Essays on Structured Finance and Housing Markets

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ABSTRACT

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The fall in housing market prices has played a major role in triggering the Great Recession. This led to the collapse of markets for mortgage-backed securities, and to a precipitous fall in their ratings. This thesis studies the downgrading of mortgaged-backed Collateralized Debt Obligation (CDO), and the factors that drive mortgage default loans.

In Chapter 1, I look at the CDO market. The downgrading of the tranches of Collateralized Debt Obligation (CDO) products backed by real estate related assets has caused severe disruptions in the housing and financial markets. The rating agencies have been criticized for the opacity in the rating process of the CDO products and also for giving the CDO tranches higher ratings than they deserved. However, not enough attention has been paid to the decision making process of the agencies to downgrade the CDO tranches. We use data from Moody's CDO database to reconstruct the process through which Moody's eventually downgraded the tranches. We use a discrete hazard rate model to study the variables that were relevant in the downgrading of the tranches of the CDOs. The empirical results show that out of the many CDO

specific variables relevant to their ratings made available by Moody's few have any explanatory power beyond the Moody's Deal Scores (MDS). We show that the MDS could be explained by the changes in the Case-Shiller Composite-20 Index and Markit ABX.HE indices. Further analysis shows that Moody's mostly relied on the changes in the Case-Shiller indexes in revising the MDS.

In Chapter 2 I look at the factors that influence default rates. The chapter uses a Structural Vector Autoregression (SVAR) model to study the dynamics of the impact of unemployment and home price index shocks on mortgage default rates from 1979 to 2000 and from 2001 to 2010. We first fit the model to the 1979 to 2000 sample and forecast the changes in the national and regional mortgage default rates from 2001 to 2010. The model did a good job in forecasting the actual changes in the mortgage default rates from 2001 to 2007; however, it failed after 2008. The results for the 1979 to 2000 and 2001 to 2010 periods indicate that the dynamic response of the mortgage default rate to unemployment and home price index shocks changed at the national, regional and state levels after 2000. Unemployment and home price shocks seem to have become more important during the 2001 to 2010 period. The two shocks are responsible on average for about 60% of the movement in the regional mortgage default rates during this period. Except for the Pacific region, California and Florida, most of the variations in the mortgage default rates at the national, regional and state levels are explained by the unemployment shocks. The post 2000 results could be attributed to the increase in the number of mortgage loan borrowers who were more susceptible to unemployment and negative home price shocks.

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Dedication

To My Mom Afia

Chapter 1

What Went Wrong? Examining Moody's Rated CDO Data

1.1 Introduction

Collateralized Debt Obligations (CDO) pool economic assets (e.g. loans, bonds, mortgage account receivables, etc.) and issue multiple classes of financial claims with different levels of seniority (or tranches) against the collateral pool. Individual asset risk should be diversified so long as the pooled assets are not perfectly correlated. CDOs bundle the cash flows from the underlying assets, which are often illiquid receivables, into tradable tranches. This theoretically facilitates the redistribution of risks within the financial sector, which could have a positive impact on financial stability. More importantly, the structured nature of the claims with different levels of seniority makes it possible for investors with different risk profiles to participate in this market. The increase in the packaging of mortgage loan related assets into CDOs during the 2003 to 2007 period contributed to improved liquidity for mortgage loans and lower borrowing costs for borrowers. However, during the 2008 to 2012 period, the collapses of these CDOs have contributed to the problems in the housing markets and also in the development of the ongoing financial crises. From the Securities Industry and Financial Markets Association (SIFMA), total[1] CDO issuance increased from $86B in 2003 to a peak of $481B in 2007. The total issuance then fell to $4.3B in 2009 before rising modestly to $10.8 in the first 2

[1] This includes mortgage related assets, car loans, student loans, etc.

quarters of 2012. The fall in the CDO origination has important implications for liquidity and borrowing costs for the mortgage market going forward.

The collapse in the CDO market was triggered by the wholesale downgrading of the tranches of the CDOs by the rating agencies. After the downgrades, financial institutions that have invested[2] in the CDO products incurred significant losses on their CDO holdings; which have led to big write-downs. The downgrades also forced some institutional investors (who were also major investors in the CDOs) to hold fire sales of their CDO holdings, thereby pushing the values of the CDO products even further down. The big three rating agencies (Moody's, S&P and Fitch) have been under criticism for their role in the collapse of the CDO market. They have been faulted for the opacity in the rating process of the CDOs, for using incorrect rating methodologies and assumptions, and also for not demanding more information from mortgage borrowers initially. There have also been conflict of interest questions raised about the relationship between CDO issuers and the rating agencies: in some cases the agencies helped the CDO issuers package the underlying assets to garner a specific rating by setting up ancillary consulting services. As a result of the large fees[3] the rating agencies were making from rating these CDOs and also from helping to package them, they may not have been as alert as they should have been. The CDO issuers could also shop[4] for better ratings, which put a lot of pressure on the rating agencies to give favorable ratings to the CDOs. Given the size and complexity of the collaterals (in some cases these assets are themselves tranches of other CDOs) in the CDO deals, it was costly for investors to independently price and evaluate all the assets in the collateral pool. As such, they relied on the ratings giving by the rating agencies to access

[2] Some were also major underwriters of the CDO deals.
[3] This represented a significant portion of their revenues.
[4] Becker and Milbourn (2011), Faltin-Traeger and Bolton et al. (2012), Skreta and Veldkamp (2009)

their credit risks and also make their investment decisions. The agencies created a perception[5] that the rated CDOs had the same risk as similarly rated corporate bonds. This attracted a lot of investors to these highly rated CDOs, fuelling the growth of the CDO market during the 2003 to 2007 years.

There have been different theories as to why the CDOs backed by real estate assets were downgraded massively during the recent financial crisis: (1) the underlying assets were of low quality to begin with and they deteriorated in value during the financial crisis causing the CDOs to fail the quality tests required to support their initial ratings. (2) The variables, default correlation[6] in particular, pertinent for the ratings of the CDOs were underestimated (the so-called "underestimation theory") leading the agencies to give generous ratings to the CDOs. As these variables were revised during the crisis the tranches of the CDOs were downgraded accordingly. (3) The ratings methodology employed by the agencies to rate the CDOs was faulty.

Obtaining reliable data on CDOs is difficult, since CDOs are not actively traded on exchanges. I have been fortunate to be given access to one of the most extensive data on CDOs compiled by Moody's Corporation. With this data this paper throws some much-needed light on how CDOs backed by real estate assets were downgraded in 2008 and 2009.

The share of real estate related assets in CDO products increased significantly after 2003 when other assets—franchise loan Asset Backed Securities (ABS), aircraft lease ABS, High Yield Collateralize Bond Obligations etc.—fared badly after the 2001-2002 economic recession. The total percentage of subprime, alternative and prime mortgage loan related assets which made up only about 15% of the total assets in CDO products in 2000 increased to over 80% by 2006.

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[5] Given their role as the assessors of credit risk (Nationally Recognized Rating Organization (NRSRO) designation) their ratings of the CDO were taken at face value. The ratings were relied on for investment and capital requirements decisions.

[6] This measures the default correlation of the underlying assets. A low default correlation value assigned to a CDO implies most of its tranches would be highly rated.

Real estate related assets became the main collateral in the CDO deals during the securitization boom.

For the CDO deals backed by real estate related assets included in the study, about 70% of the tranches were rated A or better. At the end of the sample period (May 2009), only 52% of the tranches rated AAA were still rated AAA, only 58% of the AA tranches were still rated AA and only 14% of A tranches were still rated A.

We use a discrete hazard rate model to study the variables that were relevant in the downgrading of the tranches of the CDOs backed by real estate related assets. Two categories of downgrading[7] are studied: (A) A CDO is considered downgraded if any of its tranches is downgraded, or (B) A CDO is considered downgraded if its AAA tranche is downgraded. Besides CDO specific variables that are important in the ratings of the CDOs made available by Moody's the paper also considers some CDO specific variables that might contribute to their downgrading. In addition, we also make use of Moody's Deal Scores (MDS) assigned to the CDO deals. The MDS are internally generated scores which range from -10 (best) to +10 (worst). Moody's does not release information on what they take into account when calculating the scores for the CDO deals.

For both categories of downgrading considered, (A) and (B), changes in the Moody's Deal Scores (MDS) assigned to the CDOs by Moody's are the only variable that explains tranche downgrades. However, the changes in the Moody's Deal Scores could not easily be explained by the changes in the CDO specific variables, implying that a significant variation of the MDS is based on outside information. We show that the evolution of the MDS could be explained by the changes in the Case-Shiller Composite-20 index (which measures the changes in the total value of all existing single-family housing stock) and the Markit ABX.HE indices (which track the

[7] Check Appendix A

prices of credit default swaps (CDS) of mortgage backed security) two months before Moody's adjusted the scores they gave to the deals. This suggests that Moody's based its rating changes on external housing market information than CDO-specific information. The fluctuations in the Case-Shiller Composit-20 and the Markit ABX.HE indexes provide Moody's with extra information in addition to the CDO specific variables to better assess the riskiness of the CDO deals. A further analysis measuring the relative importance of the Case-Shiller Composite-20 index and the ABX.HE indices in the evolution of the MDS showed that Moody's relied more on the changes in the Case-Shiller Composite-20 index in revising the MDS.

The paper does not find empirical support for the default correlation "underestimation theory". The overwhelming factor in the wholesale downgrading of the tranches of the CDOs backed by real estate related assets during the crisis was the collapse in the housing market.

The paper contributes to the growing empirical literature that has been examining CDO deals at the micro level. Coval et al (2009) documented some of the challenges faced by the rating agencies, in particular, the parameter and modeling assumptions that are required to arrive at accurate ratings of structured finance products. Coval et al concluded that, unlike traditional corporate bonds, whose fortunes are primarily driven by firm-specific considerations, the performance of securities created by tranching large asset pools is strongly affected by the performance of the economy as a whole. Benmelech and Dlugosz (2009) presented evidence on the relation between CDO credit ratings and the quality of the underlying collateral backing these securities. A large fraction of the CDO tranches in their sample had AAA[8] ratings (70%). They provided evidence which showed a mismatch between the rating of CDO tranches and the credit quality of the underlying assets supporting these tranches; while the credit rating of the majority

[8] Griffin and Tang (2012) also pointed to this mismatch.

of the tranches is AAA, the average credit rating of the collateral is B+[9]. Mason and Rosner (2007) showed that many of the difficulties in the CDO market backed by real estate related assets could be attributed to the incorrect ratings given to them. The incorrect ratings were a result of rating agencies rating CDO products by misapplying the methodologies used for rating corporate bonds. This methodological issue was further compounded by the inaccurate estimates of the underlying variables (e.g. default correlation of the underlying assets, etc.).

Our conclusion is similar to the conclusions reached by these papers: (1) we also observed in our analyses, limited to CDO ratings of mortgaged related assets, that CDO ratings are more affected by the performance of the economy as whole rather than CDO-specific variables. (2) The diversification benefit which was expected from pooling all the different assets, thereby influencing the ratings of CDOs backed by mortgage related assets, was not as potent as initially thought.

The paper proceeds as follows. Section 2 Introduces CDO. Section 3 discusses the general characteristics of the CDO deals included in the study. Section 4 compares the CDOs backed by real estate related assets to CDOs backed by other assets. Section 5 discusses how the downgrading of the CDOs backed by real estate related assets occurred. Section 6 presents the Hazard Model. Section 7 presents the causality model. Section 8 concludes.

1.2 Background: CDO

Collateralized Debt Obligation (CDO) is an example of Structured Finance (SF) product backed by a diversified pool of one or more classes of debt e.g., corporate and emerging market bonds, asset backed securities (ABS), mortgage backed securities (CMBS and RMBS), real

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[9] Faltin-Traeger and Mayer (2012) among others also found evidence of this.

estate investments trust (REIT), bank debt, synthetic credit instruments, such as, credit default swaps (CDS), notes issued by special purpose entity (SPE), future receivables, loans, etc. CDOs can also be backed by the tranches of other CDOs (CDO-squared) and other SF products[10].

The CDO structure consists of an asset manager in charge of managing the portfolio. The funds needed to purchase the underlying assets are obtained from the issuance of debt obligations. The debt obligations are also referred to as tranches, and they are:

- Senior tranches
- Mezzanine tranches
- Equity tranche

A rating is sought for all but the equity tranche. The tranches are prioritized depending on how they absorb losses from the underlying assets in case of default. Senior tranches only absorb losses after the mezzanine and equity tranches have been exhausted. This allows the senior tranche to get a credit rating higher than the average rating of the underlying assets as a whole. The senior tranche usually attracts at least an A rating. Since the equity tranche receives the residual cash flow, no rating is sought for the tranche. Figure 1 shows the basic CDO structure:

[10] According to Moody's , the percentage of CDOs that had other structured assets as their collateral increased from 2.6% in 1998 to 55% in 2006 as a fraction of the total notional of all securitization. In 2006 alone, issuance of structured CDO reached $350B in notional value (Hu, 2007).

Figure 1 Basic CDO Structure

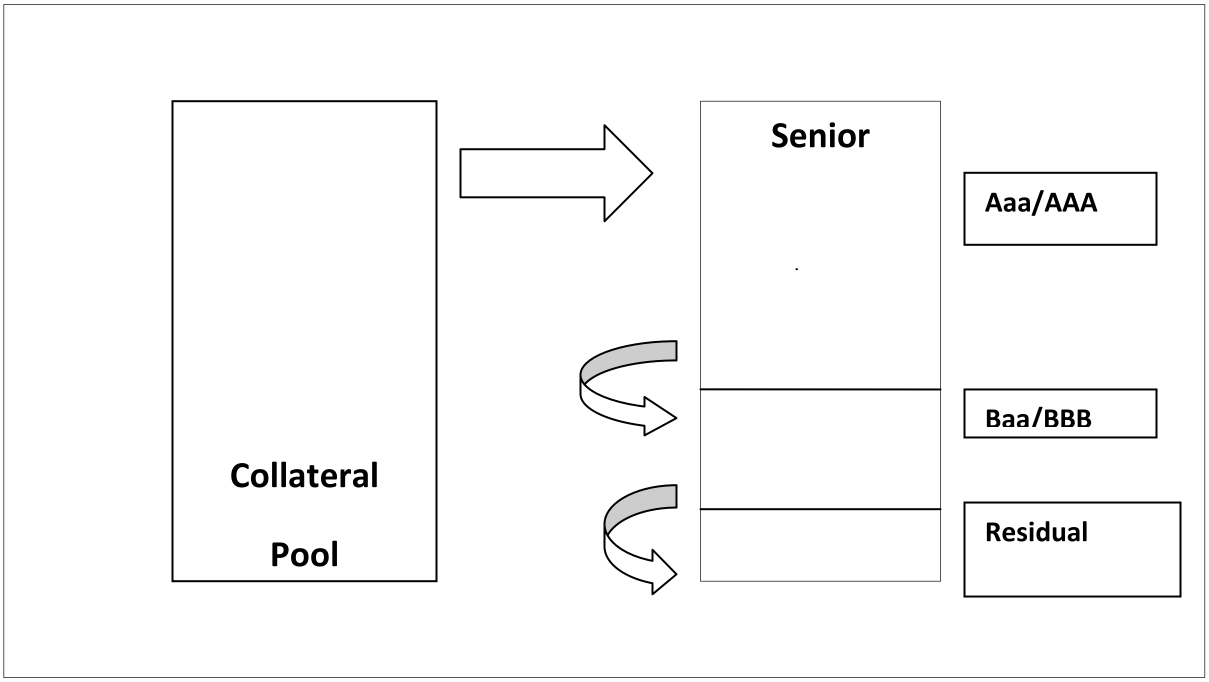


Table 1.1 is an example that shows the percentage of losses that has to be absorbed by the lower tranches before the senior tranche is affected: 5% of the notional value of the underlying assets has to default before the coupon and principal payments to the mezzanine tranches get affected. For all defaults below 5%, the only investor who gets affected is the equity tranche investor. The senior tranche does not get affected until 15% of the underlying asset defaults.

Table 1.1

This table shows the percentage of losses that has to be absorbed by the lower tranches in the case of impairment before the higher tranches could be affected.

Tranche Name	Attachment Point	Detachment Point
Equity	0	5%
Mezzanine	5%	15%
Senior	15%	100%

Table 1.2 below[11] illustrates a payment structure of a cash-flow CDO. The cash outlay to the tranche investors is the coupon payment times the principal outstanding. The equity tranche receives a higher coupon rate than the other two tranches because it is the first tranche to be affected in case of asset defaults, so it is relatively riskier than the other tranches.

Table 1.2

This table illustrates a basic cash-flow $200 million CDO structure with coupon rate offered at the time of issuance.

Tranche	Par Value	Coupon Rate
Senior	$120,000,000	Libor + 70 b.p
Mezzanine	70,000,000	Libor + 200 b.p
Equity	10,000,000	Libor + 700 b.p

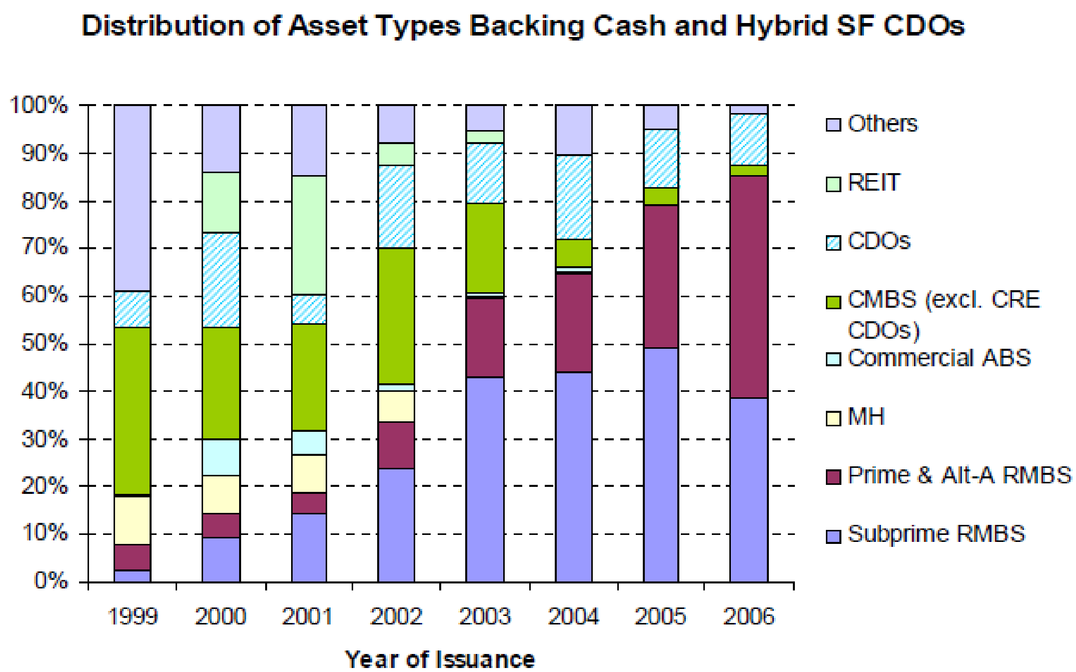
Coverage tests[12] are run to make sure that the CDO is performing within prespecified guidelines before any payments are made to the mezzanine and equity tranches. The prespecified guidelines are included in the prospectus given to investors before the tranches of the CDOs are sold. If the CDO faults the coverage tests, then excess interest on the portfolio are diverted to pay the interest and principal on the senior tranche from the mezzanine and equity tranches. Quality Tests that deal with maturity restrictions, the degree of diversification, and credit ratings of assets in the collateral portfolio must also be satisfied for the tranches of the CDO to maintain the credit rating assigned at the time of issuance.

