Residential Mortgage Credit Derivatives

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Abstract

As the fallout from subprime losses clearly demonstrates, the credit risk in residential mortgages is large and economically significant. To manage this risk, this paper proposes the creation of derivative instruments based on the credit losses of a reference mortgage pool. We argue that these derivatives would enable banks to retain whole loans while also enjoying the capital benefits of hedging the credit risk in their mortgage portfolios. In comparisons of hedging effectiveness, we show that instruments based on credit losses outperform contracts based on house-price appreciation.

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1 Introduction

With $11 trillion in debt outstanding, the credit risk in residential mortgages is potentially significant. Moreover, because mortgage investors are highly leveraged, even small losses can have major consequences. For instance, today's subprime losses of about $400 billion have had a disproportionately large impact because of both the de-leveraging by mortgage investors and the systemic failure of the securitization market.[1]

Depositories currently mitigate residential mortgage credit risk through securitization, mortgage insurance contracts, house-price index futures contracts, or over-the-counter residential mortgage credit instruments.[2] Each of these contracts, however, has limitations as hedging instruments. For example, securitization bundles the credit guarantee with mortgage securitization, which is a disadvantage for a large portion of the mortgage market due to accounting and regulatory requirements. Moreover, agency securitization can be used only on conforming loans. And mortgage insurance typically takes the first loss position, providing protection only up to a certain limit. In addition, the low capitalization of mortgage insurance companies restricts protection in the event of large, broad-based credit losses. While exchange-traded, house-price index futures and currently traded over-the-counter residential mortgage credit derivatives can circumvent some of these limitations, it is unclear how effective they are in hedging credit risk in residential mortgages. A hedge based on these instruments may be far from perfect because the loss experience of the hedged portfolio may not correlate with the cash flows of the hedging instrument, thereby introducing basis risk.

Due to the limited ability to mitigate credit risk in residential mortgage markets, the creation of derivatives with cash flows similar to the loss experience of mortgage portfolios and without the same drawbacks as the existing contracts is likely to enhance the efficiency of the mortgage finance system. To demonstrate how, take the case of adjustable-rate mortgages (ARMs). Small depositories often retain this important class of mortgages as whole

[1] See Greenlaw, Hatzius, Kashyap, and Shin (2008) and Mishkin (2008).

[2] Examples of currently traded contracts are credit default swaps (CDSs) on residential credit default obligations (CDOs), derivatives based on the home equity CDS index, ABX.HE, and the Bank of America RESI structure. See Banc of America Securities (2005) for specific information on this type of offering.

loans.[3] As a result, they have overexposure to regional economic fluctuations, which residential mortgage credit derivatives could mitigate. In turn, through such derivatives, depositories could diversify their credit exposure while also meeting all regulatory and accounting requirements. To the extent that depositories hold suboptimum portfolios, credit derivative hedges could therefore bring their credit risk closer to the optimum level, freeing capital for more effective use.

In this paper, we propose the creation of derivatives based on the credit losses of a reference mortgage pool. Naturally, the use of these derivatives to hedge the credit risk in mortgage portfolios would not have the same drawbacks as securitization and mortgage insurance contracts. Moreover, in the case that hedges performed with these derivatives have little basis risk, their creation could enhance the efficiency of the mortgage finance system. We therefore analyze the possible hedging effectiveness of these derivatives and also compare the hedging effectiveness of these contracts with that of house-price based contracts such as the ones that have been recently introduced at the Chicago Mercantile Exchange. We examine the basis risk of the hedges generated by the credit-loss derivatives and by house-price based contracts both theoretically (based on simulations of a simple default model) and empirically (based on First American's LoanPerformance Securities data on subprime mortgages). We use adjusted-R^2s as the metric for hedging effectiveness in both empirical and theoretical examinations of basis risk. We do so because accounting policies can subject hedges to specific tests of effectiveness based on this metric.

Our simulations suggest that hedges made with credit loss-based instruments perform materially better than those made with house-price indexes. Indeed, a regression of simulated portfolio losses on simulated house-price indexes results in an average R^2 close to seven percent, while a regression of simulated portfolio losses on simulated loss-based indexes results in an average R^2 of 86 percent. The strong performance of hedges based on credit-loss indexes is due to the similarities between the credit losses of mortgages portfolios and the cash flows of the derivatives based on loss indexes. Forward contracts based on house-price appreciation indexes, on the other hand, do

[3] The Federal Reserve Bulletin (2008) indicates that around three trillion of the mortgage universe is not securitized and is held by commercial banks and saving institutions. It is likely that these mortgages are primarily ARMs.

not have payoffs that resemble the credit losses in residential mortgage portfolios and as a result these derivatives perform poorly in static hedging. The empirical analysis also suggests that loss-based indexes are better than house-price based indexes for hedging credit risk in mortgage portfolios. A regression of actual monthly portfolio losses on actual monthly house-price indexes results in an average R^2 close to 4.5 percent, while a regression of portfolio losses on loss-based indexes results in an average R^2 of 13 percent. We note however that the empirical performance of instruments based on credit losses is still well below the accounting requirement to classify a hedge as "highly effective."

This paper contributes to the rapidly growing literature on real estate derivatives. Closest to our work is the paper by Case and Shiller (1996), who analyze how futures and options written on house-price indexes can hedge mortgage default risk and then show that a distributed lag model in house-price growth captures most of the variation in delinquency rates. We extend their work by focusing on credit losses in residential mortgages rather than with delinquency rates. Moreover, in addition to analyzing the performance of house-price related derivatives as a hedging tool, we also analyze derivatives based on the losses of mortgage portfolios. Less related to our article are a series of papers that study the impact of a liquid market on house-price derivatives would have for use by *consumers*. These papers include Englund, Hwang, and Quigley (2002), Shiller (2007), de Jong, Driessen, and Hemert (2008), Deng and Quigley (2007), Clapham, Englund, Quigley, and Redfearn (2006). We differ from these papers because we examine house-price derivatives and residential mortgage credit derivatives for use by *investors*. Note that these derivatives could also benefit residential borrowers to the extent that the creation of new credit derivative instruments could reduce the cost of mortgage credit risk for residential borrowers.

This work is also related to those that analyze potential for moral hazard and adverse selection related to credit risk. Gan and Mayer (2007) provide evidence of differences in servicing behavior when the servicer is exposed to the credit risk of a loan. Duffee and Zhou (2001) analyze the effects of introduction of credit derivatives on banking monitoring and find that the resulting adverse selection could worsen the market for loan sales. Writing derivative contracts on a broad reference pool will tend to mitigate these incentive problems since one any institutions' decisions on servicing and origination are likely to have limited impact on aggregate losses.

The remainder of this document is organized as follows: Section 2 describes the institutional features of the banking system that may affect the hedging problem faced by depository institutions. Section 3 describes the methodology that we use to assess hedge effectiveness. Section 4 describes the data. Section 5 describes our results.

2 Institutional features and the hedging problem

Depositories have few options for managing their residential asset portfolios. If they are an originator, they must decide which loans to retain and which to sell. Of the loans they retain, they must decide which to hold in a securitized form and which to retain as whole loans. Moreover, they also make decisions on what forms of mortgage insurance to acquire and at what levels of coverage.[4] Among the factors that influence these decisions are risk management practices, accounting practices and funding flexibility.

An important driver of decisions that impact depository holdings of credit risk is the management of interest rate risk. Depositories tend to hold mortgage assets that provide a good match with its liabilities (primarily short-term funding such as demand deposits). Because ARMs have floating rates, they are a natural choice. Small depositories therefore find it advantageous to hold ARMs because they can match duration of assets and liabilities without using dynamic hedging. The drawback of keeping ARMs as whole loans is their credit risk, which can be significant for small depositories lacking geographic diversity. The duration of fixed-rate mortgage assets, in contrast, substantially exceeds that of bank liabilities and will fluctuate with changes in the interest-rate environment (convexity risk). Hedging the duration and convexity risk of these assets requires a high level of sophistication and substantial investment in risk-management strategies. For this reason, most depositories sell or securitize the fixed-rate mortgages they originate.

[4]Mortgage insurance is the dominant form of hedging of ARMs held by depositories as whole loans. Mortgage insurance is typically required only for loans with loan-to-value ratios above 80 percent.

