# Macroeconomic Adverse Selection: How Consumer Demand Drives Credit Quality

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**Abstract**

Using the credit quality estimates from a study of US mortgage performance, we investigated the drivers of credit quality beyond standard underwriting criteria such as score and LTV. Using the Federal Reserve Bank's Senior Loan Officer Opinion Survey (SLOOS), we found that industry-wide variations in credit quality by vintage show no correlation to the loan officers' stated intend to tighten or loosen underwriting criteria. However, the measure of consumer demand for mortgages as take from the same survey correlated extremely well to credit quality by vintage. This correlation to consumer demand is also captured by comparing credit quality to macroeconomic drivers that appear to influence consumer appetite for credit.

Using changes in mortgage interest rates and house prices we were able to provide an even better explanation of credit quality by vintage over the historical data set. Both the SLOOS and macroeconomic models were extrapolated forward to show how credit quality should have changed since the initial study and predict the credit quality of future originations. We refer to this process as Macroeconomic Adverse Selection, since the macroeconomic environment is having a clear impact on the distribution of consumers applying for loans in ways that are not reflected in their credit scores.

Keywords: Survival Model, Proportional Hazards Model, Dual-time Dynamics, Retail Lending, Stress Testing, Senior Loan Office Opinion Survey

# 1 Introduction

Previous studies of the US Mortgage crisis have suggested that factors beyond those visible to the lenders had a strong impact on credit quality. Breeden, et. al. [2] analyzed a 15-year study of mortgage originations with Dual-time Dynamics [1] and found that dramatic cycles in credit quality occurred three times during the observation period even after segmenting by product type, credit score, and loan-to-value. Further, they found that these cycles correlate to macroeconomic factors such as changes in house prices and mortgage interest rates. In a similar study, Calem, et. al. used a combination competing risks model and panel regression to show that riskier households tended to borrow more on their home equity loans when the expected unemployment risk rises.

Changes in default risk that cannot be observed via standard credit scores are generally referred to as adverse selection. However, the standard example of adverse selection is where one lender in a market fails to respond to the product or pricing changes made by its peers. Through this inaction, the better credit risk consumers are drawn to other lenders leaving only the higher risk borrowers for the unresponsive lender. As with the above example, the credit risk for the pool of loans originated can be much worse than expected from the credit scores, but it is a very different mechanism from the macroeconomic drivers described above.

Therefore, just in terms of nomenclature, we have chosen to describe the studies by Breeden, et. al. and Calem, et. al. as examples of Macroeconomic Adverse Selection and relabel the standard form as Competitive Adverse Selection.

This article reexamines the analysis done by Breeden, et. al. in relation to the Senior Loan Officer Opinion Survey and other measures of consumer demand to consider the issue of Macroeconomic Adverse Selection directly for the US mortgage market.

# 2 Modeling Approach

The measure of credit quality being studied is derived by applying Dual-time Dynamics (DtD) to a mid-delinquency rate.

$$\text{Acct Flow through 60-89 DPD Rate} = \frac{\text{Accounts 60-89 DPD(t)}}{\text{Current Accounts(t-2)}} \qquad (1)$$

where DPD refers to "'Days Past Due"' and "'Current Accounts"' refers to loans that are active and not delinquent.

The delinquency rate in Eq. 1 was modeled using DtD on vintage-aggregate data (static pools). Vintage performance is measured at regular intervals from the origination date. The performance data of a vintage may be modeled as

$$\text{Acct Flow through 60-89 DPD Rate}(a,t,v) = e^{f_m(a)} e^{f_g(t)} e^{f_q(v)}, \qquad (2)$$

where $f_m(a)$ is the maturation function of months-on-book, $a$, $f_g(t)$ is the exogenous function of calendar date, $t$, and $f_q(v)$ is the quality function of vintage. The functions $f_m(a,\ f_g(t)$, and $f_q(v)$ are estimated from a set of vintages by assuming the relationship in equation 2 and solving for the unknown functions non-parametrically.

