Measuring Total Mortgage Market Credit Risk

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Abstract
This paper proposes two measures of credit risk for the population of outstanding mortgages. The first uses an average *ex ante* default probability to characterize risk, the second uses the unexpected loss generated by the asymptotic single factor risk (ASFR) model, a probabilistic model of portfolio risk. Both approaches show that average *market–wide* expected default rate and the unexpected loss per dollar of outstanding mortgage balances were roughly constant during the 2002-2006 boom in US house prices.

Key Words: mortgage credit risk, expected loss, cycles

1. Introduction

The future state of the housing finance system in the United States is the subject of active debate. Central to this discussion is the question of who should hold the exposure to mortgage credit risk in the future. This raises the question of how to measure the total mortgage credit risk. Existing measures of market-wide mortgage credit risk have focused only on newly originated loans rather than the stock of outstanding loans. Yet, from a policy perspective understanding the risk of the entire US mortgage market is of even greater importance, as it represents the total risk that is to be borne by society and the decisions about the future of housing finance will largely determine how this risk will be allocated across individuals, financial institutions and the government.

This paper proposes two related measures of market-wide mortgage risk. The first is based on an *ex ante* assessment of default probability and extends the methodology of Li and Goodman (2014) beyond new mortgage originations. This approach assesses *ex ante* default rate for all outstanding mortgages at any point in time through a weighted average of the *ex post* default experience of a 'normal' and a 'stress' cohort of loans. This measure can be thought of as a 'through the cycle' notion of default risk, as changing housing market conditions do not influence the assessment of default risk. The second measure of risk is based on an estimate of the unexpected loss of the population of mortgages. Unexpected loss is defined as the difference between the 'Value-at-Risk tail loss at a probability level α,' denoted VaR(α), and the expected loss. While expected losses can be thought as 'usual' levels of loss, the unexpected losses are deviations from the average that could put an institution's stability at risk. Unexpected loss can be thought of as the capital required to offset losses in a stress event. Financial institutions are expected to hold capital for these unexpected losses, as they cover their expected

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losses on an on-going basis by provisions and write-offs. These two measures account for changes in the risk of new originations and for changes in the risk of outstanding mortgages due to house price changes and loan seasoning effects.

This paper makes several contributions. First, it extends the approach to measuring expected default of *newly originated mortgages* developed in Li and Goodman (2014) to seasoned loans. Li and Goodman (2014) used the expected default rate of new originations as a proxy for credit availability, and showed that these expected default rates almost doubled during the 2002-2006 boom in US house prices. In contrast, this paper shows that during the same period the average *market–wide* expected default rate was roughly constant over the run-up in house prices. The increased in expected default rates for new originations during the run up in house prices were roughly offset by declines in expected default rates for seasoned loans due to house price appreciation. Li and Goodman's (2014) analysis also showed a dramatic decline in the expected default rates for new originations starting in the first quarter of 2007 associated with tightening mortgage credit availability during the house price bust. This paper shows that the total mortgage market default risk increased substantially as house prices fell beginning in 2007.

Second, by creating a measure of total mortgage market risk based on unexpected risk this paper provides a framework to size the total required capital in this market. This measure combines the impacts of both the market level of default risk with market volumes. Moreover, this total can be subdivided by funding source, providing a notion of required capital by segment. The segments are the 'privately' funded segment (i.e. bank and non-agency mortgages), Ginnie Mae backed mortgages, and GSE (i.e. Freddie Mac and Fannie Mae) funded mortgages. While the exact estimates of required capital may be imprecise, the method provides a sense of the magnitude of the capital that might be required for fully privatizing mortgage credit risk.

Finally, these measures offer new insights into the evolution of risk in the mortgage market. Contrary to much of the narrative about the crisis, total risk in the mortgage market as measured by either the expected default rate or the unexpected losses per dollar of origination UPB was effectively constant through the 2002 to 2006 housing boom.