In addition, there are several important differences in the accounting treatment of whole loans and securities. The accounting treatment of securities makes it more attractive to hold mortgages as whole loans. In typical implementations of Financial Accounting Standard (FAS) 5, many institutions set loan loss reserves for whole loans based on simplified estimates of credit-loss exposure, such as a fixed multiple of expected annual default costs. Securities, in contrast, do not reflect credit exposure until they become impaired and then are subject to fluctuations in market value, effectively marking-to-market the lifetime of future credit exposures along with any risk and liquidity premiums. Another important accounting difference relates to asset sales. Whole loan sales are covered by different accounting rules (specifically FAS 65) than mortgage-backed securities (FAS 115). These differences in treatment make it "less consequential" for an institution to sell whole loans rather than securities, allowing institutions more flexibility to adjust their portfolios.

On the other hand, for prime mortgages there are some benefits to holding residential mortgages securities issued by the government sponsored enterprises (GSEs), Freddie-Mac and Fannie-Mae. For example, a liquidity advantage to the securitization of mortgage assets is that participation certificates (PCs) allow investors to borrow funds more cheaply, because PCs allow easy access to collateralized borrowing through the 'repo' market and through 'dollar rolls.' Thus in holding whole loans, an institution may forgo some funding flexibility that securities provide. In addition, holding mortgage assets in securities rather than as whole loans has implications for regulatory capital requirements imposed on a depository. Depositories investments are constrained by both 'tier 1' and 'risk-based' capital requirements. Mortgage assets held through GSE-issued securities face lower risk-based capital charges than whole loans, in nearly all cases. Thus in periods when institutions are constrained (or likely to be constrained) by regulatory capital, this capital relief will tend to favor securitization.

Residential mortgage credit derivatives may help banks simultaneously benefit from being able to retain portfolios of whole loans and at same time enjoy the economic capital benefits of hedging the credit risk in their mortgage portfolio. Using credit derivatives, a depository could benefit from all the accounting advantages of holding whole loans in their portfolio and at same they could decrease the economic capital required to hold the loans.

Existing hedging of depositories holding whole loans is a cash flow hedging, which is a match between the time patterns of losses on a portfolio of loans with the cash flows of a derivative instrument. Traditionally, derivative hedging is based on delta-hedging procedures that hedge market value. That is to delta-hedge a portfolio of derivatives, one takes an offsetting position that makes the sensitivity of the price of the portfolio with respect to the underlying security equal to zero. Depositories holding whole loans, however, focus on cash flow hedging instead of price hedging, because the prices of the loans in a given portfolio do not affect the earning of depository institutions unless the credit quality of the loans becomes severely impaired. Moreover, the fact that whole loans are not generally marked-to-market implies that the prices of loans in the portfolio of depositories are not easily observable. As a result, we set up the hedging problem of a depository institution as a cash flow hedging.

The accounting treatment of cash flow hedging is articulated in the Financial Accounting Standards Board Statement no. 133. The standards for determining hedge effectiveness are varied, but once a standard is adopted it must be adhered to. One such standard is based on the adjusted-R^2 produced by a regression of the changes in the value of the hedged item on changes in the derivative value, and for cash-flow hedges the regression can also be based on cumulative cash flows. If a hedge is determined to be "highly effective," it can receive favorable accounting treatment. A hedge is classified as "highly effective" when the regression described above has an adjusted-R^2 of at least 80 percent (Lipe, 1996). An assessment of effectiveness is required whenever financial statements or earnings are reported, and at least every three months.

To formally define the hedging problem faced by depositories, let the loss due to default in a mortgage i at time t be given by $Loss_{i,t}$:

$$\begin{array}{c} 0 \text{ if there is no default} \\ L_i \times B_i \text{ otherwise} \end{array} \qquad (1)$$

where B_i is the original mortgage balance.[5] Also let the loss to the mortgage i at time t equal to zero ($Loss_{i,t} = 0$) if the mortgage is current, has been

[5] Losses are expressed as a percentage of the origination amount because the paper will explore the use of static hedges.

prepaid, or defaulted before time t. Let the losses in this portfolio due to default at time t be represented by:

$$Loss_t^{\Pi} = \sum_{i=1}^{N} Loss_{i,t} = \sum_{k=1}^{N_{Loss}} L_i B_i \tag{2}$$

where the latest summation in the equation above is over all the mortgage loans that are subject to a *REO* or *short sale*[6] at time t. The *loss per origination unpaid principal balance* at time t is:

$$Loss\_OUPB_t^{\Pi} = \frac{Loss_t^{\Pi}}{\sum_{i=1}^{N} B_i} = \sum_{k=1}^{N_{Loss}} L_i w_i \tag{3}$$

where w_i is the weight of mortgage i in the portfolio at time zero. Note that Equation 3 implies that as mortgages prepay or default, the $Loss\_OUPB_t^{\Pi}$ decreases, this is just a result of our assumption that the loss in the mortgage i at time t equal to zero if mortgage i prepaid or defaulted before t.

A depository that wishes to implement a *static hedge* of its portfolio of mortgage loans would buy at time zero n_0^{Π} contracts of a residential mortgage credit derivative that pays f_t every month between $t = 1$ and T. The loss of the hedged portfolio at time t is:

$$\varepsilon_t^{\Pi} = Loss\_OUPB_t^{\Pi} \times \sum_{i=1}^{N} B_i + n_0^{\Pi} \times f_t \tag{4}$$

and the number of contracts n_0^{Π} that minimizes the variance of the loss of the hedged portfolio is

$$n_0^{\Pi} = -(\sum_{i=1}^{N} B_i) \times \frac{cov[Loss\_OUPB_t^{\Pi}, f_t]}{var[f_t]} = -(\sum_{i=1}^{N} B_i) \times \beta_0^{\Pi,f} \tag{5}$$

A depository executing a *dynamic hedge,* on the other hand, would buy n_t^{Π} contracts at time t to hedge against the possibility of default at time $t + 1$.

[6] A foreclosed property is classified as real estate owned (REO) after an unsuccessful sale at a foreclosure auction, usually where the minimum bid is set as the outstanding loan balance plus additional expenses. A short sale is when a mortgage lender agrees to forgive some of the outstanding balance in order for the owner to sell the mortgage property for less than the outstanding loan balance.

The number of derivative contracts that minimizes the variance of the hedged portfolio is:

$$n_t^{\Pi} = -(\sum_{i=1}^{N} B_i) \times \beta_t^{\Pi,f} \tag{6}$$

where $\beta_t^{\Pi,f}$ is the time varying beta of the loss per origination unpaid principal balance with respect to the derivative payoff at time $t+1$. Naturally, static hedging is easier to implement than dynamic hedging. The simplicity of the static hedging, however, comes at the cost of reduced hedging effectiveness if the optimum hedge ratios vary substantially through time. As a result, the choice between static or dynamic hedging involves a trade-off between ease of implementation and effectiveness. Because of their level of sophistication, large mortgage investors may prefer dynamic hedging. Small mortgage investors, however, would probably prefer static hedging. In fact, depositories that hold ARMs instead of fixed-rate mortgages in their balance sheets due to the good matching of ARMs with the bank's funding liabilities are likely to prefer static hedging of the credit risk in their mortgage portfolios.

A depository could potentially use any of the residential mortgage credit derivatives to hedge the credit risk of a portfolio of whole loans. For instance, depositories could use contracts that have payoffs similar to the credit losses of mortgages. Specifically, we propose to write contracts that have payoffs depending on an index of mortgage losses due to credit problems. To formalize the concept of an index of losses, imagine that we create an index of losses of mortgages originated in a certain year and with certain characteristics (e.g., $ARMs$ backed by properties in California). Let the number of mortgages in our index at its creation be equal to N_{Index}. We define the value of the index at time t as the losses due to REO and short sale *per origination unpaid principal balance*. That is,

$$Index_t = \frac{\sum_{i=1}^{N_{Index}} Loss_{i,t}}{\sum_{i=1}^{N_{Index}} B_i} = \sum_{k=1}^{N_{Index}^{Loss}} L_i \frac{B_i}{\sum_{i=1}^{N_{Index}} B_i} = \sum_{k=1}^{N_{Index}^{Loss}} L_i w_i^{Index} \tag{7}$$

where the latest summation in the equation above is over all the mortgage loans in the index that are subject to a REO or *short sales* at time t. Note that we let the loss in the mortgage i at time t equal to zero if the mortgage is current, has been prepaid, or was defaulted before time t. Depositories could also use a contract based on home price appreciation, which is a contract that has payoff f_{t+1} at time $t+1$ proportional to the return of a house-price index between t and $t+1$.

