Alma Mater Studiorum - Università di Bologna

Scuola di Dottorato in Scienze Economiche e Statistiche
Dottorato di ricerca in

Metodologia Statistica per la Ricerca Scientifica
XXIII ciclo

Econometric models of financial risks

Francesca Castelli

Dipartimento di Scienze Statistiche "Paolo Fortunati"
Gennaio 2012

Alma Mater Studiorum - Università di Bologna

Scuola di Dottorato in Scienze Economiche e Statistiche
Dottorato di ricerca in

Metodologia Statistica per la Ricerca Scientifica
XXIII ciclo

Econometric models of financial risks

Francesca Castelli

Coordinatore: Prof.ssa Daniela Cocchi
Tutor: Prof. Cavaliere

Settore Disciplinare: SECS-P/05
Settore Concursuale: 13/A5

Dipartimento di Scienze Statistiche "Paolo Fortunati"
Gennaio 2012

Acknowledgments

I am grateful to my advisor Giuseppe Cavaliere for supporting me over the years. I am in debt to Reinout De Bock who believes in me and my projects more than I do. I would also like to thank Federico Boffa, Paolo Spada and Aleksey Tetenov for helpful comments. A special thank to my family and friends for encouraging me to never give up.

Contents

List of Tables

List of Figures

Motivation and Overview

Despite a widespread consensus on the contractionary effects of the US financial crisis of 2008-09, key questions remain on how stress in the financial markets has been transmitted to the wider economy. Arguably the US mortgage sector was at the centerstage when the crisis broke out. In spite of significant government intervention[1] and a recapitalization of US banks, a number of vulnerabilities remain in the housing sector up to this day. Debates on the appropriate measures that have to be taken to deal with foreclosures and negative home equity in a cost-effective way remain as heated as ever.[2] Turning to a more aggregate level, stress in the financial sector (so not necessarily related to housing) is still weighing on economic activity. To even address this problem, researchers have to develop a tool to measure the aggregate level of financial stress. Assuming one can identify this type of financial stress, a natural question is then how strains in financial markets affect the wider economy. Policymakers have additional concerns as they want to know if and to what extent policy actions can mitigate adverse effects of sharply increasing financial stress.

The goal of this dissertation is to use statistical tools to analyze specific financial risks that have played dominant roles in the recent crisis. More concretely, I propose an appropriate econometric methodology to study two types of risks. The first risk relates to the level of aggregate stress in the

[1] Most notably through putting Fannie Mae and Freddie Mac into conservatorship and bailing American International Group (AIG) out.

[2] Foreclosure is the legal process by which a mortgage lender (such as a bank) obtains a termination of a mortgage after the borrower has failed to comply with the mortgage agreement. Negative equity occurs when the value of the house used to secure a mortgage is less than the outstanding loan balance.

financial markets and the second one concerns the US housing market. There are in fact two prominent risks associated with a US mortgage, as borrowers can both prepay or default on a mortgage. Prior to the financial crisis of 2008-09 financial markets participants failed to accurately price the default risk involved with mortgage related financial products, leaving the financial system too weak and unprepared to absorb these losses internally. Unrealized losses on mortgage-backed securities then put the asset side of banks' balance sheets under pressure. Banks in turn tightened credit and stress spread from financial markets to households and firms.

Chapter 1

Key Financial Risks in 2008-09

1.1 Aggregate Financial Risk

Starting in August of 2007, the U.S. economy was hit by the most serious financial disruption since the Great Depression of the early 1930s. The subsequent financial crisis, which receded during the course of 2009, was followed by the most severe recession in the post World War II period, with unemployment rising above 10 percent. This shock to the U.S. economy has brought to the fore the importance of financial market conditions to macroeconomic outcomes.

A very rich literature has examined the interaction between the financial system and the real economy from a theoretical point of view.[1] One of the most widely discussed channels is based on a business cycle model with financial imperfections that arise as a consequence of information asymmetries between borrowers and lenders. The amplification and propagation of a credit shock then typically operates through a balance sheet effect. An increase in asset prices increases the net worth of firms, households, and improves the capacity to borrow, invest or consume. Through general equilibrium effects, this dynamic can then lead to further increases in asset prices. Conversely, a negative shock operates in the opposite direction. Of course

[1] Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) are among the most cited papers.

there are many other channels beside this so-called "financial accelerator" mechanism. Herd behavior of bank managers can lead to a deterioration of credit standards during periods of strong growth. Down the road, this can lead to a deterioration of banks' asset quality that could force bank to reduce loan growth and depress economic activity. Institutional memory can matter as well, with loan officers tending to become more lenient on lending standards as previous loan busts disappear from memory.

Chapter 2 presents an empirical macro model, based on structural VAR analysis, to estimate the impact of financial stress on economic activity. I hereby assume that higher levels of financial stress are associated with an increase in the aggregate risk implied by a large set of financial variables. Financial stress episodes are characterized by an increase in credit, liquidity and market risks. Events of market turmoil, such as the credit crunch of 2008-09, affect the real economy by boosting the cost of credit. This process can make business, households and financial institutions highly cautious and influence their consumption and investment decisions.

Though a number of recent papers have studied the effects of stress in the financial sector on the wider real economy empirically, my paper offers a number of new insights.[2] First, I shows that there is a multi-dimensional response of the real economy to financial stress. For example, there is a marked and immediate response of the labor market following an increase in financial stress increases. Moreover, my analysis hints at a significant response of monetary policy to financial stress. When financial conditions deteriorate, short-dated rates are driven lower by the monetary authorities. Another contribution of this dissertation is showing that financial market shocks also generated a significant response on the real economy *before* the credit crunch of 2008.

[2] See Cardarelli et al. (2009), Carlson et al. (2009), Davig and Hakkio (2010) and Meeks (2011).

1.2 Risks on the Mortgage Market

As the housing bubble burst in late 2006 and prices declined, mortgage holders counting on home price appreciation were unable to pay their mortgages or refinance.[3] Consequently, delinquency rates on mortgage payments and foreclosures increased. Lenders, mortgage guarantors, including the government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac and the Federal Housing Administration (FHA), and owners of MBS experienced severe losses because they underestimated the default risk of mortgages originated in the 2000s.

Three years after the financial crisis of 2008-09, many US households remain highly indebted with many having negative equity on their mortgage. Weakened household balance sheets, reduced income and widespread unemployment have left many borrowers unable to qualify for refinancing. This means that they cannot take advantage of the record low mortgage rates. In addition, lenders and mortgage guarantors have instituted more stringent underwriting requirements. This has left many borrowers unable to qualify for a new loan even if they have remained current on their existing mortgages.

Policymakers have responded to these tighten lending conditions by introducing new refinance programs, such as the GSEs' Home Affordable Refinance Program, HARP, and a number of other programs offered by FHA. Under the terms of these programs, participants should be able to lower their monthly mortgage payments and free up household income for non-housing expenditures. It could also help certain struggling borrowers avoid a future default. Although those programs have helped some homeowners, program features and eligibility criteria exclude a significant number of borrowers who would benefit from a refinancing. A refinancing program that relaxed LTV limits and income tests, waived appraisal requirements, or allowed delinquent borrowers to participate in the program, could make refinancing at current market rates feasible or less expensive for many borrowers.[4] The averted de-

[3]Refinancing refers to the replacement of an existing mortgage with a new mortgage under different terms.

[4]Loan to value (LTV) is the amount of mortgage debt outstanding divided by the assessed value of the home.

faults could benefit borrowers and lower federal guarantee costs.[5] However, it would be costly to mortgage investors, who would experience losses on mortgages that are prepaid more rapidly than in the absence of the program.

Models such as the ones presented in Chapter 3 are a central input in the analysis of the effect of mortgage policies. Any mortgage pricing, and as a consequence any policy proposal, needs to take into account the factors determining the default and prepayment probabilities of a mortgage. An econometric model can be used for scenario analysis evaluating how the policy implementation would affect borrowers decision to default or prepay. Moreover, it is very important for a mortgage originator to project the prepayment and default rates of his portfolio of mortgages and demand adequate compensation in the form of higher coupon rates.

Chapter 3 presents a micro model to estimate the default and prepayment probabilities of a mortgage given its characteristics and the macroeconomic environment. This is a challenging task because the dynamics underlying the borrower's decision process involve both financial and behavioral elements. The approach I take in this dissertation models default and prepayment probabilities in a random utility framework using multinomial logit models. These models are well suited because of the competing nature of the two risks and their ability to include time-varying covariates. A key question in specifying a mortgage model regards the potential impact of borrowers' unobservable heterogeneity on the estimated probabilities from a standard multinomial model. To address this question, I compare multinomial logit models with fixed and borrower-specific random coefficients. I find significant unobservable heterogeneity in borrowers response to factors affecting the decision to terminate a mortgage, especially by prepayment. My results signal a potentially serious misspecification under the assumption of fixed coefficients. There is nevertheless room for more work as the in-sample fitting improvement is small.[6]

[5]The GSEs and FHA, which guarantee approximately 95% of mortgages currently originated in the US, are part of the US federal government.

[6]This result is in line with the gain from accounting for unobservable heterogeneity in other types of models suggested in the literature. Deng, Quigley and Van Order (2000) propose a proportional hazard model with unobservable heterogeneity as discrete mass

I estimate the model on a set of mortgages guaranteed by FHA, which is a United States government agency that provides mortgage insurance on loans made throughout the United States. It is the largest insurer of mortgages in the world. Unlike conventional loans that adhere to strict underwriting guidelines, FHA-insured loans require very little cash investment to close a loan. The down payment required to obtain a FHA mortgage is 3.5%. FHA provides mortgage insurance to the borrower against the payment of a mortgage premium. As issuance on the subprime[7] market came to halt in 2007-08, many of the riskiest borrowers ended up borrowing from the Federal Housing Administration. In fact, the volume of mortgage origination guaranteed by FHA went from 2% in 2006 to 17% in 2010. Given this rapid growth and the weak recovery, some observers have warned that the FHA could suffer substantial losses in the next years, and the type of models developed in Chapter 3 can be used as a foundation for cost benefit analysis of different policy measures and macroeconomic scenarios.

points. The increment in the value of the likelihood in their model with unobservable heterogeneity compared to the same model without the unobservable heterogeneity is small.

[7]Subprime loans are loans offered to individuals who do not qualify for prime rate loans. They are characterized by higher interest rates and less favorable terms in order to compensate for higher credit risk.

Chapter 2

Measuring the Impact of Financial Stress on Economic Activity

2.1 Introduction

In this chapter I estimate the impact of stress in financial markets on the U.S. economy using structural VAR analysis (SVAR). In the last three decades financial markets developments not closely related to the stance of monetary policy have played an increasing role in economic activity.[1] Events of market turmoil, such as the credit crunch of 2008-2009, have affected the real economy by boosting the cost of credit and making firms, households and financial institutions highly cautious. This observation raises a number of questions. The first one relates to the way financial stress is transmitted through the economy. How are different sectors of the economy affected when financial conditions become tighter? A closely related question is more policy related. What actions can policymakers (for example a central bank) take in response to a sharp deterioration in financial conditions? More concretely, it

[1]One example of financial development not closely related to monetary policy was the increasing popularity of securitization of assets such as mortgages. Private securitization market had grown since the early 90's and came to an halt during the financial crisis of 2008-2009.

would be helpful to know which variables have responded significantly to a change in the policy rate in the past decades. To answer these questions a comprehensive statistical measure of financial stress will be needed to gauge the aggregate level of stress in the financial sector.

As market participants consider a wide range of variables to determine prevailing conditions across financial markets, I construct a financial stress index (FSI) that distills information from a broad set of variables. The selected financial indicators measure financial conditions while excluding variables closely linked to monetary policy such as the federal funds target rate set by the Federal Reserve. I measure financial stress across markets as the latent variable driving the co-movement of all the variables. Specifically, I turn to principal component analysis to estimate the FSI.

My empirical macro model shows that there is a multi-dimensional response of the real economy to financial stress. The main advantage of using SVARs is that this methodology allows for a structural interpretation of the effect of a shock in one variable (such as financial stress or the policy rate) on another variable (e.g. investment or labor market). Following an unexpected increase in FSI, there is a statistically significant drop in GDP and its components such as consumption and investment. In addition, I find that there is a marked response of the labor market to an innovation in the FSI. Moreover, my analysis hints at a significant response of monetary policy to stress. In the wake of a deterioration of financial conditions, short-dated rates are driven lower by the monetary authorities. Interestingly enough, these findings still hold if I exclude the 2008 financial crisis from the sample. It is noteworthy that traditional macroeconomic models (such as Christiano, Eichenbaum and Evans (2005)) have a very stylized approach to the financial sector. These models do not study how endogenous developments in the financial sector could have an effect on the real economy. In contrast, my results suggest that shocks emanating from the financial sector played a significant role in understanding the dynamic interaction of macroeconomic variables even prior to the financial crisis of 2008.

The chapter is organized as follow. Section 2 defines financial stress and highlights key phenomena that are generally associated with financial stress.

Section 3 discusses indices of financial stress available in the literature. Section 4 describes the financial stress index (FSI). Section 5 presents the VAR analysis, and studies the linkage between financial stress and economy activity. Section 6 analyzes the interaction between monetary policy and financial stress. Section 7 concludes the chapter.

2.2 Defining Financial Stress

Financial stress can be thought of as an interruption to the normal functioning of financial markets. This type of stress increases with expected financial loss, with risk and with uncertainty. Under the term risk, I understand a widening in the distribution of probable loss while uncertainty means lower confidence about the shape of the distribution of probable loss. It is the consequence of a growing vulnerability in the way the financial system is structured and will respond to some exogenous shock. Such a shock is more likely to result in stress when financial conditions are weak or the structure of the financial system is fragile.

Haikko and Keeton (2009) discuss the key features of financial stress which are summarized in the remainder of this section.

Increased uncertainty about fundamental value of assets

Investors and lenders are increasingly uncertain about the expected future cash flow of their investments and this uncertainty translates into greater volatility in the market prices of assets. For example, stock prices depend on expected future dividends. If investors revise their estimate of future dividends every time there is new information in the market, this will cause the stock price to move more. The greater uncertainty may reflects greater uncertainty about the macroeconomic outlook on which the future cash flow from an investment depends. Uncertainty about the fundamental value of assets can also increase when financial innovation make it difficult for lenders and investors to price assets.

Increased uncertainty about behavior of other investors

During financial stress investors tend to base their decisions on guesses about other investors' behavior. For example, this happens when investors discover that their assumptions about a new financial product were incorrect and they are uncertain about its fundamental value. If an investor decides to sell an asset before maturity, the return also depend on the actions of other market's participants. In case of increased uncertainty about the behavior of other investors prices of financial assets become less tied to fundamentals and this translates in more volatile asset prices.

Increased asymmetry of information

Asymmetry of information between investors and borrowers typically worsen during financial stress leading to an increase in the cost of borrowing. Information gaps can lead to adverse selection or moral hazard. If investors are not able to distinguish among firms of different risk they will require a return more appropriate for firms of average quality from all of them. At that rate, the higher quality companies will fund internally and the only companies willing to accept the return required by investors will be the low quality firms. As a consequence, the mix of companies worsen and investors require even higher return. Another way information asymmetry can worsen during market turmoil is when investors rely on third parties, such a credit rating agencies, to determine risks. If investors doubt the objectivity of these ratings, information asymmetry will arise and they will demand an higher return.

Increased risk aversion

Periods of market turmoil are characterized by "flight to quality", that is investors will demand higher returns for risky assets and lower returns on safe assets so that the spread between the two widens.[2] Investors' appetite for risk varies over the business cycle and in response to unexpected events.

[2] Tarashev, Tsatsaronis and Karampatos (2003) and Kumar and Persaud (2002), among others, develop theory-based indexes of risk appetite.

During booms investors tend to underestimate risk and ignore "fat tails", the non-negligible probability of extreme losses. Such euphoria leads to some bad loans and investments and investors eventually incur losses. On the contrary, after the bust they overestimate the risk of losses. Another reason why appetite for risk falls during financial crisis is people become more uncertain about the future of the economy and their future income. Therefore, they will require greater compensation to hold risky assets.

Increased liquidity risk

An illiquid asset is one that the holder cannot confidently sell to a price close to its fundamental value when faced with a sudden and unexpected need of cash. An asset may be illiquid because its secondary market may be thin, so that selling a large amount of it has a remarkable effect on the price. In addition, an asset may be illiquid because it is above-average quality and the asymmetry of information between seller and buyer prevent the owner to sell the asset at a price close to its fundamental value. During times of financial stress leveraged investors need to hold liquid assets because they can sell them more easily if they receive a margin call.[3] In the case of asset managers, they may receive redemptions requests and they need to liquidate assets to meet them. The effect of "flight to liquidity" is to increase the spread between return on liquid and illiquid assets.

2.3 Literature on Financial Stress Index

This section examines how financial stress indexes have been constructed in the literature. Illing and Liu (2006) develop one of the first and most influential composite indices of financial stress. They construct a financial

[3] Margin buying is buying securities with cash borrowed from a broker, using other securities as collateral. The net value, i.e. the difference between the value of the securities and the loan, is initially equal to the amount of one's own cash used. This difference has to stay above a minimum margin requirement, the purpose of which is to protect the broker against a fall in the value of the securities to the point that the investor can no longer cover the loan. When the margin posted in the margin account is below the minimum margin requirement, the broker or exchange issues a margin call.

stress index for the Canadian economy. In their paper, they explore several different weighting schemes to combine financial variables into a composite index. Their index is composed of a corporate bond spread, the bid-ask spread of 90-day Canada T-bill, a measure of volatility of the overall stock market and the beta of the banking sector.[4] They also include exchange rate volatility. Compared to the US, this is a key variable for an open economy such as Canada. Their FSI also includes the slope of the yield curve, which reveals more about the stance of the monetary policy than financial stress. They conduct an internal Bank of Canada survey to determine which events were perceived as stressful and they evaluate the indexes constructed with different methodologies based on their ability to match the results of the survey. They choose to weight the variables by the relative size of the market to which they pertain because this scheme is economically meaningful and it has the lowest Type I and II errors.[5]

Cardarelli et al. (2009) construct a financial stress index for 17 different countries. They limit their analysis to variables that are available for all 17 countries. The variables that they select are very similar to Illing and Liu (2006) except that they do no include any liquidity measure. Variables are weighted in the index by their variance. They use the FSIs to conduct a cross section study to examine why some financial stress episodes lead to economic downturns. They find that the likelihood that financial stress will be followed by a downturn is associated with the extent to which house prices and aggregate credit have risen prior to stress episodes. Their analysis suggests that both slowdowns and recessions preceded by banking stress tend to last longer, and are associated with larger average GDP losses, than those preceded by different types of financial stress, or no financial stress at all. Countries whose financial systems are dominated by more arm's-length based transactions, as opposed to traditional relationship-based intermediation, tend to exhibit higher pro cyclical leverage, indicating that the amplifying role of

[4]In the Capital Asset Pricing Model the beta coefficient describes the relationship between an investment's return and the overall market's return. See Campbell, Lo and MacKinlay (1997).