2. Assessing Mortgage Credit Risk

To produce estimates of total mortgage market risk through time, the loan level expected default rate must be estimated for the stock of mortgages at each evaluation date. The expected default rate for mortgage is driven by a number of loan and borrower characteristics as well as on the future evolution of the economy. State of the art models of mortgage risk use stochastic simulation of competing risk hazard models to assess this risk (see, for example, Duarte and McManus (2015)). As a pragmatic approximation to this, Li and Goodman (2014) developed an approach to assess the default risk of newly originated mortgages through using a weighted average of the default performance of a 'typical' origination year and a 'stress' origination year is used to proxy for the *ex ante* default performance.

The expected default rate is approximated through extending the approach developed by Li and Goodman (2014). This approach uses a weighted average of the *ex post* performance of a 'normal' and 'stressed' cohort as a proxy for the *ex ante* default rate. Operationally, separate default models are fit to the outstanding loan population as of

2000 and 2006 and the weighted forecasts of these models are then combined to estimate the *ex ante* default rate for the population of outstanding mortgages on a quarterly basis from 2002 through 2014. The exposure to unexpected loss for the US mortgage market is then estimated using the Asymptotic Single Factor Risk model (see Vasicek, 1997, and Gordy, 2003) whose key inputs are the expected mortgage default rate, the correlation of collateral across mortgages, and the expected loss given default.

The CoreLogic loan level servicing data if first used to fit the default models. Two samples of existing mortgages as of January 2000 and January 2006 (delinquent loans sampled at a rate of 25% and current loans at 10%). Data on borrower and loan characteristics are then merged with subsequent default performance. A mortgage is said to default if it 1) enters foreclosure or 2) becomes Real Estate Owned (REO) or 3) if the loan ever becomes 180 days or more delinquent. The third condition is included to account for states in the U.S. in which it can take years for a property to enter foreclosure. Logistic models stratified by funding channel (private, Ginnie Mae, and GSE) and by delinquency status (current vs. delinquent) are fit to this data. The details of these regressions are given in the Appendix. Finally, to adjust for the fact that a fraction of the loans will cure even after achieving this default event, the estimated default probabilities are adjusted down by a constant 30%. This adjustment factor has been calibrated to roughly match historic experience. The implementation details of this exercise are summarized in the Appendix.

Next, loan level forecasts of ex ante default probabilities are created through applying the default models to quarterly snapshots of outstanding loans in the CoreLogic servicing data. For computational efficiency, a 5% random sample of the data is extracted at each date and default forecasts are produced for each loan in the sample. Because the data is not a census, weights are used to scale this data to the aggregate US market. These are based on adjusted aggregates from the Federal Reserve's Mortgage Debt Outstanding data series, and create separate weights by investor category.

The US housing market experienced a house price bubble over the 2002 to 2011 period. For the purposes of this paper the period from January 2002 through June 2006 will be identified as the housing 'boom' period; the July 2006 through December 2006 period will be identified as the housing 'peak' period; and the January 2007 through December 2011 will be referred to as the 'bust.' These periods are based on the Freddie Mac US House Price Index, as shown as Figure 1.

