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Mortgage Default Risk and Real Estate Prices: The Use of Index-Based Futures and Options in Real Estate

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Abstract

This article makes the case for using index-based futures and options driven by region-specific movements in house prices as the basis for hedging mortgage default risk. Taking the view that mortgage holders write put options on real estate assets, the first part of the article lays out the theoretical case for a hedging strategy based on house price changes. The second part reviews the empirical literature on default risk and uses data from the Mortgage Bankers Association of America and repeat sales indices to test for the significance of house price movements in predicting mortgage default.

The results suggest that between 1975 and 1993, periods of high default rates strongly follow real estate price declines or interruptions in real estate price increases. The relation between price declines and foreclosure rates is modeled using a distributed lag. The results support the case for a hedging strategy based on house price changes.

Keywords: default; hedging; mortgage-backed securities

Introduction

In a previous article (Case, Shiller, and Weiss 1993) we argued that there is a need for a liquid, national hedging market in real estate prices. We proposed futures and options markets that are cash-settled on the basis of indices of city or regional residential real estate prices.

Individual homeowners are the largest bearers of residential real estate risk, and they have the most to gain from hedging in such markets. Homeowners are for the most part highly leveraged and undiversified. Most are unsophisticated financial managers, however, and unaccustomed to using derivative markets.

The likely reluctance of homeowners to make use of hedging markets represents an obstacle to their establishment. Homeowners would be more likely to use risk-management services that were offered by retailers that present the services in attractive packages and market them appropriately. If liquid markets for real estate risk existed, then one might expect to see eventual development of such retailers; these retailers would then use the futures and options markets to lay off the risk they acquire from selling these services. Some possible retail institutions, and their relation to hedging markets, are described by Shiller and Weiss (1994).

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Unfortunately, such a symbiotic relationship between retailers of market hedging services and futures markets may be slow to develop, since each party in the relationship needs to see the other already developed before rapid growth can occur. But this obstacle to the establishment of futures markets may not be serious if there are others who are ready to use the futures markets now, so that the markets could gain a foothold by serving them.

One group that may be ready now to use hedging markets in real estate price risk is holders of portfolios of mortgages. The values of their portfolios depend on collateral values—that is, on the current price of the mortgaged real estate.

In this article we present evidence that the value of mortgage portfolios does depend strongly on risks of price change in real estate markets, so mortgage holders ought to have a strong incentive to hedge. Risks are negligible when aggregate prices are increasing rapidly, become substantial when aggregate prices level off for a few years, and become severe when aggregate prices fall.

To accomplish this, we first develop a model of the relation of mortgage defaults to citywide real estate prices. Next, after a brief review of the empirical literature, we examine foreclosure data (for the 50 states) and house price indices, as well as other economic variables, in an effort to produce a predictive model of losses due to mortgage default. The results suggest ways that holders of mortgage portfolios might hedge in the proposed real estate futures and options markets.

Mortgage Holders as Option Writers

Those who invest in mortgages are in effect writers of two kinds of options: call options on long-term debt and put options on real estate prices. The call option on long-term debt arises from the prepayment option in the mortgage contract, which the mortgagor has an incentive to exercise should interest rates fall (long-term bond prices rise). The put option on real estate arises from the mortgagor's option of defaulting altogether. In nonrecourse states, such as California and Texas, this option is guaranteed by law. In other states, the mortgagor does not technically have this option, but lawsuits seeking deficiency judgments against non-real-estate assets of defaulting mortgagors are rare in practice. By comparison with options on corporate stocks, for example, these options are somewhat unconventional, but they are fundamentally no different.

One might think that investors who hold mortgages should eliminate the risk of the option investment by purchasing interest rate call options and real estate put options. Doing this would seem to cancel out the risk they incurred in writing the options. The matter is not so simple, however, since the owner of a portfolio of mortgages holds in effect a portfolio of options with different strike prices; a portfolio of options is not the same thing as an option. Moreover, the mortgagors will not exercise their options with anything like the predictability of holders of financial options. So there is no natural reason for hedgers to favor the options market over the futures market. They could use a dynamic hedging strategy, adjusting their hedges in either market as discussed below.

Because of the nature of the prepayment option, a mortgage is an option with not a single strike price and single exercise date, but a schedule of strike prices and exercise dates that is determined by the amortization schedule of the mortgage (Chinloy 1991). This option is related to interest rate risk, rather than real estate price risk, since prepayments occur primarily when interest rates decline. However, the option is not so simple as an option on an interest-bearing vehicle. Because of liquidity constraints, mortgagors may find themselves unable to prepay if the value of their property falls below the mortgage balance.

Those who manage portfolios of mortgages already have learned to hedge—to the extent that prepayments are determined only by interest rate movements—both the interest rate risk and the prepayment risk in the long-term interest rate futures and options markets. In fact, the very first interest rate futures market, the Government National Mortgage Association (GNMA) bond futures market established in 1975, was for prepayment risk as well as interest rate risk. A GNMA bond is a pool of mortgages that is guaranteed against default by the full faith and credit of the U.S. government, so there is no default risk.[1] But the bearer of the bond does bear all the prepayment risk. The GNMA futures market was very active until problems in its delivery procedure caused it to be supplanted by the Treasury bond futures market.[2]

The disappearance of the GNMA futures market in no way implies the disappearance of demand for hedging the prepayment risk. The hedging can be done on other existing markets, since prepayment is determined fairly well by interest rates, given other information about the mortgage pool. It is well known in the industry that holders of mortgage-backed securities are in effect writers of options on interest rates, and theories of hedging mortgage-backed securities rely on the theory of such options.[3]

If there were a futures market in real estate prices, this hedging behavior could be refined to take into account how real estate price movements affect prepayment. This would be a sort of fine-tuning of the hedging of mortgage risk, and it is not our primary concern here. We turn to a discussion of hedging the effects of default on mortgage investments.