The estimation process employed here is the same as described in [1], and has strong similarities to the iterative solution method of Generalized Additive Models [4]. In total, DtD is very similar to Age-Period-Cohort (APC) modeling [5]. For the initial decomposition, no macroeconomic or credit score factors are included. The exogenous curve is an unknown function of date, which may include seasonality, macroeconomic impacts, and management actions such as credit line increases and collections policies. These separate components of the exogenous curve are quantified in a second stage analysis. Using a single, nonparametric factor to capture calendar date impacts is a common method in APC modeling and dendrochronological analysis of global climate change [3].

A retail loan portfolio is typically segmented by product, acquisition channel, origination credit score, geographic region, or loan-to-value, to name a few possibilities. DtD is initially applied independently on each of the segments. Upon review, some segments will usually exhibit the same maturation or exogenous curves, in which case the analysis is rerun with the added constraint of the same curve being estimated for multiple segments. Typically, maturation curves will change with product, channel, and score, but not with geography. Exogenous curves (environmental impacts) are largely unchanged across subproducts, channel, or minor changes in score, but can vary significantly with geography.

Monthly vintages were analyzed for the US mortgage analysis with monthly reporting of the delinquency rate. Accounts can appear as delinquent within this rate. For display purposes, the vintage quality function $f_q(v)$ is translated in the following plots to a credit quality measure, $Q(v)$ representing the percentage difference in delinquency from the maturation curve as

$$Q(v) = exp(f_q(v)) - 1 \tag{3}$$

All of the DtD analysis on the US mortgage dataset was performed previously by Breeden, et. al. [2]. The current research takes the previously measured credit quality as a starting point to look for drivers of Macroeconomic Adverse Selection.

# 3 Measures of Quality and Demand

The US Federal Reserve Bank (FRB) conducts the Senior Loan Officer Opinion Survey to gather information on trends at lenders. As one of the questions, Lenders are asked if they are tightening underwriting standards. The FRB computes the change in underwriting standards as

$$\text{Net Percentage of Banks Tightening Standards} = \frac{\text{Number of Respondents Tightening} - \text{Number of Respondents Loosening}}{\text{Total Number of Respondents}} \tag{4}$$

Figure 1 shows the underwriting standards time series plotted against the credit quality, $Q(v)$ measured for historic vintages during the study period.

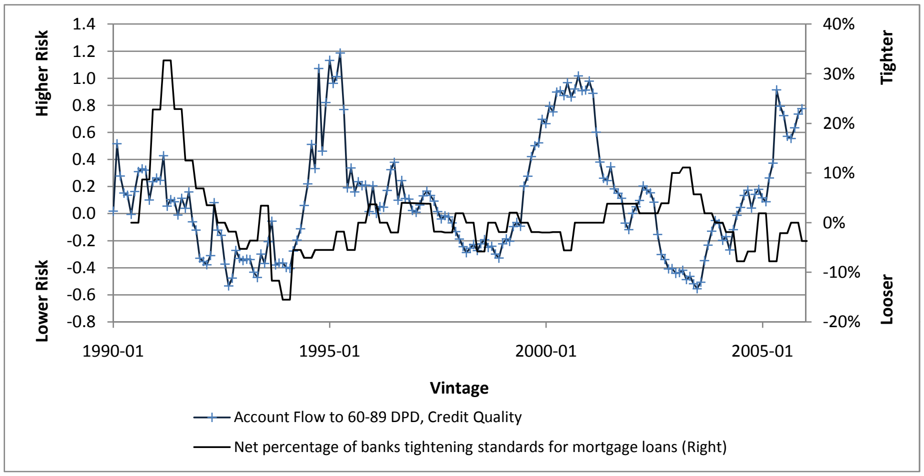


Figure 1: The credit quality by vintage for all US mortgage originations is compared to the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS) measure of changes in lender underwriting standards. Industry-wide, there has been very little relationship between self-reported underwriting standards and the credit quality obtained. The relationship is stronger since 1999.

This measure of underwriting should be anticorrelated to the DtD credit quality. As underwriting standards are tightened, credit quality $Q(v)$ should become more negative, reflecting fewer delinquencies than would normally be expected relative to the maturation function, $f_m(a)$. In fact, Figure 2 shows a correlation of only $\rho = -0.064$. Since the SLOOS measures are bounded variables between -1.0 and 1.0, the variables were transformed as

$$\acute{x} = \tan \frac{\pi}{2} x \tag{5}$$

The correlation was computed between the transformed SLOOS metric and $f_q(v)$. This is a slight correlation for the current data set, but a more accurate procedure in general.