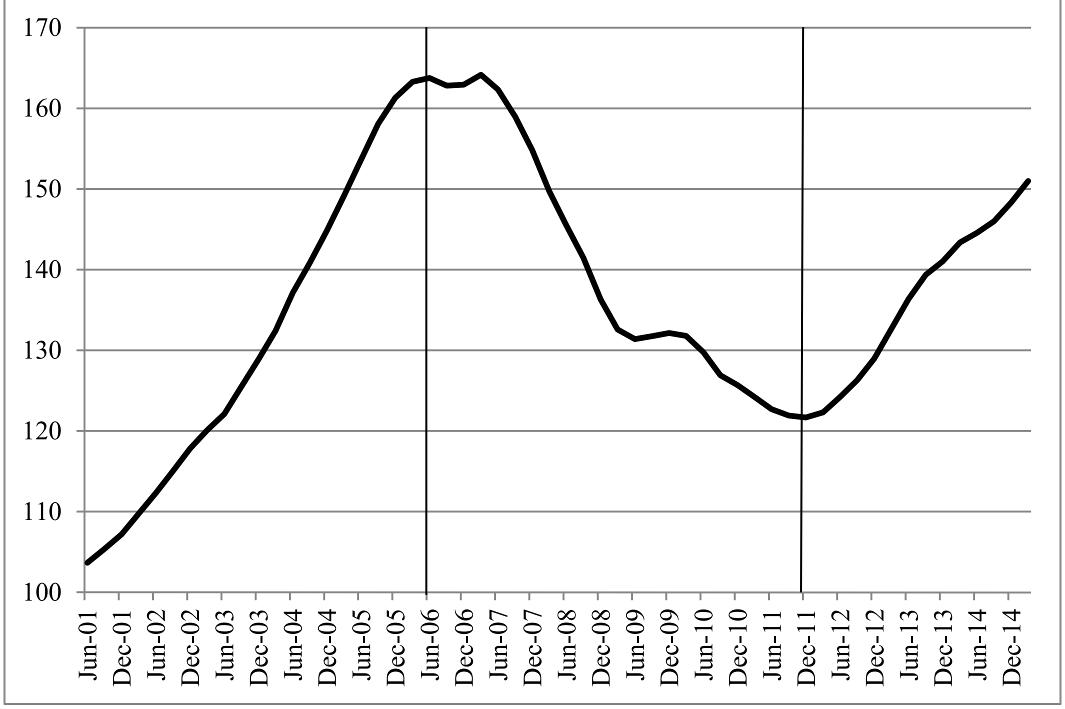


Figure 1: Freddie Mac House Price Index

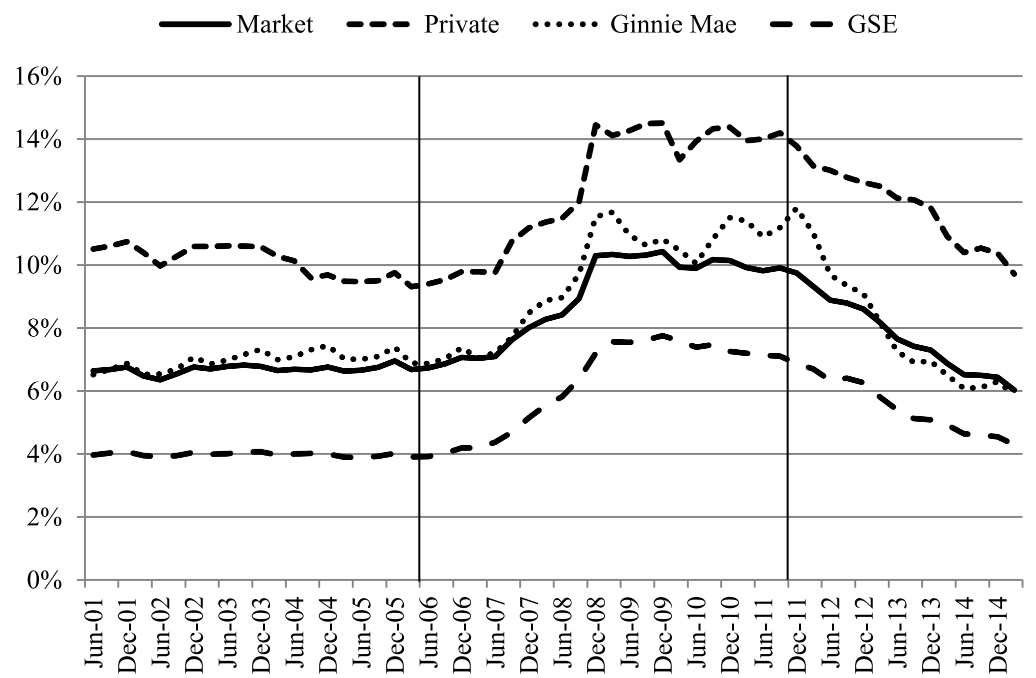
2.1 Assessing *Ex Ante* Probability of Default

The default risk of outstanding mortgages on a quarterly basis is presented in the next few graphs. Figure 2 displays the resulting time series of *ex ante* default rates both for the market as a whole and by investor over the 2001 to 2014 period. The most striking feature of this graph is that the total market risk was flat at about 6.8% over the boom years and was only slightly elevated at the market peak to about 6.9%. During the bust, the market wide default rate rapidly increased reflecting the decline in house prices, reaching a peak of about 10.4%--an increase of about 50%. This pattern is consistent with Ferreira and Gyourko's (2015) observation that house price declines were the main driver of default in the crisis. Subsequently, the market-wide default risk has declined and by March 2015 is actually lower than the any time since June 2001.

