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Residential Mortgage Credit Derivatives

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As the fallout from subprime losses clearly demonstrates, the credit risk in residential mortgages is large and economically significant. To manage this risk, this article 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, the analysis shows that instruments based on credit losses outperform contracts based on house price appreciation.

The residential finance system has experienced a systemic failure. Mortgage securitization markets—the major source of mortgage finance—no longer function, except for those with implicit or explicit government credit guarantees. While the form that the future mortgage finance system will take is an open question, it is possible that private mortgage securitization will not recover and that portfolio lenders will have to provide a greater proportion of housing finance, and hence carry a greater proportion of the credit risk of residential mortgages.

This article proposes the creation of derivatives based on the credit losses of a reference pool, arguing that such derivatives will help depositories hedge the credit risk of their portfolios without the same drawbacks that may have contributed to the failure of nonagency securitization. The creation of derivatives with cash flows similar to the loss experience of mortgage portfolios 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 loans.[1] As a result, they have overexposure to regional economic fluctuations. Residential mortgage credit derivatives could help depositories diversify their credit exposure while also

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

meeting all regulatory and accounting requirements. To the extent that depositories hold suboptimum portfolios, credit derivative hedges could bring their credit risk closer to the optimum level, freeing capital for more effective use.

Prior to the current mortgage crisis, depositories would typically mitigate residential mortgage credit risk through securitization. This approach, however, has several limitations. First, securitization requires the sale of mortgages, which is a disadvantage for a large portion of the mortgage market because of accounting and regulatory requirements. Second, the incentives of the various agents involved in the securitization process (originators, credit agencies, servicers and mortgage-backed securities underwriters) may not be perfectly aligned with investors' interests. Third, while the repeated interaction among originators, servicers and the government-sponsored enterprises (GSEs) may help to align incentives, agency securitization can be used only on conforming loans.

Other options for hedging credit risk on mortgage portfolios—mortgage insurance and credit default swaps (CDS)—also have major drawbacks. In particular, mortgage insurance typically takes the first loss position, providing protection only up to a certain limit. While at first glance CDS on nonconforming whole loans could serve as a hedging solution, they have never been traded.[2] This may reflect the fact that banks may have asymmetric information on their loans, which would create a "lemons" problem. This adverse selection problem is the same as the one described in the optimal security design literature (important examples are Allen and Gale 1989, Boot and Thakor 1993, Riddiough 1997 and DeMarzo 2005). This lemons problem could impair the trading of CDS on whole loans because banks with private information on their portfolios would adversely affect the sellers of protection, either through the decision to obtain protection on their entire pool or through the selection of which loans to obtain coverage. The lemons effect could be further amplified because the available risk transfer through CDS may result in less screening of borrowers for new originations.

In principle, depositories could use house price index futures to hedge the credit risk of their mortgage portfolios without facing the same drawbacks as securitization. In this case, they would retain the mortgages in their portfolios and

[2]Such a contract would specify some delinquency threshold (such as 120 days), after which ownership of the mortgage would be transferred to the insurance provider in exchange for a payment equal to the outstanding principal. To our knowledge, currently traded mortgage-related CDS have been written only on residential mortgage-backed securities (RMBS) instead of on nonconforming whole loans. It is not clear if the trading of CDS written on nonagency RMBS will remain because of the nonagency securitization debacle, and hence it is not clear whether CDS on RMBS will be feasible hedge instruments in the future. The same concern applies to 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.

reap the accounting and regulatory benefits of holding whole mortgages. Moreover, because a single depository's actions do not affect market house prices, depositories would have incentives to maintain strict underwriting and monitoring standards because they would bear any losses due to poor underwriting. Although exchange-traded house price index futures can circumvent some of the limitations of securitization, 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.

This article analyzes the hedging effectiveness of derivatives with cash flows similar to the loss experience of mortgage portfolios and compares the effectiveness of these contracts with that of house-price-based contracts such as those recently introduced at the Chicago Mercantile Exchange. The proposed derivative contract has cash flows similar to the losses of mortgages originated in a certain year and with certain characteristics (*e.g.*, ARMs backed by properties in Florida). The proposed derivatives have the same advantages over securitization as derivatives based on house price indexes (HPI). In addition, because the payoffs of loss-based derivatives are similar to the credit losses of depositories' portfolios, these derivatives may be more effective hedging instruments than house-price-based derivatives.

Perhaps because CDS on asset-backed securities (ABS) normally have a pay-as-you-go (PAUG) provision, the proposed credit derivative could be confounded with a CDS. We note however that the proposed credit derivative is not a CDS. The essential characteristic of a CDS is that it gives the credit-protection buyer the option to receive the difference between the underlying bond par value and its price in case of a specified credit event, such as a credit ratings downgrade or a default. CDS written on both corporate bonds and on ABS have this common feature. At the time of exercise of this option, the payoff is made and the CDS is extinguished. In addition, CDS on ABS also frequently have a PAUG provision. This provision obliges the protection seller to make payments equal to the writedown amount (of principal or interest) to the protection buyer. These PAUG-payments do not extinguish the CDS but do reduce the notional, and they hence reduce the payoff if the swap is exercised.[3] The product that we propose is distinct from a CDS because it does not give the credit-protection buyer the option to receive the difference between the underlying bond par value and its price in case of a credit event.

A further distinction between the product we describe and a CDS is that CDS are typically written on a specific tranche of a security issuance. The specific

[3]See Lehman Brothers (2005) for a detailed description of CDS on ABS.

rules that govern cash flows in a structured instrument will also introduce basis risk. Examples of such provisions include rules that allocate the priority of losses in the underlying collateral to the tranches as well as provisions that retain some component of interest income to pay for first losses. Frequently, the pool of collateral that is built up this way can be released to the residual tranche holder under certain conditions. Because CDS are a natural hedging to the risk associated with a particular tranche of a mortgage-backed security, they are less optimal for hedging the risk of whole loans.

