The Great Surge in Mortgage Defaults 2006-2009: The Comparative Roles of Economic Conditions, Underwriting and Moral Hazard

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June 2010

Abstract

In this paper we present two versions of a mortgage default model from two data sets and use the models to decompose the causes of the recent surge in defaults. We do this first by looking at aggregate data (foreclosure rates by state). With these data we decompose defaults into shares attributed to economic conditions and a time trend, which we interpret as changes in underwriting. We find approximately a 50-50 split between the two. We then turn to a large and rich sample of individual loans originated from 2000-2007 to look at the split in more detail. With these data we can observe the information available to investors and control for observable underwriting as well as economic conditions. We can also use the data to infer the share due to moral hazard. Estimates from these data suggest that most of the variation was due to economic conditions and rather little was due to observable underwriting changes and moral hazard.

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Introduction and Overview

In this paper we present estimates of a mortgage default model from two data sets and use the models to decompose the causes of the great surge in defaults from 2006-2009. We do this first with aggregated data (foreclosure rates by state) that go back to the 1990s. With these data we decompose defaults into those caused by economic conditions and those caused by underwriting, which we can only measure indirectly, using fixed effects for observation year. This decomposition suggests 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. After 2002 the favorable economic conditions that had masked underwriting deterioration changed, and defaults increased sharply.

We next turn to a more recent set of data that contains loan level information on mortgages in non-agency (not Fannie Mae, Freddie Mac or Ginnie Mae) mortgage-backed securities that were originated from 2000-2008. This data set includes the underwriting characteristics that were known to investors in the pools. With these data we decompose defaults into three parts: those due to worsening of economic conditions, those due to observable changes in underwriting standards, and a set of time varying fixed effects that we identify as moral hazard.

We identify moral hazard by looking for discontinuities or “notches” in default behavior. The underlying economics suggest that default should be a continuous function of underlying variables like loan to value ratio (LTV) and credit score, as well other, harder-to-observe variables. However, pricing and screening tend to be done over discrete intervals in the form of pricing and underwriting matrices. The conditions for moral hazard occur when loan sellers and securitize have access to better information than that available to investors. The question is: what sorts of mortgages will be delivered by traders with asymmetric information?

An 80% LTV and a 620 credit (FICO) score appear to be critical minimum standards of quality because an LTV above 80 requires insurance, and at least a 620 FICO is generally required for agency purchase. Our hypothesis is that loan sellers who possess superior information relative to investors will tend to deliver loans that just meet these minimum standards. Because of these cutoff points in the standards for loan quality, we expect to see notches in the default function at or around these points.

We do indeed find notches, particularly at 80% LTV. However, we find that they are not especially important in explaining the surge in defaults, which appears to be due primarily to deteriorating economic conditions, particularly house price declines, which had
previously been very favorable. Because economic conditions were so favorable, they masked, or perhaps even contributed to, a trend of deteriorating underwriting conditions.

In the next section we document the great surge, its implications for both prime and subprime loans, and the concurrent economic conditions, especially house prices. The third section develops and estimates models of default using the aggregate and loan level data sets. Each model is then applied to extract two types of estimates of the importance of economic conditions, underwriting and moral hazard in the great surge.

Background and Summary Data

The Long Run Trend in Foreclosures

Figure 1 graphs the time series of foreclosures started as a percent of the outstanding number of loans from 1979 through 2010. There is a rising trend with occasional leveling off. Between 1979 and 2002 foreclosure rates quadrupled from .48 to 1.96%. In an impressive surge from 2006-9, foreclosure rates almost quadrupled again from 1.60 to 5.68% in just three years. Our purpose with this research is to analyze the available data to enable a deeper understanding of both the trend and the surge.

Figure 1: All Foreclosures Started: U.S. 1979-2010 Quarterly Data

Four quarter averages annualized
Source: Mortgage Bankers Association National Delinquency Survey
The deterioration in mortgage performance has varied by loan type. Figure 2 presents data for 1998-2010 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. Note in particular the history of subprime. Foreclosures fell after the 2001 recession but then increased sharply after 2005. A similar pattern, but on a smaller scale and with about a one year lag, occurred 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 respond more quickly to financial stress than prime borrowers.