Although the full data set shows no relationship between SLOOS-reported underwriting standards and credit quality, if we constrain the analysis to just the period from January 1999 through December 2005, we get a correlation of $\rho = -0.62$ using the same transformations. This could mean that understanding and controls around credit risk have improved over the last couple decades, but we note that in the critical period from 2004 through 2005, underwriting standards were reported as loosening only slightly and yet credit quality was deteriorating rapidly.

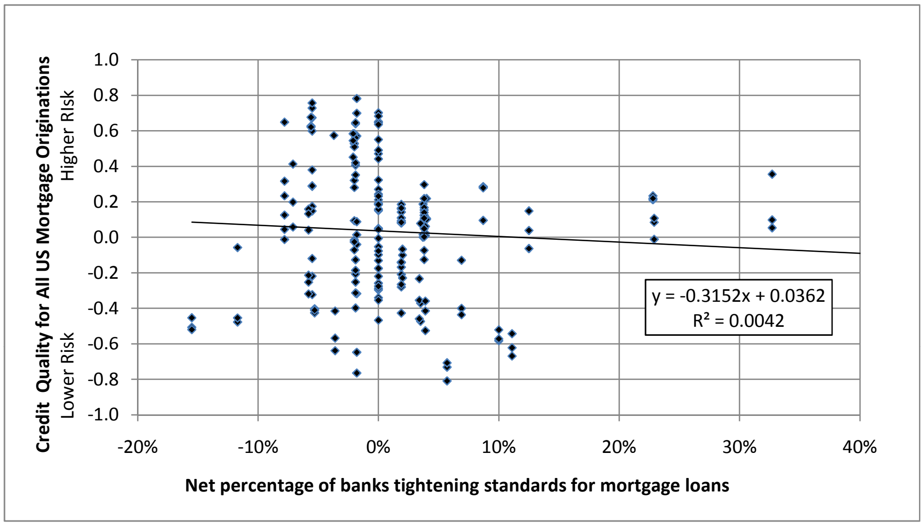


Figure 2: A scatterplot between the two lines in Figure 1 with a best fit line shown.

The SLOOS data contains another interesting variable, the Net Percentage of Banks Reporting Stronger Demand for Mortgage Loans. This variable is computed the same was as in Equation 4. Using the average of reported values three months into the future to six months in the past produces a time series with the best relationship to credit quality. This is shown in Figure 3. The relationship between demand and credit quality is clear across the full history.

Figure 4 shows the correlation between credit quality and the same average of lags -3 to +6 of reported demand. Applying the transformation from Equation 5 to the moving average of reported demand, the correlation to $f_q(v)$ cross the full dataset is $\rho = 0.804$. For the shorter period between January 1999 and December 2005 where the correlation to underwriting standards was better, the correlation to consumer demand holds steady at $\rho = 0.795$. Simply stated, the best predictor of credit quality from the Senior Loan Officer Opinion Study is not the reported change in underwriting standards, but rather the reported level of consumer demand. When consumer demand increases, it appears that the additional demand is coming from fiscally sound consumers who cause the credit quality estimates for the entire vintage to improve significantly. When those good consumers pull out of the market, overall loan demand falls and the credit quality for the vintage will be much worse.

As the previous study by Breeden, et. al. showed, even when credit quality is measured by credit score, LTV, or sub-product, the credit cycles shown in the