However, if one adopts the view that the derivative contract we propose results in payoff very close to CDS on ABS (with a PAUG structure), then from this alternative perspective, our empirical results provide evidence of the hedging effectiveness of a CDS for hedging whole loans. This result would be for a CDS with a PAUG structure where (1) the PAUG-events are credit losses, (2) the PAUG payments are defined by the credit losses on a reference pool of mortgages rather than a tranche of an ABS and (3) the swap feature of the CDS is excluded from the contract. Particularly because of the third restriction—the removal of the swap feature—most market participants would view the proposed derivative contract as distinct from a CDS.

We examine the basis risk of the hedges generated by the credit-loss-based and house-price-based contracts both theoretically (with simulations of a simple default model) and empirically (using First American's Loan Performance Securities data on subprime mortgages). We use adjusted R^2's as the metric for hedging effectiveness because accounting policies subject hedges to specific tests based on this metric. The focus here is on the hedging effectiveness of the proposed instrument with respect to house-price-based contracts rather than on formal modeling of the optimality and welfare impacts of the proposed derivative.

The simulations suggest that hedges made with credit-loss-based instruments perform materially better than those made with house-price-based indexes. Indeed, a regression of simulated portfolio losses on simulated HPI results in an average R^2 close to 7%, while a regression of simulated portfolio losses on simulated loss-based indexes results in an average R^2 of 86%. The strong performance of hedges based on credit loss indexes reflects the similarities between the credit losses of mortgage portfolios and the cash flows of the derivatives based on loss indexes. Forward contracts based on house price appreciation indexes, in contrast, do not have payoffs that resemble the credit losses in residential mortgage portfolios and thus perform poorly in static hedging.[4]

[4]While forward contracts based on house price appreciation could perform well in dynamic hedging, the emphasis here is on simple dynamic hedges.

The empirical analysis also indicates that credit-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 HPI results in an average R^2 close to 4.5%, while a regression of portfolio losses on loss-based indexes results in an average R^2 of 13%. The empirical performance of instruments based on credit losses is, however, well below the accounting requirement to classify a hedge as highly effective.[5]

This article contributes to the rapidly growing literature on real estate derivatives. Closest to our work is the paper by Case and Shiller (1996) analyzing how futures and options written on HPI can hedge mortgage default risk and demonstrating that a distributed lag model of 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 on delinquency rates. In addition to assessing the performance of house-price-based derivatives as a hedging tool, we also analyze derivatives based on the credit losses of mortgage portfolios. Our article is also related to Shiller (2008b), who argues that part of the solution for the current subprime crisis is the creation of "new markets for risks that really matter," including real estate price risk. This article posits that, while such markets may be part of the solution for the crisis, the liquidity and the acceptance of instruments spanning these risks depend on the extent to which these instruments can create easily implementable hedges with low basis risks. Moreover, we identify an important clientele that would benefit from the creation of the proposed derivative product and show that this product can result in more effective hedges than the next best option, HPI.

Less directly related to this article are a series of papers that examine the impacts that a liquid market for house price derivatives would have for consumer use (see Englund, Hwang and Quigley 2002, Clapham *et al.* 2006, Deng and Quigley 2007, de Jong, Driessen and Hemert 2008, Shiller 2008a). Our analysis differs from these papers by examining residential mortgage credit derivatives for use by investors. These derivatives could, however, also benefit residential borrowers in that they could reduce the cost of mortgage credit risk.

This work is also related to papers that analyze the potential for moral hazard and adverse selection related to credit risk. Gan and Mayer (2007) provide evidence of differences in behavior when the servicer is exposed to the credit risk of a loan. Duffee and Zhou (2001) analyze the effects of introducing CDS written on whole mortgages on bank monitoring and find that the resulting adverse selection could worsen the market for loan sales. Writing derivative contracts

[5]A hedge is classified as highly effective when a regression to measure hedging effectiveness has an adjusted R^2 of at least 80%.

on a broad reference pool will tend to mitigate these incentive problems because the servicing and origination decisions of any one institution would have limited impact on aggregate losses.

The remainder of this article is organized as follows. The next section outlines the institutional features of the banking system that may affect the hedging problem that depository institutions face. The third section presents the Monte Carlo simulations used to corroborate the methodology used to assess hedge effectiveness. The fourth section describes the empirical analysis. The last section concludes.

Institutional Features and the Hedging Problem

Depositories have few options for managing their residential asset portfolios. If they are originators, 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. They must also make decisions on what forms of mortgage insurance to acquire and at what levels of coverage.[6] Among the factors that influence these decisions are risk management practices, accounting practices and funding flexibility.

Managing interest-rate risk is an especially important consideration. Depositories tend to hold mortgage assets that provide a good match with their liabilities (primarily short-term funding such as demand deposits). Because ARMs have floating rates, they are a natural choice. Small depositories thus find it advantageous to hold ARMs because they can match the 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.

At the same time, several key differences in accounting treatment make it more attractive for depositories to hold mortgages as whole loans rather than as securities. 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

[6] 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%.

annual default costs. Securities, in contrast, 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 rules (specifically FAS 65) than mortgage-backed securities (FAS 115). These differences make it less consequential to sell whole loans than securities, thus providing institutions more flexibility to adjust their portfolios.

On the other hand, there are some benefits to holding residential mortgage securities issued by Freddie Mac and Fannie Mae. For example, a liquidity advantage of securitizing 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. By holding whole loans, an institution may therefore forgo some funding flexibility that securities provide. Moreover, holding mortgage assets in securities rather than as whole loans has implications for regulatory capital requirements. Depository investments are constrained by both tier 1 and risk-based capital requirements. In nearly all cases, mortgage assets held through GSE-issued securities face lower risk-based capital charges than whole loans. In periods when institutions are constrained (or likely to be constrained) by regulatory capital, this relief tends to favor securitization.

Residential mortgage credit derivatives may offer the best of both worlds. Using credit derivatives, a depository could benefit from all the accounting advantages of holding whole loans in their portfolios while simultaneously decreasing the economic capital required to retain the loans.

Cash Flow Hedging

Depositories holding whole loans currently use cash flow hedging, matching 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, take 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 institutions' earnings unless loan credit quality becomes severely impaired. The fact that whole loans are not generally marked-to-market also 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 hedge. The accounting treatment of cash flow hedging is articulated in the Financial Accounting Standards Board Statement no. 133. The standards for determining hedge effectiveness vary, 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. 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. For instance, a highly effective hedge instrument does not need to be marked-to-market, which eliminates possible divergence between the value of the loan book and the value of the hedging instrument in case of liquidity shocks on the hedging instrument market. A hedge is classified as highly effective when the regression described earlier has an adjusted R^2 of at least 80% (Lipe 1996). An assessment of effectiveness is required whenever financial statements or earnings are reported and at least every 3 months.

