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Deconstructing a Mortgage Meltdown: A Methodology for Decomposing Underwriting Quality

Technical progress in originating and pricing mortgages has enabled a trend since 1979 toward relaxed credit standards for lending, reflected in rising foreclosure rates. We develop a methodology for decomposing the trend in mortgage performance into a part due to economic conditions and a part due to underwriting changes, and provide natural metrics or indices of underwriting quality and economic conditions. The recent mortgage debacle can be attributed about equally to each factor. Important underwriting characteristics were eased in the 1990s, but the negative effects of lower standards were masked by strong local and national economic conditions. After 2002, there was little change in observable loan characteristics, but loan performance still eroded, even after controlling for the economic environment. Our evidence suggests that erosion after 2002 must have arisen from underwriting covariates that are unobservable to investors, consistent with the hypothesis that moral hazard in “nonagency” securitizations caused underwriting risks to be mispriced.

IN THIS RESEARCH, we develop a methodology for decomposing the rate of foreclosures in the aggregate serviced portfolio of mortgage loans into multiplicative indices that attribute the foreclosures either to changes in underwriting practices or to underlying economic conditions. It is well known that the local economic environment plays an important role in determining the rate of mortgage defaults (e.g., Capozza, Kazarian, and Thomson 1998). For example, the

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same borrower should be expected to default at a higher rate when unemployment is higher or collateral prices are falling. Separating the effects of underwriting from local economic conditions is important both for identifying the future default rates on loans and for monitoring the quality of underwriting by lenders.

We document that technical progress in originating and pricing mortgages has enabled a trend since 1979 toward more relaxed credit standards on mortgage lending, which is reflected in rising foreclosure rates. We then decompose annual variation in mortgage performance, measured by share of loans entering foreclosure, into a part due to economic conditions and a part due to underwriting changes.

We use the decomposition to illustrate that the trend toward lower standards was characterized by two major periods of deterioration, one in the middle and late 1990s and one after 2002. In the first period, the change in credit standards can be seen in deterioration of readily measurable quality indicators, for instance, an increase in the share of low down payment loans in the loan mix. This coincided with the development of credit scoring models that quantified the role of payment history in default. However, the extent of the deterioration in standards was masked by unusually favorable regional and national economic conditions.

After 2002, there was little change in readily observable indicators such as credit score and loan-to-value (LTV). Instead, the deterioration in this “meltdown” period can be attributed approximately equally to a reversal of fortune in local economic conditions and to an erosion of unobservable variables, perhaps due to an increase in moral hazard arising from the securitization process, with which it is correlated.

We hypothesize that the pattern of losses including the recent sharp increase in defaults arose from the interaction of technology in the form of credit scoring and automated underwriting systems with a short look-back period for lenders and investors when calibrating their new underwriting systems. These underwriting systems typically did not incorporate the effects of changing local and national economic conditions. As a result, when the short calibration period is economically favorable, lenders underestimate the baseline hazard and misjudge the efficacy of their models. The opposite occurs when economic conditions are unfavorable. This feedback pattern accentuates the credit cycle.¹ Our metrics for the economic environment for mortgage lending from 1990 to 2002 did indeed grow more favorable each year. In this environment, lenders misjudged the default risks on mortgages, especially subprime mortgages.

There was a second technological change in the years after 2002 that allowed for securitization of subprime and other nontraditional loans to increase sharply. During this latter period, there was a large increase in the market share of nonstandard loans and a corresponding increase in mortgage-backed securities secured by such loans. Securitization of these nonstandard loans separated the risk bearing from the originator and enabled moral hazard. This separation led to the second round

1. For more on the implications of feedback and coordination, see Ozdenoren and Yuan (2008).

of “inadvertent” declines in underwriting quality. The culprit here was probably the extremely rapid growth in the nonstandard loans, which made it difficult for mortgage originators to maintain quality and difficult for investors in complicated pieces of mortgage pools to keep up with changes in unobservable variables. At the same time, extraordinary growth in house prices disguised the poor underwriting, but the rapid price growth was not sustainable.² While hard data, such as credit scores and LTV ratios, did not erode during this period, there is indirect evidence that “soft”³ data did erode.

After about 2002, the favorable effects of the economic conditions began to reverse. The less favorable economic environment, especially falling house prices, quickly exposed the steep erosion in underwriting quality.

Our analysis uses a fairly large sample of aggregated data from the Mortgage Bankers Association (MBA) for foreclosures started each quarter. To separate underwriting from local economic conditions, we condition the data for the serviced portfolio on metrics from University Financial Associates LLC (UFA) that assess the default risk arising from the local and national economic environment for each vintage in each state. The year-fixed effects from a regression of the MBA serviced portfolio data on lags of the UFA regional risk indices by vintage are a measure of the underwriting quality of the serviced portfolio under the assumption that the UFA indices accurately assess the effects of local and national economic conditions on defaults for constant quality loans.

The fitted values from the regression minus the year-fixed effects become the basis for an index of how the economic environment at the local and national level is affecting foreclosures in the serviced portfolio. The year-fixed effects enable a corresponding index of underwriting quality. The resulting patterns of the indices are consistent with the hypotheses outlined above. The index for underwriting quality shows that absent the favorable economic environment, foreclosure rates would have doubled from 1993 to 2004 rather than increasing the actual and more modest 25%. We conjecture that indices like those developed in this research will be valuable to policymakers and investors when trying to assess risks in mortgage markets.

Because of limitations in our data set, viz., aggregation across loan vintages, we are painting with a broad brush. Our results are consistent with our underlying hypotheses, but more detailed data will be required to eliminate other explanations. In Section 1, we discuss basic facts of mortgage markets over time from different data sets. We use these stylized facts to establish some general trends. In Section 2, we present our model. In Section 3, we present results. Section 4 summarizes and concludes.

2. See Gorton (2008) for some discussion of complications arising from securitization.

3. We define “soft” data to be data that are not observable to the investor in the securitizations, although they may be known to the originator.

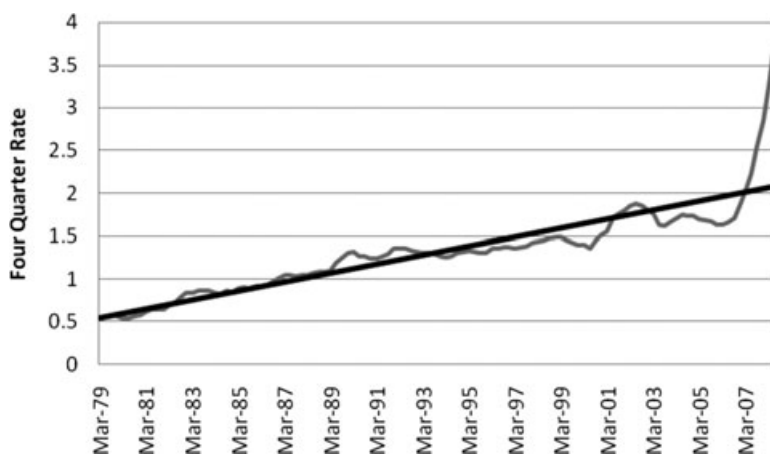


FIG. 1. All Foreclosures Started: U.S. 1979–2008 Quarterly Data. Four-Quarter Averages Annualized.

