Analysis of Modelling Deficiencies that Contributed to the High Unanticipated Loan Losses Incurred During the Housing Price Collapse of the Great Recession

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by

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Abstract

In this paper the data, modelling and the environmental factors that contributed to the collapse of the US housing market and the high mortgage loan losses during the Great Recession are explored. Deficiencies in data and modelling are discussed with an emphasis on the deficiencies in the mathematical modelling that failed to predict the high level of risk associated with mortgage originations in the mid-2000’s. It is suggested that the lack of effective modelling significantly contributed to banks offering aggressive origination guidelines and that this was a major contributing factor that led up to the housing price collapse in the late 2000’s.

Aspects of behavioral economics, longer term trends in housing affordability and ownership to rental payment ratios that were insufficiently considered in the quantitative assessment of the risk of default are reviewed.

Original research is included to obtain the perspectives of risk management experts that managed risk through the impacts of the housing collapse, as well as an evaluation of current models utilized in the industry. In addition, a model was developed that is intended to predict when the housing market is in a bubble environment.

The paper concludes with suggestions as how current risk management and modelling processes could be enhanced to better anticipate and manage mortgage risk and to minimize unexpected volatility in mortgage loan losses. Suggestions focus on going beyond classic regression modelling and including behavioral, demographic and affordability factors.
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Chapter 1

Introduction

The collapse of the housing market in the United States, following the sharp run-up in housing values that peaked in 2006, was something that the majority of consumers, analysts, politicians, retail banks and investment banks did not predict. In fact the majority of stakeholders actually felt confident that pricing would continue to escalate in spite of growing affordability issues. Surprisingly, even those who claimed their models indicated a price correction would occur anticipated a moderate reduction in housing prices.

This paper starts by examining the housing price trends during the housing boom. It reviews the rapid increases in home values, followed by the pricing declines that brought the housing price index (HPI) back to historical trends. Affordability metric and cost to own versus cost to rent provide evidence of a market gone awry and a boom/bust cycle. The examination of pricing trends is followed by a review of some of the inadequacies in the data and assumptions used to model losses. The identification of modelling inadequacies included a review of a number of scholarly publications as well as the results of original research information obtained from the surveying of industry experts who were involved in the management of risk during and after the housing crisis.

The paper then continues to suggest how current risk management and modelling processes could be enhanced to better anticipate and manage mortgage risk. From the
published and original research it was clear that all the warning signs of overvaluation were clearly present, but were mostly ignored. It was also evident that at the most senior levels of banking and government that there was a lack of understanding of the significant risk that existed regarding the significant risk of a housing pricing collapse. Models were followed almost blindly in spite of screaming indicators that the models were under predicting risk and ignoring common sense. This lack of judgement is evidenced by the financial mayhem caused by mortgage defaults that drove major banks (Washington Mutual and Wachovia) into the hands of large rivals at bargain basement prices, as well as investment banks Bear Stearns and Lehman into insolvency.

As part of the research for this paper, model development work was completed. This work produced a model designed to predict when a market is in a housing bubble utilizing four key variables.

In the final section of the paper, it is indicated that there are still deficiencies in the models utilized for mortgage loan approval and loan loss prediction and proposes stronger consideration of behavioral, demographic and affordability factors as important additions to the current regression modelling work utilized by many banks. There is also discussion of some of the regulatory and political factors creating increased risk in the mortgage marketplace.
Chapter 2

The US Housing Price Collapse

2.1 The Severity of the Housing Market Collapse in the United States

The United States housing bubble for the purposes of this paper refers to the peaking of housing prices in early 2006, and the decline that followed that ran through 2012. The sharpest declines in real estate occurred in 2008, and the market bottomed out in 2012. The housing price collapse was a very significant contributor to the 2007–2009 recession in the United States [1, 2].

Reviewing the pricing trends in Figure 2.1, the increase in the average home price was highly unusual and was out of line with historical trends. Similarly, the steepness of the decline in average home prices was unprecedented, moving from a peak of just over $275,000 to just under $175,000. While this seemed extreme on a national level, the impact in certain cities was even larger.

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This pricing trend closely resembled what economist Jean–Paul Rodrigue visualized for the path of an asset bubbles as shown in Figure 2.2, except in this case it was not tulips, beanie bags, or internet stocks; it was the major asset of most Americans.

An event of this extent had not occurred since the Great Depression and resulted in dire consequences for many Americans and dealt a fatal blow for numerous financial institutions. What had been a safe, stable and rational investment for generations of
Americans, turned into illogical buying decisions as described by Richard Thaler in his book *Misbehaving*. To quote this Nobel prize winner for his work on behavioral economics:

“Some Regions experienced especially rapid price increases and historically high price-to-rental ratios. Had both homeowners and lenders been Econs, they would have noticed these warning signals and realized that a fall in housing was becoming increasingly likely. Instead surveys by Shiller showed that these were the regions in which expectations about the future appreciation of home prices were the most optimistic. Instead of expecting mean reversion, people were acting as if what goes up must go up even more. Moreover, rational lenders would have made the requirements for getting a mortgage stricter under such circumstances, but just the opposite happened.”[5].

### 2.2 Regional Housing Pricing Impacts

While the housing price collapse was severe, many major housing markets were impacted more than others. Just as the “herd mentality” drove housing prices up, a change in consumer attitudes drove prices rapidly down. As indicated in Figure 2.3, certain housing markets (Miami and Las Vegas) declined by over 50 percent.

![Figure 2.3: Miami and Las Vegas Housing Price Index][3]
As prices declined, more and more borrowers would go delinquent on mortgages. What was once a very safe and secure long term investment for the everyday American, in many cases became a financial nightmare.

2.3 Foreclosure and Short Sale Activity

With the decline in housing values, what was generally unexpected happened, delinquency and foreclosure rates accelerated dramatically. Short sales (banks accepting a loan payoff below the mortgage amount on the home to facilitate a sale rather than a foreclosure) also saw a dramatic increase as banks struggled to manage through the housing mortgage crisis. Figure 2.4 clearly indicates how rapid and severe an increase in foreclosure rates was experienced.

![Figure 2.4: Foreclosure Rate](image)

A very interesting aspect of the increase in foreclosure was that not just subprime and high Loan-To-Value FHA/VA loans experienced an increase in foreclosures, Prime (high quality) mortgage also saw a huge spike in delinquency and foreclosures. Lenders who felt that they were isolated from the housing crisis as they did not participate in higher risk

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sub-prime lending were soon made shockingly aware that they too had major issues as even prime mortgages started to see major increases in delinquency, as seen in Figure 2.5.

![Figure 2.5: Foreclosures by Financing Type [7]](image)

The attitudes of many Americans had changed. No longer was making their mortgage payment sacred; the shame of foreclosure had greatly diminished. As indicated in one article by Esther Cho, “with negative equity and foreclosures seeming so commonplace in the state, the stigma of strategic default appears to be fading. This year’s report shows it’s more socially acceptable to strategically default on your mortgage” [8] (Strategic default is when homeowners decide to stop making their mortgage payment even though they can afford the property.)

When surveyed on the topic, 51 percent of those who were foreclosed on said there is nothing wrong with strategic default as a financial decision while 36 percent said homeowners should not choose to strategically default and have a legal and ethical obligation to make their payments if they can [8].

As indicated in Figure 2.6, a similar change in consumer behavior was reported by the
large credit bureau Trans Union who reported that delinquency on credit cards declined
during the housing bust while mortgage delinquency went up as consumers decided to
make their credit card payment but not their mortgage payment.

2.4 Impact of the Housing Crisis on the Banking Industry

As indicated earlier in the paper, the housing price collapse was a major contributor
to the 2007–2009 recession. This turned out to be the most severe recession since the
Great Depression, a recession with a larger loss in jobs and a much slower recovery than
the prior recessions, as seen in Figure 2.7.
The impact on the banking industry was severe. The impact on banks and investments banks with large mortgage loan exposure in many cases was fatal. Banks with long legacies such as Wachovia (4th largest bank holding company in the US in 2008) and Washington Mutual with over 2,000 branches ended up being forced to sell to more stable rivals (Sept 2008 and Dec 2008 respectively). Hundreds of smaller financial institutions were impacted as illustrated by the list of 387 “imploded lenders” up to October of 2008 on MI-Implode.com [11]. Not only were banks that were heavily involved in the mortgage business hurt, many commercial lenders were crippled as home builders that they were financing went bankrupt.

The extent of the negative impact was so severe that major investment banks were forced out of business. During the housing price boom, Bear Stearns was heavily involved in securitization and issued large amounts of asset-backed securities [12]. As investor losses continued to increase for securitized mortgages in 2006 and 2007, Bear Stearns actually continued to increase its exposure to the housing market and more specifically
to the mortgage-backed assets.

In March 2008, the Federal Reserve Bank of New York provided emergency funding to Bear Stearns, but it was still not enough to prevent their sudden collapse. In the end, the company was sold to JPMorgan Chase for the fire sale price of $10 per share, vastly below its pre-crisis 52-week high of $133.20 per share [13]. Six months later on September 15, 2008, Lehman Brothers filed for bankruptcy, with $639 billion in assets and $619 billion in debt. In 2007, Lehman underwrote more mortgage-backed securities than any other firm, accumulating an $85 billion portfolio, or four times its shareholders’ equity [14].

As part of the mortgage carnage, both Fannie Mae and Freddie Mac, the major providers of mortgage financing were forced into government conservatorship and received large capital infusions from the government. The most fundamental sources of funding in the mortgage industry had become insolvent.

While this chapter outlines some of the statistics to highlight the severity and impact of the housing collapse, the next chapter explores some of the more relevant factors and contributing factors leading to the collapse in US real estate prices and the very high loan losses experienced on mortgage loans.
Chapter 3

Factors that Contributed to the Housing Price Collapse and Deficiencies in Loss Models

3.1 How Could the Experts Have Been so Wrong?

The prior chapter reviewed the severity and impact of the housing price collapse. From the review of the events and opinions of this time, it is very clear that not only the everyday consumer, but also most analysts, modelers and government policy makers missed the potential severity of the housing collapse and the impact on mortgage loan performance. This was not the case of a “near miss” and “getting close to the green” in the modelling of mortgage loan defaults and loan loss severity, this was a case of entirely missing the mark.

How could the analysts, modelers, executive managers and politicians have been so wrong is a question that we will explore in this chapter. The weaknesses in data utilized, modelling practices, changes in housing affordability, and consumer behavior are explored.

In a work by Gwartney, Macpherson, Sobel and Stoup, four major causes leading to
the housing bubble were identified [15]. These causes included relaxed mortgage lending standards, an aggressive low rate policy of the Federal Reserve, high leverage in the financial system and increased debt to income for households. What was missing from this as well as many articles on the housing crisis was an underlying issue that is the core subject of my thesis – the financial modelling utilized to predict the risk of losses on mortgage originations leading up to the housing price collapse were severely flawed. This led to lenders unintentionally increasing their mortgage risk profile to an unacceptable level without fully understanding the large loan losses that would result in the future.

If the mortgage lenders, securitization markets, the government, and Fannie Mae and Freddie Mac had truly understood the risk involved in the mortgages that were being originated, the significant expansion in credit guidelines that fueled exuberant demand and a boom/bust cycle would have been much more tempered. The flaws in loss modelling during this period seems to be overlooked in most articles on the housing crisis. My thesis will focus on these flaws and what modelling and credit guideline disciplines could have lessened the extent of the housing price collapse and the elevated loan losses that were experienced.

Even analysts with models predicting a downturn failed to come even close to the depth of the issues and were missing what I would term the “contagion effect” and the impact of human behavior to overshoot and undershoot the prediction of top analysts. The incorporation of behavioral economic principles would have greatly aided in the understanding of what drove real estate prices to their unjustified peaks and what drove the prices to unjustified lows. As an example, the modelling work of a top economist called for a home pricing correction. This 2006 forecast by Mark Zandi of Moody’s Analytics called for a 12% decline in Washington and a 19% decline in the hardest hit city, Cape Coral, Florida [16]. In reality, the drop in the Cape Coral market was much more dramatic, as “the median sales price for single family homes in Lee County, peaked at $315,000 in 2005 and then bottomed out at $81,000 in 2011 [17]. In the same article that Dr.Zandi was
quoted, the economist from the National Association of Realtors indicated to the contrary that the slowdown in sales may have already bottomed out and prices could begin rising as soon as early next year [16]. Both economists had the same economic facts and the same housing data. Apparently mathematical modelling practices provided a fair amount of latitude in assumptions at this time, but seemed to insufficiently consider consumer behavior.

With this as a general background, my thesis will explore the issues with the models utilized to predict loan performance, challenges with the data incorporated in these models, and the insufficient consideration of behavioral economics leading up to and during the housing crisis.

3.2 Modelling Practices and Data Deficiencies

In the words of Naeem Siddiqi in his work on appropriate credit scoring practices, “all models describe historical data – hence the critical need to adjust expectations based on future economic cycles. The amount of confidence in any model or scorecard must be based on both the quality and the quantity of data of the underlying data, and decision making strategies adjusted accordingly. The most accurate model in the world will not help if a bank chooses not to confirm any information from credit applicants or to verify identities” [18].