Figure 2: Rate of Foreclosures started by loan type, 1998-2010 (%)
Source: Mortgage Bankers Association National Delinquency Survey

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 collateral. One implication of this approach is that the put option should be sensitive to the value of the collateral.

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1 The MBA data do not track how many actually went through foreclosure to REO, real estate owned by lenders.
2 Subprime responds earlier; but, the eventual total response is smaller in percentage terms than for prime loans, albeit much larger in absolute terms.
3 The early example is Findlay and Capozza, 1977.
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 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 1975-1997 within a narrow range. However, during the boom years from 1997-2007, 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 3: Real and Nominal House Price Indices, 1975-2008 (2008=1.0)
Source: FHFA

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) is that real house prices appreciate at rates close to zero over decades and centuries. Thus the 4-6% annual appreciation rates of the last decade are extraordinary.
Figure 4: U.S. Real House Price Appreciation, 1992-2010
Seasonally adjusted, purchase only index, quarterly data, four quarter price changes.
Source: FHFA

Figure 5 illustrates the variation in house prices for selected metro areas. It shows the extreme ups and down of some the metro areas like San Diego and Miami that had price “bubbles.” These areas currently have high foreclosure rates following price declines. 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 in the MBA serviced portfolio data.
A Summary Statistic for Economic Conditions

The figures above highlight the historical effects of economic conditions on foreclosures. In the analysis that follows we split foreclosure rates into components arising from underwriting policy and changes in economic conditions. As a summary measure of economic conditions we use the quarterly "ForeScore" Default Risk indices by state compiled by University Financial Associates (UFA), which track the effect of local and national economic conditions on the probability of a constant quality loan ever defaulting. The UFA indices begin with a model of default, using both local conditions and loan characteristics to explain default. The index holds the loan characteristics constant and projects the impact of economic conditions on default. House price changes are the most important driver of the indices with other economic, demographic, political and topographic variables explaining the balance. The indices enable parsimonious estimation of the equations that follow. The Appendix provides a more detailed explanation.

Figure 6 illustrates one use of the index to track nation-wide 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 290, i.e., the variation in economic conditions has been sufficient to cause a quadrupling of default rates from trough to peak during the last decade on a constant quality loan.
Figure 6: The Effect of Economic Conditions on Mortgage Performance by Origination Year: The UFA Default Risk Index by Vintage

Higher values of the Index indicate a less favorable economic environment and higher expected defaults for the constant quality mortgage. See the appendix for a detailed explanation.

Source: University Financial Associates LLC

There have been two trends in the Default Risk 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. The projections in the figure use actual data to the extent they are available, and then (for recent indices) use forecasts, e.g., of 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 figure suggests that indeed economic conditions could be a major factor in explaining recent history.

Default Models

We estimate variations of the same model with two data sets: the first is from the Mortgage Bankers Association and is longer, but aggregated by state; the other is a sample of non Agency pools, which is shorter (since 2000) but has large amount of loan level data. Our model is as follows:
Let the conditional probability of default for a loan to borrower \( i \), originated at time \( v \) in region \( r \), observed at time \( t \) be:

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

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 \( t-v \);

\( b, c \) and \( \delta \) are vectors of coefficients.

**Model I**

With the non Agency pool data we have a panel that allows us to estimate (2). With the MBA data we do not observe individual loans, nor do we know origination year, so we observe only \( d_{tr} \), the share of loans in region (state) \( r \) that go into foreclosure at time \( t \). We call this Model I. It is given by aggregating across individuals and origination years

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

where \( n_{rt} \) are is the number of loans originated prior to time \( t \) in region \( r \) that are still alive at time \( t \). This is what we estimate first.

Taking logarithms of both sides of (3):

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

which can be simplified to

\[
\log(d_{tr}) = bX(r,t) + \delta G(r) + e_t = m_{tr} + \delta_r f_{r} + e_t
\]

where \( f_{r} \) is a fixed effect for region \( r \) and \( m_{tr} \) is the ForeScore index that applies to loans originated in state \( r \) at time \( t \), and \( e_t \) is an error term.