SOURCE: Mortgage Bankers Association National Delinquency Survey.

1. BACKGROUND AND SUMMARY DATA: STYLIZED FACTS

Mortgage market data at the loan level, especially as they describe subprime and other nontraditional loan types, are often proprietary. Here, we discuss some aggregated results from different sources to generate “stylized facts” that provide a context for our analysis in Section 3. We begin with a discussion of trends in foreclosures, in the aggregate, and by loan type, including the recent experience of subprime loans. We then turn to a general discussion of credit risk and the determinants of foreclosures. These include the characteristics of loans and borrowers and the evolution of house prices.

1.1 *The Long-Run Trend in Foreclosures*

The first stylized fact is the trend in aggregate foreclosures. Figure 1 shows that the MBA data on foreclosures started as a percent of outstanding number of loans in servicing portfolio of mortgage bankers from 1979 through 2008.⁴ There is a rising trend with occasional leveling off. Between 1979 and 2002 foreclosure rates quadrupled from 0.12% to 0.49% quarterly. In an impressive surge from 2006 to 2008, foreclosure rates more than doubled again from 0.47% to 1.08%. Our purpose with this research is to begin the analysis of available data that will enable a deeper understanding of both the trend and the surge.

Figure 1 also includes a linear trend line. The rate of foreclosures rises above the trend line during the recessions of 1981–82, 1990–91, and 2002–03. During

4. While it is the case that these are proprietary data, they can be purchased at modest cost. The data cover almost all mortgages.

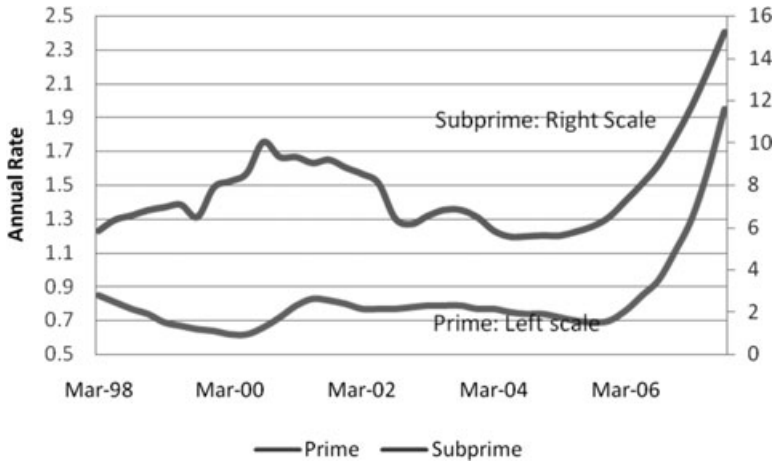


FIG. 2. Rate of Foreclosures Started by Loan Type, 1998–2007 (%). Four Quarterly Averages Annualized. SOURCE: Mortgage Bankers Association.

the intervals of expansion, the rate dips below the trend line. This evidence highlights the role of national and local economic conditions in the rate of foreclosures, which we discuss further below. To the extent that increases in foreclosure rates are recession induced, the spike from 2006 on points to a very severe recession.

The deterioration in mortgage performance has varied by loan type. Figure 2 presents data for 1998–2008 on foreclosures started by major product type. The vertical axis is the annualized percent of loans that enter the foreclosure process over each four quarters.⁵ Note in particular the history of subprime. Foreclosure performance improves after the 2001 recession but then erodes sharply. A similar pattern, but on a smaller scale and with about a 1-year lag, occurs in the prime mortgage data, suggesting that there is a common factor affecting both prime and subprime and that the surge in foreclosures is not just a subprime issue. The lag between prime and subprime makes subprime the canary in the coal mine. Subprime borrowers appear to respond more quickly to financial stress than prime borrowers.⁶

1.2 The Trends in House Prices

The data in the previous section suggest that there may be an important role that economic conditions play in the pattern of defaults. Modern contingent claims based theories of mortgage valuation treat the borrower’s position as long a put on the

5. The MBA data do not track how many actually went through foreclosure to real estate owned (REO) by lenders.

6. Subprime responds earlier, but the eventual total response is smaller in percentage terms than for prime loans.

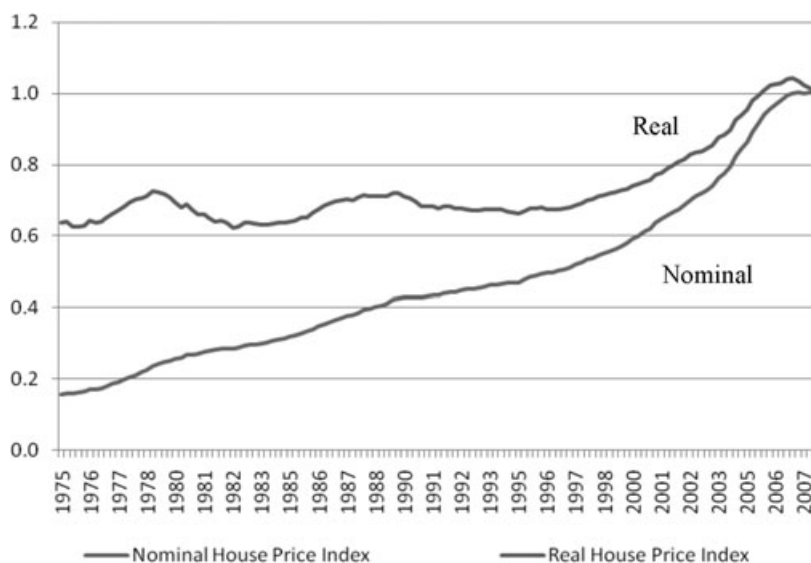


FIG. 3. Real and Nominal House Price Indices, 1975–2008; 2007 = 1.0.

SOURCE: Federal Housing Finance Agency.

collateral. One implication of this approach is that the put option should be sensitive to the value of the collateral. When collateral prices are rising, a financially stressed borrower with equity will rationally choose to sell the collateral rather than default. Correspondingly, when collateral prices are falling and equity becomes negative, the stressed borrower is more likely to rationally choose default. Therefore, it is important to understand both collateral prices and financial stress as they relate to foreclosures.

Figure 3 plots real and nominal house prices since 1975. There is a cyclical pattern to real house prices from 1975 to 1997 within a narrow range. However, during the boom years from 1997 to 2007, real house prices rose about 40% above what had been the long-run level until that time. Such steep increases should be expected to greatly reduce the need for stressed borrowers to default. Since many lenders develop underwriting models by evaluating recent loan performance data, any underwriting models created using data from this boom period would underestimate the risks to lenders in more average times.

Figure 4 provides another perspective on the recent period by plotting the real appreciation rate of house prices. The long-run evidence (e.g., Eichholz 1997) has found that real house prices appreciate at rates close to zero over decades and centuries. Thus, the 3–6% annual appreciation rates of the last decade are extraordinary. The acceleration in house prices beginning around 1999 is particularly noteworthy.

