Causes of the Surge in Defaults:
Economic Conditions, Underwriting and Moral Hazard

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DRAFT

Abstract
In this paper we use two models to decompose the causes of the recent surge in defaults. Our first model uses aggregate data (foreclosure rates by state) to decompose defaults into shares caused by 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 sample of individual loans. We use the data to model default, and we try to tease out estimates of moral hazard by looking at discontinuities or “notches” in behavior that are consistent with a “cheapest to deliver” model. The strongest evidence of moral hazard arises in discontinuities in the relation between loan-to-value ratios and defaults for low documentation loans. We find about a 50-50 split between underwriting variation and changes in economic conditions as causes of default variation across borrowers, with only a small part being explained by our moral hazard variables. We then isolate changes over time, and we find no role for changes in observed underwriting. Almost all of the difference between the actual experience of loans originated from 2005-2006 and previous history is explained by economic conditions, mainly declines in property values with a smaller (about 20% of the difference) residual part that might be due to unobserved changes in underwriting. Surprisingly, we find no separate role for low documentation.

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I. Introduction and Overview

In this paper we present estimates of mortgage default models from two data sets, and we use the models to decompose the causes of the recent surge in defaults. 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, as by 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 loan level data on fixed-rate mortgages in “private label,” alternately “Non-Agency” (not Fannie Mae, Freddie Mac or Ginnie Mae), mortgage-backed securities that were originated from 2000-2008. This data set gives detailed underwriting characteristics that were known to investors in the pools. With these data we decompose defaults into four parts: those due to worsening of economic conditions, those due to observable changes in underwriting standards, a set of time varying fixed effects that we identify as moral hazard and “vintage” or “baseline” effects which depend on loan age.

We identify moral hazard as discontinuities or “notches” in default behavior. That is, the underlying economics suggests 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. Moral hazard in our model is interpreted as a “cheapest to deliver” problem, with loan sellers and securitizers, who have superior information, selling the worst loans subject to just meeting minimal standards.

In particular, an 80% LTV and a 620 credit score (FICO score) appear to be critical minimums, the former due to requirement that LTV above 80 requires insurance and the latter as a minimum standard for purchase by Fannie Mae and Freddie Mac. Loan sellers who exploit superior information to sell bad loans will tend to deliver loans that just meet minimum standards. As a result we should see discontinuities or notches in the default function at or around these points.

Our basic results are that we do indeed find notches, particularly at 80% LTV for low documentation loans. 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 generally favorable and masked (or been a reason for) a trend in deteriorating underwriting conditions.
II. Background and Stylized Facts

The Long Run Trend in Foreclosures

Figure 1 shows foreclosures started as a percent of outstanding number of loans from 1979 through 2008. There is a rising trend with occasional leveling off. Between 1979 and 2002 foreclosure rates quadrupled from .12 to .49% quarterly. In an impressive surge from 2006-8, foreclosure rates more than doubled again from .47 to 1.08%.

Figure 1: All Foreclosures Started: U.S. 1979-2008 Quarterly Data

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\(^1\). Note in particular the history of subprime. Foreclosure performance improves after the 2001 recession, but then increases sharply. A similar pattern, but on a smaller scale and with about a one 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

\(^1\) The MBA data do not track how many actually went through foreclosure to REO, real estate owned by lenders.
and subprime makes subprime the canary in the coal mine. Subprime borrowers appear to respond more quickly to financial stress than prime borrowers.²

**Figure 2: Rate of Foreclosures started by loan type, 1998-2007 (%)**

Four quarterly averages annualized

Source: Mortgage Bankers Association

![Figure 2: Rate of Foreclosures started by loan type, 1998-2007 (%)](image)

**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. 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.³

Figure 3 plots the real appreciation rate of house prices. It shows the increase in real growth rates. 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 4-6% annual appreciation rates of the last decade are extraordinary, as are the recent declines.

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² Subprime responds earlier; but, the eventual total response is smaller in percentage terms than for prime loans, albeit much larger in absolute terms. That the subprime and prime move about the same in percentage terms suggests that we can estimate the same model with the two different loan types if we estimate models with log of default in the left hand side.