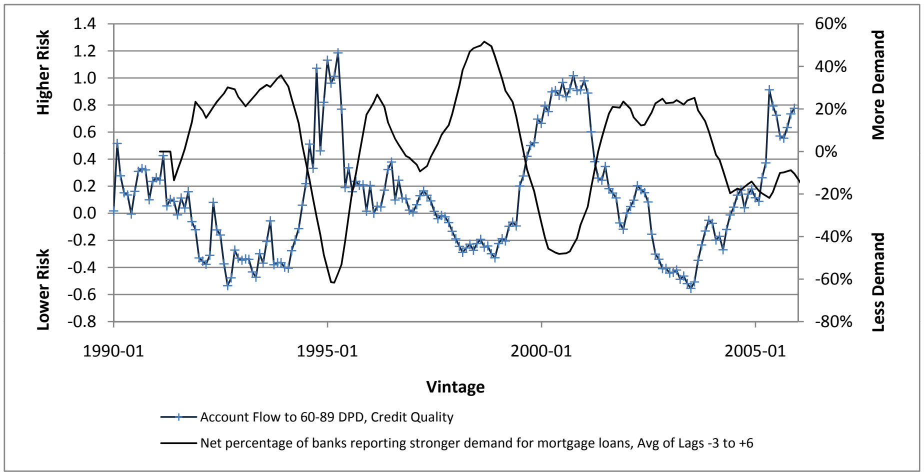


Figure 3: The credit quality by vintage for all US mortgage originations is compared to the SLOOS measure of changes in borrower demand for mortgages. When consumers want loans, credit quality will be good.

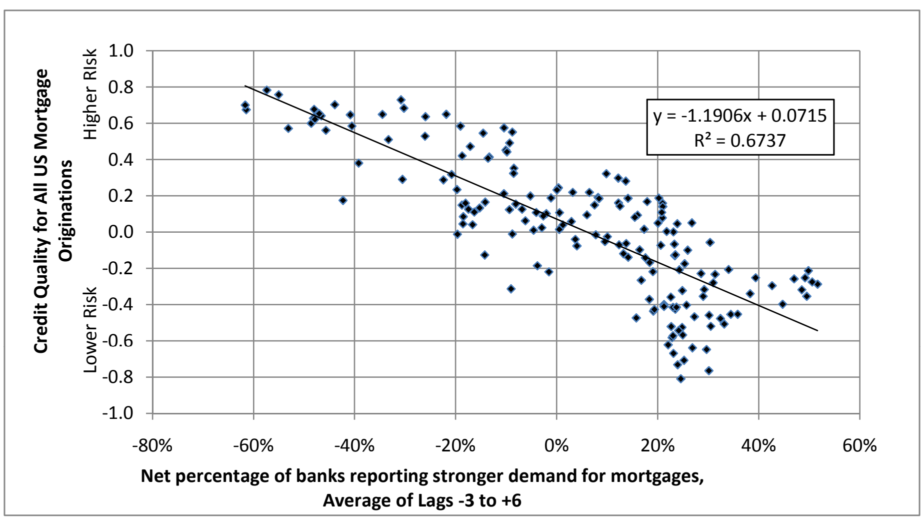


Figure 4: A scatterplot between the two lines in Figure 3 with a best fit line shown.

preceding plots persist with some minor variation. In the second quarter of 2007, the FRB started asking the SLOOS questions by risk band and product type. As that time series grows, it will be interesting to revisit these correlations.

Another option for exploring the correlation between consumer demand and credit quality is just to look at the volume of loans originated, Figure 5. In general, as demand rises, lenders will move to meet that demand.

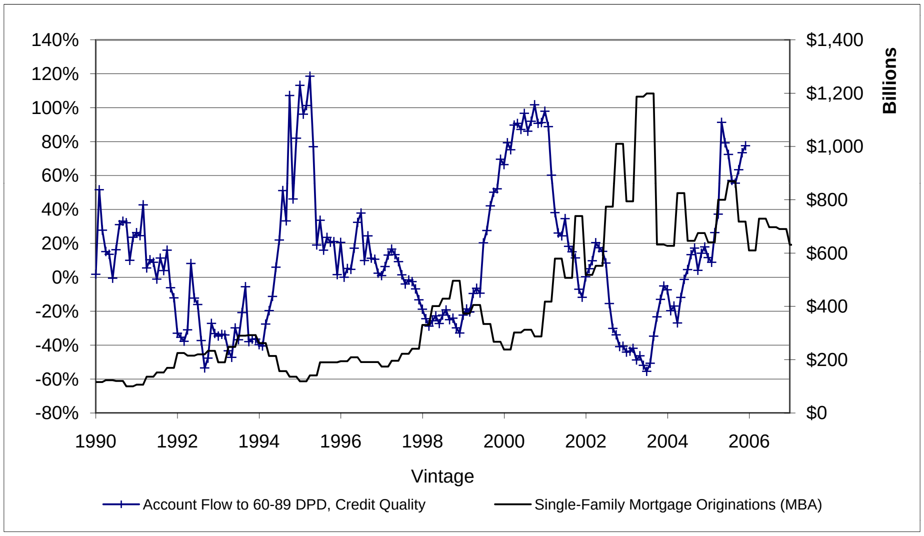


Figure 5: The credit quality by vintage for all US mortgage originations is compared to the volume of all types of mortgages originated. When origination booms happen, they are good credit quality vintages.