Figure 5 illustrates the variation in house prices for selected metro areas. It shows the extreme ups and downs of some metro areas such as San Diego and Miami that had

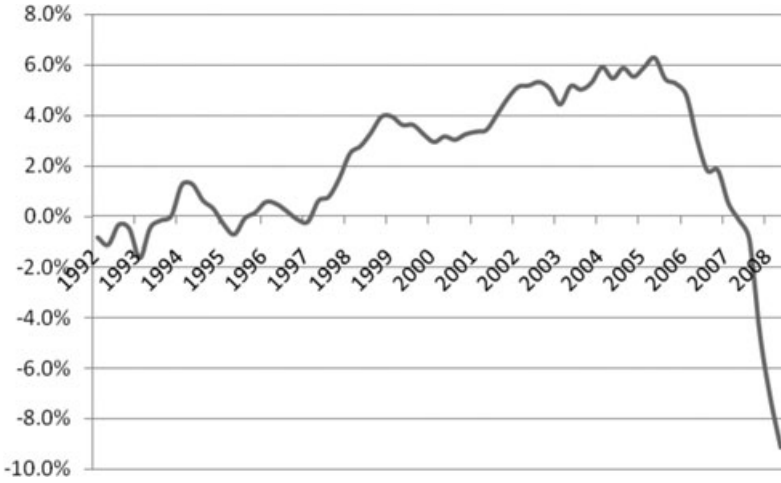


FIG. 4. U.S. Real House Price Appreciation, 1992–2008. Seasonally Adjusted, Purchase Only Index, Quarterly Data, Four-Quarter Price Changes.

SOURCE: OFHEO.

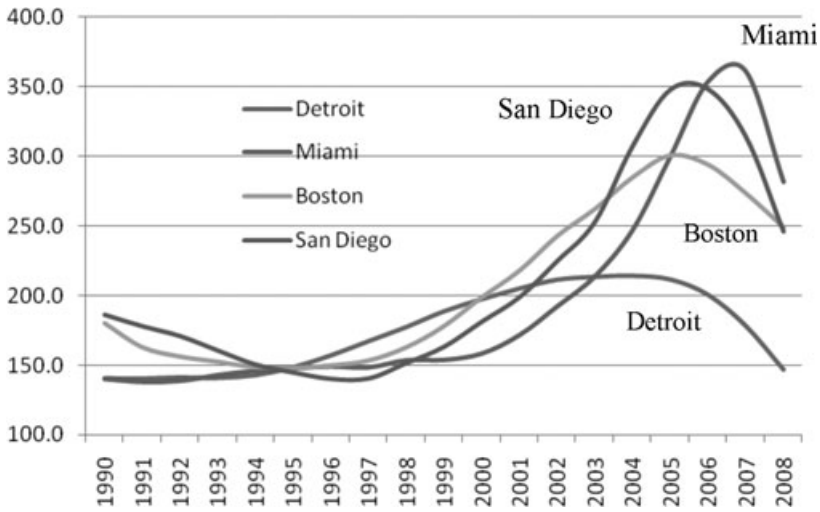


FIG. 5. Real House Prices in Representative Metro Areas 1990–2008.

SOURCE: OFHEO.

price “bubbles.” These areas currently have high foreclosure rates as prices decline. Other metro areas had smaller increases (Boston and Detroit) with slightly displaced peaks and troughs. Detroit did not experience the “bubble” level of price increases but nevertheless has been experiencing elevated default rates. High and persistent levels of unemployment in Detroit create high levels of financial stress for borrowers

that interact with the declining collateral prices. We will exploit this time and spatial variation in foreclosures in our analysis of the rate of foreclosures started in the MBA serviced portfolio data.

1.3 A Summary Statistic for Local Economic Conditions

The figures above highlight the historical effects of economic conditions on foreclosures. In the analysis that follows, we split the foreclosure rate in the serviced portfolio into two components, one arising from underwriting policy and the other from changes in economic conditions. Unfortunately, our foreclosure data are available only at the level of broad aggregates.

To separate the effects of economic conditions from underwriting, we start with the quarterly Default Risk Index compiled by UFA that tracks the effect of local and national economic conditions on a constant quality loan. UFA uses proprietary data on individual loans to estimate a competing hazards model of mortgage performance at the loan level.⁷ The model is estimated from a large data set that includes the characteristics of the loans, the properties, and the borrower (credit history, LTV, etc.) as well as local economic conditions (house prices, employment, etc.). The hazard model estimates for the conditional probabilities of default and prepayment are then used to project the probability of ever defaulting on a loan with fixed underwriting characteristics. A detailed description of the estimation is contained in the Appendix.

One assumption behind the Index is that all loans react in the same multiplicative way to the economic environment. Tests of this assumption, which are confirmed in the results below, reveal that the model is a reasonable representation of actual reactions. Perhaps surprisingly, although prime loans responded belatedly to the economic environment, the total default sensitivity to economic conditions in percentage terms is slightly higher for prime than for subprime loans.

The Risk Indices are especially useful in our modeling because they provide summary statistics for local and national economic conditions as they apply to mortgage default, and they enable parsimonious estimation of the equations in Section 3.

Figure 6 illustrates one use of the Index to track default risks over time. In this case, the constant quality loan is moved through time and space to create a national Index for each vintage by averaging across locations each year. The Index has varied between 60 and 270; that is, the yearly variation in economic conditions has been sufficient to cause more than a quadrupling of default rates from trough to peak on a constant quality loan. The UFA Risk Index reveals the importance of economic conditions for the origination and pricing of mortgages; however, few participants, including lenders,

7. For an early example of a default model with local economic conditions, see Capozza, Kazarian, and Thomson (1997).

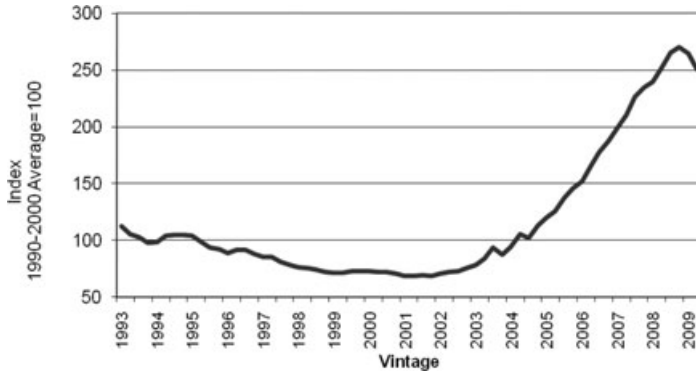


Fig. 6. The Effect of Economic Conditions on Mortgage Performance by Origination Year: The UFA National Default Risk Index by Vintage.

NOTE: Higher values of the index indicate a less favorable economic environment and higher expected defaults for the constant quality mortgage.

SOURCE: University Financial Associates LLC.

rating agencies, insurers, and investors had appropriately incorporated economic conditions into their origination and pricing decisions until recently.⁸

There have been two trends in the national Index: improvement from 1990 until around 2002 and then a sharp deterioration. It should be noted that the Index is a forward-looking life-of-loan prediction for loans of the indicated vintage. UFA forecast house prices over the life of each loan vintage. When the Index begins to increase from 2003 on, it is not necessarily because the model expects the indicated vintage to default at high rates immediately. Any increase during the life of the loan will affect the life-of-loan Index value for that vintage. The underlying house price forecasts anticipated the current house price depreciation well in advance and are incorporated into the Index.⁹ The figure suggests that indeed economic conditions could be a major factor in explaining recent history.