[5]Type I error is the probability of failing to signal a crisis. Type II error is the probability of falsely signaling a crisis.

financial system in propagating shocks is more pronounced.[6]

Hakkio and Keeton (2009) construct a financial stress index for the U.S. (KCFSI) using principal components. The index is composed of 11 indicators that capture the features of financial stress that I discuss in Section 2.2. They find that the KCFSI helps predict the Chicago Fed National Activity Index (CFNAI).[7]

A related literature focuses on measuring the broader financial conditions as a predictor of growth. The set of variables considered in financial condition indices (FCI) often include real interest rates and real exchange rate. Therefore, FCIs also evaluate the stance of monetary policy. Goodhart and Hofmann (2001) derive the weights based on the coefficients estimates in an IS equation relating the output gap to deviations of the short-term real interest rate, the effective real exchange rate, real house prices and real share prices from their long term trend. They also derive an alternative index using VAR and impulse response analyis. In this case, weights are based on the average response of inflation over the twelve quarters following a one-standard deviation shock to the same set of variables included in the IS equation. They study whether these two indexes contain useful information about future inflationary pressure. They find that the out-of-sample forecasting performance of the FCIs is rather disappointing. Guichard and Turner (2008) set the index weights from a regression of the output gap on a distributed lag of real short and long interest rates, high-yield bond spread, a measure of credit availability, real exchange rate and stock market capitalization as a share of GDP.[8] They also derive the weights from the accumulated response of GDP growth to a one-standard deviation shock to each financial variables in a VAR system of GDP growth, core inflation and the same set of financial variables.[9] Swinston (2008) also adopts the impulse response analysis approach. He set the weights from the cumulative response of GDP to an

[6]Leverage is defined as the ratio of assets to equity.

[7]The Chicago Fed National Activity Index (CFNAI) is a monthly index designed to gauge overall economic activity and related inflationary pressure in the U.S..

[8]The Federal Loan Officers Opinion Survey provides responses on the number of banks tightening credit standards over a three-month period.

[9]They follow the approach of Pesaran and Shin (1998) to perform impulse response analysis.

orthogonalized shock in each financial indicator in a VAR system. The financial variables that he includes in the VAR are lending standards, investment grade yield, LIBOR, high-yield spread , real equity returns and real effective exchange rate. Macroeconomic Advisers (1998) and Dudley and Hatzius (2000) employ large-scale macroeconometric models.

Hatzius et al. (2010) estimate a financial condition index with the latent factor of an unbalanced panel of financial indicators. They apply the EM algorithm as proposed by Stock and Watson (2002) to estimate it. In this way, the set of financial indicators included in the index grows over time as new indicators become available. They eliminate variability in the financial variables that can be explained by current and past real activity and inflation so that the first principal components reflects exogenous information associated with the financial sector rather than feedback from macroeconomic conditions. Brave and Butters (2011) extend the approach of Hatzius et al. (2010) by including variables with mixed frequency and estimate the latent factor of one hundred financial indicators with the methodology proposed by Doz, Giannone and Reichlin (2011). Both papers include variables indicative of the stance of monetary policy such as money stock and Treasury rates. One notable disadvantage of FCIs as constructed by Hatzius et al. (2010) and Brave and Butters (2011) is that their size and estimation make it more cumbersome to update and use.

2.4 Estimating the Level of Financial Stress

There are two steps in constructing a FSI. I need to determine (i) the choice of variables that make up the index and (ii) the weighting scheme. The first subsection describes the variables included in the index. I then show how the variables are aggregated into a single index.

2.4.1 Variables Included in the FSI

Each of the variables included in the FSI should capture one or more of the features of financial stress described in Section 2.2. I have also tried to be parsimonious in the choice of variables. The goal is to use a minimum set of variables that would signal financial stress. Because of common components, the qualitative patterns of many financial series are similar and the marginal informative content of additional series diminishes quite rapidly. Moreover, disruptions in one market can easily spill over to others.

I define financial stress as the key factor driving the co-movement of the different variables. Of course each variable can also change for other reasons not directly related to financial stress. The variables are chosen for their timeliness, forward-looking information content, systemic relevance, and ability to reflect agents' behavior. In addition, variables must be available since at least 1990 on a weekly basis.

Table 2.1 presents summary statistics of the variables that make up the index. The set of selected variables is similar to Hakkio and Keeton (2009). I select the same variables except for the idiosyncratic volatility of bank stock prices and a measure of the cross-sectional dispersion of stock returns in the banking sector. Instead, I consider a measure of relative riskiness of the financial sector compared to the overall corporate sector. Moreover, I also add a measure of the volatility of Treasury yields (MOVE index), a measure of risk aversion (money market mutual funds total assets as a share of NYSE capitalization) and two mortgage-related variables (the mortgage spread and the MBS spread over 10-year Treasury rate).

TED spread. The Ted spread is computed as the difference between the three-month LIBOR rate and the three-month Treasury bill rate. The LIBOR is the rate at which banks can borrow unsecured, dollar-denominated funds in the interbank market. This spread provides a measure of flight to quality, flight to liquidity and asymmetry of information in the money market. The TED spread increases when banks fear the loan may not be repaid (default risk), or because banks worry they will experience an unexpected need for funds in the short term before the loan comes due (liquidity risk). This spread also goes up when banks are afraid of adverse selection and have difficulty determining which borrowing banks are problematic.

Total assets in money market mutual funds as a percentage of NYSE capitalization. It is computed as the ratio of total assets in money market mutual funds to the NYSE market capitalization. This ratio increases when investors become more risk averse. When risk appetite for equities lowers investors move funds out of the stock market and into the safer money market.

Aaa/10-year Treasury spread. Bonds rated Aaa by Moody's pose little or no default risk. The spread of Aaa bond rate over the 10-year Treasury yield can be decomposed as the sum of a prepayment risk premium and a liquidity premium. Many Aaa corporate bonds are callable and investors demand a prepayment risk premium for the possibility that borrowers will refinance their debt if interest rates fall. The prepayment risk premium can vary over time not only due to changes in the risk that market interest rates will vary but also due to changes in the practices regarding call provisions in bond issues, as emphasized by Duffee's (1998) research. The Aaa/10-year Treasury spreads also contains a liquidity premium associated with a more stable demand for Treasury securities. The liquidity premium is usually small and less important. However, when financial markets are turbulent, the liquidity premium can become substantial as even the highest-rated corporate bonds tend to be less liquid than Treasury securities.

Baa/Aaa spread. It is computed as the difference between the yield of Moody's Baa rated bonds and the yield of Aaa bonds. This spread largely reflects default premium because corporate bonds have similar callability provisions. It is an indicator of flight to quality and asymmetry of information. The spread between Baa and Aaa is small during economic expansion and increases when investors are worried of higher default risk because of the state of the economy or the financial health of lower rated corporations. In some cases, the spread can also increase as an over-reaction to a prolonged period of excess optimism. During periods of financial stress, investors may also worry that some Baa rated companies may be riskier than other and fear adverse selection, which will cause the Baa rate to move further above the Aaa yield.[10]

High-yield bond/Baa spread. High-yield bonds are bonds rated below

[10]Bernanke and Gertler (1995) call the part of the yield due to information asymmetry external finance premium.

investment grade. These bonds have a higher risk of default but pay higher yield. The difference in default risk between high-yield and Baa bonds is generally greater than between Baa and Aaa bonds. Therefore, this spread should tend to respond earlier to flight to quality and asymmetry of information because junk bonds are issued by firms that are more vulnerable to changes in economic conditions than investment-grade borrowers. As discussed in Kwan (2001), speculative-grade bonds carry more liquidity risk because the speculative-grade bond market is thinner than the investment grade market and institutional investors are prohibited from investing in it.

2-year swap spread. An interest rate swap is a derivative contract in which a party exchanges a stream of fixed rate payments for another party's floating-rate payments. In the case of a 2-year swap contract, the two parties agree to exchange payments for two years. The floating rate is based on the three-month LIBOR rate. The two-year swap spread is the difference between the 2-year swap fixed rate and the rate of comparable maturity Treasury note. Grinblatt (2002) explains that the spread is positive for two reasons. The first one is to compensate for the default risk of the fixed payer. If the two counterparties merely exchanged the Treasury yield for the LIBOR rate, the fixed payer would have borrowed at the risk-free rate and invested an the LIBOR rate. The spread is also positive to compensate the floating payer for the lower liquidity of the swap contract compared to the two-year Treasury note. Therefore, the swap spread increases (i) when LIBOR goes up because of increased default risk in the interbank market (flight to quality), (ii) when investors are concerned that they will need the funds before the swap expires or (iii) when liquidity risk increased in the interbank market (flight to liquidity).

ABS/5-year Treasury spread. Asset-backed securities are securities whose value and income payments are derived from and collaterized by pools of credit card loans, auto loans, or student loans. These securities are typically issued in tranches, with the senior trances receiving the highest rating but also the lowest return. ABS yield is measured using the Citigroup Global Market ABS Index. The ABS spread over Treasury yield is small in normal times. It may rise during market turmoil when investors become more concerned of default by consumers and require higher compensation to hold these securities. This spread also provides a measure of asymmetry of information. In normal times issuers of securities backed by consumers loans securitize the higher quality to preserve their long run reputation (see Calomiris and Mason, 2004). During periods of financial stress, some issuers may be tempted to retain the higher-quality loans on their balance sheet and securitize the lower-quality loans. Suspecting such behavior, investors may demand higher yields to purchase asset-based securities.

MBS/10-year Treasury spread. MBS securities are asset-backed securities collaterized by mortgages. The MBS yield is measured with the Citigroup Global Markets MBS yield index. The spread is the sum of default and prepayment risk premia.

Correlation between returns on stocks and Treasury bonds. In normal times returns on stocks and government bonds are either uncorrelated or move together in response to changes in the risk-free discount rate. During financial stress investors shift out of stocks and into bonds, causing the return on the two assets to move in opposite directions (see Andersson and others, 2008; Baur and Lucey, 2009). Thus, the stock-bond correlation is a measure of risk aversion. The correlation is computed over rolling three-month periods using the total return indexes of S&P500 and 2-year Treasury bond. I take the negative value of the correlation to construct the index, so that negative correlation corresponds to an increase in financial stress.

Implied volatility of S&P500 options (VIX). The VIX is a measure of overall volatility of stock prices and it captures uncertainty about the fundamental value of assets and uncertainty about the behavior of other investors. It is considered the premier barometer of investor sentiment. The VIX index is constructed using the implied volatilities of a wide range of S&P500 index options. This volatility is meant to be forward looking and is calculated from both calls and puts. The VIX is quoted in percentage points and translates, roughly, to the expected movement in the S&P 500 over the next 30-day period, which is then annualized.

Implied volatility of Treasury options (MOVE). The Merrill Lynch Option Volatility Estimate (MOVE) Index tracks how much traders expect

Treasuries maturing in 2 to 30 years to fluctuate in a year and is a proxy of bond market risk. The MOVE is a yield curve weighted index of the normalized implied volatility on 1-month Treasury options. It is the weighted average of volatilities on the on-the-run Treasuries with maturities 2, 5, 10, and 30 years.

Off-the-run/on-the-run 10-year Treasury spread. The spread between the off-the-run and the on-the-run yields widens when investors become more concerned of liquidity risk. The on-the-run 10-year Treasury rate is the yield on the most recently issued 10-year Treasury bond while the off-the-run rate is the 10-year Treasury rate computed from the Treasury yield curve estimated using all the previous Treasury issuances that are still outstanding[11]. The market for an off-the-run Treasury security is generally not as deep as the market for an on-the-run security of the same maturity. As a result, an investor holding the off-the-run security faces more risk of having to sell the security at a discount if he faces a sudden need of cash.

Financial/Corporate bond spread. This spread measures the relative riskiness of lending to the financial sector compared to lending to the corporate sector. It is computed as the difference between the Citigroup Global Markets financial yield index and the Citigroup Global Markets corporate index.

30-year mortgage rate/10-year Treasury spread. It is computed as the difference between the 30-year mortgage rate and the 10-year Treasury rate. It is the sum of a prepayment risk premium and a default risk premium. It increases with increased expected default in the mortgage market.

2.4.2 Aggregating the Variables into a FSI

Financial stress is defined as the main factor driving co-movement of the variables described above. I estimate the FSI with the first principal component of the correlation matrix of the variables included in the index.[12] The index is constructed at monthly frequency. The selected variables are

[11] I estimate the off-the-run Treasury curve using the methodology introduced by Gurkaynak et al. (2007).

[12] See Theil (1971) for a discussion of principal component analysis.

also available at weekly frequency so that the index can be constructed weekly to monitor financial markets at a higher frequency. Table 2.1 presents sample statistics of the variables that make up the index.

Define X as the matrix of standardized variables in which each column contains T observations of a financial indicator normalized to have mean zero and standard deviation one. Table 2.2 presents Σ, the estimated correlation matrix of the variables included in the index. The spectral decomposition of Σ is given by:

$$\Sigma = Q\Lambda Q^{-1}.$$

The factor loadings of the first principal component are in q_1, the first column of Q. We normalized q_1 by dividing it by λ_1, the first element of the diagonal matrix Λ, so that the index has unit standard deviation and each coefficient represents the change in the index after one standard deviation increase in the variable.

$$FSI_t = X_t \frac{q_1}{\lambda_1} \quad t = 1, \ldots, T.$$

The estimated index is shown in Figure 2.1 and the weights assigned to the variables are presented in Table 2.3. The coefficients range from 0.04 for the MBS/10-year Treasury spread to 0.11 for ABS/5-year Treasury spread, Baa/Aaa spread, high-yield/Baa spread and the VIX index. Over the sample period, the index explains 59% of the total variation in the 14 variables.

2.4.3 Identifying Episodes of Financial Stress

The FSI does a good job in capturing past episodes of financial stress. The index first peaked during the 1990-1991 recession. The period between 1998-2002 was characterized by several financial stress events. The first peak of the period is in October 1998, just after the Russian debt moratorium in August and the bail out of the hedge fund Long Term Capital Management in September. The index peaks again in early 2000 when the prices of technology stocks collapsed. There is another peak in September 2001 after the terrorist attack in New York City. The last peak of the period 1998-2002 is in October 2002 and can be attributed to the accounting scandals of 2002 and mounting investors concern about the accuracy of corporations' financial statements.

The years 2003-2007, a period with substantial appreciation of house prices, was a buoyant period in the financial markets. In 2007 investors showed the first concerns about the quality of subprime mortgages. Major banks announced writedowns of mortgage products and rating agencies downgraded some of the monoline insurers guaranteeing these products. The FSI rose again in March 2008 when Bear Sterns collapsed. It soared to a five standard deviation away from its historical mean after Lehman Brothers filed for bankruptcy and AIG was rescued. Stress slowly retreated after the Federal Reserve expanded liquidity in the market through assets purchase programs. Finally, there is another peak in May 2010 when markets started being concerned about a Greek sovereign default.

The literature has proposed different criteria to identify episodes of financial stress. Cardarelli et al (2009) categorize episodes of financial stress as those periods when the index is more than one standard deviation above its trend. They identify the trend using the Hodrick-Prescott filter. Given their set-up of a time-varying trend, it captures the notion that financial systems have been evolving and financial stress may manifest in different ways. Illing and Liu (2006) suggest a higher cut-off of two standard deviations above the mean. A pitfall of this approach is that the number of standard deviations by which the index exceeds the mean on a given date can change drastically as observations are added to the sample. As a result, a month could be classified as one of high financial stress before the addition of new observations, but a month with low financial stress after the addition of the new observations. Consider, for example, October 1998. When the index is estimated using data only until June 2007, the index is equal to 2.6 standard deviations above the mean, while is only 1.2 when the index is estimated until 2011.

A way to circumvent this problem is to classify a month as stressful when the value of the cumulative distribution in the month is equal or exceeds the 90 percentile. An advantage of this approach is that adding extreme observations has much less effect on the 90th percentile of a sample than the standard deviation of the sample. As a result, the addition of extreme observations is less likely to cause a given month to being classified as high stress rather than low stress when the sample is changed. If we use the 90th percentile method to determine whether an event is stressful, October 1998 would be still classified as stressful. However, December 1990 would drop from the sample of stressful events.

2.5 Financial Stress and the Real Economy

The section starts off by discussing some of the transmission channels of financial stress to the wider economy that have been proposed in the literature. The section then lays out the econometric model before discussing the results. I conclude with some robustness checks and a subsample estimation.

2.5.1 Transmission of Financial Stress

Despite the apparent risk financial stress poses to the real economy, the relationship between financial stress and economic activity is complex and not well understood. The literature has, however, proposed a number of transmission channels. A combination of increased uncertainty, a more elevated cost of finance, and tighter credit standards will tend to weigh on real economic activity. When asset prices are more volatile, firms become more cautious, and will delay important hiring and investment decisions until the uncertainty is resolved. Households, on the other hand, may decide to cut back on spending as the increased volatility makes them more uncertain about their future wealth. Flight to liquidity, flight to quality and increased asymmetry of information all have the effect of boosting the cost of capital of business and interest rates on consumer debt in capital markets. In addition, the tightening of credit standards by financial institutions make it harder to qualify for loans.

Real option theory emphasizes the value of waiting before making an investment. A key result of Bernanke (1983) is that high levels of uncertainty reduce investment today. Firms may interpret financial stress as a reflection of more uncertain economic conditions in the future and they will pull back on new investment. Depending on how the uncertainty is resolved, this theory may predict more investment in the future.

The financial accelerator framework developed by Bernanke, Gertler and Gilchrist (1999) highlights the role of the "external finance premium". This is the premium that firms pay to obtain external financing and that depends on firms' financial position. When the economy is booming, firms post higher profits and have stronger balance sheets. As a consequence, they appear less risky, so that banks charge them a lower external finance premium. In turn, the external finance premium induces firms to make new investments, which further contributes to economic growth. This mechanism also works in reverse, but will then generate an "adverse feedback loop". Weakening economic conditions cause profits to decline and balance sheets to weaken. To compensate for a higher rate of expected bankruptcies banks charge a higher external finance premium, which causes firms to invest less. In the financial accelerator model, the relationship between a firm's net worth and the external finance premium depends on the uncertainty of its profitability. That is, the premium paid by a firm with a low ratio of net worth to its capital stock and a firm with a high ratio will be greater in a highly uncertain environment than in a more tranquil one.