Figure 3: U.S. Real House Price Appreciation, 1992-2008
Seasonally adjusted, purchase only index, quarterly data, four quarter price changes.
Source: FHFA

Figure 4 illustrates the variation in nominal 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 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 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 State indices compiled by University Financial Associates (UFA), which track the effect of local and national economic conditions on a constant quality loan. The index uses local conditions to explain defaults; about half the index is made up of house price changes, and the rest is made up of variables like the unemployment rate. See the appendix for an explanation of the index. The indexes enable parsimonious estimation of the equations that follow.

Figure 5 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 270, i.e., 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.
Figure 5: The Effect of Economic Conditions on Mortgage Performance by Origination Year: The UFA Default Risk Index by Vintage

The UFA Default Risk Index tracks how favorable national and local economic conditions are for subprime mortgage performance. The index follows a constant quality loan, i.e., one that holds the borrower, the property and the loan terms constant in all years, and varies only the economic environment. The index measures expected life of loan defaults for each indicated vintage relative to the average experience in the 1990s. 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

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. UFA forecasts 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. The figure suggests that indeed economic conditions could be a major factor in explaining recent history.
III. Default Models

We estimate variations of the same model from two data sets: one from the Mortgage Bankers Association, which is longer, but aggregated; the other, the 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.

In Model II below we also estimate prepayment models, which have same structure as (2).

Model I

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 $r$ that go into foreclosure at time $t$. We call this Model I. It is given by aggregating across individuals and origination years

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

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):

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

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 ForeScore index that applies to loans originated in state \( r \) at time \( t \), and \( e_i \) 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 it into time fixed effects and everything else to get:

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

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

Because the \( m_{tr} \) are the probability of ever defaulting it does 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

\[
(7) \quad \log(\tilde{d}_{tr}) = \sum_{t=-l} m_{tr} + \delta_r f_r + \delta_t f_t + \sum_{t=0} \gamma_t u_t + \varepsilon_i
\]

Bars over variables indicate a four-quarter moving average of the variable, and \( l \) and \( q \) are lag lengths.

**IV. Results for the Aggregated 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 fuller version of the model.
### 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>Standard Errors</th>
<th>All</th>
<th>Prime</th>
<th>Subprime</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 1 year</td>
<td>-.14</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>-.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 is an elasticity of the foreclosure rate to a permanent or ramp change in the UFA economic multiplier. Note that the elasticity 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 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.4

### Simulations

Next we use the estimated equations along with the fixed effects to decompose foreclosure into parts due to the economic multipliers and 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 add up to the actual level of foreclosures. Figures 6 depicts results using Model 1 for all loans.

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

However, we do not have direct measures of underwriting in this data, so we are attributing underwriting changes to what are essentially residuals, which could measure other things. We are also using a single measure of economic conditions, which makes our modeling easier, but might not always be enough. So we next turn to a shorter but more extensive sample of individual loans, and we apply direct measures of house price growth.

V. Model II: Loan Level Data

In this section we present results for Model II, which uses the 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.\(^5\) While that data set is richer than the one used in model I, it covers a shorter time span, loans originated from 2000 through 2008.

Because the data provide everything that is available to investors we can try to tease out information about moral hazard as well, both as a residual (which is a combination of moral hazard and unobservable characteristics) and by modeling a particular version of how moral hazard might work.

Moral Hazard

Moral hazard can be analyzed in the context 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 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 if borrowers or lenders (who sell to investors) have more power to choose under the new regime.

For example, investors and rating agencies tend to use models to evaluate loans, and dealers generally know the models and view them as constraints against which they deliver, which is exacerbated by Rating Agencies’ practice of not auditing the presented to them. Investors can see

\(^{5}\) 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.
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 (“silent seconds” which are recorded after loan has been sold) in addition to the first mortgages. Models used to estimate defaults that come from old data run the risk of having disturbances that were random under an old regime become nonrandom as agents learn how to select against principles in a “cheapest to deliver” sort of way.

**Estimation**

We cannot observe moral hazard directly with our data, but we can try to identify it by exploiting the “cheapest to deliver” nature of the problem as well as the discrete way that underwriting and regulation work. That is, default is likely to be a continuous function of variables like down payment and FICO score. However, because pricing and underwriting tend to be defined over discrete intervals cheapest to deliver versions of moral hazard will show up at the edges of the pricing and underwriting “matrix.” In that case we should find notches in the estimated default models where the sellers tend to deliver, in particular at credit (FICO) scores around the standard 620 minimum and at LTVs around 80.