The error term is quite complicated. It is a weighted average of underwriting characteristics of the pool of loans across the different vintages. We can decompose the error term in (5) into time fixed effects and everything else to get:
\[
\log(d_{tr}) = m_{tr} + \delta_r f_r + \delta_f f_t + u(r, t)
\]

where \( f_t \) is a set of fixed effects for time and \( u \) is again complicated. Use of the time effect, \( f_t \), 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 this 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.\(^4\)

Because the \( m_{tr} \) are the probability of ever defaulting they do not apply to the same time period as \( d_{tr} \); and because we expect lags in adjustment of \( d_{tr} \) to changes in \( m_{tr} \), we estimate versions of (6) where both \( d_{tr} \) and \( m_{tr} \) are four quarter moving averages and the right hand side has lags. We allow \( u \) to be an autoregressive process, and include state fixed effects.

We estimate equations of the form

\[
\log(\bar{d}_{tr}) = \sum_{t=-1}^{l} \alpha_t \bar{m}(r,t) + \delta_r f_r + \delta_f f_t + \sum_{t=0}^{q} \gamma_i u_i + \varepsilon_i
\]

where bars over variables indicate a four-quarter moving average of the variable, and \( l \) and \( q \) are lag lengths. From (6) we should expect the sum of the coefficients of \( \bar{m}(r,t) \) in (7) to be close to one.

**Results for MBA data: The relative roles of economic conditions and underwriting**

In Table 1 we present estimates of (7) and use the estimated equations to simulate the separate effects of the multipliers, \( m_{tr} \), and the time fixed effects, \( f_t \), on foreclosure rates over time. There are versions for all loans and for prime and subprime separately. See Anderson et al. (2010) for a more detailed description of the model.

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\(^4\) We also do not consider the possibility that the time fixed effects might be due to changes in borrower behavior, such as an increased willingness to default.
Table 1: Model I: Foreclosures Started vs. Lagged Economic Multipliers

The dependent variable is the log of foreclosures started by year and region. Independent variables are lags of the UFA Economic Multipliers. Bolded coefficients are significant at the 5% level.

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>All</th>
<th>Prime</th>
<th>Subprime</th>
<th>Coefficients</th>
<th>All</th>
<th>_Prime</th>
<th>Subprime</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 1 year</td>
<td>-1.4</td>
<td>-0.22</td>
<td>-0.28</td>
<td>0.08</td>
<td>0.14</td>
<td>0.18</td>
<td></td>
</tr>
<tr>
<td>Lag 2 year</td>
<td>1.00</td>
<td>1.28</td>
<td>1.45</td>
<td>0.10</td>
<td>0.14</td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td>Lag 3 year</td>
<td>-0.42</td>
<td>-0.82</td>
<td>-0.42</td>
<td>0.14</td>
<td>0.23</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td>Lag 4 year</td>
<td>0.59</td>
<td>1.03</td>
<td>0.34</td>
<td>0.10</td>
<td>0.19</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td>Sum of coefficients</td>
<td>1.04</td>
<td>1.27</td>
<td>1.09</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The last three columns have standard errors of parameter estimates. Most of the coefficients are significant. In all three cases, effects in the first year are small. The sum of the coefficients of \( \bar{m}(r,t) \) is close to one for all three product groups, suggesting that the UFA economic multipliers are capturing the relevant local economic effects at the right magnitude. It is worth noting also 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.5

Simulations

Next we use the estimated equations along with the fixed effects to decompose foreclosure rates 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, i.e., of default rates after controlling for economic conditions. When normalized, the fitted values from the regression, i.e., difference between the unconditional year indicators (i.e., the actual yearly foreclosure rates) and the year indicators conditional on economic conditions is an estimate of the economic component. By construction the two

5 Of course, since the absolute rate for subprime is much higher, the absolute increase will also be higher.
add up to the actual level of foreclosures. Figure 7 presents results using Model 1 for all loans.

**Figure 7: All Foreclosures Started: 4-yr distributed lag**

The yellow line gives the part due to economic conditions (how foreclosures would have moved had underwriting not changed), which promoted declining foreclosures until 2004. The pink line shows the contribution of underwriting (how foreclosures would have changed had economic conditions not changed), which was positive early in the period, negative later and sharply positive in 2006 to 2007. For example, in Figure 7 the red 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 ¾ 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.