As indicated in the above quote, a very basic principle of loan loss modelling, or any predictive modelling for that matter, is that the model development population needs to be sufficiently similar to the future population for the model to accurately predict losses. If there are significant changes in the in-the-door population versus the development sample, the model may not be fit-for-purpose. Applying such a model to new types of customers may result in outputs that are significantly flawed with limited ability to adequately predict the dependent outcomes of loan delinquency and loss severity.

This would indicate that the loss modelling work completed on borrowers during the
years leading up to the housing price collapse should have been based upon similar bor-
rowers with similar application characteristics during a somewhat similar housing envi-
ronment. As will be discussed, this basic principle of loan loss modelling was severely 
violated. FICO 04 was used for application decisioning even though it was developed 
on mortgage applicants and mortgage guidelines from pre-1999 [19]. Similarly, probabil-
ity of default models and loss severity models generally were not re-developed to reflect 
the many changes in the industry (Appendix 1). The impact of this deficiency in the 
modelling process was catastrophic and contributed to a near collapse in the US financial 
system. Let us explore major factors that negatively impacted the predictability of the 
mortgage default models (probability of default and loss severity given default) one by 
one.

(a) How similar was the population applying for mortgages in the years immediately 
   prior to the housing collapse versus the population that the models were developed 
on?

(b) How similar were the application characteristics, product guidelines, and underwrit-
   ing processes?

(c) How similar was the housing economic environment?

(d) Which aspects of Behavioral Economics contribute to poor model performance?

a) How similar was the population applying for mortgage in the years immediately 
   prior to the housing collapse versus the population that models 
   were developed on?

The basic FICO 04 model was utilized for approval of mortgages and was introduced in 
2004 [19]. FICO 04 was developed based on loans originated 1998 and prior (Appendix 3).
As indicated in Figure 3.1, the homeownership rate dramatically increased in the years preceding the housing bust. As will be indicated in subsequent sections of this paper, the increase in homeownership rates consisted of many borrowers that were dissimilar from historical borrowers in terms of their credit depth, down payment and purchase motivation. Furthermore, the models dealing with the prediction of loss severity were not built on high Loan-to-Value mortgages.

![Homeownership Rate](image)

Figure 3.1: Homeownership Rate [21]

Confirmation of modelling deficiencies due to a shift in the in-the-door population is contained in the independent research completed where modelling and risk executives from SunTrust, Union Bank (MUFG) and Synovus commented on modelling practices in the period of the housing boom (Appendix 1), with excerpts from replies to questions copied below. From a review of industry data and the responses to the independent research, I believe that it is clear that the population that the models were developed on had significant differences from the population of borrowers added in the years just prior to the housing collapse.

Do you feel there was a shift in population that impacted model performance? If so, what accounted for that shift?
“Yes. There was a new breed of exotic products that were entering into the portfolio where assumptions had to be made on the modelling side as no historical data was available or were limited.” (Tu Le – Appendix 1)

“Yes, there were multiple shifts. Some driven by management (product changes), some driven by environment (Florida court foreclosure times), some driven by regulatory (Fannie/Freddie repurchase contracts).” (Chris Pyle – Appendix 1)

**How do you think model development and mortgage guidelines could have been enhanced to be more effective in the period leading up to the Great Recession?**

“Model Validation Groups were in a very formative state at most financial institutions and since the Great Recession has rapidly evolved.” (Tu Le – Appendix 1)

“Just storing and keeping data. Pre-crisis most institutions did not keep originations data very long. I can distinctly remember trying to forecast losses on STI’s mortgage portfolio in Q2 of 2009 and being told we didn’t save anything electronically. We have to go and physically try and find the paper file to get any info.” (Chris Pyle – Appendix 1)

**Were the modelling flaws more severe in loss frequency or loss severity?**

“It was a combination of both. With unemployment affecting frequency and HPI affecting severity. Both were bad, if I had to pick one it would be PD.” (Tu Le – Appendix 1)

“There are arguments for both but I believe the flaws were more pervasive around loss frequency.” (Chris Pyle – Appendix 1)

“Not all borrowers that defaulted had neg am or negative equity in their transaction. I did not see modelling that contemplated the large number of defaults that were seen. Had that been identified I think steps could have been taken quicker to reduce the severity of the outcomes.” (Gary Walton – Appendix 1)
b) How similar were the application characteristics, product guidelines and underwriting processes?

In the years leading up to the housing price collapse, lending guidelines dramatically expanded, allowing borrowers that could not previously qualify to become mortgage borrowers. As indicated in a Washington Post article “If you were house hunting before the crash, you could choose between an array of loan products to keep your payments low such as an interest-only loan, a “choose-your-own-payment” loan, a balloon payment loan or an adjustable-rate mortgage (ARM) with an extremely high cap. If your credit score was low, you didn’t have money for a down payment or your income was erratic, you could get around all those obstacles with a no-documentation loan, sometimes for as much as 125 percent of the home value” [20]. Johnathan Kohn in the Research in Business and Economics Journal indicated that “lending standards were relaxed, bringing in a new class of borrowers who traditionally could not afford to own their homes. Home buyers could receive 100 percent loan-to-value loans, with little if any credit or income checking. Interest only loans added to speculative pressure by allowing borrowers to obtain the maximum amount of financing without regards to repaying the principal” [22]. The performance data that was utilized to build the default models were built in a period that these aggressive guidelines did not exist. The period of the FICO 04 development sample utilized pre-1999 loan applicants (Appendix 3), well before these aggressive products were in place.

Once again, referring to the independent research that was completed and is outlined in Appendix 1, the lending products and processes were very different from what the populations that the loan origination and loss models were developed upon as indicated by the questions and answers below.

How impactful was the implementation of stated income loan products in the model development process?

“How impactful as there were limited data availability on the loan products. If you
look at the loans that defaulted during the Great Recession a majority of these loans had a higher default and loss experience than non-stated income loans.” (Tu Le – Appendix 1)

“Stated income had a big impact on the industry and as I mentioned earlier was perceived to be a nominal risk because of the competition to close loans. It was not considered a risk of borrower default and thus only become a consideration for model development. A model generally only considers an input when the variable has some correlation what the model is trying to predict. Since it was broadly used there were limited instances of it showing up in the data until it was too late.” (Gary Walton – Appendix 1)

**How were people able to model negative amortization products when negative amortization was new to the industry?**

“Due to limited or lack of data availability assumptions were made and/or synthetic pools (using alternative products outside of mortgages or blended with mortgage data) were created to simulate expected performance.” (Appendix 1 – Tu Le)

“We didn’t. Insofar as anyone did, it would be a component of Loss Given Default, and given the assumption that everyone had at the time on housing prices continuing to rise, your LGD would be 0 as the collateral would always be worth more in the future than it is today.” (Appendix 1 – Chris Pyle)

“Negative amortization was contemplated and was considered acceptable but the risk was generally considered mitigated because borrowers historically paid their homes first so default was low and there was always an expected increase in home price values that offset the negative amortization.” (Appendix 1 – Gary Walton)

**How would you assess the quality of underwriting in the housing boom versus the period 10 years before the boom?**

“Credit underwriting standards became less strict in the ten years leading up to the
Great Recession. If the bank is selling the loan and does not own the risk they will migrate towards the buyer’s underwriting standards.” (Tu Le – Appendix 1) “Standards and practices decayed from that period to just before the boom.” (Chris Pyle – Appendix 1) “Underwriting eased dramatically and the quality was not good. Quality control error rates were largely ignored unless it impacted the salability of the loan.” (Gary Walton – Appendix 1)

Additional independent research was completed with Professor John Merrick, Richard S Reynolds Professor of Business. Professor Merrick confirmed that there “were overly optimistic perceptions of defaults based upon a misreading of early low default rate experience. There was limited insight into forecasting of default rate” and that “silly assumptions were also made, where the mass belief was the housing prices would continue to go up for the foreseeable future.” He also indicated that “people were qualifying on basis of teaser rates instead of fixed rate assuming that they can always refinance later as a prime borrower.” (Appendix 2)

Scholarly papers reinforce the independent research that was completed as part of this paper and indicate that the models utilized to approve clients and predict loans were not appropriate. In “Wall Street and the Housing Bubble: Bad Incentives, Bad Models, or Bad Luck?” it is indicated that Wall Street employees were too optimistic and took massive housing markets risk “because they used bad models to over extrapolate growth of home prices” and “because psychological dissonance caused them to ignore risk and warning signs,” and continued to say “that bad models view distorted beliefs and over-optimism on Wall Street resulted in individuals, even those properly incentivized, failing to anticipate the housing market crash” [23]. The paper continues to indicate the modelling deficiencies and states that “the models used by financial firms during the bubble period to value mortgage backed securities were commonly calibrated to historical housing price data and thus ignored the newly emerging correlations between different housing markets. As a result, these models under estimated the default correlations of
different mortgage loans” [24].

Regulators and politicians also misunderstood the market dynamics and the risks involved. In a Federal Reserve Board meeting in May 2006 “Chairman Bernake described the cooling of the housing boom as healthy and most other Fed officials were also expecting a manageable slowdown in the housing sector, with little damage to the financial system of broader economy” [25].

During the period leading up to the housing price collapse, it was clear that underwriting quality was subpar. This was caused by a focus on volume and revenue rather than the quality of originations. Lawsuits provide clear documentation of this bias.

“In 2014, the department settled alleged violations of the False Claims Act with SunTrust Bank (SunTrust) for $418 million. As part of the settlement, SunTrust admitted that between January 2006 and March 2012, it originated and underwrote FHA-insured mortgages that did not meet FHA requirements and were therefore not eligible for FHA mortgage insurance, that it failed to carry out an effective quality control program to identify non-compliant loans and that it failed to self-report to HUD even the defective loans it did identify. SunTrust also admitted that numerous audits and other documents disseminated to its management between 2009 and 2012 described significant flaws and inadequacies in SunTrust’s origination, underwriting, and quality control processes and notified SunTrust management that as many as 50 percent or more of SunTrust’s FHA-insured mortgages did not comply with FHA requirements” [26].

In a report the department announced that “Citigroup agreed to pay $158.3 million to settle. Hunt said her share will be $31 million, before taxes and attorney fees. Her lawyer declined to disclose those fees. In settling, Citigroup accepted responsibility for conduct alleged in the complaint dating back to 2004. The government accused CitiMortgage of misleading it into insuring thousands of risky home loans that it knew or should have known did not qualify for insurance from the Federal Housing Agency, costing taxpayers
nearly $200 million in claims. CitiMortgage had certified for FHA insurance nearly 30,000 home loans valued at more than $4.8 billion since 2004, but more than 30 percent — or 9,636 loans — had gone into default. The default rate topped 47 percent for such loans made in 2006 and 2007, it added” [27].

One might ask, was this poor loan performance really due to a loosening of underwriting guidelines and lack of a focus on the quality of underwriting, or was this just the housing market impacting the default rate? A look at a similar economy with a similar boom in housing prices provides an interesting perspective. In Canada, house prices increased at a similar rate to the United States, but as indicated in Figure 3.2 and Figure 3.3, never experienced the housing price decline or the sharp increase in delinquency.

I attribute much of this performance difference to the more robust underwriting requirements in Canada during this same time period. In Canada the stated income products did not exist, and most Canadian mortgages are retained on bank balance sheets as there is no equivalent to Fannie Mae and Freddie Mac.

![Exhibit 3: Mortgage delinquency rates in Canada remain low (90+ day delinquency rates, Canada vs. US)](image)

Figure 3.2: Canadian Delinquency [28]
As just indicated, the Canadian real estate market did not experience a similar decline to the US due to stricter products underwriting standards, but significant risk exists. The two major risks that I would identify for the Canadian are interest rate risk and affordability. These two factors hint that a day of reckoning and a price correction have a significant probability of occurring.

In terms of interest rates, Canada does not have 30 year fixed mortgage rates, and the majority of mortgages are for a five year term, with 44% of borrowers opting for shorter term, lower rate, variable rate mortgages in 2018 [30]. Without the rate protection of the 30 year fixed rate offered in the US market, any significant rate increase could have a huge impact on affordability not just for new buyers but also for existing homeowners.

Further increasing the affordability risk is the already high debt levels of the Canadian consumer. As indicated in Figure 3.4, debt levels in Canada have far exceeded those experienced in the United States during the Great Recession. The lack of longer fixed rate terms available in Canada, combined with the high debt load of Canadians put the Canadian real estate market at a large risk of a major correction, a significant increase in rates could prove to the tipping point for the pricing correction.
Moving back the United States, with a large shift to higher risk guidelines (high LTV, Negative Amortization, Stated Income, etc.), there was a large difference between the type of loans being originated and the guidelines that were in place versus the data utilized for the modelling development samples. The ability of models to accurately predict outcomes was negatively impacted by a major shift towards much more flexible product guidelines. This negative impact on model performance was further amplified by poor underwriting quality. These were not the product guidelines and credit characteristics that the FICO 04 and loss prediction models were based upon. How can one expect a loss model to accurately predict an outcome if there is a significant shift in the guidelines from the original development sample, there is a shift in the population characteristics and the independent variables are not consistently calculated properly by the loan underwriters? As one would expect, the models were not able to accurately predict the loss frequency or loss severity with these changes to the origination population. The outcome was dramatically high default rates and much higher loss severity when default occurred.