[11] This example is a modified version of the examples in Goodman and Fabozzi (2002).

[12] The information about the tests is provided in the prospectus before the sale. Coverage tests are designed to protect note holders against deterioration of the existing portfolio. There are two categories of tests—overcollateralization tests (OC) and interest coverage (IC) tests. The OC for a tranche is found by computing the ratio of the principal balance of the collateral portfolio over the principal balance of the tranche and all tranches senior to it. The higher the ratio, the greater protection for the note holders; the value is usually compared to the required minimum ratio specified in the guidelines. The IC test is the ratio of scheduled interest due on the underlying collateral portfolio to scheduled interest to be paid to that tranche and all the tranches senior to it. Again the higher the IC ratio, the greater the protection; the value is usually compared to the required minimum ratio specified in the guidelines.

The share of real estate related assets in CDO products increased significantly after 2003 partly due to the increase in home price appreciation after the 2001-2002 recessions. The cash and hybrid SF CDO (these two make up over 90% of the total CDO issued) deals rated by Moody's had more than 80% of its collateral comprise of real estate related assets, especially, subprime residential mortgage backed securities (RMBS) by 2006. Figure 2 shows the distribution of CDO underlying asset types over the years. Since 2001, the share of the Subprime, Alt and Prime RMBS has increased over time.

Figure 2



Hu (2007); Exhibit 5

1.3 Data

The data was obtained from Moody's and it contains information (collateral, deal and tranche levels) on Moody's rated CDO deals. The data on the underlying assets of the CDO deals are: the type of the assets (loans, equity, or bond), the price that was paid for the underlying assets, who rated the included assets (Moody's, Fitch or S&P), the recovery rate of the underlying assets, industry classification of the assets, the expected average life of the assets, yield to maturity of the assets, seasoning (how long the assets have been in existence) etc. The deal level data include: the notional values of the CDOs, the par value of the defaulted securities, the par value of the defaulted securities loss, principal and interest cash collected from the underlying assets, The tranche level data include the initial and current ratings of the tranches, the amount of each tranches issued in relation to the total value of the CDO deal, coupon rate of the tranches, the estimated net asset value of the tranches, and the attachment and detachment points of the tranches.

1.3.1 Deals Included

The sample is divided into three categories: (a) All CDOs backed by collateral consisting of only real estate related assets[13] (Real Estate), (b) All CDOs backed by collateral consisting of only non-real estate related assets (Non Real Estate), and (c) All CDO backed by both real estate related assets and non-real estate related assets (Mixed).

[13] CMBS, RMBS, Mortgage loans, etc.

There are 1936 Moody's rated CDOs included in this study[14]; of which 1119 are only Real Estate Deals, 121 are Non Real Estate Deals, and 696 are Mixed Deals by my classification.

1.3.2 Total Tranche Amount of the Deals

Table 1.3 reports the average par value of the collateral of the deals included in the study. The Real Estate only deals have an average of $902M, the Non Real Estate deals have an average of $243M and the Mixed deals have an average of $550M.

Table 1.3
Original Par Value of Collateral
This table reports the total amount of issued tranches in the CDO deals ($Million)

Type of CDO	Max	Min	Mean	Standard Deviation
Real Estate	163666	5	902	4328
Non Real Estate	1716	0.65	243	228
Mixed	50000	6	550	632

1.3.3 Types of Tranches

About 85% of the tranches of the Real Estate deals were either senior or mezzanine (both these tranches are rated). Since losses are allocated from the bottom up, it takes significant losses from the underlying assets for the senior tranches to be affected when there are large numbers of mezzanine tranches. The Real Estate CDO deals have more mezzanine tranches, making the senior tranches more attractive to investors since they are better "protected" from losses.

[14] About 674 of the deals from the Moody's database were not included because we could not classify the underlying assets into the three categories.

Table 1.4
Types of Tranches
This table reports the types of tranches issued

Type of CDO	Senior	Mezzanine	Subordinate(Equity)
Real Estate	2582(30%)	4872(56%)	1207(14%)
Non Real estate	395(58%)	184(27%)	98(14%)
Mixed	2026(45%)	1675(37%)	794(18%)

1.3.4 Tranche Ratings

Due to the costs involved for investors to independently monitor all the assets in a CDO portfolio, investors rely on the credit ratings of the CDOs to judge how risky they are and also to make investment decisions. In the absence of hard data on some of the assets underlying the CDO products, the rating agencies make assumptions about the values of these variables and rely mainly on simulations to determine the ratings they give to the CDOs. For example, until 2007, Moody's did not require issuers seeking ratings on products backed by mortgages to provide information on borrowers' debt-to-income ratio, appraisal type and which lender originated the loan.[15] There is also very limited empirical work on CDO tranche losses in the event of defaults due to their very short history

1.3.4.1 How CDOs are Rated

According to Moody's Approach to Rating Multisector CDOs (2000), Moody's consider these variables in determining CDO Ratings:

- Collateral diversification
- Likelihood of default of underlying assets
- Recovery rates

[15] Moody's Revised US Mortgage Loan-by-Loan Data Fields, April 3, 2007

Collateral Diversification*:* a *diversity score* is calculated by dividing the assets in the CDO portfolio into different classifications. This also measures the default correlation of the underlying assets. A higher diversity score implies that it is less likely that all the assets would default at the same time. It plays a very important role in the ratings of the tranches; depending on how high the diversity score is, a large fraction of the issued tranches can end up with a higher rating than the average rating of the underlying pool of assets. This means that there will be a bigger percentage of higher-rated tranches (senior and mezzanine) in the CDO. To get a high diversification score, a CDO will normally include a lot of different securities.

Likelihood of Default is provided by the *weighted average rating factor* (WARF). The WARF is a guide to asset quality of the portfolio and is meant to incorporate the probability of default for each of the bonds in the CDO. For example, a WARF score of 610 means that there is a 6.1% probability of default for each independent and uncorrelated asset in 10 year period.

Recovery Rates are dependent on the desired rating of the CDO tranche. Ratings agencies have data on the historical recovery rate[16] of bonds they have rated, and based on this data they calculate a weighted recovery rate for the portfolio.

The agencies have an expected loss permissible for each CDO tranche to garner a specific rating. For each tranche of the deals, a simulated expected loss is compared to the maximum permitted for any given rating.

Table 1.5 reports the distribution of the initial ratings for the Real Estate (8661 total tranches), Non Real Estate (677 total tranches), and Mixed (4495 total tranches). The equity tranches are not rated. About 90% of the Moody's rated tranches of the Real Estate Deals were rated BBB or better (investment grade), about 86% for the Non Real Estate deals, 87% of the

[16] Recovery rates are calculated based on the secondary price of the defaulted instrument one month after default.

Mixed Deals. Only 2 tranches out of a total of 10487 tranches were rated CCC or lower ("Junk grade").

Table 1.6 reports the distribution of the tranches as of May 13th 2009. About 59% of the tranches of the Real Estate CDOs were downgraded[17] to B or lower ("Junk"), about 30% of the Non Real Estate deals were downgraded to B or lower, and about 42% of the Mixed CDOs were downgraded to B or lower.

Table 1.5
Initial Moody's Rating[18]
This table reports the initial Moody's rating for the tranches

Type of CDO	AAA	AA	A	BBB	BB	B	CCC	CC	C
Real Estate	2295	1211	1191	1319	669	27	0	0	0
Non Real estate	157	70	58	125	52	17	0	1	0
Mixed	1084	519	498	781	382	31	1	0	0

[17] A transition matrix for the Real Estate CDOs is provided in Table 1.12.
[18] The equity portion of the tranches is not rated.

Table 1.6
Current Moody's Rating
This table reports the current Moody's rating for the tranches as of 05/13/2009

Type of CDO	AAA	AA	A	BBB	BB	B	CCC	CC	C
Real Estate	1317	816	217	615	646	651	506	434	1730
Non Real estate	6	17	8	13	17	17	27	46	56
Mixed	344	272	142	256	288	253	223	190	442

1.4. Comparisons

This section reports some of the characteristics of the underlying assets for the three categories of the CDO deals: Real Estate, Non Real Estate and Mixed.

1.4.1 Average Weighted Seasoning of Collateral

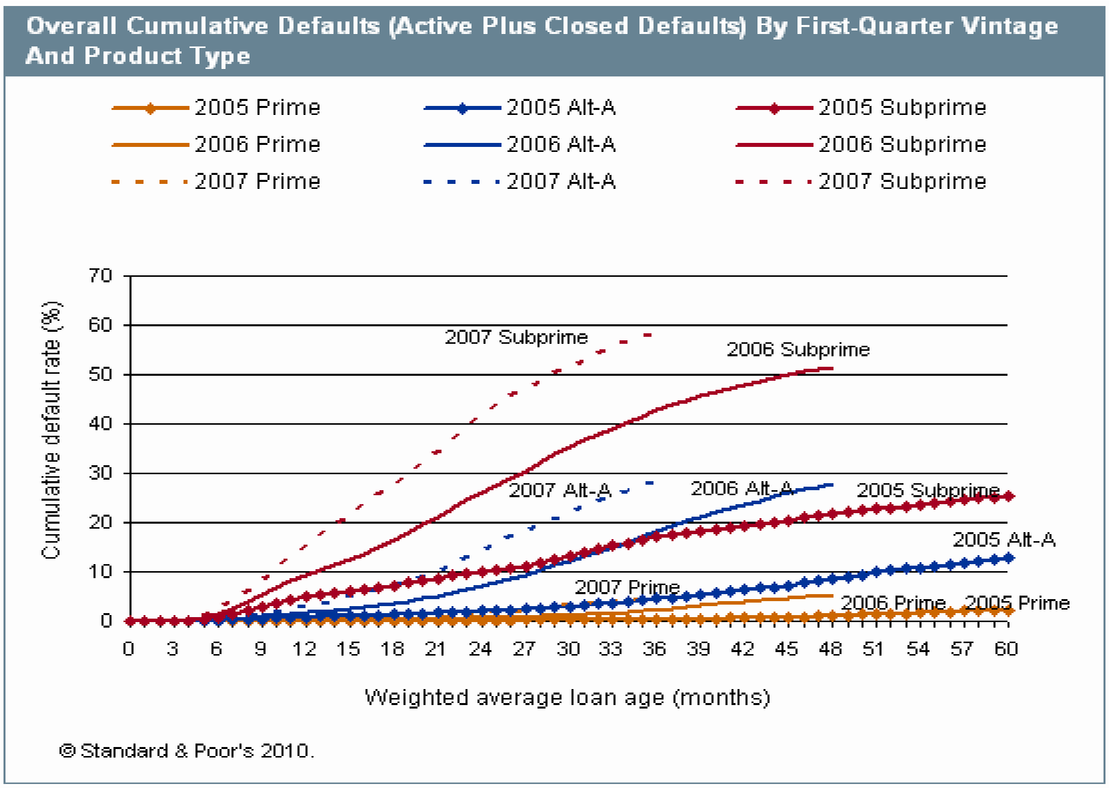
On average the securities in the Non Real Estate deals are more seasoned than the Real Estate Deals.

Table 1.7
This table reports the average number of years since the securities in the collaterals were issued.

Type of CDO	Max	Min	Mean	Standard Deviation
Real Estate	23.667	0.08	3.190	1.384
Non Real estate	22.417	0.08	6.380	3.134
Mixed	39.167	0.08	5.27	2.759

Figure 3 shows a graph of the cumulative defaults rates of subprime, Alt-A and Prime mortgage loans compiled by Standard and Poor's. The cumulative default metric includes both "active defaults" (seriously delinquent loans that have not been liquidated yet and "closed defaults" loans that have already being liquidated. As it appears from Table 1.8, a large percentage of Real Estate CDOs contain a significant amount of mortgage loans, especially, subprime loans[19], as figure 3 shows even after three years (36 months) the cumulative default rate for the subprime loan is yet to plateau, this is especially true of the subprime 2005, 2006 and 2007 loans which make up the bulk of the underlying loans in the real estate related assets backed CDOs.

Figure 3



1.4.3 Types of Assets in Collateral of the Deals

A large fraction of the Real Estate CDO deals issued over the course of the last several years have subprime loans, and subprime RMBS as the underlying asset. The increase in the mortgage loan default rates from 2007 to 2009 affected subprime mortgage loans the most. Some

[19] 2004, 2005, 2006 2007 vintages

of the CDOs are themselves also made of tranches[20] of other CDOs and asset backed securities. It is also difficult for Moody's to incorporate ratings of CDO products into their model, especially, if they are rated by other agencies. Moody's noted in their *CDO Asset Exposure Report* 2006 that it takes between three to seven weeks to normally incorporate ratings change from other agencies into their own CDO ratings for CDO-squared deals. The percentage of the Real Estate deals with mortgage loans as their underlying asset is about 60%.

Table 1.8

Type of Collateral

This table describes the number and percentage of the deals with these types of collateral

Type of CDO	Loan	Equity	CDO	Bond	ABS	RMBS/MBS/CMBS
Real Estate	671(60%)	46(4%)	306(27%)	467(42%)	168(15%)	240(21%)
Non Real Estate	45(37%)	57(47%)	17(14%)	81(67%)	9(7%)	0
Mixed	314(45%)	136(20%)	126(18%)	456(66%)	32(5%)	107(15%)

1.4.4 Weighted Average Maturity

On average, the securities in the collateral of the Real Estate deals have more years left for them to mature. As a result, the Real Estate deals might be subject to more market risk.

Table 1.9

Weighted Average Maturity

This table reports the par weighted average life of the securities in collateral (in other words, the average years left for the securities in the collateral to mature)

Type of CDO	Max	Min	Mean	Standard Deviation
Real Estate	24.51	0	13.859	11.171
Non Real estate	29.621	0	5.30	4.284
Mixed	49.970	0.08	10.37	8.459

[20] Usually the mezzanine tranches.

1.5 How the Downgrades Occurred

This section provides more information about the tranche downgrade process. There are 1119 Real Estate CDO deals in the data. The deals have a total of 8661 tranches of which 6712 are rated.[21] 4344 (65%) of the tranches have been downgraded from their initially assigned ratings. 94 (out of a total of 1119) of the CDO deals have never had any of their tranches downgraded. 1025 of the CDO deals have at least one of their tranches downgraded. Of the 1119 Deals, 989 have AAA tranches; 415 of the CDO deals had had their AAA tranche downgraded.

Table 1.10
Initial Moody's Rating
This table reports the initial Moody's rating for the Real Estate backed CDO tranches

Type of CDO	AAA	AA	A	BBB	BB	B	CCC	CC	C
Real Estate	2295	1211	1191	1319	669	27	0	0	0

[21] The equity tranches are usually not rated.

Table 1.11
May, 13 2009 (Final Date)

This table reports the final transition ratings matrix of the tranches as of May, 13 2009 in percentages. The rows represent the initial ratings of the tranches, and the columns represent the ratings as of May, 13, 2009

	AAA	AA	A	BBB	BB	B	CCC	CC	C	WR[22]
AAA	52%	2%	1%	1%	1%	2%	4%	12%	21%	6%
AA	0	58%	1%	1%	1%	2%	2%	4%	29%	3%
A	0	0	14%	22%	24%	2%	2%	3%	29%	4%
BBB	0	0	0	19%	16%	26%	3%	3%	30%	4%
BB	0	0	0	0	9%	25%	38%	3%	21%	3%
B	0	0	0	0	0	11%	44%	26%	15%	4%

Only 52% of the tranches rated AAA were still rated AAA on May, 13 2009; 37% were downgraded to CCC or lower. Also, only 58% of the AA tranches were still rated AA, most were downgraded to CCC or lower. There seem to be shorter jumps in the downgrading of the lower tranches compared to the AAA and AA tranches of the CDOs.

[22] WR indicates the rating was withdrawn by Moody's but no new ratings were given.

1.6 Explaining Downgrades

The downgrading of the CDO tranches caused investors to write down significant amounts of money on their highly-rated CDO holdings, especially during the 2008-2009 financial crisis. This section proposes a model to explain the downgrade probability of CDOs backed by real estate related assets. The observation window is from 1st Quarter of 2008 to 1st Quarter of 2009.[23] Two definitions of downgrading are studied: (a) A CDO is considered downgraded if any of its tranches is downgraded, (b) A CDO is considered downgraded if its AAA tranche is downgraded. In addition to the default correlation and a measure of the quality of the underlying asset, the paper also considers some CDO specific characteristics that might contribute to their downgrading. In addition, we also make use of Moody's Deal Scores (MDS).