Theory of Defaults and Hedging

Strong evidence, discussed below, shows that the best single predictor of default is the current ratio of loan to market value for each property. This suggests that as prices fall, the probability of defaults will rise. Unfortunately, the cost to lenders of default also rises as prices fall. While default probabilities and default losses rise with falling prices, default losses will rise nonlinearly and faster than house prices fall. Therefore, the mortgage holder would ideally want a nonlinear, or dynamic, hedge. In this section we derive a nonlinear model that indicates how dynamic hedging should proceed.

[1] Default risk does exist in these bonds only in the sense that when default occurs the mortgage is prepaid by GNMA; it thus translates into some prepayment risk.

[2] The GNMA futures market eventually lost out to the Treasury bond futures market apparently because the delivery option in the GNMA contract made the futures price a poor hedge against the risk of prepayment for the representative mortgage-backed security (Johnston and McConnell 1989).

[3] For example, Toevs (1985) defined the concept of "option-adjusted duration" to allow hedging of prepayment risk in interest rate markets.

We follow the notation of Case and Shiller (1987): Household i buys a house at time t_i, and the logarithm of the house price at time t is P_{it}. We suppose that P_{it} is the sum of three components:

$$P_{it} = C_t + H_{it} + N_{it}\,, \tag{1}$$

where C_t is the logarithm of the citywide level of housing prices at time t, H_{it} is a Gaussian random walk (where ΔH_{it} has mean 0 and variance σ_H^2 that is uncorrelated with C_t), and N_{it} is a time-of-sale house-specific random error (which has mean 0 and variance σ_N^2 for all i and is serially uncorrelated and uncorrelated with C_t and N_{it} at all leads and lags) due to unpredictable noise in the sales process. This model imposes a β of 1 with respect to the citywide price level for all houses, an assumption that could be relaxed.

Suppose that the house is financed with a fixed-rate mortgage. The logarithm of the mortgage balance, M_{it}, is determined by a schedule specified at time t_i that depends on the mortgage rate and the length of the mortgage.

The risk of default is related to the logarithm of the loan-to-value ratio, $L_{it} = M_{it} - P_{it}$, as well as to a vector $\mathbf{X}_{it}$ of other economic conditions that affect default, such as unemployment rates. Note that there is a hazard of default even if L_{it} is negative, though as it becomes large and negative the hazard tails off toward zero.

Our model says that the probability p_{it} of defaulting at time t for house i is a nonlinear function:

$$p_{it} = f(L_{it}, \mathbf{X}_{it})\,. \tag{2}$$

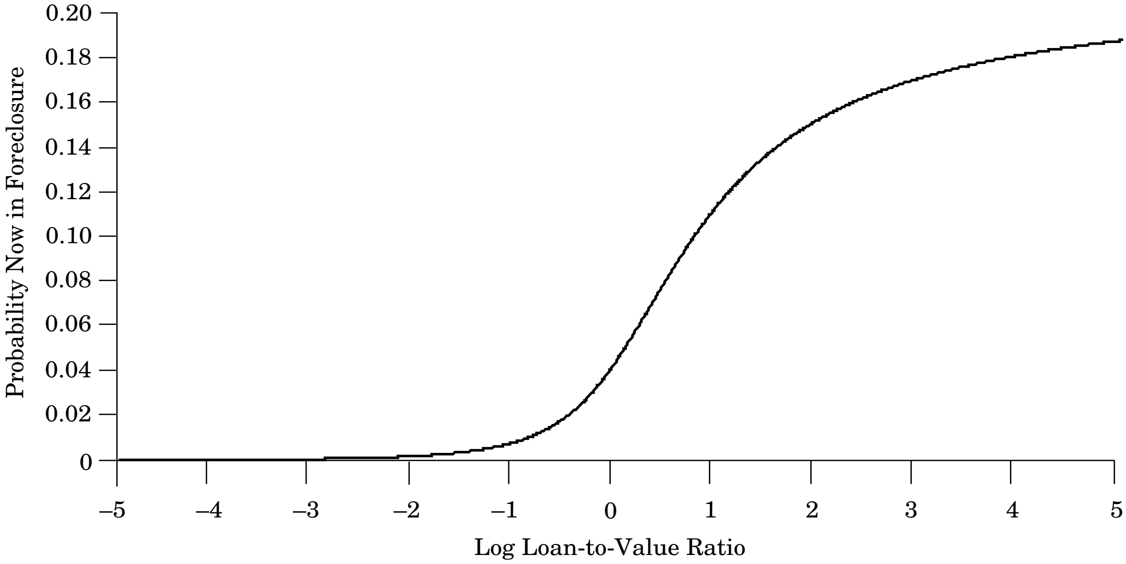
It is important that we represent the function as nonlinear, since with very low values of L_{it} there will be virtually no defaults. A hypothetical example of such a function is plotted in figure 1 for a given value of $\mathbf{X}_{it}$. Note that for large negative values of L_{it} the function approaches zero; virtually no one would want to default in these circumstances. As the loan-to-value ratio grows, the probability of default becomes higher and higher. Because the function is nonlinear, the cross-sectional variance of house prices matters for aggregate portfolio behavior, as shown below.