More formally, consider our basic equation, repeated here with a disturbance, $u$, attached:

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

The problem is that some of the elements of $X$ are endogenous, chosen by borrowers or screened by lenders or deal makers. For instance borrowers choose the loan to value ratio. This is not a problem if the reason for choosing is not correlated with $u$ in (2'), for instance if the borrower chooses the smallest down payment allowed or an amount equal to what he/she has in the bank.

Suppose, however, that in the rate on the loan varies by LTV and borrowers chose their LTV subject to that pricing schedule and price is related to default. Then we have a classic identification problem because we have two equations with default rate and LTV: a behavior one, like (2') and the borrower’s choice equation; alternately, LTV will be correlated with $u$.

We handle the problem by exploiting the nature of pricing to identify the LTV choice function. In particular pricing and underwriting tend to done by discrete intervals over which price or underwriting condition is fixed. This can be for regulatory reasons, like requiring loans with
LTV over 80 to have insurance. Alternately it can arise endogenously because of fixed underwriting costs (see Bubb and Kaufman (2009)). Above 80 LTV loans are generally required to have insurance, which raises costs to borrowers, and below LTV price does not fall (at least not for a while).

Now consider a particular reason for cheating, “silent seconds,” which are loans with unreported second mortgages. Second mortgages are a way of avoiding mortgage insurance, but the existence of a second mortgage increases the probability of the first mortgage defaulting and should raise the price (or require compensating variations in other standards like credit score). If the lender “cheats” and does not report a second mortgage the loan can be delivered to a pool without penalty. We assume that there is a cost for cheating, which varies across time and borrowers and lenders. Some will cheat, those loans will have large positive disturbances, and they will be delivered right at 80 LTV (their purpose is to avoid the mortgage insurance require, so they will never be above 80, and they do not get a price break if they go below 80). Hence 80 is a signal of cheating.

Then the choice function will be identifiable as being flat everywhere except for a “notch” at 80, and at that point defaults will be worse than usual. For LTV not equal 80 choice of LTV will be independent of u. This suggests identification by adding a fixed effect for being at 80.

There are, however, other reasons for delivering at 80. For instance, some borrowers save up for an 80 LTV, and such borrowers might be better than average (unobserved thrift dimension to u). To identify cheating we exploit information Ashcraft and Scheuerman) that the silent second share increased over time beginning around 2003. Furthermore, we would expect this form of cheating to be associated not just with LTV=80, but especially with low documentation loans (they don’t ask for source of down payment). Hence, our hypothesis is that the silent second effect is correlated with LTV at 80 and low documentation and increases after around 2003.

More broadly because of the discrete ranges over which pricing and underwriting are held constant, we should expect to see a “cheapest to deliver” phenomenon at the edge of these ranges—notches in behavior that identify selection. At these notches u will tend to be above average. For instance, it has been argued (e.g., see Keyes et al (2007)) that 620 is a special level of FICO score because that was a de facto minimum for acceptance by Fannie Mae and Freddie Mac. Hence, there are incentives to deliver loans with FICO scores that are just above 620. To the extent that FICO score can be manipulated or (see Keys et al) there is soft information that lenders can exploit we should expect (and Keyes et al find it) that loans with FICO scores just above the 620 notch should perform worse.

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 at LTV just at 80 having higher rates. More broadly, we experimented with fixed effects for other possible notches, but those two
seemed to be the most important and statistically significant (though perhaps not economically significant in explaining overall defaults).

**Estimates**

Here we present results of our estimates. Our default measure is similar to one used in estimating Model I, foreclosures started.\(^6\) First we present Figure 7, which shows defaults as a function of the ForeScore index and FICO score. Clearly there are important relationships in the data.

![Figure 7: Actual Defaults by ForeScore Zip Quintile](image)

Table 2 presents maximum likelihood estimates of equation (2) from our set of non agency loans; all are fixed rate mortgages.\(^7\) The explanatory variables are divided into four groups: observable underwriting, economic conditions, moral hazard, and baseline time trends.

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\(^6\) 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.