Lown and Morgan (2006) suggest that a tightening of credit standards may lead to an additional decline in spending, beyond that caused by the increase in loan rates. They find that shocks to credit standards affect lending and output in a VAR model that control for forward looking variables (forecasted GDP and interest rate spreads) and firms and banks financial health. This evidence indicates that changes in credit standards provide an additional channel through which financial stress may affect economic activity.

2.5.2 Econometric Model

I analyze the impact of financial stress on economic activity by calculating the impulse responses to an unpredicted shock to the FSI in a Vector

Autoregression (VAR) model of real and financial variables.[13] The baseline VAR model includes eight variables; government consumption and investment (G), net tax revenue (T), output (Y), consumption (C), investment (I), labor (L), the FSI (F) and a short rate (R):

$$Z_t = [G_t, T_t, Y_t, C_t, I_t, L_t, F_t, R_t]$$

The definition of the variables and data sources can be found in Appendix A. The macro literature generally uses the Fed funds rate or three-month Treasury bill as short term rate. I use the 1-year Treasury rate because the three month T-bill rate has been around zero over the last year but the Fed has continued an active monetary policy through quantitative easing targeted on bringing rates on longer dated government debt down. The model is fitted to U.S. quarterly data from 1990Q4 through 2011Q1.

All variables except the FSI enter the model in growth rates, consistent with stationary tests. Based on model-selection criteria, I estimate a VAR with one lag of the endogenous variables, although the central results are qualitatively robust to using longer lag lengths. The estimated model has the reduced form:

$$Z_t = \mu + BZ_{t-1} + u_t, \quad E(u_t u_t') = V,$$

where μ is a 8×1 vector of constants; B is a 8×8 matrix of parameters; u_t is the reduced form error and V is the 8×8 error covariance matrix.

To obtain impulse responses we define the structural error e_t as:

$$u_t = Ae_t, \quad E(e_t e_t') = I, \quad V = AA',$$

where A is the matrix with $N(N-1)/2$ identification restrictions. I assume that A is the Choleski decomposition of V . Given the ranking of variables in Z_t, this identification scheme implies that monetary policy responds contemporaneously to an unpredicted shock in all variables whereas the FSI responds

[13]See Chapter 10 and 11 of Hamilton (1994) for a discussion of Vector Autoregression and impulse response analysis.

contemporaneously to shocks in all macro variables except monetary policy.

2.5.3 Results

The SVAR analysis shows that economic activity contracts significantly following an unpredicted financial markets shock. The responses to a one standard deviation shock in the FSI are presented in Figure 2.2. Tax revenue, output, consumption, investment and labor all decrease following an adverse shock in financial markets stress. The response of government spending is not significant and the response of consumption is smaller compared to the responses of other macro variables. The estimated response of the one-year Treasury suggests that monetary policy authorities cut interest rates following a shock in financial markets. In the two years following a shock to FSI, net taxes fall by a cumulative 2.6 percent, GDP falls by 1.5 percent, consumption by 0.2 percent, investment by 1.4 percent, hours worked per capita by 1.6 percent, and the 1-year Treasury rate by 9.2 percent.

2.5.4 Robustness and Subsample Estimation

Shocks to the financial stress index account for about 15 percent of the long-run variance of, respectively, GDP, investment, net taxes, consumption and the 1-year Treasury rate. In addition, they explain about 25 percent of the variance of hours worked per capita.

Results are robust to the order of the variables. Moreover, results are similar when the responses to a FSI shock are estimated on smaller systems that include only subsets of the variables in Z_t. The results are also similar when the Fed funds rate is used instead of the 1-year Treasury and the model is estimated in levels.

Except for consumption, responses to a shock in the FSI are significant although weaker when the system is estimated excluding the financial crisis of 2008-09. Figure 2.3 shows the responses to a FSI shock when the system is estimated until 2007Q4.

2.6 Monetary Policy and Financial Stress

In this section I examine the potential interaction between monetary policy and financial stress. The goal is to analyze to what extent monetary policy can reduce strains observed in the financial markets. I identify changes in monetary policy by looking at an orthogonalized innovation to R_t. Arguably this approach is the most widely used identification scheme for this type of shock. Somewhat comforting, the monetary policy shocks I identify are highly correlated to shocks identified as in Bernanke and Kuttner (2005).[14]

I compare the responses to a monetary policy shock in the model presented above and in the same model without the FSI. In the alternative model the set of variables is:

$$Z_t' = [G_t, T_t, Y_t, C_t, I_t, L_t, R_t].$$

The responses to a monetary policy shock in the two models are presented in Figure 2.4. Real variables do not respond to a monetary policy shock in the model without FSI. This is consistent with Barakchianan and Crowe (2010) who estimate the VAR of Christiano, Eichenbaum and Evans (1996) starting from 1988. This sample excludes the monetary tightening and disinflation under chairman Volcker. They find that there is no significant contractionary response of real variables to a monetary policy shock when the model is estimated starting from the late 80's. This finding is sometimes explained by arguing that U.S. monetary policy has become more systematic, and responds faster to the variables in policymakers' information set. As a consequence, the signal/noise ratio of the shock component of policy actions has shrunk, making it harder to identify the effect of such shocks.

Interestingly, my results suggest that the FSI helps to identify the monetary policy shock, and policymakers' actions have a significant effect on financial conditions. In the model with the FSI, the response of investment to a monetary policy shock is significant. Moreover, FSI responds to a monetary policy shock. In addition, the responses of the labor market and GDP

[14]Bernanke and Kuttner (2005) use a different identification scheme based on monthly fed funds futures data that I have time aggregated for comparison.

growth is significant at 90% confidence level.[15] This finding would suggest that monetary policy gets transmitted through financial markets.

The results change when I re-estimate the system excluding the credit crunch of 2008-2009 (see Figure 2.5). There is not longer a significant response of real variables and FSI to a monetary policy shock in the model with FSI at 95% confidence level while the response of investment is significant at 90% confidence level. This leads me to conclude that it is hard to identify monetary policy shocks when the two biggest shocks are excluded - the Volker monetary tightening in the early 80's and the Fed's assets purchase programs and sharp interest rate cut following the financial crisis of 2008-2009.

2.7 Conclusion

In this chapter I estimate the impact of financial stress on economic activity. Financial stress rises with increases in the expected financial loss on assets, risk (a higher probability of loss) and uncertainty (reduced confidence about the distribution of probable loss). I discuss the key characteristics of financial markets stress and I construct a FSI using principal components analysis. The index identifies past episodes of financial markets turmoil.

The impulse response analysis of a VAR with real and financial variables, including the FSI, shows that real variables contract following an unpredicted financial markets shock. GDP, consumption, investment, labor, and monetary policy all respond negatively to an innovation in the financial stress index. Moreover, including the financial stress index in the model helps to identify monetary policy shocks. In addition, my results suggest that monetary policy is transmitted through its effect on financial markets.

The findings presented in this chapter suggest that future macroeconomic models should study in greater depth how stress in the financial sector spreads to other sectors. Even prior to the financial crisis of 2008, innovations in FSI generated effects on key aggregate variables. Future work could also focus on

[15] In macreconometrics it is common to use 90% or 68% confidence level when the sample is small.

the role of FSI in the transmission of monetary policy shocks using different identification schemes for the monetary policy shock. Another promising extension would be examining the effect of financial stress on banks' balance sheet. In particular, one topical question is to what extent monetary policy managed to halt deleveraging in recent years.

Table 2.1: Descriptive Statistics of Variables in FSI

Variable	Mean	Standard deviation
TED spread	0.51	0.50
Money market mutual funds total assets	16.78	5.91
Aaa/Treasury spread	1.35	0.47
Baa/Aaa spread	0.95	0.44
High-yield/Baa spread	2.90	1.84
2-year swap spread	0.40	0.20
ABS/Treasury spread	0.58	1.01
MBS/Treasury spread	0.74	0.54
Stock-bond correlation	0.03	0.38
VIX	20.24	8.01
MOVE	102.45	24.10
Off-the-run/on-the-run spread	0.18	0.10
Financial/Corporate bond spread	-0.17	0.48
Mortgage spread	1.64	0.32

Note: The table presents descriptive statistics of the variables included in the index. All interest rate spreads are in percentage points. Money market mutual fund total assets is measured as percentage of NYSE capitalization. The negative of the stock-bond correlation is taken, so that negative stock-bond correlation is associated to an increase in financial stress. The VIX and MOVE indexes are percentage change in monthly prices at annual rate. Sample statistics are computed from December 1990 until July 2011.

Table 2.2: Correlation Matrix of Variables in FSI

	TED spread	% Money Market	Aaa/ Treasury spread	Baa/ Aaa spread	High-yield/ Baa spread	Swap spread	ABS/ Treasury spread	MBS/ Treasury spread	Stock-bond correlation	VIX	MOVE	Off-the-run/ on-the-run spread	Financial/ Corporate spread	Mortgage spread
TED spread	1.00													
% Money Market	0.40	1.00												
Aaa/ Treasury spread	0.27	0.73	1.00											
Baa/ Aaa spread	0.57	0.89	0.61	1.00										
High-yield/ Baa spread	0.50	0.76	0.66	0.83	1.00									
Swap spread	0.75	0.36	0.38	0.48	0.56	1.00								
ABS/ Treasury spread	0.84	0.65	0.48	0.81	0.73	0.66	1.00							
MBS/ Treasury spread	0.53	-0.15	-0.11	0.08	0.18	0.63	0.46	1.00						
Stock-bond correlation	0.24	0.57	0.64	0.48	0.38	0.44	0.33	-0.10	1.00					
VIX	0.59	0.67	0.73	0.70	0.76	0.57	0.71	0.16	0.51	1.00				
MOVE	0.50	0.57	0.55	0.56	0.57	0.36	0.52	0.14	0.18	0.62	1.00			
Off-the-run/ on-the-run spread	0.34	0.55	0.70	0.59	0.71	0.45	0.52	0.16	0.34	0.68	0.55	1.00		
Financial/ Corporate spread	0.64	0.62	0.30	0.64	0.44	0.44	0.77	0.26	0.26	0.47	0.29	0.18	1.00	
Mortgage spread	0.52	0.52	0.70	0.59	0.64	0.78	0.60	0.39	0.61	0.65	0.47	0.62	0.30	1.00

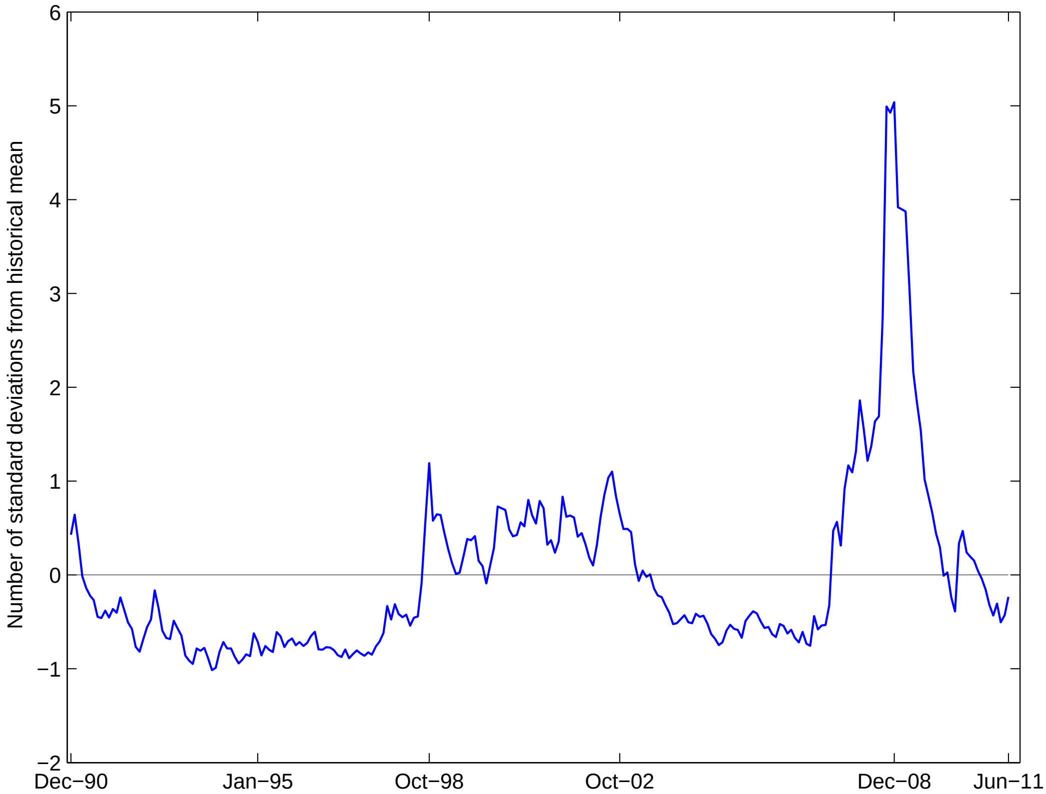
Note: The table presents the correlation matrix of the variables included in the FSI estimated using monthly data from December 1990 until July 2011.

Table 2.3: Estimated Coefficients on FSI variables

Variable	Coefficient in FSI
ABS/Treasury spread	0.11
Baa/Aaa spread	0.11
VIX	0.11
High-yield/Baa spread	0.11
Money market mutual funds total assets	0.10
Mortgage spread	0.10
Aaa/Treasury spread	0.10
2-year swap spread	0.09
Off-the-run/on-the-run spread	0.09
TED spread	0.09
MOVE	0.09
Financial/Corporate bond spread	0.08
Stock-bond correlation	0.07
MBS/Treasury spread	0.04

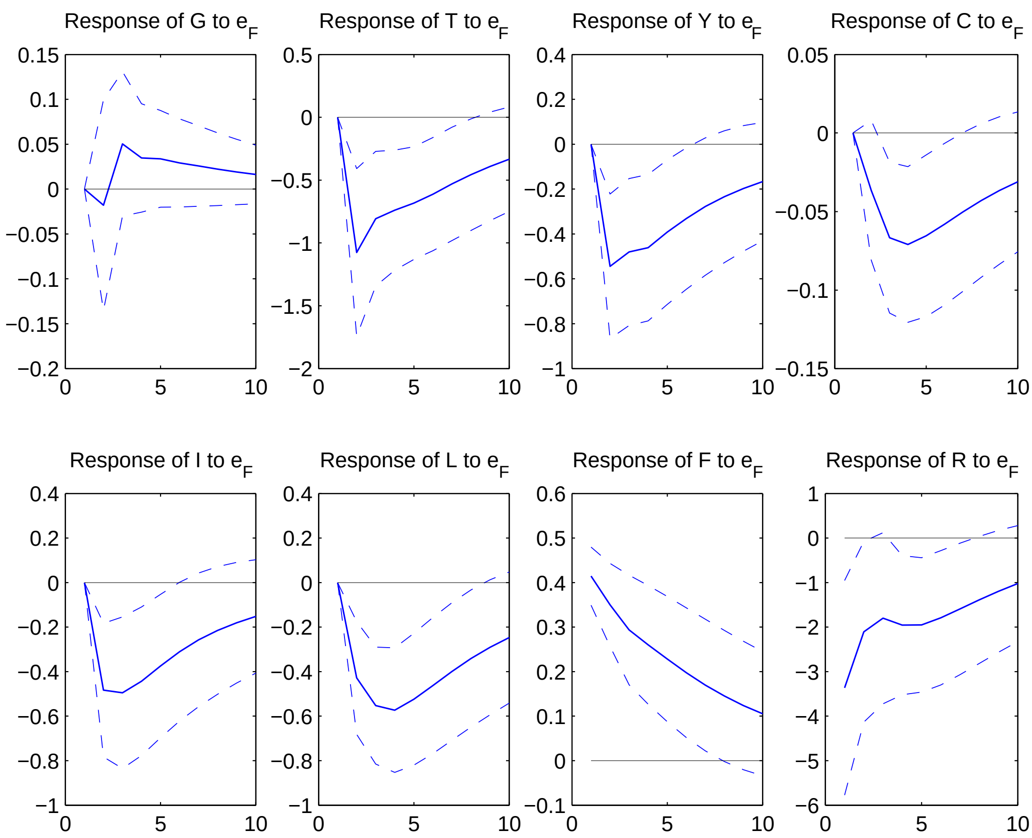
Note: The table presents weights assigned to each variable in FSI. Each coefficient represents the change in the index after a one standard deviation increase in the variable. Each coefficient is estimated by the factor loading of each standardized variable in the first principal component of the variables correlation matrix, standardized by the variance of the first principal component. The coefficients are calculated using monthly data from December 1990 until July 2011.

Figure 2.1: Financial Stress Index (FSI)



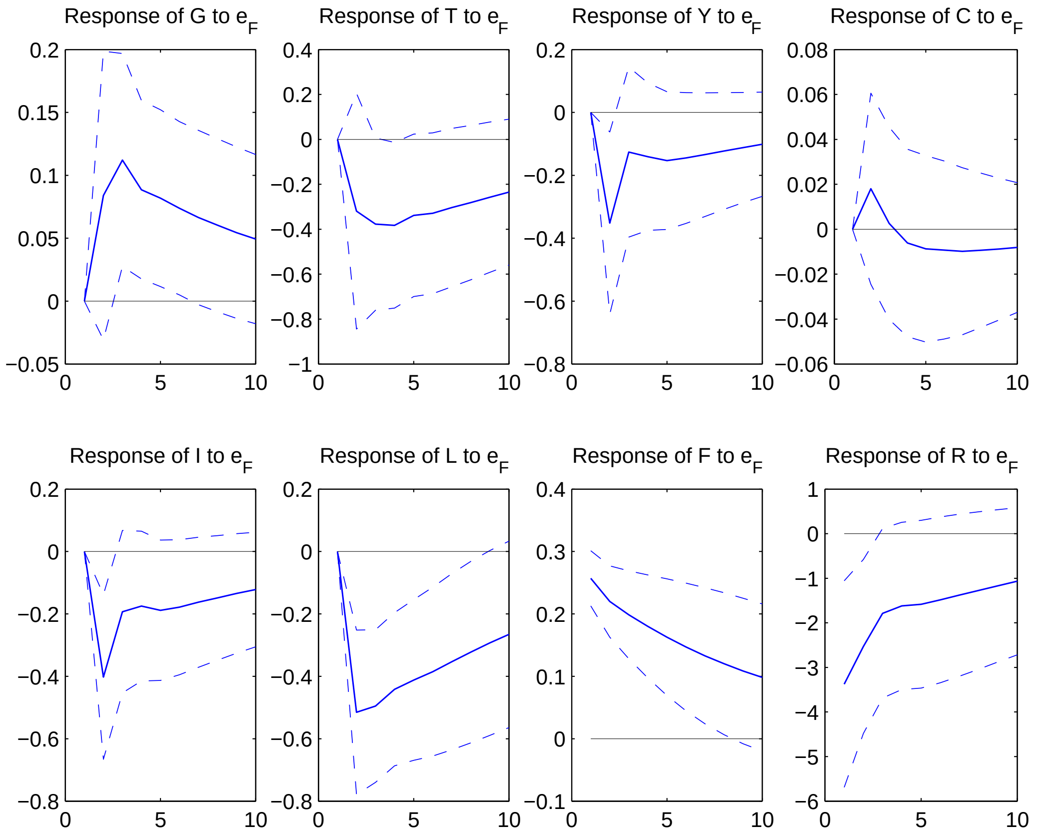
Note: FSI is measured as number of standard deviations from historical mean and has unit variance. Index is calculated using monthly data from December 1990 to July 2011.

