

An Emphasis on Underwriting Variables: A Look at Their Importance on Default  
& Prepayment of US Mortgages

By

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## Abstract

Since the Great Recession of the early 2000's an added scrutiny has been placed on the US mortgage industry. This new focus has put an emphasis on the underwriting standards of mortgages. I hypothesize that mortgage underwriting guideline characteristics, or variables, are good indicators of potential loan defaults and prepayments. Using a newly available public dataset of loan-level characteristics and performance for home loans, I show that the existing standard variables used in mortgage underwriting are predictive in determining potential prepayment or default. My findings are consistent with existing research in mortgage literature that used more limited datasets.

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## Chapter I: Introduction

Since the Great Recession in the early 2000's a greater interest and added scrutiny has been placed on the US mortgage industry. Instruments termed Mortgage-Backed-Securities and entities called Freddie Mac and Fannie Mae once obscure are now in the national zeitgeist. This scrutiny has placed an emphasis on the mortgage underwriting practices in economic research. Existing studies into the US mortgage industry often rely upon aggregated pool data and/or loan-level datasets purchased from a third-party source when conducting research on the effects of underwriting variables. Some of the existing mortgage research includes studies by: Foote, Gerardi, and Willen (2008), Calhoun and Deng (2002), Elul (2015), and Anderson and Dokko (2016). Using a newly available public dataset of loan-level characteristics and performance for home loans, I show that existing standard variables used in mortgage underwriting are predictive in determining potential prepayment or default. My findings are consistent with existing research in mortgage literature that used more limited datasets.

My study will differentiate itself from existing work with the use of the newly available Freddie Mac Single Family Loan-Level Dataset (SFLLD). The SFLLD contains loans originated in the US mortgage industry from 1999 through the first quarter of 2015. This period as defined by the SFLLD will be the focus of this paper. Going forward, I shall refer to this specific time as the Mortgage Crunch or Crunch. A brief introduction to the US mortgage industry and underwriting guideline variables is necessary to better understand the variable's importance.

“Almost by definition, the creation of a subprime mortgage implies a deterioration of underwriting standards” (Sengupta and Noeth, 2010). The Mortgage Crunch was a period that saw the continued usage of predatory and unethical lending practices. One such lender, Novastar

Financial, headquartered locally in Kansas City had gained national notoriety. One of Novastar Financial's popular mortgage products included waiving the requirement of a credit report and FICO score. Other firsthand accounts during the early 2000's included senior management encouraging mortgage processors to keep the borrowers' file as "thin as possible." Keeping the files "thin" meant turning away documentation the loan processor would normally collect. The less documentation a mortgage processor had to review meant more loans the lender could close. This benefited Novastar Financial by increasing their monthly volume of loans originated and drove up profits.

Another issue in the mortgage industry not just limited to Novastar Financial was the aggressive use of Adjustable-Rate Mortgage (ARM) products. In my experience working within the mortgage industry, the borrower's primary focus is their monthly payment. To keep payments low predatory lenders would offer a 1-Year ARM product that included a "teaser" rate. The ARM product is amortized over 30 years keeping payments lower than similar short-term products: 10-Year Fixed or 15-Year Fixed. This "teaser" rate program would often have little to no documentation required. "Borrowers need less income to qualify, but soon face much larger payments (Ferguson and Boehling, 1986). This "teaser" program involved giving the borrower a low monthly payment they wanted combined with a low interest rate. After the ARM's 1-Year fixed term expires, the low "teaser" interest rate becomes the prevailing market rate. This "teaser" expiration leads to a sudden increase in the interest rate and payment size hurting borrowers and increased financial hard times.

The past few paragraphs have highlighted some of the importance of the underwriting variables and their disregard in predatory lending. Previous mortgage research has underlined the importance of underwriting variable thresholds lenders use. There is also a focus on an options

theory in mortgage loans. In options theory, the borrower has an embedded prepayment (call) or default (put) option (Calhoun and Deng, 2002). This call/put decision is executed by the borrower's choice. The borrower can delay using either option when/if the value of their call/put continues to increase. Given the nature of the two options, default and prepayment are mutually exclusive. If one option has been exercised, the other cannot, and the mortgage loan will be terminated.

Previous literature has also focused on discrete choices made by the borrower during the life of a mortgage. "As such, discrete-time models often conform more closely to the way events are measured in empirical data, even when the underlying decision-making process may be defined in continuous time" (Calhoun and Deng, 2002). On the surface, a 30-Year mortgage is continuous, but to the lender a 30-Year mortgage is 360 discrete monthly payments. These 360 discrete payments are similar to a first-mover advantage game between the lender and borrower. The lender faces asymmetric information in this game. The lender has no knowledge of the borrower's decision until the scheduled payment is due. For example, suppose a payment is due on September 1<sup>st</sup> and the borrower did not plan to make that payment. The borrower would not be listed as delinquent until October 1<sup>st</sup> by the lender. During this exchange, the borrower had full knowledge of their actions while the lender did not become aware until the end of the payment period.

Options theory stresses the binomial choice, between the two mutually exclusive prepayment and default choices. For example, prepayment, the loan either prepays or it does not. Since prepayment is a binomial variable, a logistic regression is used in mortgage data analysis. The logistic model has become the norm when dealing with this type of binary event. The same is true for the default option. If the loan defaults it either defaults or does not. A more specified

logistic regression, the multinomial logit, provides a joint model for probabilities of prepayment and default. Calhoun and Deng (2002) used a multinomial logit model when comparing the options theory of ARM and Fixed-Rate Mortgage (FRM) products. While my data only includes FRM loan-level data, I will use a similar approach given their conclusion that there is no difference in the way an ARM borrower will behave when compared to a FRM borrower given similar financial conditions. My similar approach will utilize the standard binary logistic regression due to no difference between ARM and FRM products.

Default and prepayment decisions are made by borrowers and could be influenced by unobserved factors in the mortgage data. Common in previous mortgage research using origination data, those studies merged additional datasets to approximate exogenous shocks: Ferguson and Boehling (1986), Foot et al. (2008), Heitfield and Sabarwal (2004), and Elul (2015). For example, these additional metrics often include: unemployment rate, current market interest rate, and/or divorce rates. I will be introducing the civilian unemployment rate, lagged by one-month, and the current 30-year mortgage market interest rate. These measures are used as a proxy to gain a better understanding of the factors underlying the borrower's decision to prepay or default.

Heitfield and Sabarwal (2004) studied prepayment and defaults of subprime automobile loans and listed their similarities to mortgage borrowers. I expect the subprime auto borrowers to behave comparable to home loan borrowers given the same financial conditions. Both sets of subprime borrowers have similar financial characteristics. The additional metrics that Heitfield and Sabarwal incorporated in their subprime auto research were: the current market interest rate and unemployment rates. They find that increases in unemployment lead to higher default rates in automobile loans. A borrower losing his/her job would be a significant financial shock and



effect ability to repay the debt obligation. I expect mortgage borrowers to act similar to the auto loan dataset and find an increased chance of default with higher unemployment. They did not find any refinance relationship with subprime automobile prepayment and the current market interest rates. In contrast, I would expect to see when the market rates fall a homeowner would choose to refinance their current loan.