\(^7\) 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 also estimated prepayment models, which are used in making projection in Figure 10. They are not shown here.
(seasoning or ‘vintage’ effects). The left hand side of the equation is the probability of foreclosure. Definitions of the variables are contained in the Appendix in Table A-1.

Table 2: Results for Non Agency Fixed Rate Mortgages (2000-2007)
(Wald Chi Squared around 4 indicates significance)

<table>
<thead>
<tr>
<th>Variable Type:</th>
<th>Class Value</th>
<th>Estimate</th>
<th>Wald Chi Sq</th>
<th>Standardized Est</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observable Underwriting</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Original Term</td>
<td>0.00</td>
<td>4</td>
<td>0.13</td>
<td></td>
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<tr>
<td>log Balance</td>
<td>0.16</td>
<td>15</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>Original LTV</td>
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<td>146</td>
<td>0.22</td>
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<tr>
<td>CreditScore</td>
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<td>209</td>
<td>(0.34)</td>
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<td>0.23</td>
<td>26</td>
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<td>Excess coupon</td>
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<td>461</td>
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<td>Economic Geography</td>
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<td>ForeScore Zip Default</td>
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<tr>
<td>Current LTV / OLTV</td>
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<td>36</td>
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<td>Moral Hazard</td>
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<td>Credit1_leq_620</td>
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<tr>
<td>loanage_5*Oltv_eq_80</td>
<td>1</td>
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<td>2</td>
<td></td>
</tr>
<tr>
<td>Year<em>LimDoc</em>OLTV80</td>
<td>2000</td>
<td>6.22</td>
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<tr>
<td>Year<em>LimDoc</em>OLTV80</td>
<td>2001</td>
<td>-1.09</td>
<td>9</td>
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</tr>
<tr>
<td>Year<em>LimDoc</em>OLTV80</td>
<td>2002</td>
<td>-1.24</td>
<td>34</td>
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<tr>
<td>Year<em>LimDoc</em>OLTV80</td>
<td>2003</td>
<td>-1.28</td>
<td>83</td>
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<tr>
<td>Year<em>LimDoc</em>OLTV80</td>
<td>2004</td>
<td>-1.12</td>
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<tr>
<td>Year<em>LimDoc</em>OLTV80</td>
<td>2005</td>
<td>-0.81</td>
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<tr>
<td>Year<em>LimDoc</em>OLTV80</td>
<td>2006</td>
<td>-0.50</td>
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</tr>
<tr>
<td>Year<em>LimDoc</em>OLTV80</td>
<td>2007</td>
<td>-0.47</td>
<td>37</td>
<td></td>
</tr>
<tr>
<td>Loan Age Baseline (months)</td>
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<td></td>
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<td></td>
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<tr>
<td>Intercept</td>
<td>-8.30</td>
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<td></td>
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<td>dlage0_to_4</td>
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<td>217</td>
<td>(0.69)</td>
<td></td>
</tr>
<tr>
<td>loanage_5_15</td>
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<td>1</td>
<td>0.01</td>
<td></td>
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<tr>
<td>loanage</td>
<td>0.02</td>
<td>72</td>
<td>0.16</td>
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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 \( \exp(-.31) \), which means that holding all else constant owner-occupied housing has a default rate about \( 2/3 \) that of rental.

The most important underwriting variables are: original loan balance (given LTV this is the same as property value), original combined LTV (includes second mortgages if reported), credit (FICO) score and excess coupon, which is the excess of the rate on the loan above the current market rate (this is meant to cover other risk factors, which are revealed to investors). All are significant and signs are as expected. Note that the documentation variable is not significant by itself. However, it is significant below when interacted with other variables. The excess coupon variable is meant to capture risks not included in the other underwriting variables. It is relative to the expected rate on a mortgage with comparable characteristics determined by a separate regression. It can be interpreted as a measure of the borrower’s ability to bargain or as a premium for underwriting characteristics not captured in our model but known to lenders.

The “economic geography” variables are the ForeScore indices by state and current (updated) LTV, using current property values in the state, relative to original LTV. It is the only time-varying covariate; ForeScore is applied only at origination. Both variables are significant. Hence, changes in property values add something to the ForeScore indices.