Figure 2.2: Responses to a Shock to FSI (1990-2011 sample)



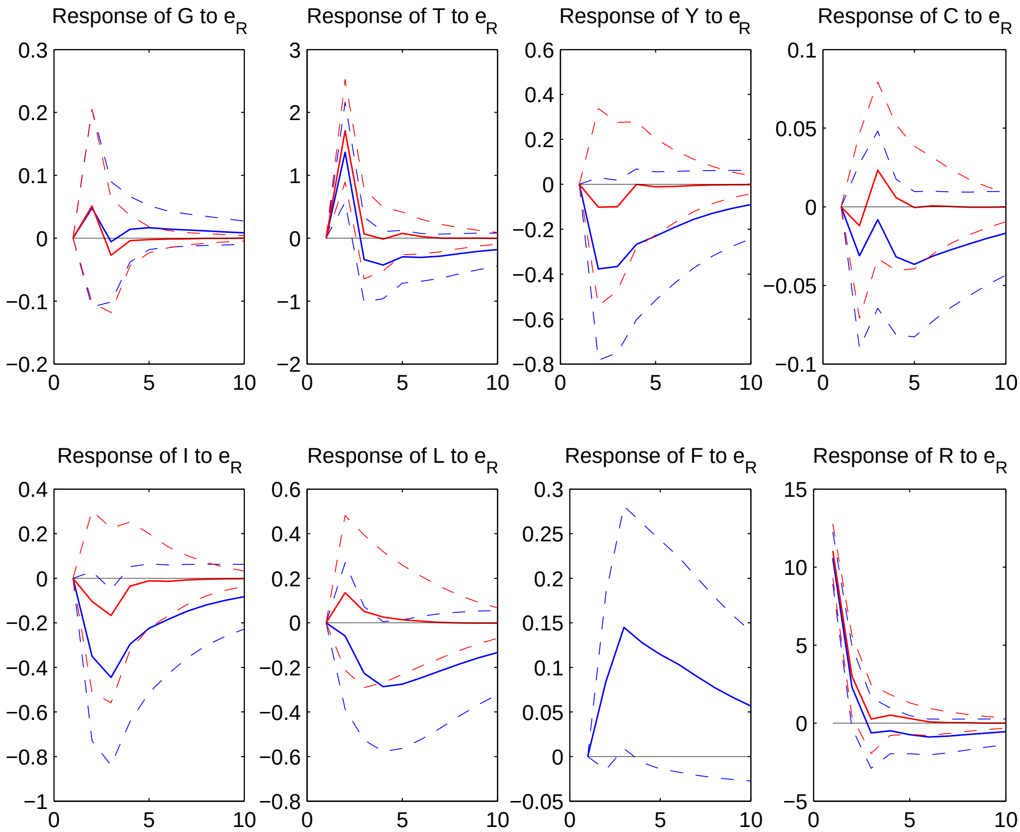
Note: Responses to one-standard deviation structural shock in FSI over the subsequent 10 quarters. Except for FSI, units are quarterly annualized growth rates. The response of the FSI is in number of standard deviation from its historical mean. Model is estimated from 1990Q4 to 2011Q1 using the Choleski decomposition $[GTYCILFR]$. Dotted lines represent two standard deviations confidence bands.

Figure 2.3: Responses to a Shock to FSI (1990-2007 sample)



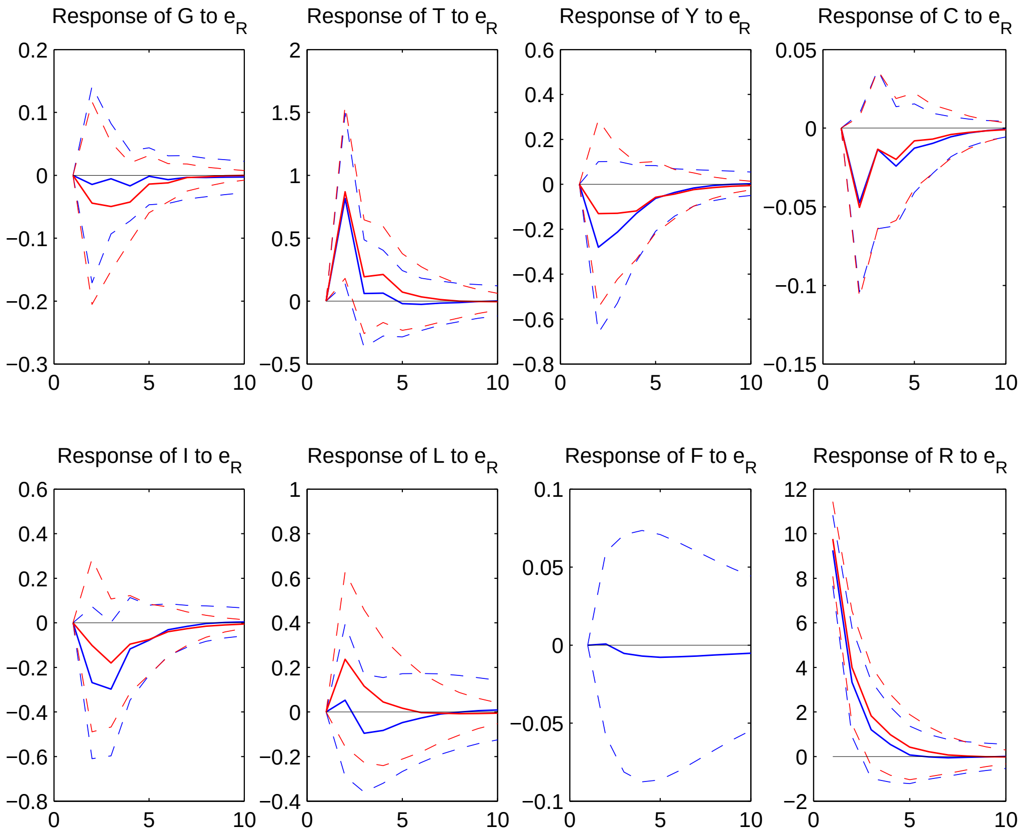
Note: Responses to one-standard deviation structural shock in FSI over the subsequent 10 quarters. Except for FSI, units are quarterly annualized growth rates. The response of FSI is in number of standard deviations from its historical mean. Model is estimated from 1990Q4 to 2007Q4 using the Choleski decomposition $[GTYCILFR]$. Dotted lines represent two standard deviations confidence bands.

Figure 2.4: Responses to a Monetary Policy Shock (1990-2011 sample)



Note: Responses to one-standard deviation structural shock in 1-year Treasury rate over the subsequent 10 quarters. Blue line corresponds to the model with FSI while red line corresponds to the model without the FSI. Both models are estimated from 1990Q4 to 2011Q1 with Choleski decomposition, respectively, $[GTYCILFR]$ and $[GTYCILR]$. Except for FSI, units are quarterly annualized growth rates. The response of FSI is in number of standard deviations from its historical mean. Dotted lines represent two standard deviations confidence bands.

Figure 2.5: Responses to a Monetary Policy Shock (1990-2007 sample)



Note: Responses to one-standard deviation structural shock in 1-year Treasury rate over the subsequent 10 quarters. Blue line corresponds to the model with FSI while red line corresponds to the model without the FSI. Both models are estimated from 1990Q4 to 2011Q1 with Choleski decomposition, respectively, $[GTYCILFR]$ and $[GTYCILR]$. Except for FSI, units are quarterly annualized growth rates. The response of FSI is in number of standard deviations from its historical mean. Dotted lines represent two standard deviations confidence bands.

Chapter 3

Default, Prepayment Risks and Unobservable Heterogeneity

3.1 Introduction

This chapter draws on insights from option theory to estimate an empirical model that can be used to predict prepayment and default rates on a portfolio of mortgages. My analysis provides a novel contribution to the literature by estimating a multinomial logit model that allows for borrower-specific random coefficients determining the joint probability of prepayment and default.[1] Models with random coefficients could be particularly useful in this setting, as they capture correlation patterns in the behavior of borrowers that arise as a result of unobserved heterogeneity, taste variation and path dependence.

A mortgage may be terminated for a number of reasons. These could be nonfinancial, such a new job, divorce, or death in the family, prompting a borrower to change residence. In addition, there are financial reasons, such as a changing interest rate environment, that could lead to a termination. Using principles from option theory mortgages can viewed as long-term bond issued by borrowers who retain embedded call (prepayment) and put (default) options. Well informed borrowers in a perfectly competitive market, with no

[1] Multinomial models with random coefficients are also known as mixed logit.

transaction and reputation costs, will exercise the financial options embedded in their mortgage contract when doing so increases their net wealth. The key variables that determine the value of the two options are interest rates and the value of the underlying property. Borrowers can maximize their wealth by defaulting on a mortgage when the market value of the mortgage equals or exceeds the value of the house. Similarly, they can increase wealth by prepaying and refinancing their mortgage when the market rate is lower than the coupon rate on their mortgage.[2] While people often prepay mortgages for personal reasons, this is seldom the case of a default. As a consequence, default rarely occurs when the value of the property is more than the market value of the loan.

As prepayment and default are competing risks and mutually exclusive events, I study models in which default and prepayment probabilities are determined jointly. This approach avoids the mispricing of the two options.[3] Kau and Keenan (1995) provide a complete survey of option-theoretical models of mortgage pricing. Initially, researchers assumed that default and prepayment are independent decisions and priced the two options separately. Cunningham and Hendershott (1984) and Epperson, Kau, Keenan, and Muller (1985) price default options while Dunn and McConnel (1981), Buser and Hendershott (1984), and Brennan and Schwartz (1985) price the prepayment option. However, Titman and Torous(1989), Kau, Keenan, Muller and Epperson (1992, 1995) provide theoretical option models in which the optimal default and prepayment strategy are determined simultaneously.

While the standard options framework provides important insights to the borrower's choice problem, it does not fully explain prepayment or default decisions. Empirical evidence shows that mortgagors do not exercise their options to prepay and default in the same manner that investors exercise fi-

[2]In this sense, the homeowner is very much in the position of an issuer of a callable bond. The issuer of such a bond can pay bondholders some strike price to repurchase the bond and be free of the obligation to make further payments.

[3]A homeowner who exercises the default option today gives up the option to default in the future, but he also gives up the option to prepay the mortgage.

nancial options.[4] Increasingly, researchers have focused on transaction costs and borrowers' heterogeneity to explain these differences. For example, the existence of transaction costs connected to default might imply that negative equity does not necessarily lead to a default, but that a so-called "trigger event" needs to occur before the borrower is forced to leave the house. Examples of such "trigger events" are divorce, illness or job loss. Similarly, refinancing involves explicit costs like points and a closing fee as well as implicit costs such as reaching the ability to qualify or a possible house price depreciation that affects the amount that can be borrowed aside from other factors.[5] Kau, Keenan and Kim (1993) discuss how a suboptimal exercise of a default option can arise in the presence of transaction costs. Quigley and Van Order (1995), on the other hand, estimate modified option models in which exercise is a function of both "trigger events" (like unemployment or divorce) and also the extent to which the default option is "in the money".[6] Aside from these reasons, there are also unobservable differences in astuteness among borrowers.

Empirical models of prepayment and default estimated on micro data can be divided in two groups: duration models such as the proportional hazard model (PHM) and multinomial logit models (MNL). The hazard function in a PHM is constructed in a path-dependent framework, that is, the hazard rate of termination is conditioned on the subject surviving up to time $t-1$. Therefore, any event between t and $t-1$ is not an i.i.d. event. Since Green and Shoven (1986) first introduced the PHM to analyze mortgage termination as a consequence of refinancing, there have been several major

[4] See Vandell (1995) for a discussion.

[5] Points are a form of prepaid interest. One point equals one percent of the loan amount. By charging a borrower points, a lender effectively increases the yield on the loan above the amount of the stated interest rate. Borrowers can offer to pay a lender points as a method to reduce the interest rate on the loan, thus obtaining a lower monthly payment in exchange for this up-front payment.

[6] Moneyness is a measure of the degree to which a derivative is likely to have positive monetary value at its expiration, in the risk-neutral measure. An in-the-money option has positive intrinsic value as well as time value. A call option is in the money when the strike price is below the spot price. A put option is in the money when the strike price is above the spot price. The borrower default option is in the money when the house value of the house is below the value of the mortgage.

developments to improve the application of PHM to mortgage termination analysis. Deng, Quigley and Van Order (2000) and Pennington-Cross and Ho (2010) apply the PHM allowing correlated competing risks and accounting for unobservable heterogeneity as discrete mass points. Their framework considers the joint survival probability and estimates the conditional probability of termination risks over time. It acknowledges that only the duration associated with the type that terminates first is observed. To take this effect into account, they make an adjustment to the equations describing the probabilities of competing risks. The duration of the mortgage until termination by either default or prepayment is a function of option-related variables, variables that account for observable heterogeneity and variables correlated with trigger events. They include unobservable heterogeneity by treating individual mortgage borrowers as coming from three distinct groups with unobserved characteristics. The three groups of borrowers are very astute, passive, and others situated in a zone in between these two extremes. The model cannot directly observe which group each individual belongs to, but it can estimate the discrete probability distribution that each type influences the hazard function.

The second type of empirical model of prepayment and default uses a MNL framework with restructured event history data. The application of logit models to mortgage termination issues is well established. Mattey and Wallace (2001), Ambrose and Capone (1998), Berkovec et al. (1998), Archer, Ling and McGill (1996), Quigley and Van Order (1995), Calhoun and Deng (2002), Philips, Rosenblatt and VanderHoff (1995), Cunningham and Capone (1990) and the Federal Housing Administration (FHA) Actuarial Review for 2010 have used binomial logit or MNL models. The MNL directly models the probability of observing one risk versus another as the probabilities of termination risks and the probability of continuing to pay must sum to 1. Thus, an increase in one termination probability must be offset by a decline in probability for one or more of the alternatives. On the other hand, the MNL cannot allow for correlations among the termination risks through unobservable variables, as implied by the independence from irrelevant alternatives

(IIA) assumption.[7] In addition, the MNL requires the assumption that the borrower behavior is independent in each payment period. This assumption is not an accurate representation of the borrower's decision process. Clapp et al. (2006) extend unobserved heterogeneity to the MNL model in the context of mortgages terminated by refinance or move. They develop a mass-point mixed multinomial and compare this model to the mass-point PHM of Deng, Quigley and Van Order (2000). They find that the latter dominates in sample and out of sample. However, they argue it is sometimes difficult to obtain convergence for both models. Pennington-Cross (2010) also apply the mass-point mixed model to examines what happens to mortgages in the subprime mortgage market once foreclosure proceedings are initiated.

In this chapter, I study the decision of a borrower to default and prepay using multinomial logit models. As discussed above, MNL models provide greater flexibility and are extensively used in the literature. I assume that the probability of default and prepayment are a function of some observable variables, such as variables that approximate the financial value of the two options, borrower characteristics, loan characteristics and economic conditions. I analyze the impact of each variable on the borrower's decision to see if it follows what economic theory would suggest.

I find that there is unobservable heterogeneity in the effect some variables have on the borrower's decision to default and prepay. To account for such unobservable heterogeneity and time-dependent correlations, I extend the standard MNL model by allowing the coefficients to be borrower specific random variables. The use of random coefficients in situations of repeated choice (like a borrower that has to decide each month whether to make a mortgage payment) allows the researcher to capture heterogeneity that arises from behavioral factors such as variation in preferences across households.

I estimate the model on a dataset of single-family 30-year mortgages guaranteed by FHA.[8] Mortgages guaranteed by FHA require a lower down

[7]The IIA property implied by MNL restricts the odds ratio of choice probabilities, i and k, so that they do not depend on any other alternatives other than i and k. This in turn implies no correlation between the unobserved components of utility for alternatives. See Chapter 3 of Train (2009) for a detailed discussion on MNL and the IIA property.

[8]The Federal Housing Administration (FHA) is a United States government agency

payment than conventional mortgages and are considered riskier. Following the subprime mortgage crisis, the share of home purchases financed with FHA mortgages went from 2 percent in 2007 to 15 percent in 2010 as conventional mortgage lending dried up in the credit crunch. Therefore, it is more important than ever to monitor and model the performance of mortgages guaranteed by FHA.

The chapter is organized as follows. Section 2 presents the MNL model with fixed and random coefficients and defines the explanatory variables. Section 3 describes the data and examines summary statistics. Section 4 discusses the results while Section 5 concludes the chapter.

3.2 Models

At the time of each payment between mortgage origination and maturity, a borrower faces a choice among three alternatives: continue to pay his mortgage, default or prepay. Each choice is associated with a latent utility. Define U_{ntj}, the utility that borrower n obtains from alternative j at time t. The borrower chooses the alternative that provides the greater utility at time t, that is, he chooses U_{nti} if and only if $U_{nti} \geq U_{ntj}$, $\forall j \neq i$.