1.6.1 Estimation Procedure—Discrete Hazard Rate Model

The framework chosen for the analysis is a discrete time proportional hazard rate model. Let T^i be a discrete duration random variable for a CDO i, where $i = \{1, \dots, n\}$

The conditional hazard rate, $h(j, x_i(j))$, is the probability of a downgrade of CDO i in any Quarter j given covariates $x_i(j)$:

$$(1) \qquad h\big(j, x_i(j)\big) = \Pr(T^i = j \parallel T^i \geq j, x_i(j))$$

The survival probability at Quarter j is defined as the probability of a CDO i not experiencing a downgrade, which is defined as:

[23] This is the period during which most of the downgrading occurred in the sample.

$$(2) \qquad S\big(j, x_i(j)\big) = \Pr\Big(T^i > j \parallel j, x_i(j)\Big)$$

$$= \Pr\Big(T^i \neq j \parallel T^i \geq j, x_i(j)\Big) \times \Pr\Big(T^i \neq j-1 \parallel$$

$$T_t^i \geq j-1, x_i(j)\Big) \ldots \times \Pr\Big(T^i \neq 1 \parallel T^i \geq 1, x_i(j)\Big)$$

$$= \prod_{\mathrm{k=1}}^{\mathrm{j}} \Big(1 - h\big(k, x_i(k)\big)\Big)$$

Suppose the duration of the study is made up of J Quarters periods. A CDO i could be downgraded in any Quarter j, which implies that $T^i = j_i$ or the study concludes without being downgraded, i.e. $T^i > J$, in other words, the CDO is censored.

For the uncensored CDOs with $T^i = j_i$, the likelihood may be expressed in terms of the hazard as:

$$(3) \qquad P(T^i = j_i)$$

$$= \Pr\Big(T^i > j_i \parallel T^i \geq j_i, x_i(j_i)\Big)$$

$$\times \Pr\Big(T^i \neq j_i \parallel T^i > j_i - 1, x_i(j_i)\Big) \ldots \times \Pr\Big(T^i \neq 1 \parallel T^i > 1, x_i(j_i)\Big)$$

$$= h\big(j_i, x_i(j_i)\big) \times \prod_{\mathrm{k=1}}^{j_i - 1} \Big(1 - h\big(k, x_i(k)\big)\Big)$$

For the censored CDO, $T^i > J$ (which implies $j_i > J$), let us assume that $j_i = J + 1$, then the likelihood can be expressed as:

$$(4) \qquad P(T^i > J) = P\big(T^i > j_i - 1\big) = \prod_{\mathrm{k=1}}^{j_i - 1} \Big(1 - h\big(k, x_i(k)\big)\Big)$$

The likelihood for the full sample is:

$$(5)\ L = \prod_{i=1}^{n}\left[h\big(j_i, x_i(j_i)\big) \times \prod_{k=1}^{j_i-1}\Big(1 - h\big(k, x_i(k)\big)\Big)\right]^{d_i}\left[\prod_{k=1}^{j_i-1}\Big(1 - h\big(k, x_i(k)\big)\Big)\right]^{1-d_i}$$

Where $d_i = 1$ if the ith CDO is uncensored and zero otherwise.

The log likelihood function can then be expressed as:

$$(6)\ LogL = \sum_{i=1}^{n} d_i logh\big(j_i, x_i(j_i)\big) + \sum_{i=1}^{n}\sum_{k=1}^{j_i-1} log\left(1 - h\big(k, x_i(k)\big)\right)$$

In this study, there are five quarters: $j = \{1,2,3,4,5\}$[24]

1.6.2 Data

The data consist of quarterly CDO variables from January 2008 to April 200. Section 6.2.A reports the summary statistic of the CDOs that have had any of their tranches downgraded during this period and section 6.2.B reports the summary statistics of the CDOs that have had only its AAA tranches downgraded.

1.6.2.A—Summary Statistic of the CDOs with any of their Tranches Downgraded

Table 1.12 reports the average statistics of the differences[25] in the Moody's Deal Scores for the downgraded (D) and the non-downgraded (ND) CDOs in four Quarters. The trend shows

[24] The periods are from 1st Quarter of 2008 to 1st Quarter of 2009.

that before the downgrading of the tranches occurred the Moody's Deal Scores were revised upwards by Moody's.

Table 1.12

This table reports the summary statistics of the averages of the differences of the Moody's Deal Scores for the downgraded (D) and the non-downgraded (ND) deals. The differences are calculated as follows: in Quarter (2, 3, 4, and 5), the difference of the MDS, $\Delta MDS = MDS_t - MDS_{t-1}$, are calculated for both the downgraded and the non-downgraded deals.

Quarter		**∆MDS**	
		ND	**D**
2	Mean	0.19	**1.07**
	SD	0.81	**1.44**
3	Mean	0.07	**2.02**
	SD	0.57	**1.76**
4	Mean	0.02	**2.25**
	SD	0.25	**1.76**
5	Mean	0.96	**1.53**
	SD	0.77	**0.49**

Table 1.13 reports the dynamics of the downgraded deals and the non-downgraded deals over the five Quarters. The percentage of the assets in the CDO portfolio that are rated at CCC or below (PR) is higher for the downgraded CDOs than the non-downgraded CDOs in all the quarters. The CDOs with higher weighted average maturity (WAM) were downgraded earlier than the other CDOs. The weighted average coupons (WAC) of the bond securities in the CDO

[25] The differences are calculated as follows: in Quarter (2, 3, 4, and 5), the difference of the MDS, $\Delta MDS = MDS_t - MDS_{t-1}$, are calculated for both the downgraded and the non-downgraded deals. The variables of the downgraded CDOs are not collected anymore after the Quarter in which it was downgraded; each Quarter presents new deals that were downgraded in that Quarter.

portfolios are higher for the non-downgraded CDOS in all the Quarters. Likelihood of Defaults (represented by the WARF factor of the CDOs), did not exhibit the trend which was expected except for the second and third quarters.

Table 1.13

This table reports the summary statistics of variables for the downgraded CDOs (D) and non-downgraded CDOs (ND). The values represent the average quarterly values from 01/2008 to 03/2009.

Quarter		CD		WARF[26]		WAM		PR		WAS		WAC	
		ND	**D**	ND	**D**	ND	**D**	ND	**D**	ND	**D**	ND	**D**
1	Mean	62.4	**34.6**	2.17	**1.21**	8.23	**26.3**	3.39	**8.25**	2.51	**1.56**	8.39	**5.67**
	SD	18.2	**20.2**	0.71	**1.00**	7.85	**5.06**	3.89	**9.81**	0.77	**0.72**	2.19	1.14
2	Mean	61.4	**39.6**	2.05	**3.21**	7.66	**25.9**	4.23	**24.4**	2.56	**1.41**	8.17	**5.58**
	SD	17.8	**24.0**	0.70	**1.46**	6.74	**7.81**	4.89	**13.1**	0.88	**0.82**	2.52	**1.88**
3	Mean	61.0	**19.6**	2.44	**2.54**	5.69	**27.1**	4.33	**16.9**	2.73	**1.26**	8.49	**5.45**
	SD	18.7	**9.11**	0.41	**1.48**	3.24	**9.22**	3.89	**12.5**	0.69	**0.70**	2.66	**1.22**
4	Mean	61.9	**39.1**	2.58	1.31	5.23	**19.4**	6.68	**7.69**	2.79	**3.13**	8.79	**5.7**
	SD	17.6	**25.8**	0.41	1.45	2.37	**9.52**	4.62	**9.87**	0.70	**9.12**	2.41	**2.16**
5	Mean	39.9	**63.7**	2.83	**2.78**	5.70	**4.93**	6.66	**9.69**	3.24	**2.79**	8.10	**8.01**
	SD	15.2	**15.7**	0.84	0.34	3.78	**2.08**	7.58	**4.87**	1.49	**0.51**	3.40	**3.11**

1.6.2.B— Summary Statistic of the CDOs with Downgraded AAA Tranches

Table 1.14 reports the average statistic of the differences in the Moody's Deal Scores for the downgraded (D) and the non-downgraded (ND) CDOs in four Quarters. The trend shows that

[26] The WARF score is in thousands

before the downgrading of the tranches occurred the Moody's Deal Scores were revised upwards by Moody's.

Table 1.15 reports the dynamics of the downgraded deals and the non-downgraded deals over the five Quarters. These dynamics are similar to 6.2.A (Tables 1.12 and 1.13), the case where any of the tranches of the CDOs were downgraded.

Table 1.14

This table reports the summary statistics of the averages of the differences of the Moody's Deal Scores for the downgraded (D) and the non-downgraded (ND) deals. The differences are calculated as follows: at Quarter (2, 3, 4, and 5), the difference of the MDS, $\Delta MDS = MDS_t - MDS_{t-1}$, are calculated for both the downgraded and the non-downgraded deals.

Quarter		**ΔMDS**	
		ND	**D**
2	Mean	0.02	**1.68**
	SD	0.24	**1.86**
3	Mean	0.04	**2.42**
	SD	0.53	**1.35**
4	Mean	0.03	**3.38**
	SD	0.29	**1.66**
5	Mean	1.32	**2.53**
	SD	0.54	**0.63**

Table 1.15

This table reports the summary statistics of variables for the downgraded CDOs (D) and non-downgraded CDOs (ND). The values represent the average quarterly values from 01/2008 to 03/2009.

Time		WARF[27]		WAM		PR		WAS		WAC	
		ND	**D**	ND	**D**	ND	**D**	ND	**D**	ND	**D**
1	Mean	2.12	**1.46**	13.3	**26.7**	6.04	**10.3**	2.24	**1.55**	7.53	**5.62**
	SD	1.04	**1.21**	11.7	**6.38**	8.93	**12.1**	0.91	**0.82**	2.41	**0.76**
2	Mean	2.17	**2.60**	6.20	**27.2**	3.87	**18.6**	2.65	**1.39**	8.53	**5.61**
	SD	0.55	**1.60**	4.10	**5.0**	3.83	**14.0**	0.78	**0.87**	2.50	**1.56**
3	Mean	2.40	**0.64**	6.18	**13.1**	4.43	**1.16**	2.71	**2.34**	8.31	**6.93**
	SD	0.71	**0.49**	4.64	**6.88**	4.39	**1.11**	0.75	**7.01**	2.64	**1.05**
4	Mean	2.60	**1.38**	5.13	**18.29**	6.79	**7.45**	2.77	**1.71**	8.83	**6.33**
	SD	0.40	**1.35**	1.54	**9.66**	4.62	**9.10**	0.62	**1.56**	2.36	**1.60**
5	Mean	2.81	**2.94**	4.81	**5.15**	9.29	**11.1**	2.83	**3.36**	8.07	**7.86**
	SD	0.39	**0.67**	1.05	**0.96**	5.40	**6.89**	0.59	**1.11**	3.09	**4.92**

[27] The WARF score is in thousands

1.6.3 Model Estimation

Jenkins (1995) described an easy estimation procedure for discrete duration models. He showed that the discrete proportional hazard model can be estimated using a regression model for a binary dependent variable. Following Jenkins (1995), we define a variable $D_{j_i} = 1$ if $d_i = 1$ and $T^i = j_i$, and $D_{j_i} = 0$ otherwise. For CDOs that do not have any of their tranche(s) downgraded in any Quarter, $D_{j_i} = 0$ for all the Quarters. For CDOs that have had any of their tranche(s) downgraded in any Quarter, j , $D_{j_i} = 0$ for all the previous quarters except the quarter in which they were downgraded when $y_{j_i} = 1$. Using this indicator variable, the log likelihood function can be rewritten as:

$$(7) \qquad LogL = \sum_{i=1}^{n} \sum_{k=1}^{j_i} D_{j_i} logh\big(k, x_i(j_k)\big) + \sum_{i=1}^{n} \sum_{k=1}^{j_i - 1} log\left(1 - \ h\big(k, x_i(k)\big)\right)$$

Equation (7) has the same form as the standard likelihood function for regression analysis of a binary variable with D_{j_i} as the dependent variable. This allows the discrete time hazard models to be estimated by binary dependent variable methods.

The hazard function $h\big(j, x_i(j)\big)$ is assumed to take the form:

$$(8) \qquad h\big(j, x_i(j)\big) = \frac{1}{1 + \mathrm{e}^{-[\alpha/\lambda(\mathrm{j}) + \beta/x_i(j)]}}$$

Where λ(j) is the baseline hazard function and is modeled by using dummy variables indexing time periods.

1.6.4.1 Estimation Results of the Baseline Model for the CDOs with any of its Tranches Downgraded

Table 1.16

This table reports the estimation results for the hazard rate with just the MDS as covariate

Variables	Coefficient	Standard Errors	P-Value
Moody's Deal Score (MDS)	**0.803**	**0.038**	**0.000**
$\lambda(1)$	-4.742	0.336	0.000
$\lambda(2)$	-4.879	0.339	0.000
$\lambda(3)$	-3.991	0.299	0.000
$\lambda(4)$	-4.001	0.320	0.000

Table 1.16 reports the estimation results for the discrete time hazard baseline model.

Moody's Deal Score (MDS) has a positive impact on the probability of downgrading, i.e. deals with higher MDS have higher hazard and hence shorter survival rate. Moody's does not release information on what they take into account when calculating the scores for the CDO deals[28]. But it is reasonable to assume that Moody's take into consideration some of the indexes that track the real estate market (e.g. Markit Indices and the Case-Shiller Composite-20 index) in their calculation; section 7 of the paper explores whether the changes in these indexes have impact on the changes in the Moody's Deal Scores.

[28] Only 30% of the variations in the Moody's Deal Scores could be explained by the other CDO variables in section 6.2.

The estimated coefficients on the duration dummy variables suggest that the hazard decreases from the first quarter to the second quarter, but rises afterwards.

1.6.4.2 Estimation Results of the Full Model for the CDOs with any of its Tranches Downgraded

Table 1.17

This table reports the estimation results for the Hazard rate for the full model with all the covariates.

Variables	**Coefficient**	**Standard Errors**	**P-Value**
Collateral Diversification (CD)	0.033	0.014	0.018
Likelihood of Defaults (WARF)	-0.002	0.001	0.161
Weighted Average Maturity (WAM)	0.112	0.091	0.217
Weighted Average Coupon Rate (WAC)	-0.247	0.099	0.012
Percentage of CCC rated securities or below (PR)	0.173	0.076	0.022
Weighted Average Spread (WAS)	1.052	0.667	0.115
Moody's Deal Score (MDS)	**0.403**	**0.136**	**0.003**
$\lambda(1)$	-5.067	0.803	0.000
$\lambda(2)$	-5.399	0.841	0.000
$\lambda(3)$	-5.636	0.692	0.000
$\lambda(4)$	-5.140	0.585	0.000

In the Full Model the Moody's Deal Score (MDS) still has a positive impact on the probability of downgrading, but the effect is lower (0.803 vs. 0.403).

The Collateral Diversification (CD) measures how correlated the assets in the CDO portfolio is. It is an important variable in the rating methodology of the CDOs; a higher CD score plays an important role in determining how many of the CDO tranches will be given higher ratings. From the estimation, CD scores have a positive impact on a probability of a deal being downgraded, i.e. deals with higher CD scores have a higher hazard rate, and hence shorter survival time. As Moody's revise the initial CD scores downwards, it downgraded the tranches.

Portfolios with a higher percentage of CCC or lower rated underlying assets are likely to be downgraded during the crises because the underlying assets are most likely to default. These CCC and below assets also have lower recovery rates after default. As the results show, the percentage of CCC rated securities or below (PR) has a positive impact on the probability of downgrading, i.e. deals that have a higher percentage of their assets downgraded to CC or worse have higher hazard and hence shorter survival rate. Table 1.18 reports the average defaulted amount of the underlying assets of the downgraded and the non-downgraded deals, and the average loss of the defaulted assets, i.e. the amount that could not be recovered after the default.

Table 1.18

This table reports the average total value of the underlying assets, the average defaulted value, and the average defaulted amount loss of the downgraded and the non-downgraded CDO deals.

Deals	**Par Value of the Deals**	**Defaulted Par (% of par value)**	**Defaulted Asset Loss (% of defaulted par)**
Downgraded Deals	1,242,000,000	87,985,741 (7%)	51,970,331 (59%)
Non-Downgraded deals	642,000,000	41,331,390 (6.4%)	13,963,055 (34%)

The par value of the deals is the average total par value of the underlying assets of the CDOs. On average about 7% of the underlying asset of the downgraded deals and about 6.4% of the Non-downgraded deals defaulted, but only 41% of the defaulted assets were recovered while 66% of the defaulted securities of the non-downgraded deals were recovered. Since the downgraded deals had a higher percentage of their underlying assets rated CCC or below, the table shows that the CDO managers were not able to recover as much compared to non-downgraded deals which had a lower percentage of CCC assets when the assets defaulted.

Although bonds with high coupon rates usually have high default rates, a high coupon rate bond with a short maturity usually has shorter duration as it receives more cash flows upfront. As Table 1.17 shows, Weighted Average Coupon Rate (WAC) has a negative impact on the probability of downgrading, i.e. deals with higher assets coupon rates have lower hazard and hence longer survival rate. In economic crises, CDO portfolios with more cash flows (or deals that have built up a sizable cash reserve from their earlier cash flows) are more likely to pass their overcollateralization and the interest coverage tests; as such they might be less likely to be downgraded.

I find no effect of the Likelihood of Default (WARF), Weighted Average Maturity (WAM) and the Weighted Average Spread (WAS) on the survival of the CDOs. Theoretically an increase in the WARF (which should occur during financial crises as more of the underlying assets get downgraded) should increase the probability of the downgrade of the tranches. For any given CDO deal rated by Moody's, hundreds of the underlying assets are rated by Moody's and other rating agencies. The lack of clear upward trend of the WARF scores in Tables 1.13 and 1.15 might indicate a delayed effect of Moody's correctly updating the new ratings of the underlying assets as they are changed. This would imply that the reported WARF scores do not correctly reflect the riskiness of the underlying assets leading to an absence of any effect on the downgrading probability. From Table 1.13 the downgraded deals had a higher WAM than the non-downgraded deals for all the Quarters. The absence of any effect of the WAM on the probability of the downgrade suggests that the average time left for the underlying assets to mature in the CDO portfolios was not as important as the quality of the assets. The market risk exposure for these long term maturity assets was not significant.

1.6.4.3 R^2 Comparison of Baseline Model and Full Model

A comparison of the R^2 of the Baseline (which has only the Moody's Deal Scores (MDS) as the covariate) Model to the Full Model (which has the MDS and other CDO variables as the covariates) show that the changes in the MDS are the only variable that explains tranche downgrade.