The evolution of expected default risk for each the channel follows a similar pattern to the entire market. The default risk was roughly constant to declining starting in 2001 until about June 2006, and then rapidly increasing through June 2009, cresting in 2011, and then declining as house prices improve. Since the peak, the default rate for mortgages held by the private investors has decreased by about 30%, and Ginnie Mae and the GSEs have declined by about half. The ordering of the default risk is consistent across investors: privately funded mortgages are riskiest, and then Ginnie Mae, and then the least risky are the GSE funded mortgages.

The relative constancy of default risk in the boom period is in sharp contrast with the newly originated mortgages, in which Li and Goodman (2014, Figure 2) demonstrate strongly increasing risk of new origination, especially for the private segment, over the boom period. This is consistent with the increasing risk in new originations being offset by lower risk in existing loans through the lower LTVs caused by house price appreciation and seasoning. It is also interesting that by this measure, the total mortgage market appears to have a lower risk now than any other time examined. This is reflective of the shift in product mix towards safer loans and the shift away from the private channel.

Figure 2: Ex Ante Probability of Default



2.2 Assessing Unexpected Losses

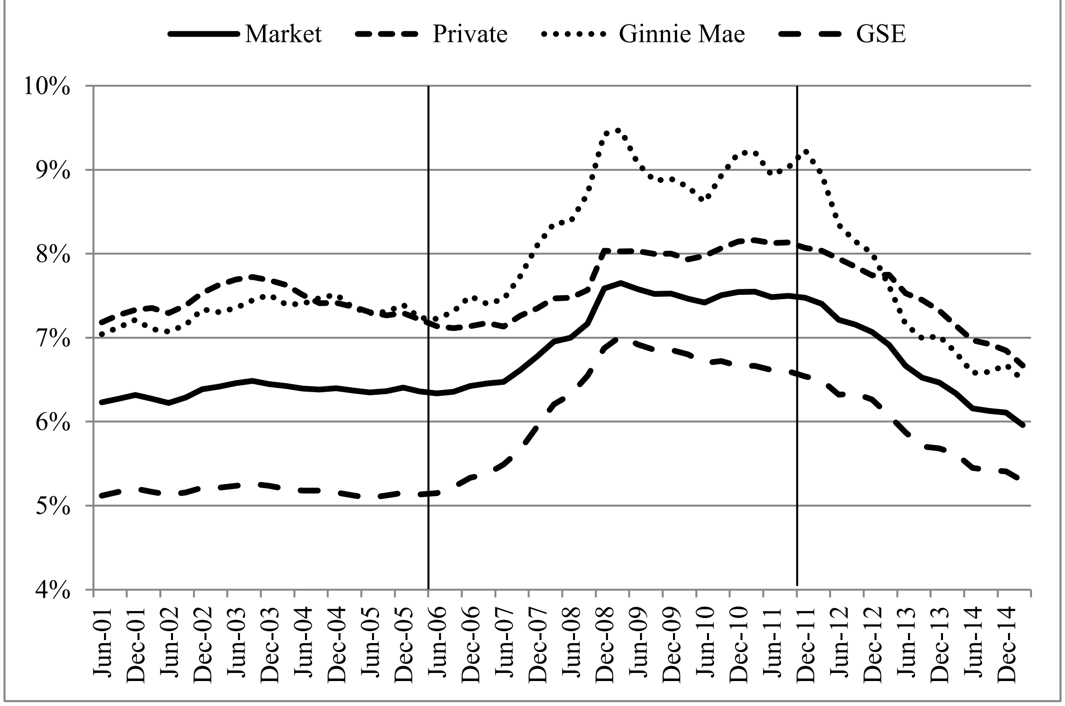
A common model used for determining portfolio credit risk is the Vasicek (1997) asymptotic single factor risk model. It envisions a portfolio with identical loans and where these loans default when the value of the underlying asset drops below a threshold D. The value of each asset is determined by the weighted sum of a market wide factor (for mortgages think of the market wide factor as US house price growth) and an idiosyncratic factor specific to that asset. Under appropriate conditions, as the number of loans become large, the asymptotic distribution of losses can be expressed analytically, and thus can be used to assess the unexpected losses (UL). Key to the derivation of the asymptotic distribution is the use of the law of large numbers to define the limiting losses conditioned on the market factor (which diversifies away the idiosyncratic risk). The form of this conditional distribution is then used to calculate the unconditional distribution of losses, induced through a transformation of the of the market factor. Under normality, the key parameters needed to calibrate this model are the default probability (PD), the correlation of the underlying house values (ρ), and the loss given default (LGD). Let the cumulative default function of the normal distribution be denoted by Φ. This ASFR model formula for unexpected loss is given in the following equation:

$$UL(\alpha) = LGD * \Phi\left(\frac{\sqrt{\rho} * \Phi^{-1}(\alpha) + \Phi^{-1}(PD)}{\sqrt{1-\rho}}\right) - LGD * PD \qquad (1)$$

As a simplifying assumption the correlation of collateral for mortgages is taken from the Basel II capital standards, as ρ = 0.15, and the loss given default is assumed to be a constant at LGD = 40%. Finally, the formula (1) will be used to quantify unexpected losses at α = 99% level. These assumptions are aimed at providing a pragmatic estimate of the total and components of the US mortgage market credit risk.

Figure 3 plots the resulting unexpected losses per dollar of outstanding mortgage balance for the entire market and for each funding segment. In parallel to Figure 2, the level of risk in the stock of mortgages is approximately flat during the boom in house prices. The market-wide unexpected loss per dollar of mortgage balance was approximately flat at 0.0625 during the boom period, and reached a peak at about 0.075. Subsequently, the market-wide default risk has declined and is actually lower than the any time since June 2001, approximately 0.06. Across funding channel, the GSE loans have the least risk, and private and Ginnie Mae loans being similarly risky except for the 2007 to 2011 period in which Ginnie Mae loan were the riskiest.

Figure 3: Unexpected Loss per Dollar of Mortgage Debt



The total mortgage market unexpected loss combines the impacts of both default risk and market volumes. Figure 4 plots the total market unexpected losses, and provides the breakdown by investor segment. It is notable that the total unexpected loss was increasing approximately linearly over the boom period, reaching a peak of about $770 B in March 2009. This was largely driven by increases in total mortgage debt outstanding and by the shift in market share to the private segment. Subsequently total unexpected losses declined by about 30% to $539 B by March 2015. These reductions were mainly driven by declines in the unexpected losses per dollar of outstanding mortgage balance.

Figure 4 also shows the total unexpected losses for each funding segment. During the boom period, the total capital from private funding sources greatly increased relative to GSE and Ginnie Mae. After the housing market peaked the GSE and Ginnie Mae total unexpected losses started to grow at a faster rate, the private segment to contract.