The utility that each borrower receives from each alternative can be decomposed as $U_{ntj} = V_{ntj} + \epsilon_{ntj}$, where V_{ntj} is the part of the utility that we can observe and it is explained by some observable factors, such as option-related variables, loan and borrower characteristics. Assume that V_{ntj} is linear in parameters, $V_{ntj} = \beta_j' X_{nt}$. The factors that affect the borrower's choice but are unobservable are represented by the random term ϵ_{ntj}. The probability that borrower n chooses alternative i at time t conditioning on being active at the beginning of the period is:

$$
\begin{aligned}
P_{nti} &= Prob(U_{nti} > U_{ntj} \forall j \neq i) \\
&= Prob(V_{nti} + \epsilon_{nti} > V_{ntj} + \epsilon_{ntj} \forall j \neq i) \\
&= Prob(\epsilon_{nti} - \epsilon_{ntj} > V_{ntj} - V_{nti} \forall j \neq i).
\end{aligned}
$$

that insures loans made by banks and other private lenders for home building and home buying.

Below I briefly discuss how the MNL with fixed and random coefficients are derived.

3.2.1 Multinomial Logit with Fixed Coefficients

The MNL model is obtained by assuming that ϵ_{ntj} are independent and identically distributed as a Gumbel. The cumulative density of each unobserved component of utility is:

$$F(\epsilon_{ntj}) = e^{-e^{-\epsilon_{ntj}}}, \tag{3.1}$$

which means that the error difference is distributed as a logistic:

$$F(\epsilon_{ntj} - \epsilon_{nti}) = F(\epsilon^*_{ntji}) = \frac{e^{\epsilon^*_{ntji}}}{1 + e^{\epsilon^*_{ntji}}}.$$

The key assumption is that the errors are independent of each other. This independence means that the unobserved portion of utility from choosing prepayment is unrelated to the unobserved portion of utility from choosing default or continue to pay. Moreover, the optimal choice is made in each period independent of future periods. It follows from (3.1) that:[9]

$$P_{nit} = \frac{e^{V_{nti}}}{\sum_{j=0}^{2} e^{V_{ntj}}}. \tag{3.2}$$

Normalize to zero the coefficients of alternative $j = 0$ and we obtain the familiar multinomial logit model:

$$\begin{aligned} P_{nt0} &= \frac{1}{1 + e^{\beta_1' X_{nt}} + e^{\beta_2' X_{nt}}} \\ P_{nt1} &= \frac{e^{\beta_1' X_{nt}}}{1 + e^{\beta_1' X_{nt}} + e^{\beta_2' X_{nt}}} \\ P_{nt2} &= \frac{e^{\beta_2' X_{nt}}}{1 + e^{\beta_1' X_{nt}} + e^{\beta_2' X_{nt}}}, \end{aligned} \tag{3.3}$$

where $j = 0$ corresponds continue to pay, $j = 1$ to default and $j = 2$ to

[9]See Chapter 3 of Train (2009) for a derivation of (3.2).

prepay, and β_1 and β_2 are the parameters vectors.

The assumption underlying a MNL model is that all previous behavior is captured by the choice in the preceding period, and correlation over time is induced through time-invariant covariates or thorough variables that are linked to past conditions, such as a burnout variable to measure foregone opportunities to refinance at lower interest rates. Logit cannot handle situations where unobserved factors are correlated over time. The logit can represent systematic taste variation but not differences in tastes that cannot be linked to observed characteristics. In addition, the MNL requires IIA: the odds ratio for any pair of alternatives is independent of any other alternative and elimination of one alternative does not change the ratios of probabilities for the remaining alternatives.

The model can be easily estimated by maximum likelihood with loglikelihood function:

$$LL = \sum_{n=1}^{N} \sum_{t=1}^{T_n} \sum_{j=0}^{2} d_{ntj} \ln P_{ntj},$$

where d_{ntj} is an indicator variable that takes value 1 when borrower n chooses alternative j at time t. Because prepayment and default lead to termination, the observed choice stream of each borrower has a special form. Each borrower n in all periods prior to T_n chooses the alternative continue to pay. The last element in the choice stream is equal to 1 if the borrower exits the sample by default, to 2 if he exits the sample by prepayment, to 0 if the loan matures or if the observation is right censored.

In a MNL model it is also possible to allow the set of explanatory variables of each alternative to be different. Following the approach suggested by Begg and Gray (1984), it is possible to estimate separate binomial logit models for the alternatives continue to pay/prepayment and continue to pay/default, and then mathematically recombined the parameter estimates to compute the corresponding multinomial logit probabilities.[10] This is the estimation methodology that I use in the model discussed in Section 3.4.1.

[10]Define the conditional default and prepayment probabilities estimated by the two separate logit models as P^B_{nt1} and P^B_{nt2}. From Bayes theorem, it follows that the multinomial conditional probabilities can be computed as $P_{nt1} = \frac{P^B_{nt1}(1-P^B_{nt2})}{(1-P^B_{nt1}P^B_{nt2})}$ and $P_{nt2} = \frac{P^B_{nt2}(1-P^B_{nt1})}{(1-P^B_{nt1}P^B_{nt2})}$.

3.2.2 Multinomial Logit with Random Coefficients

The MNL model fails to capture differences in propensity to exercise the default and prepayment options that cannot be linked to observed characteristics or that are purely random. Random coefficients are used to capture correlation in the behavior that is a result of unobserved heterogeneity, taste variation and path dependence. In a multinomial model with random coefficients, the coefficients that enter the utility function are borrower-specific random variables from a given distribution. The utility of borrower n at time t from alternative i is specified as:

$$U_{nti} = \beta'_{ni} X_{nt} + \epsilon_{nti}, \quad i = 0, 1, 2,$$

where β_{ni} varies over decision maker in the population with density $f(\beta_i)$ of parameters θ_i. The probability that borrower n makes the sequence of choices $I = \{I_1, I_2, \ldots, I_{T_n}\}$ is the product of logit probabilities:

$$L_{nI} = \prod_{t=1}^{T_n} \left[\frac{e^{\beta'_{nI_t} X_{nt}}}{\sum_{j=0}^{2} e^{\beta'_{nj} X_{nt}}} \right].$$

Define $\beta' = [\beta'_1, \beta'_2]$ with parameters $\theta' = [\theta'_1, \theta'_2]$ and set $\beta_0 = 0$ as identification condition, the unconditional probability is the integral of this product over all values of β:

$$P_{nI} = \int L_{nI}(\beta) f(\beta|\theta) d\beta.$$

I assume that β_j's are distributed as independent random normal:

$$\beta_j \sim N(\mu_j, \sigma_j), \quad j = 1, 2.$$

For K explanatory variables, μ_j and σ_j have length K. Therefore, for J alternatives the total number of parameters is $(K + K) * (J - 1)$ and the set of parameters is $\theta' = [\mu'_1, \sigma'_1, \mu'_2, \sigma'_2]$.

Multinomial logit model with random coefficients can be estimated by simulated maximum likelihood. The simulated probability of the sequence of choices of borrower n:

$$\hat{P}_{nI} = \frac{1}{R}\sum_{r=1}^{R} L_{nI}(\beta^r),$$

where R is the number of draws and β^r is the vector of coefficients of borrower n in the r draw. $\hat{P}_{nI}$ is an unbiased estimator of P_{nI} by construction. The simulated probabilities are inserted into the log-likelihood function to give a simulated log likelihood:

$$SLL = \sum_{n=1}^{N} \ln \hat{P}_{nI}.$$

The maximum simulated likelihood estimator (MSLE) is the value of θ that maximizes SLL.[11] I optimize the simulated log-likelihood function using the BHHH algorithm of Berndt, Hall, Hall, and Hausman (1974).[12] Revelt and Train (1998) find that optimization algorithms that use an approximation of the Hessian, such as the BHHH algorithm, resulted in computationally faster estimation than calculating the Hessian from formulas for the second derivatives.

3.2.3 Explanatory Variables

This subsection discusses the set of explanatory variables included in the models that I examine.

Probability of negative equity

The key determinant of the default option is the equity position of the borrower defined as the difference between the market value of the property securing the loan, H_t, and the unpaid principal balance based on the scheduled amortization, B_t :

$$EQ_t = H_t - B_t,$$

[11]See Chapter 10 of Train (2009) for the properties of this estimator.

[12]In the BHHH algorithm the Hessian is approximated with the outer product of the gradient.

where H_0 is the house price at origination and B_0 is the original loan amount. Ideally, we should have observations of the values of individual properties at the same frequency of the scheduled mortgage payments. In practice, they are not available and this introduces significant asymmetries of information between the borrower and the lender which complicates the computation of the value of the option. The home value can change as a result of home improvements (or deterioration) as well as changes in home prices over time in the local housing market.

I estimate H_t using the OFHEO house price index in the same Metropolitan Statistical Area (MSA) or state in which the property is located. The OFHEO house price indexes are derived by assuming that individual house prices obey a non-stationary log-normal diffusion process.[13] Based on this hypothesis, the individual house price appreciation since mortgage origination is normally distributed with the expected rate of appreciation equal to the change in the drift of the house price process since mortgage origination and variance σ_t^2. The house price index is an estimate of the drift of the house price process obtained by applying a modified version of the weighted-repeat-sales methodology of Case and Shiller (1987). Define I_t the value of the regional house price index at time t, the estimated expected value of the house at time t is:

$$H_t = H_0 \frac{I_t}{I_0},$$

which means that house prices in each MSA (or state) grows at the same rate of the MSA (or state) house price index. Following Deng, Quigley and Van Order (2000) and Calhoun and Deng (2002), rather than representing the equity status of the borrower with a point estimate, I compute the *ex-ante*

[13]Under the non-stationary lognormality assumption, the logarithm of the individual house price H_{it} at time t can be decomposed as $\ln(H_{it}) = \beta_t + V_{it} + N_{it}$, where the drift β_t represents the average behavior of housing values in the region, V_{it} is a Gaussian random walk and N_{it} is a white noise. The Gaussian random walk is such that $E[V_{i,t+k} - V_{it}] = 0$ and $E[(V_{i,t+k} - V_{it})^2] = ak + bk^2$, which means that the deviation of the individual house price growth rate from the regional growth rate is a quadratic function of time. The white noise represents purely idiosyncratic differences, that is, $E[N_{it}] = 0$ and $E[N_{it}^2] = c$. The estimated OFHEO regional house price index I_t is given by $I_t = 100e^{\hat{\beta}_t}$, where $\hat{\beta}_t$ is the estimate of the drift. See Calhoun (1996) for a detailed description on how he OFHEO house price indexes are constructed.

probability that at time t the value of the house falls below the outstanding balance:

$$\begin{aligned} Prob(EQ_t < 0) &= Prob(B_t > H_t) = Prob(B_t - H_t > 0) \\ &= Prob\left(B_t - H_0 \frac{I_t}{I_0} > 0\right). \end{aligned}$$

It follows from the assumption of non-stationary log normality for the house price process that the probability that the value of the house falls below the remaining mortgage balance at time t is:

$$Prob\left(B_t - H_0 \frac{I_t}{I_0} > 0\right) = \Phi\left(\frac{\ln B_t - \ln\left(H_0 \frac{I_t}{I_0}\right)}{\sigma_t}\right),$$

where $\Phi(x)$ is the standard normal cumulative distribution function evaluated at x. The probability of negative equity depends on the loan amortization, the drift and volatility of the house price appreciation rate.[14] Clearly, we expect that for increasing values of the probability of negative equity the default risk increases and the prepayment risk decreases.

Mortgage premium and other interest rate variables

The decision to exercise the prepayment option requires comparison of the scheduled payments with payments under the current refinancing rate. The value of the call option of the mortgage is a function of the difference between the present value of the future stream of mortgage payments discounted at the current market interest rate R_t, and the present value of the mortgage evaluated at the current note rate, C_t. The value of the call option can be approximated by the relative spread between the current coupon rate on the mortgage and the market rate of interest, which I call mortgage premium.[15]

[14] The volatility of the individual house price is $\sigma_t = \sqrt{at + bt^2}$, where the parameter a and b are estimated jointly with the house price index when applying the repeated sales methodology of Case and Shiller. See Calhoun (1996) for a detailed description on how the OFHEO house price indexes are constructed.

[15] See Calhoun and Deng (2002) for a derivation of this approximation.

The mortgage premium MP_t at time t is

$$MP_t = \frac{C_t - R_t}{R_t}.$$

For fixed rate mortgages the current coupon is always equal to the coupon at origination. The prepayment option becomes more valuable as the market interest rate decreases. The increase in the prepayment risk declines the probability of default. On the other hand, if the borrower is in negative equity, a market interest rate lower that the coupon rate may trigger default.

The most responsive borrowers tend to prepay first, so that the remaining sample of borrowers are those with lower conditional probabilities of prepayment. For this reason, I also include a variable that indicates whether the borrower has missed a previous refinancing opportunity. I define the burnout at time t, $BURNOUT_t$, as the 8-quarter moving average number of basis points the borrower was in the money, in the quarters the borrower was in the money:

$$BURNOUT_t = \frac{1}{8}\sum_{k=1}^{8}(C_{t-k} - R_{t-k})I(C_{t-k} - R_{t-k} > 0),$$

where $I(x)$ is an indicator function that takes value 1 when x is positive. Borrowers who do not exercise the prepayment option are likely to be experiencing financial difficulties.

Expectations about future interest rates influence refinancing. For this reason, the yield curve slope is added to the set of explanatory variables. I measure the yield curve slope as the ratio between the 10-year and the 1-year Treasury rate.

Taking vintage effects into account

I add the age of the mortgage in the set of covariates. Conditional prepayment and default rates exhibit age patterns: they increase during the first years following origination, peak sometime between the fourth and seventh year and decline thereafter. The age profiles can be partly attributed to unobservable differences among individuals. The existence of demographic and economic processes that may trigger mortgage default, and the inability to measure the diffusion of house prices and the distribution of borrower equity precisely, imply the need to account directly for age specific differences in conditional rates of default and prepayment. I consider two different functions to capture the relationship between age and prepayment and default: a quadratic age function and a piecewise linear function.

Variables describing borrowers' heterogeneity, transaction costs and economic conditions

I also consider covariates to account for observable borrowers heterogeneity and transaction costs. (1) The LTV ratio is an indicator of the income and net worth of the borrower at mortgage origination and of his borrowing constraint. Higher origination LTV increases the probability of default and lower the probability of prepayment because there is a greater probability that the borrower will be in a negative equity position early in the life of the loan. High LTV borrowers are also more likely to have fewer economic resources to finance the transaction costs of prepayment or endure spells of unemployment or other trigger events. However, higher LTV ratio at origination may indicate more strict underwriting standards, or high downpayment requirements for risky loans, which lower the default risk of mortgages with high LTV. (2) FICO score at origination.[16] The FICO score measures the consumer's ability to meet prior financial obligations and is a determinant of mortgage loan approval. Borrowers with higher credit scores are expected to default less often and be more easily approved for refinancing. I also insert a dummy variables that takes value 1 when the credit score of the borrower is not available.[17] (3) An indicator that identifies whether the purpose of the mortgage was to purchase a home or to refinance an existing mortgage because these two type of loans have different transaction costs. (4) Dummy variables for each quarter of the calendar year were also taken into account,

[16]FICO score measures individuals credit quality on a scale from 300 to 850.

[17]In the dataset borrower's credit score is not available for loans originated prior to 2004.

to control for the potential impact of weather, school schedules, and seasonal employment patterns on residential mobility. (5) I also include some time dummy variables to control for the impact of changes in FHA underwriting standards over time, the subprime market activity period and the housing crisis.

3.3 Data and Summary Statistics

The dataset is composed of 6000 30-year fixed rate, single-family, owner-occupied, mortgages originated between 1995 and June 2010 and guaranteed by FHA. The mortgage history period ends in the second quarter of 2010. Loans are observed in each quarter from the quarter in which the amortization begins through the quarter of termination, or through the second quarter of 2010 for loans that are still active. I observe the date in which FHA receives a claim for mortgage guarantee from the lender. Therefore, I define a mortgage in default when the lender submits a claim to FHA.

Table 3.2 reports sample statistics of key variables at mortgage origination and at mortgage termination and Table 3.1 reports variables definitions. The average loan-to-value at origination of mortgages guaranteed by FHA is 94 percent. This is a much higher value than the typical initial loan-to-value of conventional mortgages. The average LTV of defaulted loans is 96 percent which is statistically significantly higher than the average for all mortgages. Borrowers with higher initial LTV default more often because they are more borrowing-constrained. The average credit score of defaulted loans is lower of the average credit score of prepaid loans.

The average age at default and prepayment is similar. By the ninth year 95 percent of defaulted loans default and 95 percent of prepaid loans prepay by the tenth year. The average of the estimated probability of being in negative equity of defaulted loans is almost double the average of the estimated probability of prepaid loans. The median probability of being underwater at termination is 8 percent for defaulted loans and 3 percent for prepaid loans. The average probability of negative equity of outstanding loans is strikingly high, signaling that we should expect a high default rate on these loans. The mean mortgage premium at termination of defaulted loans is similar to the mean mortgage premium of prepaid loans. When the call option is out of the money a borrower looks for a way to escape.[18] If he is not borrowing constrained he will refinance otherwise he may decide to default depending on the amount of equity of the house value he owns.

To gain a better understanding of the relationship between age and default and prepayment, I conduct a preliminary analysis of our sample using the non-parametric Kaplan-Meir estimator of the conditional and cumulative prepayment and default rates.[19] Figure 3.1 display the Kaplan-Meier conditional prepayment rate (Panel A), the conditional default rate (Panel B), the cumulative prepayment rate (Panel C) and the cumulative default rate (Panel D) at quarterly frequency. The spike in the estimated conditional prepayment rate at 80 quarters is due to fewer observations available. As loans get older the censorship problem becomes more severe, making the estimates less reliable.

3.4 Specifications and Results

3.4.1 Multinomial Logit Model with Fixed Coefficients

In this section I discuss estimates of a multinomial logit model with fixed coefficients as defined in equation (3.3). The model is estimated on the data described in the previous section.[20] The explanatory variables that I consider in the default and prepayment equations are the same but lag length varies. Therefore, following the approach of Begg and Gray (1984)

[18] A call option is out-of-the-money when the strike price is above the spot price of the underlying security.

[19] Define n_t, the number of outstanding loans at time t, and $d_{t,t+\Delta}$ and $p_{t,t+\Delta}$, respectively, the number of loans that defaulted and prepayed between time t and $t+\Delta$. The Kaplan-Meier estimate of the conditional prepayment and default rates between t and $t+\Delta$ are:

$$\lambda_{p,t,t+\Delta} = \frac{p_{t,t+\Delta}}{n_t}, \ \lambda_{d,t,t+\Delta} = \frac{d_{t,t+\Delta}}{n_t}.$$

[20] The specification is similar to the model of the Actuarial Review of the Federal Housing Administration for fiscal year 2009.

discussed in Section 3.2.1, I estimate two separate logit models for default and prepayment and then recombine them to get the corresponding multinomial logit probabilities.