We seek now to describe the relationship between the change in value of a portfolio of mortgages on houses and the price level C_t for the city in which the house is situated. For this portfolio, we have a list of the dates of mortgage origination for each property and hence a specification of the function M_{it} for each property. The probability that property i will go into foreclosure during the relevant period is

$$p_{it} = f(M_{it} - (C_t - C_{t_i} + H_{it} - H_{it_i}) - P_{it_i}, \mathbf{X}_{it})\,. \tag{3}$$

Note that the time-of-sale error N_{it} does not affect the default decision, since we have assumed that N_{it} is not known to the homeowner until the house is actually sold. The curve shown in figure 1 was drawn for a given specific value of the vector $\mathbf{X}_{it}$; we hypothesize that varying the elements of $\mathbf{X}_{it}$ will shift the curve to the left or right without affecting its basic shape. An owner of a mortgage portfolio with information about the selling prices, the mortgage terms of the underlying properties, and the values of $\mathbf{X}_{it}$ still does not know the relation of p_{it} to the city price C_t because the house-specific noise component $H_{it} - H_{it_i}$ is not known. Fortunately, our Gaussian model of the variance of

Figure 1. **Hypothetical Example of the Function *f* Relating the Probability of Foreclosure to the Natural Logarithm of the Loan-to-Value Ratio**



changes in H allows us to calculate the functional relationship between average losses due to foreclosure E and the citywide price level C_t. Suppose, for a simple example, that all houses in a portfolio were purchased by the mortgagors on the same date t_i at the same log price P_{it_i}, have identical schedules M_{it} and identical vectors $\mathbf{X}_{it}$ of economic conditions affecting default, and are otherwise randomly selected. Then the expected fraction F of properties in foreclosure at time t is

$$F = \int_{-\infty}^{+\infty} f(M_{it} - (C_t - C_{t_i} + s\sqrt{t - t_i}) - P_{it_i}, \mathbf{X}_{it}) n_H(s)\, ds, \tag{4}$$

where $n_H(s)$ is the normal density function with mean 0 and variance σ_H^2. Moreover, assuming that the expected loss to the mortgagee when the property defaults (taking account of the distribution of the time-of-sale noise term N_{it}) is given by the function $V(M_{it} - P_{it}, \mathbf{X}_{it})$, the expected average loss in the portfolios due to foreclosure is

$$E = \int_{-\infty}^{+\infty} V(M_{it} - (C_t - C_{t_i} + s\sqrt{t - t_i}) - P_{it_i}, \mathbf{X}_{it}) \\ f(M_{it} - (C_t - C_{t_i} + s\sqrt{t - t_i}) - P_{it_i}, \mathbf{X}_{it}) n_H(s)\, ds. \tag{5}$$

Equation (5) can then be used to define the positions in futures or options markets to hedge the risk of losses due to mortgage default. In practice, of course, where portfolios are not so uniform, one would have to expand the analysis to take account of the joint distribution of purchase dates, purchase prices, and economic conditions.

The same analysis represented by equation (4) can allow us to compute the empirical relationship between foreclosures in a geographic area, such as a state, and the variables that determine overall foreclosures. However, the analysis is complicated by the many vintages of mortgages, issued at times when prices and interest rates were different. Moreover, many of these mortgages are paid off or defaulted and disappear in response to changing economic conditions, allowing for such things as echo effects of past changes in interest rates or prices. Moreover, we do not have data on all the vintages for a geographic region such as a state.

It is beyond the scope of this article to derive analytically the relationship between average foreclosures for a state and the citywide price level C_t, but some general principles emerge from the analysis. First, we note that foreclosures tend to be determined by a sort of distributed lag on past price changes. The length of the distributed lag depends on the vintages of mortgages whose balances have not been reduced so far below prices that the put is in the near-zero portion of the function f. Presumably, the distributed lag dies faster at higher rates of price increase. There need not be aggregate price declines for there to be foreclosures; five years or so of flat prices will tend to cause a burst of foreclosures, since mortgage balances are not reduced much by amortization in the first five years, and five years is enough time for a good number of houses to see their value drift downward randomly because of the H_{it} term and such things as changing neighborhood characteristics. The effects of the other variables $\mathbf{X}_{it}$ such as the unemployment rate interact with the effects of the distributed lag of price changes: If prices have been rising smartly, then other variables will have less effect on foreclosures.

Each of the inputs to the strategy noted above—the loan-to-value ratios of the portfolio, the metropolitan area price to neighborhood price b values, and the default discounts—can change through time. Therefore an ideal hedging strategy would require the mortgage holder to update its hedging analysis regularly.