In Figure 6 we show a comparison between the year-over-year change in mortgage originations and the SLOOS report of consumer demand. Clearly these time series have strong similarities, but when we actually compute the correlation between $f_q(v)$ and the log(volume(t)/volume(t-12), we obtain $\rho = -0.49$ for the full dataset and the correlation actually drops from the period between January 1999 and December 2005 to $\rho = -0.32$. Again, the SLOOS report of consumer demand is our best predictor of credit quality.

# 4 Macroeconomic Drivers

When asked why consumer demand changes and why it correlates well to credit quality, one naturally considers the macroeconomic environment impacting consumers. After considering a range of possible factors, we found that changes in house prices, Figure 7, and changes in the offered mortgage interest rates, Figure 8 appear to explain the changes in credit quality well.

After considering a range of lags and transforms, we found that the 2-year difference of the offered mortgage interest rate and the log of the ratio of house

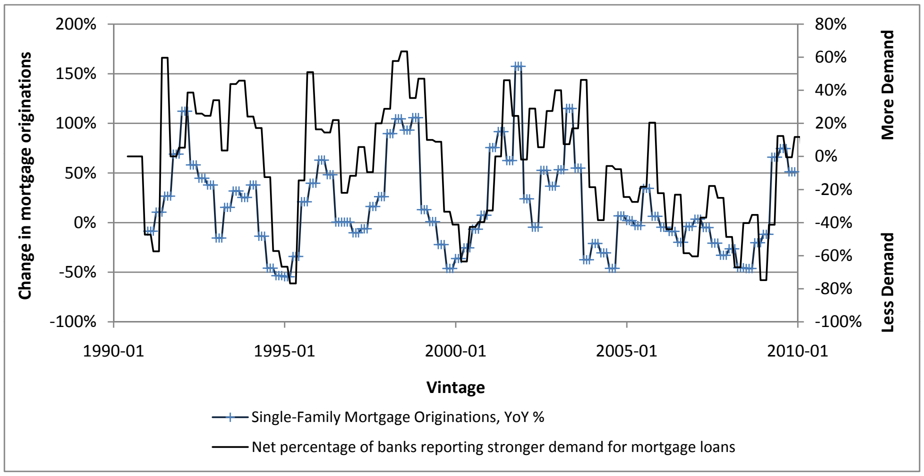


Figure 6: Annual changes in mortgage origination volume is compared to the SLOOS measure of changes in consumer demand. The two track very closely, suggesting that when consumers want loans, they are usually able to obtain them.