The probability of negative equity, the mortgage premium and the yield curve slope are lagged by three quarters in the default equation. As discussed in the previous section, I define a loan in default when a lender submits a claim for the guarantee to FHA. As the lender's claim is a consequence of an earlier decision of the borrower to default, the probability of default should depend on the value of the put option in the quarter the foreclosure begins. It takes approximately three quarters between when the lender starts the foreclosure process and when he submits a claim to FHA. Therefore, the probability of negative equity, the mortgage premium and the yield curve slope are lagged in the default equation. This idea is theoretically appealing and leads to a slightly better statistical fit.

Estimates largely meet expectations in term of statistical significance and coefficient signs. Table 3.3 presents maximum likelihood estimates of coefficients of the two binomial logit for quarterly conditional probabilities of mortgage prepayment and default. For all variables except age, the coefficient represents the contribution of the corresponding explanatory variable to the estimated probability. For each age variable the coefficient is the slope of the line segment in the interval between the two knot points.

The results provide strong support for the option theory, according to which the financial motivation is the main driver governing the prepayment and default behavior. The simultaneity of the two options is very important empirically. In particular, factors that trigger one option are also important in triggering or foregoing exercise of the other. The probability of negative equity, representing the value of the put option, and the mortgage premium, representing the value of the call option, have large effect on the estimated probabilities of prepayment and default. The conditional probability of prepayment is positively related to the mortgage premium value and the conditional probability of default is positively related to the probability of negative equity. In addition, conditional prepayment rates are negatively related to the probability of negative equity, which is consistent with the expectation that borrowers will be less likely to refinance or sell their properties in a declining housing markets.

While the results support the basic predictions of the option theory, borrowers' heterogeneity plays an important role as well. The magnitude of the coefficients corresponding to age, LTV and FICO indicate statistical significance of borrowers heterogeneity. There is a strong positive relationship between LTV and default, and little impact on prepayment. The prepayment and default risk increase as the original LTV increases, except for the highest LTV category.[21] Higher default risk is associated with higher original LTV. This is consistent with the argument that information is asymmetric and riskier borrowers choose high LTV loans. For loans with original LTV over 97 percent, all else equal, the probability of default is less than the probability of default of loans with LTV between 95 and 97 percent. An possible explanation is that borrowers with very high initial LTV are typically screened more carefully. The prepayment risk of borrowers with initial LTV larger than 97 percent decreases because these homeowners have less resources to pay the transaction costs required when refinancing.

Results indicate that FICO is a good measure of credit quality. Higher credit scores at origination are associated with large decreases in the probability of default and more modest increases in the probability of prepayment. The effect of the burnout is quite remarkable in the default equation.The burnout is a proxy of the current credit condition of the borrower and missing opportunities to refinance signals that that the borrower may be credit constrained. There is a sharp increase of the probability of default when the burnout is larger than 200 basis points.

The effect of the yield curve slope on prepayment means that borrowers are more likely to exercise the call option when confronted with upward sloping yield curve. The slope of the yield curve is generally considered to be a predictor of economic growth. A steep yield curve signals a growing economy with rising house prices in which people are more likely to prepay.

The subprime time dummy is positive in both prepayment and default

[21] A similar finding arises from the prepayment and default model estimated in the 2009 FHA Actuarial Review.

equations. The dummy for the housing crisis is also significant and points out that since the housing bubble exploded, the default probability has increased and the prepayment probability has decreased. There are seasonal variation in conditional probabilities of prepayment and default although the effect is very small except for the effect of the spring quarter on prepayment. The coefficient corresponding to the refinance dummy indicates that loans that have been originated for the purpose of refinancing an existing mortgage default and prepay more often.

Table 3.4 and Table 3.5 present the estimated cumulative prepayment and default rates by year of origination and age. The model predicts termination of most of the cohorts very well. The default rates of loans originated in 2004-2008 is extremely higher than previous cohorts.

3.4.2 Fixed versus Independent Random Coefficients

This section evaluates to what extent unobservable heterogeneity matters for modeling default and prepayment options. I compare the MNL model with fixed coefficients with one that incorporates random coefficients and check how the estimates presented in the previous subsection hold up.

The estimation of a random coefficients model implies that both the mean and variance of the distribution for each coefficient will be estimated. In fact, a fixed coefficients model can be written as a special case of the random coefficients model, where the variance is assumed to be zero and the fixed coefficients estimates make up the mean vector of the distribution. I set the intercept of the random coefficients models presented in this subsection fixed so that the unobservable heterogeneity in the model can be linked only to observable variables. I also analyze specifications in which the intercept is random but the estimate of its standard deviation is not statistically different from 0.[22]

Similarly to Deng, Quigley and Van Order (2000), I first estimate a model that assumes no transaction costs and "ruthless" exercise of the two op-

[22]Estimates are available upon request.

tions.[23] The explanatory variables included in the model are the probability of negative equity, the mortgage premium and the age of the mortgage. I assume a quadratic function for the effect of each of these variable on prepayment and default probabilities to control for non linearities.[24]

The results reported in Table 3.6 show that there is unobservable heterogeneity in the borrowers' decision to exercise the two options. The standard deviation of the probability of negative equity in the prepayment equation is significantly different from 0 and has nearly the same magnitude as the estimated mean. This suggests that the effect of a particular borrower's equity position on the decision to exercise the prepayment option is quite substantial. There is also heterogeneity in the effect of the mortgage premium on both the prepayment and default decision. Interestingly, I find that the mean effect of the mortgage premium on the decision to default is not statistically different from zero, and its standard deviation is almost as big as the coefficient of mortgage premium in default equation in the model with fixed coefficients. Moreover, the estimated coefficients of the probability of negative equity and of the mortgage premium in the MNL with fixed coefficients and their mean in the random coefficients model are quite different.

The unobservable heterogeneity suggested by the "ruthless" model may be due to omitted variables as this specification does not include any variable that measures observable heterogeneity or transaction costs. This motivates me to extend the model in Table 3.6 by adding all the variables that were also considered in the model presented in Section 3.4.1.[25] The results relative to extended model are presented in Table 3.7. The estimated mean of the random coefficients corresponding to the probability of negative equity, the

[23]The term "ruthless" was first applied by Foster and Van Order (1984, 1985). They defined ruthless default behavior as occurring immediately when the value of the property dropped below the value of the mortgage.

[24]In the previous section I use a step function specification to describe how the factors under consideration affect borrower's decision. My goal in this section is to study whether there is unobservable heterogeneity. As simulated likelihood is computationally intensive assuming quadratic or linear function greatly reduce the number of parameters to estimate. The shape of the function is a question for a later stage of research.

[25]The seasonal dummies, "fiscal year of origination $<$ 1992" and "fiscal year of origination $\geq$ 1996" were left out because their estimated effect in the model presented in Subsection 3.4.1 is small.

mortgage premium, the burnout, the slope of the yield curve and the housing crisis in the default equation are quite different from the estimated coefficients in the fixed coefficient model. The mean effect of the mortgage premium, the burnout, the slope of the yield curve, the housing crisis and subprime market in the prepayment equation are the ones with the most sizable difference compared to the fixed coefficients model.

The extended model also shows that there is unobservable heterogeneity in the effect the probability of negative equity and the mortgage premium have on the propensity to exercise the prepayment option. It is also noteworthy that there is unobservable heterogeneity in the effect of the burnout. The effect of the burst of the housing bubble on the prepayment decision is very heterogeneous as the magnitude of the standard deviation of the random coefficient suggests.

The only random coefficient with standard deviation significantly different from zero in the decision to default is the burnout. The burnout factor measures whether the borrower has missed previous opportunities to refinance. The standard deviation of the mortgage premium, which is significantly different from 0 in the ruthless specification, is not significantly different from zero at 99% confidence level.

Though the random coefficients model has a better fit than both fixed coefficients models, goodness of fits indicator suggest that the improvements are relatively small. Since the random coefficients model has a larger parameter space than the fixed coefficients model, I use the adjusted log-likelihood ratio index of Ben-Akiva and Lerman (1985) to measure goodness of fit. This index includes a penalty for the number of parameters.[26] The relative improvement in the likelihood function that one realizes by moving from the fixed coefficients model to a model with the random coefficients is in line with the literature. Deng, Quigley and Van Order (2000) document an equivalent improvement in fit when they move from a proportional hazard model without to one with heterogeneity.

[26]The formula for the Ben-Akiva and Lerman adjusted log-likelihood ratio index is $1 - \frac{LL-K}{LL_0}$, where K is the number of parameters, LL is the log-likelihood value of the full model, and LL_0 is the log-likelihood value for a model with only an intercept.

3.5 Conclusion

In this chapter I study different random utility models that can be used to estimate the joint probability that a mortgage defaults or prepays. The model in Section 3.4.1 can be implemented to project the prepayment and default probabilities of a portfolio of mortgages given their characteristics and forecasts of future interest rates and house price. Results show that factors that trigger one option are also important in triggering or foregoing exercise of the other. The probability of negative equity and the mortgage premium have large effect on the estimated probabilities of prepayment and default. Observable heterogeneity, such as credit score or the burnout, play a key role. The positive housing crisis dummy show that the default rate since the beginning of the crisis increased whilst the prepayment rate decreased because many homeowner are currently in negative equity.

A key issue is the impact of unobservable heterogeneity in borrowers' propensity to exercise a default or prepayment option. I tackle this question by comparing MNL models that allows for random coefficients with one that is estimated under the assumption of fixed coefficients. The results signal a potentially serious misspecification under the assumption of fixed coefficients. The random coefficients model fits the data better but the improvement is small.

I find that the impact of a random coefficients model is most notable in the borrower's decision to exercise the prepayment option. The estimated standard deviation of the random coefficients corresponding to the probability of negative equity, the mortgage premium and the burnout in the prepayment equation is almost as big as the mean. This result hints at the presence of wide heterogeneity in the size of the effects of these factors on a given borrower's decision to prepay. The effect of the housing crisis on prepayment also varies widely among borrowers. Turning to the default option, I find that unobservable heterogeneity only plays a significant role in the case of the burnout factor.

Future research should compare the MNL model with fixed and random coefficients out-of-sample as the small improvement in sample could reveal a bigger gain out-of-sample. In addition, it would be interesting to assume that borrowers could be divided into different groups, each of which has his own choice behavior. In this case, the vector of coefficients of the prepayment and default equation has a discrete distribution and the probability of belonging to each group could be estimated together with the values of the random coefficients in each group.

Table 3.1: Variables Definitions

Variable	Definition
AGE	Age of the mortgage computed from the time when the principal amortization begins, in quarters
FICO	Fair Isaac credit score at origination
LTV	Original loan amount divided by the minimum between the house appraisal value and purchase price, in percentage
C	Mortgage coupon rate, in percentage
PNEG	Probability of negative equity computed using the OFHEO MSA or state house price index where the house is located
MP	Difference between the mortgage coupon and the conventional mortgage rate in the state where the property is located divided by the mortgage coupon, in percentage
SLOPE	10-year Treasury rate divided by the one year Treasury rate
BURNOUT	Moving average number of basis points the prepayment option was in the money during quarters in the money over the preceding eight quarters
Subprime time	Dummy indicating the observation is between 2004 and 2006
Dummy loan modification tool	Dummy indicating the observation is between 1996 and 2001
Housing crisis	Dummy indicating the observation is after 2006 when US house prices started to fall.

Table 3.2: Descriptive Statistics on Mortgage Loans Mean Values at Origination and Termination

Variable	At Origination			At Termination		
	All loans	Defaulted	Prepaid	Outstanding	Defaulted	Prepaid
LTV	94.460	96.029	94.603	-	-	-
	(6.841)	(4.644)	(6.742)	-	-	-
FICO	665.561	612.294	653.551	-	-	-
	(65.831)	(60.042)	(66.317)	-	-	-
C	7.043	7.602	7.627	-	-	-
	(1.346)	(1.262)	(1.161)	-	-	-
MP	5.185	6.299	4.958	21.386	18.694	19.149
	(11.673)	(13.416)	(11.336)	(11.749)	(14.887)	(12.696)
SLOPE	2.5708	1.5074	1.5469	9.1842	2.8672	2.4236
	(2.5057)	(0.6811)	(0.7731)	-	(2.7555)	(1.9049)
AGE	-	-	-	14.177	17.419	16.175
	-	-	-	(15.934)	(9.907)	(11.872)
PNEG	-	-	-	0.274	0.153	0.076
	-	-	-	(0.263)	(0.205)	(0.131)
Sample size	6000	339	3575	2086	339	3575

Note: Standard deviations are in parenthesis.

Table 3.3: Binomial Logit Coefficient Estimates for the Quarterly Conditional Prepayment and Default Probabilities

	Default	Prepayment
McFadden R-squared	0.0896	0.0794
Estrella R-squared	0.0045	0.0261
LR-ratio, 2*(Lu-Lr)	33582	202164
LR p-value	0.0000	0.0000
Log-Likelihood	-170634	-1171370
Nobs	78007	80226
Nvars	47	44
Variable		
Constant	-17.670	-8.858
$0 \leq PNEG_{t-3} \leq 0.05$		-
$0.05 < PNEG_{t-3} \leq 0.1$	0.642	-
$0.1 < PNEG_{t-3} \leq 0.15$	0.806	-
$0.15 < PNEG_{t-3} \leq 0.2$	0.952	-
$0.2 < PNEG_{t-3} \leq 0.25$	1.079	-
$0.25 < PNEG_{t-3} \leq 0.3$	1.088	-
$PNEG_{t-3} > 0.3$	1.516	-
$0 \leq PNEG_{t} \leq 0.05$	-	
$0.05 < PNEG_{t} \leq 0.1$	-	-0.382
$0.1 < PNEG_{t} \leq 0.15$	-	-0.511
$0.15 < PNEG_{t} \leq 0.2$	-	-0.637
$0.2 < PNEG_{t} \leq 0.25$	-	-0.737
$0.25 < PNEG_{t} \leq 0.3$	-	-0.837
$PNEG_{t} > 0.3$	-	-0.692
$MP_{t-3} \leq 0$		-
$0 < MP_{t-3} \leq 10$	0.271	-
$10 < MP_{t-3} \leq 20$	0.472	-
$20 < MP_{t-3} \leq 30$	0.628	-
$MP_{t-3} > 30$	0.808	-

Table 3.3 (continued)

Variable	Default	Prepayment
$MP_t \leq 0$	-	
$0 < MP_t \leq 10$	-	0.270
$10 < MP_t \leq 20$	-	0.814
$20 < MP_t \leq 30$	-	1.300
$MP_t > 30$	-	1.338
$AGE_t \leq 2$	3.845	2.114
$2 < AGE_t \leq 6$	0.695	0.177
$6 < AGE_t \leq 8$	0.171	-
$8 < AGE_t \leq 10$	0.098	-
$10 < AGE_t \leq 12$	0.053	-
$12 < AGE_t \leq 14$	0.101	-
$14 < AGE_t \leq 36$	-0.019	-
$6 < AGE_t \leq 12$	-	-0.004**
$12 < AGE_t \leq 18$	-	-0.033
$AGE_t > 18$	-0.054	-0.019
$LTV \leq 80$		
$80 < LTV \leq 90$	0.509	0.071
$90 < LTV \leq 95$	0.518	0.260
$95 < LTV \leq 97$	0.668	0.293
$LTV > 97$	0.527	0.206
$0 \geq SLOPE_{t-3} \leq 1$		-
$1 < SLOPE_{t-3} \leq 1.2$	-0.081	-
$1.2 < SLOPE_{t-3} \leq 1.5$	-0.202	-
$SLOPE_{t-3} > 1.5$	-0.157	-
$0 \geq SLOPE_t \leq 1$	-	
$1 < SLOPE_t \leq 1.2$	-	0.099
$1.2 < SLOPE_t \leq 1.5$	-	0.191
$SLOPE_t > 1.5$	-	0.294
$0 < BURNOUT_t \leq 50$		
$50 < BURNOUT_t \leq 100$	0.124	0.033
$100 < BURNOUT_t \leq 150$	0.277	0.097

Table 3.3 (continued)

Variable	Default	Prepayment
$150 < BURNOUT_t \leq 200$	0.483	0.075
$BURNOUT_t > 200$	0.850	-0.004*
$FICO \leq 499$		
$499 < FICO \leq 559$	-0.341	-0.070*
$559 < FICO \leq 599$	-0.525	0.055*
$599 < FICO \leq 639$	-0.745	0.197
$639 < FICO \leq 659$	-0.946	0.339
$659 < FICO \leq 679$	-1.108	0.383
$679 < FICO \leq 719$	-1.417	0.447
$FICO > 719$	-1.823	0.542
FICO not available	-0.716	-0.082*
First calendar quarter		
Second calendar quarter	0.003*	0.201
Third calendar quarter	-0.067	0.059
Fourth calendar quarter	-0.087	0.074*
Subprime time	0.307	0.150
Loan modification tool	0.349	0.240
Housing crisis	0.562	-0.508
Fiscal year of origination < 1992	0.009*	-0.017**
Fiscal year of origination ≥ 1996	0.307	-0.040
Loan purpose refinance	0.129	0.166

Note: Binomial logit models are estimated by maximum likelihood. The separate sets of logit parameter estimates were recombined mathematically to derive the corresponding multinomial logit for the joint probabilities of prepayment and default. All variables except age are dummy variables taking value 1 for the defined categorical outcome. The coefficients corresponding to AGE variables are the slope of the corresponding piecewise linear segment between the two knots. Blank entries indicate that outcome is a member of the baseline category. An asterisk (*) indicates that the coefficient is not statistically significant at the 5 percent level for an asymptotic-normal test. An asterisk (**) indicates that the coefficient is not statistically significant at the 1 percent level for an asymptotic-normal test. A dash (-) indicates that the variable is not included in the estimated logit equation.