Mortgages and House Prices: Methods of Dealing with Price Risk

Because of the nonlinear relationship between actual losses (deficiencies) and house prices, even regionally diversified mortgage portfolios are exposed to potentially catastrophic risk from sharp regional price drops (as further discussed below). Given the experiences of Texas, New England, Alaska, and California, the increasing rush to shed risk is not surprising. First, there is increasing pressure for broader and deeper private mortgage insurance. Agencies are offering reduced "guarantor fees" in exchange for deep pool coverage when acquiring pools.

One way of dealing with mortgage risk is securitization, but securitization simply transfers the risks directly to mortgage-backed securities holders. Non-agency investor worries, particularly about California, have led to demands for credit enhancement of mortgage-backed securities via a "super-senior" structure, in which classes of securities are set aside to bear any default losses ahead of more senior protected paper.

All these complex methods of passing on default risk could be avoided if a hedging vehicle were available.

Empirical Literature on Default Risk

There is no shortage of evidence on the importance of house prices and equity in the default decision. Quercia and Stegman (1992, 375) reviewed 29 empirical studies done over a 30-year period and concluded:

> Consistently, home equity, or the related measure of loan-to-value ratio, has been found to influence the default decision. There is a consensus in most recent default studies that the correct measure of a borrower's net equity is the contemporaneous market value of property less the contemporaneous market value of the loan, a measure that also incorporates borrower expectations.

Kau, Keenan, and Kim (1994, 287) reached the same conclusion:

> There exists a significant literature examining causes of default. In conformity with this paper's approach, considerable empirical evidence exists showing that it is the house versus the mortgage value, rather than such personal characteristics as the homeowner's liquidity position, that explains default.[4]

Even more recently, in a study using a discrete proportional hazard model, micro-level mortgage data from Freddie Mac, and weighted repeat-sales price indices, Quigley, Van Order, and Deng (1993, 24) stated:

> The results show that the probability of negative equity ratio is the main time varying covariate influencing mortgage holders' default decision.

The history of the mortgage industry provides dramatic evidence that default risk is related nonlinearly to house prices. Losses from default depend not only on the incidence of defaults, but also on the severity of deficiencies after collateral liquidation. Unfortunately, almost no data on aggregate claims over time are available on a nonproprietary basis. But this is an area where history is well known. The catastrophic losses in recent years have been in Texas and other parts of the Southwest, in Alaska, in New England, and in California. In all four cases, house prices dropped sharply. While the number of defaults increased, actual losses soared. In other areas of the country, default rates rise and fall with economic conditions, but actual deficiencies are kept to reasonable levels by collateral values when real estate prices have not fallen.

If default risk was randomly distributed across the country, a regionally diversified portfolio would be sufficient to control the risks of default losses. But experience has shown that even regionally diversified portfolios can suffer catastrophic losses when large regions suffer significant price declines.

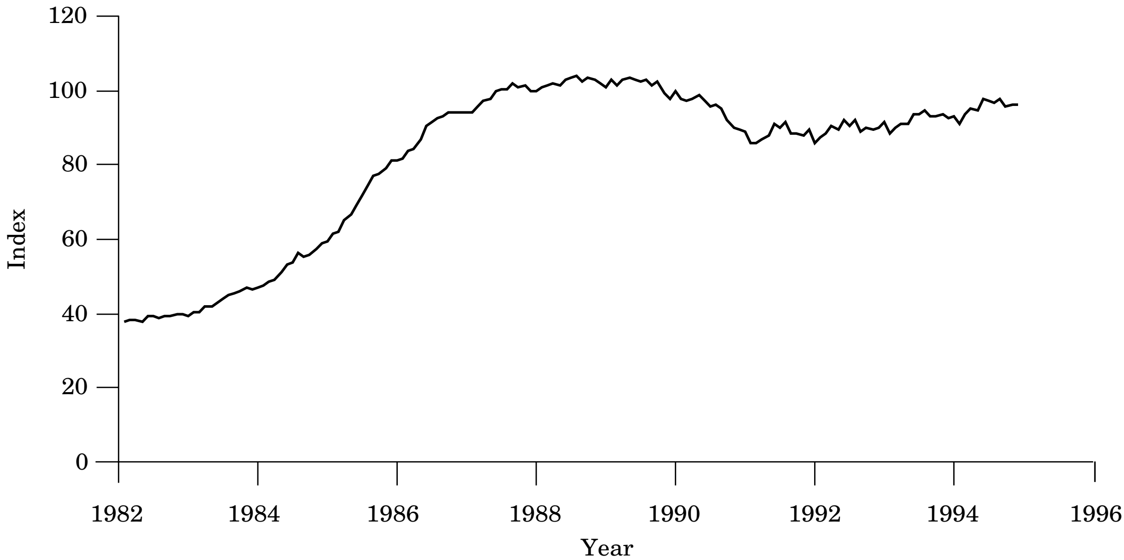
House Prices and Default Risk: Additional Evidence

Recent years have seen dramatic swings in house prices, and nowhere have they been more dramatic than in Massachusetts and California. The pattern of single-family house price movements in the Boston consolidated metropolitan statistical area and Los Angeles County are shown in figures 2 and 3, respectively.[5] Between 1982 and 1988, house prices in Boston rose 177 percent. Following a gentle peak that lasted two full

[4] The authors cite Jackson and Kaserman (1980), Foster and Van Order (1984), Waller (1988), and Cunningham and Capone (1990).