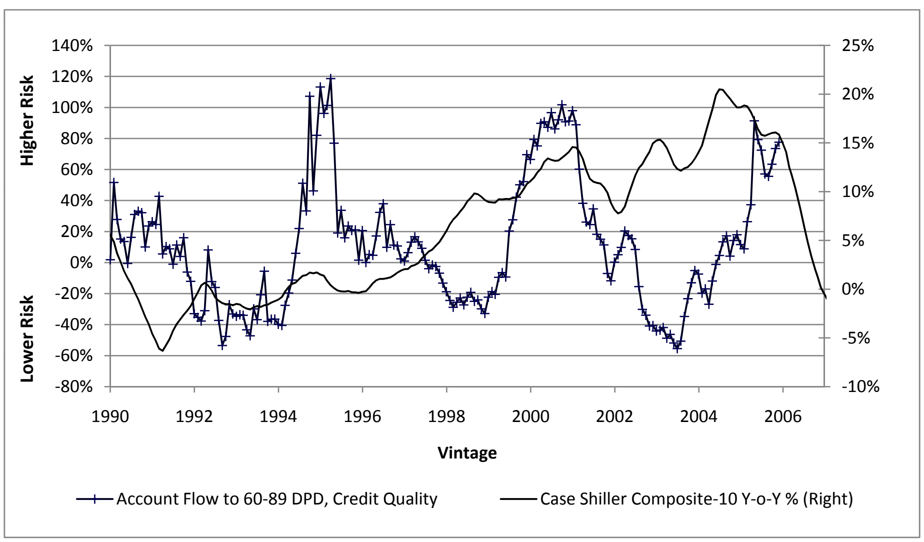


Figure 7: Year-over-year percentage change in house prices as measured by the Case-Shiller Composite-10 index compared to credit quality by vintage.

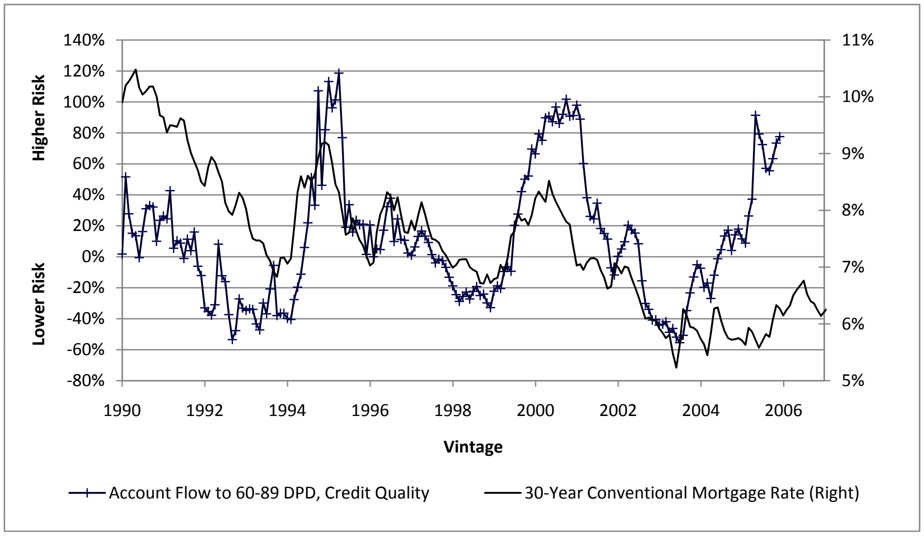


Figure 8: The interest rate offered on a 30-year fixed-rate mortgage compared to credit quality by vintage.

prices over a 12-month period created the best model of credit quality. However, when studying the residuals, Figure 9, we find that the relationship is asymmetric between house price increases and house price declines.

Because of this asymmetry, we estimated separate linear coefficients for increasing and decreasing HPI. This improved the multiple $R^2$ only slightly from 0.791 to 0.808, but the residuals plot flattened out significantly. In addition, Figure 9 suggests that a linear fit to house price increases may not precisely reflect consumer response. Instead, the true situation could be that rates of increase between 0% and 7% have little impact of consumer response, but that rates of increase above 7% are proportionately more disturbing to potential new home buyers.

Table 1 shows the final regression statistics.

| | Coefficients | Std Err | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 0.1670 | 0.0292 | 5.80 | $2.7210^{-8}$ | 0.112 | 0.2278 |
| 2-yr Diff in Interest Rate | 33.90 | 1.83 | 18.55 | $2.4610^{-44}$ | 30.30 | 37.51 |
| HPI Log-Ratio, Declines | -5.99 | 1.51 | -3.96 | $1.03910^{-4}$ | -8.97 | -3.01 |
| HPI Log-Ratio, Increases | 0.418 | 0.292 | 1.43 | 0.1543 | -0.158 | 0.994 |

Table 1: Regression outputs for the macroeconomic model of credit quality

The final macroeconomic model of credit quality has a correlation of $\rho = 0.808$ compared to $\rho = 0.75$ for the model based upon SLOOS reported consumer demand for mortgages. Over the training period, these models are roughly equivalent, but the macroeconomic model gives us a way of explaining shifts in