The spectacular increase in foreclosures after 2005 is unprecedented in the data. 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 2002-2005, 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 data suggest that the post 2005 increase in foreclosures can be apportioned about equally between the underwriting and economic conditions explanations.

Model II: Loan Level Data

In this section we present results for Model II, which uses a large set of individual loans to estimate a full version of equation (2). The data come from non Agency or “private label” securities, and they include prime, subprime and Alt-A loans. While that data set is richer than the one used in model I, it covers a shorter time span, loans originated from 2000 through 2007. It turns out that despite problems with the data in Model I, Model II gives very similar results, except that the underwriting share is lower once we control for vintage effects.

Because the data provide everything that is available to investors we can use fixed effects to try to tease out information about moral hazard as well. In Model I we measured all underwriting effects by fixed effects for time. This was problematic both because we could not control for origination year and vintage effects and because we could not separate effects into those known to investors and those not known. Here we can control for both and we can look at what is left over to find sources of moral hazard.

Moral Hazard

Moral hazard can be viewed as an example of the “Lucas Critique” (see Lucas (1976)), which argued against trying to predict the effects of a change policy using relationships observed in past data. The basic idea is that the parameters of historical models are not

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6 The loan categories are identified by the corresponding identity of the pools they belong to. The prime loans are primarily “jumbo” loans, which are above the maximum loan size eligible for Agency purchase.
truly structural and are apt to change with changes in policy regime. Default models based on historic underwriting practices that are used to evaluate loans originated under different underwriting policies are subject to severe parameter deterioration.

For example, investors and rating agencies tend to use models to evaluate loans and they tend to take the data as given. Lenders and dealers generally know the models and view them as constraints against which they deliver. In this arrangement there is considerable room to game the investors and rating agencies. For instance, investors 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”. And they cannot tell if borrowers are taking out large unreported second mortgages in addition to the first mortgages (aka “silent seconds” which are recorded after loan has been sold).

We cannot observe moral hazard directly with our data, but we can try to identify it. We do so by looking at “notches,” as described in section I. That is, without other constraints, default is likely a continuous function of variables like down payment and credit score, but notches in the default function are indicative of a “cheapest to deliver” model of moral hazard. An illustrative example for credit score is graphed in Figure 8.

Figure 8: Notches in risk variables

More formally, consider our basic equation, repeated here:
Assume there is a true version of this, but we estimate a version with available data where we do not have all of the underwriting variables, X. Specifically, assume that one of the underwriting variables is the degree of documentation, a zero or one variable for full documentation or low documentation. As a result there are really two models, depending on documentation. The case where documentation=1 (low doc) is not just a case where the default curve is higher, it is also one where the coefficients are different because items like income and LTV, for which low documentation might be important, will be less predictive.

If the model used for underwriting is estimated from data containing only documented loans, it will provide a biased estimate of the true model; and it will enable those with better information about the true model to deliver lower quality mortgages that still satisfy underwriting standards of investors or rating agencies. Similar stories apply to rating agencies that use historical models, especially when the investment bankers who create the pools have access to the models used by the rating agencies.

At the same time, for both transaction cost and regulatory reasons, pricing and underwriting decisions are often discontinuous (see Bubb and Kaufman (2009). For instance, regulations generally require that loans with LTVs above 80 have insurance, which is costly and provides no benefit to the borrower. It has been argued that 620 is a special level of FICO score because it was a de facto minimum for acceptance by Fannie Mae and Freddie Mac. Hence, there are incentives to deliver loans with LTVs less than or equal to 80% and FICO scores that are just above 620. Furthermore, because pricing is in discrete intervals there is little incentive to borrow at LTV less than 80.

Recent work by Keys et al. (2007) presents indirect evidence of moral hazard. They found that the loans just above 620 actually performed worse than those just below 620, suggesting that loan sellers manipulate the either the credit scores or the unobservable data so that borrowers can be above the Agency hurdle.

For 80% LTV loans the moral hazard scenario is to deliver loans with higher but hidden LTVs. One vehicle for doing this is a “silent second,” which hides the second mortgage and is abetted by the low documentation, which does not require documenting source of down payment. There is some evidence (see Ashcraft and Scheuerman) that there was a steady increase in the share of silent seconds after 2002 in private pools (see their Table 5)\(^7\) We

\(^7\) This share comes from going back after the fact to look second mortgages taken out shortly after origination but acknowledged in pools. See

\[ d_{tr}^{vi} = a(t-v)e^{bX(r,t)+cY^i(r,v)+\delta G(r)} \]
cannot observe these with our data set, but we should expect these loans to have observed LTVs at 80, and we should expect the effect to have increased over time.