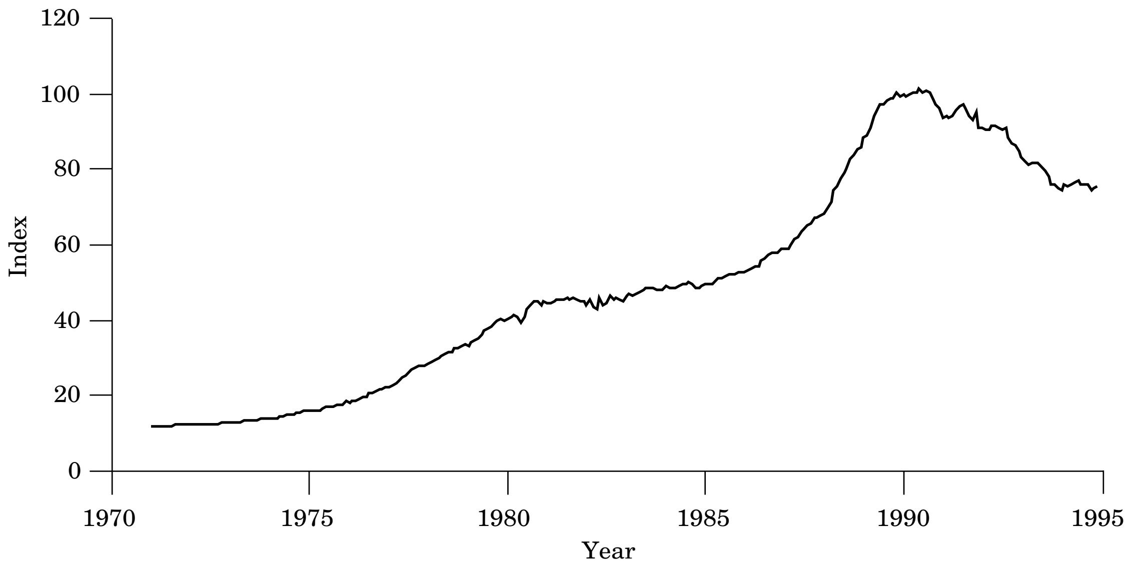
[5] The indices plotted are repeat-sales indices following the method of Case and Shiller (1987, 1989) estimated from data on more than 1.5 million sale pairs in Los Angeles and more than 85,000 sale pairs from the five eastern counties in Massachusetts.

Figure 2. **Case-Shiller Monthly Home Price Index, January 1982 to December 1994, January 1990 = 100, Greater Boston**



Source: Case Shiller Weiss, Inc.

Figure 3. **Case-Shiller Monthly Home Price Index, January 1971 to December 1994, January 1990 = 100, Los Angeles County**



Source: Case Shiller Weiss, Inc.

years, prices dropped sharply in 1990, bottoming in January 1992, down 18 percent. Prices have since been on a gradual uptrend in Boston, wiping out most of the loss since the peak.

Similarly, housing prices in Los Angeles County boomed from 1986 to 1989, rising 92 percent. Following a much sharper peak than in Massachusetts, prices began falling in 1990 and fell 26 percent by January 1994, followed by an apparent leveling off of the price decline starting with early 1994. It is of course impossible to tell whether this leveling is just a temporary interruption of the decline.

In Massachusetts, we calculated repeat-sales price indices for 64 separate geographic areas made up of individual ZIP codes or ZIP code clusters. For each of the 64 areas, the increase in price from 1982 (second quarter) to the peak was calculated, as was the decline since the peak (through June 1993). Nearly all areas peaked during the second half of 1988 or the first half of 1989. Summary statistics are given in table 1.

Table 1. **Price Increases and Decreases, 64 Areas in Massachusetts**

	1982–Peak	Peak–1993
Minimum (%)	136	–2
Maximum (%)	235	–56
Mean (%)	170	–17
Standard deviation (%)	21	8
Coefficient of variation	0.12	0.50
1st quartile (%)	156	–13
3rd quartile (%)	182	–19