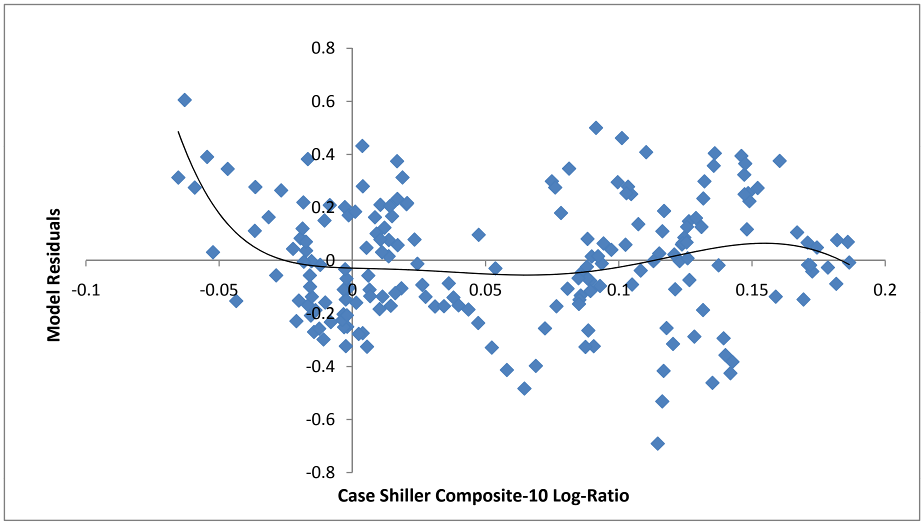


Figure 9: Plotting the residuals of a simple linear interest rate and HPI model versus changes in HPI shows that significant asymmetry in consumer responses to rising and falling house prices. A piecewise-linear model was created in Table 1 to capture this effect.

consumer demand. When the offered mortgage interest rate has been falling, mortgage demand from intrinsically good credit risk consumers increases. With house prices, the faster house prices appreciate, the less demand there is from good credit risk consumers. Conversely, falling house prices are also not desirable, as falling house prices cause the good credit risk consumer to again pull out of the market. The best situation is to have modest house price appreciation between 0% and 7% year-over-year as this is apparently what creates an attractive buying environment for consumers.

We also considered whether other measures of house price appreciation would work better. The primary alternative to the Case Shiller House Price Index in the US is the Federal Housing Finance Authority (FHFA) House Price Index. Whereas Case-Shiller is a measure of price changes for repeat sales of the same home, FHFA applies the same approach only to conforming mortgage sales. Figure 10 shows a comparison of these two measures. Over the period of the credit quality estimates, there was no statistical advantage to using one over the other. However, in the time since the study ended, the two measures have shown significant divergences. It would be interesting to reconsider this question comparing to the credit quality of recent originations.

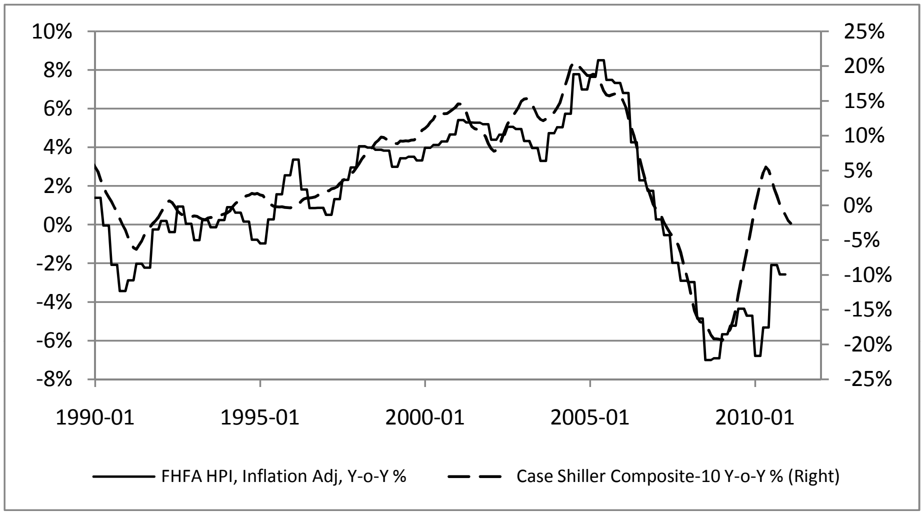


Figure 10: A Comparison of the two primary house price indices in the US.