1.4 The Model

Recall that our goal is to decompose the rate of foreclosures started in the national serviced portfolio, as reported by the MBA, into an underwriting component and a component arising from economic conditions. The decomposition arises naturally from our multiplicative model, which is a variant of hazard models that are used widely to model defaults.¹⁰ However, the MBA data track the number of foreclosures

8. Many lenders do monitor regional performance of their loan portfolios, but the technology for appropriately integrating local economic conditions into origination and pricing has only recently become available. See, for example, Capozza, Kazarian, and Thomson (1997) and www.ufanet.com.

9. See <http://www.ufanet.com/studiesDeconsAppB.asp> for more details on the sensitivity of the UFA Risk Indices to house prices.

10. See, for example, Capozza, Kazarian, and Thomson (1997, 1998) or Deng, Quigley, and Van Order (2000).

each quarter for all previous vintages. As a result, we must find a way to account for the aggregation of vintages. Let the conditional probability of default for a loan to borrower i , originated at time v in region r , observed at time t be:

$$d_{tr}^{vi} = a(t - v)e^{bX(r,t) + cY^i(r,v) + \delta G(r)}, \quad (1)$$

where $X(r,t)$ is a vector of time-varying covariates that describe the economy in region r at time t , $Y^i(r,v)$ is a vector of characteristics of loans in region r at time of origination, v , $G(r)$ is a vector of variables that are not time varying and describe region r , $a(t - v)$ is the baseline hazard for loan age $t - v$, and b , c , and δ are vectors of coefficients.

In the MBA data, we actually observe d_{tr} , the share of loans in region r that go into foreclosure at time t . It is given by aggregating across individuals and origination years

$$d_{tr} = e^{bX + \delta G(r)} \sum_v \sum_i a(t - v)e^{cY^i(r,v)} / n_{rt}, \quad (2)$$

where n_{rt} is the number of loans originated prior to time t in region r that are still alive at time t . Taking logarithms of both sides:

$$\log(d_{tr}) = bX(r, t) + \delta G(r) + \log \left(\sum_v \sum_i a(t - v)e^{cY^i(r,v)} / n_{rt} \right), \quad (3)$$

which can be simplified to

$$\log(d_{tr}) = bX(r, t) + \delta G(r) + e_t = m_{tr} + \delta_r f_r + e_t, \quad (4)$$

where f_r is a fixed effect for region r , m_{tr} is an economic multiplier that aggregates the information in $bX(r,t)$, and e_t is an error term given by the last term in (3).

There are two parts to the error: (i) changes in underwriting relative to the constant quality loan used in estimating $m(r,t)$, and (ii) the effects of different vintages having different weights. We cannot measure the underwriting changes directly, but we can examine the effects of changes in them over time by decomposing the error term in (4) into time-fixed effects and everything else to get:

$$\log(d_{tr}) = m_{tr} + \delta_r f_r + \delta_t f_t + u(r, t), \quad (5)$$

where f_t is a set of fixed effects for time and u is again complicated. Use of the time effect, δ_t , as our proxy for credit standards means we cannot distinguish changes in loan quality that are deliberate changes in the Y vector from other unobserved changes in loan characteristics.

A shortcoming of the aggregation across vintages is that it risks confusing changes in standards with changes in the historic distribution of loans by vintage and their survival rates. Loan-level data may be able to overcome this limitation in the future as

they become available. Here, we proxy the “multipliers,” m_{tr} , with the UFA Local Risk Index described earlier. This metric conserves degrees of freedom in the estimation.¹¹

Because the m_{tr} are the probability of ever defaulting, they do not apply to the same time period as d_{tr} . For this reason, and because we expect lags in adjustment of d_{tr} to changes in m_{tr} , we estimate versions of (5) where both d_{tr} and m_{tr} are four-quarter moving averages and the right-hand side has lags. The error term, u , is a complicated process, which we represent as an autoregressive process.

We run estimates for different lag structures and lengths as well as for different loan products, for example, prime versus subprime. Our estimated equations are of the form:

$$\log(\bar{d}_{tr}) = \sum_{t=-1}^{-l} \alpha_t \bar{m}(r, t) + \delta_r f_r + \delta_t f_t + \sum_{t=0}^{-q} \gamma_t u_t + \varepsilon_t, \tag{6}$$

where bars over variables indicate a four-quarter moving average of the variable, and l and q are lag lengths.

We consider two lag formulations: one where l is fixed and the weights are unrestricted, and another where l is infinite and the weights decline exponentially, the Koyck lag. It is well known that the Koyck lag leads to:

$$\log(\bar{d}_{tr}) = \alpha_t \bar{m}(r, t - 1) + \beta \log(\bar{d}_{tr}(t - 1)) + \delta_r f_r + \delta_f f_t + \sum_{t=0}^{-l} \gamma_t u_t + \varepsilon_t. \tag{7}$$

2. RESULTS: THE RELATIVE ROLES OF ECONOMIC CONDITIONS AND UNDERWRITING

Our maintained hypothesis is that the slopes are constant across states and time, but there are separate constant terms for each state and time effects, which do not change across states. We estimate variants of (6) and (7) and use the estimated equations to simulate the separate effects of the multipliers, m_{tr} , and the time-fixed effects, δ_t , on foreclosure rates over time. There are versions for all loans and for prime and subprime separately.

We present two versions of our model. Model 1 is equation (6) with four-quarter moving averages and four yearly lags for the multipliers with no restrictions on the lags. Model 2 has a geometrically distributed Koyck lag, equation (7), with the first lagged UFA Local Default Risk Index and the lagged dependent variable on the right-hand side. We also present versions by loan type: prime versus subprime. Time periods vary because the data were not recorded separately for prime and

11. This is especially important for our estimates of subprime and prime equations, because the length of the time series is shorter.

TABLE 1

MODEL 1: FORECLOSURES STARTED VERSUS LAGGED ECONOMIC MULTIPLIERS

	Coefficients			Standard errors		
	All	Prime	Subprime	All	Prime	Subprime
Log lag 1 multiplier	-0.14	-0.22	-0.28	0.08	0.14	0.18
Log lag 2 multiplier	1.00	1.28	1.45	0.10	0.14	0.19
Log lag 3 multiplier	-0.42	-0.82	-0.42	0.14	0.23	0.26
Log lag 4 multiplier	0.59	1.03	0.34	0.10	0.19	0.21
Sum of coefficients	1.04	1.27	1.09			
Number of observations	900	450	450			

NOTES: The dependent variable is the log of foreclosures started by year and region. Independent variables are lags of the UFA Local Risk Indices and year-fixed effects (not reported below). Bolded coefficients are significant at the 5% level. All regressions estimated via restricted maximum likelihood using SAS PROC MIXED, which enables blocking and heterogeneity in the error structure. Blocking was specified by state. The covariance structure is Toeplitz with two parameters.