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

$$\begin{array}{ll} 0 & \textit{if there no default at time } t \\ L_i \times B_i & \textit{otherwise}, \end{array} \tag{1}$$

where B_i is the original mortgage balance, and L_i is the loss per dollar of original mortgage balance. Losses are expressed as a percentage of the origination amount because the focus is primarily on static hedges. Note that the loss to the mortgage i at time t is equal to zero ($Loss_{i,t} = 0$) if the mortgage is current, has been prepaid or if the borrower 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 last summation in the above equation is over all the mortgage loans that are subject to a real estate owned (REO) or short sale[7] 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 are prepaid or go into default, the

[7]A foreclosed property is classified as real estate owned 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 loan to allow the owner to sell the mortgaged property for less than the outstanding balance.

$Loss\_OUPD_t^{\Pi}$ decreases. This simply results from the assumption that the loss in the mortgage i at time t is equal to zero if the mortgage is prepaid or in default before time 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 number of contracts n_0^{Π} that minimizes the variance of the loss of the hedged portfolio is $-(\sum_{i=1}^{N} B_i \times \beta_0^{\Pi,f})$, where $\beta_0^{\Pi,f}$ is the beta of $Loss\_OUPD_t^{\Pi}$ with respect to f_t. A depository executing a dynamic hedge, in contrast, would buy n_t^{Π} contracts at time t to hedge against the possibility of default at time $t + 1$. The number of derivative contracts that minimizes the variance of the hedged portfolio is $-(\sum_{i=1}^{N} B_i \times \beta_t^{\Pi,f})$, where $\beta_t^{\Pi,f}$ is the time-varying beta of the loss per origination unpaid principal balance with respect to the derivative payoff.

Static hedging is of course easier to implement than dynamic hedging. The simplicity of the static hedging does, however, come at the cost of reduced effectiveness if the optimum hedge ratios vary substantially over time. As a result, the choice between static and 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 while small mortgage investors probably prefer static hedging. In fact, depositories that hold ARMs instead of fixed-rate mortgages in their balance sheets due to the close matching of ARMs with the bank's funding liabilities are likely to prefer static hedging of the credit risk in their mortgage portfolios.

Depositories could potentially use any of the residential mortgage credit derivatives to hedge the credit risk of a portfolio of whole loans. For instance, they could use contracts that have payoffs similar to the credit losses of mortgages. In this case, we propose writing contracts that have payoffs that depend on an index of realized credit losses for a reference pool of mortgages. To formalize this concept, imagine an index of losses of mortgages originated in a certain year and with certain characteristics (*e.g.*, ARMs backed by properties in Florida). Let the number of mortgages in the index at its creation be equal to N_{Index}. The value of the index at time t equals the losses due to REO and short sales per origination unpaid principal balance. That is,

$$Index_t = \frac{\sum_{i=1}^{N_{Index}} Loss_{i,t}}{\sum_{i=1}^{N_{Index}} B_i} = \sum_{k=1}^{N_{Index}^{Loss}} L_i \frac{B_i}{\sum_{i=1}^{N_{Index}} B_i} = \sum_{k=1}^{N_{Index}^{Loss}} L_i w_i^{Index}, \tag{4}$$

where the latest summation in the equation above is over all mortgage loans in the index that are subject to an REO or short sale at time t. Note that the loss in mortgage i at time t equals zero if the mortgage is current, has been prepaid or was in default before time t.

Depositories could also use a contract based on home price appreciation, which would have a payoff f_{t+1} at time $t+1$ proportional to the return of a house price index between t and $t+1$. Because both types of contracts offer similar accounting and capital benefits, the choice between derivatives based on HPI or on credit loss indexes depends on how effective they are as hedging instruments. The remainder of this article therefore analyzes the hedging effectiveness of such contracts. Most of the discussion addresses static hedging because small depositories that hold ARMs as whole loans are likely to prefer this approach. We do, however, analyze one dynamic hedging procedure for the benchmark contract based on house price appreciation.

Methodology to Estimate 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 instrument is analyzed through the regression:

$$Loss\_OUPB_t^{\Pi} = \alpha + \beta^{\Pi,j} \times CF_t^j + \epsilon_t, \tag{5}$$

where CF_t^j is the cash flow of jth hedge instrument at time t. We calculate $Loss\_OUPD_t^{\Pi}$ according to Equation (3) for a series of proxy mortgage portfolios, termed pseudo portfolios. We then estimate the regression above for each of these portfolios, comparing the efficiency of different instruments using a standard accounting measure of hedging effectiveness, that is, the adjusted R^2 of the above regression.

To assess the hedging performance of derivatives based on credit loss indexes, we assume that such derivatives have cash flow at time t, CF_t^j proportional to the loss-based index calculated according to Equation (4) for a given reference pool. (Construction of the pseudo portfolios and of the reference pools of indexes is detailed later.) To benchmark the performance of derivatives based on credit loss indexes, we also examine the hedging performance of derivatives based on house price appreciation indexes. These derivatives have cash flow at time $t+1$ (CF_{t+1}^j) proportional to house appreciation between t and $t+1$.