Table 1.19
This table reports the statistic and p-value for the Likelihood Ratio Tests

Model	R^2
Baseline	0.584
Full	0.614

1.6.6 Non-Proportional Hazard

The hazard model postulated implicitly assumes that a predictor has an identical effect every time period. By interacting the time dummies λ(j) with the covariates in the hazard model we can show whether the effect of the covariates differs from time period to time period. A second regression involving CD, MDS, WAC and PR and the interaction terms between the time dummies was run. The results of the regression from the interaction term produced very few significant terms; only $\lambda(1)\mathrm{CD}$ and $\lambda(3)\mathrm{MDS}$ were significant at 5% and we could not reject the null hypothesis that the coefficients of the interaction terms were jointly zero. This suggests that the effects of the covariates are probably identical in every time period.

1.6.7 Estimation Results for the Full Model for the CDOs with Downgraded AAA Tranches

In both categories of downgrading the Moody's Deal Scores plays a significant role in whether the tranches of the CDO deals would be downgraded or not.

Table 1.20

This table reports the estimation results for the Hazard rate when the tranche downgrade is restricted to only the AAA tranches

Variables	**Coefficient**	**Standard Errors**	**P-Value**
Collateral Diversification (CD)	-0.098	0.037	0.008
Likelihood of Defaults (WARF)	-0.005	0.004	0.133
Weighted Average Maturity (WAM)	-0.055	0.142	0.698
Weighted Average Coupon Rate (WAC)	0.886	0.528	0.093
Percentage of CCC rated securities or below (PR)	0.327	0.258	0.204
Weighted Average Spread (WAS)	0.265	1.482	0.858
Moody's Deal Score (MDS)	**2.854**	**0.867**	**0.001**
$\lambda(1)$	0.639	2.790	0.819
$\lambda(2)$	-2.900	2.635	0.271
$\lambda(3)$	-1.894	2.588	0.233
$\lambda(4)$	-2.574	2.219	0.246

1.7 Causality

In Section 6 we showed that the Moody's Deal Score (MDS) significantly increases the hazard of downgrading of the CDO tranches. Figures 4 to 9 shows the monthly trajectory of the MDS for a randomly selected six downgraded CDO deals included in the study. The first month is January 1st 2008 and the last month is April 30th 2009. For deals represented in Figures 1 to 5 their MDS were raised months before their tranches were downgraded in the fourth quarter of 2008. For the deal represented in Figure 6, it tranches where downgraded in the 1st quarter of 2009. All the CDOs had an increase in their MDS before their tranches were downgraded. Table 1.21 also reports the quarterly differences of the Moody's Deal Score for the downgraded and the non-downgraded deals from first quarter of 2008 to the first quarter of 2009 for both types of downgrading considered. As can be seen, the downgraded deals experience an increase in their Moody's deal scores.

Since CDOs are not traded on an exchange it is usually difficult to gauge the overall direction of the CDOs backed by real estate related assets. However, movements in the Markit ABX.HE indices (ABX.HE indices track CDS on US home equity loans (HEL)) and the Case-Shiller Composite-20 index (Case-Shiller Home Price indexes measure the changes in the total value of all existing single-family housing stock) could be used as a proxy to gauge the overall direction of the real estate backed CDO market. Moody's can, for instance, observe what is happening in the Markit ABH.HE (AA and A) tranches and the Case-Shiller Composite-20 index and adjust the scores they give to the CDOs accordingly. Since the lower tranches of a CDO offer "protection" to the upper tranches, looking at the movement in the ABX.HE AA tranche—which offers "protection" to the AAA tranche, or the ABX.HE A tranche—which offers "protection" to both the AAA and AA tranches will inform Moody's as to the level of "protection" the upper tranches of the CDOs have.

The Markit ABX indices and the Case-Shiller Composite-20 index also experienced significant changes during the period when the tranches of the CDOs were being downgraded the most (Figures 10 and 11). Granger causality tests will be useful in investigating the causality link between Markit ABX indices and the Case-Shiller Composite-20 index Moody's Deal Scores of the CDOs.

Graph of Changes in the Moody's Deal Scores of Some Selected CDO Deals

Figure 4

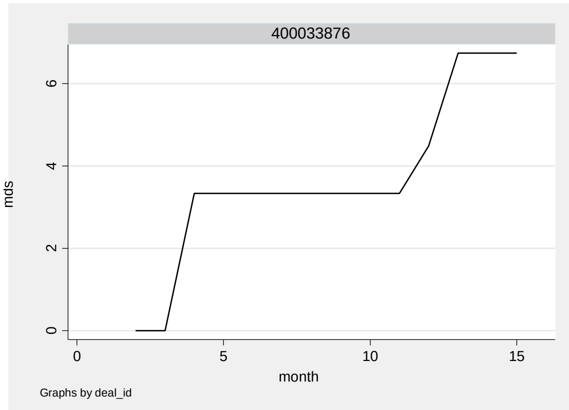


Figure 5

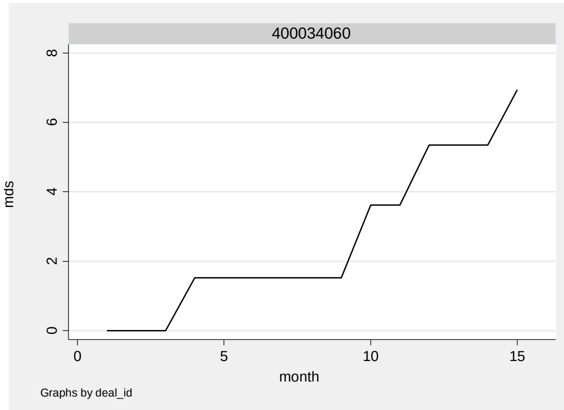


Figure 6

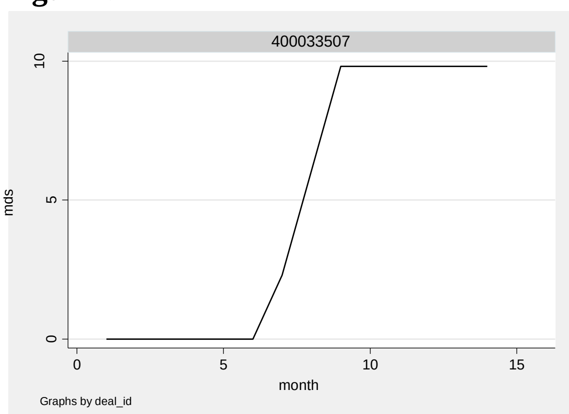


Figure 7

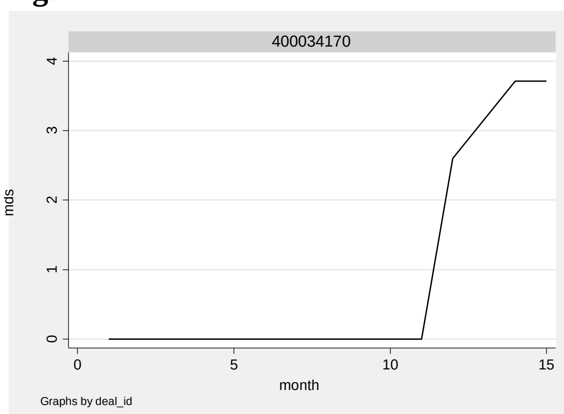


Figure 8

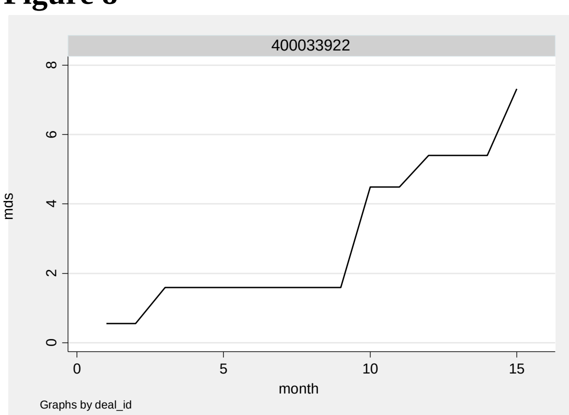


Figure 9

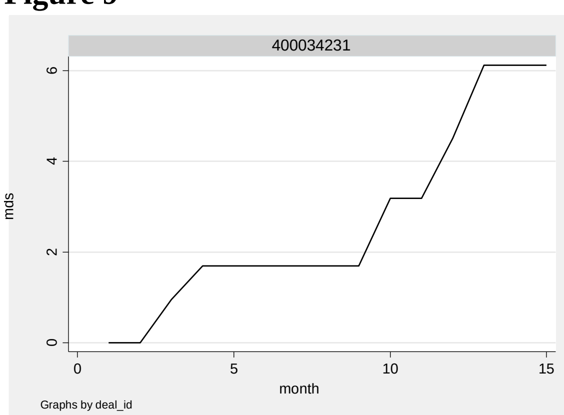


Table 1.21

This table reports the summary statistics of the averages of the differences of Moody's Deal Scores for the downgraded (D) and the non-downgraded (ND) CDOs. The differences are calculated as follows: at t (2, 3, 4, 5), the difference of the MDS, $\Delta MDS = MDS_t - MDS_{t-1}$, are calculated for the both the downgraded and the non-downgraded deals

Quarter		**ΔMDS (Any tranche Downgrades)**		**ΔMDS (Only AAA Downgrades)**	
		ND	**D**	ND	**D**
2	Mean	0.19	**1.07**	0.02	**1.68**
	SD	0.81	**1.44**	0.24	**1.86**
3	Mean	0.07	**2.02**	0.04	**2.42**
	SD	0.57	**1.76**	0.53	**1.35**
4	Mean	0.02	**2.25**	0.03	**3.38**
	SD	0.25	**1.76**	0.29	**1.66**
5	Mean	0.96	**1.33**	1.32	**2.53**
	SD	0.77	**0.49**	0.54	**0.63**

1.7.1 Estimation Method—Multivariate Panel Granger Causality Test

A stationary time series x_t is said to "Granger cause" y_t if—under the assumption that all other information is irrelevant—the inclusion of past values of x_t reduces the predictive error variance of y_t. Granger causality tests are carried out by regressing y_t on its own lags and on lags of x_t. If the lags of x_t are found to be to be statistically significant, then the null hypothesis that x_t does not Granger cause y_t can be rejected.

Let us consider covariance stationary variables X and y_i observed on T periods and N CDOs. For each individual CDO $i = 1, \dots, N$ and time $t = 1, \dots, T$, we have the following heterogeneous autoregressive model:

$$(9) \qquad y_{it} = \alpha_i + \sum_{k=1}^{K} \gamma_k y_{it-k} + \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_k^j x_{t-k}^j + \varepsilon_{it}$$

where y_{it} represents the Moody's Deal Scores of the CDOs. The individual effects α_i are assumed to be fixed. The $x's$ are the variables (Markit indices and Case-Shiller Composite-20 index) that granger cause y.

The autoregressive parameters γ_k and the regression coefficients slopes β_k^j are assumed to be the same for all CDOs. However, for each cross section $i = 1, \dots, N$, individual residuals $\varepsilon_{it}\ \forall t = 1, \dots, T$ are i.i.d $(0, \sigma_t^2)$.

We can examine Granger causality from $x \ to \ y$ by testing the null hypothesis:

$$(10) \qquad H_0 = \beta_1^j = \beta_2^j = \cdots = \beta_K^j = 0 \qquad \forall j$$

7.2 Variables

1.7.2.A Markit ABX Indices

Although Markit ABX.HE indices were not meant to be the barometer of the general risk associated with entire market of CDOs backed by real estate related assets, they have evolved to be the general measure of risk in the market. With the collapse of the sub-prime RMBS and CDO trading, the more liquid market for the ABX.HE indexed CDS has become an important benchmark for market pricing of sub-prime mortgage related securities.

Credit Default Swaps (CDS)[29] and indices on CDS have allowed market participants to transfer risk from one party to the other. The indices have allowed market participants to trade credit risk of reference entities without having to enter into multiple swap positions and without having to own the referenced obligation. The premiums on CDS contracts are believed to show a better measure of credit worthiness for corporations (or pool of assets like CDOs). Markit ABX.HE indices are the most prominent indices that track the price of CDS of mortgage backed security (MBS). The ABX.HE indices track CDS on US home equity loans (HEL) MBS. HELs include subprime residential mortgage loans, second lien mortgage loans, home equity line of credit (HELOCs), and high-loan to value (LTV) loans. HEL usually has a long maturity, so the maturity of the CDS contract tends to march that of the reference bond. The indices have risen to prominence during the recent financial turmoil; the collapse in their prices tracked perfectly the meltdown in the housing sector.

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[29] A CDS is a derivative contract that works like an insurance policy against the credit risk of an asset or company. The seller of the CDS assumed the credit risk of the asset in exchange for periodic payments of a protection premium.

The first ABX.HE indices started trading[30] on January 19, 2006 and are made up of equally weighted portfolios of 20 CDS backed by HEL MBS. Each ABX series is made up of 20 new MBS deals issued during a six month period prior to the index formation. Due to this, the vintage indices could be different from newer indices as underwriting, credit enhancement and collateral standards change over time. The index series consists of five sub-series each referencing exposures to the same underlying HEL deals and their tranches. The sub-series are AAA (Moody's Aaa), AA (Moody's Aa2 and Aa1), A (Moody's A2, A1 and Aa3), BBB (Moody's Baa2, Baa1, and A3) and BBB- (Moody's Baa3). The criteria used in selecting the deals are; large and liquid deals with at least $500 Million of deal size and an average FICO score set at 660 per deal. The index also limits the deals that could be included originating from the same servicer, and all the deals included should be rated by both Moody's and Standard and Poor's. The first series of the indices is ABX.HE.06-01 (issued in January 2006), the second series is ABX.HE.06-02 (issued in July, 2006), the third series is ABX.HE.2007-01 (issued in January, 2007) and the fourth series is ABX.HE.07-01 (issued in July, 2007). The ABX.HE.08-01 series was supposed to be issued in January 2008 but was cancelled due to insufficient RMBS origination and trading.

One of the criticisms of the ABX indices is that since they are computed from a small fraction of deals issued on the market, they do not accurately reflect the overall risk in the housing market. For example, each series is made up of about $20 Billion worth of subprime mortgages, but the total outstanding vintage MBS of subprime quality from 2004-2008 is estimated to be around $600 Billion. This implies that each series is about 5% of the overall subprime MBS outstanding. Despite this limitation, there are no other indices that tracks the

[30] The trading volume on the first day was $5 billion. The market makers for the indexes are Bank of America, BNP Paribas, Deutsche Bank, Lehman brothers, Morgan Stanley, Barclays, Citigroup, Goldman Sachs, RBS, Greenwich capital, UBS, Bear Sterns, Credit Suisse, JP Morgan, Merrill Lynch and Wachovia

fluctuations in the real estate related asset backed structured finance products better than the ABX.HE indices.

The ABX.HE indices trade on price rather than spread terms with a predetermined fixed coupon[31] which is determined prior to the launch of a new series. The protection buyer pays (usually monthly) the fixed rate amount over the life of the contract based on the current notional amount of the index. The index contract is not terminated when a credit event occurs (short fall of interest rate or principal), rather it continues with a reduced notional amount until maturity.

7.2. B Case-Shiller Home Price Index

The Case-Shiller Home Price Index indices are designed to measure the changes in the total value of all existing single-family housing stock. The index also tracks the overall direction of the housing market. Rating agencies might take the fluctuations of this index into an account when they are revising the ratings they have already given to the tranches of the CDOs backed by real estate related assets. The index is based on repeat-sales methodology[32] developed by Karl Case and Robert Shiller. The repeat sales method uses data on properties that were sold at least twice, in order to capture the true appreciated value of constant-quality homes. The index computes a three month moving average of the repeat sales of single family houses in 20 metropolitan [33] (Composite-20 SPCS20R) areas based on Case et al (1993) repeat sale methodology. The method produces a cap-weighted index for residential real estate in nine US

[31] For example, the coupon rate for the AAA ABX.HE-06-1 is 18 bases point, i.e., to protect $1 million in value of AAA tranche, the protection buyer would pay $1,800 per year in monthly installment. The buyer pays more when the tranche trades at a discount.

[32] This methodology is recognized as the most reliable means to measure housing price movements. For more information on the methodology, see http://www2.standardandpoors.com/spf/pdf/index/SP_Case_Shiller_Home_Price_Indices_FAQ.pdf

[33] Boston, Chicago, Denver, Las Vegas, Los Angeles, Miami, New York, San Diego, San Francisco, Washington, DC, Atlanta, Charlotte, Cleveland, Dallas, Detroit, Minneapolis, Phoenix, Portland, Seattle and Tampa.

census regions. The national composite is then produced from the regional indices using census weight.

1.7.3 Data

Table 1.22 presents the monthly summary statistic of the Markit ABX.HE.AA-06, ABX.HE.A-06, and the Case- Shiller Composite index. The data is from January 2008 to May 2009. Table 1.23 reports the correlation matrix of the variables. As can be seen from the table the Markit Indices and the Case-Shiller Composite-20 index are positively correlated with each other—0.975 between the AA index and Case-Shiller Index and 0.896 between the A index and the Case-Shiller index.

Table 1.22
This table reports the monthly summary statistic of the Markit Indices, Case-Shiller Composite Index and the Yield on the 10 year Treasury bond

	Max	**Min**	**Mean**	**Standard Deviation**
AA	84	16.88	50.157	22.543
A	60.33	7.5	23.922	15.215
Case-Shiller	180.68	139.26	159.984	13.046

Table 1.23
This table reports the correlation of the Markit Indices and the Case-Shiller Composite-20 Index

	AA	**A**	**Case-Shiller**
AA	1		
A	0.914	1	
Case-Shiller	0.975	0.896	1

Figure 10 graphs the trajectory of the Markit indices. Both the AA and the A indices have been on a downward trajectory since January 2008. However, the AA index experience the largest fall during the period.