Moreover, another parallel between the automobile and mortgage borrowers is that both types of loans are collateralized by an asset. The borrower has an incentive to meet the debt obligation or the asset can be repossessed. “Yet although some lenders have developed proprietary models to underwrite subprime loans, very little academic research has examined the risks associated with subprime lending” (Heitfield and Sabarwal, 2004). The lack of publicly available data has hindered the advancement of research into this topic as the authors had to use aggregated pool data. The loan-level approach I have taken has only been made possible by the recent publication of SFLLD.

Ferguson and Boehling (1986) also incorporated exogenous variables. The additional variables included: unemployment rate, divorce rate, and the percentage of the mortgage payment to the family’s income. They found that these identified variables did have significant outcomes on the potential probability of delinquency leading to default. The percentage of the mortgage payment to the family’s income was the highest contributing factor. Ferguson and Boehling also found that divorce was a key factor when dealing with short-term delinquency. In their study the unemployment rate had the weakest impact on delinquency.

A more recent study published at the end of 2016 by Anderson and Dokko offers a contrarian viewpoint to the existing literature and adding exogenous datasets. Anderson and

Dokko focused only on home loan default and the timing of tax payments. They argue against using additional metrics since it can introduce measurement error and interfere with interpretation. Anderson and Dokko reason that the effects of changing: unemployment rates, divorce rates, or credit card delinquency, etc. are endogenous within the mortgage data.

Anderson and Dokko used the timing of property tax due dates and the effect it had on household liquidity. A key issue in their argument was that any borrower that does not have an escrow account would face a greater financial burden upon property taxes becoming due. As of June 2013, the requirement of collecting escrow accounts is left up to the lender and if they meet certain requirements: lending primarily in rural areas or to underserved communities, less than 500 loans originated per year, less than \$2 billion in assets, and do not typically require escrow accounts<sup>1</sup>. An escrow account allows the borrower to pay a third party the same flat rate over their amortization schedule, holding taxes constant, instead of paying taxes separately when due.

Without an escrow account the individual payment is lower, but the borrowers incur a lump-sum tax payment leading to constrained liquidity. A borrower with an escrow account would not see decreased liquidity since they pay the same fee regardless of property tax due date. Anderson and Dokko (2016) found borrowers who had to pay taxes within the first three months of origination were 2-6% greater chance to default. A 2006 survey estimated 12% of mortgage delinquencies were caused by tax liabilities (Anderson and Dokko, 2016). Loans with the longest exposure to tax due dates are expected to miss 2-4 payments. Anderson and Dokko (2016) found a causal effect of property tax due dates on borrowers without escrow accounts. They conclude that the lack of escrow accounts before the Crunch was the reason that many borrowers defaulted. A possible solution could be suspending tax liabilities to prevent other defaults. They

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<sup>1</sup> "What the new escrow account requirements mean for consumers." [www.consumerfinance.gov](http://www.consumerfinance.gov)

did not find evidence for strategic timing of loan origination as a way for borrowers to avoid the financial burden. They posited that their approach is better than the standard discrete-time hazard models common in literature. The inclusion of additional datasets increases the difficulty of finding an unbiased relationship between those additional datasets and the default or prepayment. While my dataset does not include any information on tax liabilities or escrow accounts, this argument will aid in the interpretation of my results.

The mortgage industry is a complex part of the economy. To gain a better understanding of the mortgage industry, Chapter II reviews standard underwriting variable thresholds: FICO score, LTV/CLTV, and DTI. Also, examined within Chapter II is the role of the two Government Sponsored Entities (GSEs)<sup>2</sup>. These specified standard variable thresholds are what I use in a regression analysis. Chapter III discusses the binary logistic regression model used. Chapter IV dives much deeper into what is included in the newly available public Freddie Mac Single Family Loan-Level Dataset (SFLLD). Chapter V serves as a discussion of my results and how my findings relate back to the existing research. Chapter VI forms a conclusion and discussion of future research.

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<sup>2</sup> The Federal National Mortgage Association and Federal Home Loan Mortgage Corporation colloquially called Fannie Mae and Freddie Mac, respectively.

## Chapter II: Underwriting Guidelines

Underwriting guidelines are the backbone of the lending industry. These guidelines and requirements are used to signal qualified borrowers by the lender's underwriting department. On a loan-level basis, the characteristics that become the most important for determining Loan-Level Price Adjustments (LLPAs) are minimum and maximum threshold values of some commonly used variables: LTV/CLTV ratios, FICO scores, and DTI ratios. These minimum and maximum thresholds of the variables are defined below. LLPAs determine what the borrower will pay based on the perceived risk of the loan. This risk based pricing is published by the GSEs and assessed on mortgage loan through increases to the borrower paid price. LLPAs are measured costs associated with the loan amount. For example, a common LLPA could have the borrower pay 0.500% of the loan amount for any given interest rate. LLPAs are paid in addition to any lender credit received or origination points paid by the borrower for a specific interest rate offered. Over the next sections, I will go into more depth about the threshold measures.

### Loan-to-Value (LTV) and Combined-Loan-to-Value (CLTV)

One underwriting guideline that is very important is the amount of equity a borrower had to put down on a home. The LTV is determined by the ratio of the loan amount and the appraised value of the home. Traditionally, the homebuyer would have a down payment of at least twenty percent of the home's value. This initial investment is thought to be sufficient to keep the borrower making payments in case of any adverse shocks. CLTV signals when the borrower has a second mortgage on the same property. The CLTV is the sum of the first mortgage plus the second mortgage and is divided by the appraised value of the home. For example, a borrower could have a \$50,000 first mortgage and a \$20,000 second mortgage on a home for \$100,000. The CLTV for this borrower would be a 50% LTV/70% CLTV. This borrower would be

required to pay a secondary financing LLPA from the GSEs as a perceived increased risk due to the inclusion of a second lien.

At the beginning of the Crunch some borrowers would be signing loans that awarded them upwards of 125% of the home's value. For example, a loan having an LTV of 125% meant that when the borrower bought a \$200,000 home the bank lent \$250,000. The borrower was happy to collect extra money and the loan officer received a larger commission. This strategy would be successful if housing prices kept appreciating. Shortly before 2008-2009 the values of homes depreciated drastically and left homebuyers with limited liquidity. A house is not easily convertible to cash leaving many borrowers stuck in their homes after house prices dropped. To continue our 125% LTV example, the market now values the home at \$150,000 and the borrower received \$250,000. The borrower sees the declining housing prices and wants to sell. The borrower goes to sell their house and finds a buyer willing to pay \$150,000. The homeowner still owes \$100,000 leaving them underwater from their previous mortgage while looking for a new home. Often, this borrower would simply walk away from their \$250,000 mortgage and leave the bank with an asset with a severely inflated value. The lender would then sell that home for pennies on the dollar at a foreclosure sale.