Figure 4: Market Exposure to Unexpected Mortgage Losses

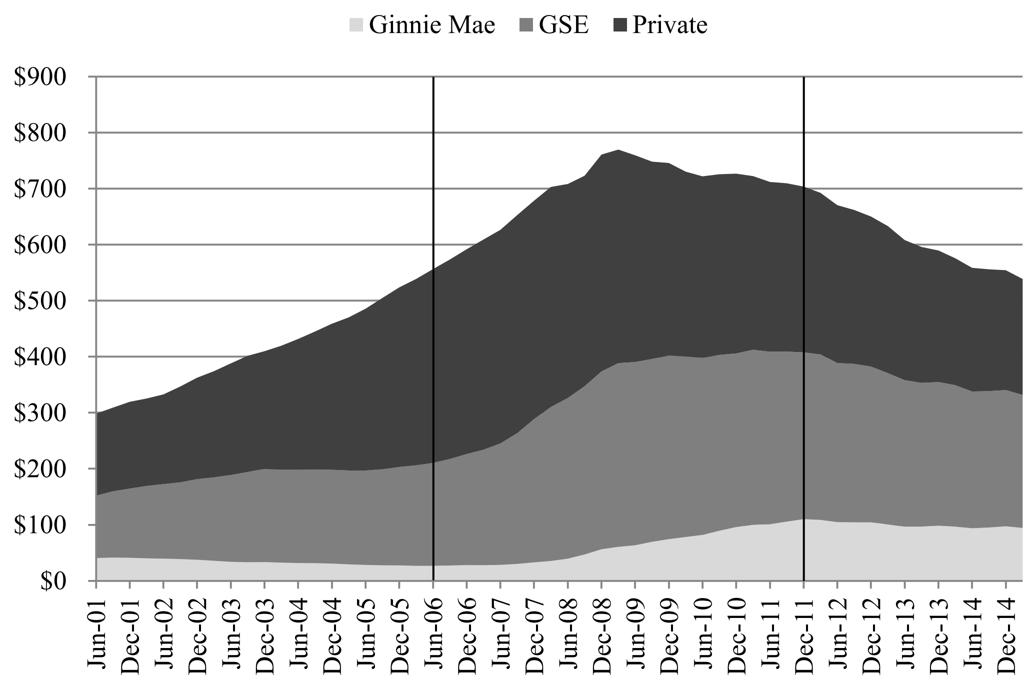
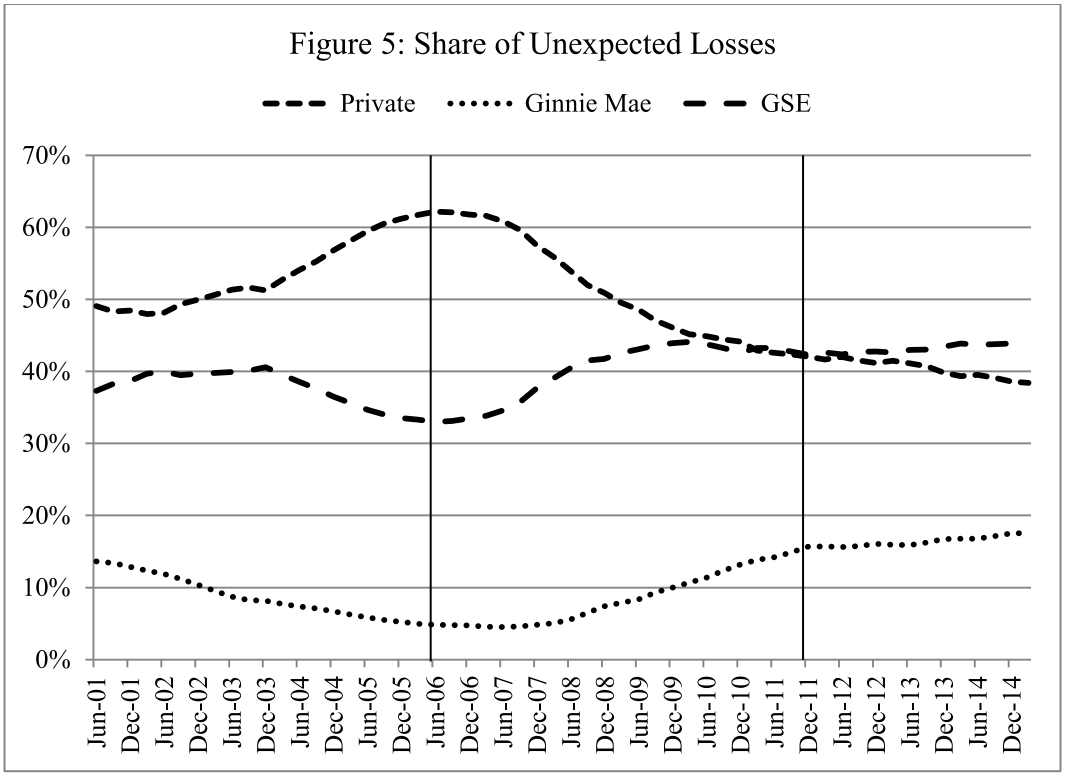


Figure 5 plots the *share* of total unexpected losses by investor segment over time. During the boom period, the private share of unexpected losses rose rapidly from about 48% to about a peak of about 62%. In contrast, over this same period, the combined share of GSE and Ginnie Mae unexpected losses declined from about 52% to about 38%. The share of unexpected losses in the private segment declined after the boom period, starting in September 2006 dropping to only 39% by March 2015.