Table 3.4: Estimated and Actual Cumulative Default Rates by Year of Origination, MNL Model with Fixed Coefficients

Year of Origination/Age		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1995	actual	0.02	0.66	2.38	4.01	5.42	6.32	7.06	7.61	8.06	8.34	8.53	8.68	8.77	8.83	8.91					
	predicted	0.05	0.77	2.12	3.70	4.86	5.55	6.11	6.61	7.01	7.26	7.41	7.53	7.63	7.69	7.74					
1996	actual	0.01	0.81	2.32	3.74	5.04	5.91	6.63	7.20	7.51	7.65	7.77	7.90	7.99	8.07						
	predicted	0.06	0.94	2.57	4.26	5.26	6.07	6.80	7.36	7.76	8.02	8.21	8.37	8.47	8.55						
1997	actual	0.04	0.81	2.28	3.52	4.54	5.62	6.36	6.83	7.12	7.30	7.45	7.55	7.71							
	predicted	0.05	0.90	2.34	3.52	4.52	5.37	6.06	6.51	6.82	7.06	7.25	7.37	7.48							
1998	actual	0.02	0.70	1.75	2.87	3.99	4.81	5.36	5.73	5.99	6.19	6.36	6.56								
	predicted	0.06	0.75	1.70	2.81	3.73	4.50	5.04	5.39	5.66	5.89	6.04	6.19								
1999	actual	0.04	0.86	2.11	3.64	4.83	5.69	6.19	6.58	6.82	7.02	7.22									
	predicted	0.05	0.70	1.81	3.04	4.04	4.71	5.13	5.45	5.74	5.94	6.11									
2000	actual	0.05	1.16	3.10	4.65	5.58	6.18	6.53	6.84	7.13	7.36										
	predicted	0.06	0.87	2.66	4.39	5.44	6.05	6.52	6.92	7.21	7.45										
2001	actual	0.03	0.90	2.45	3.80	4.67	5.27	5.76	6.14	6.56											
	predicted	0.07	0.88	2.43	3.84	4.71	5.31	5.80	6.18	6.58											
2002	actual	0.03	1.01	2.54	3.65	4.35	5.05	5.61	6.32												
	predicted	0.07	0.97	2.50	3.76	4.68	5.46	6.05	6.68												
2003	actual	0.12	1.14	2.35	3.54	4.42	5.32	6.56													
	predicted	0.07	0.82	1.96	3.19	4.38	5.35	6.39													
2004	actual	0.30	1.22	2.66	4.28	5.83	7.72														
	predicted	0.06	0.77	2.00	3.55	4.88	6.34														
2005	actual	0.06	1.34	3.51	5.59	8.39															
	predicted	0.06	0.96	2.65	4.63	6.92															
2006	actual	0.16	1.40	4.17	8.26																
	predicted	0.08	1.50	4.24	8.23																
2007	actual	0.11	2.01	6.35																	
	predicted	0.09	1.89	6.34																	
2008	actual	0.07	1.50																		
	predicted	0.07	1.87																		
2009	actual	0.05																			
	predicted	0.06																			
2010	actual	0.00*																			
	predicted	0.00*																			

Note: The table presents the quarterly cumulative default rate estimated by the model presented in Table 3.3, together with the actual cumulative default rate by year of origination and age (in number of quarters). The asterisk (*) denotes that the data is computed only on a portion of the year.

Table 3.5: Estimated and Actual Cumulative Prepayment Rates by Year of Origination, MNL Model with Fixed Coefficients

Year of Origination/ Age		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1995	actual	3.59	9.64	19.76	34.47	41.81	49.25	58.51	68.63	75.09	79.02	81.44	83.00	83.83	84.40	84.83					
	predicted	3.80	11.41	23.20	34.09	40.09	48.80	60.06	70.41	76.77	80.62	82.85	84.07	84.91	85.72	86.40					
1996	actual	1.37	10.85	25.67	33.54	41.67	52.72	64.75	73.71	78.55	81.26	82.98	84.06	84.67	85.07						
	predicted	3.02	13.42	25.40	32.17	41.31	53.28	65.25	73.29	78.03	80.77	82.22	83.13	84.05	84.85						
1997	actual	3.18	16.87	24.98	34.13	47.23	61.97	72.40	77.87	80.85	82.73	83.70	84.35	84.97							
	predicted	5.10	16.98	24.98	36.27	50.90	65.01	73.73	78.85	81.70	83.22	84.21	85.19	86.03							
1998	actual	2.22	7.44	16.32	30.60	50.93	65.87	73.87	78.22	80.63	82.10	83.05	83.79								
	predicted	3.65	10.35	20.99	36.77	56.06	68.32	75.50	79.13	81.05	82.33	83.74	84.98								
1999	actual	1.50	11.56	28.92	48.85	64.81	73.08	77.52	80.14	81.43	82.46	83.17									
	predicted	3.04	15.28	33.88	54.29	67.71	75.29	79.51	81.56	82.83	84.17	85.40									
2000	actual	13.89	43.23	63.09	74.31	79.79	83.01	84.52	85.41	85.94	86.38										
	predicted	8.01	32.25	55.81	69.38	76.85	80.99	83.14	84.42	85.58	86.52										
2001	actual	5.98	35.63	59.28	69.69	75.15	78.05	79.77	81.10	82.05											
	predicted	8.28	35.79	56.78	68.61	74.30	77.24	79.16	81.22	82.95											
2002	actual	13.01	41.11	56.16	64.54	68.97	71.78	73.83	75.79												
	predicted	11.88	35.24	52.83	61.66	65.87	68.60	71.86	74.80												
2003	actual	6.52	24.48	37.86	45.46	49.79	53.00	56.50													
	predicted	7.68	23.82	34.76	40.26	43.70	48.18	52.50													
2004	actual	7.30	21.64	30.46	35.74	39.82	44.13														
	predicted	9.26	23.18	31.69	37.06	43.41	49.15														
2005	actual	4.12	11.97	18.03	22.44	27.40															
	predicted	5.75	14.87	21.61	29.74	36.92															
2006	actual	4.14	12.61	21.70	29.57																
	predicted	4.52	13.28	25.07	35.08																
2007	actual	7.45	20.62	29.23																	
	predicted	4.36	17.02	29.49																	
2008	actual	14.73	28.33																		
	predicted	6.51	20.18																		
2009	actual	3.80																			
	predicted	4.46																			
2010	actual	0.86*																			
	predicted	0.93*																			

Note: The table presents the quarterly cumulative prepayment rate estimated by the model presented in Table 3.3, together with the actual cumulative prepayment rate by year of origination and age (in number of quarters). The asterisk (*) denotes that the data is computed only on a portion of the year.

Table 3.6: Comparison of MNL Model with Fixed and Random Coefficients, Specification with Only Option-Related Variables and Age

	Fixed		Random			
Adj. LL Ratio Index	0.057		0.062			
Log-Likelihood	-14436		-14346			
Nobs	81582		81582			
Nvars	7		7			
Variable	Default	Prepayment	Default		Prepayment	
Constant	-8.9428	-4.0176	-9.148		-4.1938	
	(0.2625)	(0.0578)	(0.35)		(0.0822)	
			Mean	Std. Dev.	Mean	Std. Dev.
$PNEG_t$	5.4755	-4.2234	6.2736	0.8894*	-5.7236	3.3311
	(0.8779)	(0.3372)	(1.2575)	(1.3761)	(0.5192)	(0.5008)
Squared $PNEG_t$	-4.4296	4.1695	-6.1277	1.3901*	4.1603	1.4604*
	(1.1125)	(0.4209)	(2.3926)	(2.3097)	(0.8388)	(1.4152)
MP_t	0.0391	0.0445	0.0211*	0.0308	0.035	0.0263
	(0.0051)	(0.0017)	(0.0121)	(0.0124)	(0.0034)	(0.0045)
Squared MP_t	0.0001	0.0001	-0.0001*	0.001	0.0007	0.0007
	(0.0000)	(0.000)	(0.0005)	(0.0004)	(0.0001)	(0.0002)
AGE_t	0.2952	0.0744	0.3236	0.0021*	0.0885	0.0033*
	(0.0259)	(0.0062)	(0.0362)	(0.0216)	(0.0077)	(0.0105)
Squared AGE_t	-0.0066	-0.0024	-0.0075	0.0012*	-0.0024	0.0001*
	(0.0007)	(0.0002)	(0.0012)	(0.0006)	(0.0002)	(0.0004)

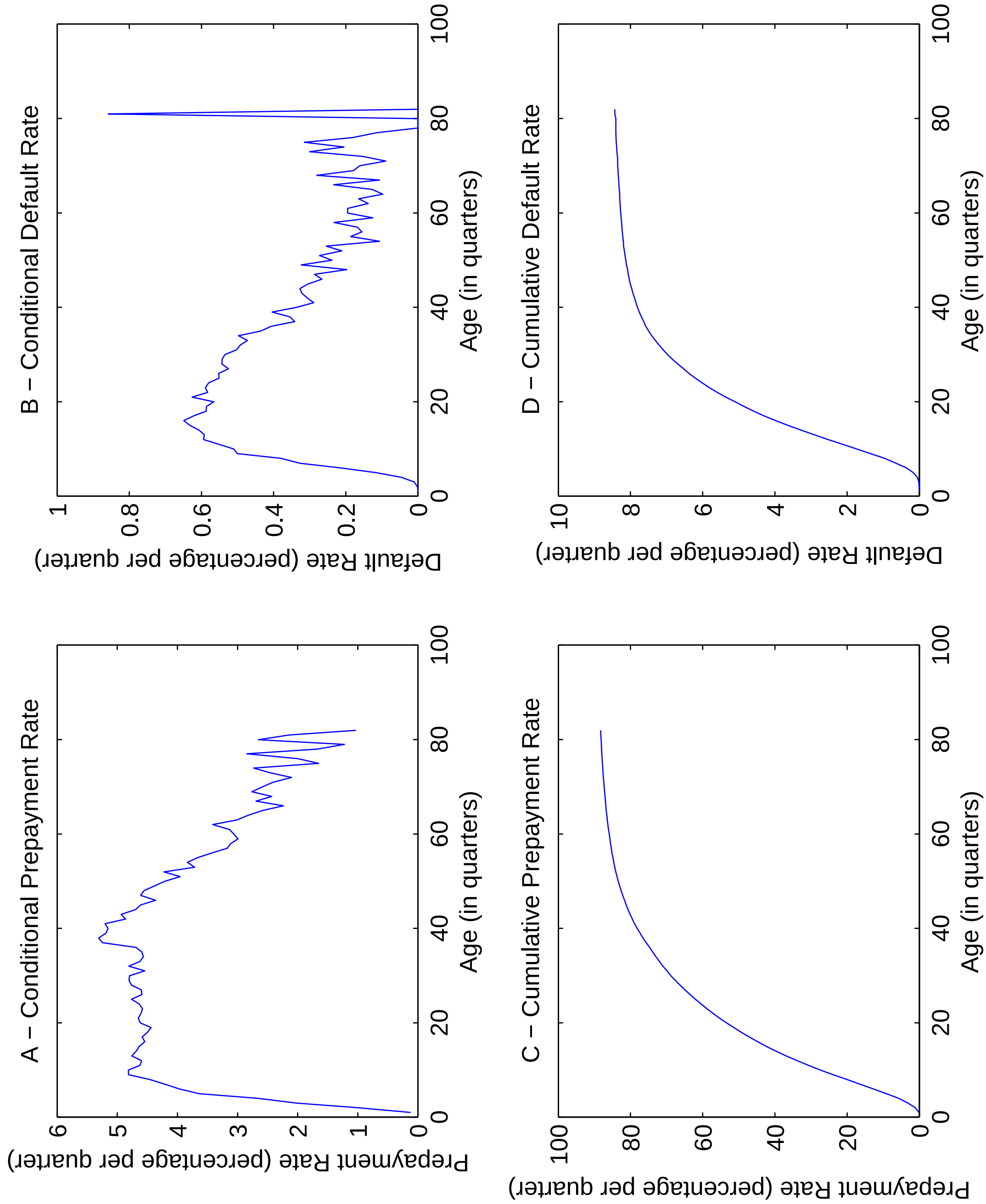
Note: The MNL model with fixed coefficients is estimated by maximum likelihood while the MNL model with random coefficients is estimated by simulated maximum likelihood. In both models prepayment and default are estimated jointly. The adjusted log-likelihood ratio index follows Ben-Akiva and Lerman (1985). An asterisk (*) indicates that the coefficient/parameter is not statistically significant at the 5 percent level for an asymptotic-normal test. An asterisk (**) indicates that the coefficient/parameter is not statistically significant at the 1 percent level for an asymptotic-normal test. Standard errors are reported in parenthesis.

Table 3.7: Comparison of MNL Model with Fixed and Random Coefficients, Specification with Variables that Measure Observable Heterogeneity and Transaction Costs

	Fixed		Random			
Adj. LL Ratio Index	0.06		0.07			
Log-Likelihood	-14324		-14258			
Nobs	81582		81582			
Nvars	14		14			
Variable	Default	Prepayment	Default		Prepayment	
Constant	-12.0193	-5.1157	-12.7950		-5.0670	
	(1.5349)	(0.3369)	(1.8324)		(0.3816)	
			Mean	Std. Dev.	Mean	Std. Dev.
$PNEG_t$	5.0305	-4.0113	6.1129	0.2940*	-4.9304	3.0276
	(1.0518)	(0.3818)	(1.4345)	(1.7234)	(0.5583)	(0.5294)
Squared $PNEG_t$	-3.9820	4.2374	-6.1269	1.7535*	4.4222	0.2827*
	(1.1708)	(0.4423)	(2.3553)	(1.3689)	(0.7709)	(1.6285)
MP_t	0.0238	0.0511	0.0143*	0.0263**	0.0348	0.0213
	(0.0078)	(0.0023)	(0.0125)	(0.0130)	(0.0036)	(0.0055)
Squared MP_t	0.0000*	0.0001	-0.0001*	0.0007*	0.0007	0.0006
	(0.0000)	(0.0000)	(0.0005)	(0.0005)	(0.0001)	(0.0002)
AGE_t	0.2577	0.0966	0.2915	0.0083*	0.1021	0.0030*
	(0.0278)	(0.0071)	(0.0388)	(0.0207)	(0.0094)	(0.0105)
Squared AGE_t	-0.0063	-0.0025	-0.0074	0.0014**	-0.0023	0.0000*
	(0.0007)	(0.0002)	(0.0012)	(0.0006)	(0.0002)	(0.0004)
LTV	0.0343**	0.0094	0.0375**	0.0046*	0.0072*	0.0001*
	(0.0157)	(0.0035)	(0.0188)	(0.0042)	(0.0040)	(0.0017)
$SLOPE_t$	0.0250*	0.0433	-0.0080*	0.0787*	0.0524	0.0452*
	(0.0298)	(0.0123)	(0.0570)	(0.0718)	(0.0199)	(0.0455)
$BURNOUT_t$	0.0036	-0.0030	0.0016*	0.0064	-0.0021	0.0024
	(0.0012)	(0.0004)	(0.0022)	(0.0019)	(0.0006)	(0.0008)
FICO	-0.0009	0.0002*	-0.0009	0.0001*	-0.0003*	0.0001*
	(0.0004)	(0.0001)	(0.0004)	(0.0015)	(0.0002)	(0.0007)
Subprime	0.1802*	0.0990**	0.2116*	0.3677*	0.2466	0.0779*
	(0.1660)	(0.0503)	(0.2535)	(0.6780)	(0.0603)	(0.2984)
Housing crisis	0.5532	-0.6806	0.6500	0.2935*	-0.9770	1.2624
	(0.2016)	(0.0832)	(0.2748)	(0.5521)	(0.1809)	(0.2068)
Loan Purpose Refinance	0.3812**	0.1298**	0.1371*	0.8926*	0.1231*	0.1854*
	(0.1937)	(0.0610)	(0.5340)	(0.7824)	(0.0758)	(0.3038)

Note: The MNL model with fixed coefficients is estimated by maximum likelihood while the MNL model with random coefficients is estimated by simulated maximum likelihood. In both models prepayment and default are estimated jointly. The adjusted log-likelihood ratio index follows Ben-Akiva and Lerman (1985). An asterisk (*) indicates that the coefficient/parameter is not statistically significant at the 5 percent level for an asymptotic-normal test. An asterisk (**) indicates that the coefficient/parameter is not statistically significant at the 1 percent level for an asymptotic-normal test. Standard errors are reported in parenthesis.

Figure 3.1: Kaplan-Meier Estimate of Quarterly Prepayment and Default Rates



Concluding Remarks

In this dissertation I study specific financial risks that have played dominant roles in the US financial crisis of 2008-09. Chapter 2 estimates the impact of financial stress on economic activity using a structural VAR analysis. In the chapter, I show that there is a multidimensional response of the real economy to financial stress. GDP, consumption, investment, labor, and monetary policy all respond negatively to an unexpected shock to the financial stress index even prior to the financial crisis of 2008. In addition, my results suggest that including financial stress in the analysis helps to identify monetary policy shocks.

Reading Chapter 2, it is natural to ask how sensitive the results are to the methodology used to estimate the level of financial stress. Preliminary works suggests that my results are fairly robust. Brave and Butters (2011) estimate a financial condition index as the latent factor of more than one hundred financial indicators that have mixed frequency and different starting dates of available data. In this way, they expand data history and coverage. They apply the large approximate dynamic factor framework of Doz, Giannone, and Reichlin (2006) for the estimation. In my work, I measure the level of financial stress with the first principal component of the correlation matrix of 14 financial variables. The index that I construct in Section 2.4 is strongly correlated with the index proposed by Brave and Butters (2011). Not surprisingly, using their index in the model presented in Section 2.5.2 would not affect the results.

Turning to future research I want to investigate how the results presented in Section 2.6 hold up under alternative ways to identify monetary policy shocks. The accuracy of estimates of the effects of monetary policy depends crucially on the validity of the measure of monetary policy that is used. In my identification scheme for monetary policy shocks I use orthogonalized innovation to the short term interest rate. Arguably this is the most popular methodology for identifying such shocks but the literature has also proposed alternative schemes. For example, Kuttner (2001) turns to Fed funds futures data to separate changes in the target funds rate into anticipated and unanticipated components. In this dissertation, I show that my monetary policy shocks are highly correlated to shocks that are time aggregated from an identification scheme close to Kuttner (2001) but more research is needed to examine the robustness of my results. I certainly would like to examine how my results hold up when monetary policy is identified as in Romer and Romer (2004). Romer and Romer (2004) identify monetary policy shocks with changes in the federal funds rate that are the result of deliberate decisions by the Federal Reserve made at meetings for which there is a forecast prepared by the staff. They then remove the portions of these moves in the intended funds rate that represent the Federal Reserve's usual response to its economic forecasts. The resulting series is largely free of interest rate movements that are either endogenous responses to economic developments or attempts by policy makers to counteract likely future developments.