**c) How similar was the housing economic environment?**

“Just as rising prices reinforced the continuing rise in home prices, falling home prices
reinforced the continued fall in home prices” [2]. As home prices spiraled down, the so-called super prime loans at 80% loan to value with a high credit score began to act very differently than normal models would predict. There also started to be a change in consumer attitudes that “turning the keys to the bank” did not hold the same degree of social stigma.

“All the participants who contributed to the housing bubble (government, regulators, mortgage lenders, investment bankers, credit rating agencies, Foreign investors, insurance companies, and home buyers) acted on the assumption that home prices would continue to rise” [2].

For example, Business week (2005) quoted Frank Nothaft, chief economist of Freddie Mac as saying “I don’t foresee any national decline in home price values. Freddie Mac’s analysis of single family houses over the last half century hasn’t shown a single year when the national average housing prices has gone down” [32]. Surprising, what was missing from consideration was that the growth in housing pricing was being fueled by factors that had never existed before, These factors included:

(a) Lending products that never existed previously that allowed people to obtain homes that they could not have qualified for in the past (Stated Income, Stated Assets, 100% Loan-to-value, qualifying on lower payments made possible by negative amortization)

(b) Liquidity in the mortgage market provided by the international securitization of loans

(c) Government pressure to housing agencies to increase homeowner ship, reaching historic highs in the late 2005, followed by a consistent decline towards more historical norms started in October of 2007 [33].

When ones looks at metrics that reflect the state of the housing economic environment, it was very clear that changes had occurred. Key metrics related to housing affordability
were dramatically different from the data utilized in the development of the loss models. These key metrics were shouting at a problem, and a change from historical norms were clearly evident, but generally received insufficient attention. Some of the metrics that indicated a housing boom and contributed to a huge increase in loan losses exposure included:

- Household debt service payment rising to historic highs (Figure 3.5)
- The cost of buying becoming much more expensive than renting (Figure 3.6)
- The home price to rent ratio increasing from close to 1 to 2 (Figure 3.7)
- The indication of an impending housing bust as the months of housing supply climbed (Figure 3.8)

As indicated in “Housing Bubbles” by Edward Glaeser, in his review of various modelling methodologies for housing prices, he concluded that “it seems silly now to believe that housing prices changes are orderly and driven entirely by obvious changes in fundamentals operating through a standard model” [34]. While this does not apply directly to loan loss default models, it does lead one to conclude that models that are influenced by housing prices need to be more adaptive to changes in the environment.

Figure 3.5: Household Debt Service Payments as a Percentage of Disposable Income [35]
Not only was buyer behavior changing, but the political environment was pressuring banks to be more aggressive in increasing the homeowner ship rate in the country. As indicated in the NYTimes in 2008 “companies were constantly under pressure to buy riskier mortgages. Once, a high-ranking Democrat telephoned executives and screamed at them to purchase more loans from low-income borrowers, according to a Congressional source. Shareholders attacked the executives for missing profits by being too cautious” [38].

A most interesting work in housing pricing models was the modelling work completed

They found that the independent variables that came out of the regression modelling were very different for the pre-bubble versus the bubble period. (See Appendix 5) When the Pre-bubble model was tested on the bubble period loans, “Striking differences were found” with what they felt were usually the most important factors in the housing market (Mortgage rates and personal income). “Another major difference was the very high levels of co-linearity among the independent variables, in sharp contrast to the pre-bubble model. The fact that the co-linearity was not observed during the pre-bubble period as opposed to the overwhelming effect during the bubble period lends further support for the housing bubble effect” [40].

It was very clear that housing affordability deviated very significantly from the mean and this was not reflected adequately in the models to predict the probability of default or the severity of loss given default [41].

d) Which aspects of Behavioral Economics contributed to poor model performance?

One major factor which negatively impacted the performance of the loan default models was a change in consumer behavior. Loss forecast models assume that consumer behavior for new applications is very similar to the consumer behavior that occurred in the development sample utilized to build the models. In the period leading up to the boom, there was a large change in consumer behavior versus the pre-boom period. This change is discussed in Jonathan Kohn and Sarah Bryant paper in the Research in Business and Economics Journal. In contrast to prior home buyers, the buyers in the housing boom period had “the prevailing attitude of bigger is better or as much as one can afford, or
buy now avoid future higher prices” as the driving force to buy a home [42]. The paper continued to state that “a home that normally would be considered too expensive by the home buyer is now accepted because of expected future price rises” [43]. As consumers looked to get in on the housing boom, home buyers stretched to either get into the housing market and to buy larger homes if possible. As this happened, people stretched their budgets as illustrated by the ratio of housing price to income jumping to unprecedented levels. It rapidly moved from under 3 times their income to over 4 times their income as indicated in the following chart (Figure 3.9).

![Home Price-to-Income Ratio](image.png)

Figure 3.9: Home Price-to-Income Ratio [44]

The stretching in consumer budget was not just to purchase a home, but to purchase a larger home if possible. This move to purchase a larger home is illustrated in Figure 3.10 where the average size of a new privately owned home moved from 2200 square feet in 1999 to over 2500 square feet in 2007.
This increase in average housing size and increased real estate pricing was not driven by declining interest rates. As outlined in Figure 3.11, the mortgage interest rates between 2002 and 2008 experienced fluctuations but actually increased if a best fit line were drawn. As a result, I would conclude that the increase in average home size was driven by a change in consumer behavior and definitely not increased affordability. In fact, affordability reached exceptionally challenged levels.

Another behavioral change was the decline in savings rate, as seen in Figure 3.12.
People were stretching themselves more and more and saving less. Consumer behavior showed a shift to consumer spending, higher debt loads and less savings.

One of the pioneers in behavioral economics “challenged the popular view in economics that individual decision making was rational, predictable and easily modelled” [48]. In his work Misbehaving, Nobel prize winner Richard Thaler describes behavioral economics as “economics done with strong injections of good psychology and other social sciences. The primary reason for adding Humans to economic theories is to improve the accuracy of the predictions made with those theories” [49]. In looking at housing prices, Thaler indicates that prices grew modesty until the mid 1990’s and then “shot upward” [50]. He continued that “after a long period during which the ratio of the purchase price of a home to the cost of renting a similar home hovered at 20:1, home prices diverged sharply from this benchmark” [51].

Thaler indicated that “instead of expecting mean revision, people were acting as if what goes up must go up even more. As shown in Figure 3.13, home prices revert to the mean. Moreover, rational lenders would have made the requirements for getting a mortgage stricter under such circumstances, but just the opposite happened. Mortgages were offered with little or no downpayment required and scant attention was paid to the
credit worthiness of the borrowers. These “liar loans fueled the booms, and policy makers took no action to intervene” [52].

A further reference to the impact of behavior change by mortgage borrowers was provided by the former Chief Credit Officer of Washington Mutual, Cliff Rossi. One of the largest financial institutions in the US with over 2000 branches was forced to sell to JP Morgan Chase due to the large losses in their mortgage business. In the words of Mr. Rossi, “A profound shift in mortgage borrower attitudes caught the industry off guard and could not be detected by models relying on structural data” [53].

Figure 3.13: National Home Price Index. Chart showing home prices reversion to the mean.

This large change in consumer expectations and behavior was a significant contributor to the default models lack of ability to accurately predict loss levels. They were developed during a time when the consumer was acting rationally, and then there was a large shift in consumer behavior. Prime borrowers that had performed in past models changed behavior with “a sizable fraction of prime borrowers, who levered up to buy more housing expecting to soon realize capital gains, find themselves with negative equity and chose to default” [54].
What I have termed the “contagion effect” took hold. A significant segment of the population changed their attitudes towards defaulting on a mortgage loan. The degree of social stigma of foreclosure had lessened. People caught the bug. As neighbor’s homes went into foreclosure property values fell, creating negative equity for other homeowners resulting in additional default. Banks soon learned that even if they only issued loans to prime borrowers, they were being significantly impacted as the percentage of homes with negative equity reached close to 30% as indicated in Figure 3.14. “One unexpected event in the housing collapse was the problems for homeowners with good credit, in 2007 the largest US mortgage lender at the time, Countrywide Financial warned that a housing recovery was not expected to occur at least until 2009 because home prices were falling “almost like never before, with the exception of the Great Depression” [56].

![Negative Equity Volumes and Rates](image)

**Figure 3.14: Negative Equity Volumes and Rates [55]**
3.3 Conclusion

At the beginning of this chapter I had indicated that the core subject of my thesis was that the financial models utilized to predict the risk of losses on mortgage originations leading up to the housing price collapse were flawed. I then went on to explore the factors that contributed to the weakening in the predictive capability of these models.

I believe that the independent research, an examination of key housing metrics, and a review of scholarly research by experts in this field clearly prove that the models in use were severely flawed. The evidence presented supported a large change in population, dramatically different application characteristics and guidelines, and weak underwriting processes contributing to uncertainly regarding the true application characteristics, all items that violate the basic principles for quality model development. Furthermore, I advocate for the impact of behavioral change in further weakening the predictability of the models.

The impact of these modelling flaws was an inability to predict the large spike in mortgage defaults and decisions to lend to unqualified borrowers, further feeding a housing boom and contributing to a later collapse in housing prices. The consequences of these poor models contributed to a spike in mortgage delinquency (Figure 3.15) that was unprecedented since the Great Recession, very negative impacts on borrowers, financial institutions and the economy as a whole.

Figure 3.15: Delinquency Rate [57]
Chapter 4

Enhancements to the loss modelling process that could have better mitigated the large loan loss exposure

4.1 Canary in the Coal Mine

Before the implementation of modern carbon monoxide detectors, miners used to carry caged canaries while at work. If there was a high level of carbon monoxide in the mine, the canary would die before gas levels became hazardous to humans, warning the miners as to a safety issue. Similarly, delinquency vintage curves are the “canary in the coal mine” for lending losses, indicating that changes need to be made when there is a significant change in the shape of the vintage curve.

These changes can take several forms:
(a) The model can be redeveloped based on utilizing updated data

(b) Cutoff scores can be adjusted to better compensate for unexpectedly high risk levels

(c) Independent variables contributing to the score can be made more stringent (down payment, documentation, debt-to-income)

Ample evidence was provided in the previous chapter that the basic principles of model development and model utilization had been violated. There was a large shift in the population, a massive change in the housing environment with prices deviating from long-term-norms, unprecedented negative changes in housing affordability (see Figure 4.1) and very large changes in consumer behavior.

Figure 4.1: Median House Price to Income Ratio [58]
Given all this happening, two interesting questions present themselves:

(a) Were there signs of potential model performance problems (was the “canary in the coal mine” looking unhealthy?)

(b) Could earlier action have been taken?

Clearly, metrics on housing affordability were screaming red, but one should also consider loan performance. When reviewing the vintage performance of loans that went into default (Figure 4.2), it appears that there were fairly strong indications of something gone awry as illustrated in the 2005 (brown line) vintage.

![Figure 4.2: Vintage Default Rate](image)

Defaults rose early in the total 2005 vintage, a blaring signal of a problem and housing affordability measures were at unprecedented levels. This leads us to address
the second question of whether earlier action could have been taken. The first step in answering this second question requires a determination of when action was taken and is discussed in section 4.2 (The Light Bulbs Went On).

4.2 The Light Bulbs Went On

It is difficult to find a general indicator of when lenders, investment banks and government regulators came to the realization that changes were required as the models that were being utilized had not been effective in adequately evaluating the risk of mortgage loan losses. Reactions to the increasing delinquency varied significantly among different market participants. Generally speaking, the reaction by mortgage lenders seemed to have gained momentum in 2007. In a press release from the Federal Reserve in 2007 it was indicated that “of the 44 domestic banks that originated nontraditional residential mortgages, 45% said they tightened standards for those loans. Those 44 banks accounted for about two-thirds of home mortgage loans on the books of all commercial banks as of the end of 2006” [60]. On March 2, 2007, “the Federal Reserve and other regulators proposed tougher rules for subprime lending, saying lenders should inform consumers of potential payment increases and prepayment penalties associated with such loans. Lenders should approve loans only when they know borrowers can repay them, they added” [60].

Similarly, Fannie Mae looked to address lending risk in 2007 and was particularly concerned with the poor quality of appraisals and indicated that some of the appraisal values they were receiving were inflated. In July 2007, Fannie Mae issued a bulletin indicating a need for appraisal guidance due to recent declining markets and the potential for “the overstatement of property values in appraisal reports” [61]. The bulletin continued, ”the appraiser is expected to use the most recent and similar comparable sales available as part of the sales comparison approach, because excessive sales concessions can artificially inflate the sales price of a property, particular attention should be given to unusual sales or financing concessions in markets” [61]. This, as well as other Fannie Mae actions, were
too little and too late with the government putting Fannie Mae and Freddie Mac into conservatorship in February 2008.

