.817
Interest Only FRM retail channel	0.265*** (0.042) 1.304	0.076* (0.032) 1.079	0.417*** (0.088) 1.517
Interest Only FRM non-retail channel	0.524*** (0.034) 1.688	0.210*** (0.027) 1.234	0.610*** (0.078) 1.840
One-year ARM retail channel	-0.154* (0.069) 0.858	0.014 (0.059) 1.014	0.690*** (0.091) 1.995
One-year ARM non-retail channel	0.122* (0.053) 1.130	0.373* (0.158) 1.452	0.530*** (0.129) 1.698
2- or 3-year ARM retail channel	0.392*** (0.038) 1.479	0.132 (0.070) 1.141	1.032*** (0.078) 2.806
2- or 3- year ARM non-retail channel	0.785*** (0.034) 2.192	0.255*** (0.064) 1.291	0.520*** (0.064) 1.682
Origination FICO score	-0.004*** (0.000) 0.996	-0.006*** (0.000) 0.994	-0.004*** (0.000) 0.996
Dummy variable for missing FICO	-3.608*** (0.050) 0.027	-4.853*** (0.047) 0.008	-3.185*** (0.085) 0.041

Indicator variable for jumbo loan	-0.168*** (0.028) 0.845		0.152** (0.047) 1.164
Jumbo loan interacted with 2005 vintage	0.072* (0.030) 1.075		-0.154** (0.056) 0.857
Jumbo loan interacted with 2006 vintage	0.209*** (0.030) 1.233		-0.231*** (0.056) 0.794
Jumbo loan interacted with 2007 vintage	0.189*** (0.034) 1.208		-0.073 (0.054) 0.929
Indicator for original term to maturity < 30 years	-0.075** (0.026) 0.928	-0.699*** (0.018) 0.497	0.153*** (0.030) 1.166
Indicator for two-to-four unit property	0.158*** (0.019) 1.171	0.253*** (0.021) 1.288	0.255*** (0.040) 1.290
Indicator for unknown occupancy status	0.215*** (0.011) 1.240	0.152*** (0.011) 1.165	0.326*** (0.027) 1.386
Indicator for second home	0.033 (0.019) 1.033	0.084*** (0.016) 1.087	-0.024 (0.037) 0.976
Indicator for investor property	0.155*** (0.011) 1.168	0.246*** (0.012) 1.279	-0.0028 (0.023) 0.972
Subprime loan indicator (self-reported by servicer)	0.324*** (0.011) 1.383		
Indicator for teaser rate	0.345*** (0.016) 1.412	0.471*** (0.015) 1.602	0.487*** (0.025) 1.628
Yield curve measure (gap between 10 and 3-month Treasury rates)	-0.453*** (0.006) 0.636	-0.504*** (0.006) 0.604	-0.421*** (0.011) 0.656
Spread at origination: ARM without teaser	0.050*** (0.004) 1.051	0.083*** (0.005) 1.086	0.127*** (0.007) 1.135
Spread at origination: ARM with teaser	-0.014 (0.009) 0.986	-0.166*** (0.039) 0.847	-0.084*** (0.013) 0.919
Spread at origination: FRM	0.196*** (0.006) 1.217	0.212*** (0.007) 1.236	0.168*** (0.009) 1.183
Change in county unemployment rate over prior 12 months	0.476*** (0.018) 1.610	0.013 (0.020) 1.013	0.511*** (0.034) 1.666
Indicator for updated LTV < 50 percent	-1.871*** (0.032) 0.154	-3.644*** (0.044) 0.026	-1.341*** (0.039) 0.262
Indicator for updated LTV 50-60 percent	-2.788*** (0.054) 0.062	-2.983*** (0.038) 0.051	-2.809*** (0.093) 0.060
Indicator for updated LTV 60-70 percent	-2.182*** (0.032) 0.113	-2.514*** (0.027) 0.081	-2.125*** (0.055) 0.119
Indicator for updated LTV 70-80 percent	-1.562*** (0.019) 0.210	-2.048*** (0.019) 0.129	-1.688*** (0.038) 0.185
Indicator for updated LTV 80-90 percent	-1.204*** (0.014) 0.300	-1.652*** (0.014) 0.192	-1.342*** (0.029) 0.261