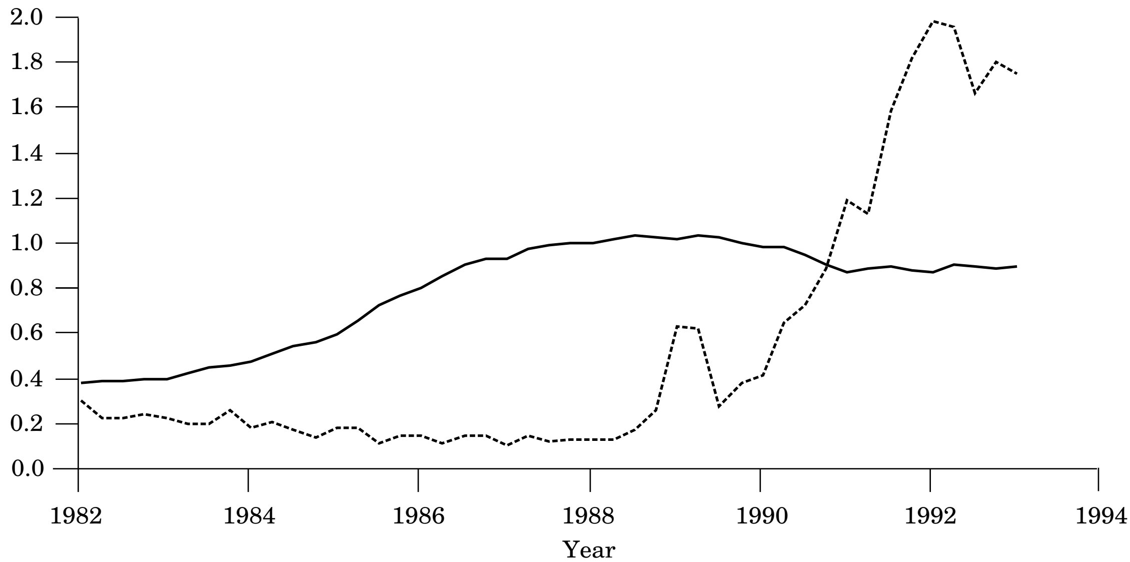
The important point here is that the variation in declines across areas is larger than the variation in increases across the same areas. We have argued above that during periods of price decline, losses are likely to increase in a nonlinear way, since both the number of claims and the severity increase when prices drop. Further, recall that in figure 1 we argued that the likelihood of default increases nonlinearly with the logarithm of the loan-to-value ratio. This implies that if the cross-area variance of the log price change increases when prices drop, this would push clusters of properties into the category of severely depressed, sharply increasing default probability and severity of deficiency.

This is exactly what happened in Massachusetts. Thirteen of the 64 areas experienced declines of more than 20 percent from the peak, wiping out virtually all equity for first-time buyers between 1987 and 1989. The worst three areas (Lowell –56 percent, Brockton –44 percent, and Chelsea/Revere –38 percent) are all large, severely impacted industrial areas with high rates of unemployment. In these three areas, more than half of all recorded sales in 1994 were foreclosure sales.

During the same period, four ZIP code clusters that include 13 towns showed declines of 7 percent or less.

The effect of house price movements on default rates during the boom-bust cycle in Massachusetts is illustrated in figure 4. Default rates are “total default inventory”

Figure 4. **Total Foreclosures for Massachusetts in Percent (Dashed Line) and Case-Shiller Massachusetts Home Price Index as Fraction of Base Value (Solid Line), Quarterly, First Quarter 1982 to First Quarter 1993**



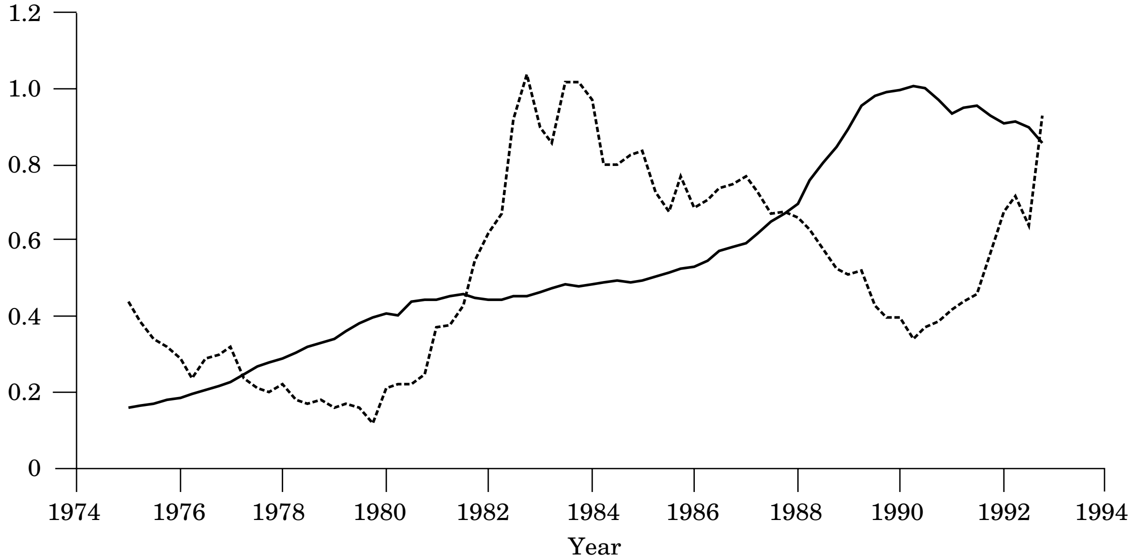
Source: Mortgage Bankers Association of America and Case Shiller Weiss, Inc.

obtained from the Mortgage Bankers Association of America (MBA) *National Delinquency Survey* (1975–93, quarterly). From 1982 through 1988, housing prices rose sharply, and default rates were pushed nearly to zero as loan-to-value ratios increased. As soon as prices flattened and ultimately dropped, total foreclosures rose sharply. Finally, as prices bottomed and stabilized, total foreclosures also stabilized.

The data for California show a similar pattern but over a longer period (figure 5). Sharp price increases during the first California boom, from 1975 through 1980, pushed foreclosure rates down steadily to nearly 0.1 percent. The dislocation of the 1981–82 recession, combined with stable prices in the early 1980s, increased foreclosures to more than 1 percent. The second California boom, from 1986 through 1989, again decreased loan-to-value ratios, and foreclosure rates fell sharply. When prices turned around and began falling in 1990, foreclosure rates shot up and were still climbing in 1994.