Reviewing the very large financial losses experienced by the mortgage industry, banks, investment banks and FannieMae/Freddie Mac, it is very clear that action was taken far too late. It also appears that the warning signs were present much earlier than action was taken, but these warnings did not receive sufficient attention. The canary had died, but no one was watching!

4.3 The Time Traveler - What Could Have Been Done Differently?

While hindsight is 20/20, if I was able to travel through time, there are a number of recommendations that I would have made to improve the modelling of loan performance and to mitigate the outsized losses that were experienced. The primary activities that I believe should have done differently include:

1. Examined long-term-trends in demographics, affordability, and rent to own ratios. Look to see if a separate model development focused on the high Debt-to-income population would validate rather than utilize the same model on the entire population.

2. Closely monitored performance of newer loan products (i.e., stated income and negative amortization loans). Consideration for the development of separate loan performance models for these populations given the potential of very different loan performance.

3. Increased the quality review of loan files for the higher risk populations to ensure that the independent variables (Debt-to-Income, Loan-to-Value, owner occupied...
versus investment property, appraisal quality review) were being calculated properly. Evaluate loan performance for each type of error to determine which errors were most impactful and to prioritize where operational changes should be made.

4. Strong management and oversight of loan performance. At the early signs of increasing vintage delinquency in 2005, to start the model redevelopment process with particular attention paid to segmented models (i.e., separate models for stated income and higher Loan-to-values). Utilization of housing affordability norms and rent/own cost ratios in modelling process.

5. As 2005 vintages showed weakness, tighten lending guidelines (larger down payments, higher credit score requirements, stricter income reasonability checks on stated income) rather than waiting until 2007 to take action.

6. Completing stress testing under multiple scenarios to determine the potential impact on loan losses. The results of these stress tests could have informed executive management and allowed for a determination as to whether the downside risk fell within the risk appetite of the financial institution. Stress tests would have included declining property values and increases in unemployment, Figure 4.3 shows the strong correlation between unemployment rates and mortgage delinquency). In the independent research contained in Appendix 1, it was consistently indicated that routine stress testing was not completed. This lack of stress testing in the modelling process was a huge miss that allowed financial institutions to put billions of dollars of mortgages on their balance sheet without understanding the true risk in a stressed economic situation. The result, as indicated earlier, was the failure of two of the largest US banks (Washington Mutual and Wachovia) and two of the largest investment banks (Bears Sterns and Lehman).
4.4 Better Late Than Never

In reviewing the loan performance results, the independent research, and the timing of action taken, it appears that there were inadequate risk management practices in place. The signs of potential modelling issues and loan performance vulnerability were clearly present, but appropriate actions occurred in a manner that was too little and too late.

Following the Great Recession, significant action has been taken by both industry and regulators to better address, moderate and measure mortgage loan default risk. Five years after the housing price collapse, regulators issued a rule that owner occupied mortgage loans need to be underwritten to determine the customers’ ability to repay a mortgage. Under the Qualified Residential Mortgage (QRM) regulations that were released in October 2014, “The QRM rule considers a qualified borrower if they have debt-to-income ratio of 43 percent” [63] and prohibits the utilization of stated income. Additionally, the
Federal Reserve and the Office of the Comptroller of the Currency (OCC) require mortgage portfolio stress testing as part of their bank examination process. This practice did not exist prior to the Great Recession.

In the case of financial institutions, there is now much more attention paid to the quality of loan underwriting, stress testing, the size of their mortgage business and their loan requirement guidelines (down payment, debt to income, score). There is now much more robust scorecard and portfolio monitoring reports and loan performance reporting.

There is no question that the actions taken post the Great Recession have lowered the risk of an outsized increase in mortgage delinquency and subsequent losses. No longer can someone buy a home to live in based on stated income and no longer can banks have huge portfolios of mortgages on their balance sheet without completing stress testing. That being said, there are still improvements that can be made. The next chapter discusses some of the current modelling practices and suggests some areas of improvements.
Chapter 5

Review of Current Mortgage Loss Modelling Practices and Potential Enhancements

5.1 What Was Learned

It is very clear from the research that has been completed and highlighted in this paper that the regulators and the banks learned a great deal from the housing collapse and related mortgage crisis. Two major changes occurred in the industry that should significantly lessen the severity of future declines in the housing market – regulatory changes in qualification requirements and enhanced bank stress testing modelling.

It is hard to even imagine that the regulators and government supported the lending agencies (Fannie Mae and Freddie Mac) in actively supporting the products that drove much of the increase in higher risk home purchases, but political pressure and poor modelling had its way. When the regulators realized the error in their ways, they implemented regulations prohibiting the utilization of stated income for owner occupied homes. This disallowance of stated income is part of the requirement for banks to clearly document the
ability for the homeowner to make the monthly payments on owner occupied mortgage loans. The impact of these regulations has clearly changed the composition of the mortgage loans that are being originated. As noted in the November 2019 article in Kiplinger’s Personal Finance, “While the number of unconventional mortgages has grown, they were still less than 3% of loans made in 2018, compared with 39% in 2006, right before the housing bust began” [64].

The banks now have built out significant modelling capabilities to better predict the percentage of loans that are anticipated to default and the loss severity given a default. They are running their models to reflect both the expected experience in the current economic environment as well as loss scenarios to reflect the anticipated experience during a severe recession. This modelling work allows banks to better set aside the necessary capital to weather a deep recession, as well as to set portfolio limits (i.e., only wanted 25% of their balance sheets to be in mortgages) to better manage overall risk.

5.2 Current Practices in Bank Risk Modelling

In my conversations with risk management executives at a number of banks, completed as part of my independent research, major US banks continue to utilize credit related and general economic conditions as the main drivers in their loss models. (See second to last question and replies in Appendix 1). Items mentioned as included in the loss models included credit score, debt to income (DTI), property type, employed or self-employed, past delinquency on loans, unemployment rate, GDP changes, and home price index changes. One bank was willing to provide their loss model, providing they were not identified, as shown in Figure 5.1. As you can see below, while credit score, home pricing, payment history, Debt to income (DTI), payment history and type of loan are included, there were no variables that deal with large housing environmental changes (e.g. ownership versus rent costs, home price to rent ratios, months of housing inventory, population trends) or consumer behavioral/attitudinal changes.
Additionally, while the banks indicate that they update their loss prediction models on a frequent basis, FICO 04 continues to be utilized by the industry for initial loan approvals. This model was developed on an average loan population that was from approximately 20 years ago. As Andrew Ackerman outlined in the August 13th 2019 article in the Wall Street Journal, the Federal Housing Agency (FHFA) which oversees Freddie Mac and Fannie Mae has finally instructed these lending agencies to consider the utilization of alternate scores. The article quoted Mark Calabria from the FHFA,
“One of my priorities is to ensure that the American people have a safe and sound path to sustainable homeownership, which requires tools to accurately measure risk.” The new rule “is an important step toward achieving that goal.” [65].

So, while there has been significant progress in the risk management of mortgage loans and that loss modelling practices have greatly improved, I would suggest that there are still significant deficiencies in the risk management practices for mortgage loan approvals, as well as the models and stress testing practices to predict potential loan losses. I would also suggest that there is additional data and safeguards that could be incorporated into modelling practices to better reflect the evaluation of the true level of risk of mortgage loan portfolios.

5.3 Potential Enhancements to Current Modelling Practices

I would propose that traditional mortgage loss modelling should supplement the utilization of traditional credit based risk modelling variables, such as credit score, debt to income (DTI), property type, employed or self-employed, past delinquency on loans, unemployment rate, GDP changes, and home price index changes, with additional data. More specifically, I would propose that more behavior-based variables be added to the loss modelling as well as some additional macroeconomic factors. These additional data elements could become part of the model, or an overlay to help assess pending risks that may drive a significant increase in loss severity that is not predicted in the core model.

Suggested behavioral data would include variables that indicate a change in consumer attitudes towards the desirability of homeownership that would significantly impact demand, and therefore the valuation of homes and potential loan loss severity. Behavioral trends towards stretching to own a home would indicate an overheated market with a
higher probability of a future increased default rates. Behavioral data to be considered would be items such as home costs as a percent of income and housing inventory.

In March 2019 the Global Association of Risk Professionals (GARP) webinar on “How Banks Can Leverage Behavioral Analytics,” Dr. Cliff Rossi indicated that up to this point banks tended to use proxies of behavior (e.g. FICO score as a reflection of a consumer willingness to repay a loan) and leaned on traditional analysis but did not include consumer preferences, cognitive biases and risk attitudes. He stated that “A profound shift in mortgage borrower attitudes caught the industry off guard and could not be detected by models relying on structural data” [66]. He indicated that risk modelers should augment the traditional data with behavior analysis and unstructured data to significantly enhance effective risk models. Dr. Rossi continued to say that we are used to structured data in risk management and that we should supplement these risk models with unstructured data (text, social media, nontraditional credit). In his specific words, by doing this we “can really improve the predictive quality of the model” [66]. Dr. Rossi concluded the webinar by saying that behavioral analysis can improve risk management, but that “its real power has yet to be realized. From better credit risk assessment, to reputation risk and even operational risk management, opportunities abound for behavioral analysis as part of the risk manager’s toolkit for the future. Bottom line is behavioral analysis techniques applied to borrower attitudes towards homeownership and credit augmented with similar applications to collateral will revolutionize mortgage credit risk assessment” [66].

When I consider Dr. Rossi’s comments, and behavioral economics in general, it leads me to suggest that risk managers should not only include additional behavioral data in their models, but should also identify triggers that indicate behavioral changes or behavioral bias that could lead to overheated housing markets with later corrections.
Moving on to macroeconomic factors, I suggest that they have a large impact on loan losses and are not sufficiently considered in the modelling. None of the banks that I spoke to consider interest rates, affordability measures or regional economic factors. They indicated a focus on Gross Domestic Product and Unemployment rates.

I believe that interest rates should definitely be considered in loan loss prediction. Currently mortgage rates are very low. If mortgage rates increase by 2%, there will be a large impact on housing demand. Buyers will have challenges in affording prices at the higher rates and existing homeowners with renewing mortgages will face higher rates. This would likely result in price declines and higher loan losses, but interest rates were not considered in the banks that I interviewed. Consideration of other affordability measures would also add to the long term assessment of long term mortgage risk. This would include trends in affordability and trends in the cost of rent versus ownership.

Another macroeconomic factor to consider is the examining long term trends in demographics. The movement of the generations into (Gen X) and out of (Boomers) the housing market will affect supply and demand. The size of each generation will have a large impact on housing pricing and therefore the probability of default and the loss severity on defaulted loans.

A final macroeconomic factor to consider is regional geographic segmentation of models. Banks are utilizing FICO 04 for loan approvals without separate models or model adjustments by region. Obviously, this is a weakness that should be addressed in mortgage approval models. Cities that are facing the loss of jobs or population decreases due to other factors will have different loan loss experience than cities that are growing. This was proven in the Great Recession where some cities saw much higher property value declines and losses than others, as indicated by Figure 5.2 that shows default rates varying from 10% to 40% depending on state.
Clearly, a consideration of regional economics (economic growth, home building activity, population changes) and model segmentation by region would result in more accurate loan approval and loss models.

5.4 To Summarize, The Patient Is Doing Better but Not Fully Cured

In reviewing the actions taken by regulators and banks, very significant improvements have been made to control risk and to more accurately model loan losses. The elimination of stated income mortgage loans and the need for lenders to assess a borrower’s ability to pay their mortgage are foundational changes that will prevent a repeat of mortgage losses anywhere near what was experienced during the Great Recession. Additionally, modelling is much more accurate with more robust data, better quality control in the mortgage origination process and the utilization of stress testing to ensure lenders understand their loss
exposure in both normal economies and stressed economic situations. That being said, the state of mortgage loss modelling practices leave significant opportunity for improvement.

The two major opportunities for improvement include the utilization of behavioral data and macroeconomic variables. The utilization of these additional sources of data could be integrated into the loss models, or used as an external overlay to indicate potential volatility of the output of the loss models. By this I mean for example that if the quantitative loss models produce a loss rate of $X$, given certain behavioral or macroeconomic factors a loss rate of 1.4 or 1.5 times $X$ may be more appropriate.

This type of change will likely be slow to occur, but experts in the behavioral economics field like Dr. Thaler and Dr. Rossi are researching and raising awareness of the opportunities. Credit Scores were invented in the 1950’s and the first FICO score in 1989 [68]. Prior to credit scores, loan approval decisions were judgmental, not statically based and subject to human bias. Today credit scoring is considered standard practice in the lending industry. In time I expect credit scoring to be further developed to include behavioral data and well as incorporate a greater utilization of macroeconomic data.
Chapter 6

Modelling for Bubble Prediction

6.1 Model Objective

In this chapter I will review my work on the utilization of the Generalized Linear Model regression (GLM) and Generalized Least Squares regression (GLS) in R where I focused on modelling an indicator of there being a significant risk of being in a housing bubble. Through my research, I collected 10 macroeconomic time series variables from the St.Louis FED website that had the potential to contribute to the indicator model. The data utilized covered the time period from 1999–2018. Any data that was quarterly or annual was adjusted utilizing a cubic spline interpolation to estimate monthly data points.