Figure 10
This graph represents the trajectory of the Markit ABX.HE-06 AA, A and BBB indices from January 2008 to April 2009

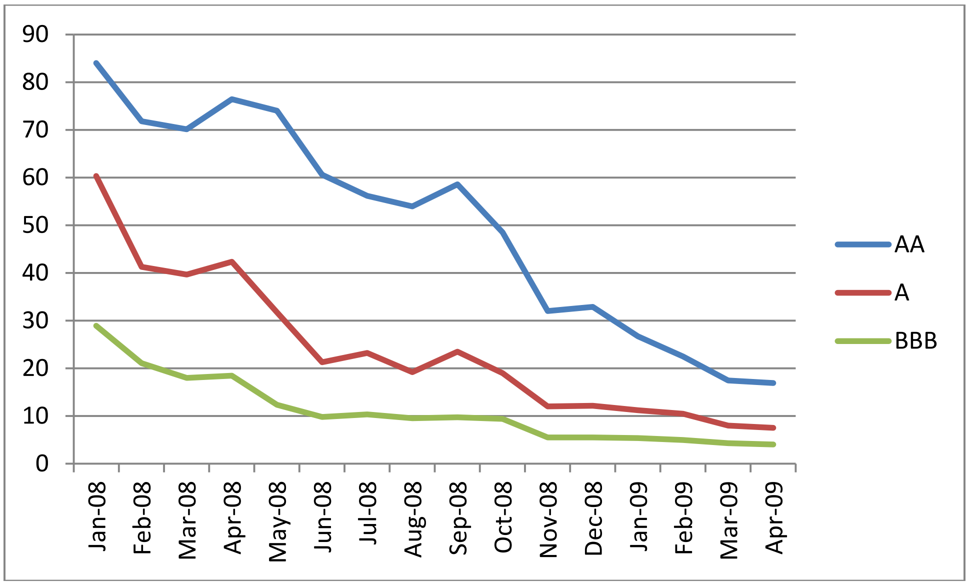


Figure 11 graphs the monthly trajectory of the Case-Shiller Composite-20 index. The index has also been on a downward trajectory; within this period we observe some of the lowest figures ever reported for the index. Figure 12 graphs the distribution of the Moody's Deal Scores from January 2009 to April 2008[34]. There are two clusters—the values less than 2 are the initial values that were given to the deals, and the values above 5 are the revised values that were given to the deals after Moody's reassessment. The Moody's Deal Scores ranges from -10 (best) to +10 (worst).

[34] This is the period during which almost all the downgrading took place in the sample.

Figure 11

This graph represents the trajectory of the Case-Shiller Composite-20 index from January 2008 to April 2009

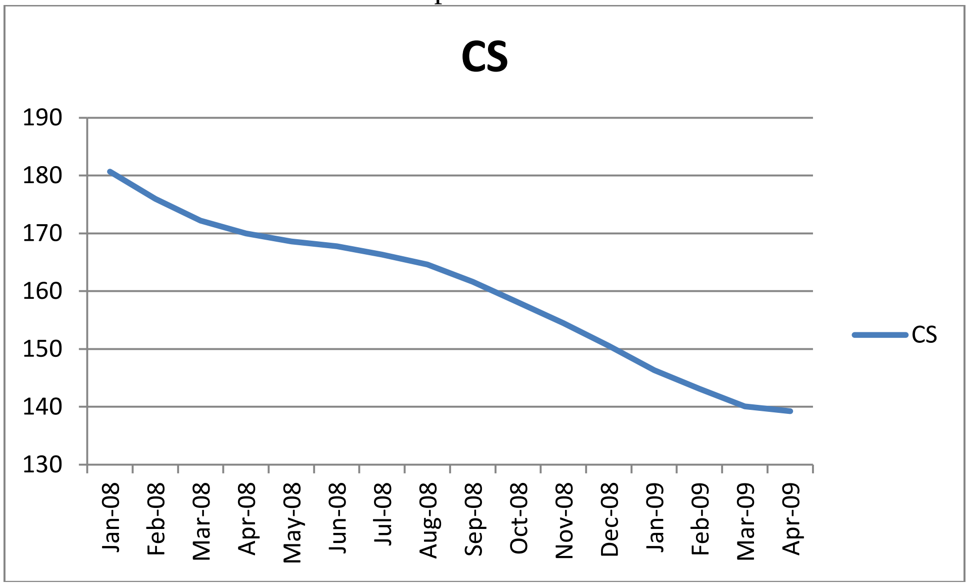
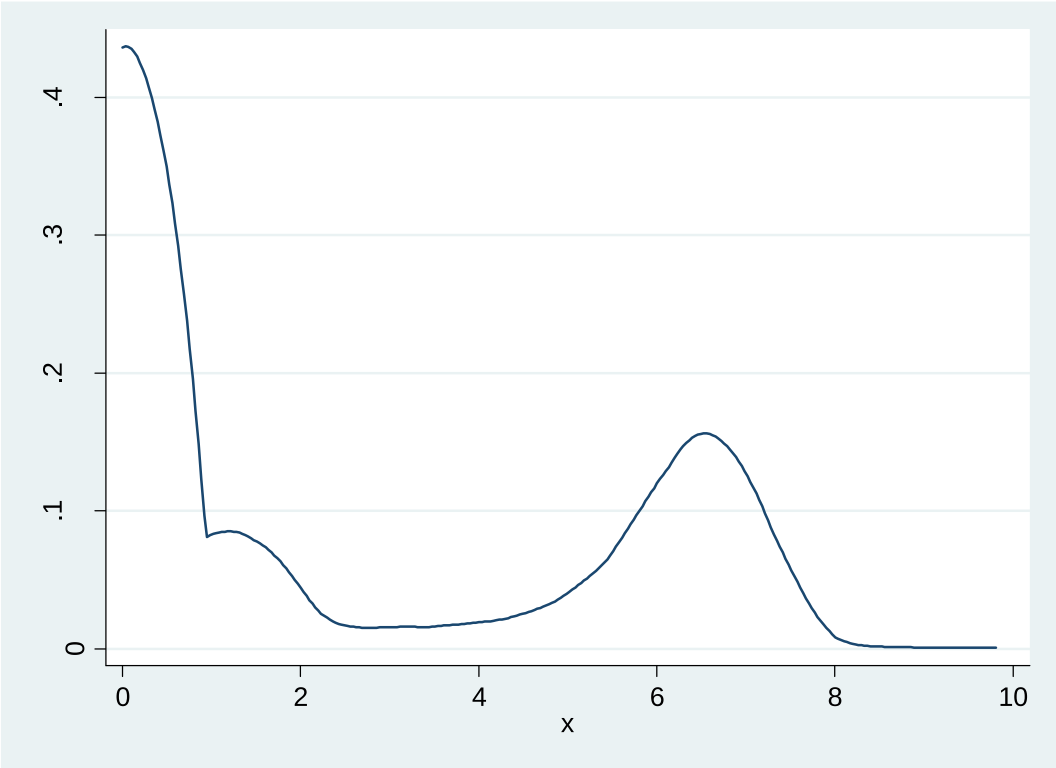


Figure 12

This graph represents the distribution of the Moody's Deals Score for the CDOs from January 2008 to April 2009



1.7.4 Empirical Results

We follow Arellano and Bond (1991) GMM estimation procedure which differences the model to get rid of the individual specific effects. This also gets rid of any endogeneity that may be due to the correlation of the individual effects and the right hand side regressors. The moment conditions utilize the orthogonality conditions between the differenced errors and lagged values of the dependent variable. This assumes that the original disturbances are serially uncorrelated. Based on the estimation results, a conclusion on causality will be reached by running Wald tests on the coefficients of the lagged x to check whether they are statistically different from zero.

Table 1.24 reports the results for estimating equation (9) using the Arellano-Bond system GMM estimator. Model 1 uses the Markit ABH.HE.06.AA as one of the $x's$, while Model 2 uses ABH.HE.A-06 as one of the $x's$. Both models use the Case-Shiller index as the other x. In Model 1 the changes in the second lagged AA Markit index can predict the changes in the Moody's Deal Scores. The first lagged AA Markit index does not seem to have an effect on the changes in the Moody's Deal Scores. In model 2 both the first and second lagged A Markit indices can predict the changes in the Moody's Deal Scores. Also, in both models the first lagged Case-Shiller can predict the changes in the Moody's Deal Scores.

Table 1.24
This table reports the estimation results of equation (9)

Model	Variables[35]	Coefficients	Standard Error	p-values
1	Mds_{t-1}	0.8102	0.069	0.000
	Mds_{t-2}	0.1681	0.069	0.015
	AA_{t-1}	- 0.0042	0.003	0.182
	AA_{t-2}	- 0.0361	0.003	0.000
	CS_{t-1}	- 0.1995	0.029	0.000
	CS_{t-2}	0.2685	0.038	0.000
2	Mds_{t-1}	0.7938	0.069	0.000
	Mds_{t-2}	0.1826	0.069	0.008
	A_{t-1}	- 0.0246	0.006	0.000
	A_{t-2}	- 0.0606	0.006	0.000
	CS_{t-1}	- 0.1109	0.027	0.000
	CS_{t-2}	0.1595	0.032	0.000

Table 1.25 reports the results of testing the null hypothesis:

$$H_0 = \beta_1^j = \beta_2^j = \cdots = \beta_K^j = 0 \qquad \forall j$$

Table 1.25
This Table reports the results for the null hypothesis

	Statistic Chi-Squared (4)	P-Value
Model 1	144.68	0.000
Model 2	137.68	0.000

In both Models 1 and 2 the changes in the Markit ABX.HE indices and the Case-Shiller Composite index Granger cause the Moody's Deal Scores. This implies that

[35] The constants are omitted

Moody's take into account the movements in these indices to adjust the scores they assign to the CDOs deals backed by real estate related assets.

1.7.5 Relative Importance of Markit ABX.HE and Case-Shiller Composite-20 Index

This section discusses how much of the variation in the Moody's Deals Scores (MDS) is explained by the Markit ABX.HE indices and the Case-Shiller Composite-20 index if we assume that Moody's based its revision of the Moody's Deal Scores solely on these two indexes.

$$(11) \qquad y_{it} = \varsigma_i + \phi_7 CS_{t-1} + \phi_8 CS_{t-2} + \varpi_{it}$$

where y_{it} represents the Moody's Deal Scores and CS_t represents the Case-Shiller Composite-20 index. The residual ϖ_{it} is assumed to be independent of the Case-Shiller index and it is also assumed to be independently distributed.

In other to check the relative importance of the Markit ABX.HE indices and the Case-Shiller Composite-20 index in explaining the changes in the MDS, we also estimate this equation:

$$(12) \qquad y_{it} = \tau_i + \phi_1 ABX_{t-1} + \phi_2 ABX_{t-2} + \phi_3 CS_{t-1} + \phi_4 CS_{t-2} + \psi_{it}$$

where ABX_t represents Markit ABH.HE.06.AA and ABH.HE.06.A indices. The residual ψ_{it} is assumed to be independent of the Markit and Case-Shiller indices and it is also assumed to be independently distributed.

Equations (11) and (12) are distributed lags models. Table 1.26 reports the adjusted-R^2 for equation (11) and (12). The R^2's indicate that the changes in the Case-Shiller Composite-20 index explains most of the variation in the Moody's Deal Scores; adding the Markit indices does not improve the R^2.

Table 1.26

This Table reports the results of the estimation of equations (11) and (12)

Equation	$Adjusted - R^2$
(A) 11	
Case-Shiller Index	**0.339**
(B) 12	
Markit ABX.HE06.AA	**0.344**
Markit ABX.HE.06.A	**0.344**

1.8 Conclusion

The collapse of the market for CDOs backed by real estate related assets has caused severe disruptions in the housing and financial markets. It is now much more difficult to package newly originated mortgage loans to be sold to CDO managers. The mortgage packaging frenzy of the 2002 to 2006 years left little time for thorough examination of the quality of these loans which were being packaged into CDOs. The waves of CDO tranche downgrades have prompted a review of the underlying assets of the CDO portfolios. This paper documents some of the characteristic of the underlying assets of the CDOs which might have contributed to the downgrades of the CDO tranches. The underlying assets (which were mostly mortgage loans related assets) of the CDO portfolios were not seasoned. These unseasoned loans defaulted in significant numbers during the economic recession. Also, a sizable percentage of the underlying assets were of low quality assets which defaulted in bigger numbers during the economic crises.

The paper uses a discrete hazard rate model to study the variables that contributed the most to the downgrading of the tranches of the CDO deals. The empirical results showed that the Moody's Deal Score, the default correlation of the underlying assets, the percentage of the underlying assets of the CDO portfolios rated at CCC or below and the Weighted Average Coupon rate of the assets in the CDO portfolio were all important in determining whether the tranches of the CDOs would be downgraded or not. However, the changes in the Moody's Deal Scores impacted the downgraded probabilities the most. During the crises Moody's revised the initial values of the Moody's Deal Scores it gave to the CDO deals leading to mass downgrades after the revision. A causality test showed that in revising the initial Moody's Deal Scores giving to the deals, Moody's took into account the changes in the Markit ABX.HE.AA-06 and ABX.HE.A-06 indices and also especially Case-Shiller Composite-20 Index.

Chapter 2

Dynamics of Unemployment and Home Price Shocks on Mortgage Default Rates

2.1 Introduction

The traditional model of mortgage default posits that borrowers default if and only if they have negative equity. A classic example is the option-based mortgage default model examined by Foster and Van Order (1984) in which default is a put option. Borrowers would exercise the put option when the value of the house plus any costs of exercising the option falls below the mortgage value. However, recent studies[36] have shown that many borrowers with negative equity do not necessarily default. These borrowers continue to honor their contractual obligation to the lenders even though their houses are worth less than the loans outstanding. These studies found that default is often associated with a negative income shock; i.e. being unemployed usually is a bigger factor than negative equity. Foote et al. (2009) found that a 1% increase in the unemployment rate raises the probability of default by 10-20%, while a 10% point fall in housing prices raises the probability of default by more than 50%. On the other hand, there have also been documented cases where borrowers have exercised the option to default when they have negative equity even though they could afford to pay their mortgages. Ashworth et al. (2010) concluded that negative equity shocks are far more important predictor of mortgage defaults than unemployment shocks. However, they also found that employment shocks can amplify the default rate if the borrower has already experienced a negative equity shock. As Mayer et al (2009) showed areas that experienced increased unemployment rates also experienced decline in

[36] Neil Bhutta et al. (2010)

house prices. As such, it is not easy to establish whether defaults in these areas are due to unemployment or house prices.

In this paper, we attempt to disentangle the interrelations between the home price index (which tracks housing prices) and unemployment shocks and mortgage default rates by studying the dynamics of these two shocks on mortgage default rates from 1979 to 2010. The 2001 to 2010 period represents a time when there have been significant changes in unemployment, house price indices and mortgage default rate at the same time. As such, this period presents a perfect period to empirically test which of these two shocks have had a bigger impact on mortgage default rates. We also want to know how the dynamics of the impacts of these two shocks in 2001 to 2010 have deviated from their historical dynamics (1979 to 2000). Not only have there been significant changes in these three variables during the 2001 to 2010 period, underwriting standards also deteriorated significantly during the period as the growing number of subprime loans originated during this period shows. Incentives in the mortgage market also shifted to the "originate-to-distribute" model, under which mortgage brokers originated loans and then sold them to institutions that securitized them. Because these brokers do not have to bear the cost of default, they may not be stringent in screening potential mortgage borrowers (Keys, Mukherjee, Seru, and Vig, 2008). About 700,000 subprime mortgage loans[37] were originated annually between 1998 and 2000 (Mayer and Pence, 2009); this increased to an average of 1.5 million between 2003 and 2006 annual. Lax underwriting standards were not the only factor in the increase in origination of subprime loans. A contributing factor was the house price appreciation after 2001 which made subprime origination easier as homeowners could easily resell their

[37] Subprime loans are usually targeted to borrowers who have bad credit, little savings available for a downpayment and in some case no verifiable income or assets.

homes. Mayer and Pence (2009) documented that areas with high house price appreciation also experienced an increase in subprime mortgage origination.

Given the different composition of mortgage borrowers and the different types of mortgage loans originated during the two periods, a study of the impact of the unemployment and home price shocks on mortgage defaults over these two periods is necessary.

Mortgage default rates are influenced by the unemployment and home price shocks at the national, regional and state levels. However, describing the joint behavior of these three variables is not easy. This paper utilizes a Structural Vector Autoregression (SVAR) to decompose the national, regional and state mortgage default rates into unemployment and home price index shocks. The data consist of unemployment rates, home price indices and mortgage default rates at the national, regional[38], and state[39] levels covering a period from 1979 to 2010 at a quarterly frequency. The mortgage default rate is defined as the number of seriously delinquent mortgage loans as a percentage of all loans serviced in each quarter. The seriously delinquent loans are mortgage loans that are 90+ delinquent, i.e., they are loans for which the borrowers have not paid the mortgage in 90+ days.

We first fit the SVAR model to the 1979 to 2000 national and regional data and forecast the changes in the national and regional mortgage default rates for the 2001 to 2010 period. Not only are we interested in how well the model performs out-of-sample, we are more interested in its performance during the housing boom years of 2003 to 2006, and also during the recent Great Recession from 2008 to 2010. We examine the forecast errors from 2001 to 2010 and explore some of the factors that might have contributed to the model not fitting the data well during the

[38] See Appendix A for more details about the census regions.
[39] The states considered are Arizona, California, Florida, Michigan, Nevada and Pennsylvania.

Great Recession. We test for a structural break in the mortgage defaults rates during 2008 to 2010.

We then also estimate the model for the 2001 to 2010 sample and estimate the implied impulse response functions from the identification for both the 1979 to 2000 and 2001 to 2010 periods for the national, regional and state data. This allows us to examine whether there have been changes in the dynamics of the home price index and unemployment shocks on mortgage default for both periods. Finally, we measure the importance of the two shocks in explaining the changes in the mortgage default rate by performing variance decomposition for both sample periods.

The forecasted changes in the national and regional mortgage default rates from 2001 to 2010 using estimated results from fitting the SVAR model to the 1979 to 2000 sample were not far off from the actual changes in the mortgage default rates from 2001 to 2007. The model did well even during the housing boom years of 2003 to 2006. However, the model failed to forecast the changes in the mortgage default rates during the Great Recession. There has been a structural break in the national and regional mortgage default rates during the 2008 to 2010 period which could not have been anticipated by the model.