Note that the plots in figures 4 and 5 show total foreclosure inventory as a fraction of total loan portfolios. A more accurate picture would be obtained by looking at foreclosure rates by vintage year. The highest foreclosure rates are for mortgages written in California in 1989 and 1990, while in Massachusetts the highest rates are for mortgages written in 1988 and 1989.

Figure 5. **Total Foreclosures for California in Percent (Dashed Line) and Case-Shiller Los Angeles Home Price Index as Fraction of Base Value (Solid Line), Quarterly, First Quarter 1975 to Fourth Quarter 1992**



Source: Mortgage Bankers Association of America and Case Shiller Weiss, Inc.

Regression Results

While the ideal data for studies of default incidence are microdata on individual seasoned mortgages from which hazard models might be estimated, we decided to look at default and foreclosure data from the MBA since 1975.

Three sets of regressions have been run. First, we regressed the logarithm of the MBA total foreclosure rate for the state on a distributed lag of the difference of the logarithms of the repeat-sales indices described in tables 2 and 3. Since there is likely to be an autocorrelated residual, the regressions were run by the Cochrane-Orcutt procedure to estimate the residual autocorrelation coefficient r.

In both Los Angeles and Massachusetts, the set of lagged price changes explains much of the overall variation in foreclosure. The adjusted R^2 is 0.87 for Massachusetts and 0.94 for Los Angeles.

Although extraordinary default risk is created when a substantial boom is followed by a sharp downturn, as was the case in California and in New England, what portion of the variation in default and foreclosure nationally can be explained by collateral depreciation?

Table 2. **Distributed Lag Regression, Massachusetts, Quarterly, Third Quarter 1985 to Fourth Quarter 1991 (Dependent Variable: Logarithm of Total MBA Foreclosure Rate for Massachusetts)**

Independent Variable	Coefficient	t Statistic
Intercept	–0.205	–0.948
DP_{t-1}	0.732	0.153
DP_{t-2}	–3.605	–0.758
DP_{t-3}	–3.362	–0.486
DP_{t-4}	–0.977	–0.133
DP_{t-5}	–11.065	–1.352
DP_{t-6}	7.891	0.994
DP_{t-7}	2.263	0.283
DP_{t-8}	–9.016	–1.134
DP_{t-9}	–2.121	–0.310
DP_{t-10}	–7.863	–1.117
DP_{t-11}	–7.594	–1.218
DP_{t-12}	2.876	0.497
r	0.425	1.531

Note: $N = 26$, adjusted $R^2 = 0.870$. Regressions were run by Cochrane-Orcutt procedure.
$DP_t = \log \text{Price}_t - \log \text{Price}_{t-1}$, where Price = Case-Shiller house price index for Massachusetts.

Table 3. **Distributed Lag Regression, Los Angeles, Quarterly, Third Quarter 1978 to Fourth Quarter 1991 (Dependent Variable: Logarithm of Total MBA Foreclosure Rate for California)**

Independent Variable	Coefficient	t Statistic
Intercept	–0.042	–0.197
DP_{t-1}	0.005	0.005
DP_{t-2}	0.248	0.228
DP_{t-3}	–0.568	–0.503
DP_{t-4}	–2.506	–2.204
DP_{t-5}	–2.580	–2.311
DP_{t-6}	–1.674	–1.506
DP_{t-7}	–1.714	–1.538
DP_{t-8}	–1.683	–1.427
DP_{t-9}	–2.821	–2.392
DP_{t-10}	–3.456	–2.881
DP_{t-11}	–2.064	–1.771
DP_{t-12}	–1.330	–1.300
r	0.886	13.184

Note: $N = 54$, adjusted $R^2 = 0.943$. Regressions were run by Cochrane-Orcutt procedure.
$DP_t = \log \text{Price}_t - \log \text{Price}_{t-1}$, where Price = Case-Shiller house price index for Los Angeles County.

To estimate the effect of house prices on foreclosure rates across all states, we have assembled a database containing a number of state-level economic variables quarterly since 1975 as well as default and foreclosure data from the MBA. The results of a simple model of foreclosure rates, a time-series cross-section regression where each observation of the dependent variable is a state in a given quarter, are shown in table 4. We used 2,603 observations of these state-quarter foreclosure rates; note that start dates for various series differ across states. The ordinary least squares regression included a simple

Table 4. **Time-Series Cross-Section Regressions, 50 States, Quarterly, First Quarter 1975 to First Quarter 1993 (Dependent Variable: Total MBA Foreclosure Rate in State)**

Independent Variable	Coefficient	t Statistic
Intercept	2.725	5.589
Unemp[a]	0.048	6.545
PCY_{t-4}[b]	0.027	4.131
ChPCY[c]	–1.582	–3.437
$PCNM_{t-4}$[d]	–24.421	–18.417
$Natfor_t$[e]	1.141	7.780
$BUST_t$[f]	1.277	17.283

Note: N = 2,603, adjusted R^2 = 0.297. Regressions were run by ordinary least squares. Start dates for series differ across states.
[a] Average unemployment rate in state over the past eight quarters.
[b] Per capita personal income in the state lagged four quarters.
[c] Change in the logarithm of per capita personal income in the state over the past four quarters.
[d] Per capita net migration for the state lagged four quarters.
[e] National foreclosure rate.
[f] Dummy variable for quarters in which nominal house prices fell significantly in AK, CA, CT, MA, NH, NJ, NY, OK, RI, and TX.

dummy variable for quarters when available data suggested significant declines in house prices. Such declines have occurred in 10 states in four areas: the Southeast during the mid-1980s, the Northeast and California during the early 1990s, and Alaska during the late 1980s.