Several limitations of the approach taken here should be kept in mind. First, the assessment of ex ante default uses a 'through the cycle' notion of default risk and so does not account for momentum in housing markets. Second, the expected loss assessment does not include impact of GSE credit risk transfers, such as through STACR and Connecticut Avenue securities or through private mortgage insurance. Finally, because the calibrations of default, asset correlation, and loss given default are only approximate, these estimates best used for relative comparisons of risk.

3. Conclusions

How much risk is in the US mortgage market? Two measures of mortgage market risk offer complementary insights into the dynamics of credit availability mortgages during the last credit cycle. First, that increasing credit risk in new originations in the boom period was largely offset by lower LTVs on existing mortgages caused by house price appreciation. Second, declining house prices were the primary driver of the increase in total mortgage market risk in the bust period. Third, the risk as measured by both the average default probability and by the unexpected losses per dollar of outstanding mortgage balances had dropped to levels below those at the start of the house price bubble. Finally, that the total risk of outstanding mortgages has dropped about 30% below the peak, but still above the pre-bubble levels, primarily due to the increase in mortgage debt outstanding over the bubble period.

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Appendix

The default models used to assess risk were created as follows. Table 1 provides descriptive statistics for the CoreLogic data in default model calibration.

Table 1: Descriptive Statistics

Variable	Normal Scenario (Jan 2000)			Stressed Scenario (Jan 2006)		
	Count	Mean	Standard Deviation	Count	Mean	Standard Deviation
Default	3216837	0.118	0.322	4226893	0.279	0.449
Age	3216837	44.4	46.8	4226893	38.3	41.7
CLTV	3216837	63.8	22.2	4226893	55.9	25.1
FICO	2470330	692	78.2	3180498	679	82.9
Delinquent	3216837	0.147	0.354	4226893	0.318	0.466
ARM	3216837	0.127	0.333	4226893	0.151	0.358
Hybrid	3216837	0.007	0.083	4226893	0.065	0.246
Other	3216837	0.034	0.181	4226893	0.033	0.177

The default rate for both of these origination years is estimated using logistic models stratified by investor type (GSE, Ginnie Mae, Private) and by delinquency status (Current, Delinquent). A mortgage is said to default if it 1) enters foreclosure or 2) becomes Real Estate Owned (REO) or 3) if the loan ever becomes 180 days or more delinquent. The third condition is included to account for states in the U.S. in which it can take years for a property to enter foreclosure. The explanatory variables used in this regression are: age of loan to capture seasoning effects (in categories by number of months: 1-12, 13-36, 37-84, 85-180, greater than 180 months), current loan-to-value ratio (CLTV) which is the outstanding unpaid loan balance divided by an estimate of the current value of the property. This estimate of current value is calculated by updating the origination value of the property using the ZIP-Code level Freddie Mac House Price Index (FMHPI).[2] CLTV enters the model as a linear spline with knot points at 80 LTV (CLTV_80), 100 LTV (CLTV_100), and 120 LTV (CLTV_120). The origination FICO score enters as a categorical variable with categories: less than 620, 621-660, 661-700, 701-740, 741-780, greater than 780 and a category for missing FICO score (fico_miss). The loan product is also included in the regression with categories: fixed-rate, ARM(arm), hybrid (hyb), and other (otr). For the regressions using data on delinquent loans, the depth of delinquency enters the models (with categories: 30, 60, and 90+ days of delinquency). Regression results are reported by delinquency status.

Tables 2a and 2b provides the parameter estimates for the default models. Most variables in this table are statistically significant and have the expected signs.

The estimated default models are applied to quarterly samples of the CoreLogic servicing data. For computational efficiency, a 5% random sample of the data is extracted at each for the first month of each quarter and default forecasts for ‘normal’ and ‘stressed’ scenarios are produced for each loan in the sample. A single forecast of default probabilities are created by taking a weighted average of these two scenarios, with the ‘normal’ case being given a 90% weight, and the ‘stressed’ case a 10% weight. Finally,

[2] For a description the FHMPI, see http://www.freddiemac.com/finance/fmhpi/docs/FMHPI.pdf

these forecasts are decreased by 30% to account for loans reaching the default event but that will eventually cure instead of resulting in a loss.