The variables collected were intended to predict the probability of a housing bubble. The goal of the model development was to obtain a probability between 0 and 1 for the bubble index variable created to measure this probability. Results near 0 would mean there is little probability that we are in a housing bubble and results closer to 1 would indicate a higher probability that we are in a housing bubble. I describe in more detail in the work below how I decided to estimate 2002–2007 as the time period for the bubble (prices rising) and 2008 for the onset of the bust period when prices started to decline.
The variables used to build the prediction model are:

1. **Homeownership Rate** - The ownership rate dramatically increased in the years preceding the housing bust (about 2008).
2. **Total Household Debt** - Generally speaking, applicants had a much higher debt load than in prior periods.
3. **Debt Payments as Percent of Income** - Household debt service payment rose to historic highs.
4. **Home Price to Rent Ratio** - The cost of buying became much more expensive than renting and were very different from long term norms.
5. **Supply of housing** - An indication of an impending housing bust as the months of housing supply climbed.
6. **Home Price to Income Ratio** - People stretched their budgets as illustrated by the ratio of housing price to income jumping to unprecedented levels. It rapidly moved from under 3 times their income to over 4 times their income as indicated in Figure 6.1.
7. **Personal Savings Rate** - There was a decrease in personal savings in the bubble time period. This reflects that households generally had more debt, less savings, and this contributed to the inability to make loan payments.
8. **House Size** - Is an indication of a change in consumer behavior. An increase in house size might also reflect a positive consumer sentiment and changing consumer behavior.
9. **Consumer Sentiment** - Consumer sentiment is an estimate of future spending and savings, and likely affects home prices.
10. **Unemployment Rate** - The rate was decreasing 2002–2007 (possible bubble indicator) and started to dramatically rise around 2008 (possible bust indicator).

Once the variables were established, the next step in the process was to work on model preparation.
6.2 Model Preparation

After gathering the 10 variables for the predictive analysis, data quality was assessed as well as reviewed for inconsistencies in frequency. After adjusting the data, the graph of all the variables were reviewed and behavior over-time was assessed. In addition to other research and exploratory methods, the graphical representation of the variables helped to determine the bubble time frame used in the analysis (2002-2007). Once this work was completed, the bubble indicator was created. Then a correlation matrix was created to assess the relationship between the variables and their contribution for predicting a bubble.

Missing/Inconsistent data

Ideally, monthly data would be utilized for all variables. Unfortunately, this was not possible because some of the variables were only available on a quarterly or annual basis. Out of the 10 variables, 4 did not have monthly data. They were:
- Homeownership rate (annual)
- Total household debt (annual)
- Debt payments as a percent of income (quarterly)
- Home price to rent ratio (quarterly)

In these cases, the data was smoothed using cubic spline interpolation in R. The cubic splining generated monthly estimates as an approximation technique and does not provide new actual monthly points. Quarterly data points were utilized, with $n-1$ spaces between them. Across each space, we can draw a cubic polynomial connecting two points forming a piecewise polynomial function. To connect these lines smoothly, the cubic spline function forces all the first and second derivatives to be continuous and satisfy certain endpoint conditions. We are left with a $(4n - 4) \times (4n - 4)$ linear system that can be solved for coefficients of all $n - 1$ polynomials. Then the $x$ values are plugged in for the monthly time interval as desired to give us estimated monthly points [69].
Graphing the variables

To begin the analysis, I first looked at the graphs of the individual variables. The 10 variables are displayed in Figure 6.1 from 1999–2018.

Figure 6.1: The 10 variables graphed overtime from 1999–2018.

Defining the bubble time period

After reviewing the graphs of the variables, it was necessary to decide what time-frame to classify as the “bubble.” It is in this time frame that we are looking for our results from
the modelling discussed later in this chapter. Through research and empirical analysis, the bubble period is defined from 2002–2007. Figure 6.2 shows the 10 variables, with the points in red, highlighting the 2002–2007 time-frame to help see the trend of each indicator during that time period.

Figure 6.2: The 10 variables graphed overtime from 1999–2018 with the 0-229 shown on the x axis representing the number of months. Highlighted in red is the bubble timeframe.

**Correlation matrix**

After graphing the data and defining a bubble time-frame of 2002–2007, we take a
look at the relationships between the variables, as shown in the correlation matrix. From the matrix in Table 6.1, it is evident that many of the variables are highly correlated with each other. Examples include total household debt and homeownership rate (.62), debt payments as a percent of income and homeownership rate (.98), and home price to rent ratio and home price to income ratio (.89). As a result, it becomes difficult in the modelling process to pinpoint any one variable that contributes the most to understanding if we are in a bubble or not. However, as we explore further with the modelling, we will be able to see which individual variables are significant and what combination of variables would be most predictive in developing a bubble indicator. For example, in this preliminary correlation matrix, we can see that debt payments as percent of income (.642) and home price to rent ratio (.884) have higher correlations with the Bubble Index so these variables are likely important in the determination of our bubble indicator.

<table>
<thead>
<tr>
<th></th>
<th>Home Ownership</th>
<th>Total Household Debt</th>
<th>Debt as % of Income</th>
<th>Home Price to Rent</th>
<th>Supply of Housing</th>
<th>Home Price to Income</th>
<th>Personal Savings Rate</th>
<th>House Size</th>
<th>Consumer Sentiment</th>
<th>Unemployment Rate</th>
<th>Bubble Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home Ownership</td>
<td>1</td>
<td>0.622</td>
<td>0.929</td>
<td>0.706</td>
<td>0.020</td>
<td>0.441</td>
<td>-0.736</td>
<td>-0.748</td>
<td>0.042</td>
<td>-0.145</td>
<td>0.572</td>
</tr>
<tr>
<td>Total Household Debt</td>
<td>0.622</td>
<td>1</td>
<td>0.470</td>
<td>0.425</td>
<td>-0.654</td>
<td>0.401</td>
<td>-0.517</td>
<td>-0.516</td>
<td>0.634</td>
<td>-0.596</td>
<td>0.226</td>
</tr>
<tr>
<td>Debt as % of Income</td>
<td>0.929</td>
<td>0.474</td>
<td>1</td>
<td>0.782</td>
<td>0.259</td>
<td>0.486</td>
<td>-0.789</td>
<td>-0.662</td>
<td>-0.050</td>
<td>-0.212</td>
<td>0.642</td>
</tr>
<tr>
<td>Home Price to Rent</td>
<td>0.929</td>
<td>0.424</td>
<td>0.782</td>
<td>1</td>
<td>0.243</td>
<td>0.891</td>
<td>-0.760</td>
<td>-0.189</td>
<td>0.015</td>
<td>-0.353</td>
<td>0.884</td>
</tr>
<tr>
<td>Supply of Housing</td>
<td>0.020</td>
<td>-0.654</td>
<td>0.259</td>
<td>0.243</td>
<td>1</td>
<td>0.077</td>
<td>-0.057</td>
<td>0.088</td>
<td>-0.675</td>
<td>-0.355</td>
<td>0.319</td>
</tr>
<tr>
<td>Home Price to Income</td>
<td>0.441</td>
<td>0.400</td>
<td>0.486</td>
<td>0.891</td>
<td>0.077</td>
<td>1</td>
<td>-0.552</td>
<td>0.118</td>
<td>0.072</td>
<td>-0.354</td>
<td>0.778</td>
</tr>
<tr>
<td>Personal Savings Rate</td>
<td>-0.736</td>
<td>-0.317</td>
<td>-0.789</td>
<td>-0.760</td>
<td>-0.057</td>
<td>-0.552</td>
<td>1</td>
<td>0.436</td>
<td>-0.208</td>
<td>-0.452</td>
<td>-0.645</td>
</tr>
<tr>
<td>House Size</td>
<td>-0.748</td>
<td>-0.516</td>
<td>-0.662</td>
<td>-0.185</td>
<td>0.088</td>
<td>0.118</td>
<td>0.436</td>
<td>1</td>
<td>-0.162</td>
<td>0.066</td>
<td>-0.035</td>
</tr>
<tr>
<td>Consumer Sentiment</td>
<td>0.042</td>
<td>0.634</td>
<td>-0.050</td>
<td>0.015</td>
<td>-0.675</td>
<td>0.072</td>
<td>-0.208</td>
<td>-0.162</td>
<td>1</td>
<td>-0.745</td>
<td>0.074</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>-0.145</td>
<td>-0.595</td>
<td>-0.212</td>
<td>-0.353</td>
<td>0.355</td>
<td>-0.354</td>
<td>0.452</td>
<td>0.066</td>
<td>-0.745</td>
<td>1</td>
<td>-0.296</td>
</tr>
<tr>
<td>Bubble Index</td>
<td>0.572</td>
<td>0.226</td>
<td>0.642</td>
<td>0.884</td>
<td>0.319</td>
<td>0.778</td>
<td>-0.654</td>
<td>-0.035</td>
<td>-0.074</td>
<td>-0.296</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6.1: Correlation matrix shows that many of the variables are highly correlated.

6.3 Generalized Linear Model Regression Analysis (GLM)

With the model preparation completed, the next step in the process was to complete the GLM regression.
Building the GLM model

To explore which variables would be helpful in determining a bubble indicator, a generalized linear regression model was utilized. The data with the 10 variables was read into R. Then a Bubble Index was created, a vector of 0’s and 1’s, designed to indicate whether or not there is a bubble during a given time. This Bubble Index captures the 2002–2007 timeframe. The results of the first run with all of the variables is shown below in Figure 6.3.

Results GLM

The first run of the model is shown below and indicates there is a high correlation among variables.

![Figure 6.3: First run of GLM](image)

Figure 6.3: First run of GLM
As a result of the high correlation, certain variables that showed multicollinearity were removed and the model was rerun. The results are below in Run 2, Figure 6.4.

```
Call:
glm(formula = Bubble.Index ~ debt.payments.as.percent.of.income +
    home.price.to.income.ratio + supply.of.housing + unemployment.rate,
    family = binomial, data = housing_data_ts_trunc, control = glm.control(maxit = 50))

Deviance Residuals:    
Min 1Q Median 3Q Max
-1.795e-05 -2.110e-08 -2.110e-08 2.110e-08 1.846e-05

Coefficients:  
Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.034e+04 3.622e+07 -0.001  0.999
debt.payments.as.percent.of.income  1.537e+03 2.079e+06  0.001  0.999
home.price.to.income.ratio  3.029e+03 4.020e+06  0.001  0.999
supply.of.housing  -1.095e+00 1.745e+05  0.000  1.000
unemployment.rate  9.285e+01 2.352e+05  0.000  1.000

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2.4435e+02  on 199  degrees of freedom
Residual deviance: 8.0229e-10  on 195  degrees of freedom
AIC: 10

Number of Fisher Scoring iterations: 34
```

Figure 6.4: GLM Run 2.

Unfortunately, the model produced inconclusive results both times saying that “fitted probabilities numerically 0 or 1 occurred” meaning that the probabilities generated were zero or one, and in this case, they were all zero or one. This does not create a good model for future predictions since it does not provide viable probabilities of success. Therefore, the GLM model did not provide any insight of the probability of being in a bubble.

Given this, I decided to try another method, step regression to find a possible subset of variables that may produce a better model.
Stepwise regression for GLM

Using forward step regression, I found a subset of variables that were less correlated from run 2 above. The GLM results are in Figure 6.5.

Call:
```r
glm(formula = Bubble.Index ~ home.price.to.rent.ratio + debt.payments.as.percent.of.income,
     family = binomial, data = housing_data_ts_trunc, control = glm.control(maxit = 50))
```

Deviance Residuals:

<table>
<thead>
<tr>
<th>Mean</th>
<th>10</th>
<th>Median</th>
<th>100</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2.294e-05</td>
<td>-2.110e-08</td>
<td>-2.110e-08</td>
<td>2.110e-08</td>
<td>2.229e-05</td>
</tr>
</tbody>
</table>

Coefficients:

| Estimate | Std. Error | z value | Pr(>|z|) |
|----------|------------|---------|---------|
| (Intercept) | -32867.3 | 33370948.9 | -0.001 | 0.999 |
| home.price.to.rent.ratio | 16886.9 | 17262095.0 | 0.001 | 0.999 |
| debt.payments.as.percent.of.income | 717.3 | 736320.4 | 0.001 | 0.999 |

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 2.4435e+02 on 199 degrees of freedom
Residual deviance: 1.1061e-09 on 197 degrees of freedom
AIC: 6

Number of Fisher Scoring iterations: 34

Figure 6.5: Results from stepwise regression.

Again, the regression for GLM did not help produce a model for prediction. From the correlation matrix in Table 6.1, we know that we are likely running into an issue of multicollinearity in which many of the variables are highly correlated with one another. Therefore, it was decided to run analyses using a GLM for each individual variable. After running individual tests on significance, it was confirmed that 8 of the 10 original variables are significant. As indicated in Table 6.2, debt payments as percent of income, supply of housing, home price to income ratio, unemployment rate, homeownership rate, total
household debt, home price to rent ration, and personal savings rate are all individually significant.