The most significant variables are per capita net migration for the state lagged one year and the BUST dummy. Both have the expected signs. The average unemployment rate over the past eight quarters is highly significant with the expected sign. The level of per capita income has the wrong sign, but the change in per capita income has the expected sign.

Finally, we have incorporated the distributed lags that were found to be so predictive in table 2 for Massachusetts and table 3 for Los Angeles into the time-series cross-section analysis for the 50 states. Doing this enables us to use data on all the states to see whether distributed lags are really predictive of foreclosures in a wide variety of settings. In table 5 we present the results of the time-series cross-section model estimated with the same database, this time using the Hildreth-Lu method to control for autocorrelation within individual states and fixed effects to control for differences across states. The logarithm of the total foreclosure rate is regressed on distributed lags of changes in the National Association of Realtors' median house prices for the state and on the ratio of real per capita personal income in the state for the quarter to its level four quarters earlier. The constant term and the coefficients of the state dummies are not shown in the table. Because of the 16-quarter distributed lag on changes in per capita personal income and the 12-quarter distributed lag on house price changes (as well as the problem that start dates for some series are later for some states), the number of observations is reduced to 914. Even though the distributed lag coefficients were unconstrained (no polynomial or other functional relationship having been imposed), all the price coefficients are negative, as we would expect; they are almost always significant at conventional levels, and the model explains 86 percent of the variation in foreclosures over the period. The peak effect of price changes on foreclosure occurs at a lag of about two years.

Table 5. **Time-Series Cross-Section Distributed Lag Regressions, 50 States, Quarterly, First Quarter 1975 to First Quarter 1993 (Dependent Variable: Logarithm of Total MBA Foreclosure Rate in State)**

Independent Variable	Coefficient	t Statistic
Unemp*	0.266	3.297
DPY_{t-1}	–4.515	–3.073
DPY_{t-2}	–1.376	–0.965
DPY_{t-3}	0.298	0.213
DPY_{t-4}	0.658	0.460
DPY_{t-5}	–0.193	–0.117
DPY_{t-6}	1.051	0.631
DPY_{t-7}	3.747	2.211
DPY_{t-8}	3.640	2.147
DPY_{t-9}	–1.092	–0.683
DPY_{t-10}	0.752	0.477
DPY_{t-11}	3.018	1.885
DPY_{t-12}	1.386	0.882
DPY_{t-13}	1.908	1.381
DPY_{t-14}	0.683	0.507
DPY_{t-15}	0.445	0.314
DPY_{t-16}	2.940	2.031
DP_{t-1}	–0.017	–3.253
DP_{t-2}	–0.023	–2.496
DP_{t-3}	–0.030	–2.550
DP_{t-4}	–0.037	–2.747
DP_{t-5}	–0.040	–2.833
DP_{t-6}	–0.045	–3.230
DP_{t-7}	–0.049	–3.728
DP_{t-8}	–0.049	–4.125
DP_{t-9}	–0.043	–4.121
DP_{t-10}	–0.032	–3.761
DP_{t-11}	–0.018	–2.938
DP_{t-12}	–0.005	–1.535

Note: $N = 914$, adjusted $R^2 = 0.857$. Regressions were run by Hildreth-Lu procedure with fixed effects for states. $DPY_t = PCY_t/PCY_{t-4}$, where PCY_t = real per capita personal income in state for period t. $DP_t = \log Price_t - \log Price_{t-1}$, where Price = National Association of Realtors median price of existing single-family homes.
* Average unemployment rate in state over the past eight quarters.

Conclusion and Further Research

The purpose of this article is to add information relevant to our earlier argument (Case, Shiller, and Weiss 1993) for establishing index-based futures and options markets in real estate for a variety of cities. The largest single group that would benefit from the ability to hedge in such markets is homeowners, who are generally underdiversified and highly leveraged. Unfortunately, homeowners are not well informed about the use of derivatives to reduce risk; thus, use of such markets would be likely to evolve over a long time as insurance and financial service companies develop consumer products to take advantage of the new markets.

The real issue is what other groups stand to gain from the establishment of real estate futures and options markets that would have the requisite knowledge to use appropriate hedging to reduce risk. One obvious example is the group of mortgage holders or those that currently "own" the default risk associated with mortgages (private mortgage insurers or mortgage-backed securities holders).

Mortgage holders face risks from interest rate increases, from prepayments, and from default and foreclosure. Interest rate risk and prepayment risk can be hedged easily in interest rate futures and options markets, but foreclosure risk is uncorrelated with any existing hedging vehicle.

The empirical part of the article presented evidence that house prices do indeed predict foreclosure and that a set of derivative products based on regional price movements would provide an appropriate vehicle for hedging default risk.

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