In our data set moral hazard should manifest itself in loans with FICO scores just below 620 having lower defaults than expected and low doc loans with LTV just at 80% having higher defaults than expected. Furthermore, because of evidence that the silent second share increased over time, we should expect to see notches in the form of fixed effects for LTV at 80% with low doc and which vary over time.

**Estimates of Model II**

Our estimates for model II use a similar default measure to one used in estimating Model I, foreclosures started. Figure 9 plots a cross-tabulation of defaults versus the UFA ForeScore index and credit score. Clearly there are important relationships in the data.

**Figure 9: Cross Tabulation of Bureau Score and ForeScore Zip with Defaults**

![Figure 9](image.png)

Table 2 presents maximum likelihood estimates of equation (2) from our set of non agency loans. All loans in the sample are fixed rate mortgages. The explanatory variables are

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8 The main difference is that the data have occasions where a property was lost by the borrower without a foreclosure—for instance short sales. So we add to default events that appear to be equivalent to foreclosures.
divided into four groups: observable underwriting, economic conditions, moral hazard and baseline or aging effects. The left hand side of the equation is an indicator of foreclosure for the loan. We can interpret the coefficients as the logs of multipliers attached to each variable; if $b$ is the coefficient, then $\exp(b)$ is the multiplier. For categorical variables the coefficient is the multiplier for being in that state. For instance, the multiplier for being an owner-occupier relative to a rental is $\exp(-.11) = .90$.

The most important underwriting variables are: original combined LTV (includes second mortgages if reported), credit score and excess coupon, which is the excess of the rate on the loan above the current market rate and which is meant to proxy for other risk factors not revealed to investors. All are significant and signs are as expected.

The “economic geography” variables are the ForeScore default risk indices by zip code and current LTV, which updates original LTV using current property values in the zip code, relative to original LTV. They too are significant.

The “Loan age baseline” is a series of fixed and linear effects for loan age that are used to control for normal seasoning. It suggests positive vintage effects and especially low default rates in the first four months after origination.

Major moral hazard variables include original LTV = 80% and credit score above and below 620. Also included are four time trend variables to test whether the variables undisclosed to investors were eroding over the data period. The year time trend rises by .13 per year indicating that the quality of loans was eroding during this period. The other three time trends interact year with Limited Doc, LTV=80%, and both Limited Doc and LTV=80%. In all three cases the slope is positive, which means that not only was the quality of the undisclosed variables of all loans eroding; but quality was eroding even more if the loans were Limited Doc or LTV=80% or both. This is consistent with the hypothesis that low quality is more likely to be hidden when the loan is Limited Doc or LTV=80%. The sum of the four coefficients is .25 and can be interpreted as implying that undisclosed loan quality for Limited Doc loans with LTV=80% increased defaults about 28% per year during the sample period. Hence, over the four years from 2003 to 2007 the default rate on these loans more than doubled. We did not find much of an effect for FICO score above and below 620.

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9 We have estimated different versions of the model, which all have more or less the same results. The version presented here has dropped most of the statistically insignificant explanatory variables. We experimented with various versions of the moral hazard variables at the bottom of the table with little change in story.

10 The spread variable presents possible endogeneity problems; it might affect other coefficients (like low documentation) that are not well measured in our data (we do not have degree of low documentation) and which are better accounted for in pricing. We have included on the grounds that it is observable by investors and rating agencies.
Table 2: Results for Non Agency Fixed Rate Mortgages (2000-2007)