### Debt-to-Income (DTI)

DTI is an underwriting guideline that was calculated differently from lender to lender during and prior to the Crunch. The DTI is the threshold ratio of monthly debt payments to annual pre-taxed income. If a potential borrower has a DTI ratio of 50% the lender evaluates that half of the borrower's income is tied up in debt obligations. In the early to mid-2000's, Fannie Mae would approve borrowers with 65% DTI ratios if they had good FICO scores and reasonable LTVs, whereas currently even the most qualified buyers face a 45% DTI ceiling

(Sichelman, 2013). A mortgage compliance issue at the time of the Crunch was called a Stated/Wage earner program and used a reasonableness test. The Stated/Wage earner was a way to have the loan officer essentially lie to get a loan. The loan officer would state the borrower's wage at whatever income they needed to close the loan. A reasonableness test was the following; if the borrower had a reasonable wage for their current employment the borrower would be eligible for a loan. The reasonableness test was often skewed, however. The loan officer would calculate the borrower's debt, double that debt and add \$500-\$1000 dollars. This new figure would become the borrower's income. This income figure would put the borrower's DTI somewhere below 50%. The file would pass through underwriting with the bogus income figure.

As an example, suppose the reasonable test was performed for a Wal-Mart door greeter in 1999, who had \$35,000 in debt. After the reasonableness test that Wal-Mart employee was calculated to make over \$70,000 annually. The reasonableness test would allow the loan officer to put this borrower into a home that they truly could not afford. Again, the borrower is left with constrained liquidity and is unable to move in the event of an adverse shock.

### FICO (Credit Score)

The FICO score aids lenders in the decision-making process to quickly determine the probability that they will be repaid for the mortgage loan by the potential borrower. Prior to the FICO score being used industry wide, the lender had a more personal relationship with the borrower. The lender would manually look over the borrower's credit report to determine eligibility. This was a time consuming and subjective process. The FICO score's purpose is to objectively give borrowers a credit score per myfico.com. A FICO score is comprised of payment history, amount owed on debit and credit, length of credit history, new credit and the type of credit. Fair Isaac Corp was founded in the late 1950's as an analytic credit scoring

solution to make credit more widely available to consumers. The FICO score is prohibited from including income or length of employment when calculating a score. Anyone can have a credit score regardless of demographics.

Prior to 2006, the Fannie Mae and Freddie Mac required the minimum FICO score to be 620 for the loan to be eligible for sale to the investors (Sichelman, 2013). Around 2006-2008 this minimum FICO shrunk, a common phrase at the time, “If you could fog a mirror you could get a loan.” In the mortgage industry prior to the Crunch thousands of loans were sold to investors with no FICO scores. At the time of underwriting a loan it is important for lenders to determine whether they will be paid back for the loan. The FICO helps quickly assess risk on potential borrowers with average delinquency measures without the lender having to devote precious man hours to manually review credit history.

### The Mortgage Industry Post-2009

After the 2008-2009 financial crash mortgage compliance had a pendulum effect and began to swing towards tightening regulations. The mid-1990’s to 2010 had the loosest regulations in the mortgage industry. Prior to 2010, a borrower could verbally verify employment, now the lender will confirm the borrower’s employer. Investment properties and cash-out refinances only required 15% down payments. Post 2010, investment and cash-out loans need at least a 20% down payment or the borrower is ineligible for the loan program. Cash reserves were also less stringent before 2010; a borrower had to maintain at least six months’ worth of payments. Today, a borrower will need a full year’s worth of payments in cash reserves.

Two years, 2009-2010, saw the strictest regulation changes from Private Mortgage Insurance (PMI) companies. In 2009, the PMI companies passed thirteen guidelines for

borrowers to meet before becoming eligible to receive PMI. The first change in January 2009, made the minimum FICO score to qualify 580, not to be confused with Fannie Mae and Freddie Mac's earlier minimum requirement. This tells us one key piece of information; a minimum FICO did not exist prior to 2009 to obtain mortgage insurance. If a borrower's down payment is less than 20% of the value of the home that borrower is required to have mortgage insurance. After 2009, anyone needing mortgage insurance would need to have that minimum of 580 to qualify.

In late 2010, the Dodd-Frank Act was passed as a response the Subprime Mortgage Crunch. The Dodd-Frank was a part of the new wave of regulations had begun by this time. The Dodd-Frank's primary intention was to prevent another major collapse of a financial institution, for example Bear Sterns and Lehman Brothers. The Dodd-Frank created the CFPB<sup>3</sup> to protect consumers from 'unscrupulous business' (Koba, 2012). The CFPB's main concern is to protect against abusive lending and mortgage practices of predatory lenders along with the power to prosecute individual loan officers. In the past, only the lender could be sanctioned, but now the CFPB can take the one employee to trial. The CFPB hosts a hotline for consumers to call along with providing information about mortgage loans and credit reports in layman's terms. The CFPB also oversees payday loans, consumer loans, credit, and debit cards along with credit reporting agencies.

In the wake of the Crunch, the credit ratings agencies have been put under stricter regulation since those agencies have been viewed as misleading investors with giving high ratings to risky assets. The two largest credit ratings agencies: Standard & Poor's and Moody's have been placed under the regulation of the Securities and Exchange Commission (SEC) and

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<sup>3</sup> Consumer Financial Protection Bureau



the CFPB. A common held belief is that the credit agencies mislead investors by giving subprime Mortgage-Backed-Securities (MBS) AAA credit. An MBS is a financial asset made up of thousands of mortgage loans that uses those mortgages as collateral. In late 2016, Moody's was readying to go to court over the allegation of inflating credit ratings (Scully 2016). Standard & Poor has previously paid over one billion dollars to the Department of Justice for the same allegation of inflating the ratings of MBS's. In the case against Moody's, the Department of Justice cites "sloppy mortgage underwriting and lax bond ratings" that led to the Crunch. In the aftermath, the ratings downgrades on the MBS's due to defaults eliminated upwards of \$11 trillion from household wealth in the US in the mid-2000's. This has been some of the back story into why the US mortgage industry played a part in one of the biggest financial disasters in modern history.

## Chapter III: Model Description

I use a binary logit model. My model will share some similarities to the model used by Calhoun and Deng (2002). My model will differ; however, with the use of the Freddie Mac Single Family Loan-Level Dataset (SFLLD) and the study of Fixed term products. Previous research into mortgage literature had to: rely on data from third parties, use aggregated data, and/or incur a cost to gain access to this type of loan-level data. The SFLLD is maintained by one of the two largest investors in US mortgage loans, the other being Fannie Mae. To signal an increase in ethical lending Freddie Mac has begun to upload their loan-level data at no monetary cost for academic or personal use. I use two models that estimate the probabilities of default( $P_D$ ) and prepayment( $P_p$ ). The logit models for default and prepayment are given by:

$$P_D = f_D(t, Spread, Year, Urate, X(t))$$

$$P_p = f_p(t, Spread, Year, Urate, X(t))$$

$t$  represents mortgage age in months. The age of a mortgage loan is an important indicator of whether a certain borrower will either prepay or default.  $Year$  represents an ongoing continuous variable for the year of origination moving from 1999 to 2015.  $Urate$  represents the one-month lagged civilian unemployment rate obtained from the St Louis Federal Reserve. The civilian unemployment rate measures the percentage of unemployed in the labor force of US citizens aged 16 or older that live in the 50 US states or D.C. Within the model,  $Spread$  predictor was calculated at the most recent loan observation's current Market Interest Rate and the interest rate at origination.