A simple stylized model of default is useful in motivating the form of Equation (5) above. Assume that the price of a residential property backing a mortgage is $S_{i,t}$ at time t follows the log-normal process:

$$\frac{dS_{i,t}}{S_{i,t}} = \mu_i\, dt + \sigma_i \rho_i dZ_t + \sigma_i \sqrt{1-\rho_i^2} dZ_{i,t}, \tag{6}$$

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 equal to or less than an exogenous default trigger level D_i at time $t + \Delta t$. The loss due to default at time $t + \Delta t$ is zero if $S_{t+\Delta t} > D_i$ and $L_i \times B_i$, otherwise where L_i is a constant. Also assume that the house price index in the region follows the process:

$$\frac{dS_t}{S_t} = \mu dt + \sigma dZ_t, \tag{7}$$

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

Using a Monte Carlo simulation, we run 1,000 paths of the model above and estimate Regression (5) for each path. We estimate the regressions with either the loss-based index or house-price-based index, where house price appreciation is based on Equation (7). In this simulation exercise, a mortgage investor has a portfolio of 1,000 loans collateralized by properties that have the same initial value of \$100,000. Default trigger points $D_i^{\prime}$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 30 years later. The reference pool has 10,000 mortgages, including the 1,000 mortgages from the investor. The properties collateralizing the mortgages also have initial values equal to \$100,000, and their default triggers are randomly selected from the same distribution as above. Both the mean house price appreciation and the mean index appreciation are 5% per year ($\mu_i = \mu = 0.05$); the annualized volatility of both the house prices and the index is 15% ($\sigma_i = \sigma = 0.15$); and the correlation between the returns on the houses and the house price index is 50% ($\rho_i = 0.5$). The default severity is 30% ($L_i = 0.3$).

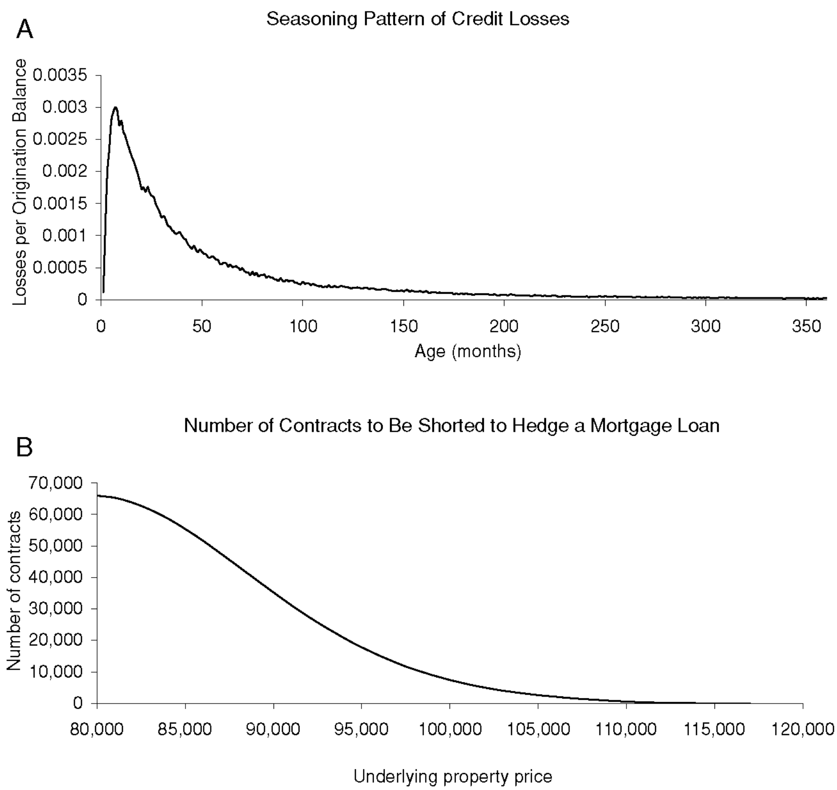
The simulations indicate that the hedging performance of the loss-based index is quite promising, while that of the house price appreciation index is poor. As the results presented in Table 1 show, the average R^2 is quite high at 0.86 when the loss-based index is used to hedge, but only 0.07 when the monthly return of the HPI is used as an independent variable. In addition, the statistical significance of house price appreciation disappears when the house price appreciation and loss-based indexes are both in the regression. Indeed, when house price appreciation is alone in the regression, it has an average t statistic of –4.99; when used with the loss-based index, the average t statistic is –0.14.

Table 1 ■ Regression results based on the simulated sample.

	1	2	3	4	5	6	7	8	9
INTERCEPT	0.0004	0	0	0.0010	0	0	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		0	−0.0053		0	−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 × *AGEDUM*				0.0003	0	0			0.0003
				(4.49)	(−0.26)	(−0.25)			(5.42)
AGE				0	0	0			0
				(−8.46)	(−0.13)	(−0.15)			(−9.85)
HPI × *CHPIDUM*							−0.0093	−0.0017	−0.0061
							(−2.67)	(−0.75)	(−1.74)
AGE × *HPI*								0	0
								(3.82)	(5.07)
AGEDUM × *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

Notes: This table displays the means of the point estimates, t statistics and R^2's of regressions based on 1,000 simulated samples of 360 monthly observations. The dependent variable 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 portfolio (*AGE*), a dummy variable with a value of one if *AGE* is smaller than eight (*AGEDUM*), interactions of *AGE* and *AGEDUM* with *HPI* as well as interaction of *HPI* with a dummy variable with a value of one if the cumulative appreciation of the house price index is less than –1% (*CHPIDUM*). t-Statistics are in parentheses.

Figure 1 ■ Features of the simulated credit model.



Notes: Panel A presents the average of losses per origination balance across 1,000 simulations of the simple credit model. Losses are presented as a function of the age of the loans in the portfolio. Panel B presents the number of contracts that must be sold to hedge the one-month-ahead loss of one mortgage, based on the price of the underlying property. The derivative based on house price appreciation pays the rate of return on the house price index during 1 month. The mortgage is in default if the house price is below $80,000 1 month ahead.

One possible reason for the poor performance of the contracts based on house price appreciation is the seasoning pattern of the credit losses. The top panel of Figure 1 depicts the average loss in the portfolio as a hump-shaped function of loan age, with a peak around 8 months. This seasoning pattern is common to first-passage models of default (see Duffie and Singleton 2003). A static hedge based on house price appreciation may not be able to account for this nonlinearity. Hedges based on the loss indexes, in contrast, may be able to do so because the index itself is a nonlinear 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 (*AGE*) into the regression, along with a dummy variable (*AGEDUM*) that has a value of one if the age is less than 8 months, and zero otherwise. The break point of the variable *AGEDUM* is set to 8 months because this is the age when losses peak. As Table 1 indicates, once age-related variables are added to the regression with house price appreciation, the R^2 increases substantially to 0.32. This increase, however, does not result in a substantial change in the point estimate of the coefficient on house price appreciation. While this suggests that controlling for loan age may improve the low R^2 of the regression with the HPI, doing so does not result in a better hedge performance because the hedge ratio does not change.