Major moral hazard variables are credit score just below 620 and low doc loans with LTV at 80 by origination year. The latter is had a large positive coefficient for the year 2000 (origination year), but was negative after that. What is important is the increase from 2003 to 2007, which says the effect of low doc high LTV 80 more than doubled (log of multiplier went from -1.28 to -0.47), which is consistent with the role of silent seconds growing over time. We also find, along with Keyes et al, that FICO just below 620 was associated with lower default. Note that being at LTV=80 only mattered for low doc and over time.

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

A curious result is that low documentation does not matter (perhaps a negative effect) except for the deterioration in the low doc 80 LTVs over time. Low documentation loans have been correlated with default but also with house price decline. Apparently the correlation was spurious and what mattered most was the time and place where the Low Doc loans were made—at least for this sample of fixed rate loans.
Implications

Some of the moral hazard variables are significant, but that does not tell us about their economic significance, as measured by contribution to actual defaults. Here we look at that in two ways: first in a cross section sort of way; then over time.

“Cross Section” Variation

Figure 8 depicts Lorenz Curves for various versions of the model. The horizontal axis arrays our estimated default probabilities from lowest to highest, by loan across all origination months. For instance the first (10th percentile) group contains the loans in the sample that are estimated to be least likely to default. The vertical axis is actual cumulative defaults as a function of rank. If the model cannot discriminate among default probabilities at all, the relationship between rank and actual accumulated would be the 45 degree line. Perfect prediction would be the horizontal axis until we got to 100%, then vertical.

The top line (just under the 45 degree line) is the Lorenz Curve using the estimated model with only 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 Lorenz Curve for the whole model. The Gini ratio, which is the area above that curve and under the 45 degree line divided by the area under the 45 degree line, is about 60%. That is, the model gets us about 60% of the way to perfect explanation.

The box inside the picture gives the shares of what is explained in the model. These are “Mini” Gini ratios relative to overall Gini ratio. 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 vintage effects from underwriting. Here the vintage variables do that and suggest that about 20% is explained by vintage effects. Hence, abstracting from the vintage effects and looking at economic effects vs. underwriting, about 60% of the variation is explained by economic effects.
However, the mini Gini coefficients do not capture the same thing as Model I. Model I results in Table 1 look at variation in underwriting only across time; whereas the Lorenz Curve captures variation both over time and across borrowers. Other data (see Anderson et al (2010)) indicate that observable underwriting standards (LTV, FICO etc.) did not change much over time; though of course they vary considerably across individuals. Hence, the share of increased defaults over time might not be well explained by changes in observed underwriting. At the same time, our measure of more hazard, which relies on notches in behavior, may miss important changes in unobserved underwriting.

**Contributions over time**

To get at these problems we use estimates of the model from 2000-2004 to predict cumulative defaults for the 2005 and 2006 vintages. We leave out the moral hazard variables in Table 2, and estimate the model using only the baseline, observable underwriting and economic effects. This allows us to break down the causes of changes over time, and by leaving out the moral hazard.
variables we can use the difference between actual and model predictions as an overestimate of the effect of changes in all unobserved underwriting.

Figure 9 presents our results. We estimated sequential versions of Model II (as in Table 2) with data through 2004 and then used the estimated versions to predict defaults, as function of age, for loans originated in 2005 and 2006.

In the figure the horizontal axis gives loan age (time since origination) and the vertical axis gives actual and predicted cumulative default rates. The top line gives actual average cumulative default rates by month after origination for the 2005 and 2006 vintages. After 25 months defaults were around 4.75%. The second line from the bottom gives forecasts using the model with nothing but time from origination as explanatory variables, which amounts to projecting past “baseline” rates. This gives an historical baseline of cumulative defaults after 25 months of 2.5%. The line just below that uses estimates of Model II with both the underwriting variables and the baseline and again makes a forecast. Note that this forecast is actually a bit below the forecast using only the baseline variables, which means that the observed underwriting contribution was actually negative; underwriting mattered, but the observed part of it got somewhat better. The second line from the top uses estimates of the full model (without moral hazard variables). It is close to the top and predicts cumulative defaults of around 4.25%.

Basic results are that of 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).
Figure 9: Projected and Actual Defaults for Different Versions of Model II
VI. Comments and Conclusions

We find notches in the default function, particularly for low documented loans at 80% LTV, that are consistent with moral hazard, and that the notches increased over time, which is consistent with the apparent increase in silent seconds over the same period. However, we find that the notches 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 generally favorable and masked (or been a reason for) a trend in deteriorating underwriting conditions.