Let *Spread* be the ratio:

$$Spread = \frac{Market\ Interest\ Rate - Interest\ Rate\ at\ Origination}{Market\ Interest\ Rate}$$

The Market Interest Rate was recorded from mortgage rate data available from the St. Louis Federal Reserve. The 30-Year Mortgage Rate is collected by Freddie Mac weekly. Freddie Mac surveys 125 lenders nation-wide regarding their most popular rate and points offered for the 30-Year product that week. The points offered could include any origination paid by the borrower or lender credit received at that interest rate. *Spread* is measure that I anticipate seeing positively affect prepayment options. “Research on residential mortgages consistently finds a strong negative relationship between prevailing market interest rates and prepayment rates. . .” (Heitfield and Sabarwal 2004). As the *Spread* increases, the market rate becomes larger than the origination rate; I would expect the borrower to not exercise their call option as the market interest rate is higher than at the time of their rate lock. Conversely, as the *Spread* gets smaller and becomes negative, prepaying will become worthwhile and borrowers would refinance with the lower market rate.

In Calhoun and Deng (2002), they note that a common issue with analysis ran with mortgage data is the computational constraints. Given the size of mortgage data files this type of analysis requires a significant amount of computational resources. Due to resource constraints, all other explanatory variables are dummy variables and represented by  $X(t)$ . Recoding the explanatory variables as dummy variables avoids the need to sample the data. This process

decreases the possibility of a data sampling missing any rare events, default or prepayment, being eliminated.

The other variables represented by  $X(t)$  include: the LTV, the occupancy status, DTI, FICO and the property type. The LTV measures are divided into several buckets that have significantly different LLPA risk based pricing. I expect the higher the LTV the higher the probability that the borrower will default(put) on the current mortgage. Higher LTV loans are associated with borrowers that would fall into the subprime category. As such they have less liquidity options to prepay(call) on the mortgage loan. The occupancy status includes two dummy variables: second home and investor properties. If a borrower is an investor they do not inhabit that property as their primary dwelling and rent the home. I expect that borrowers who are in the investor role would be more prone to default(put) if financially intriguing. Several dummy predictors for FICO were also used. Finally, a dummy variable was included to denote if the property was not a single-family dwelling. I expect any mortgage not underwritten by a single-family home has increased odds of default.

## Chapter IV: Data Description

Freddie Mac's Single Family Loan-Level Dataset (SFLLD) used for my analyses is provided freely to the public at the direction of the Federal Housing Finance Agency. The dataset follows fully fixed amortizing loans over the life of each loan. A large majority is 30-Year terms with full-documentation; some of the more recent vintage years can include 20-Year and 15-Year terms included for a total of over 16 million loans. My dataset also differs with the inclusion of different property types such as: condominiums and manufactured housing. The earliest available data was originated in 1999 with the most current vintage year through the first quarter of 2015.

Within the SFLLD user guide<sup>4</sup> (p 16), Freddie Mac published a Valid Values grid containing ranges some of the underwriting guidelines had to maintain. If a FICO was outside the range of 300-850 it was reported as unknown, if the DTI was above 65% it was reported as unknown and if LTV was greater than 105% or the CLTV was greater than 200% it was reported as unknown. I reached out the Freddie Mac for clarification on the Valid Values table; they noted it was not their policy to disclose any of those figures when outside their defined ranges. It is possible that any loan containing figures outside the Valid Values are outliers and can potentially be used to single out certain borrowers, prompting a compliance issue.

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<sup>4</sup> [http://www.freddiemac.com/news/finance/pdf/user\\_guide.pdf](http://www.freddiemac.com/news/finance/pdf/user_guide.pdf)

<b>Table 1</b>		<b>Total</b>				
<b>Year</b>	<b>Loan Count</b>	<b>Original UPB (\$B)</b>	<b>Average FICO Score</b>	<b>Average LTV</b>	<b>Average CLTV</b>	<b>Average DTI</b>
<b>1999</b>	586,612	\$137.9	711.5	75.47	75.53	32.1
<b>2000</b>	786,252	\$103.7	706	77.78	78.16	34.3
<b>2001</b>	1,755,335	\$259.5	711.2	75.46	75.97	32.9
<b>2002</b>	1,164,517	\$261.7	711.4	74.88	75.54	33.4
<b>2003</b>	731,625	\$311.2	732.2	72.45	73.56	32.8
<b>2004</b>	888,199	\$188.1	718.8	73.37	74.84	34.6
<b>2005</b>	1,691,634	\$289.3	721.2	69.72	71.24	35.6
<b>2006</b>	1,260,384	\$226.5	717.8	71.27	73.53	36.8
<b>2007</b>	1,220,044	\$223.8	715.9	72.97	75.33	37.2
<b>2008</b>	1,179,008	\$240.2	732.9	71.11	72.24	36.9
<b>2009</b>	1,846,417	\$423.1	757.8	67.01	68.17	32.79
<b>2010</b>	606,052	\$265.1	761.2	66.43	67.46	31.76
<b>2011</b>	953,015	\$207.8	762.6	67.60	68.58	31.65
<b>2012</b>	923,608	\$295.3	796	68.15	69.15	30.86
<b>2013</b>	1,297,368	\$282.9	760.1	70.42	71.25	31.85
<b>2014</b>	345,963	\$212.2	751	75.53	76.03	33.69
<b>2015</b>	319,121	\$159.8	754.9	72.70	73.33	33.32
<b>Total</b>	17,555,154	\$4,087.8	-	-	-	-
<b>Average</b>	-	-	736.09	71.90	72.94	33.68

Contained in this dataset and *Table 1* is the information for over 17 million origination loans sold to Freddie Mac representing over \$4 trillion in loan sales<sup>5</sup>. Each vintage year contains a subset of origination and ongoing monthly performance data. The origination data is static and was recorded at the time the loan closed with the lender. The monthly performance data is ongoing and tracked by Freddie Mac. This ongoing data includes: mortgage age and if the loan had been paid off or defaulted. The following figures contain the means for the top 10%, bottom 10% and the overall mean of every year within the SFLLD.