Table 2a: Default Model Parameters for Current Loans

	Normal Scenario			Stressed Scenario		
Variable	Ginnie Mae	GSE	Private	Ginnie Mae	GSE	Private
Intercept	-3.578***	-4.437***	-3.286***	-2.028***	-1.455***	-2.673***
age_0_12	-0.064***	-0.119***	0.180***	0.151***	0.219***	0.390***
age_37_84	-0.078***	0.154***	-0.247***	-0.099***	-0.147***	-0.060***
age_85_180	-0.395***	-0.073***	-0.441***	-0.079***	-0.533***	0.164***
age_181+	-0.789***	0.161***	-0.640***	-0.756***	-0.443***	0.311***
cltv	0.001	0.013***	0.005***	0.012***	0.004***	0.016***
cltv_80	0.034***	0.049***	0.045***	0.021***	0.014***	-0.005***
cltv_100	0.046***	-0.006	-0.043***	0.108***	0.155***	0.103***
cltv_120	-0.075***	-0.048***	-0.019***	-0.118***	-0.185***	-0.093***
fico_miss	0.423***	-0.009	0.483***	-0.053**	-0.274***	-1.362***
fico_0_620	1.233***	1.709***	2.380***	-0.024	0.106***	0.364***
fico_621_660	0.812***	1.011***	1.605***	0.009	0.036***	0.180***
fico_661_700	0.403***	0.475***	0.833***	-0.026	0.015**	0.100***
fico_741_780	-0.285***	-0.289***	-0.878***	0.000	0.068***	-0.055***
fico_781+	-0.415***	-0.211***	-1.295***	0.111	0.138***	-0.101***
arm	0.293***	0.027	-0.187***	-0.719***	0.205***	0.048***
hbd	-0.468	0.610***	-0.225***	-1.095***	-0.810***	0.021**
otr	0.008	-0.282***	-0.073***	0.732	-1.243***	0.051***
# Observations	461674	1447723	834246	174003	1259396	1447733

Table 2b: Default Model Parameters for Delinquent Loans

	Normal Scenario			Stressed Scenario		
Variable	Ginnie Mae	GSE	Private	Ginnie Mae	GSE	Private
Intercept	-1.888***	-2.048***	-0.815***	-1.831***	-1.558***	-1.206***
age_0_12	0.228***	-0.131***	0.119***	0.122***	-0.048***	0.250***
age_37_84	-0.444***	0.004	-0.449***	-0.034**	0.197***	-0.034***
age_85_180	-0.787***	-0.140***	-0.769***	-0.028	0.179***	0.029***
age_181+	-1.131***	-0.009	-0.960***	-0.561***	0.256***	0.282***
cltv	0.002	0.010***	0.002***	0.017***	0.013***	0.011***
cltv_80	0.021***	0.036***	0.042***	0.029***	0.026***	0.014***
cltv_100	0.033***	-0.020***	-0.032***	0.079***	0.090***	0.050***
cltv_120	-0.048***	-0.016	-0.011*	-0.110***	-0.142***	-0.065***
dq_6	0.764***	0.932***	0.776***	0.645***	0.668***	0.774***
dq_9	1.612***	1.492***	1.478***	1.633***	1.326***	1.560***
fico_miss	0.517***	0.362***	0.487***	0.073**	-0.208***	-0.850***
fico_0_620	0.635***	0.740***	0.990***	0.070**	0.303***	0.304***
fico_621_660	0.346***	0.439***	0.604***	0.029	0.189***	0.250***
fico_661_700	0.209***	0.257***	0.309***	0.005	0.126***	0.150***
fico_741_780	-0.216**	-0.241***	-0.358***	-0.010	-0.157***	-0.253***
fico_781+	-0.284*	-0.282***	-0.455***	0.016	-0.195***	-0.419***
arm	0.202***	-0.061***	0.026**	-0.328***	0.081***	-0.210***
hbd	0.765	0.352***	0.295***	-0.123	0.164***	0.007
otr	0.063	-0.020	-0.098***	0.311	-0.499***	0.172***
# Observations	124197	139225	209772	157202	293608	894951