<table>
<thead>
<tr>
<th>Variables</th>
<th>P-Value</th>
<th>Significant?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Debt Payments as Percent of Income</td>
<td>$1.11 \times 10^{-8}$</td>
<td>yes</td>
</tr>
<tr>
<td>Supply of Housing</td>
<td>$2.98 \times 10^{-5}$</td>
<td>yes</td>
</tr>
<tr>
<td>Home Price to Income Ratio</td>
<td>$4.18 \times 10^{-10}$</td>
<td>yes</td>
</tr>
<tr>
<td>Consumer Sentiment</td>
<td>0.765</td>
<td>no</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>$1.05 \times 10^{-6}$</td>
<td>yes</td>
</tr>
<tr>
<td>homeownership Rate</td>
<td>$1.21 \times 10^{-9}$</td>
<td>yes</td>
</tr>
<tr>
<td>Total Household Debt</td>
<td>0.00508</td>
<td>yes</td>
</tr>
<tr>
<td>Home Price to Rent Ratio</td>
<td>0.0027</td>
<td>yes</td>
</tr>
<tr>
<td>Personal Savings Rate</td>
<td>$5.31 \times 10^{-12}$</td>
<td>yes</td>
</tr>
<tr>
<td>House Size</td>
<td>0.343</td>
<td>no</td>
</tr>
</tbody>
</table>

Table 6.2: Each variable tested individually for significance to the Bubble Index.

The GLM modelling approach did not give us the results we are looking for, as the model had certain limitations. This issue led to testing a more comprehensive modelling methodology, the Generalized Least Squares (GLS).

6.4 Generalized Least Squares Analysis (GLS)

After attempting the GLM method and finding it deficient, the Generalized Least Squares (GLS) regression was applied as it was felt that it might be more suited to the data set.
Building Generalize Least Squares (GLS) model

GLS regression allows for unequal error variances and correlations between different errors. Note that the data points that are interpolated by the cubic splines in our data set are systematically related to each other by a cubic polynomial, so they violate standard OLS assumptions for independence. We use modelling techniques like GLS to address this issue.

In addition, the independent variables are time series variables, GLS also allows for an estimation of time-series regression. This means one would not be able to assume the errors are independent. Before running the GLS model, there are a few preliminary tests that needed to be run to better understand the results. First, an Ordinary Least Squares (OLS) regression was run to get a general idea of the significance of the variables and the beta values. The next step is to look into an ACF test to explore the correlation of the errors. Finally, Durbin–Watson tests were completed to help determine what ARMA model to use in the GLS model.

OLS Regression

As a first step, a summary of the variables with a preliminary OLS regression was run. This produced the results below indicated in Figure 6.6 and tells us that all the variables apart from home price to rent ratio, supply of housing, and house size are significant with a high adjusted $R^2$ of .89.
ACF tests

The next step was to explore the correlation of the errors of a time series for the OLS residuals, using the ACF function to show autocorrelation and the partial ACF test to show partial autocorrelation.

The lag for each autocorrelation estimate is indicated by the height of the vertical bars (the ACF at lag 0 is always 1). The blue, horizontal dashed lines represent lag-wise confidence intervals centered at zero. These are used for determining the statistical significance of an individual autocorrelation estimate at a given lag versus a lag with no autocorrelation (value of 0). Autocorrelation (ACF) is the correlation of a variable
with itself at differing time periods (lags). Note the ACF graph produces 5 lags, which
reveals that the first five lags yield statistically significant autocorrelation function values.
The partial autocorrelation (Partial ACF) is most useful for identifying the order of an
autoregressive model. The partial ACF only has 1 lag.

Looking at the ACF and partial ACF graphs in Figure 6.7, we might be able to
determine a general correlation pattern to give us a $p$-value for ARMA input in the GLS
model. For example, the partial ACF might tell us that our model is an autoregressive
model of order 1 (AR(1)). However, we cannot make that conclusion at this time because
it may not make sense with the 5 lags and so further testing is required.

In this case, we don’t have an obvious pattern for the ACF graphs, so we can test
different lags to see which gives the best model fit. The number of lags determined from
the ACF and partial ACF tests must also be taken into account when completing the
Durbin–Watson test.

Figure 6.7: ACF and PACF for the OLS residuals. Shows 5 lags for the ACF test and 1
lag for the partial ACF.
**Durbin–Watson test**

As the final step, to follow up on the ACF test, we compute the Durbin–Watson statistics for the OLS regression, as shown in Figure 6.8. After exploring various lag values, we saw that any lag value after 5 was not significant, so we decided to use the maximum lag of 5. This confirms the ACF test we did previously that produced 5 lags. The Durbin–Watson test will help determine the number of lags to use in the ARMA input for GLS model.

![Durbin-Watson Test Results](image)

Figure 6.8: Durbin-Watson Tests concluded the first 5 lags are significant.

**Running the GLS model**

After completing the previous steps, various lag values were tested and AIC and BIC were assessed for goodness of fit and RSE of model accuracy. It was determined that the model with a lag of 5 was not more accurate than with a lag of 2. Therefore, it was decided to use the simpler model with a lag value of 2 for the ARMA function in the GLS. With this decision, the GLS model was run. Using the “nlme” package in R and the GLS function in R with all 10 variables, a summary of the model results are in Run 1, Figure 6.9.
This original run had high \( p \)-values, so it was decided to complete additional runs until the \( p \)-values were all significant. Note the AIC here is \(-356.42\) and the BIC is \(-313.54\). Assessing these values will allow for the comparison of goodness of fit with the final model. The AIC and BIC add a penalty that increases the error when including additional variables, with the BIC penalizing slightly more aggressively. See final run, Figure 6.10.
Figure 6.10: Final run GLS

This shows that homeownership rate, total household debt, home price to income ratio, unemployment rate were all significant. However, we still have negative beta values on unemployment rate and total household debt indicating these values cannot be interpreted due to multicollinearity. They can only be used in the prediction equation for prediction. Note the AIC is $-358.5$ the BIC is $-332.12$, which is smaller than in the first GLS run and tells us this model has better goodness of fit.

In the calculation of the final GLS model, the GLS function takes into account the number of lags, as discussed earlier. The number of lags determined gives us the order of
the autoregressive model. In our model we have a second order autoregression (AR(2)) with form \( y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + v_t \). Using the \( \phi \) values produced by the GLS function, the final equation is \( y_t = 0.8498\hat{y}_{t-1} - 0.0006\hat{y}_{t-2} + v_t \). This model allows one or more variables to affect \( y \) with a lag. In this model, the response variable in the previous time period has become the predictor and the errors have our usual assumptions about errors in a simple linear regression model. An autoregressive (AR) model predicts future behavior based on past behavior. It’s used for forecasting when there is some correlation between values in a time series and the values that precede and succeed them.

Our final GLS model incorporates the information from the autoregressive model and uses it to create the coefficients for the final regression equation in the form of \( \hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_3 + \hat{\beta}_4 x_4 \). This gives us a regression model with fitted values and residuals – predictions of the response and the errors of the predictions. Here the \( \hat{y} \) and \( \hat{\beta} \) indicate that the model is an expression of fitted values (estimates) versus known values. Therefore, using the results from the final run of the GLS model, we have that our regression equation is:

\[
\hat{y} = -9.584 + 0.121x_1 - 0.060x_2 + 0.820x_3 - 0.102x_4
\]

In this equation, \( x_1 \) is homeownership rate, \( x_2 \) is total household debt, \( x_3 \) is home price to income ratio, and \( x_4 \) is unemployment rate. This model is intended to tell us the trade-off between \( y \) and the \( x \)'s. How much \( x \) increases, or decreases, will affect the probability of being in a bubble. This model can be used in predicting a future bubble occurrence based on the characteristics of the bubble during 2002–2007 [70].

### 6.5 Creating the Bubble Indicator

After the results from the GLS model, we are able to take this information to compare to the original bubble index with the raw data. We may compare the results of the GLS
to create a cutoff where past this point, it would indicate there is a housing bubble. We experimented with three different methods to create a bubble indicator as outlined below.

We intend to restrict our response variable, $\hat{y}$ to be between 0 and 1, but there is no guarantee that the GLS will always yield predicted values in this range. In this case, we see that values of $\hat{y}$ can be negative and can be greater than 1.

- **Method 1)** $\hat{y} > 0.45$
- **Method 2)** $\frac{e^{\hat{y}}}{1 + e^{\hat{y}}} > 0.60$
- **Method 3)** $\left(\frac{\sqrt{3}/\pi}{\hat{y}/\sigma(\hat{y})}\right) > 0.60$ [71]

**Method 1)** The first method is a simple heuristic that uses the prediction and determines a cut-off value. Through experimentation, we found that 0.45 is a good cutoff value. Anything greater than 0.45, indicates that we are in a housing bubble. Anything less than 0.45 will predict that we are not in a bubble.

**Method 2)** Converts the predicted values into probabilities. It is an exponential transformation of the GLS fitted model data with a cutoff of .6. Anything greater than 0.6, indicates that we are in a housing bubble. Anything less than 0.6 will predict that we are not in a bubble.

**Method 3)** The third method is a standardization of our response variable multiplied by $(\sqrt{3}/\pi)$ to account for logistic regression. Anything greater than 0.6, indicates that we are in a housing bubble. Anything less than 0.6 will predict that we are not in a bubble.

**Results**

With the results from the final run of the GLS model, it was found that the actual data matches method 1 produced the best results. With this method, it results in all 1’s (indicating in a bubble) during the 2002–2007 time period with the addition of a month before and a month after indicating a bubble. Therefore, the variables from the last run:
homeownership rate, total household debt, home price to income ratio, unemployment rate are definitely all significant variables in assessing if there is a housing bubble or not. Methods 2 and 3 overestimate by a few months more than method 1 before and after the assumed bubble time period. In the prediction section below, this overestimation captures data points outside of our assumed bubble time period and will be considered for its predictive capabilities.

6.6 Predictions

In this section the predictive capability of the model was tested to assess whether a bubble is being experienced during the 2016–2018 time-frame. To complete this, an analysis was performed on the more recent data from 2016 through the first month of 2018.

Running the GLS from 1999–2015, the values from 2002–2007 were higher, indicating that a bubble was occurring during this time-frame. After running the indicator test with all three methods, it was observed that the data values increase around the middle of 2017 and more drastically towards the end of 2017. Method 1 indicates that a bubble started in September 2017. Method 2 goes back further and suggests that there is a bubble starting in May 2017. Method 3 may go too far back and indicates that there was a bubble starting at the end of 2016. Method 2 may be the preferred method to use in prediction, as it may be predicting a bubble is coming earlier than the other methods.

The data that I have only goes through January 2018, but if we were to use this indicator on more recent data, we would be able to see a longer-term trend. The ability to predict a housing bubble could be very useful for adjusting lending guidelines in a timely manner before elevated losses are incurred.
6.7 Conclusion

The modelling work completed as part of the thesis research was able to produce a model that appears to effectively predict when a market is in a housing bubble. Model development and testing was conducted utilizing GLM and GLS modelling methodologies. It was found that the GLM modelling was inconclusive due to perfect separation issues, fortunately when the GLS model was run it produced valuable results.

The GLS model was able to tell us which variables are significant in predicting a bubble. The specific variables that the model indicated were significant included homeownership rate, total household debt, home price to income ratio, and unemployment rate. The other variables that were highly correlated with these would also be significant, but they are all so similar that adding them into the model would not add value.

The GLS model that was produced could be used as an indicator of a housing bubble. When modelling output, if one sees the probabilities are increasing towards 1 then there is a high probability that the market is in a housing bubble. In the model, the time periods with 1’s show there was a housing bubble during 2002–2007. If the model is run on more current years, and the model shows “1’s”, this is a warning that lending guidelines may need to be adjusted to avoid unanticipated loan losses.

The GLM model showed homeownership rate, total household debt, home price to income ratio, and unemployment rate are significant predictive variables. These variables are relevant for monitoring behavioral economic factors in modelling.

The GLS model also showed that home price to income ratio and homeownership rate are indicators of behavioral economics. See Table 6.3 below for detail.
<table>
<thead>
<tr>
<th>Variables</th>
<th>P–Value</th>
<th>Significant?</th>
<th>Behavioral Economics Indicator?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Debt Payments as Percent of Income</td>
<td>$1.11 \times 10^{-8}$</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Supply of Housing</td>
<td>$2.98 \times 10^{-5}$</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Home Price to Income Ratio</td>
<td>$4.18 \times 10^{-10}$</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Consumer Sentiment</td>
<td>0.765</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>$1.05 \times 10^{-6}$</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Homeownership Rate</td>
<td>$1.21 \times 10^{-9}$</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Total Household Debt</td>
<td>0.00508</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Home Price to Rent Ratio</td>
<td>0.0027</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Personal Savings Rate</td>
<td>$5.31 \times 10^{-12}$</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>House Size</td>
<td>0.343</td>
<td>no</td>
<td>yes</td>
</tr>
</tbody>
</table>

Table 6.3: Each variable tested individually for significance to the Bubble Index. Displays whether each variable is an indicator of behavioral economics as well.

Close attention should be paid to the behavioral economic variables identified in Table 6.3 as they indicate there may be shifts in consumer behavior that are impacting the current housing market environment.