Indicator for updated LTV 90-100 percent	-0.975*** (0.013) 0.377	-1.314*** (0.013) 0.269	-1.091*** (0.026) 0.336
Indicator for updated LTV 100-110 percent	-0.690*** (0.012) 0.502	-1.004*** (0.012) 0.366	-0.863*** (0.023) 0.422
Indicator for updated LTV 110-130 percent	-0.452*** (0.010) 0.636	-0.666*** (0.010) 0.514	-0.644*** (0.020) 0.525
Indicator for updated LTV 130-150 percent	-0.194*** (0.011) 0.824	-0.298*** (0.011) 0.742	-0.293*** (0.021) 0.746
Log of change in county HPI over prior 12 months	-4.332*** (0.116) 0.013	-6.327*** (0.122) 0.002	-6.553*** (0.223) 0.001
Number of Observations	401,017	1,100,972	151,058
Number (and %) Censored	312,498 (78%)	1,011,935 (92%)	126,564 (84%)

***Significant at 0.1% level **Significant at 1% level *Significant at 5% level

Table 7: Relative Proportional Hazards of Default: Compared to Bank Portfolio

	Public Securitized	Private Securitized	Bank Portfolio	Bank Portfolio Relative to Private Securitized	Bank Portfolio Relative to Public Securitized
	Parameter (SE) Hazard Ratio	**Parameter (SE) Hazard Ratio**	**Parameter (SE) Hazard Ratio**	**Parameter Hazard Ratio**	**Parameter Hazard Ratio**
Holder dummy	--	0.089 (0.037)* 1.093	-0.232 (0.048)*** 0.793	-0.320*** 0.726	-0.232*** 0.793
ARM nonretail channel	-0.011 (0.033) 0.989	0.210 (0.041)*** 1.234	0.076 (0.060) 1.079	-0.454*** 0.635	-0.144** 0.866
Fixed rate retail channel	-0.602 (0.022)*** 0.548	-0.418 (0.033)*** 0.658	-0.146 (0.046)** 0.864	-0.048* 0.953	0.224*** 1.251
Fixed rate nonretail channel	-0.376 (0.021)*** 0.687	-0.188 (0.032)*** 0.828	0.130 (0.047)** 1.139	-0.002 0.998	0.274*** 1.316
Option ARM retail channel	0.325 (0.034)*** 1.384	0.441 (0.034)*** 1.555	0.577 (0.049)*** 1.781	-0.184*** 0.832	0.020 1.020
Option ARM nonretail channel	0.532 (0.029)*** 1.702	0.554 (0.031)*** 1.739	0.863 (0.045)*** 2.370	-0.011 0.989	0.099*** 1.105
Interest-only ARM retail channel	0.579 (0.025)*** 1.785	0.294 (0.033)*** 1.342	0.350 (0.051)*** 1.418	-0.264*** 0.768	-0.461*** 0.630
Interest-only ARM nonretail channel	0.469 (0.024)*** 1.599	0.606 (0.032)*** 1.833	0.533 (0.048)*** 1.704	-0.394*** 0.675	-0.168*** 0.845
Interest-only FRM retail channel	0.215 (0.030)*** 1.240	0.064 (0.041) 1.066	0.669 (0.084)*** 1.952	0.285*** 1.330	0.222** 1.249
Interest-only FRM nonretail channel	0.317 (0.026)*** 1.373	0.369 (0.034)*** 1.446	0.694 (0.076)*** 2.002	0.005 1.005	0.146* 1.157
1-year ARM retail channel	0.035 (0.059) 1.036	-0.131 (0.069) 0.877	0.780 (0.089)*** 2.182	0.591*** 1.807	0.513*** 1.670
1-year ARM nonretail channel	0.398 (0.157)* 1.488	-0.050 (0.051) 0.952	0.492 (0.128)*** 1.635	0.222 1.248	-0.137 0.872
2- or 3-year ARM retail channel	0.128 (0.070) 1.136	0.268 (0.037)*** 1.308	0.804 (0.077)*** 2.235	0.217** 1.242	0.445*** 1.561
2- or 3- year ARM nonretail channel	0.253 (0.064)*** 1.287	0.661 (0.033)*** 1.938	0.430 (0.063)*** 1.537	-0.551*** 0.576	-0.054 0.948
Number of observations: 1,653,047					
Number (and %) censored: 1,450,997 (88%)					

***Significant at 0.1% level **Significant at 1% level *Significant at 5% level

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