The choice between derivative contracts based on house-price indexes or based on loss-based indexes depends on the ability of performing simple and effective hedges. Either contracts based on house-price indexes or loss-based indexes may help depositories benefit from being able to retain portfolios of whole loans and at same time enjoy the capital benefits of hedging the credit risk in their mortgage portfolios. The choice of contract therefore depends on the hedge effectiveness of the hedge performed with each of these types of contracts. In the remainder of this paper, we analyze the hedging effectiveness of contracts based on house-price appreciation and of contracts based on the loss-based indexes. We base most of our analysis on static hedging because it is likely that small depositories that hold ARMs as whole loans prefer static hedging. However, we also analyze one dynamic hedging procedure for the benchmark contract based on house-price appreciation.

3 Estimating hedge effectiveness

Given the losses per dollar of origination balance of the portfolio at time t, $Loss\_OUPB_t^{\Pi}$, the hedging performance of a given hedging instrument is analyzed through the regression:

$$Loss\_OUPB_t^{\Pi} = \alpha + \beta^{\Pi,i} \times CF_t^i + \varepsilon_t \tag{8}$$

where CF_t^i is the cash flow of ith hedge instrument at time t. We calculate $Loss\_OUPB_t^{\Pi}$ according to Equation 3 for a series of proxy portfolios of mortgages, which we call *pseudo* portfolios. We then estimate the regression above for each of these portfolios. We compare the efficiency of different instruments using a standard accounting measure of hedging effectiveness, which is the adjusted-R^2 of the regression above. To examine the hedging performance of derivatives based on loss-based indexes, we assume that derivatives based on these indexes have cash flow at time t (CF_t^i) proportional to the loss-based index calculated according to Equation 7 for a given reference pool. The construction of the pseudo portfolios and of the reference pools of indexes are presented in detail in Section 5. To benchmark the performance of derivatives based on loss-based indexes, we also examine the hedging performance of derivatives based on house-price appreciation indexes. We assume that derivatives based on house-price appreciation have cash flow at time $t+1$ (CF^i_{t+1}) proportional to the house appreciation between t and $t+1$.

A simple stylized model of default is useful in motivating the form of the Equation 8 above. Assume that the price of a residential property backing a mortgage is $S_{i,t}$ at time t follows the log-normal process:

$$\frac{dS_{i,t}}{S_{i,t}} = \mu_i dt + \sigma_i \rho_i dZ_t + \sigma_i \sqrt{1-\rho_i^2} dZ_{i,t} \tag{9}$$

where μ_i, σ_i and ρ_i are constant and Z_t and $Z_{i,t}$ are standard Brownian motions. Default in mortgage i occurs if the property value reaches a level below or equal to D_i at time $t+\Delta t$. Therefore, the loss due to default at time $t+\Delta t$ is 0 if $S_{t+\Delta t} > D_i$ and $L_i \times B_i$ otherwise where L_i is a constant. Also assume that the average price of residential properties in the region of this residential property follows the process:

$$\frac{dS_t}{S_t} = \mu dt + \sigma dZ_t \tag{10}$$

which implies that the correlation between the property i and the average of the local real estate market is ρ_i.

We assess the hedging performance of derivatives based on a loss index and on house-price appreciation indexes using a Monte Carlo simulation. We run $1,000$ simulation paths of the model above and estimate for each simulation path Regression 8. We estimate these regressions with either loss-based index or house-price appreciation index, where the house-price appreciation is based on Equation 10. In this simulation exercise, we assume that a mortgage investor has a portfolio of $1,000$ loans collateralized by properties that have the same initial value, $\$100,000$. Default trigger points $D_i s$ are randomly selected from a uniform distribution with support between $\$70,000$ and $\$90,000$. Default may happen any month after the origination of the mortgage until its maturity. Mortgages are assumed to have 30 years to maturity. The reference pool has $10,000$ mortgages, including the $1,000$ mortgages from the investor. The properties collateralizing these mortgages also have initial values equal to $\$100,000$ and their default triggers are also randomly selected from the same distribution as above. Both the mean house-price appreciation and the mean index appreciation are five percent per year ($\mu_i = \mu = 0.05$); the annualized volatility of both the house prices and of the index are 15 percent ($\sigma_i = \sigma = 0.15$); and the correlation between the returns of the houses and the house-price index is 50 percent ($\rho_i = 0.5$). We also assume that default severity is 30 percent ($L_i = 0.3$).

In this framework, the simulations indicate that the hedging performance of the loss-based index is quite promising, while the hedging performance of the house-price appreciation index is poor. To show this result, we display in Table 1 the average of the R^2s of Regression 8. Note that the average R^2 of Regression 8 when the loss-based index is used to hedge is quite high at 0.86, while this average is only 0.07 when the monthly return of the house-price index is used as independent variable. Moreover, note that house-price appreciation statistical significance disappears when house-price appreciation and loss-based indexes are together in the regression. Indeed, when house-price appreciation is alone in the regression, it has an average t-statistic of -4.99, while when used together with the loss-based index, it has an average t-statistic of -0.14.

One possible reason for the poor performance of the contract based on house-price appreciation is the seasoning pattern of the credit losses. To show this pattern, we plot in the first panel of Figure 1 the average loss in the portfolio as a function of the loan age in our simulation. Note that average loss is a hump-shaped function of loan age with a peak around eight months. This non-linear seasoning pattern is common to first-passage models of default and may account for the poor performance of a static hedge based on the house-price appreciation, which may not be able to account for this non-linearity.[7] Hedges based on the loss indexes, on the other hand, may account for this non-linearity since the loss index itself is a non-linear function of the age of the loans in the reference pool. To check this, we add the age of the loans in the pseudo portfolio into the regression (AGE) along with a dummy variable that has a value of one if the age is less than eight months and zero otherwise ($AGEDUM$). We set the break point of the variable $AGEDUM$ equal to eight months because this is the point when the losses peak. The results of the regressions with AGE and $AGEDUM$ are in Table 1. Note that once we add age-related variables to the regression with house-price appreciation, the R^2 increases substantially to 0.32. This

[7] See Duffie and Singleton (2003) for examples of these seasonality patterns.

increase, however, does result in a substantial change in the point estimate of the coefficient on house-price appreciation. The inclusion of age-related variables in the regression with the loss-based index does not improve the fit to the data, indeed the R^2 of the regression with age variables and loss-based index is the same as the R^2 of the regression with loss-based index alone. We interpret these results as an indication that the low R^2 of the regression with house-price index may indeed be improved with we control for loan age. However, this improvement in the fit of the regression does result in better hedges since the hedge ratio of contracts based on house-price appreciation does not change when we control for loan age.

The poor hedging performance of the house-price appreciation index is partially a result of the fact that the optimal hedge ratio of a loan varies with the level of the house price. To understand this point, assume that an investor in this mortgage wishes to hedge its credit exposure with a contract written on the house-price appreciation of the region; The payoff of this contract at time $t+\Delta t$ is equal to the house-price appreciation between t and $t+\Delta t$, that is $f_{t+\Delta t} = (S_{t+\Delta t}/S_t - 1)$. We derive an equation for the optimal number of forward contracts needed to be shorted to hedge the residential mortgage credit risk in a mortgage in this model (see Appendix). We plot the optimal number of forward contracts as a function of the price of the underlying property in the second panel of Figure 1. To make this plot, we assume that the mortgage investor wishes to hedge the losses in a mortgage due to default one month ahead ($\Delta t = 1 - month$), and default happens if the price of the house one month from now is below $\$80,000$ (D_i). The other parameters are assumed to be same as those used in the simulations. Figure 1 indicates that the hedge ratio varies sharply with house prices. Indeed, the optimal hedge ratio increases 7.5 times if the underlying house-price decreases from $\$100,000$ to $\$85,000$. The variability of this hedge ratio implies that an investor trying to hedge the credit risk of a mortgage portfolio would have to sell a much larger number of contracts based on the house-price appreciation index as the prices of the underlying properties drop.

We also analyze the performance of house-price appreciation contracts in dynamic hedging to improve the performance of our benchmark based on house-price appreciation index. To do so, we add the interaction of the house-price appreciation with a dummy variable that has a value of one if the house-price index decreases more than a constant c and zero otherwise

($CHPIDUM$). By adding this dummy variable, we effectively allow the hedge ratio with respect to the house-price index contract to vary through time. Indeed, if the house-price index decreases by more than c, the hedge ratio is the coefficient on the house-price appreciation plus the coefficient on the interaction term. On the other hand, if the house-price index does not decrease by more than c, then the hedge ratio is the coefficient on the house-price appreciation. Naturally, we could construct optimal hedge ratios based on the presented model, but our intention is not to evaluate or estimate the simple model of default presented herein. Instead, we want to use this model to understand simple ways to empirically estimate the hedge effectiveness of a residential mortgage credit derivative. In our simulations we set c equal to one percent because this is the value that we use in our empirical analysis in Section 5 and we want to keep the simulations consistent with our empirical application. We also interact the house-price index with loan age-related variables. These interactions are equivalent to allow the hedge ratio with respect to house-price index contract to vary with the age of the loans in the pseudo portfolio.