A number of other extensions to the work presented in Chapter 2 also come to mind. One extension is a cointegration analysis of the empirical macro model presented in Section 2.5.2. Finally, I would like to examine more closely how financial stress affects banks' balance sheets. In essence I would like to improve our understanding of how monetary policy has been transmitted through the financial system in recent years. My results certainly suggest that the transmission of looser monetary policy primarily happens through a reduction of stress on financial markets. In turn, a fall in financial stress improves the real economy (as shown by e.g. a strong response of labor market variables). However, questions remain on how monetary policy can ease funding conditions for banks (on the liability side of banks' balance sheet) or promote different forms of lending (on the asset side).

In Chapter 3, I study random utility models to estimate the default and prepayment probabilities of a mortgage given its characteristics and the macroeconomic environment. The model presented in Section 3.4.1 can be used for mortgage pricing and a cost-benefit analysis of different mortgage policies. In fact, following the increase in mortgage defaults due to sharp fall in US house prices in 2007 legislators have been proposing different programs to modify the terms of mortgage contracts of underwater borrowers. The models in this dissertation can be used to evaluate the effect of these proposals in limiting future mortgage defaults.

The work done in Chapter 3 can also serve as foundation for further research. First, I would like to develop an appropriate methodology to compare random utility models with and without random coefficients out-of-sample. The in-sample comparison of MNL models with fixed and random coefficients in Section 3.4.2 signals a potentially serious misspecification under the assumption of fixed coefficients. Moreover, the impact of a random coefficient model is most notable in the borrower's decision to exercise the prepayment option.

Another objective is to apply Bayesian methods to estimate the MNL model with random coefficients. In this dissertation I estimate the multinomial model with random coefficients using simulated likelihood. However, simulated likelihood is a computationally intensive method, even with today's computing power, and there could be substantial gains in alternative estimation techniques. Such techniques could support the practical implementation of MNL models with random coefficients for mortgage and policy analysis.

Appendix A

This appendix describes the data used in the VAR model discussed in Chapter 2.

- G The sum of real federal, state, and local government consumption expenditures and gross investment, chained dollars, seasonally adjusted annual rate, NIPA.

- T The sum of real federal, state, and local government receipts less transfer payments, federal grants-in-aid, and net interest paid, chained dollars, seasonally adjusted annual rate, NIPA.

- Y Real GDP, chained dollars, seasonally adjusted annual rate, NIPA.

- C Real personal consumption expenditures on non durable goods, chained dollars, seasonally adjusted annual rate, NIPA.

- I The sum of real gross private investment and personal consumption expenditures on durable goods, chained dollars, seasonally adjusted annual rate, NIPA.

- L Hours per capita in non-agricultural establishments, computed as the ratio between aggregate hours in non-agricultural establishments and civilian population aged 16-year and older, seasonally adjusted annual rate, BLS.

- R One-year Treasury bill rate, Federal Reserve Bulletin H.15.

Bibliography

[1] Ambrose, B. W., and C. A. Capone, 1998, "Modeling the Conditional Probability of Foreclosure in the Context of Single-Family Mortgage Default Resolutions," *Real Estate Economics*, Vol. 26, No. 3, pp. 391-429.

[2] Andersson, M., E. Krylova, and S. Vahamaaand, 2008, "Why Does the Correlation Between Stock and Bond Returns Vary over Time," *Applied Financial Economics*, Vol. 18, No. 2, pp. 139-151.

[3] Archer, W. R., D. C. Ling, and G. A. McGill, 1996, "The Effect of Income and Collateral Constraints on Residential Mortgage Terminations", *Regional Science and Urban Economics*, Vol. 26, No. 3-4, pp. 235-261.

[4] Barakchian, S. M., and C. Crowe, 2009, "Monetary Policy Matters: New Evidence from a New Shock Measure," IMF Working Paper No. 10/230, International Monetary Fund.

[5] Baur, D. G., and B. M. Lucey, 2009, "Flights and Contagion-An Empirical Analysis of Stock-Bond Correlations," *Journal of Financial Stability*, Vol. 5, No. 4 , pp. 339-352.

[6] Begg, C. B., and Gray, R., 1984, "Calculation of Polychotomous Logistic Regression Parameters Using Individualized Regressions," *Biometrika*, Vol. 71, No. 1, pp. 11-18.

[7] Ben-Akiva, M., and S. Lerman, 1985, *Discrete Choice Analysis: Theory and Application to Travel Demand*, Cambridge, MA: The MIT Press.

[8] Berkovec, J. A., G. B. Canner, S. A. Gabriel, and T. H. Hannan, 1998, "Discrimination, Competition, and Loan Performance in FHA Mortgage Lending," *Review of Economics and Statistics*, Vol. 80, No. 2, pp. 241-250.

[9] Bernanke, B. S., 1983, "Irreversibility, Uncertainty, and Cyclical Investment," *Quarterly Journal of Economics*, Vol. 98, No. 1, pp. 85-106.

[10] Bernanke, B. S., and M. Gertler, 1989, "Agency Costs, Net Worth, and Business Fluctuations," *American Economic Review*, Vol. 79, No. 1, pp. 14-31.

[11] Bernanke, B. S., and M. Gertler, 1995, "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives*, Vol. 9, No. 4, pp. 27-48.

[12] Bernanke, B. S., M. Gertler, and S. Gilchrist, 1999, "The Financial Accelerator in a Quantitative Business Cycle Framework," *Handbook of Macroeconomics*, Vol. 1, Ch. 21, pp. 1341-1393.

[13] Bernanke, B. S., and K. Kuttner, 2005, "What Explains the Stock Market's Reaction to Federal Reserve Policy?" *Journal of Finance*, Vol. 60, No. 3, pp. 1221-1257.

[14] Berndt, E., B. Hall, R. Hall, and J. Hausman, 1974, "Estimation and Inference in Nonlinear Structural Models", *Annals of Economic and Social Measurement*, Vol. 3, No. 4, pp. 653-665.

[15] Brave, S., and R. A. Butters, 2011, "Monitoring Financial Stability: A Financial Conditions Index Approach," *Economic Perspectives,* Q I, pp. 22-43.

[16] Brennan, M. J., and E. S. Schwartz, 1985, "Determinants of GNMA Mortgage Prices," *Real Estate Economics*, Vol. 13, No. 3, pp. 209-228.

[17] Buser, S. A., and P. H. Hendershott, 1984, "The Pricing of Default-Free Fixed Rate Mortgages," *Housing Finance Review*, Vol. 3, No. 4, pp. 405-429.

[18] Calhoun, C. A., 1996, "OFHEO House Price Indexes: HPI Technical Description," Office of Federal Housing Enterprise Oversight, Washington.

[19] Calhoun, C. A., and Y. Deng, 2002, "A Dynamic Analysis of Fixed- and Adjustable-Rate Mortgage Terminations," *The Journal of Real Estate Finance and Economics*, Vol. 24, No. 1-2, pp. 9-33.

[20] Calomiris, C. W., and J. R. Mason, 2004, "Credit Card Securitization and Regulatory Arbitrage," *Journal of Financial Services Research*, Vol. 26, No. 1, pp. 5-27.

[21] Campbell, J. Y., A. W. Lo, and A. C. MacKinlay, 1997, *The Econometrics of Financial Markets*, Princeton: Princeton University Press.

[22] Cardarelli, R., S. Elekdag, and S. Lall, 2009, "Financial Stress, Downturns, and Recoveries," IMF Working Paper No. 09/100, International Monetary Fund.

[23] Carlson, M. A., T. B. King, and K. F. Lewis, 2008, "Distress in the Financial Sector and Economic Activity," Finance and Economics Discussion Series 2008-43, Board of Governors of the Federal Reserve System (U.S.).

[24] Case, K. E., and R. J. Shiller, 1987, "Prices of Single-Family Homes Since 1970: New Indexes for Four Cities," *New England Economic Review*, Federal Reserve Bank of Boston, Issue September, pp. 45-56.

[25] Christiano, L. J., M. Eichenbaum, and C. L. Evans, 1996, "The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds," *Review of Economics and Statistics*, Vol. 78, No. 1, pp. 16-34.

[26] Christiano, L. J., M. Eichenbaum, and C. L. Evans, 2005, "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, Vol. 113, No. 1, pp. 1-45.

[27] Clapp, J. M., Y. Deng, and X. An, 2006, "Unobserved Heterogeneity in Models of Competing Mortgage Termination Risks," *Real Estate Economics*, Vol. 34, No. 2, pp. 243-273.

[28] Cunningham, D. F., and C. A. Jr. Capone, 1990, "The Relative Termination Experience of Adjustable to Fixed-Rate Mortgages," *Journal of Finance*, Vol. 45, No. 5, pp. 1687-1703.

[29] Cunningham, D. F., and P. H. Hendershott, 1984, "Pricing FHA Mortgage Default Insurance," *Housing Finance Review*, Vol. 3 , No. 4, pp. 373-392.

[30] Davig, T., and C. Hakkio, 2010, "What Is the Effect of Financial Stress on Economic Activity?" Federal Reserve Bank of Kansas City, *Economic Review*, 2Q, pp. 35-62.

[31] Deng, Y., J. Quigley, and R. Van Order, 2000, "Mortgage Terminations, Heterogeneity and the Exercise of Mortgage Options," *Econometrica*, Vol. 68, No. 2, pp. 275-307.

[32] Doz, C., D. Giannone, and L. Reichlin, 2011, "A Two-Step Estimator for Large Approximate Dynamic Factor Models Based on Kalman Filtering," *Journal of Econometrics*, Vol. 164, No. 1, pp. 188-205.

[33] Duca, J. V., 1999, "What Credit Market Indicators Tell Us," Federal Reserve Bank of Dallas, *Economic and Financial Review*, Third Quarter.

[34] Dudley, W., and J. Hatzius, 2000, "The Goldman Sachs Financial Conditions Index: The Right Tool for a New Monetary Policy Regime," Global Economics Paper No. 44, Goldman Sachs.

[35] Duffee, G. R., 1998, "The Relation Between Treasury Yields and Corporate Bond Yield Spreads," *Journal of Finance*, Vol. 53, No. 6, pp. 2225-2241.

[36] Dunn, K. B., and J. J. McConnell, 1981, "Valuation of GNMA Mortgage-Backed Securities", *Journal of Finance*, Vol. 36, No. 3, pp. 599-616.

[37] Epperson, J. F., J. B. Kau, D. C. Keenan, and W. J. Muller, 1985,"Pricing Default Risk in Mortgages," *Real Estate Economics*, Vol. 13, No. 3, pp. 261-272.

[38] Foster, C., and R. Van Order, 1984, "An Option-Based Model of Mortgage Default," *Housing Finance Review*, Vol. 3, No. 4, pp. 351-372.

[39] Foster, C., and R. Van Order, 1985, "FHA Terminations: A Prelude to Rational Mortgage Pricing," *Journal of The American Real Estate and Urban Economics Association*, Vol. 13, No. 3, pp. 273-291.

[40] Goodhart, C., and B. Hofmann, 2001, "Asset Prices, Financial Conditions, and the Transmission of Monetary Policy," Paper prepared for the conference on 'Asset Prices, Exchange rates, and Monetary Policy', Stanford University, March 2-3, 2001.

[41] Green, J., and J. B. Shoven, 1986, "The Effect of Interest Rates on Mortgage Prepayments," *Journal of Money, Credit and Banking*, Vol. 18, No. 1, pp. 41-50.

[42] Grinblatt, M., 2002, "An Analytic Solution for Interest Swap Spreads," *International Review of Finance*, Vol. 2, No. 3, pp. 113-149.

[43] Guichard, S., and D. Turner, 2008, "Quantifying the Effect of Financial Conditions on US Activity," OECD Economics Department Working Papers, No. 635, OECD Publishing.

[44] Gurkaynak, R. R., B. Sack, and J. H. Wright, 2007, "The U.S. Treasury Yield Curve: 1961 to Present," *Journal of Monetary Economics*, Vol. 54, No. 8, pp. 2291-2304.

[45] Hakkio, C. S., and W. R. Keeton, 2009, "Financial Stress: What Is It, How Can Be Measured, and Why Does It Matter?" Federal Reserve Bank of Kansas City, *Economic Review*, 2Q, pp. 5-50.

[46] Hamilton, J. M., 1994, Time Series Analysis, Princeton: Princeton University Press.

[47] Hatzius, J., P. Hooper, F. Mishkin, K. L. Schoenholtz, and M.W. Watson, 2010, "Financial Conditions Indexes: A Fresh Look After the Financial Crisis," US Monetary Policy Forum Paper Series.

[48] Illing, M., and Y. Liu, 2006, "Measuring Financial Stress in a Developed Country: an Application to Canada," *Journal of Financial Stability*, Vol. 2, No. 3, pp. 243-265.

[49] Integrated Financial Engineering, Inc., 2010, *Actuarial Review of the Federal Housing Administration Mutual Mortgage Insurance Fund Forward Loans for Fiscal Year 2010*, prepared for U.S. Department of Housing and Urban Development, Washington DC.

[50] Integrated Financial Engineering, Inc., 2009, *Actuarial Review of the Federal Housing Administration Mutual Mortgage Insurance Fund Forward Loans for Fiscal Year 2009*, prepared for U.S. Department of Housing and Urban Development, Washington DC.

[51] Kau, J. B., and D. C. Keenan, 1995, "An Overview of the Option-Theoretic Pricing of Mortgages," *Journal of Housing Research*, Vol. 6, No. 2, pp. 217-244.

[52] Kau, J. B., D. C. Keenan, and T. Kim, 1993, "Transaction Costs, Suboptimal Termination and Default Probabilities," *Journal of The American Real Estate and Urban Economics Association*, Vol. 21, No. 1, pp. 247-263.

[53] Kau, J. B., D. C. Keenan, W. J. Muller, and J. F. Epperson, 1992, "A Generalized Valuation Model for Fixed-Rate Residential Mortgages," *Journal of Money, Credit and Banking*, Vol. 24, No. 3, pp. 279-299.

[54] Kau, J. B., D. C. Keenan, W. J. Muller, and J. F. Epperson, 1995, "The Valuation at Origination of Fixed Rate Mortgages with Default and Prepayment," *The Journal of Real Estate Finance and Economics*, Vol. 11, No. 1, pp. 5-36.

[55] Kiyotaki, N., and J. Moore, 1997, "Credit Cycles," *Journal of Political Economy*, Vol. 105, No. 2, pp. 211-48.

[56] Kumar, S. M., and A. Persaud, 2002, "Pure Contagion and Investors' Shifting Risk Appetite: Analytical Issues and Empirical Evidence," *International Finance,* Vol. 5, No. 3, pp. 401-436.

[57] Kuttner, K. N., 2001, "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, Vol. 47, No. 3, pp. 523-544.

[58] Kwan, S., 2001, "Rising Junk Bonds Yields: Liquidity or Credit Concerns?" Federal Reserve Bank of San Francisco, *Economic Letter*, No. 2001-33, November 16.

[59] Kwan, S., 2009, "Behavior of Libor in the Current Financial Crisis," Federal Reserve Bank of San Francisco, *Economic Letter*, No. 2009-04, January 23.

[60] Lown, C. S., and D. P. Morgan, 2006, "The Credit Cycle and the Business Cycle," *Journal of Money, Credit, and Banking*, Vol. 38, No. 6, pp. 1575-1597.

[61] Mattey, J., and N. Wallace, 2001, "Housing-Price Cycles and Prepayment Rates of US Mortgage Pools," *Journal of Real Estate Finance and Economics*, Vol. 23, No. 2, pp. 161-184.

[62] Meeks, R., 2011, "Do Credit Market Shocks Drive Output Fluctuations? Evidence from Corporate Spreads and Defaults," *Journal of Economic Dynamics and Control*, forthcoming.

[63] Pennington-Cross, A., 2010, "The Duration of Foreclosures in the Subprime Mortgage Market: A Competing Risks Model with Mixing," *The Journal of Real Estate Finance and Economics*, Vol. 40, No. 2, pp. 109-129.

[64] Pennington-Cross, A., and G. Ho, 2010, "The Termination of Subprime Hybrid and Fixed-Rate Mortgages," *Real Estate Economics*, Vol. 38, No. 3, pp. 399-426.

[65] Pesaran, M. H., and Y. Shin, 1998, "Generalized Impulse Response Analysis in Linear Multivariate Models," *Economics Letters*, Vol. 58, No. 1, pp. 17-29.

[66] Phillips, R. A., E. Rosenblatt, and J. VanderHoff, 1995, "The Probability of Fixed and Adjustable Rate Mortgage Terminations", *Journal of Real Estate Finance and Economics*, Vol. 13, No. 2, pp. 95-104.

[67] Quigley, J. M., and R. Van Order, 1995, "Explicit Tests of Contingent Claims Models of Mortgage Default," *The Journal of Real Estate Finance and Economics*, Vol. 11, No. 2, pp. 99-117.

[68] Revelt, D., and K. Train, 1998, "Incentive for Appliance Efficiency in a Competitive Energy Environment: Random-Parameters Logit Models of Households' Choice," *Review of Economics and Statistics*, Vol. 80, No. 4, pp. 647-657.

[69] Romer, C. D., and D. H. Romer, 2004, "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, Vol. 94, No. 4, pp 1055-1084.

[70] Stock, J. H., and M. W. Watson, 2002, "Forecasting Using Principal Components from a Large Number of Predictors," *Journal of American Statistical Association*, Vol. 97, No. 460, pp. 1167-1179.

[71] Swinston, A. J., 2008, "A U.S. Financial Conditions Index: Putting Credit Where Credit is Due," IMF Working Paper No. 08/161, International Monetary Fund.

[72] Tarashev, N., K. Tsatsaronis, and D. Karampatos, 2003, "Investors' Attitude towards Risk: What Can We Learn from Options?" *BIS Quarterly Review*, June.

[73] Taylor, J. B., and J. C. Williams, 2008, "A Black Swan in the Money Market," Federal Reserve Bank of San Francisco, Working Paper No. 2008-04.

[74] Theil, H., 1971, *Principles of Econometrics*, New York: JohnWiley and Sons.

[75] Titman, S., and W. Torous, 1989, "Valuing Commercial Mortgages: An Empirical Investigation of the Contingent Claims Approach to Pricing Risky Debt," *Journal of Finance*, Vol. 44, No. 2, pp. 345-373.

[76] Train, K., 2009, *Discrete Choice Methods with Simulations*, Cambridge: Cambridge University Press.

[77] Vandell, K. D., 1993, "Handing Over the Keys: A Perspective on Mortgage Default Research," *Journal of The American Real Estate and Urban Economics Association*, Vol. 21, No. 3, pp. 211-246.