Rate spread, over the expected rate, given loan characteristics, was significant. Low documentation was not significant. It mattered only when interacted with LTV=80 and over time and as captured by rate spread. We do not have borrower income in the data set, so we cannot for its effect. That documentation is not important is surprising.

The analysis from Models I and II 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 the reality. When economic conditions reversed and house prices began falling in most of the country, diversified pools were not of much help.

There is much to be done. In particular we need to run the model for adjustable rate loans and for separate products (Alt-A and subprime). But results so far suggest the overwhelming importance of economic conditions, mostly the decline in property values, rather than changes in underwriting. Our data set cannot tell the extent to which changes in underwriting and the growth in subprime and Alt-A played a part in causing the boom and bust in property values.
REFERENCES


Appendix: Derivation of the ForeScore Indices

UFA uses proprietary data on individual loans to estimate a competing hazards model of mortgage performance at the loan level. 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 UFA indices arise from first estimating a hazard model for the conditional probability of default and prepayment of the form

\[ O(i, v, t) = a(t - v)e^{bX(r,t) + cY(i)} \]

where \( O(i, v, t) \) is the conditional outcome (default, \( d \), or prepayment, \( p \)) for loan \( i \) originated at vintage time \( v \) and observed at time \( t \).

\( X(r,t) \) is a vector of time varying covariates that describe the economy at time \( t \) in region \( r \) where the property is located;

\( Y(v) \) is a vector of characteristics of the loan, the borrower and the property at the time of origination;

\( a(t-v) \) is the baseline hazard for a loan of age \( t-v \).

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

Life of loan default, \( D(i,r) \), and prepayment, \( P(i, r) \), probabilities are then calculated by taking the balance weighted expected default and prepayment probabilities over the entire life of the loan. When the loan, borrower and property characteristics are held constant, by holding \( Y \) constant, a multiplicative factor of the effect of economic conditions on a constant quality loan is created. Normalizing to a base year creates the indices for the constant quality loan that track the effect of economic conditions on loan performance.

Note that the index uses actual variables (interest rates, house prices, unemployment etc) to estimate parameters of the index. When the index is applied to loans at origination it is uses forecasts of future explanatory variables. In our case, however, the index is ex post, and we use actual explanatory variables for as long as we have actual data, and then we use forecasts. In our estimates of Model II it applies only at origination; i.e., it is not time varying.

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8 For an early example of a default model with local economic conditions see Capozza, Kazarian and Thomson (1997)
9 See [www.ufanet.com](http://www.ufanet.com) for additional details.
A-2 Variables

Default= Foreclosure or equivalent

Observable Underwriting

Original Term in years
log of Loan Balance
Original LTV (including second mortgages
Credit Score (FICO score)
purpose=1 if purchase
purpose=2 if refinance
purpose=3 cash-out refinance
Prop type=1 if single family
Documentation Type=1 if Full
Occupancy type=1 if owner occupied
Occupancy type=2 if investor
Excess coupon=difference between coupon rate and expected market
given characteristics (e.g., FICO and LTV) rate at origination

Economic Geography

ForeScore Zip Default
Current LTV / OLTV

Moral Hazard

CreditSco*OLTV_eq_80=credit score if LTV=80

OLTV_eq_80=1 if OLTV=80
Credit1_leq_620=1 of credit score is from 615 to 620

loanage_5*OLTV_eq_80=loanage if OLTV=80 and within 5 months of origination

loanag*DocTyp*Oltv_e=same as above if full documentation

Year =2000*LimDoc*OLTV80 =1 if originated in 2000 and
documentation=0 (low doc) and LTV =80
Year =2001)*LimDoc*OLTV80 Same but originated in 2001
Year*LimDoc*OLTV80 etc
Year*LimDoc*OLTV80
Year*LimDoc*OLTV80
Year*LimDoc*OLTV80
Year*LimDoc*OLTV80

Loan Age Baseline (months)

Intercept
dlage0_to .4 = 1 for each of first 4 months after origiantion
loanage_5_15 =a separate set of fixed effects for the 5th through 15th
months
Loanage in months