The performance of the dynamic hedge based on the house-price appreciation index is better than the performance of the static hedging based on this index. However, the static hedge based on the loss-based index is still the best-performing hedge. The last two columns of Table 1 display the results of the regressions analyzing the dynamic hedging with the house-price appreciation index. Note that by allowing the hedge ratio to change with AGE, $AGEDUM$ and $CHPIDUM$, we can get a substantial improvement in the hedge effectiveness of the contract based on house-price appreciation. Indeed, the R^2 of the regression where the hedge ratio moves with these characteristics is 0.21, which is much higher than the R^2 of the regression with house-price appreciation only (0.07). In addition to allow the hedge ratio to change over time, we also control for age-related effects on the mean losses of mortgages. The results of controlling for age effects are displayed in the last column of Table 1. Controlling for such age effects improves the assessed hedge effectiveness of house-price based contracts substantially.

Overall, the simulations above suggest some controls that may be used in the empirical evaluation of the hedging effectiveness of contracts written on loss-based indexes and on house-price indexes. In Section 5, we use the same analyses as the ones developed in the simulations with actual data on mortgage losses.

4 Data and summary statistics

We create indexes of credit losses based on First American's LoanPerformance data. These data come from two main sources: loan servicing and securities performance records. The LoanPerformance subprime data are drawn from subprime securities and include more than four million subprime mortgages. We use data from mortgages originated from 1997 to 2006. Mortgage performance data are also available through securities, because issuers of non-agency mortgage- and asset-backed securities typically disclose information about the delinquency, default, and loss performance of loans that form the collateral for the security. The LoanPerformance securities database contains loan-level information on over $1.5 trillion in non-agency mortgage- and asset-backed securities representing more than 85 percent of this segment of the market.[8] We use data on asset-backed securities (Alt-A and non-prime) at the loan level.

We match the securities and the servicing LoanPerformance databases to create a large database of mortgage loans. Attributes on loans in this data set include age of loan, LTV, loan purpose (refinancing or purchase), loan size, loan term, coupon, borrower FICO score, loan credit rating, type of mortgage, whether the borrower took cash out of the transaction, whether the purchase is for investment or for primary residence, and property type. These data can be aggregated at several levels−national, regional, state, and MSA or by origination date−and contain information on delinquency, foreclosure, REO, and loss amount. We display some summary statistics of these data in Table 2 and in Figure 2.

The top panel of Figure 2 displays the percentage of different types of mortgages by origination years. This panel reveals that the importance of fixed-rate mortgages in the subprime universe decreased over time. Specifically, about 50 percent of the mortgages originated in 1997 are fixed-rate mortgages, while less than 30 percent of the mortgages originated in 2006 are fixed-rate. Adjustable-rate mortgages, on the other hand, compose the majority of the mortgages in the subprime universe. Figure 2 also reveals

[8]Information on the LoanPerformance securities data is as of 12/4/2006.

that balloon and interest-only mortgages are not observed often in our sample. The second panel of Figure 2 displays the number of mortgages originated by year in the sample along with the percentage of mortgages with low-documentation and prepayment penalties. The second panel of Figure 2 clearly shows the growth of the subprime market.

Table 2 displays the distribution of some of the characteristics of the loans in the sample. The results in this table indicate that the median origination balance of the loans in the sample is $122,000, the median loan-to-value is 80 percent and the median borrower FICO score is 613. Based on the originator specific credit ratings, LoanPerformance assigns standardized letter-grades for the mortgage loans in its sample. More than 80 percent of the loans in the sample are classified as A-. These loans tend to be made to borrowers with higher credit scores and they have larger balances and higher LTVs. The results in Table 2 also indicate that the LoanPerformance credit ratings are consistent with the borrowers' FICO scores. Indeed, the median FICO score of the borrowers in the A- loan group is 626, while the median FICO score of the borrowers in the D loan group is 549.

We work with a subset of the data used to build Table 2 and Figure 2 in our empirical analysis described in Section 5. Specifically, we select all the loans that are in asset-backed securities collateralized by pools of mortgages containing at least 1,000 mortgages. This criterion is important because LoanPerformance does not report losses on all the loans in its database. By working with pools with at least 1,000 mortgages, we guarantee that all the pools that we work with have reported losses. In addition, to avoid affecting our analysis by the short history that we have on balloons and interest-only mortgages, we do not use these types of mortgages in our empirical analysis.

In addition to the LoanPerformance data on mortgage losses, we also use the Office of Federal Housing Enterprise Oversight (OFHEO) house-price indexes (HPI). OFHEO creates quarterly HPI for conforming single-family detached properties using a repeat-sales methodology. The index is estimated from repeat transactions (sales or refinance) taken from mortgages purchased or securitized by Freddie Mac or Fannie Mae starting from the first quarter of 1975. The OFHEO methodology is a variation of that developed by Bailey, Muth, and Nourse (1963) and Case and Shiller (1989), and explained in detail by Calhoun (1996). This methodology fits a house-price appreciation path that is most consistent with the collection of observed value changes that occur between repeat transactions of the same property in a particular geographic area. The HPI is updated each quarter as additional repeat transactions enter the sample. In this paper we use the state-level house-price indexes based on purchase transactions.[9]

5 Empirical application

To create the dependent variable for hedge effectiveness regressions, we build pseudo portfolios of mortgages by selecting mortgages from the securitized pools that are backed by properties in a given state and have a given origination year. We then calculate the average loss per dollar of origination amount of these portfolios for every month of the sample according to Equation 3. We expect that this portfolio construction method results in portfolios that resemble those held by small depository institutions that have exposure to a given state. Moreover, we segment by origination year because the loss experience of a given portfolio of mortgages depends on variables for which we do not control in Regression 8. For instance, a large interest-rate drop during the life of mortgages in a given portfolio triggers refinancing, which decreases the credit losses of the portfolio. As a result, by creating indexes based on origination year, we put together mortgages that are subject to the same history and control for macroeconomic variations that affect the amount of losses in the portfolio. We discard portfolios with less than 200 mortgages. The time series of losses starts in December 1997 and ends in August 2007, and so the maximum number of monthly observations for a given pool is 117. We have a total of 3,199 security pools for which we can examine hedge effectiveness.

While using securitized loans may be one of the only ways to analyze the hedge effectiveness of residential mortgage credit derivatives, doing so may bias the results. We may overstate the effectiveness of the hedge if the loans that were held in an investor's portfolio differed from those assets securitized (and hence in the reference pool) by unobservable characteristics. There is some possibility that this may be the case. For example, Stanton and Wallace (1998) show that there will be a separating equilibrium in the mortgage origination market in which borrowers with different mobility will

[9] We do not use the SP/Case-Shiller indexes because they cover only 20 metropolitan areas. See Standard and Poor's (2008).

select different combinations of points and coupon rates. Because points paid are typically observable to the originator but not to the secondary market, this could result in systematic differences between loans held in portfolio from those that are securitized.

The set of independent variables includes house-price appreciation indexes because we want to analyze the effectiveness of future contracts based on these indexes as hedging instruments. House-price appreciation is a proxy for the cash flows of future contracts based on house-price appreciation (CF_t^i in Equation 8). The house-price indexes are state-level, purchase-transaction, repeat-sales. Quarterly growth rates are calculated using this index, and converted into a monthly series by assigning the growth at a constant level over the three months in the quarter. So, for example, if Georgia had a quarterly growth rate of 2 percent in the first quarter of 2007, the growth rate for January, February, and March of 2007 would be set to 0.66 percent. Table 3 displays some percentiles of the sample distribution of monthly house-price appreciation in each state for which we create pseudo portfolios. These percentiles reveal that most of the states had substantial house-price increases during our sample period. Indeed, the mean monthly house-price appreciation in the sample is 50 basis points per month with a first quartile around 30 basis points. Table 3 also displays the amounts of loans in each state relative to the entire sample. This table reveals that subprime loans are highly concentrated in some states. In fact, the top six states in terms of the total origination amounts account for more than 50 percent of the origination amount in our sample. Moreover, the states used in the hedging effectiveness regressions have close to 94 percent of the total origination amount of the entire LoanPerformance sample.