# 5 Forecasts

The specific study being analyzed had data through the end of 2006, from which credit quality for vintages through the end of 2005 was estimated. With the predictive models for credit quality developed here, we can forecast credit quality beyond the end of the study period based upon observations of macroeconomic variables and the SLOOS measures. Also, with a macroeconomic scenario we can predict possible future Macroeconomic Adverse Selection.

Figure 11 shows the in-sample and extrapolated credit qualities by vintage using these two models. In-sample, the models are largely indistinguishable, however, during the worst originations of the US Mortgage Crisis, the macroeconomic model predicts significantly worse performance than the SLOOS demand forecast. Based upon the author's experience, most mortgage portfolios experienced credit quality deteriorations somewhere between these two values.

Going forward, the baseline macroeconomic scenario incorporated a slow rise in mortgage interest rates from 4.7% in December 2010 to 6% in December 2013. House prices were assumed to reach 2006 levels by December 2013. The house price scenario is probably too optimistic, but were that to happen along with rising interest rates, we should expect to see a steady deterioration in credit quality into 2014.

# 6 Conclusions

As we analyze the performance data from the "'Great Recession"' in the US and the Global Financial Crisis, we are seeing more examples where the available underwriting metrics do not explain the observed credit quality. The swings

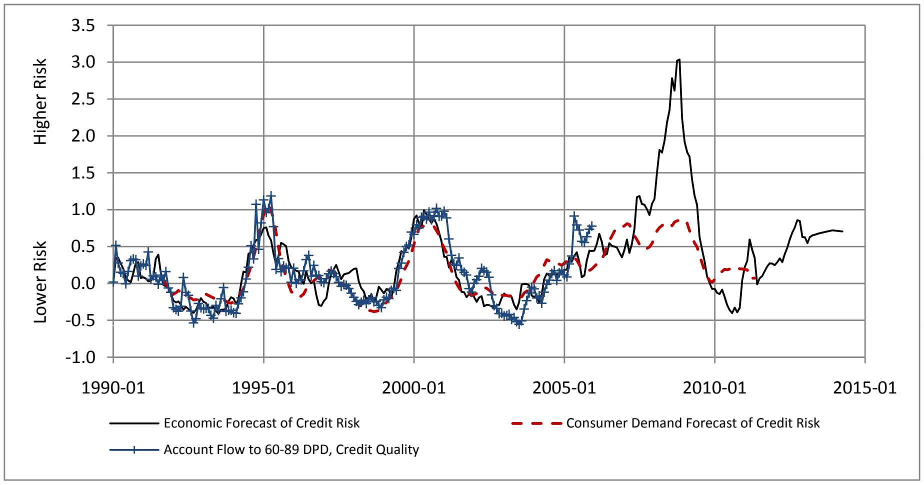


Figure 11: Forecasts from the econometric and consumer demand models for credit quality compared to the in-sample credit quality data and extrapolated forward given a simple macroeconomic scenario.

in credit quality shown here for US mortgage has been observed by the author across all loan types with different magnitudes of impact, but publishable data is difficult to come by. In the currently study, the relationship between swings in credit risk and measures of consumer appetite for risk strongly suggests what we should expect to be true – that consumers do not blindly take on debt. Just as banks and regulators have been talking about controlling risk appetite, consumers appear to time their desire for additional debt to macroeconomic conditions. Just as we have value-shoppers who know how to wait for a sale, those seeking mortgages are most interested when the home appears to be affordable, both from the perspective of the price of the home and the price of the loan.

Consumer risk appetite is likely to be sensitive to factors beyond those observed here. Many factors that impact borrowers' financial confidence could appear as drivers of Macroeconomic Adverse Selection. For that reason, we cannot be certain that either of the forecast models shown here will be robust in future environments, but they appear to be a very good start for anticipating changes in credit risk.

Overall, it is sobering to see that the consumers' self-assessment of credit risk as reflected in changing demand for credit is a more accurate predictor of credit risk than the loan officers' assessment of changes in credit risk via underwriting standards. Few models appear to take consumer demand into account, but it would appear to provide unique information about the loans that are eventually booked.

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