The poor performance of the house price appreciation index in part results from the fact that the optimal hedge ratio of a loan varies with the house price level. To understand this point, assume that an investor in this mortgage wishes to hedge the credit exposure with a contract written on house price appreciation in the region. The payoff of this contract at time $t + \Delta t$ is equal to 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 that need to be shorted to hedge the credit risk in a mortgage in this model. (See the Appendix for details.) The bottom panel of Figure 1 plots the optimal number of forward contracts as a function of the price of the underlying property. To create this chart, we assume that the investor wishes to hedge the losses in a mortgage due to default 1 month ahead ($\Delta t = 1$ – month), and default happens if the price of the house 1 month from now is below \$80,000 (D_i). The other parameters are assumed to be same as in the simulations. The results indicate 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 the 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. This implies that the hedging performance of derivatives based on HPI may be substantially improved with dynamic hedges.

We also analyze the performance of house price appreciation contracts in dynamic hedging to improve the performance of the benchmark based on the house price appreciation index. To do so, we add the interaction of house price appreciation with a dummy variable (*CHPIDUM*) that has a value of one if the house price index decreases more than a constant c, and zero otherwise. Addition of this dummy variable in effect allows the hedge ratio with respect to the HPI contract to vary over time. If the HPI decreases by more than c, the hedge ratio is the coefficient on the house price appreciation plus the coefficient on the interaction term. If the HPI decreases by less than c, the hedge ratio is the coefficient on the house price appreciation. While we could construct optimal hedge ratios based on this simple default model, we are using the model only to illustrate a simple way to empirically estimate the hedge effectiveness of a residential mortgage credit derivative.

In the simulations, we set c equal to 1% to be consistent with the value used in the empirical analysis described later. We also interact the HPI with loan age-related variables. These interactions are equivalent to allowing the hedge ratio with respect to the HPI contract to vary with the age of the loans in the pseudo portfolio. The dynamic hedge based on the house price appreciation index performs better than the static hedge based on that index. Nevertheless, the static hedge based on the loss-based index outperforms them both. As the last two columns of Table 1 show, allowing the hedge ratio to change with *AGE*, *AGEDUM* and *CHPIDUM* substantially improves the hedge effectiveness of the contract based on house price appreciation. The R^2 of the regression where the hedge ratio moves with these characteristics (0.21) is much higher than the R^2 of the regression with house price appreciation only (0.07). In addition to allowing the hedge ratio to change over time, we also control for age-related effects on the mean losses of mortgages. The last column of Table 1 indicates that controlling for such age effects also substantially improves the hedge effectiveness of house-price-based contracts. Overall, the simulations thus suggest some controls that may be used in the empirical evaluation of the hedging effectiveness of contracts written on credit loss and HPI.

Empirical Analysis

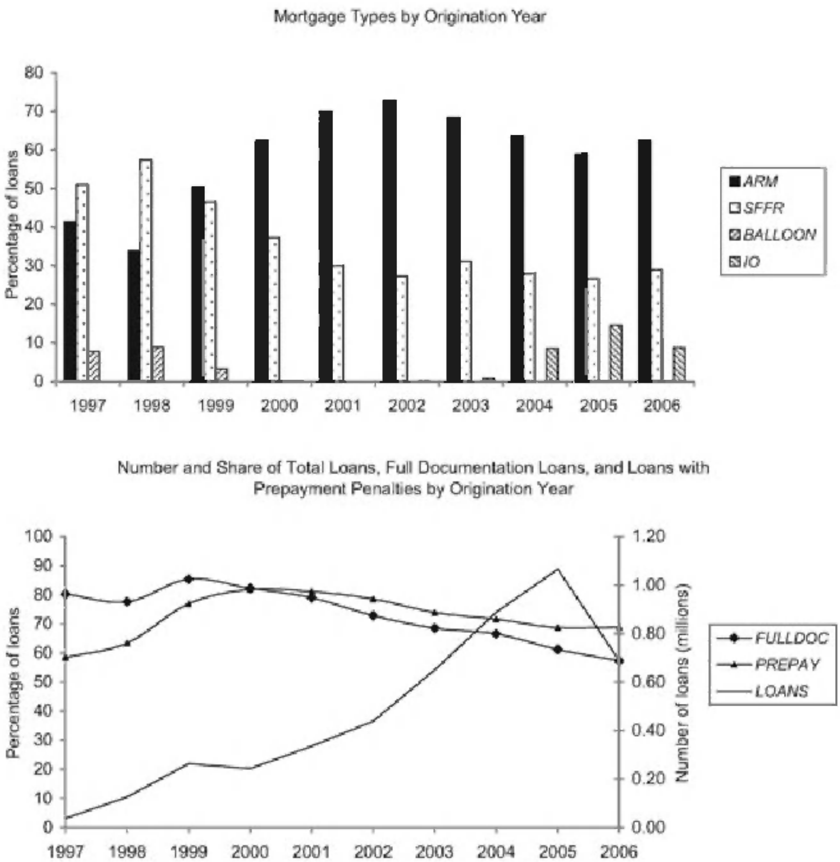
This section presents an analysis of the hedge performance of the proposed instrument and of the HPA indexes using Loan Performance data.

Data and Summary Statistics

We create indexes of credit losses based on First American's Loan Performance data, primarily from loan servicing and securities performance records. The Loan Performance subprime data are drawn from subprime securities and include more than four million mortgages originated from 1997 to 2006. Mortgage performance data are also available through securities, because issuers of nonagency securities typically disclose information about the delinquency, default and loss performance of loans that form the collateral for the securities. The Loan Performance securities database contains loan-level information on more than $1.5 trillion in nonagency mortgage backed securities and ABS, representing more than 85% of this segment of the market. We use data on ABS (Alt-A and nonprime) at the loan level. Information on the Loan Performance securities data is as of December 4, 2006.

We match the loan servicing and securities databases to create a large database of mortgage loans. Loan attributes include age, loan-to-value ratio (LTV),

Figure 2 ■ Summary statistics for Loan Performance database.