TABLE 2

MODEL 2: FORECLOSURES STARTED VERSUS UFA ECONOMIC MULTIPLIER WITH KOYCK LAG

	Coefficients			Standard errors		
	All	Prime	Subprime	All	Prime	Subprime
Log lag 1 multiplier	0.46	0.57	0.57	0.02	0.03	0.03
Log lag 1 foreclosures	0.69	0.77	0.66	0.01	0.03	0.02
“Sum” of coefficients	1.47	2.45	1.68			
Number of observations	950	400	400			

NOTES: The dependent variable is the log of foreclosures started by year and region. “Sum” is the first coefficient divided by one minus the second [$1.47 = 0.46/(1 - 0.69)$]. The Koyck lag forces smoothness on the adjustment with a geometrically declining lag structure. In both models 1 and 2 the long-run elasticity of foreclosure with respect to the multiplier is close to one, but larger with the Koyck lag, which implicitly uses all lags rather than just the first four. Bolded coefficients are significant at the 5% level. All regressions estimated via restricted maximum likelihood using SAS PROC MIXED, which enables blocking and heterogeneity in the error structure. Blocking was specified by state. The covariance structure is Toeplitz with two parameters.

subprime until 1998. For the estimates for all loans, our data set is a panel of rates of foreclosures started by state and by quarter from 1979 through 2007. For the separate estimates by subprime and prime, the sample covers 1998–2007. Table 1 presents estimates of model 1 and Table 2 has results for model 2. The year-fixed effects are not shown in Tables 1 and 2.

The last three columns have standard errors of the parameter estimates. Most of the coefficients are significant. In all three cases, effects in the first year are small. The sum of the coefficients is an elasticity of the foreclosure rate to a permanent or ramp change in the UFA Regional Risk Index. Note that the elasticity is close to one for all three product groups suggesting that the UFA Risk Indices are capturing the relevant local economic effects at the right magnitude. It is worth noting that the elasticity for prime loans is higher than for subprime loans. That is, the results confirm that any given change in local economic conditions has a larger percentage impact on prime loans than on subprime.¹²

12. Of course, since the absolute rate for subprime is much higher, the absolute increase will be higher.

2.1 Projections

Next, we use the estimated equations along with the fixed effects to decompose foreclosures into a part due to the economic multipliers and a part due to the year-fixed effects. The year-fixed effects conditional on the multipliers are our estimates of the underwriting component, that is, of default rates after controlling for economic conditions. When normalized, the fitted values from the regression, that is, the difference between the unconditional year indicators (actual yearly foreclosure rates) and the year indicators conditional on economic conditions is an estimate of the economic component. By construction the two add up to the actual level of foreclosures. Figures 7 and 8 present results using model 1 for all loans and subprime loans, respectively.

The estimated variations by product and lag structure all tell a similar story. For this discussion, we focus on “All” foreclosures started, which have the longest time series and deepest data. The dark solid line gives actual foreclosures started relative to the 1999 baseline. The light dotted line is the part due to economic conditions, that is, how foreclosures would have moved had underwriting not changed. The declining curve indicates that economic conditions promoted lower foreclosures until 2004. The medium dashed line shows the contribution of underwriting, that is, how foreclosures would have changed had economic conditions not changed, which was positive early in the period, negative later, and sharply positive in 2006–07. For example, in Figure 7, the medium dashed curve for underwriting in 2004 is 1.0, while actual defaults are 0.25 and the economic conditions index is -0.75 . The interpretation is that while actual default rates rose 25% from 1990 to 2004, if economic conditions had not been so favorable, foreclosures started would have risen by 100% instead of 25%. Stated differently, underwriting quality eroded enough to double the level of foreclosures started by 2004, but only a 25% increase was realized because favorable economic conditions offset three-fourths of the potential increase. During this period, house prices appreciated steadily in most of the country.

Note that the underwriting effects refer to the year in which the loans are observed, not the year in which they were originated. The poor underwriting results in 2006 and 2007 are for loans that were originated earlier. The figure suggests that the post-2005 increase in foreclosures can be apportioned about equally between the underwriting and economic conditions as of the beginning of 2008.

The recessions of the early 1990s and of 2001–02, when unemployment was rising, are visible in the light dotted local economic conditions curves of Figures 7 and 8, but they are dominated by the other very favorable economic effects like rising house prices. Both recessions were accompanied by brief periods when underwriting standards tightened as reflected by declines in the medium dashed underwriting curves, confirming that lenders do respond to recent loan performance by adjusting underwriting standards.

The spectacular increase in foreclosures after 2005 is unprecedented in the data since 1979. Economic conditions and underwriting quality typically moved in opposite directions in the 1990s. This negative correlation is consistent with lenders becoming more conservative when economic conditions are weak. However, after

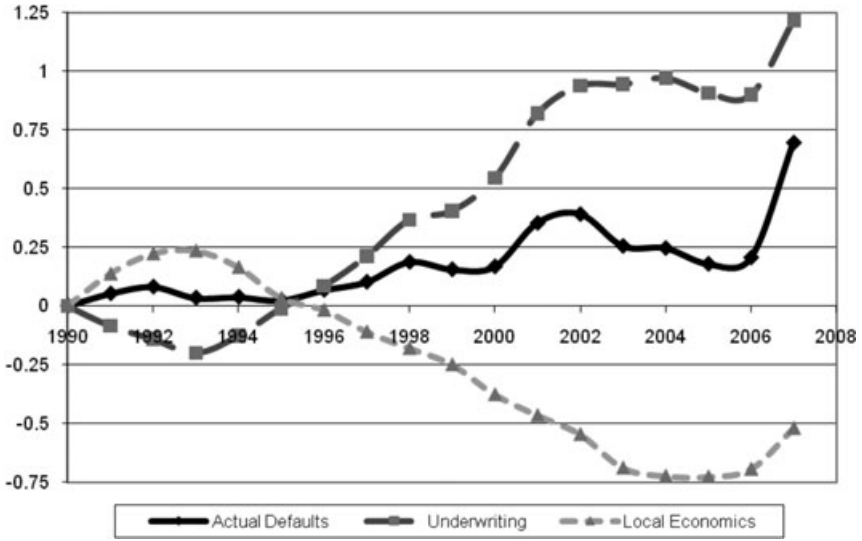


Fig. 7. All Foreclosures Started: 4-Year Distributed Lag.

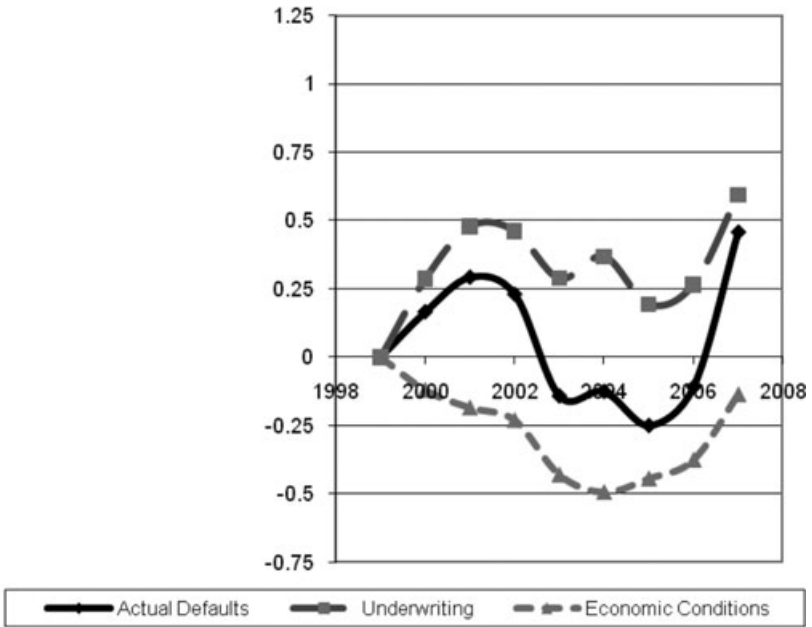


Fig. 8. Subprime Foreclosures Started: 4-Year Distributed Lag of Multipliers.