<sup>5</sup> [http://www.freddiemac.com/news/finance/sf\\_loanlevel\\_dataset.html](http://www.freddiemac.com/news/finance/sf_loanlevel_dataset.html)

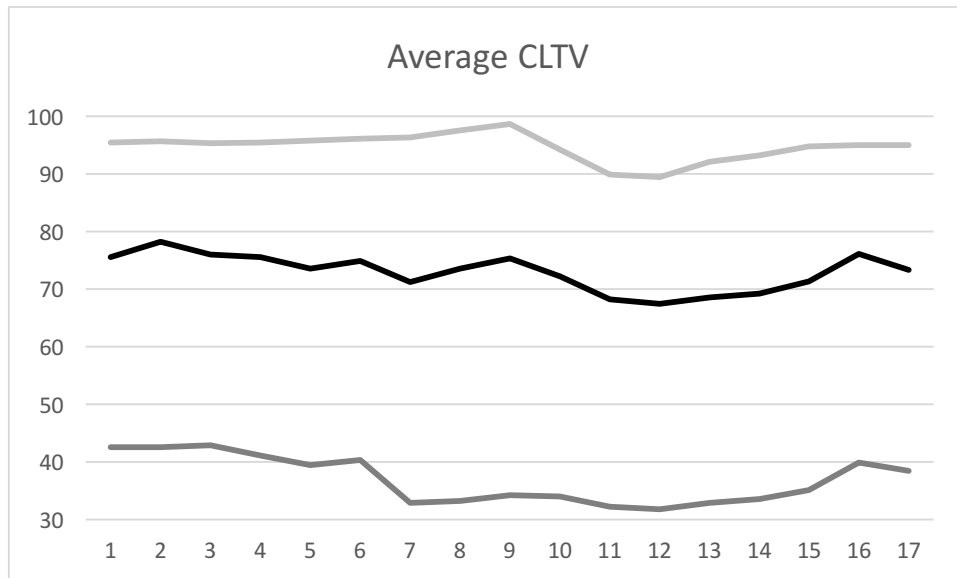


Figure 1

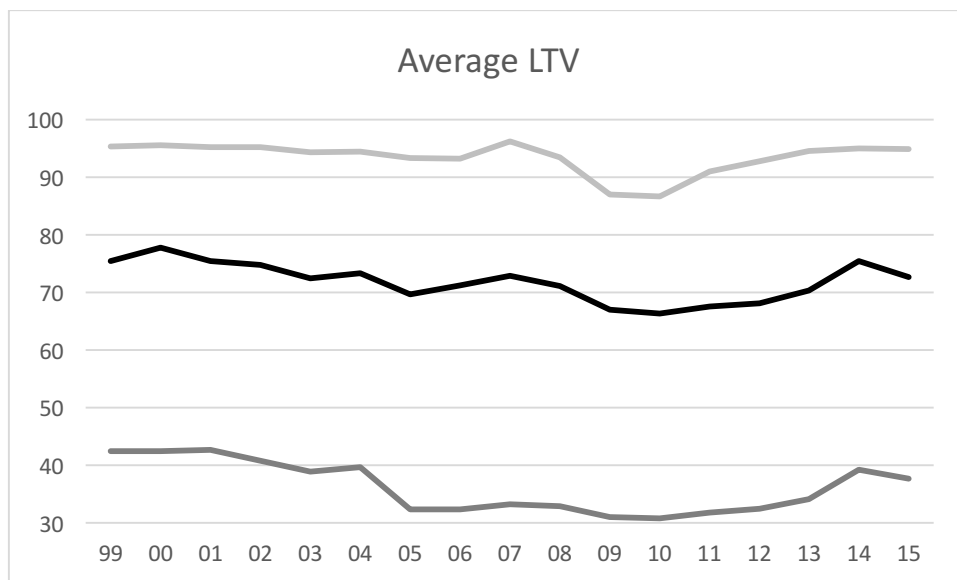


Figure 2

Figure 1 displays the average percentages CLTV ratios while Figure 2 displays the same for LTV. From the Figure 1 and Figure 2 it becomes clear that both the average CLTV and LTV ratios were decreasing until 2010 and began increasing post-2010. This could be from the mortgage industries tightening of regulations and the decreased amount of loans originated after 2010 as seen in Table 1. Neither average ever passed 80% mark. It is common within the

mortgage industry to have a cutoff at 80% LTV. Any loan over 80% LTV will have PMI and higher LLPAs. Contained in the SFLLD, a total of 76.03% of loans were below 80% LTV. A total of 82.14% of loans were below 80% CLTV. With CLTV often mirroring what LTV did the two measures are highly correlated. This mirroring makes sense as any effects in LTV would be present in the CLTV. Higher CLTV measures would be interesting, but were outside of Freddie Mac's policy to disclose.

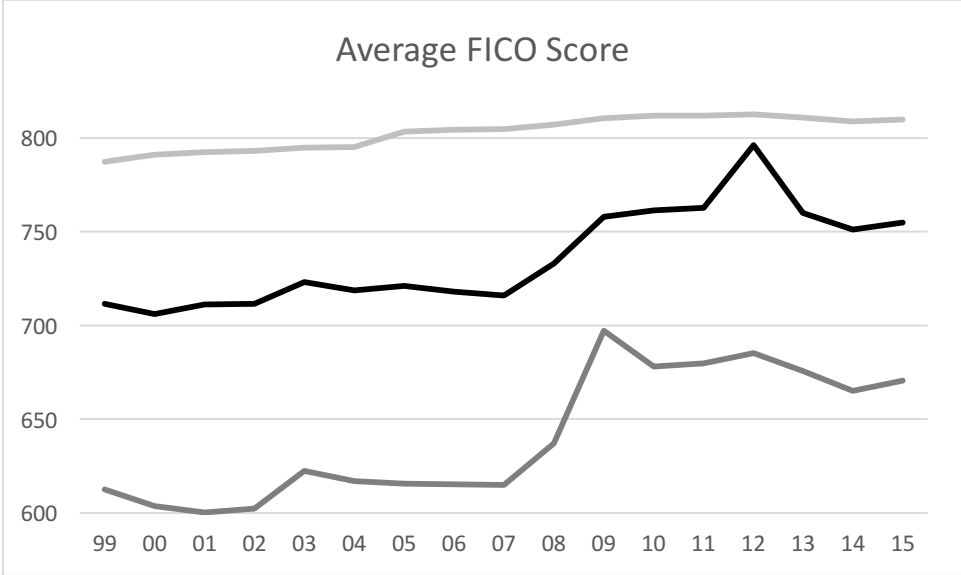


Figure 3

The FICO score ranges from 850 to down to 300 in the dataset. *Figure 3* depicts the average FICO scores seen over the duration of the SFLLD. What is clear from looking at this graph is the average FICO score never dipped below 700. 25.23% of all loans were below the 700 FICO score mark. The year 2007 saw the highest number of loans below FICO 700 with 34% and 2012 had the lowest recorded loans with 6.96%. A sub-700 FICO score is generally associated with subprime borrowing. In the aggregate, borrowers were getting better through the Great Recession. The large spike in the bottom 10% average FICO shows that borrowers were becoming better. The average FICO score did change over time, but the biggest jump was seen



after 2007 increasing from 715.9 to 796 in 2012. This jump is possibly the mortgage industry responding to tighter regulations. The peak FICO score in 2012 is interesting, that year may have been an outlier since the average for 2013 drops right down to 2011 levels. What is not reflected here is that any score that was below 300 are not recorded as values in the dataset due to Freddie Mac's own policy, however, the bottom 10% of FICO scores never averaged below 600.