Notes: Panel A displays the shares of each type of loan in each origination year in the sample. ARMs are adjustable-rate mortgages; SFFRs are single-family fixed-rate mortgages; BALLOONs are mortgages with a balloon payment; IOs are interest-only mortgages. Panel B displays the shares of loans requiring full documentation (FULLDOC) and of loans with some type of prepayment penalty (PREPAY), as well as the number of loans (LOANS) per origination year.

purpose (refinancing or purchase), size, term, coupon, borrower FICO score, loan credit rating, mortgage type, whether the borrower took cash out of the transaction, whether the purchase is for an investment or primary residence and property type. These data can be aggregated at several levels—national, regional, state and metropolitan area, or by origination date—and contain information on delinquency, foreclosure, REO status and loss amount.

Summary statistics on the loans are presented in Figure 2. The top panel displays the percentage of different types of mortgages by origination years;

it reveals how important ARMs became after 2000. Specifically, about 50% of the mortgages in the Loan Performance database originated in 1997 had fixed rates, while less than 30% of loans originated in 2006 did so. ARMs thus composed the majority of subprime mortgages. Figure 2 also indicates that balloon and interest-only mortgages make up only a small share of the sample.

The bottom panel of Figure 2 displays the number of mortgages originated by year, along with the percentage of mortgages with full documentation requirements and prepayment penalties. This panel clearly shows the growth of the subprime market along with the relaxation of mortgage underwriting standards.

As Table 2 shows, the median origination balance of the loans in the sample is \$122,000, the median LTV is 80% and the median borrower FICO score is 613. Based on originator-specific credit ratings, Loan Performance assigns standardized letter grades for mortgage loans. In this sample, more than 80% are classified as A−. These loans tend to be made to borrowers who have higher credit scores, larger balances and higher LTV ratios. The statistics in Table 2 also indicate that the Loan Performance credit ratings are consistent with borrowers' FICO scores. Indeed, the median FICO score of borrowers in the A− loan group is 626, while the median FICO score of those in the D loan group is 549.

The empirical analysis summarized in the next section uses a subset of the data described in Table 2 and Figure 2. Specifically, we select all the loans that are in ABS collateralized by pools of mortgages containing at least 1,000 loans. This criterion is important because Loan Performance does not report losses on all loans in its database. Working with pools with at least 1,000 mortgages guarantees that all pools in the analysis have reported losses. Because of their short history, balloon and interest-only mortgages are excluded from the empirical analysis.

In addition to the Loan Performance data on mortgage losses, we also use the Office of Federal Housing Enterprise Oversight (OFHEO) 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 variant 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 for a particular property in a particular geographic area. The HPI is updated each quarter as

Table 2 ■ Summary statistics for the Loan Performance database.

			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

Notes: 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 Loan Performance database. The loan-to-value (LTV) and borrowers' credit scores (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.

additional repeat transactions enter the sample. This article uses the state-level HPI based on purchase transactions. We do not use the S&P/Case-Shiller HPI because they cover only 20 metropolitan areas (see Standard and Poor's 2008).

Estimating the Hedge Effectiveness

To create the dependent variable for the hedge effectiveness regressions, we build pseudo portfolios of mortgages by selecting loans from the securitized pools that are backed by properties in a given state and with 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). This method should result in portfolios resembling those held by small depository institutions with exposure in a given state.

We segment by origination year because the loss experience of a given mortgage portfolio depends on variables for which Regression (5) does not control. For instance, a large interest-rate drop during the life of mortgages in a portfolio triggers refinancing, which decreases the credit losses of the portfolio. 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, so the maximum number of monthly observations for a given pool is 117. There are 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. This approach may overstate the effectiveness of the hedge if the loans held in an investor's portfolio differ from assets that are securitized (and hence in the reference pool) in unobservable ways. Some evidence suggests 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 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 and those that are securitized.

The set of independent variables includes house price appreciation indexes because we want to analyze the effectiveness of futures contracts based on these indexes as hedging instruments. House price appreciation is a proxy for the cash flows of futures contracts based on house price appreciation (CF_t^i in Equation (5)). The HPI are state-level, purchase transaction, repeat sales.

Quarterly growth rates are calculated using this index, and they are converted into a monthly series by assigning the growth at a constant level over the 3 months in the quarter. For example, if Georgia had a growth rate of 2% in the first quarter of 2007, the growth rate for January, February and March would be set to 0.66%.

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 the sample period. Indeed, the mean appreciation is 50 basis points per month, with a first quartile around 30 basis points. Table 3 also presents the amounts of loans in each state relative to the entire sample and indicates that subprime loans were highly concentrated in a few states. In fact, the top six states account for more than half of the origination amount in the sample. Moreover, the states used in the hedging effectiveness regressions have close to 94% of the total origination amount of the entire Loan Performance sample.

The set of characteristic-based loss indexes to choose from is quite large because the Loan Performance database is so rich. For instance, we could create an index based on the losses of ARMs backed by properties in California with an origination LTV ratio above 90% and borrower FICO scores below 630. As a result, we could create thousands of indexes based on these data, which would improve the assessed hedging performance at the risk of overfitting. To keep the analysis parsimonious and to allow direct comparison with the house price appreciation indexes, we restrict the focus to indexes based on mortgage origination year and the state in which the property is located.

The empirical analysis starts with the seasoning pattern in Figure 3, which shows the average loss per origination principal balance ($Loss\_OUPD^{\Pi}$) for a given age across all the pseudo portfolios. The average $Loss\_OUPD^{\Pi}$ is largest when mortgages are around 25 months old and then decreases thereafter and becomes quite noisy. The hump-shaped pattern of losses is consistent with those predicted in first-passage models of default and with the pattern of losses generated by the simulations (Figure 1). The break point of the variable *AGEDUM* in the empirical analysis is set in the same way as in the simulation, that is, equal to one if *AGE* is less than 25 months (when losses peak), and zero otherwise.

Recall that house prices increased substantially during the sample period. As a result, only a few pseudo portfolios were subject to house price declines. This is an issue for the empirical analysis because some regressions add the interaction of house price appreciation with a dummy variable ($CHPIDUM_{t-3}$) that has a value of one if the HPI decreases more than a constant c between the mortgage

Table 3 ■ House price appreciation in the states and period used in the hedging effectiveness regressions.