SOURCE: University Financial Associates LLC.

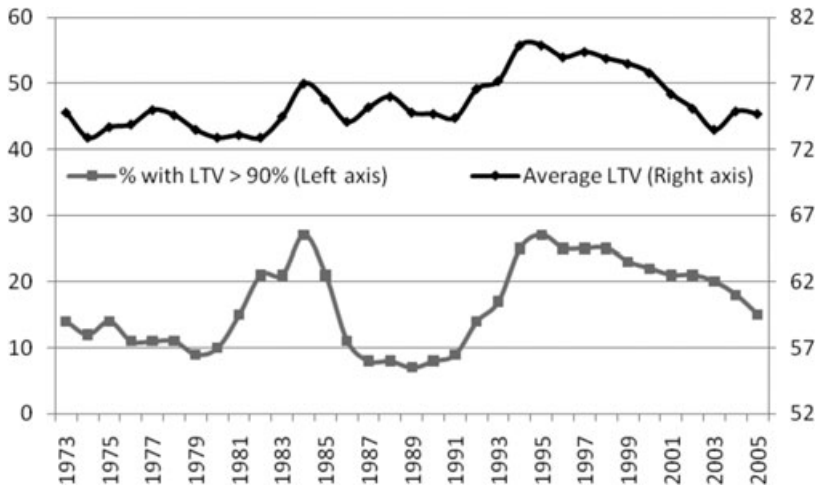


FIG. 9. Long-Run Trends in Loan-to-Value Ratio (%).

SOURCE: Federal Housing Finance Agency: Mortgage Interest Rate Survey.

2002–05, economic conditions and quality both deteriorated, breaking the earlier pattern and suggesting a possible structural break or regime shift in this market that is consistent with a moral hazard story. The post-2005 increase in foreclosures can be apportioned about equally between the underwriting and economic conditions explanations.

3. UNDERWRITING QUALITY: OBSERVABLES OR UNOBSERVABLES?

The results in the previous section attribute about half of the recent explosion in foreclosures to changes in underwriting. In this section, we present indirect evidence that suggests that the most important observable underwriting risk factors actually improved in recent years. This implies that much of the increase in defaults in recent vintages arose in covariates that are usually unobservable to investors in securitizations, although they may be known to the originator.

3.1 Underwriting and Moral Hazard: Changes in Loan Characteristics

Figure 9 shows average LTV and share of loans with LTV greater than or equal to 90% for all loans originated from 1973 through 2005. There have been cycles in LTV since the 1970s. The LTV distribution worsened in the first half of the 1990s. The average LTV rose from 0.75 to 0.80 and the proportion of loans with LTV above 90 reversed its earlier slide but improved subsequently.

Table 3 displays market shares of originations by major loan category. It shows a sharp increase in nontraditional loans, viz., subprime, Alt-A, and home equity after

TABLE 3
MARKET SHARES OF SINGLE FAMILY ORIGINATIONS BY LOAN TYPE

Year	FHA&VA	Conventional conforming	Jumbo	Subprime	Alt-A	Home equity loans	Total (\$billion)
2001	7.4%	57.2%	19.4%	8.6%	2.7%	4.6%	2,215
2002	6.4%	59.3%	20.0%	8.0%	2.4%	3.9%	2,885
2003	5.8%	62.4%	16.6%	8.5%	2.2%	4.6%	3,945
2004	4.6%	41.4%	17.6%	18.5%	6.8%	11.0%	2,920
2005	2.7%	35.0%	18.3%	20.0%	12.5%	11.5%	3,120

NOTE: FHA = Federal Housing Administration; VA = Veteran's Administration.
SOURCE: Inside Mortgage Finance, The 2006 Mortgage Market Statistical Annual Volume 1.

2003. This sharp increase raises the question of whether such a large increase could have been accomplished so quickly without a major deterioration in loan quality.

Chomsisengphet and Pennington-Cross (2006) present data on characteristics of subprime loans originated from 1995 through 2004, using data from Loanperformance.com. Their data show a similar but mixed pattern of LTV over time. Most important is their data on distributions of credit scores. The share of loans with very low credit scores (below 500) dropped continuously throughout the period, from an initial level of around 70% to around 10% by 2004; the share between 500 and 600 increased in the first half of the period and declined after 2000. Hence, there was a general trend from more lax standards on credit and LTV in the late 1990s to generally tighter standards by 2004.

Table 4 presents more complete data on characteristics of nonagency loans in mortgage-backed security pools, combined by origination year. The data are grouped in a manner similar to the MBA data: all mortgages, subprime mortgages, and everything but subprime mortgages.

The data are paradoxical. The steeply rising level of defaults after 2005, even after controlling for local and national economic conditions leads us to expect erosion in the most important credit variables such as LTVs and bureau scores in advance of the spike, but we do not see it. The only credit variable in the table that suggests lower credit standards is the decrease in full documentation. Other indicators not reported in the table, such as the share of loans that were for cash-out refinancing showed no trend.

It is also the case that the subprime market increasingly emphasized adjustable rate mortgages (ARMs). It may have been that rate resets were a factor, but with the exception of a brief surge in the fall of 2008 the rate to which they were mostly indexed, London InterBank Offer Rate (LIBOR), has fallen over the period. Figure 10 presents cumulative foreclosure rates for subprime and Alt-A loans by origination year from Cutts and Merrill (2008). Extremely high foreclosure rates occur in the early months of the loans for the worst origination years. These foreclosures were realized well before rate resets, which were typically after 2 or 3 years. Both the initial interest rates and the margin on subprime ARMs fell through most of the period, which suggests that the loans should perform better than earlier vintages