The set of characteristic-based loss indexes we have to choose from is quite large because the LoanPerformance database is very rich in terms of the information about the mortgages in the database. For instance, we can create an index based on the losses of ARMs backed by properties in California with an origination LTV above 90 percent and borrower FICO score below 630. As a result, we could potentially create thousands of indexes based on these data, which would improve the assessed hedging performance at the risk of overfitting. Hence, to keep the analysis parsimonious, we restrict our initial analysis to indexes based on origination year and state in which the underlying property is located. In addition to being parsimonious, this restriction also renders direct comparison with the house-price appreciation indexes.

We start our empirical analysis with the seasoning pattern displayed in Figure 3. This figure displays the average of the loss per origination principal balance ($Loss\_OUPB^{\Pi}$) for a given age across all the pseudo portfolios. The average $Loss\_OUPB^{\Pi}$ is largest when mortgages are around 25 months old. After this period, the losses decrease but they also become quite noisy. The hump-shaped pattern of the losses is consistent with those predicted in first-passage models of default and with the pattern of losses in Figure 1, which was generated by simulations. We set the break point of the variable $AGEDUM$ in the empirical analysis in the same way that we set it in the simulation. That is, the variable $AGEDUM$ is equal to one if AGE is smaller than 25 months (when losses peak) and zero otherwise.

Recall that house prices substantially increased during our sample period. As a result, we have only a few pseudo portfolios that were subject to house-price decreases in the period. This is an issue for our empirical analysis because in some of our regressions we add the interaction of house-price appreciation with a dummy variable that has a value of one if the house-price index decreases more than a constant c since the mortgage originations until month $t-3$, and and zero otherwise ($CHPIDUM_{t-3}$).[10] Ideally, we would like to set the constant c equal to a negative number that represents a substantial decrease in the house-price index. The cost of doing so, however, is that $CHPIDUM$ would then be equal to zero for most of the entire history of the losses of the pseudo portfolios that we have in our sample. We therefore set c equal to minus one percent, which is not a substantial decrease in house prices. However, we have only 252 pseudo portfolios that have $CHPIDUM$ equal to one at some point in their history of losses. From these portfolios, we have only 49 pseudo portfolios where $AGEDUM$ equals zero at some point of their history.

Table 4 displays the means of the point estimates, t-statistics, R^2s and adjusted-R^2s of the hedging effectiveness regressions across all the 49 pseudo portfolios that satisfy the conditions mentioned above. As in the simulations, the R^2s of the regressions with house-price appreciation alone are quite

[10]Because our HPI is quarterly, we lag the $CHPIDUM$ in our regressions by three months to avoid any possible look ahead bias.

low with an average value of two percent. As opposed to the simulation results, the point estimates of the house-price index are not significant with an average t-statistic of -0.05. The loss-based indexes fit the loss of the portfolios better than the house-price indexes with an average adjusted-R^2 close to 13 percent. Perhaps not surprisingly, the R^2s of the regression with the loss-based index using actual data are smaller than the R^2s using simulated data. As in the simulations, the average point estimates of the coefficient on the loss-based index are close to one and statistically significant.

In addition to running the regressions with cash flows of derivatives contemporaneous to the cash flow of losses, we also estimate regressions in which the cash flow of derivatives are lagged for up to three months. We do this to make sure that the assessed hedging effectiveness is not affected by asynchronicity between cash flows of derivatives and losses in the pseudo portfolios. Indeed, different servicers have different procedures to report and to deal with the losses in the portfolios that they serve. As a result of these differences, the losses in the overall market may be not synchronous with the losses of one pseudo portfolio of mortgages. The results of our regressions in Table 4 indicate that this indeed may be happening because the average R^2 and the average adjusted-R^2 increase to 17 and 15 percent respectively once we add the lagged loss indexes in the regression.

Controlling for age effects or allowing for dynamic hedging with a house-price based contract does not seem to improve the hedge effectiveness. The results of Regression 6 in Table 4 show that the adjusted-R^2 more than doubles once we control for age in the regression with the house-price appreciation index. This increase, however, is not related to any significant change in the estimation of the coefficients of the house-price index, which are not statistically different from zero. Moreover, the average of the point estimates of the coefficient of the house-price index is positive which is not consistent with credit risk models. Allowing the hedge ratio of the house-price index to change with the cumulative house-price appreciation makes the average point estimates of the hedge ratio negative, which is consistent with the theory. However, there is no increase in the hedging effectiveness as measured by the average of the adjusted-R^2s, which is only five percent in Regression 9 in Table 4. Allowing hedge ratios to change with age effects and the cumulative house-price appreciation seems to make a difference in the hedging with house-price index. Even though all the coefficients of Regression 10 in

Table 4 are not statistically different from zero, the adjusted-R^2 is relatively high at twelve percent. However, the adjusted-R^2 of Regression 10 is still smaller than the one in the regression based on the index only.

Table 5 displays the means of the point estimates, t-statistics, R^2s and adjusted-R^2s of the hedging effectiveness regressions across all the pseudo portfolios. The results in Table 5 are analogous to those in Table 4, indicating that the superior performance of the hedge with derivatives written on the loss-based index is not just a result of the small sample of pseudo portfolios used to calculate the means in Table 4.

What do we make of all these results? *Static hedges* with loss-based indexes still seem to have a reasonable amount of basis risk as measured by the adjusted-R^2s. However, this basis risk is smaller than the one present in simple *dynamic hedges* with house-price appreciation indexes. As a result, loss-based indexes may be a promising direction to expand the risk management tools of agents carrying real estate risks. Also, there is some indication that the population of loans that we examine is especially challenging for hedging instruments as there are substantial issuer and servicer effects that create some asynchronicity between the losses of pseudo portfolios and cash flows of the index of losses. These effects may contribute to the relatively large amount of basis risk in the hedged positions that we examine.

6 Conclusion

Creating an effective market for mortgage credit risk is likely to be economically beneficial. The ability to disperse credit-risk exposure widely would likely decrease the cost of credit risk as well as reduce the degree of concentration of these risks. In this paper, we propose the creation of derivative contracts based on the credit loss of mortgage portfolios. We argue that such instruments would complement the menu of available instruments to hedge the credit risk in mortgage portfolios and would contribute to the development of real estate derivatives advocated by Shiller (2008).

This paper explores the effectiveness of instruments based on loss-based indexes and benchmarks their performance with house-price indexes. The analysis is on hedging credit risks for the population of subprime loans that are securitized. We find that loss-based indexes are better than house-price based indexes for hedging credit risk in mortgage portfolios. We also find that hedges with loss-based indexes still carry a substantial amount of basis risk, which we partially attribute to issuer and servicer effects.

We see our results on the amount of basis risk on the hedges performed with the loss-based indexes as an upper bound because there are ways to improve the hedge efficiency of loss-based contracts. A hedge based on a loss-based index that resembles the characteristics of the portfolio to be hedged likely has less basis risk than the hedges that we examined herein. For instance, if the portfolio to be hedged is composed of ARMs backed by properties in California with an origination LTV above 90 percent then an index based on a large pool of mortgages with the same characteristics as the hedged portfolio could be created. It is quite likely that the hedging performance of such an index would be better than the ones that we assessed. We leave the examination of this type of index for future research.