The empirical results also show that unemployment and home price index shocks on average had very little impact on mortgage default rate at the national, regional and state level during the 1979 to 2000 period. At the national level, an increase of one standard deviation in the unemployment and home price index led to an increase of 1.3% and a decrease of 1% in the mortgage default rate respectively during this period. At the regional level, the unemployment and the home price index shocks produced on average an increase of 1.2% and a decrease of 1.1% respectively during the period. For the 2001 to 2010 period, a standard deviation increase in the national unemployment and the home price index shocks during this period led to an increase of 7.2% and a decrease of 4.9% respectively in the national mortgage default rate. At the regional level, there was an average increase of 12.9% for the unemployment shock and an average decrease of 7.3% for the home price index shock during this period. The divergence of the national and regional estimates in the 2001 to 2010 period is due to the strong effect of the shocks in the West South Central, East South Central and East North Central regions.

On average, the unemployment shocks seem to have had a bigger impact on the mortgage default rate than the home price index shocks.

Also during the 2001 to 2010 period, the unemployment shocks explained on average about 43% of the variation in the regional mortgage default rate, while the home price index shocks explained on average about 20% of the variation in the regional mortgage default rate. In effect, these two shocks were responsible on average for about 60% of the movement in the regional mortgage default rates during this period. The two shocks explained very little of the variation in the mortgage default rate during the 1979 to 2001 period.

The results indicate that the dynamic response of the mortgage default rate to unemployment and home price index shocks changed at the national, regional and state levels after 2000. Although there have been periods of higher national, regional and state unemployment during the 1979 to 2000 period, they seemed to not have impacted the mortgage default rates that much during this period. Except for the Pacific region, California and Florida, unemployment shocks have had a bigger impact on the national, regional and state mortgage default rates and can also explain more of the variation in the mortgage default rates than the home price index shocks during the 2001 to 2010 period. The post 2000 results could be attributed to the increase in the number of mortgage loan borrowers who were more susceptible to unemployment and negative home price shocks. These borrowers have little savings they could use to cushion them against unemployment and negative home price shocks. Mayer et al (2009), Demyanyk and Van Hemert (2008) and Mian and Sufi (2009) also documented declining underwriting standards as a factor in mortgage default crises.

The paper proceeds as follows; Section 2 describes the SVAR model. Section 3 describes the data used. Section 4 provides the results for the forecast errors from 2001 to 2010 and the structural break tests. Section 5 provides the results for the impulse response functions and the variance decompositions for the 1979 to 2000 and 2001 to 2010 periods. Section 6 provides results for the impulse response functions and variance decompositions of the selected states. Section 7 concludes.

2.2 SVAR Model

The goal of the empirical analysis is to assess the impact of unemployment and home price index shocks on mortgage default rates. The SVAR system can be represented as:

$$(1) \qquad \begin{bmatrix} U_t \\ D_t \\ P_t \end{bmatrix} = A_1 \begin{bmatrix} U_{t-1} \\ D_{t-1} \\ P_{t-1} \end{bmatrix} + \cdots + A_p \begin{bmatrix} U_{t-p} \\ D_{t-p} \\ P_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^U \\ \varepsilon_t^D \\ \varepsilon_t^P \end{bmatrix}$$

where D_t denotes the first difference of mortgage default rate, U_t denotes the first difference of unemployment rate and P_t denotes the first difference of the home price index. Each A_i is a 3×3 matrix.

Let $\begin{bmatrix} U_t \\ D_t \\ P_t \end{bmatrix} = y_t$ and $\begin{bmatrix} \varepsilon_t^U \\ \varepsilon_t^D \\ \varepsilon_t^P \end{bmatrix} = \varepsilon_t$. Equation (1) can then be written as

$$(2) \qquad y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t$$

The innovations $\varepsilon_t \sim N(O, \Sigma_\varepsilon)$ and $E\left[\varepsilon_t \varepsilon_s^/\right] = \mathbf{0_3}$ for all $s \neq t$. Multiplying equation (2) by matrix $\boldsymbol{B}$, equation (2) can then be represented as:

$$(3) \qquad \boldsymbol{B}\left[I_K - A_1 L^1 - A_2 L^2 \ldots - A_p L^p\right] y_t = \boldsymbol{B}\varepsilon_t = \boldsymbol{D} e_t$$

Where L is the lag operator, $\boldsymbol{B}, \boldsymbol{D}$ *and* $\boldsymbol{A_i}$ are 3×3 matrices of parameters, and e_t is a 3×1 vector of orthogonalized disturbances: i.e. $e_t \sim N(O, \mathrm{I}_3)$ and $E\left[e_t e_s^/\right] = \mathbf{0_3}$ for all $s \neq t$. It is usually better to transform $\boldsymbol{B}\varepsilon_t$ into mutually uncorrelated innovations before we can effectively analyze the effect of one time increase in the ith element of ε_t on the jth element of y_t. Let $\boldsymbol{D}$ be a matrix such that: $\boldsymbol{B}\Sigma_\epsilon \boldsymbol{B}^/ = \boldsymbol{D}\boldsymbol{D}^/$. Then[40] $E\left\{\boldsymbol{D}^{-1}\boldsymbol{B}\varepsilon_t\left(\boldsymbol{D}^{-1}\boldsymbol{B}\varepsilon_t\right)^/\right\} = \mathrm{I}_3$ and $\{\boldsymbol{D}^{-1}\boldsymbol{B}\varepsilon_t = 0\}$. These transformations of the innovations allow us to analyze the dynamics of the system in terms of a change to an element of e_t.

2.1 Short-Run Identification

In a short-run SVAR model, identification is obtained by placing restrictions on $\boldsymbol{B}$ *and* $\boldsymbol{D}$ matrices which are assumed to be nonsingular. At least 3 identifying restrictions are needed to be imposed to achieve unique identification. We impose restrictions on the SVAR system by applying equality constraints with the constraint matrices:

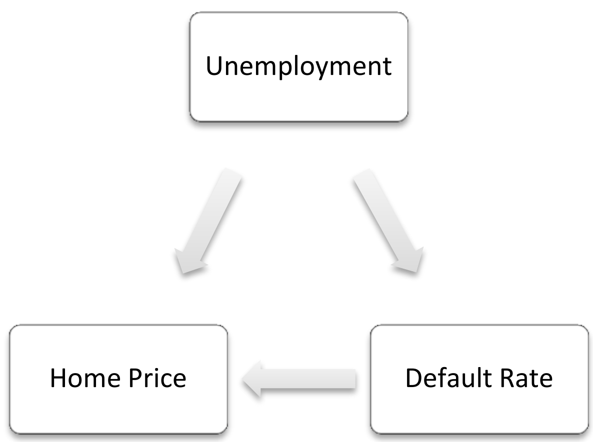
$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & a_{32} & 1 \end{bmatrix} \quad \text{and} \quad \boldsymbol{D} = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix}$$

---

[40] $E\{\boldsymbol{D}^{-1}\boldsymbol{B}\varepsilon_t(\boldsymbol{D}^{-1}\boldsymbol{B}\varepsilon_t)^/\} = \boldsymbol{D}^{-1}\boldsymbol{B}E\{\varepsilon_t\varepsilon_t{}^/\}\boldsymbol{B}^/\left(\boldsymbol{D}^/\right)^{-1} = \boldsymbol{D}^{-1}\boldsymbol{B}\Sigma_\epsilon\boldsymbol{B}^/\left(\boldsymbol{D}^/\right)^{-1} = \mathbf{I}_3$

Because $y_t = (U_t, D_t, P_t)'$, the identification scheme implies that changes in the unemployment rates are not contemporaneously affected by the changes in the home price indices and the mortgage default rates. It also implies that changes in the mortgage default rates are affected by the contemporaneous changes in the unemployment rates (if $a_{21} \neq 0$) but not the house price indices. Finally, it also implies that changes in the home price indices (if $a_{31} \neq 0$) are affected by contemporaneous changes in the unemployment rates and the mortgage default rates (if $a_{32} \neq 0$).

Contemporaneous Effects



We have enough restrictions that the innovations and the associated unique impulse responses are just-identified. We believe this identification strategy is reasonable: unemployed borrowers will experience difficulties paying their mortgages thereby leading to an increase in the default rate in the same quarter that they were unemployed, but borrowers who experience a negative equity do not make the decision to default in the same quarter. The second part was motivated by Deng, Quigley and Van Order (2000), which empirically tested some mortgage default theories and found that borrowers do not default as soon as home equity becomes negative; they prefer to wait since default is irreversible and house prices may increase.

2.3 Data

The nine census regions are: Pacific Census Division (P), Mountain Census Division (MT), West North Central (WNC), West South Central (WSC), East North Central (ENC), East South Central (ESC), New England (NE), Middle Atlantic (MA) and South Atlantic (SA)[41]. The states are Arizona, California, Florida, Michigan, Nevada, and Pennsylvania.

The mortgage default rate is defined as the total number of seriously delinquent mortgage loans as a percentage of all loans serviced in each quarter. The seriously delinquent loans are mortgage loans that are in 90+ delinquent, i.e., they are loans for which the borrowers have not paid the mortgage in 90+ days. The data is obtained from Mortgage Bankers Association National Delinquent Survey. The data consist of quarterly mortgage default rates from the second quarter of 1979 to the third quarter of 2010 for the national, 9 census regions and 6 states.

The house price indices data were obtained from The Federal Housing Agency House Price Indices (HPI)[42]. The indices are constructed from quarterly house price using data on conventional conforming mortgage transactions obtained from the Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National Mortgage Association (Fannie Mae). The HPI measures broadly the movement of single-family house prices. It is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales or refinancing on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975.

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[41] Appendix A provides more information about the census regions.

[42] There are other House Price Indices, (e.g. Case-Shiller Indices) which could have been used. The HPI is used here because it has a longer series than other indices.

The unemployment rates were obtained from the Bureau of Labor Statistics.

2.4 Empirical Results

This section discusses the results of the forecast errors from 2001 to 2010 for the regional and national mortgage default rates using the SVAR estimates from 1979 to 2000.

2.4.1 Forecast Errors of Mortgage Default Rate: 2001 to 2010 Period

Given the SVAR system:

$$(4) \qquad \boldsymbol{B}\left[I_K - A_1L^1 - A_2L^2 \ldots - A_pL^p\right]y_t = \boldsymbol{D}e_t \qquad t = 1, \ldots, T$$

The optimal $l - step$ forecast (after T) of the system is given by:

$$(5)^{43} \qquad \hat{y}_T(l) = \hat{v} + \hat{A}_1\hat{y}_T(l-1) + \cdots + \hat{A}_p\hat{y}_T(l-p) \qquad l = 1, 2, \ldots$$

The forecast error for the mortgage default rate is represented as:

$$(6) \qquad Forecast\ Error = y^D_{T+l} - \hat{y}^D_T(l)$$

Where y^D_{t+l} is the national and regional mortgage default rate observed at time $T + l$ and $\hat{y}^D_T(l)$ is the forecasted national and regional mortgage default rate at time $T + l.$

Figures[44] 1 to 4 represent the graphs of the forecast errors for the national and New England, East South Central and Mountain regions. The SVAR model was not far off in forecasting the changes in the national and regional mortgage default rates from 2001 to 2007. The big deviations in the forecast errors from 2006 to 2007 for the national and East South

[43] More information on the estimation of the forecast is provided in Appendix B.
[44] The forecast error graphs shown are similar in the regions not shown.

Central—which are also present in the forecast error graph for West South Central—are due to the effects of Hurricane Katrina. The model did a good job in forecasting the changes in the mortgage default rate even in the housing boom years from 2003 to 2006. However, the model failed during the Great Recession period (2008 to 2010). Section 4.2 explores some of the reasons behind this forecast failure.

Figure 1 National
Forecast Error 2001 to 2010

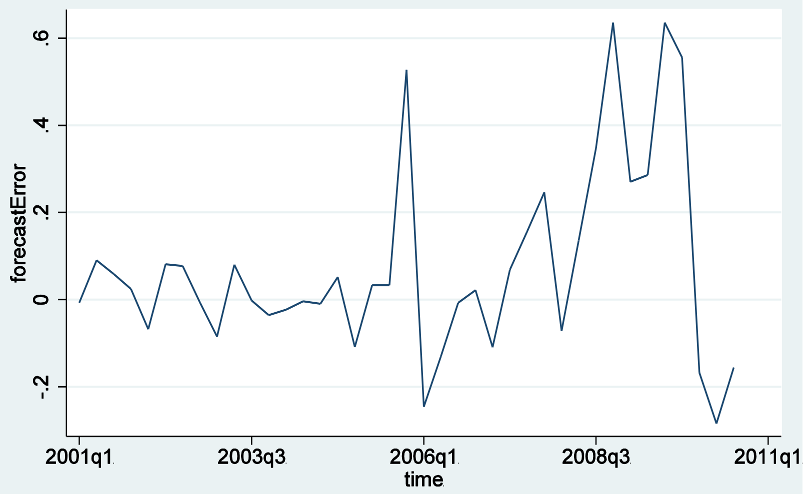


Figure 2 New England
Forecast Error 2001 to 2010

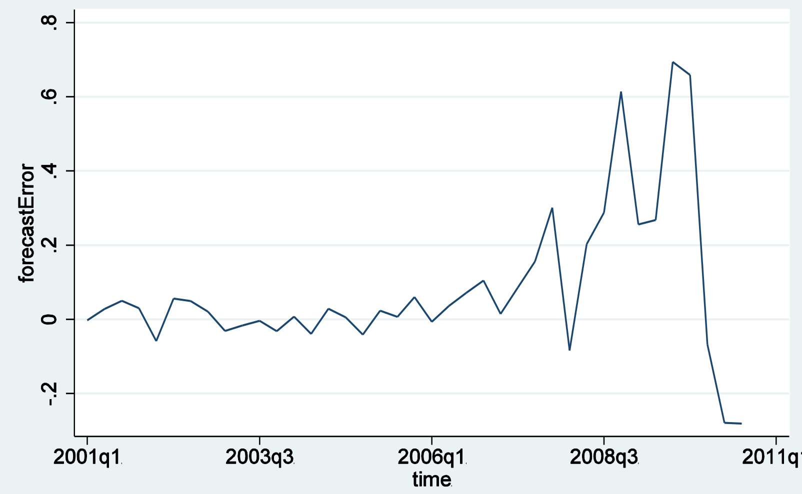


Figure 3 East South Central
Forecast Error 2001 to 2010

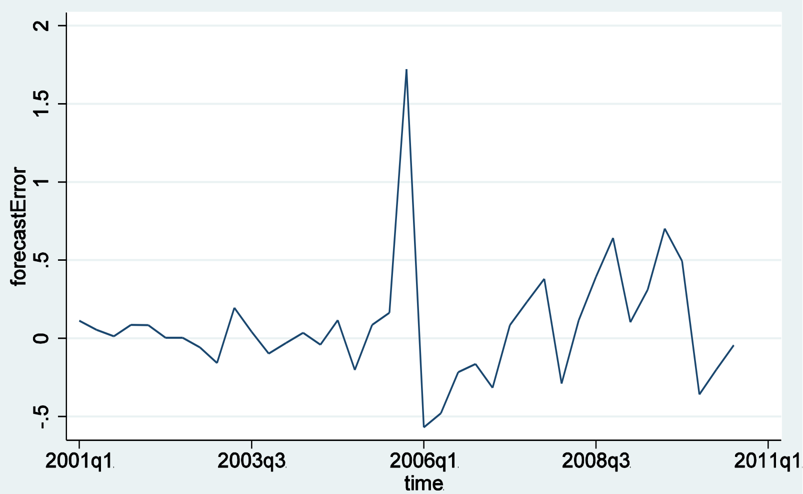
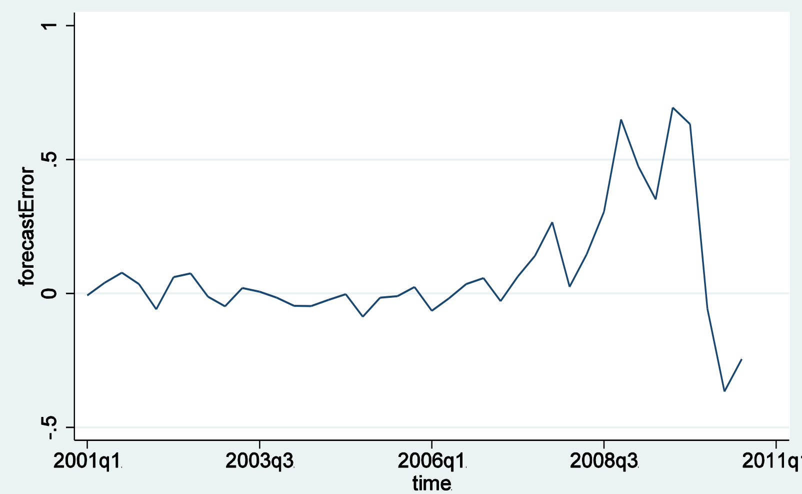


Figure 4 Mountain Census Division
Forecast Error 2001 to 2010



Given that the unemployment and negative shocks reinforce each other, a second model specification where unemployment rate was interacted with the home price index was tried, but it failed to improve the forecasted default rates from 2001 to 2010.

2.4.2 Possible Reason for the Poor Fit during the Great Recession

(A) Joint Structural Break Test

A possible explanation for the poor performance of the model during the Great Recession is that there might have been a structural change in the trivariate system during this period which the model could not have anticipated.

This section outlines a procedure for testing for such a structural break. The test is based on Lutkepohl (1989).

Let the optimal $l - step$ forecast error of the SVAR system be represented as:

$$(7) \qquad e_T(l) := y_{T+l} - \hat{y}_T(l) = \sum_{i=0}^{l-1} \Theta_i e_{T+l-i} = [\Theta_{l-1} : \dots : \Theta_1 : I_3] \boldsymbol{e}_{T,l}$$

Where $\boldsymbol{e}_{T,l} := \left(\Theta'_{T+1}, \dots, \Theta'_{T+l}\right)'$. The Θ_i is the coefficient of the canonical MA representation of y_t; Equation (13)[45]. Because $\boldsymbol{e}_{T,l} \sim N(O, I_l \otimes \Sigma_e)$, the forecast error is a linear transformation of a multivariate normal distribution and,

$$e_T(l) \sim N(0, \Sigma_y(l))$$

where:

---

[45] (13) $\qquad y_t = \Theta_0 e_t + \Theta_1 e_{t-1} + \Theta_2 e_{t-2} + \cdots = \sum_{i=0}^{\infty} \Theta_i e_{t-i}$

$\Sigma_y(l) = \sum_{i=1}^{l-1} \widehat{\Theta}_i \hat{\Sigma}_e \widehat{\Theta}_i^{/} + \frac{1}{T}\Omega(l)$[46] is the forecast MSE matrix.