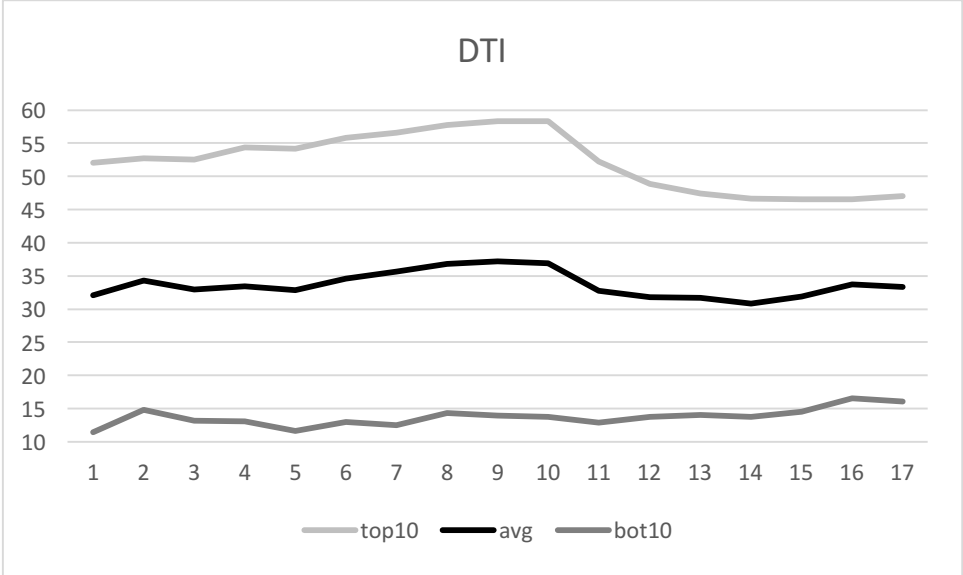


Figure 4

Figure 4 depicts the average DTI measures with 63.80% of all loans having a DTI ratio over 30%. The increasing curve in the middle of the data is interesting to note. As mentioned previously during the early 2000's the DTI ratio was subject to varying standards during reporting. If the years 2004 through 2009 were removed the average DTI almost stayed constant. The five-year period after 2004 does encapsulate one of the worst periods in the mortgage industry. The average DTI began to decrease after the year 2008. I believe that this is also a similar response that the average FICO score saw. This decrease could be due in part to the mortgage industry reacting to tighter regulations.

The monthly data set also includes a Zero Balance Effective Code, this field is used by Freddie Mac to designate loans that have defaulted or prepaid. The following numbers code whether a loan defaults (03 or 09) or a prepaid loan was coded (01 or 06).

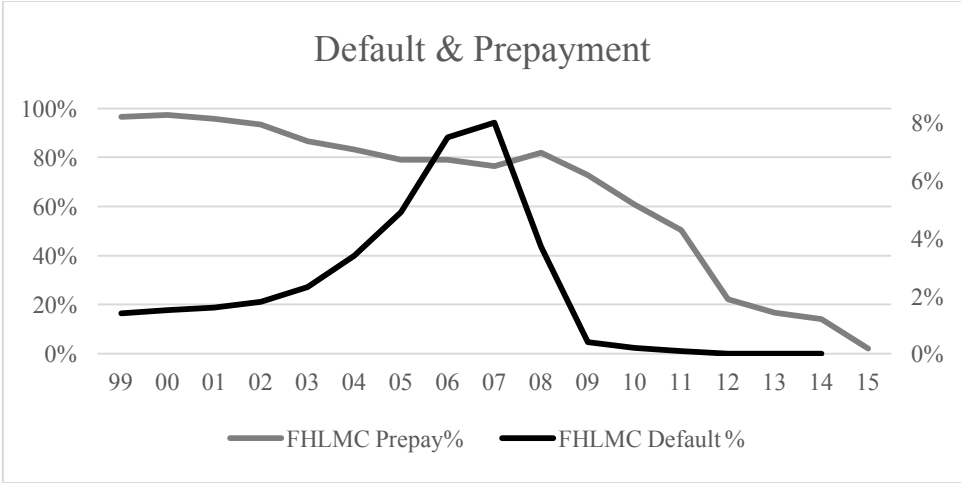


Figure 5



Figure 6

Figure 5 represents the percentage of loans per year that either defaulted or prepaid from the dataset. This graph was prepared using the data supplied by Freddie Mac in their summary statistics guide. What is interesting to note from the graph is that a majority, roughly 90%, of all loans originated from 1999-2002 have either been prepaid or defaulted. Most of those 1999-2002

loans have been prepaid. This behavior is not surprising as most mortgage loans tend to be prepaid well before the end. The peak percentage of loans defaulted per year came in 2007 with 8%. The peak for prepaid mortgages was lagged one year with 82% being paid off in 2008. The number of prepaid mortgages drops off precipitously after 2010. I believe the declining prepay numbers are due to the loans in the dataset not meeting the appropriate seasoning. It is common that most borrowers only stay in their first mortgage loan for five to seven years; it follows that any loans originated in 2007 would begin to start prepaying in 2014-15. Any loan originated in 2010 is too young to have been prepaid. *Figure 6* depicts the 30-Year market interest rate over the course of the SFLLD. The current interest rate is a large driver of prepayments on loans. Recently, the overall market interest rate has been low, since November 2014 the market rate has been below 4.00%. A low market rate offers little to no incentive for borrowers in their current mortgage to refinance into a newer loan with a similar rate.

To manipulate my data, I utilized Amazon's Web Services. Amazon Web Services is designed to give developers and other users scalable cloud computing on demand. Under Amazon's umbrella Web Services featured is their Elastic Cloud Computing (EC2) service. EC2 offers many ranges of computers with differing amounts of RAM to CPU and/or storage. Once a CPU/RAM tier option has been chosen an Amazon Machine Image (AMI) is created that represents your configuration. A benefit of using Amazon's service is that once an AMI is created you are assigned a website address with access to the cloud computer allowing you to run your analysis from anywhere with an internet connection.

I followed Ken Kleinman's blogpost on r-bloggers.com to set up an AMI with the statistical package R pre-installed. R is a free open source statistical package that is available for Macs, PCs, and Linux. Since I was using a cloud computer that had no access to my local

external hard drive I had to upload my data to the cloud also. I chose to host my data on Dropbox.

## Chapter V: Discussion

For brevity, I will show tables of the regressed predictors for the current loan characteristic that we are discussing. The following tables are created from my logistic regression output. The predictors in a logistic regression are returned in log odds or logit units. The log odds allow for the interpretation of a one-unit change in the variable gives a beta-unit increase to the response variable. Many observations were duplicates, these were thrown out. Only the most recent loan observation recorded was kept. The final pool in the regression represents over 17 million mortgage loan observations.