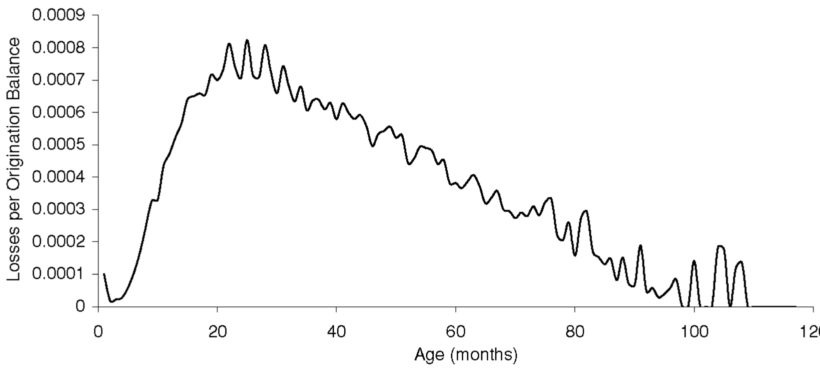
	Monthly House Price Appreciation (in percent)							*Percent of Total*
State	Mean	Std. Deviation	p1	p25	Median	p75	p99	*Origination Amount*
CA	0.9	0.7	−1.4	0.6	1.0	1.4	2.2	26.4
FL	0.8	0.6	−1.1	0.5	0.8	1.1	2.2	9.2
NY	0.7	0.4	−0.1	0.5	0.7	1.1	1.2	5.1
TX	0.4	0.2	0.0	0.2	0.4	0.6	0.8	4.8
IL	0.5	0.3	−0.2	0.3	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

Notes: This table presents summary statistics of the monthly house price appreciation in every state for which there is at least one pseudo portfolio. Also displayed is each state's share of the total amount of subprime mortgage originations.

origination and month $t - 3$, and zero otherwise.[8] Ideally, we would set the constant c equal to a negative number that represents a substantial decrease

[8]Because our HPI is quarterly, we lag the *CHPIDUM* in the regressions by 3 months to avoid any possible look-ahead bias.

Figure 3 ■ Average credit losses in the pseudo portfolios.



Notes: This figure presents the average losses per origination principal balance across all 3,199 pseudo portfolios created from the Loan Performance database. Losses are displayed as a function of the age of the loans in the portfolio.

in the HPI. The cost of doing so, however, is that *CHPIDUM* would be equal to zero throughout most of the history of the losses in the pseudo portfolios. We therefore set c equal to –1%, which is not a substantial decrease in house prices. However, there are only 252 pseudo portfolios that have *CHPIDUM* equal to one at some point in their history. Of these, just 49 pseudo portfolios have *AGEDUM* equal to zero at some point in their history.

Table 4 displays the means of the point estimates, t statistics, R^2's and adjusted R^2's of the hedging effectiveness regressions across these 49 pseudo portfolios. As in the simulations, the R^2's of the regressions with house price appreciation alone are quite low with an average value of 2%. Unlike the simulation results, however, the point estimates of the HPI are not significant with an average t statistic of –0.05. The loss-based indexes fit the loss of the portfolios better than the HPI, with an average adjusted R^2 close to 13%. 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 the cash flows of derivatives contemporaneous with the cash flows of losses, we also estimate regressions in which the cash flows of derivatives are lagged up to three months because servicers have different reporting procedures, and as a result, losses in the overall market may be not synchronous with the losses of one pseudo portfolio of mortgages. The results in Table 4 indicate that this may in fact be happening because the average R^2 and the average adjusted R^2 increase to 17% and 15%, respectively, once the lagged loss indexes are added into the regression.

Table 4 ■ Results of hedging effectiveness regressions for selected pseudo portfolios.

	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)					
$HPI \times CHPIDUM$									0.1109	0.0404
									(0.75)	(0.41)
$AGE \times AGEDUM$						5.44E-05	−1.42E-05	−1.46E-05		6.95E-05
						(1.05)	(−0.11)	(−0.13)		(1.01)

Table 4 ■ continued

	1	2	3	4	5	6	7	8	9	10
AGE						−5.70E-06	−7.33E-06	−7.48E-06		6.52E-07
						(0.34)	(0.22)	(0.22)		(0.40)
AGE × *HPI*										0.0047
										(0.27)
AGEDUM × *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

Notes: This table shows the means of the point estimates, t-statistics, R^2's and adjusted R^2's of regressions for 49 pseudo portfolios created from the Loan Performance database. The dependent variable is the loss per origination balance at month t of a pseudo portfolio with at least 200 loans. A pseudo portfolio comprises loans from a securitized pool of mortgages from the same state and with the same origination year. The independent variables are the appreciation in the house price index (*HPI*) in the state at month t, the index of losses of a reference pool of mortgages in the same state and with the same 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}, HPI_{t-3}), the index of mortgage losses lagged by one to three months ($INDEX_{t-1}$, $INDEX_{t-2}$, $INDEX_{t-3}$). the age in months of the mortgage portfolio (AGE_t), a dummy variable with a value of one if AGE_t is less than 25 months ($AGEDUM_t$), interactions of AGE_t and $AGEDUM_t$ with HPI_t as well as interaction of HPI_t with a dummy variable ($CHPIDUM_{t-3}$) that has a value of one if the house price index appreciated less than −1% between the securitization of the pool and three months before month t. The means are calculated only with pseudo portfolios with a least one observation in which $CHPIDUM_{t-3}$ is one and $AGEDUM_t$ is zero. t statistics are in parentheses.

Table 5 ■ Results of hedging effectiveness regressions for all pseudo portfolios.