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Appendix

To compute $n_{i,t}$, let's change variables from $S_{t+\Delta t}$ and $S_{i,t+\Delta t}$ to $\ln(S_{t+\Delta t})$ and $\ln(S_{i,t+\Delta t})$

$$\begin{aligned}
\ln(S_{t+\Delta t}) &= \ln(S_t) + (\mu - 0.5\sigma^2)\Delta t + \sigma \Delta Z_{t+\Delta t} \quad (11)\\
\ln(S_{i,t+\Delta t}) &= \ln(S_{i,t}) + (\mu_i - 0.5\sigma_i^2)\Delta t + \sigma_i \rho_i \Delta Z_{t+\Delta t} + \sigma_i \sqrt{1-\rho_i^2}\Delta Z_{i,t+\Delta t}
\end{aligned}$$

Also, let's define the distance to default as $x_t = \ln(S_t/D_i)$, that is default happens when x_t reaches zero. The covariance $cov[f_{t+\Delta t}, Loss_i]$ is given by $E[(S_{t+\Delta t}/S_t - 1) \times Loss_i] - E[(S_{t+\Delta t}/S_t - 1)]E[Loss_i]$, which is:

$$\begin{aligned}
cov[f(S_{t+\Delta t}), Loss_i] = \; & L_i \times B_i \times e^{\mu \Delta t} \times \\
& \int_{-\infty}^{\infty} \{N[\frac{-x_t - (\mu_i - 0.5\sigma_i^2)\Delta t - \sigma_i \sqrt{1-\rho_i^2}\Delta Z_{i,t+\Delta t} - \sigma\sigma_i\rho_i\Delta t}{\sigma_i \rho_i \sqrt{\Delta t}}] \\
& -N[\frac{-x_t - (\mu_i - 0.5\sigma_i^2)\Delta t - \sigma_i \sqrt{1-\rho_i^2}\Delta Z_{i,t+\Delta t}}{\sigma_i \rho_i \sqrt{\Delta t}}]\} \quad (12) \\
& \times f(\Delta Z_{i,t+\Delta t}) d\Delta Z_{i,t+\Delta t}
\end{aligned}$$

where $N[x]$ is the standard cumulative normal distribution evaluated at x.

$$n_{i,t} = -\beta_t^{i,f} = -\frac{cov[f_{t+\Delta t}, Loss_i]}{var[f_{t+\Delta t}]} = -\frac{cov[f_{t+\Delta t}, Loss_i]}{e^{\mu \Delta t} \times (e^{\sigma^2 \Delta t} - 1)} \quad (13)$$

Table 1 – Regressions based on simulated sample. This table displays the means of the point estimates, t-statistics and R^2s of regressions based on 1,000 simulated samples of 360 monthly observations. The dependent variable in these regressions is the loss per origination balance of a mortgage portfolio with 1,000 loans. The independent variables are the simulated house price index (HPI), the simulated index of losses of a reference pool with 10,000 mortgages (INDEX), the age in months of the mortgage portfolio (AGE), a dummy variable with value one if AGE is smaller than eight (AGEDUM), interactions of AGE and AGEDUM with HPI, and an interaction of HPI with a dummy variable that has value one if the cumulative appreciation of the house price index is below minus one percent (CHPIDUM). Please see Section 3 for a description of the simulated model. T-statistics are in parenthesis.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
INTERCEPT	0.0004	2.68E-06	3.08E-06	0.0010	7.47E-06	8.66E-06	0.0003	0.0003	0.0009
	(7.65)	(0.14)	(0.16)	(11.34)	(0.18)	(0.20)	(7.77)	(7.89)	(12.88)
HPI	-0.0057		-5.57E-05	-0.0053		-6.01E-05	-0.0039	-0.0118	-0.0116
	(-4.99)		(-0.14)	(-5.61)		(-0.15)	(-3.37)	(-4.77)	(-6.03)
INDEX		0.9802	0.9795		0.9808	0.9797			
		(57.90)	(55.70)		(48.95)	(46.56)			
AGE x AGEDUM				0.0003	-8.66E-06	-8.25E-06			0.0003
				(4.49)	(-0.26)	(-0.25)			(5.42)
AGE				-3.48E-06	-2.44E-08	-2.8E-08			-3.39E-06
				(-8.46)	(-0.13)	(-0.15)			(-9.85)
HPI x CHPIDUM							-0.0093	-0.0017	-0.0061
							(-2.67)	(-0.75)	(-1.74)
AGE x HPI								4.29E-05	4.54E-05
								(3.82)	(5.07)
AGEDUM x HPI								-0.0057	-0.0044
								(-2.92)	(-2.81)
R^2	0.0683	0.8639	0.8643	0.3199	0.8669	0.8673	0.1123	0.2133	0.4569

Table 2 – Summary statistics of the loans in the LoanPerformance database. This table displays some moments of the distribution of the characteristics of these loans for a given credit rating and for the entire sample. Credit ratings from A- to D are assigned to loans in the LoanPerformance database. The loan-to-value (LTV) and borrowers' credit score (FICO) are the ones prevailing at the origination of the loans. These sample statistics are calculated over more than 4.7 million loans originated between 1997 and 2006.

			Origination Amount				LTV				FICO			
Class	Observations	Percent of Sample	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3
A-	3,816,227	81%	164,023	78,000	130,000	214,000	0.82	0.80	0.80	0.90	628	590	626	662
B	594,334	13%	122,741	62,000	97,750	156,400	0.76	0.72	0.80	0.85	561	531	555	587
C	289,143	6%	114,989	56,443	91,000	150,000	0.70	0.65	0.74	0.80	546	519	540	566
D	37,329	1%	98,561	47,600	76,500	126,000	0.68	0.60	0.65	0.80	569	521	549	608
Total	4,737,033		155,334	73,100	122,089	201,060	0.80	0.75	0.80	0.90	614	570	613	653

Table 3 – House-price appreciation in the states and period used in our hedging effectiveness regressions. This table displays summary statistics of the monthly house-price appreciation for every state for which there is at least one pseudo portfolio used in the hedging effectiveness regressions. It also displays the percentage of the total origination amount from mortgages in each individual state.

	Monthly house-price appreciation (in percent)							Percent of total
State	mean	std. deviation	p1	p25	median	p75	p99	origination amount
CA	0.9	0.7	-1.4	0.6	1.0	1.4	2.2	26.4
FL	0.8	0.6	-1.1	0.5	0.8	1.1	2.2	9.2
NY	0.7	0.4	-0.1	0.5	0.7	1.1	1.2	5.1
TX	0.4	0.2	0.0	0.2	0.4	0.6	0.8	4.8
IL	0.5	0.3	-0.2	0.3	0.4	0.6	1.1	4.3
MI	0.2	0.4	-1.0	0.1	0.3	0.6	0.9	3.3
NJ	0.8	0.5	-0.3	0.5	0.9	1.2	1.7	3.2
MD	0.8	0.6	-0.2	0.4	0.7	1.3	2.1	3.1
MA	0.7	0.6	-0.7	0.4	0.7	1.2	1.8	2.8
AZ	0.8	0.7	-0.7	0.3	0.6	0.9	3.3	2.5
GA	0.4	0.2	-0.3	0.3	0.4	0.6	0.9	2.5
VA	0.7	0.4	-0.2	0.4	0.7	1.0	1.6	2.5
WA	0.7	0.4	0.0	0.4	0.5	0.9	1.9	2.4
CO	0.4	0.4	-0.3	0.1	0.3	0.9	1.1	2.3
OH	0.3	0.3	-0.5	0.1	0.2	0.5	0.8	2.1
PA	0.6	0.4	0.0	0.3	0.6	0.9	1.3	2.1
MN	0.6	0.5	-0.6	0.3	0.6	0.9	1.4	1.8
NC	0.4	0.2	0.0	0.2	0.4	0.5	0.9	1.5
CT	0.7	0.5	-0.4	0.3	0.6	1.1	1.6	1.4
MO	0.4	0.3	-0.2	0.2	0.4	0.6	1.0	1.2
TN	0.4	0.2	0.0	0.2	0.3	0.5	1.0	1.2
IN	0.2	0.3	-0.7	0.1	0.2	0.5	0.9	1.2
WI	0.4	0.3	-0.2	0.1	0.4	0.7	1.1	1.1
OR	0.7	0.5	-0.1	0.4	0.7	1.0	2.0	1.1
UT	0.6	0.5	-0.1	0.2	0.5	1.1	1.6	0.8
SC	0.4	0.2	0.0	0.2	0.4	0.6	1.0	0.8
LA	0.5	0.3	-0.1	0.3	0.4	0.6	1.6	0.7
AL	0.4	0.3	-0.1	0.2	0.4	0.6	1.0	0.7
NH	0.5	0.6	-0.7	0.4	0.5	0.9	1.8	0.5
KY	0.3	0.2	-0.1	0.1	0.3	0.5	0.7	0.5
OK	0.4	0.3	-0.1	0.2	0.3	0.6	1.0	0.4
MS	0.4	0.3	-0.2	0.1	0.3	0.6	1.1	0.4
							Total	93.9