### Age of Loan ( $t$ )

<b>Table 2</b>	<b>Default Est. (Std. Error)</b>	<b>Prepayment Est. (Std. Error)</b>
<b>Age (<math>t</math>)</b>	-1.25E-01 (2.02E-04)	-2.59E-02 (8.95E-05)
<b>Age Squared (<math>t^2</math>)</b>	6.59E-04 (1.26E-06)	-9.92E-05 (4.75E-07)

I defined age of the mortgage loan as  $t$  months. I had earlier predicted that the increasing in the age of the loan would lead to higher potential prepayment much the same as the subprime auto borrowers. In the subprime automobile loan analysis Heitfield and Sabarwal (2004) found prepayment rates rise with loan age. These findings could be due to the nature of automobile loans. With home loans, house prices tend to appreciate over time. An automobile's value depreciates at a high rate; older automobiles will have corresponding lower loan amounts and pose less of a financial burden. The reduced burden leads to prepayment rates being higher and more frequent with auto loans. From *Table 2* we see that a one-month increase in the age of a loan, will decrease the log odds of a default by roughly 0.12. As the loan grows older it has less

of an effect and every one-year increase leads to a 0.02 decrease in the odds of the borrower prepaying the loan. Lenders may have become efficient at determining which borrowers will not default or prepay in the short term. The lenders incentives are to find borrowers that will continue to pay into the full amortization schedule. While both the  $Age(t)$  and  $Age Squared(t^2)$ , were significant at any level the  $Age Squared(t^2)$  variable had an almost 0% effect on either default or prepayment.

### Spread

<b>Table 3</b>	<b>Default Est. (Std. Error)</b>	<b>Prepayment Est. (Std. Error)</b>
<b>Spread</b>	-4.54E+00 (2.29E-02)	1.06E-01 (8.14E-03)
<b>Spread<sup>2</sup></b>	-1.85E+00 (2.25E-02)	-6.17E-01 (1.02E-02)
<b>Urate</b>	1.23E-01 (1.49E-03)	1.34E+00 (1.07E-03)

The Spread predictor in *Table 3* has the expected effect on the borrower using their Prepayment option and a very large effect on default. Every one-unit increase in the Spread between the current market rate and their interest rate results in a 0.1062 increase in the log odds of a Prepayment. As the *Spread* variable increases, I expect a 4.536 decrease in the log odds of default. If the market rate decreases, it becomes financially beneficial for the borrower to prepay while those who cannot are stuck in their loans. Those borrowers who cannot prepay face a default option that is costlier since the prepayment option has become a much better alternative with the increasing *Spread* variable. The *Urate* represents the effect that the unemployment rate had on the log odds of a default or prepayment. For every one-percent increase in the unemployment rate I expect the log odds of default to increase by 0.1225 and the log odds of prepayment to increase by 1.339.

## Year of Origination

<b>Table 4</b>	<b>Default Est. (Std. Error)</b>	<b>Prepayment Est. (Std. Error)</b>
<b>Year</b>	5.31E+02 (1.32E+00)	2.00E+02 (2.45E-01)
<b>Year<sup>2</sup></b>	-1.33E-01 (3.30E-04)	-5.00E-02 (6.11E-05)

The Year coefficient was left as a continuous variable similar to the Age ( $t$ ) of the mortgage loan. The Year coefficient represents what vintage year the mortgage observation was originated. *Table 4* indicates that for every one-year increase, from 1999 to 2015, I expect to see a 531.4 increase in the log odds of default. The odds of prepayment decrease as the Year variable increases, I expect that for every one-year increase the odds of prepayment increase by 200.1. This is consistent with the Default and Prepayment percentages depicted in *Figure 5*. The Default percentages seen in the dataset were the worst in the early 2000s. *Figure 5* also displayed the overall number of prepayments declined over the recorded period. The overall prepaid percentage of the dataset began declining in the vintage year of 2007. If a loan was originated in 2007 I would expect it to not refinance until after the dataset ended. The vintage years post-2008 some of leanest years for loans originated. The years of 2007-2008 also contained the beginning of the Great Recession.

## LTV/CLTV

<b>Table 5</b>	<b>Default Est. (Std. Error)</b>	<b>Prepayment Est. (Std. Error)</b>
<b>LTV &lt;=60%</b>	-0.701E-01 (2.15E-02)	1.34E-01 (7.48E-03)
<b>LTV &gt;60% &amp; &lt;=80%</b>	8.64E-01 (2.04E-02)	-1.51E-01 (7.33E-03)
<b>LTV &gt;80% &amp; &lt;=100%</b>	1.43E+00 (2.06E-02)	-3.84E-01 (7.60E-03)
<b>LTV &gt;100%</b>	3.03E+00 (5.26E-01)	-1.87E+00 (4.70E-01)

The LTV ratios were broken into the different buckets to better explain the behavior seen from borrowers at the respective LTV ratio in *Table 5*. The largest change in the log odds of default were seen when the potential borrower when from >100% LTV. When a borrower has an LTV >100% I expect the log odds of default to increase by 3.032. In this >80% & <=100% LTV the log odds of default increase by 1.428. The only bucket that decreased the log odds of a potential default was if the borrower had <60% LTV, the log odds were decreased by 0.7011.

The odds of prepayment were also consistent with the hypothesized effect. If the borrower had <60% LTV the log odds of prepayment were increased by 0.1339. All other LTV buckets negatively affect the potential prepayment. The higher LTV ratio corresponds to the lower amount of equity that the borrower has in the home. A borrower that has very little equity will find an increased difficulty trying to prepay their mortgage loan. The same can be said for a potential default, the higher the LTV ratio and less equity the borrower has in the home can put the default option as financially attractive.

## Occupancy Status, Loan Type, and Property Type

<b>Table 6</b>	<b>Default Est. (Std. Error)</b>	<b>Prepayment Est. (Std. Error)</b>
<b>Occupancy, Second Home</b>	-6.78E-02 (9.02E-03)	-1.99E-02 (4.39E-03)
<b>Occupancy, Investor</b>	1.55E-01 (7.27E-03)	-3.88E-02 (4.00E-03)
<b>Loan Type, Cash-out</b>	4.44E-01(4.49E-03)	-4.27E-01 (2.38E-03)
<b>Loan Type, Rate/Term</b>	2.73E-01 (4.68E-03)	-3.86E-01 (2.26E-03)
<b>Property, Condo</b>	2.94E-01 (6.51E-03)	3.06E-03 (3.61E-03)
<b>Property, Leasehold</b>	7.81E-02 (8.21E-02)	-2.37E-02 (3.99E-02)
<b>Property, PUD</b>	-1.08E-01 (5.60E-03)	7.90E-02 (1.85E-02)
<b>Property, Manufactured</b>	2.76E-01 (1.40E-02)	-4.02E-01 (9.48E-03)
<b>Property, Coop</b>	-3.23E-01 (6.55E-02)	7.22E-02 (1.85E-02)

The above *Table 6* lists the estimates for occupancy status of: second home and investor, the loan type of refinance and the property types of: condo, leasehold, PUD, manufactured and coop. If the property was a second home the log odds of default decreased by 0.06. The log odds of prepayment decrease by 0.02 when the borrower is in a second home. When the property type was investor instead of a primary dwelling the log odds of default increased by 0.15 and decreased the log odds of prepayment by 0.04. The investor occupancy status saw the largest effect on the potential default in a loan followed by the property type of manufactured. A single-family home was left as the reference for any property type dummy variable. If the property type was manufactured, then the log odds of default were increased by 0.27 when compared to the property being single-family home. A manufactured home decreased the log odds of prepayment by 0.40. The PUD designation signals that the house has not been built yet as opposed to an existing dwelling. Any borrower who entered a PUD contract would behave much the same as a borrower with a single-family dwelling. If the borrower had a PUD property type their log odds of default decreased by 0.11. The PUD property type increased the log odds of prepayment by 0.079. The loan type of purchase was left as the reference for refinance. Included in the loan type refinance are both cash-out and rate/terms refinances. A rate/term refinance denotes any



borrower who is opening a new mortgage loan and not taking any equity from their home. When the loan type was a rate/term refinance the log odds of default increased by 0.27 when compared to a purchase loan and if the purpose was a cash-out it increased the log odds of a default by 0.44.