The optimal 1 $to\ l - steps$ are also jointly normal:

$$(8) \qquad \boldsymbol{e}_T(l) \coloneqq \begin{bmatrix} e_{T,1} \\ \vdots \\ e_{T,l} \end{bmatrix} = \boldsymbol{\Theta}_l \boldsymbol{e}_{T,l} \sim N(0, \boldsymbol{\Sigma}_y(l)),$$

As was shown in Lutkepohl (2005)[47],

$$(9) \qquad \hat{\lambda}_l = \frac{T}{3l(T+3p+1)} \boldsymbol{e}_T(l)^{/} \left(\boldsymbol{\Sigma}_y(l)\right)^{-1} \boldsymbol{e}_T(l) \approx F(3l, T-3p-1)$$

Where 3 represents the numbers of endogenous variables in the SVAR. The test assumes that $y_{T+k},\ k = 1, \ldots, l$ are generated by the same $SVAR(p)$ process that generated the $y_t\ \ for\ t \le T$. $\hat{\lambda}_l$ test the null hypothesis that y_{T+k} is generated by the same Gaussian $SVAR(p)$ process that generated $y_1, \ldots, y_T$.

The SVAR model is estimated from 1979 to 2007 period and the mortgage default rate is forecasted for the period 1st quarter of 2008 to 3rd quarter of 2010 (11 quarters). Table 2.1 presents the results of the test together with the p-values. The p-value is the probability that the test statistic assumes a value greater than the observed test value, if the null hypothesis is true. The results show that with the exception of East North Central region there does not seem to be a structural break in the underlying parameters for the other regions.

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[46] This term accounts for small sample and also for the fact that the forecasts are based on estimated process. Appendix B has more details

[47] Pages 187-188 and Appendix C

Table 2.1

This table reports the test statistic and the p-values for the joint structural break tests for the mortgage default rate, the unemployment rate and the home price index for the national and 9 regions. The estimation of the model (equation 3) is done using data from 1979 to 2008, and the forecast for the default rate, unemployment and home price index is from 2008 to 2010 (the Great Recession period).

National and Regions	**Test Statistic** $\hat{\lambda}_l$	**p-values**
National	0.390	0.99
East North Central	1.584	0.04
East South Central	0.624	0.94
Middle Atlantic	0.209	0.99
Mountain	0.532	0.98
New England	0.423	0.99
Pacific	0.274	0.99
South Atlantic	0.482	0.99
West North Central	0.323	0.99
West South Central	0.194	0.99

(B) Individual Structural Break Test

Lutkepohl (1989) showed that the power of a test based on joint variables may be lower than the power of a test based on the individual variables. Therefore we also run structural break tests for the national and regional mortgage default rates for the 2001 to 2010 period[48].

Suppose that the mortgage default rates follow an $ARMA(p,q)$ stochastic process represented as:

$$(10) \qquad \theta(L)X_t = \varphi(L)\gamma_t$$

[48] We know from the analysis of the forecast errors that, if there is a structural break in the mortgage default rate it will occur post 2000.

Where L is the lag operator, $\theta(L) = 1 - \theta_1 L - \cdots - \theta_p L^p$ and $\varphi(L) = 1 - \theta_1 L - \cdots - \theta_q L^q$. γ_t is a Gaussian white noise with variance σ_γ^2.

The MA representation is

$$(11) \qquad X_t = \beta(L)\gamma_t$$

Where $\beta(L) = \frac{\varphi(L)}{\theta(L)} = \sum_{i=1}^{\infty} \beta_i L^i$

A test statistic to test for a structural break is constructed as follows: Let the sum of squared residuals of the estimation of Equation (11) using data from 1979 to 2007 be represented as $\hat{\gamma}^{1979\ to\ 2007}$, and let the sum of squared residuals using data from 1979 to 2010 be represented as $\hat{\gamma}^{1979\ to\ 2010}$. Then a test for structural break in the mortgage default rate from 2008 to 2010 is:

$$(12) \qquad \tau = \frac{[\hat{\gamma}^{1979\ to\ 2010} - \hat{\gamma}^{1979\ to\ 2007}]/N_2}{[\hat{\gamma}^{1979\ to\ 2007}]/N_1 - k} \approx F(N_2, N_1 - k)$$

Where N_2 is the number of observations from 2008 to 2010, N_1 is the number of observations from 1979 to 2007 and $k = p + q$, the number of parameters to be estimated.

Table 2.2 presents the results of the structural break test together with the p-values. The results show that there has been a structural break in the national and regional mortgage default rates during 2008 to 2010. This break in the mortgage default rates accounts for the huge deviations in the forecast errors observed during the Great Recession (2008 to 2010). The SVAR model using just estimates from fitting the model to the 1979 to 2000 sample to forecast the mortgage default rates from 2001 to 2010 could not have anticipated this structural change. The graphs of the national and regional mortgage default rates (Appendix D) show that there was not much variation in the mortgage default rates until after 2007.

Table 2.2

This table reports the test statistic and the p-values for the individual structural break test for the mortgage default rate of the national and 9 regions. The estimation of the model (Equation 11)[49] is done using data from 1979 to 2010 and also data from 1979 to 2007.

National and Regions	Test Statistic (τ)	p-value
National	8.431	0.000
East North Central	11.439	0.000
East South Central	30.078	0.000
Middle Atlantic	27.557	0.000
Mountain	7.104	0.000
New England	18.327	0.000
Pacific	8.124	0.000
South Atlantic	17.479	0.000
West North Central	4.050	0.011
West South Central	18.344	0.000

2.5 Analysis of the Dynamics of the Unemployment and Home Price Index shocks on the Mortgage Default Rate (National and Regional): 1979 to 2000 vs. 2001 to 2010

In this section we evaluate the impact of the home price index and unemployment shocks on the mortgage default rates by examining the impulse response functions and the variance decomposition from 1979 to 2000 and also from 2001 to 2010. Not only are we interested in the dynamics of the two shocks on the mortgage default rates during both periods; we also want to

[49] The exact specification of the model for the national and the 9 regions are presented in Appendix C

assess the relative importance of the shocks in explaining the variation in the mortgage default rates.

2.5.1 Orthogonalized Impulse Response

An MA representation of equation (3) based on e_t is given by:

$$(13) \qquad y_t = \Theta_0 e_t + \Theta_1 e_{t-1} + \Theta_2 e_{t-2} + \cdots = \sum_{i=0}^{\infty} \Theta_i e_{t-i}$$

Where $\Theta_j = \left[I_K - A_1 L^1 - A_2 L^2 \ldots - A_p L^p\right]^{-1} \boldsymbol{B}^{-1}\boldsymbol{D} \qquad (j = 0,1,2, \ldots)$. The elements of the Θ_j matrices represent the responses to e_t shocks.

2.5.2 Variance Decomposition

A variance decomposition is performed to measure the contribution of the home price and unemployment shocks to the changes in default rates. Using equation (13), the error optimal $h - step$ ahead forecast at time t, $\hat{y}_{t+h:t}$ is:

$$(14) \qquad y_{t+h} - \hat{y}_{t+h:t} = \sum_{l=0}^{h-1} \Theta_l e_{t+h-l}$$

Denoting the $mn - th$ element of Θ_l by $\theta_{mn,l}$, then the $h - step$ forecast error of the $m - th$ component of $y_{m(t+h)}$becomes:

$$(15) \qquad y_{m(t+h)} - \hat{y}_{m(t+h):t} = \sum_{n=1}^{3} \left(\theta_{mn,0} e_{t+h}^{n} + \cdots + \theta_{mn,h-1} e_{t+1}^{n}\right)$$

Thus the forecast error of the $m-th$ component consists of all the innovations: e_t^1, e_t^2 and e_t^3. Because the $e_t^{n\prime}s$ are uncorrelated and have unit variances, the mean square error of $\hat{y}_{m(t+h):t}$ can then be expressed as:

$$(16) \qquad MSE(\hat{y}_{m(t+h):t}) = \sum_{n=1}^{3} \left(\theta_{mn,0}^2 + \cdots + \theta_{mn,h-1}^2\right)$$

The contribution $\phi_{mn}(h)$ of the nth component to the MSE of the h-step ahead forecast of the mth component is

$$(17) \qquad \phi_{mn}(h) = \frac{\sum_{l=0}^{h-1} \Theta_{mn,l}^2}{MSE(\hat{y}_{mt+h:t})}$$

This is the proportion of the $h-step$ forecast error variance error of variable m accounted for by e_t^1, e_t^2 and e_t^3 innovations. We focus here on the proportion of the forecast error variance of the mortgage default rate accounted by the unemployment and home price index shocks.

2.5.3 Home Price Index and Unemployment Data: 2000 to 2010

The 2000 to 2010 period represents a time of significant changes in unemployment and house prices. Table 2.3 presents the percentage appreciation and depreciation of the house price index at the national and regional levels from 2000 to 2010.[50] The table shows some variations across the regions of the extent of house price appreciation and depreciation during this period. House prices in the Pacific region had the largest appreciation and also the largest depreciation

[50] This period was chosen because it has the highest home price index and also the period when the index depreciated (measuring from the peak value) the most. The window is wide enough to observe the scale of house price appreciation for the regions and the subsequent collapse in house prices for some of the regions.

during this period. There has not being significant house price depreciation in the West North Central, West South Central and East South Central regions. The East North Central region had the smallest house price appreciation but one of the largest house price depreciation. Housing prices in New England and Middle Atlantic experienced large appreciation, but not significant depreciation.

Table 2.3

This table reports the maximum House Price Index appreciation and the minimum House Price Index depreciation from 1st quarter 2000 to 3rd Quarter 2010[51].

National and Regions	House Price Index Appreciation %	House Price Index Depreciation %
National	66	-13
East North Central	33	-11
East South Central	43	-4
Middle Atlantic	87	-9
Mountain	76	-28
New England	82	-12
Pacific	124	-38
South Atlantic	83	-18
West North Central	45	-5
West South Central	47	-2

Table 2.4 also reports the lowest and highest national and regional unemployment rates during 2001 to 2010. The table shows that there were significant increases in the unemployment rates both at the national and regional level during this period. East North Central and East South Central regions have their highest unemployment rates above the highest national unemployment

[51] **National** [Peak (1st qtr. 2007)]: **ENC** [Peak (1st qtr. 2007): **ESC** [Peak (1st qtr. 2008)]: **MA** [Peak (1st qtr. 2007)]: **MT** [Peak (2rd qtr. 2007)]: **NE** [Peak (1st qtr. 2007): **P** [Peak (4th qtr. 2006)]: **SA** [Peak (1st qtr. 2007)]: **WNC** [Peak (2nd qtr. 2007)]: **WSC** [Peak (2nd qtr. 2008)]. For the national and all the regions the minimum house price index depreciation after the peak occurred during the 2nd qtr. 2010.

rate. The two tables show that there were significant changes in house price indices and unemployment rates during this period. This presents a perfect sample to test the relative significance of home price index and unemployment shocks on the mortgage default rate.

Table 2.4

This table reports the lowest and highest national and regional unemployment rates 2001 to 2010. The dates for the lowest and highest values are provided in the brackets.

National and Regions	Lowest Unemployment rate	Highest unemployment rate
National	**4.2** (1st qtr. 2001)	**9.9** (4th qtr. 2009)
East North Central	**4.3** (1st qtr. 2001)	**11.1** (4th qtr. 2009)
East South Central	**4.6** (1st qtr. 2001)	**10.7** (4th qtr. 2009)
Middle Atlantic	**4.1** (1st qtr. 2001)	**9.1** (4th qtr. 2009)
Mountain	**3.2** (1st qtr. 2007)	**9.2** (1st qtr. 2010)
New England	**3.3** (1st qtr. 2001)	**8.6** (4th qtr. 2009)
Pacific	**4.6** (1st qtr. 2007)	**9.7** (4th qtr. 2009)
South Atlantic	**4.0** (2nd qtr. 2006)	**9.6** (4th qtr. 2009)
West North Central	**3.3** (1st qtr. 2001)	**6.5** (2nd qtr. 2009)
West South Central	**4.1** (1st qtr. 2008)	**7.7** (1st qtr. 2010)

2.5.4 Impulse Response Functions

This section presents the results of the impulse response functions for the mortgage default for the 1979 to 2000 and 2001 to 2010 samples.

Figures 5 to 8 represent the dynamics of the impulse response functions of the mortgage default rates for the national, East South Central, West North Central and Middle Atlantic regions[52] respectively to an increase of one standard deviation in the home price index and the unemployment rate. In response to the unemployment shocks, the national and regional mortgage default rates increase and they take about 15 quarters after the shocks to get back to their pre

[52] The dynamics of the other regions are similar to those reported here.

shock level. The home price shocks are unchanged in the period of impact because of our identification scheme, which implied that it takes more than a quarter for the home price index shocks to have an impact on the mortgage default rates. In response to the home price index shocks the national and regional mortgage default rates decrease and they also take about 15 quarters to get back to their pre-shock levels. The national and regional mortgage default dynamics after the shocks seem to be similar; however, there are regional variations in the peaks and troughs of the impulse response functions.

Table 2.5 reports the peak and trough of the national and regional mortgage default rates after the unemployment and home price index shocks. From 1979 to 2000 the national unemployment and home price index shocks led to a maximum increase of 1.3% and a decrease of 1% in the national mortgage default rates respectively. For the regions, the unemployment and home price index shocks led to an average increase of 1.2% and a decrease of 1.1% in the regional mortgage default rate respectively. Compared to the 2001 to 2010 period, the national unemployment and the home price index shocks led to maximum increase of 7.2% and a decrease of 4.9% in the national mortgage default rate respectively. For the regions, the unemployment and the home price index shocks led to an average increase of 12.7% and a decrease of 7.3% respectively. The unemployment changes during 1979 to 2000 at the national and regional levels did not seem to have impacted the national and regional mortgage default rates that much. The results for the home price index during this period are not surprising because the indices did not change much during the period.

For the 2001 to 2010 period, the unemployment results for the East South Central (which had one of the highest unemployment rates at 11.1%) and West South Central (influenced by Louisiana in particular) were mainly driven by the effects of hurricane Katrina. These two regions were among the regions with the smallest house price index appreciation and depreciation (Table 2.3); however the house price shocks seem to have generated a big impact on the mortgage default rates.

Overall the response to the unemployment shocks is larger than the response to the home price index shocks.

Table 2.5

This table reports the peak and trough of the impulse response functions of the national and regional mortgage default rates due to a one standard deviation increase in the national and regional unemployment rate and the national and regional home price indices.

National and Regions	1979 to 2000		2001 to 2010	
	Unemployment %	Price Index %	Unemployment %	Price Index %
National	**1.3**	**-1.0**	**7.2**	**-4.9**
East North Central	**1.9**	**-1.5**	**11.4**	**-6.0**
East South Central	**1.4**	**-1.7**	**18.0**	**-12.5**
Middle Atlantic	**1.1**	**-0.2**	**6.9**	**-5.1**
Mountain	**1.0**	**-1.2**	**10.4**	**-5.9**
New England	**1.2**	**-1.1**	**8.4**	**-5.6**
Pacific	**0.6**	**-1.6**	**5.9**	**-5.7**
South Atlantic	**0.7**	**-1.0**	**9.1**	**-7.8**
West North Central	**1.4**	**-0.5**	**5.4**	**-3.7**
West South Central	**1.4**	**-1.5**	**39.0**	**-8.7**