Default regression results using loan level data. Bolded coefficients are significant. Dependent variable is log of default probability.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>WaldChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Underwriting</strong></td>
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<td></td>
</tr>
<tr>
<td>Original Term</td>
<td>0.00</td>
<td>22</td>
</tr>
<tr>
<td>Log of Balance</td>
<td>0.09</td>
<td>32</td>
</tr>
<tr>
<td>LTV at Origination</td>
<td>2.39</td>
<td>867</td>
</tr>
<tr>
<td>Term=other</td>
<td>-0.12</td>
<td>11</td>
</tr>
<tr>
<td>Term=180</td>
<td>0.10</td>
<td>3</td>
</tr>
<tr>
<td>Credit Score</td>
<td>-0.01</td>
<td>2083</td>
</tr>
<tr>
<td>Purpose=purchase</td>
<td>0.24</td>
<td>176</td>
</tr>
<tr>
<td>Purpose=refinance</td>
<td>-0.04</td>
<td>2</td>
</tr>
<tr>
<td>Purpose=Cash-out</td>
<td>-0.07</td>
<td>18</td>
</tr>
<tr>
<td>Type=condo</td>
<td>-0.07</td>
<td>7</td>
</tr>
<tr>
<td>Type=single family</td>
<td>-0.004</td>
<td>0.07</td>
</tr>
<tr>
<td>Limited Documentation</td>
<td>-0.10</td>
<td>14</td>
</tr>
<tr>
<td>Owner occupied</td>
<td>-0.11</td>
<td>24</td>
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<tr>
<td>Not owner occupied</td>
<td>0.43</td>
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<td>ForeScore Zip Default Index</td>
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</tr>
<tr>
<td>Current LTV / Original LTV</td>
<td>1.28</td>
<td>251</td>
</tr>
<tr>
<td><strong>Loan Age Baseline</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-8.62</td>
<td>766</td>
</tr>
<tr>
<td>Loan Age 0 to 2 months indicator</td>
<td>-13.3</td>
<td>0.04</td>
</tr>
<tr>
<td>Loan Age =3</td>
<td>-4.4</td>
<td>38</td>
</tr>
<tr>
<td>Loan Age 4 to 16 months</td>
<td>0.11</td>
<td>916</td>
</tr>
<tr>
<td>Loan Age</td>
<td>0.0004</td>
<td>0.2</td>
</tr>
<tr>
<td><strong>Moral Hazard</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LTV = 80% indicator</td>
<td>-0.06</td>
<td>3</td>
</tr>
<tr>
<td>Credit Score = 610 to 619</td>
<td>0.05</td>
<td>5</td>
</tr>
<tr>
<td>Credit Score 620 to 629</td>
<td>0.07</td>
<td>16</td>
</tr>
<tr>
<td>Origination Year (0=2000)</td>
<td>0.11</td>
<td>248</td>
</tr>
<tr>
<td>Origination Year * Limited Doc</td>
<td>0.07</td>
<td>191</td>
</tr>
<tr>
<td>Origination Year * LTV=80%</td>
<td>0.04</td>
<td>36</td>
</tr>
<tr>
<td>Origination Year * Limited Doc * LTV=80%</td>
<td>0.01</td>
<td>26</td>
</tr>
</tbody>
</table>

**Implications**

Figure 10 is a variation of a Gini chart. The horizontal axis groups our sample of predicted default probabilities, by borrower and by exposure month, by percentile. For instance the
first 10 percentile group contains the least likely borrower/exposure months for default. The vertical axis is actual accumulated defaults. If the model could not discriminate among default probabilities the relationship between the predicted by percentile and actual accumulated would be the 45 degree line. Perfect prediction would be the horizontal axis until 100%, then vertical.

The top line (under the 45 degree line) is this relationship using the estimated model but only accounting for the vintage effects (shutting off economic geography, underwriting and moral hazard variables). The second line adds economic geography, the third the underwriting, and the fourth includes the moral hazard part. The lowest curve is the whole model. The Gini ratio, which is the area above that curve divided by the area under the 45 degree line, is about 60%.

The picture gives the percentages of explanatory power resulting from each element of the model. Very little (4%) is explained by the moral hazard variables. As with model I about half (49%) is explained by economic conditions. A weakness of Model I was an inability to separate out aging effects from underwriting. Here, the aging variables are available and suggest that about 20% is explained by aging effects (that younger loans default less often). Hence, abstracting from the aging effects and looking at economic effects vs. underwriting, about 60% of the variation is explained by economic effects.