If there is an indicator of a bubble, it is suggested that there should be an adjustment to mortgage lending guidelines. This could take the form of more restrictive credit scores or lower LTVs. If the indicator shows a high probability of a bubble, there should also be an evaluation on whether it is time to redevelop the model, particularly if there may be concerns regarding a population shift.

There should also be stress testing to assess the implications on loan losses so that the financial institution can determine if they are operating at an acceptable level of risk and if there is adequate capital to absorb a potential escalation in loan losses.
Chapter 7

Conclusion

After considering all the research that I completed in the compilation of this thesis, I have come to the conclusion that there were no innocent parties for the huge issues experienced in the housing crisis. All the parties were co-conspirators in the harm caused to consumers, the housing market and the shareholders of financial institutions. The finger of guilt points clearly to a wide range of politicians, regulators, risk managers, banks, bond rating companies and investment banks.

The beginning of the thesis, in Chapter 2, outlines the severity of the housing price collapse and the huge escalation in loan losses at frequencies and severities that were unprecedented since the Great Depression 80 years earlier. The information presented indicates that the housing price collapse clearly fell into the category of a bubble, with a run up in pricing that did not make logical sense, followed by a rapid sharp collapse in values. The difference from most other bubbles is the enormous harm to consumers and financial institutions. The chapter concludes with a review of the financial havoc that was created by this bubble and the insufficient risk practices that contributed to the government takeover of Fannie Mae and Freddie Mac and the destruction of major financial institutions including Wachovia, Washington Mutual, Bear Stearns, and Lehman Brothers.
Chapter 3 then continues to review the factors that contributed to the housing crisis and the deficiencies in loss models. Chapter 3 clearly provided hard evidence that loss models leading up to the housing price collapse were totally inadequate. The chapter questions how the experts could have been so wrong and attributes much of the fault in judgement to inadequate models that completely miscalculated the frequency and severity of losses that would be experienced based on the loan characteristics, housing environment and consumer behavior at the time. Modelling practices and data practices were researched by examining scholarly articles and completing independent research. The conclusion from this research was that there was a significant shift in population that invalidated the appropriateness of the loss models that were utilized. It was indicated that the new application population was significantly different from the population that the loss models were developed on, the application guidelines and underwriting guidelines were dramatically different, the housing environment and housing environment had dramatically changed and large changes in consumer behavior had occurred.

Put more simplistically, older models were utilized that did not adequately reflect the risk of loan default occurring, borrowers were given loans with little to no documentation and lower credit scores, the underwriting review of applications was poor, housing affordability as a percent of income reached historically high levels, and home buyers were in somewhat in a frenzy to purchase homes with homeownership rates hitting historic highs.

The impact of these modelling flaws was the inability to predict the large spike in mortgage defaults, decisions to lend to unqualified borrowers and the subsequent unexpected flood of loan losses. Accentuating the surprise and the negative impact of the elevated loan losses was the lack of stress testing practices in much of the industry. The poor modelling, combined with the lack of robust stress testing practices, contributed to the collapse of a wide range of financial institutions.

While the prior chapters dealt with documented evidence that the loan default and loss severity models were severely flawed, Chapter 4 outlines changes to the loss modelling
process that could have been utilized to better mitigate the loan loss exposure. The chapter starts with the question as to whether there were early signs of issues and indicates that based on a review of vintage default curves that there was ample evidence that the losses were escalating and that earlier action could have been taken. Vintage delinquency started to indicate issues in 2005, but research indicates that significant action was not taken until 2007.

The chapter continues to suggest what could have been done differently given the information available at the time and suggests 6 actions that should have been taken. These actions include consideration of long-term trends in demographics and affordability, the close monitoring of performance of the newer loan products (i.e., stated income), increases the file loan quality review of higher risk populations, start the model redevelopment process at early signs of vintage delinquency with particular attention to segmented models (i.e., separate models for stated income), tightening lending guidelines as 2005 vintages started to show weakness (i.e., higher downpayment requirement, higher minimum credit score), and completing stress testing to better understand the potential loss exposure in the case of a change in the economic situation.

The chapter concludes with a review of actions that were taken, albeit late, that if implemented earlier would have likely significantly lowered the severity of the housing crisis and loan losses. These changes included the regulatory requirement to document the mortgage applicant’s ability to afford the payments as well as the need for financial institutions to complete stress testing on their lending portfolios.

Chapter 5 reviewed the current mortgage loss modelling practices and suggests potential enhancements. It is suggested that progress has been made in loss modelling but that there are still significant opportunities for improvement. More specifically, it is suggested that additional data be utilized in model development or as loss severity overlays to the current models. Suggested additional data includes behavioral based variables as well as additional macroeconomic factors. Behavioral data elements would include variables
that indicate changes in consumer attitudes towards homeownership that would impact housing demand. Additional macroeconomic factors to consider would include interest rates (due to impact on affordability), home affordability ratios, and a stronger focus on regional economic trends.

Chapter 6 outlined model development work completed as part of the thesis research. The intent of the modelling was to produce a model that effectively predicts when a market is in a housing bubble.

The OLS multiple regression run with all 10 variables had an excellent $R^2$ of .89, indicating that the variables selected were very relevant factors in determining if there was a housing bubble. GLM and GLS modelling techniques were utilized in the modelling research. I was pleased to observe that the GLS model produced valuable results and was able to identify which variables were significant in predicting a bubble. The specific variables that the model indicated as significant included homeownership rate, total household debt, home price to income ratio, and unemployment rate.

The final GLS model gave us a regression equation of 
\[ \hat{y} = -9.584 + 0.121x_1 - 0.060x_2 + 0.820x_3 - 0.102x_4 \] where how much the \( x \)'s increase or decrease, will affect the probability of being in a housing bubble.

Reflecting on this thesis, a fitting closing would be to summarize the key takeaways from the real estate and mortgage debacle of the Great Recession for loss modelers and risk managers. Key takeaways and suggestions are discussed below.

The first takeaway that I would like to highlight is the need to step outside of the data. Consider what is happening in the general environment, ask whether there have been major societal or economic changes consider future trends. Ask whether the populations used for the model development are sufficiently similar to the population that will be coming in the door. Ask if there are major changes that would impact short-term demand such as major demographic changes, for example a wave of baby boomers planning to sell their homes. Are there other factors that could result in a large change in short or long-term
demand. If so, consider overlays to model results, or more rapid model redevelopment. Housing modelling requires frequent updating of models incorporating more recent loan performance. This becomes critical when prices rise above normal fundamentals suggested by cost for rent versus own and cost versus income.

A second takeaway is to realize that models that are highly linear can result in large miscalculations and that tail risk (low probability high risk events) need to be considered. In the Great Recession, loss rates were far from linear and had dramatic growth when the market changed. Losses increased dramatically in a short period of time.

A third takeaway, think locally. Modelling loan losses on a national basis without considering local economic situations can lead to poor models. There are major variances in regional economies as population trends and economic growth rates differ by area. Where possible, models need to have regional segmentation to incorporate local markets dynamics. Loss model development needs to model populations with similar price trends and similar credit availability and inventory trends.

The final and very important lesson is to consider consumer attitudes and the current economic environment. Will the assumptions in the model, based on recent history, be similar in the future? Are there factors such as high student debt or changes in immigration that may change demand and therefore housing prices, and therefore loan default rates? I will reference an interesting quote from a paper completed by Sarah Bryant and Jonathon Kohn, “Perhaps most damaging were expectations that this boom cycle would continue. As a result, consumers went on spending sprees, based on higher and higher real and perceived home equity values, as well as equity market increases. The prevailing attitudes of “bigger is better . . . as much as one can afford . . . buy now, avoid future higher prices” became the driving forces. “Home buyers could receive 100 percent loan-to-value loans, with little if any credit or income checking” [72]. “Excessive expectations are also likely to help buyers rationalize the high prices because they consider the risk of falling prices to be small. These factors tend to spur the demand for housing by
reinforcing the bubble mentality” [73]. This was not the consumer behavior, or the loan application loan to values, on which the original loss models were built. The models built on prior default frequency and loss severity levels proved to be completely inadequate in a scenario of flat and declining house pricing. When consumer behavior reverted to the norm (payments needed to be affordable) home values plunged and loan losses soared. Models built on rising prices, hid borrower’s ability to pay because as prices increased, they could just sell and cash out.

A Moody’s Analytics white paper on loss modelling further reinforces the need to consider consumer behavior. “Traditional approaches only seek to predict the behavior of loans that have already been booked, over which managers can no longer exert the ultimate form of control—the power to reject an application. As a result, managers are typically assumed by the forecasting process to be inert in the face of future economic events” [74]. The paper continued that “the faster the rate of appreciation at origination, the poorer the performance of the loans booked” [75].

Throughout the thesis paper, I have provided comments on modelling and what could have been changed. There is one point that I did not emphasize, and with which I wanted to conclude the paper, the concept of Risk and Return.

There is nothing wrong with taking elevated risk as long as the risk is understood, the potential volatility in losses is modelled, and the loans are adequately priced to compensate for the risk. There was something very wrong with what happened leading up to the Great Recession. The risk being taken was not properly understood. Many lenders did not understand the risk they were taking and did not adequately price for that risk. The mismatch in risk and return was so large that it impacted the financial viability of numerous financial institutions. The divergence in risk management practices ended up separating survivors from victims, as very large banks such as Washington Mutual and Wachovia who offered negative amortization loans failed and banks such as Chase, Wells and Citi lived to fight another day.
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Chapter 8

Appendices

8.1 Appendix 1 - Jennifer Shulman - Original Research (August 2019)

Survey Summary of Industry Experts:

- Tu Le - SunTrust Bank - Head of Data and Analytics
- Chris Pyle – Synovus - Group Executive, Consumer and Small Business Lending
- Gary Walton – MUFG Union Bank - Chief Credit Officer
<table>
<thead>
<tr>
<th>Question</th>
<th>Tu Le</th>
<th>Chris Pyle</th>
<th>Gary Walton</th>
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<tr>
<td>What type of models were utilized to evaluate expected loan performance immediately prior to the great recession and the housing price collapse?</td>
<td>Historically most loss forecasting and reserves were done with logistic regression and incorporated PD (Probability of Default) and LGD (Loss Given Default).</td>
<td>This depends on the segment of the business. Indirect Auto – roll rate model Credit Card – roll rate model Small business – roll rate model HELOC – none Mortgage – none Pre-crisis mortgage losses were running ~0.02bps and HELOC ~0.03. Given to infrequency of defaults, we did not have enough data to build any type of model.</td>
<td>Prior to the recession, many institutions did not model their expectations for mortgage loan performance. The primary reason for this was limited housing downturns which were generally localized to a region like New England or California. The expectation was house prices would continue to go up and eventually a borrower or bank would sell with minimal loss. Those institutions that did use modeling to estimate loan performance primarily used linear regression, CHAID, roll rates or a combination.</td>
</tr>
<tr>
<td>What can you tell me about the data utilized to build the models?</td>
<td>The power of the models were built on historical experience and incorporated more than 3 years of history. Models could incorporate sources to ten years of historical data. The majority of the data were credit characteristic related (credit score, debt-to-income ratio, loan product type, property type, loan to value, occupancy type, and self-employment status to name a few).</td>
<td>For the roll rate model, a rolling 24 months of delinquency history from 30 days past due to 120 days was utilized. No, for the real estate models that were built. This was not the case due to the fact that originsations basically stopped compared to pre-crisis volumes along with the rapid discontinuation of products (i.e. Interest Only Lot Loans, 100% LTV Construction to Perm Loans, 1/1 ARM's, etc.)</td>
<td>In many ways the populations were very similar. What really was different was the level of underwriting (due diligence) that changed for segments of the population. Most notably was the increase in the amount no income, stated income type qualification that occurred. This was extremely prevalent in individuals that were individuals that were not W2 type employees meaning self-employed which usually had to provide 2 year tax returns when to no income documentation.</td>
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<th>Gary Walton</th>
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<tr>
<td>Do you feel there was a shift in population that impacted model performance? If so, what accounted for that shift?</td>
<td>Yes. There was a new breed of exotic products that were entering into the portfolio where assumptions had to be made on the modeling side as no historical data was available or were limited. These incorporated the No Income and/or No Asset loan products. In addition, the historical models were built on a consensus probability scenario where housing prices continued on an upward trajectory and employment was steady.</td>
<td>Yes, there were multiple shifts. Some driven by management (product changes), some driven by environment (Florida court foreclosure times), some driven by regulatory flat (Fannie/Freddie repurchase contracts)</td>
<td>I think this follows on my comment to the prior question. There was a lot of competition in the industry and speed to close was a driver of expectation. Because the secondary market got involved with conduits, warehousing and other off balance sheet vehicles, originators were taking increased risk they thought they would not be exposed to. The reality is it did come back on the originators and servicers as much as the street.</td>
</tr>
<tr>
<td>Were stress scenarios evaluated during the 2005/2006 time period?</td>
<td>There were no standardized stress scenarios across the industry and each financial institution had their own benchmarks. The modeling teams may produce monte-carlo simulations which were then grouped into probabilities of events occurring. The end result were that the historical models were built on a consensus probability scenario where housing prices continued on an upward trajectory and employment was steady based upon historical data.</td>
<td>No, we did not look at different economic scenarios pre-crisis. This was due to the fact that we had no economists on staff and third parties that did have them often could not deliver forecasts in a way consumable by models.</td>
<td>Most institutions were considered to be well capitalized and stress testing was not that broadly utilized except as required under Basel. The bit of stress testing that was completed was not focused on the drivers of a downturn but more on the impact of on balance sheet exposures going bad. The mortgages that really hurt the industry were the ones that were off balance sheet and largely overlooked during stress testing. Any scenarios contemplated during 2005/2006 would not have forecasted such a precipitous drop in home prices and on such a large scale.</td>
</tr>
<tr>
<td>Question</td>
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<tr>
<td>How were people able to model negative amortization products when negative amortization was new to the industry?</td>
<td>Due to limited or lack of data availability assumptions were made and/or synthetic pools (using alternative products outside of mortgages or blended with mortgage data) were created to simulate expected performance.</td>
<td>We didn’t. Insofar as anyone did, it would be a component of Loss Given Default, and given the assumption that everyone had at the time on housing prices continuing to rise, your LGD would be 0 as the collateral would always be worth more in the future than it is today.</td>
<td>Negative amortization was contemplated and was considered acceptable but the risk was generally considered mitigated because borrowers historically paid their homes first so default was low and there was always an expected increase in home price values that offset the negative amortization. The little bit of risk that was considered possible was managed by putting a cap of say 110% LTV on the loan. When home prices dropped, homeowners found themselves with no equity or commitment to the home.</td>
</tr>
<tr>
<td>How impactful was the implementation of stated income loan products in the model development process?</td>
<td>Highly impactful as there were limited data availability on the loan products. If you look at the loans that were nominal during the great recession a majority of these loans had a higher default and loss experience than non-stated income loans. The exception occurred for Doctor related mortgages.</td>
<td>It created an easy segment to model on its own with loads of defaults.</td>
<td>Stated income had a big impact on the industry and as I mentioned earlier was perceived to be a nominal risk because of the competition to close loans. It was not considered a risk of borrower default and thus only became a consideration for model development. A model generally only considers an input when the variable has some correlation the model is trying to predict. Since it was broadly used there were limited instances of it showing up in the data until it was too late.</td>
</tr>
<tr>
<td>Did the large investor groups that were buying mortgage pools review and evaluate the mortgage loss models that were utilized in setting mortgage guidelines? This would include both origination modeling and loss forecasts</td>
<td>All securitization of loan products were modeled internally (by risk) and externally (by assurance or rating agencies)</td>
<td>Not to my knowledge.</td>
<td>The large investor groups did consider loss models but the changes such as stated income, negative amortization and off balance sheet vehicles had not been in place long enough to impact the outcomes of a model. Most models were used for setting risk tranches in securitizations and then determining the amount of overcollateralization needed to ensure the cashflow of the security.</td>
</tr>
<tr>
<td>How significant do you feel government and management pressure was in the development, application and refinement of models utilized for mortgage origination and guidelines?</td>
<td>It's a question of risk tolerance and sophistication of the investor. If a bank originates a loan and keeps it on their books then they hold all of the risk of default. If a bank originates a loan and sells it to an agency or securitizes the asset then the risk is migrated to purchaser. From a bank perspective the purchaser of the asset should have the responsibility to complete their own due diligence and modeling efforts subject to the underlying loan information being complete and accurate.</td>
<td>Very significant. With the deployment of TARP and then the move the CCAR the FRB became extremely prescriptive in the approach and methodology to modeling losses. Even so far as favoring certain techniques over others.</td>
<td>I have to comment on pre- and post-recession. Pre-recession there was little pressure except as required under Basel and that was generally applied across all products in the institution. Post-recession there has been considerable increase in model development, methodology and governance/oversight. The OCC/FRB both require independent model risk management within their regulatory oversight and has become its own risk discipline as such.</td>
</tr>
<tr>
<td>Were macro housing affordability (cost of median home versus median income) and the cost of renting versus home ownership considered in the development of models and mortgage guidelines?</td>
<td>No. HPI (Home Price Index) and Unemployment data were the two major Macro Economic indicators used prior to the great recession.</td>
<td>No. In our case, macro variables such as GDP change in employment rate, total household spending, were drivers.</td>
<td>Affordability has always been a consideration but was not generally an input of modeling. Affordability and rent vs own were used more in the discussion of the strength of the housing market from the perspective of home sales/purchase.</td>
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<td>Question</td>
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<td>How do you think model development and mortgage guidelines could have been enhanced to be more effective in the period leading up to the Great Recession?</td>
<td>Standardization of assumptions and modeling techniques (calculations). Model Validation Groups were in a very formative state at most financial institutions and since the great recession has rapidly evolved.</td>
<td>Just storing and keeping data. Pre-crisis most intuitions did not keep origination data very long. I can distinctly remember trying to forecast losses on STF mortgage portfolio in Q2 of 2009 and being told we didn’t save anything electronically. We have to go and physically try and find the paper file to get any info.</td>
<td>This is certainly an answer based on hindsight and not anything that I would have thought of during that time. I am not sure what changes to model development could have taken place other than increased requirements to consider broader stressed scenarios. I do think mortgage guidelines should have been held to more traditional standards (full income verification) as riskier features such as neg am were incorporated. The confluence of each standard easing was individually contemplated and not broadly evaluated against each easing.</td>
</tr>
<tr>
<td>Were the modelling flaws more severe in loss frequency or loss severity?</td>
<td>It was a combination of both. With unemployment affecting frequency and HPI affecting severity.</td>
<td>Both were bad, if I had to pick one it would be PD.</td>
<td>There are arguments for both but I believe the flaws were more pervasive around loss frequency. Not all borrowers that defaulted had neg am or negative equity in their transaction. I did not see modeling that contemplated the large number of defaults that were seen. Had that been identified I think steps could have been taken quicker to reduce the severity of the outcomes.</td>
</tr>
<tr>
<td>What where the major variables utilized in the loss models during time of housing bubble?</td>
<td>The majority of the data were credit characteristic related (credit score, debt-to-income ratio, loan product type, property type, loan to value, occupancy type, and self-employment status)</td>
<td>Product type, Previously delinquent, how many times del in past 12 months, CLTV, lien position, FICO, primary/secondary residence, judicial/non-judicial foreclosure state, foreclosure timeline</td>
<td>The major variables driving loss estimation were the ones that generally drive models today – credit score, prior delinquency on loan, occupancy and purpose (purchase, refi, cashout).</td>
</tr>
<tr>
<td>How would you assess the quality of underwriting in the housing boom versus the period 10 years before the boom?</td>
<td>Credit underwriting standards became less strict in the ten years leading up to the great recession. If the bank is selling the loan and does not own the risk they will migrate towards the buyer’s underwriting standards.</td>
<td>Standards and practices decayed from that period to just before the boom.</td>
<td>Underwriting eased dramatically and the quality was not good. Quality control error rates were largely ignored unless it impacted the salability of the loan.</td>
</tr>
<tr>
<td>What Major variables do you utilize in your modeling for probability of default (i.e. origination (FICO), LTV, HPI adjusted (LTV, DTI, Delinquency) and how do you adjust for economic scenarios?</td>
<td>The majority of the data were credit characteristic related (credit score, debt-to-income ratio, loan product type, property type, loan to value, occupancy type, and self-employment status to name a few). Economic scenarios were determined by historical data. If your data results in 90% probability of increasing HPI and unemployment stability then you would not migrate towards a more defensive posture with regards to loss expectations. If the models were 50% probability then yes you would increase loss expectations via PD and LGD. The folly was that there wasn’t a downward expectation in HPI or unemployment prior to the great recession in an overall consensus probability.</td>
<td>Previously delinquent, how many times del in past 12 months, CLTV, lien position, FICO. At my current bank, economic scenarios are handled as overlays to the base forecast.</td>
<td>There are a variety of variables that are predictive for modeling PD and you have captured them. I tend to think about variables by category type such as application data, loan characteristics (form, LTV, credit score), performance data (delinquency months on book, HPI adjusted (LTV, refreshed credit score) and macroeconomic variables. I generally find that macroeconomic variables are the easiest to manipulate such as home price declines or higher unemployment to manage the scenario. One item to always consider is not having to many variables with high correlation to each other as it tends to overweight or mask certain outcomes.</td>
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8.2 Appendix 2 - Original Research Interview on October 16th, 2019 - Professor Merrick

1. **Question:** Do you feel there was a shift in population that impacted model performance? If so, what accounted for that shift?

**Merrick:** It was similar to when junk bonds first came out—there were overly optimistic perceptions of defaults based upon a misreading of early low default rate experience. There was limited insight into forecasting of default rate. It was an ageing question, there needed to be more experience to understand true default prospects—couldn’t tell from early data.

Silly assumptions were also made, where the mass belief was the housing prices would continue to go up for the foreseeable future (in finance, we tend to see asset prices as following a random walk that responds to “news”). Echoed Tu Lee’s response that the historic models were built on a consensus probability scenario where housing prices continued on an upward trajectory and employment was steady.

2. **Question:** How significant do you feel government and management pressure was in the development, application and refinement of models utilized for mortgage originations and guidelines?

**Merrick:** There were two aspects. Aside from the models, there was no responsibility on the loan originator. There was only an incentive to sell as much as possible. Usually
government involvement is minimal, and lets market have free reign (unusual to have rules imposed).

Another big player are the credit rating agencies (Moody’s, Standard and Poor’s, and Fitch). They had their own modelling of how to rate subprime mortgage-backed security debt. They were passing them off as safe. The credit rating agencies are agents for the issuers of such debt, not agents for the buyers. They are out for themselves, so there is conflict of interest. After the mass amount of subprime loans defaulted during the housing collapse, thee agencies couldn’t get sued, they would say it was just their opinion and not take any blame for intentional malpractice.

3. Question: Is there any additional information that you feel would be helpful in understanding what led to the inability of origination and loss models to predict the severity of the default and losses that were experienced in the housing bust?

Merrick: This goes back to WallStreet. There was a push to keep finding new business. There was also not enough good collateral and a lot of competitive pressure expanded deals beyond what was actually good for the buyer.

3.a Question: And what about government pressure to give out loans? Credit rating agencies- CRA?

Merrick: The Community Reinvestment Act (CRA) may have started it, but was not the main problem. There was an aspect from the demand side, which fed the housing bubble. There should have been more governance over the loan originator- the originator should have taken losses. It is important to have long-run incentives/punishments if things go wrong.

Merrick Summary of Contributing Issues:

1. No one took any responsibility. “No skin in the game.” This has changed now – (may be a part of Dodd–Frank risk retention in asset backed securities). There was previously a lack of risk retention.

2. Ratings agencies were paid to consult (even supplied their ratings models to issuers) -
so there was bias as well.

3. People were qualifying on basis of teaser rates instead of fixed rate assuming that they can always refinance later as a prime borrower. On mortgage qualifications, this is not done anymore (along with other silly things like no loan documentation).

8.3 Appendix 3 - FICO 04 - Development Data Performance Period

Sent: Sunday, October 27, 2019 6:52 PM
Subject: FW: FICO Marketing Solutions Scoping and Discussion points for BMO Harris.docx
From: Nicole Brennan
Sent: Thursday, October 17, 2019 4:35 PM

Subject: RE: FICO Marketing Solutions Scoping and Discussion points for BMO Harris.docx

I just got this back from our subject matter expert:

The Trans Union FICO® Score 04 development data performance period is from Oct 1998-Oct 2000. New accts in this development data set were booked beginning November 1998 through April 1999. Existing accts in the development sample were originated in Oct 1998 or earlier. We unfortunately do not readily have a product sheet for this score as it is a very old score.

Nicole Brennan | FICO | NicoleBrennan@fico.com | C: 438.820.9400
8.4 Appendix 4 - FICO 04 - Still Utilized 20 Years After Development
8.5 Appendix 5 - Modelling of Housing Prices -
Jonathan Kohn and Sarah Bryant


Independent variables that came out of the regression modelling were very different for the pre-bubble versus bubble period. High levels of co-linearity among the independent variables, in sharp contrast to the pre-bubble model [38].


H1: CPI positively influences MAP: Reject
H2: Housing Inventory negatively influences MAP: Reject
H3: Mortgage Rates negatively influences MAP: Reject
H4: Personal Income positively influences MAP: Accept
H5: Population positively influences MAP: Reject
H6: Vacancy Rates negatively influences MAP: Accept
H7: Median Asking Rents positively influences MAP: Reject

**Bubble Hypotheses: 1/1997-12/2007**

H1: CPI positively influences MAP: Accept
H2: Housing Inventory negatively influences MAP: Accept
H3: Mortgage Rates negatively influences MAP: Reject
H4: Personal Income positively influences MAP: Reject
H5: Population positively influences MAP: Reject**
H6: Vacancy Rates negatively influences MAP: Reject**
H7: Median Asking Rents positively influences MAP: Accept
H8: Model Relationships for pre-bubble and bubble periods are different: Accept (**significant but reverse direction)