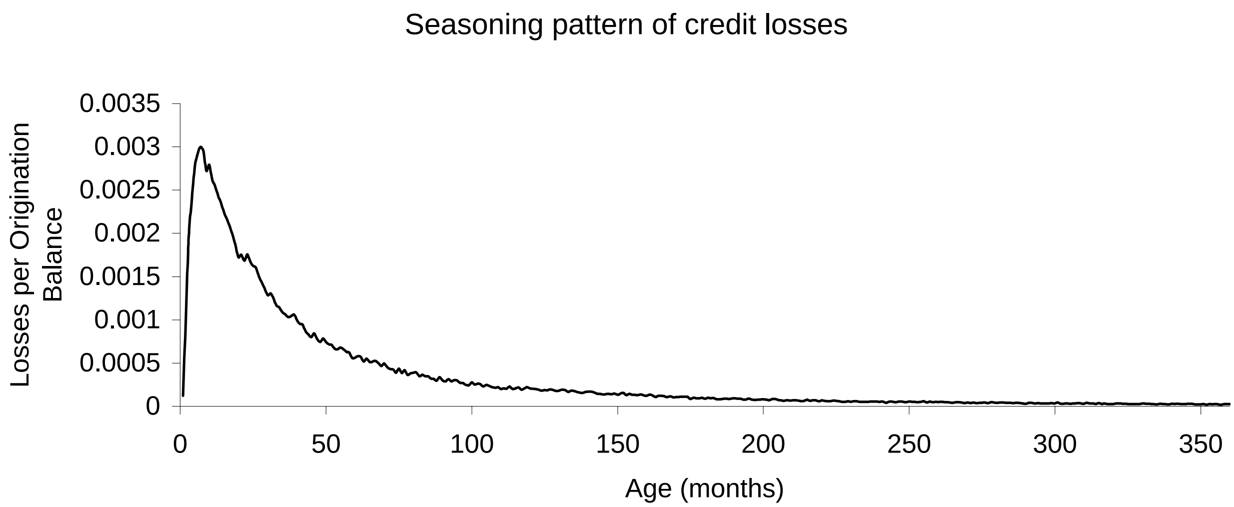
Table 4 – Regressions estimated with LoanPerformance loss data. This table displays the means of the point estimates, t-statistics, R^2s, and adjusted-R^2s of regressions estimated with LoanPerformance database. The dependent variable in these regressions is the loss per origination balance at month t of a pseudo portfolio with at least 200 loans. A pseudo portfolio is comprised of loans from a securitized pool of mortgages that are in the same state and have the same origination year. The independent variables are the appreciation in the house-price index (HPI_t) in the state at month t, the index of losses of a reference pool of mortgages with the same state and origination year as the loans in the pseudo portfolio ($INDEX_t$), the appreciation in the house-price index lagged by one to three months (HPI_{t-1}, HPI_{t-2} and HPI_{t-3}), the index of mortgage losses lagged by one to three months ($INDEX_{t-1}$, $INDEX_{t-2}$ and $INDEX_{t-3}$), the age in months of the mortgage portfolio (AGE_t), a dummy variable with value one if AGE_t is smaller than 25 months ($AGEDUM_t$), interactions of AGE_t and $AGEDUM_t$ with HPI_t, and an interaction of HPI_t with a dummy variable that has value one if the appreciation of the house-price index between the securitization of the pool and three months before month t is below minus one percent ($CHPIDUM_{t-3}$). The means are calculated only with pseudo portfolios that have at least one observation in which $CHPIDUM_{t-3}$ is one and $AGEDUM_t$ is zero. The means of t-statistics are in parenthesis.

	1	2	3	4	5	6	7	8	9	10
INTERCEPT	0.0012	0.0001	0.0001	0.0012	0.0001	0.0007	0.0002	0.0001	0.0012	0.0005
	(3.08)	(0.30)	(0.30)	(2.97)	(0.28)	(0.38)	(0.01)	(0.00)	(3.13)	(0.25)
HPI_t	0.0096		0.0064	0.0429		0.0083		0.0028	-0.0281	-0.1823
	(-0.05)		(-0.08)	(0.21)		(0.11)		(0.10)	(-0.44)	(-0.47)
$INDEX_t$		0.8464	0.8643		1.0240		1.0310	1.0361		
		(1.91)	(1.94)		(0.83)		(1.60)	(1.58)		
HPI_{t-1}				-0.0429						
				(-0.24)						
HPI_{t-2}				-0.0116						
				(-0.02)						
HPI_{t-3}				0.0065						
				(-0.17)						
$INDEX_{t-1}$					-0.0978					
					(-0.17)					
$INDEX_{t-2}$					0.0533					
					(0.16)					
$INDEX_{t-3}$					-0.1797					
					(-0.02)					
HPI x CHPIDUM									0.1109	0.0404
									(0.75)	(0.41)
AGE x AGEDUM						5.44E-05	-1.42E-05	-1.46E-05		6.95E-05
						(1.05)	(-0.11)	(-0.13)		(1.01)
AGE						-5.70E-06	-7.33E-06	-7.48E-06		6.52E-07
						(0.34)	(0.22)	(0.22)		(0.40)
AGE x HPI										0.0047
										(0.27)
AGEDUM x HPI										0.0069
										(0.52)
R^2	0.0450	0.1306	0.1767	0.1274	0.2354	0.1616	0.2206	0.2479	0.0845	0.2574
Adjusted-R^2	0.0450	0.1306	0.1500	0.0356	0.1564	0.1054	0.1685	0.1697	0.0547	0.1197
Obs.	49	49	49	49	49	49	49	49	49	49

Table 5 – Regressions estimated with all pseudo portfolios from LoanPerformance data. This table displays the means of the point estimates, t-statistics, R^2s, and adjusted-R^2s of regressions estimated with LoanPerformance database. The dependent variable in these regressions is the loss per origination balance at month t of a pseudo portfolio with at least 200 loans. A pseudo portfolio is comprised of loans from a securitized pool of mortgages that are in the same state and have the same origination year. The independent variables are the appreciation in the house-price index (HPI_t) in the state at month t, the index of losses of a reference pool of mortgages with the same state and origination year as the loans in the pseudo portfolio ($INDEX_t$), the appreciation in the house-price index lagged by one to three months (HPI_{t-1}, HPI_{t-2} and HPI_{t-3}), the index of mortgage losses lagged by one to three months ($INDEX_{t-1}$, $INDEX_{t-2}$ and $INDEX_{t-3}$), the age in months of the mortgage portfolio (AGE_t), a dummy variable with value one if AGE_t is smaller than 25 months ($AGEDUM_t$), interactions of AGE_t and $AGEDUM_t$ with HPI_t, and an interaction of HPI_t with a dummy variable that has value one if the appreciation of the house-price index between the securitization of the pool and three months before month t is below minus one percent ($CHPIDUM_{t-3}$). The means are calculated across all the pseudo portfolios. The means of t-statistics are in parenthesis.

	1	2	3	4	5	6	7	8	9	10
INTERCEPT	0.0004	7.18E-07	3.03E-06	0.0005	-6.99E-06	0.0004	-0.0001	-0.0001	0.0006	0.0005
	(1.97)	(0.11)	(0.15)	(1.69)	(0.06)	(0.86)	(-0.09)	(-0.10)	(1.91)	(0.25)
HPI_t	-0.0029		-0.0014	0.0070		0.0007		0.0018	-0.0162	-0.1823
	(0.01)		(0.04)	(0.23)		(-0.01)		(0.02)	(-0.30)	(-0.47)
$INDEX_t$		0.9337	0.9468		0.9451		0.9314	0.9383		
		(2.53)	(2.40)		(1.57)		(2.29)	(2.25)		
HPI_{t-1}				-0.0058						
				(-0.04)						
HPI_{t-2}				-0.0203						
				(-0.21)						
HPI_{t-3}				-0.0065						
				(-0.08)						
$INDEX_{t-1}$					0.0096					
					(0.06)					
$INDEX_{t-2}$					0.0259					
					(0.04)					
$INDEX_{t-3}$					-0.0276					
					(0.01)					
HPI x CHPIDUM									0.0456	0.0404
									(0.54)	(0.41)
AGE x AGEDUM						1.25E-05	5.49E-06	5.34E-06		6.95E-05
						(0.71)	(0.32)	(0.31)		(1.01)
AGE						-1.17E-06	1.69E-06	1.70E-06		6.52E-07
						(-0.23)	(0.10)	(0.10)		(0.40)
AGE x HPI										0.0047
										(0.27)
AGEDUM x HPI										0.0069
										(0.52)
R^2	0.0348	0.1497	0.1738	0.1230	0.2569	0.1004	0.1852	0.2032	0.1854	0.2574
Adjusted-R^2	0.0348	0.1497	0.1441	0.0251	0.1763	0.0588	0.1469	0.1457	0.1139	0.1197
Obs.	3182	3199	3179	3090	3096	2442	2442	2442	252	49

Figure 1 – Features of the simulated credit model. The first panel of this figure presents the average of losses per origination balance across 1,000 simulations of our simple credit model. The losses are presented as function of the age of the loans in the portfolio. The second panel presents the number of contracts based on house price appreciation that must be sold to hedge the one-month ahead loss of one mortgage in the simulated credit model. The number of contracts is presented as function of the price of the underlying property. The derivative based on house price appreciation pays the rate of return on the house price index during one month. The mortgage defaults if the house price is below 80,000 one month ahead.