**Figure 10: Gini Graph for Defaults**

The Gini graph captures variation both over time and cross-sectionally. We are also interested (as in figure 7) in how much of the variation during the surge is explained by economic conditions vs. underwriting. At the same time, while we found statistically
significant effects for our moral hazard variables they did not explain much. That may be because they were miss-specified. We now turn to a model where we overestimate these effects by attributing all of the residual effects, after controlling for aging, observable underwriting and economic conditions, to moral hazard (more precisely unobserved underwriting).

Figure 11 provides results from an out of sample experiment. We estimated Model II with data through 2004, without the moral hazard variables, and then use the model to predict cumulative defaults as a function of loan age for loans originated in 2005 and 2006. In the figure the horizontal axis is loan age, and the vertical axis is actual and predicted cumulative default rates. The red line predicts defaults using only the vintage variables in the estimation and the orange line below it adds underwriting variables. Since the curve with vintage and underwriting is below the vintage only curve, the implication is that (observable) underwriting variables actually improved during this period relative to the estimation period, albeit only slightly.

The green curve adds economic geography to the vintage and underwriting variables. The figure illustrates that economic geography explains almost all of the defaults above pure loan age effects. These results are similar to the earlier model I results in the sense that about half of total cumulative defaults can be attributed to the location-specific variables.

For example, after 25 months defaults were around 4.75%. The historical baseline of cumulative defaults after 25 months (the red line) was 2.5%. The second line from the top (the green line) predicts cumulative defaults of around 4.25%. Hence, the 2.25% increase (4.75%-2.50%) in defaults after 25 months relative to the baseline about 1.75% (4.25%-2.50%) is explained by economic conditions, and none is by observable underwriting. The remainder, 0.50%, represents changes in the model and is an upper bound for the effects of unobserved underwriting changes. These results are similar to those of Bardwaj and Sengupta (2008).
Comments and Conclusions

In this paper we use two very different data sets to decompose the causes of the great surge in defaults. The first data set is aggregate data on foreclosure rates by state for all vintages in the serviced pool of mortgages. With these data we decompose the causes of defaults into about a 50-50 split between underwriting and economic conditions.

We then turn to a large and rich sample of individual loans originated from 2000-2007 where we can observe the information available to investors and control for observable underwriting as well as economic conditions. We can also use the data to infer the share due to moral hazard. Estimates from these data suggest that most of the variation was due to economic conditions, and none was due to observable underwriting changes. We find notches in the default function, particularly at 80% LTV, which are consistent with moral hazard, and we find that the notch effects increased over time. However, the notches are not especially important in explaining the surge in defaults. One possibility for the small
role of notches is the paper’s focus on fixed rate mortgages. It may well be that adjustable rate loans were a better vehicle for moral hazard.

Low documentation by itself was not significant. It mattered only when interacted with LTV=$80\%$ and over time. We do not have borrower income in the data set; so we are silent on its effect.

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 performance was tolerable, that credit score and LTV based underwriting models worked well and that nationally diversified pools of mortgages were safe; this made extending securitization into non-traditional areas look promising. However, the favorable economic conditions of the 1990s made mortgage lending look better than it really was. When economic conditions reversed and house prices began falling in most of the country, diversified pools were not of much help.

That in Model II relatively little of the surge can be attributed to underwriting changes, both observed and not, is consistent with other results but nonetheless surprising. It suggests that the place to look to explain the default surge is the price bubble and its correlation with things like the emergence of the subprime market. It may be (see Lai and Van Order (2010) and Glaeser et al (2010)) that the bubble had little to do with fundamentals and is very difficult to explain with the usual suspects.
REFERENCES


Capozza, D. and C. Findlay, ”The Variable Rate Mortgage and Risk in the Mortgage Market,”. of Money Credit and Banking, May 1977, 9, pp. 356 364.


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\(^{11}\). The estimated equations are of the form:

\[
(1) \quad d_{tr}^{\bar{x}_i} = a(s)e^{bX(r,t)+cY^i(r,\tau)+dG(r)}
\]

\[
(2) \quad p_{tr}^{\bar{x}_i} = a(s)e^{bX(r,t)+cY^i(r,\tau)+dG(r)}
\]

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 \(\tau\) 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 \(r\);
- \(a, b, c\) 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 unconditional 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.

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\(^{11}\) For an early example of a default model with local economic conditions see Capozza, Kazarian and Thomson (1997).