	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)					
$HPI \times CHPIDUM$									0.0456	0.0404
									(0.54)	(0.41)
$AGE \times AGEDUM$						1.25E-05	5.49E-06	5.34E-06		6.95E-05
						(0.71)	(0.32)	(0.31)		(1.01)

Table 5 ■ continued

	1	2	3	4	5	6	7	8	9	10
AGE						−1.17E-06	1.69E-06	1.70E-06		6.52E-07
						(−0.23)	(0.10)	(0.10)		(0.40)
AGE × *HPI*										0.0047
										(0.27)
AGEDUM × *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.	3,182	3,199	3,179	3,090	3,096	2,442	2,442	2,442	252	49

Notes: This table shows the means of the point estimates, t-statistics, R^2's and adjusted R^2's of regressions for all pseudo portfolios created from the Loan Performance database. The dependent variable is the loss per origination balance at month t of a pseudo portfolio with at least 200 loans. A pseudo portfolio comprises loans from a securitized pool of mortgages from the same state and with the same origination year. The independent variables are the appreciation in the house price index (*HPI*) in the state at month t, the index of losses of a reference pool of mortgages in the same state and with the same 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}, HPI_{t-3}), the index of mortgage losses lagged by one to three months ($INDEX_{t-1}$, $INDEX_{t-2}$, $INDEX_{t-3}$), the age in months of the mortgage portfolio (AGE_t), a dummy variable with a value of one if AGE_t is less than 25 months ($AGEDUM_t$); interactions of AGE_t and $AGEDUM_t$ with HPI_t; and interaction of HPI_t with a dummy variable ($CHPIDUM_{t-3}$) that has a value of one if the house price index appreciated less than –1% between the securitization of the pool and 3 months before month t. t-Statistics are in parentheses.

Controlling for age effects or allowing for dynamic hedging with a house-price-based contract does not seem to improve 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 HPI is positive, which is not consistent with credit risk models.

Allowing the hedge ratio of the HPI to change with 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 hedging effectiveness as measured by the average of the adjusted R^2's, which is only 5% in Regression (9). Allowing hedge ratios to change with age effects and the cumulative house price appreciation seems to make a difference in the hedging with the HPI. Even though all the coefficients of Regression (10) are not statistically different from zero, the adjusted R^2 is relatively high at 12%. Nevertheless, the adjusted R^2 is still smaller than that in the regression based on the credit loss index only.

Table 5 displays the means of the point estimates, t statistics, R^2's and adjusted R^2's of the hedging effectiveness regressions across all the pseudo portfolios. The results 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.

Static hedges with loss-based indexes still seem to have a reasonable amount of basis risk as measured by the adjusted R^2s. Even so, the basis risk is smaller than that present in simple dynamic hedges with house price appreciation indexes. Loss-based indexes may therefore provide a promising direction to expand the risk management tools of agents carrying real estate risks. In addition, there is some indication that the population of loans examined here is especially challenging for hedging instruments because there are substantial issuer and servicer effects that create asynchronicity between the losses of the pseudo portfolios and the cash flows of the index of losses. These effects may contribute to the relatively large amount of basis risk in the hedged positions examined.

Conclusion

Creating an effective market for mortgage credit risk is likely to be economically beneficial in that widely dispersing depositories' exposure would likely decrease the cost of these risks. This article proposes the development of derivative contracts based on the credit loss of mortgage portfolios. We argue that such instruments would complement the menu of available tools for hedging the credit risk in mortgage portfolios and would contribute to the development of real estate derivatives advocated by Shiller (2008a). This analysis explores the effectiveness of instruments based on credit loss indexes and benchmarks their performance with house price appreciation indexes. The results indicate that loss-based indexes are better than house-price-based indexes for hedging credit risk in mortgage portfolios.

Hedges with loss-based indexes do, however, carry a substantial amount of basis risk, which may be due in part to issuer and servicer effects. The amount of basis risk found here may be viewed as an upper bound because there are ways to improve the hedge efficiency of loss-based contracts. For instance, if the portfolio to be hedged is composed of ARMs backed by properties in California with an origination LTV ratio above 90%, 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 assessed here. We leave the examination of this type of index for future research.

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Appendix

To compute n_i,t, let us change variables from $S_{t+\Delta t}$ and $S_{i,t+\Delta t}$ to $\ln(S_{t+\Delta t})$ and $\ln(S_{i,t+\Delta t})$.

$$\ln(S_{t+\Delta t}) = \ln(S_t) + (\mu - 0.5\sigma^2)\Delta t + \sigma \Delta Z_{t+\Delta t}, \tag{A.1}$$

$$\ln(S_{i,t+\Delta t}) = \ln(S_{i,t}) + (\mu_i - 0.5\sigma_i^2)\Delta t + \sigma_i \rho_i \Delta Z_t + \Delta t + \sigma_i \sqrt{1 - p_i^2}\, \Delta Z_{i,t+\Delta t}. \tag{A.2}$$

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. Under this model, $n_{i,t}$ is

$$n_{i,t} = -\beta_t^{i,f} = -\frac{\mathrm{cov}[f_{t+\Delta t}, Loss_i]}{\mathrm{var}[f_{t+\Delta t}]} = -\frac{\mathrm{cov}[f_{t+\Delta t}, Loss_i]}{e^{\mu \Delta t} \times (e^{\sigma^2 \Delta t} - 1)}. \tag{A.3}$$

The covariance cov[$f_{t+\Delta t}$, $Loss_i$] is given by $E[(S_{t+\Delta t}\,/\,S_t\text{-}1) \times Loss_i] - E[(S_{t+\Delta t}/$ $S_t - 1)] \times E[Loss_i]$, which is

$$\mathrm{cov}[f(S_{t+\Delta t}), Loss_i] = L_i \times B_i \times e^{\mu \Delta t}$$

$$\times \int_{-\infty}^{\infty} \left\{ N\left[\frac{-x_t - (\mu_i - 0.5\sigma_i^2)\Delta t - \sigma_i\sqrt{1 - p_i^2}Z_{i,t+\Delta t} - \sigma\sigma_i p_i \Delta t}{\sigma_i p_i \sqrt{\Delta}} \right] \right.$$

$$\left. -N\left[\frac{-x_t - (\mu_i - 0.5\sigma_i^2)\Delta t \sigma_i\sqrt{1 - p_i^2}Z_{i,t+\Delta t}}{\sigma_i p_i \sqrt{\Delta}} \right] \right\}$$

$$\times f(\Delta Z_{i,t+\Delta t}) d\Delta Z_{i,t+\Delta t} \tag{A.4}$$

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