TABLE 4
 LOAN CHARACTERISTICS AT ORIGINATION BY VINTAGE: NONAGENCY MORTGAGES

		All									
		2000	2001	2002	2003	2004	2005	2006	2007	2008	
ARM share	%	41%	31%	51%	50%	70%	66%	62%	51%	64%	
Coupon ^a -if ARM	%	10.2	8.7	7.5	6.5	6.4	6.9	7.9	7.7	6.4	
Margin ^b -if ARM	%	5.6	5.2	5.2	4.6	4.5	4.8	4.8	4.0	2.3	
Coupon ^a -if FRM	%	9.6	8.0	7.5	6.4	6.7	6.7	7.5	7.2	6.7	
Credit score		629	672	663	679	666	668	664	682	750	
% full documentation	%	57%	62%	64%	57%	56%	47%	41%	38%	59%	
Combined LTV ^c	%	77%	76%	75%	74%	77%	77%	77%	76%	73%	
%LTV ≥ 90	%	19%	19%	20%	17%	20%	16%	17%	16%	8%	
		Not subprime									
		2000	2001	2002	2003	2004	2005	2006	2007		
ARM share	%	30%	24%	43%	44%	67%	61%	57%	48%		
Coupon ^a -if ARM	%	9.2	7.6	6.5	5.7	5.8	6.4	7.4	7.3		
Margin ^b -if ARM	%	4.5	4.1	4.0	3.7	3.8	4.1	4.1	3.3		
Coupon ^a -if FRM	%	8.9	7.7	7.1	6.1	6.4	6.5	7.2	6.9		
Credit score		700	712	708	713	702	703	698	709		
% full documentation	%	57%	60%	58%	52%	48%	38%	30%	30%		
Combined LTV ^c	%	76%	74%	74%	72%	77%	76%	77%	76%		
%LTV ≥ 90	%	18%	16%	17%	15%	18%	14%	14%	14%		
		Subprime									
		2000	2001	2002	2003	2004	2005	2006	2007		
ARM share	%	52%	52%	68%	71%	79%	81%	75%	64%		
Coupon ^a -if ARM	%	10.8	10.0	9.1	8.0	7.7	7.8	8.8	8.9		
Margin ^b -if ARM	%	6.3	6.6	6.8	6.4	6.2	6.3	6.2	6.2		
Coupon ^a -if FRM	%	10.8	9.6	9.1	8.0	7.7	7.9	8.9	9.1		
Credit score		556	562	565	568	571	574	575	573		
% full documentation	%	57%	70%	77%	73%	75%	71%	69%	69%		
Combined LTV ^c	%	78%	80%	79%	78%	79%	78%	79%	78%		
%LTV ≥ 90	%	20%	28%	25%	23%	25%	23%	25%	24%		

NOTES: This table summarizes selected loan characteristics of a large database of most (70–80%) securitized, nonagency mortgages originated from 2000 to 8 from LPS Applied Analytics. The table includes only first mortgages on residential properties. Where there are reported second mortgages they are included as a part of Combined LTV. The mortgages are a combination of subprime, Alt-A, and loans above the limit allowed for purchase by Fannie Mae and Freddie Mac. FRM = fixed-rate mortgage.

^a Coupon is the rate on the loan if an ARM it is the initial rate.

^b Margin is spread of rate on the loan over index to which the ARM rate is indexed. Most ARMs have fixed initial rates for a year or more, so the loan only attains the full index rate over time. For instance for subprime loans, the initial rate might be 6.6% (see 2005) and fixed for 2 years, but after than set at LIBOR plus 5.0%.

^c Combined LTV is loan-to-value ratio including second mortgages if reported.

because lower interest rates reduce the payment burdens for homeowners. Thus, it does not appear that ARM characteristics *per se* were an important factor for foreclosure; however, ARMs may be a signal of risky borrowers, and their increasing share an indicator of increased risk.

While we do not have direct evidence of moral hazard in originations during this period, we do know that borrowers with unverifiable or nonexistent income or assets would naturally gravitate toward low or no documentation loans. Dropping the important verification step from the underwriting process opens the mortgage

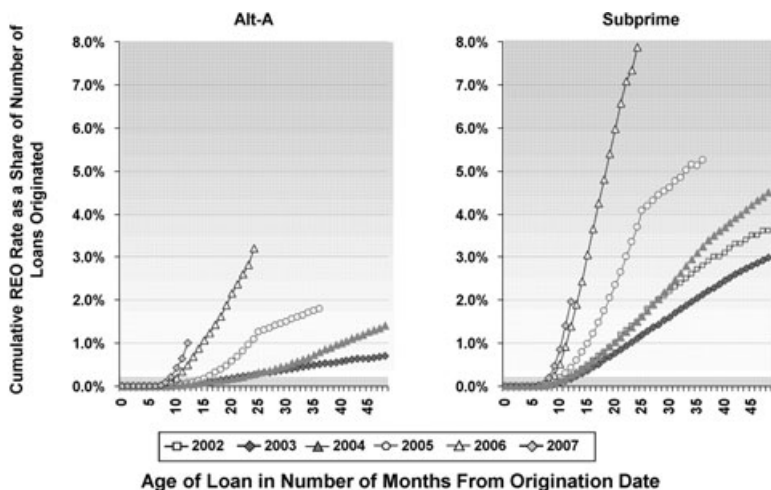


FIG. 10. Cumulative REO Rates for Alt-A and Subprime Mortgages by Vintage.

NOTE: Data represent cumulative number of loans where borrowers lost the property by origination year divided by number of loans originated that year in the data base.

SOURCE: Cutts and Merrill (2008).

window to large numbers of borrowers who would not qualify ordinarily. Unobservable borrower quality could drop precipitously and investors would be unaware for months or years before worsening performance became high enough to reveal that a significant change in borrower quality had occurred.

3.2 Securitization and Moral Hazard: Changes in Funding

Although the mortgage debacle is often attributed to the rise of securitization, and the separation of loan origination from investment and risk taking, securitization is not new. It has been pervasive in the U.S. mortgage market for decades and until recently has been dominated by three “Agencies,” Fannie Mae, Freddie Mac, and Ginnie Mae. Historically, the Agencies have generally had good performance. In particular, the closest substitute for subprime loans, government insured loans with lower implicit bureau scores, and higher LTVs have been securitized by Ginnie Mae since the 1970s without significant problems.

While securitization is not new and subprime mortgages are not new, securitizing subprime mortgages is relatively new. Although nonagency mortgage-backed securities (mostly jumbo loans) had been 15–20% of total securitizations since 1991, they leapt from 20% in 2003 to over half in 2006 (see Figure 11). This increase is largely the bundling of the surge in subprime and Alt-A loans.

Securitization of subprime loans is more difficult than securitization of prime loans because subprime default rates are higher, and more important, their valuation is more sensitive to small mistakes in underwriting. This made them harder to sell to investors, particularly institutional investors who are justifiably concerned with being sold “lemons” by more knowledgeable originators and investment bankers.

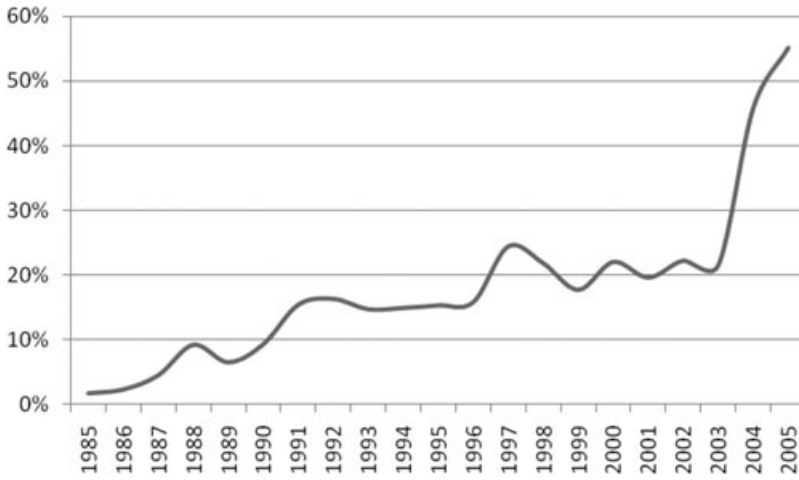


FIG. 11. Market Share of Nonagency (Not Fannie Mae, Freddie Mac, or Ginnie Mae) Securitization.

To mitigate the lemons problem securitizations were structured by dividing the risk in the securities so that some investors took the first loss via “subordinated” pieces or “tranches” while others held “senior” tranches that could earn AAA ratings despite the low quality of the loans in the pools. This approach satisfied the institutional investors and enabled 80% of the loans to be securitized by 2005.