## FICO

<b>Table 7</b>	<b>Default Est. (Std. Error)</b>	<b>Prepayment Est. (Std. Error)</b>
<b>FICO &lt;=620</b>	3.28E-02 (3.08E-02)	7.96E-02 (2.18E-02)
<b>FICO &gt;620 &amp; &lt;=700</b>	-2.51E-01 (3.02E-02)	1.97E-01 (2.14E-02)
<b>FICO &gt;700 &amp; &lt;=720</b>	-5.79E-01 (3.06E-02)	3.72E-01 (2.16E-02)
<b>FICO &gt;720 &amp; &lt;=740</b>	-7.60E-01 (3.06E-02)	4.30E-01 (2.15E-02)
<b>FICO &gt;740</b>	-1.26E+00 (3.04E-02)	5.48E-01 (2.14E-02)

The coefficient estimates for the FICO are of interest in *Table 7*. I hypothesized that borrowers with FICO score 700 or less would see more defaults. For example, if the borrower had a FICO score of 620 or less the log odds of default were increased by 0.03. Any FICO score above 620 would decrease the log odds of default. All FICO buckets positively affected the log odds of prepayment in the SFLLD. The largest effect came from borrowers having a FICO score >740. If the borrower had a FICO score above 740 the log odds of prepayment increase by 0.547.

## DTI

<b>Table 8</b>	<b>Default Est. (Std. Error)</b>	<b>Prepayment Est. (Std. Error)</b>
<b>DTI &lt;=30%</b>	-1.91E-01 (1.19E-02)	-3.54E-02 (5.37E-03)
<b>DTI &gt;30% &amp; &lt;=35%</b>	8.59E-02 (1.22E-02)	-7.13E-03 (5.63E-03)
<b>DTI &gt;35% &amp; &lt;=40%</b>	2.13E-01 (1.20E-02)	-3.21E-02 (5.69E-03)
<b>DTI &gt;40% &amp; &lt;=45%</b>	3.09E-01 (1.21E-02)	-3.90E-02 (5.69E-03)
<b>DTI &gt;45% &amp; &lt;=50%</b>	3.75E-01 (1.23E-02)	-1.24E-01 (5.91E-03)
<b>DTI &gt;50%</b>	4.07E-01 (1.22E-02)	-3.23E-01 (6.08E-03)

As seen in *Table 8* every DTI ratio bucket decreased the log odds of prepayment while having a positive relationship with default. If the borrower had a DTI ratio above 50% the log odds of prepayment decrease by 0.32 where the log odds of default increase by 0.41. If the borrower had a DTI ratio below 30% was the only time the log odds of default were decreased. The DTI variable shows a very responsive relationship with default.

## Chapter VI: Summary and Conclusion

The analysis performed used loan level data to calculate a discrete-time model for default(put) and prepayment(call) options using a binary logistic regression. The explanatory variables included continuous measures, age of mortgage, and other fixed point characteristics. Using these explanatory variables, I hypothesized that given loan characteristics or underwriting variables are indeed good indicators of default or prepayment options. As we saw from the regression analysis results much of the log odds of a potential prepayment or default can be determined from those underwriting variables. Even with the inclusion of other data: the current market interest rate and the civilian unemployment rate, the largest impacts on the potential for default and prepayment were seen from the underwriting variables lenders require.

In the Freddie Mac dataset are loans with full documentation. What cannot be captured in the analysis is the impact of the most aggressive subprime lenders that could have had a larger impact on the outcomes for default. These lenders often left loan files thin when selling on the secondary market to investors. Elul (2015) suggested that the asymmetry of information for the loan would be the highest for low/no documentation loans. He found low/no documentation loan default probability to be significantly higher than full documentation loans. Regardless of full documentation loans or not being present in the SFLLD, loans originated with no documentation would have sent a significant shock when those borrowers began defaulting and contributed to the increase in defaults nationwide.

Other factors that are not caught within this model are those of the various shocks that were not only felt in the US, but worldwide at the time of the Crunch. As a precursor to the spike in defaults average house prices began to decline for the first time in the US since the Great

Depression. As stated by Ferguson and Boehling (1986), “Borrowers facing some financial crises may have little equity to forfeit in the early years of the loan.” Borrowers who were put into new homes would not have sufficient equity to keep them in their home and defaults would increase. Artificial inflation of housing prices also contributed to this problem faced by new homebuyers. No regulation existed that the loan officer could not hire their own appraiser the early 2000’s. Inflating the purchase price would net the loan officer a larger commission. This artificially inflated home price could be used in the sale price calculation of the same home or a neighboring home.

The US also saw increasing unemployment rates nationwide. As a result, I added the civilian unemployment rate, lagged one-month, to approximate the macro-economic shocks faced in the US during 1999 through 2015. Asymmetrical information does exist in the mortgage data. The strategic decisions to either prepay(call) or default(put) are made at a micro level. Due to this micro nature, anticipating the needs of each individual household is difficult. Not only are unemployment rates important, but divorce rates can impact the decision. In existing research, it is appropriate to introduce exogenous macro-economic data; however, the recent study by Anderson and Dokko (2016) comes to mind. They argue that these shocks are endogenously captured in the dataset.

To combat this uncertainty, I presented an empirical regression analysis using the Freddie Mac Single Family Loan-Level Dataset. The SFLLD consists of mortgage loans that include not only geographically and demographically diverse loans, but were also separated by time. These results are consistent with existing mortgage research. The standard underwriting variables I defined are good indicators of mortgage prepayment and default. The high levels of default we

saw during the years of 2005-2007 could have been precipitated by those macroeconomic factors outside of the underwriting variables.

### Considerations for Future Research

Given Freddie Mac has only recently begun to make their data publically available a large opportunity for future research regarding the data supplied is virtually untapped. Freddie Mac updates their mortgage database on a regular basis. It would be interesting to further investigate this database in a few years when we have more information on loans originated post-2010 as those newer loans continue to season. It may also be advantageous in future research to look at a mortgage loans originated in each vintage year and follow the first seven years of the loan's life. By looking at the loans in these seven year pools could relieve the effect of the zero-sum I found within my analysis by using the entire fifteen-year database.

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