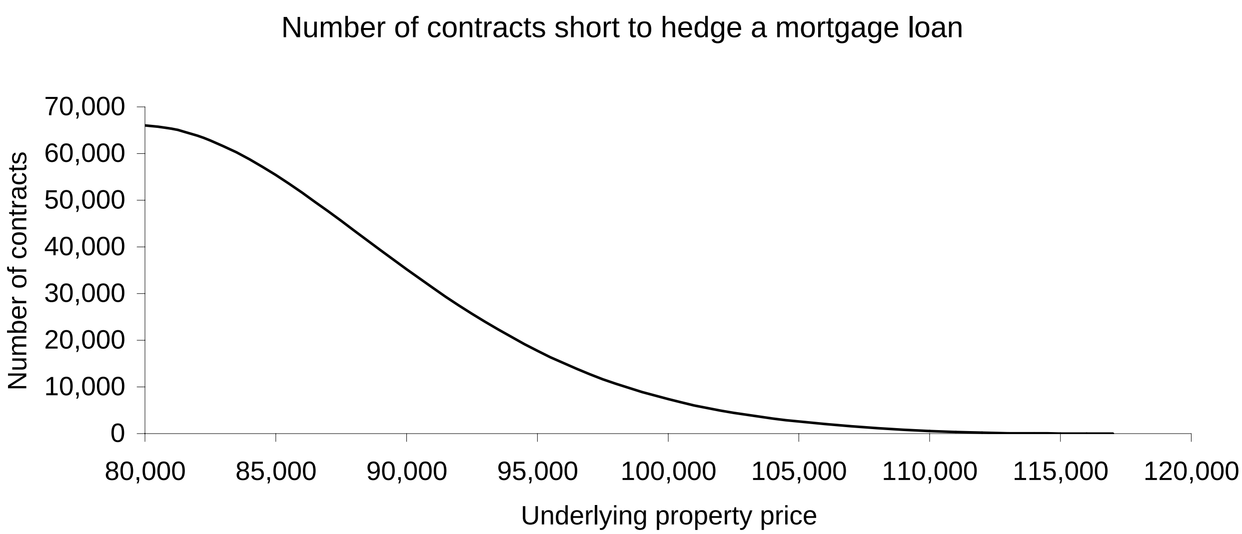
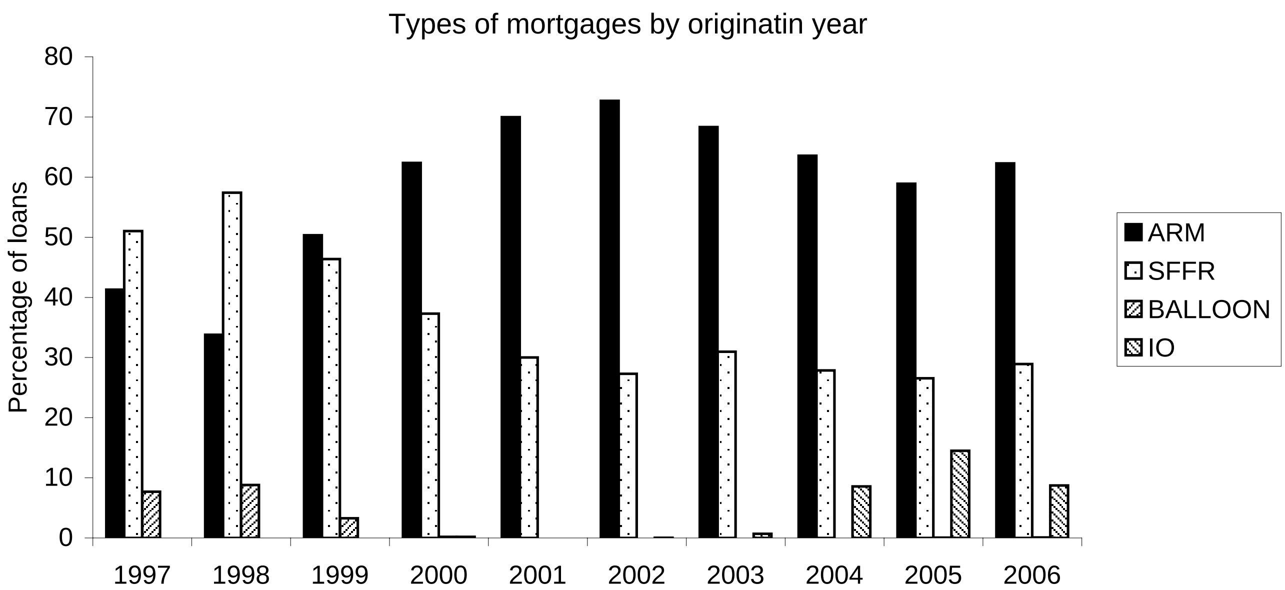


Figure 2 - Summary statistics of LoanPerformance database. This figure displays some summary information on the characteristics of the loans in the LoanPerformance database. The first panel displays the percentage of each type of loan in each origination year in the sample. ARMs are adjustable rate mortgages, SFFR are single family fixed rate mortgage, IOs are interest only mortgages. The second panel displays the percentage of full documentation loans (FULLDOC), of loans with some type of prepayment penalty (PREPAY) as well as the number of loans (LOANS) per origination year.



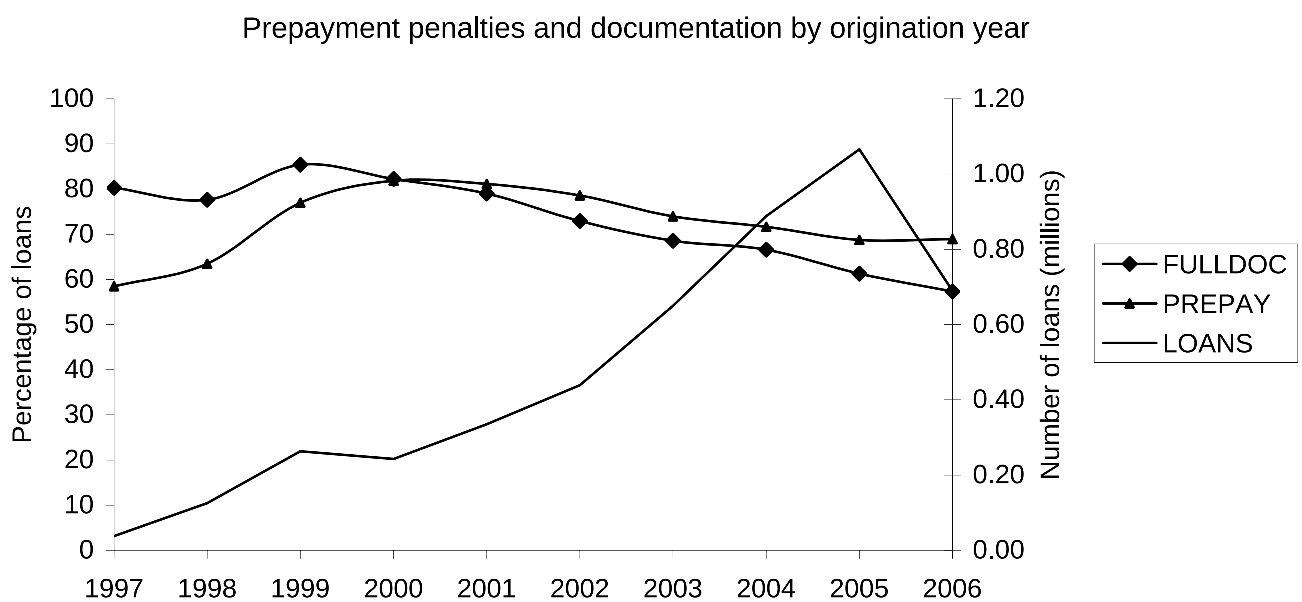


Figure 3 – Average credit losses in the LoanPerformance database. This figure presents the average of losses per origination balance across all the pseudo portfolios created from the LoanPerformance database. The losses are presented as function of the age of the loans in the portfolio.