Structuring has sometimes worked well, but the subprime and Alt-A structures can be very difficult to understand. The parts of the deals that are most important are the subordinated pieces, which carry the bulk of the risk. The problem is that these pieces were not always easy to sell and were quite often resecuritized into similar security structures with senior and subordinated parts. In some cases, pieces of these deals were securitized again, making them even more difficult to assess (see Gorton 2008, Gerardi et al. 2008). In particular, the path from specific tranches of subprime deals back to the loans securing them and in turn to the likely costs to the investors is very opaque.

The obfuscation was an open invitation to moral hazard at origination. This can be viewed as a variation on the “Lucas Critique” (see Lucas 1976), which argued against trying to predict the effects of a change in policy using relationships observed in past data. The basic idea is that the parameters of historical models are not truly structural and are apt to change with changes in policy regime. In this case, default models based on historic underwriting practices should not be used to evaluate loans delivered by sellers who have no stake in the loans and who are willing to exploit their better information. These sellers can deliver the worst loans that meet the standards set by the models of investors or rating agencies. The increased share of loans with low documentation probably facilitated this process.

For example, investors and rating agencies can see the ratio of loan value to property “value,” but they cannot see if the property appraisals were overstated, particularly for borrowers refinancing existing mortgages to take out equity. They can

tell whether or not loans are fully documented, but they cannot tell if the consequences of low documentation (“liar loans”) have changed over time. Nor can they always tell whether the borrower will actually occupy the house rather than rent it or whether the down payment was “gifted.” They also cannot tell if borrowers are taking out large unreported second mortgages (“silent seconds”) in addition to the first mortgages. The latter could be a major problem. For instance, Ashcraft and Schuermann (2007) present some aggregated data (see their Table 5) that document a sharp increase in the share of silent seconds after 2003. This suggests that the combined LTV data available to investors in our Table 4 understated actual leverage.

Some recent work by Keys et al. (2010) presents indirect evidence of moral hazard. Six hundred and twenty is a special credit score because loans with scores above 620 are more likely to be eligible for Agency purchase. Historically, credit scores have been a good predictor of default. Keys et al. analyze defaults on loans just above and below 620. They control for a range of other factors but find that loans just above 620 actually performed worse than those just below 620. Investors in pools can observe the hard data such as credit score or LTV but not the soft data. They conclude that the soft data were treated differently just above 620 in order to keep loans eligible for Agency pools. Clearly, there is a lot of work left to be done fleshing out the role of moral hazard.

3.3 *Limitations*

The data that we have impose several limitations. First, because we do not have data by vintage we have put vintage effects into the disturbance. We do, however, model the errors as an autoregressive process to mitigate the problems from aggregating across vintages.

Second, because our data set does not have loan-level data, we cannot control for changes in observable loan characteristics (such as credit score, LTV, etc.) directly, which would be useful in making the case that our time effects are due to moral hazard. We instead argue from the summary data cited above (see Table 4) that observable characteristics of loans in the aggregate do not appear to have changed very much during the recent high foreclosure period. The important exception is the share of loans with low or no documentation, which did increase. This is consistent with the moral hazard story in the sense that the low documentation is a way to hide the moral hazard. For example, when borrowers are not asked the source of the down payment, it is easier for second mortgages to be “silent.”

Our empirical results are consistent with the underlying hypotheses, but more detailed data will be required to eliminate other explanations. We get similar results for both prime and subprime loans; however, interpretation must be cautious because our data do not separate Alt-A from other prime loans.¹³ There is evidence that Alt-A, though not as bad as subprime, performed much worse than other prime loans.

13. Note that our estimates are in logs, so similar coefficients mean similar multiplier effects, but subprime and Alt-A are much larger numbers to begin with, so their effects in levels are much bigger.

4. COMMENTS AND CONCLUSIONS

The long-standing deterioration in foreclosure rates since 1979 was marked by two periods. The first was accompanied by a lowering of standards such as LTV ratios in the 1990s. The second change, which was not seen in observable loan characteristics such as down payment and credit history, was associated with the rise of the subprime market and nonagency securitization after 2000.

The surge in defaults after 2005, especially subprime defaults, was undoubtedly the result of several factors operating at once. Unfortunately, available metrics do not monitor the causes of default effectively. In this research, we develop a methodology for separating the sources of default into a component due to local and national economic conditions and a residual component that can be attributed to underwriting quality. The model and empirical analysis enable us to create indices of both underwriting quality and economic conditions for mortgage loans. These indices should be valuable to policymakers and investors who wish to monitor or assess the risks in mortgage pools and mortgage markets.

The results indicate that the surge in defaults through 2007 was equally caused by economic conditions and underwriting quality. Aggregate data on observable loan characteristics after 2000 show little evidence of erosion during the problematic years, suggesting that most of the recent decline in underwriting quality occurred in the unobservables.

The analysis is consistent with the following interpretation of events: the long-run trend since the 1970s of technical progress in underwriting and pricing of mortgages enabled lenders to gradually buy deeper into the credit spectrum. The performance history, especially in the 1990s, suggested that subprime and Alt-A performance was tolerable and could be priced, that credit score and LTV-based underwriting models worked well, and that nationally diversified pools of mortgages were safe. This made extending securitization into nontraditional areas look promising. However, the favorable economic conditions of the 1990s made mortgage lending look better than the reality. When economic conditions reversed and house prices began falling in most of the country, diversified pools were not of much help. At the same time, securitization invited moral hazard in ways that credit scores and LTV could not detect.

APPENDIX: THE LOCAL RISK INDICES

The indices of local economic conditions (the “multipliers”) are created from estimates of hazard equations for prepayment and default using a proprietary loan level data set of subprime mortgages. The estimated equations are of the form:

$$d_{tr}^{\tau si} = a(s)e^{bX(r,t) + cY^i(r,\tau) + dG(r)}, \quad (\text{A1})$$

$$p_{ir}^{\tau si} = a(s)e^{bX(r,t) + cY^i(r,\tau) + dG(r)}, \quad (\text{A2})$$

where d and p are probabilities during a quarter of the loan defaulting (d) or prepaying (p) on a loan to borrower i , originated at time τ in region r that is s periods old and is observed at time t , and $X(r,t)$ is a vector of time-varying covariates that describe the economy in region r at time t , $Y^i(r,\tau)$ is a vector of characteristics of loans in region r at time of origination, $G(r)$ is a vector of variables that are not time varying and describe region r , and a , b , c , and d are vectors of coefficients. The estimates of these two equations use current and lagged values of $X(r,t)$.

The model then uses current and forecast data of $X(r,t)$ to estimate balance-weighted defaults and prepayments over time in each region for a representative subprime mortgage, holding the Y variables (loan characteristics) constant. The probability of *ever defaulting* on a loan originated at time t in state r is estimated from the summation of the balance-weighted conditional default probabilities over the life of the loan.

The average performance of the 1990s is set to 100, and yearly values of the index are relative to this baseline. Increases in the index correspond to increases in the probability of default. Changes in the index over time and by region are excellent proxies for the regional multipliers, $m(r,t)$, in equation (4). The indices provide a panel of metrics for the effect of regional economic conditions on the performance of mortgage loans over time and regions.¹⁴

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