Impulse Response Functions 1979 to 2000 vs. 2001 to 2010: National and Regional

Figure 5 National

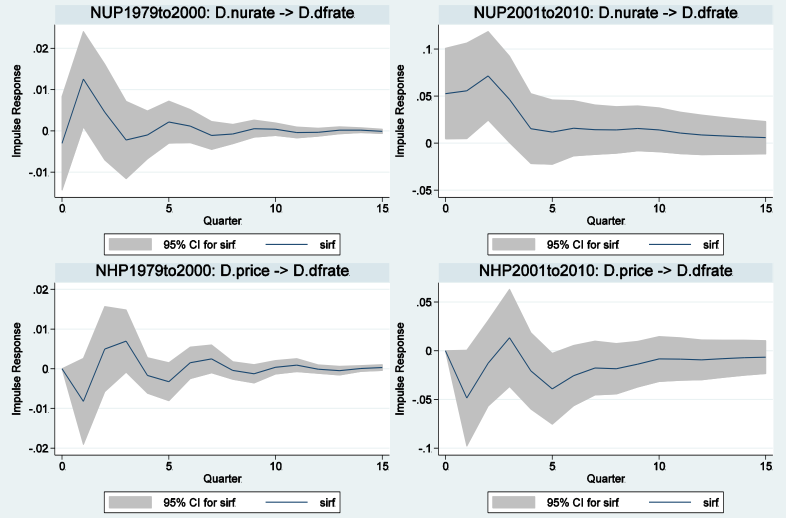


Figure 6 East South Central

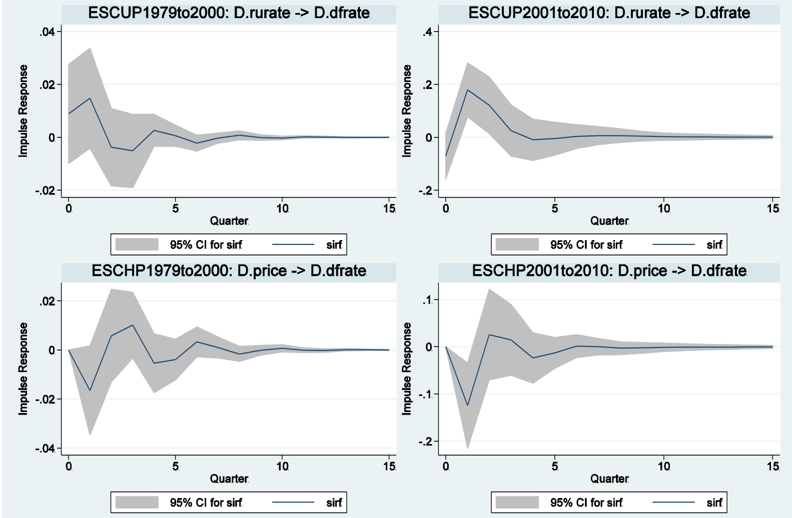


Figure 7 West North Central

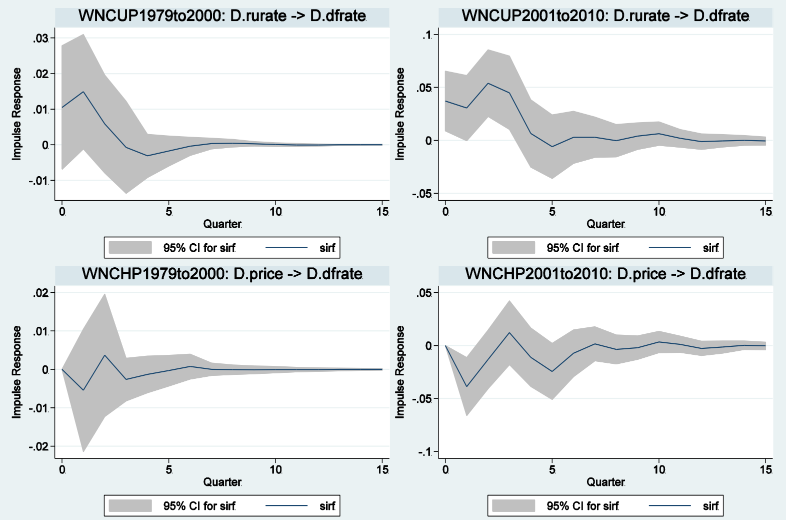
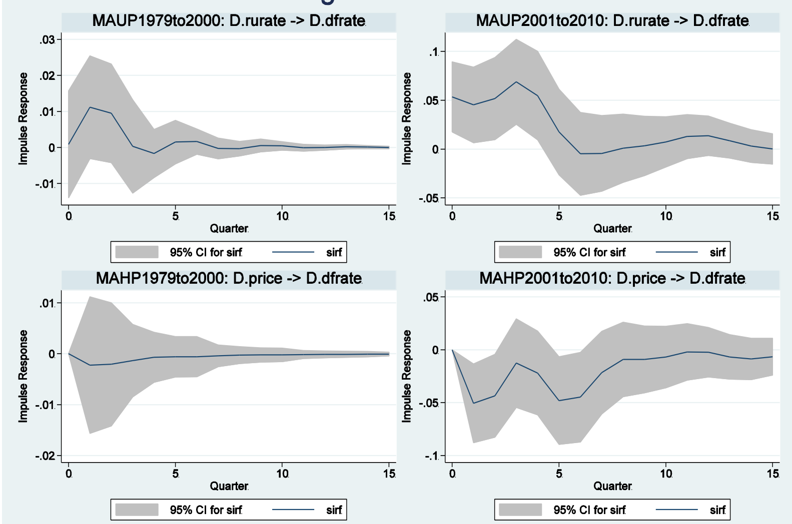


Figure 8 Middle Atlantic



2.5.5 Variance Decomposition

To gauge the relative contributions of the unemployment and the home price index shocks to the variance of the mortgage default rates during both the 1979 to 2000 and the 2001 to 2010 periods; the variance decompositions are constructed for the SVAR system using Equation (17) at $h = 4\ (year)$ and $h =\ 8(two\ years)$[53]. Table 2.6 presents the results of the variance decomposition. Again in this case also, the unemployment and home price index shocks do not explain much of the variation in the forecast errors of the mortgage default rates at both the national and regional levels for the 1979 to 2000 period. Although there are some regional variations in the impact of the unemployment and home price index shocks during the 2001 to 2010 period, on average, employments shocks explain a larger percentage in the movement of the mortgage default rates than the home price index shocks. The unemployment shocks explain about 44% of the movement in the mortgage default rates at $h = 4\ (year)$ and 43% $h = 8(two\ years)$. While the home price index shocks explains about 13% at $h = 4\ (year)$ and 20% $h = 8(two\ years)$. In effect, the two shocks are responsible on average for about 60% of the movement in the regional mortgage default rates.

The empirical results show that unemployment shocks have been a bigger contributor to national and regional mortgage default rates than the home price index shocks.

[53] As h increases, the decomposition of the variance of the forecasting error coincides with the decomposition of the unconditional variance.

Table 2.6

This table reports the variance decompositions, equation (17), of the national and regional mortgage default rates for 1979 to 2000 and 2001 to 2010 samples for $h = 4\ (a\ year)$ and $h = 8\ (two\ years)$. The decompositions are expressed in percentages.

National and Regions	1979 to 2000				2001 to 2010			
	Unemployment		**Price Index**		**Unemployment**		**Price Index**	
	$h = 4$	$h = 8$	$h = 4$	$h = 8$	$h = 4$	$h = 8$	$h = 4$	$h = 8$
National	**4.7**	**4.2**	**3.5**	**3.6**	**32**	**31**	**7**	**12**
East North Central	**5.0**	**5.1**	**2.3**	**2.7**	**56**	**51**	**11**	**14**
East South Central	**3.3**	**3.4**	**4.0**	**4.5**	**37**	**37**	**11**	**12**
Middle Atlantic	**3.4**	**3.3**	**0.2**	**0.2**	**38**	**38**	**14**	**24**
Mountain	**3.3**	**3.7**	**5.1**	**5.3**	**61**	**57**	**14**	**22**
New England	**2.3**	**2.6**	**1.9**	**2.2**	**36**	**39**	**15**	**21**
Pacific	**1.3**	**2.1**	**3.4**	**5.0**	**23**	**22**	**26**	**41**
South Atlantic	**2.1**	**2.1**	**2.0**	**2.1**	**43**	**38**	**20**	**30**
West North Central	**5.0**	**5.1**	**0.7**	**0.7**	**42**	**39**	**11**	**14**
West South Central	**2.6**	**2.5**	**3.6**	**3.6**	**63**	**63**	**4**	**4**

2.6 Dynamics of Some Selected States

The dynamics of the home price index and unemployment shocks on the mortgage default rates were examined for Arizona, California, Florida, Michigan, Nevada, and Pennsylvania. These states have had mortgage default rates higher than the national average. Some of the states (Michigan, Nevada and Pennsylvania) have also had unemployment rates higher than the national average. Arizona, California, Florida, Michigan and Nevada have also experienced some of the biggest drop in housing prices during the 2001 to 2010 period.

2.6.1 Home Price Index and Unemployment Data: 2000 to 2010

From Table 2.7 Florida had the largest appreciation in the house price index from 2000 to 2010 and also one of the largest house price index depreciations during the period. Michigan had one of the lowest appreciations in the house price index, but also one of the largest house price index depreciation during the period. Nevada had the largest depreciation in the home price index. Michigan had the smallest home price appreciation but a large home price index depreciation. There does not seem to be have been much depreciation in housing prices in Pennsylvania. Mayer and Pence (2009), document that areas with high house price appreciation experienced an increase in subprime mortgage origination. Mayer et al (2009) also showed that in California, Florida, Arizona and Nevada over half of subprime borrowers had negative equity in their home and over a third of borrowers in Michigan had negative equity by mid-2008.

Table 2.7

This table reports the maximum House Price Index appreciation and the minimum House Price Index depreciation from 1st quarter 2000 to 3rd Quarter 2010.

States	House Price Index Appreciation %	House Price Index Depreciation %
Arizona	132	-36
California	353	-30
Florida	387	-36
Michigan	27	-23
Nevada	169	-45
Pennsylvania	72	-6

Table 2.8 also reports the lowest and highest state unemployment rates during this period. The results show that there have been significant increases in the unemployment rates for these states during this period. With the exception of Pennsylvania, all the states have their highest unemployment rates above the highest national unemployment rate and also larger house price

index depreciation than the national. Again, these states present a perfect sample to test the relative significance of home price index and unemployment shocks on the mortgage default rate.

Table 2.8
This table reports the lowest and highest state unemployment rates 2001 to 2010. The dates for the lowest and highest values are provided in the brackets.

National and Regions	Lowest Unemployment rate	Highest unemployment rate
Arizona	**3.6** (2nd qtr. 2007)	**10.4** (4th qtr. 2009)
California	**4.8** (3rd qtr. 2006)	**12.5** (3rd qtr. 2010)
Florida	**3.3** (2nd qtr. 2006)	**11.7** (3rd qtr. 2010)
Michigan	**4.7** (1st qtr. 2001)	**14.1** (3rd qtr. 2009)
Nevada	**4.2** (4th qtr. 2006)	**14.9** (3rd qtr. 2010)
Pennsylvania	**4.2** (1st qtr. 2007)	**8..8** (1st qtr. 2010)

2.6.2 Impulse Response Functions

This section presents the results of the impulse response functions for the mortgage default for the 1979 to 2000 and 2001 to 2010 samples.

Figures 9 to 14 represents the dynamics of the impulse response functions of the mortgage default rates for the states to an increase of one standard deviation in the home price index and the unemployment rate. The dynamics of the states' mortgage default rates after the unemployment and home price shocks are similar to the dynamics of the national and regional mortgage default rates after the shocks. That is, in response to the unemployment shocks the states mortgage default rates increase and they take about 15 quarters after the shocks to get back to its pre shock level. The home price shocks are also unchanged in the period of impact due to the implication of our identification scheme. In response to the home price index shocks the states mortgage default rates decrease and for some of the states it takes about 20 quarters to get back to their pre shock level during the 2001 to 2010 period. However, for these selected states the peak and trough of the impulse response functions are higher and lower for the unemployment and home price index shocks respectively.

Table 2.5 reports the peak and trough of the state's mortgage default rates after the unemployment and home price index shocks. For the selected states also, there does not seem to have been much of an impact on the mortgage default rates during the 1979 to 2000 period for both the unemployment and home price shocks.

For the 2001 to 2010 period, the home price index shocks produced a larger impact on the mortgage default rates of California and Florida than the unemployment shocks. For the other 4 states the impact of the unemployment shocks was larger. For Nevada—which had the largest home price depreciation and the highest unemployment rate during this period—the unemployment shocks seem to have had a bigger impact on its mortgage default rates.

Table 2.9

This table reports the peak and trough of the impulse response functions of the state mortgage default rates due to a one standard deviation increase in the state unemployment rate and the state home price indices.

National and Regions	1979 to 2000		2001 to 2010	
	Unemployment %	**Price Index %**	**Unemployment %**	**Price Index %**
Arizona	**1.1**	**-1.2**	**19.9**	**-12.0**
California	**1.8**	**-0.7**	**8.0**	**-10.4**
Florida	**2.3**	**-0.8**	**11.6**	**-14.8**
Michigan	**1.5**	**-0.6**	**15.1**	**-7.7**
Nevada	**2.4**	**-0.6**	**19.8**	**-11.4**
Pennsylvania	**0.6**	**-1.4**	**7.1**	**-3.7**

Impulse Response Functions 1979 to 2000 vs. 2001 to 2010: States

Figure 9 Arizona

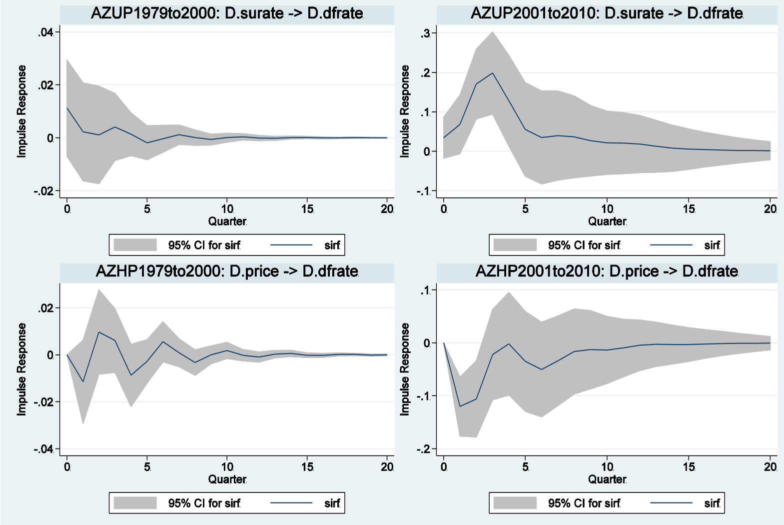


Figure 10 California

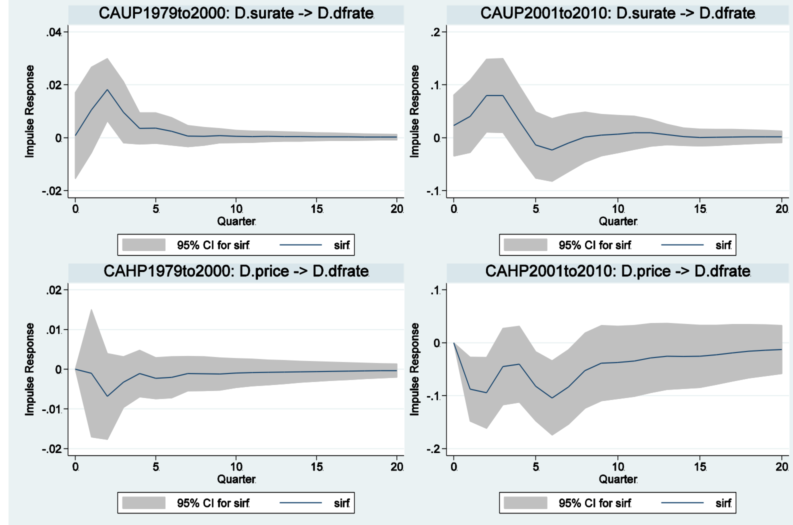


Figure 11 Florida

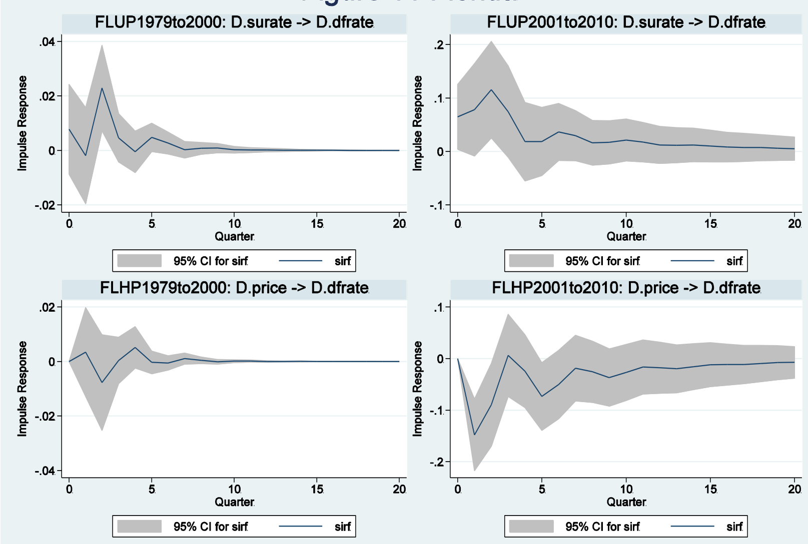
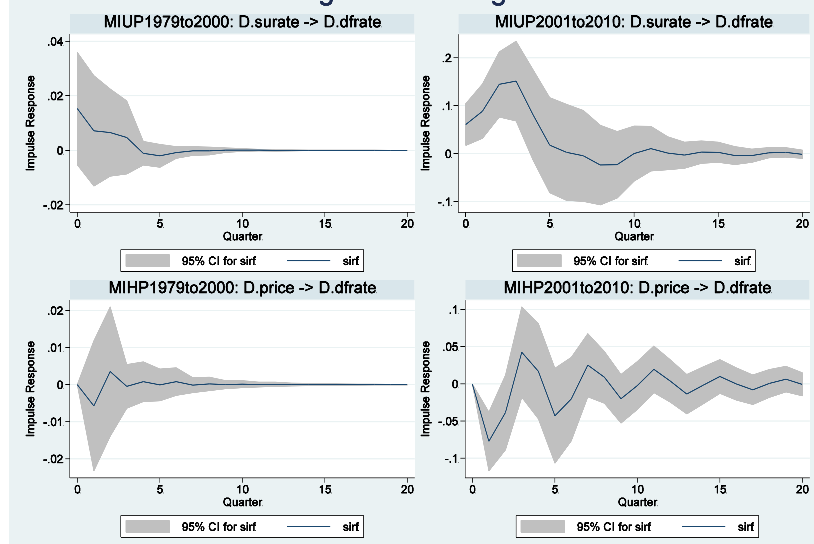
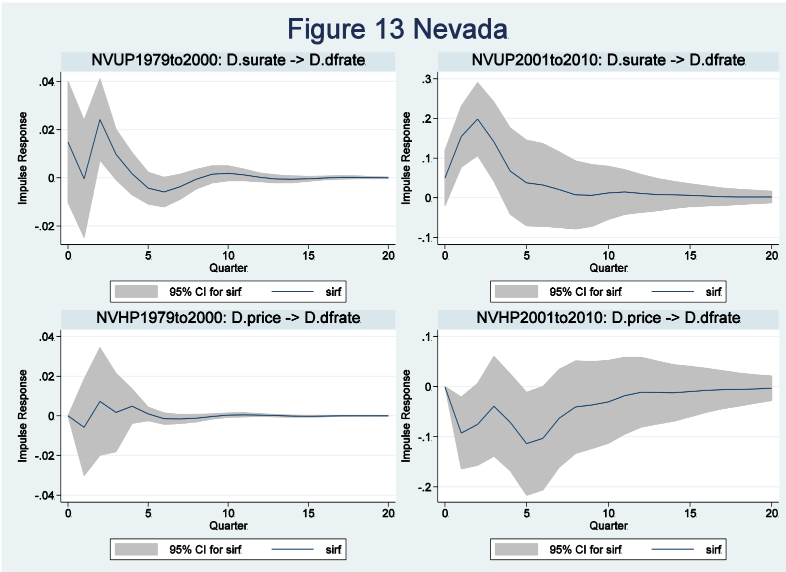
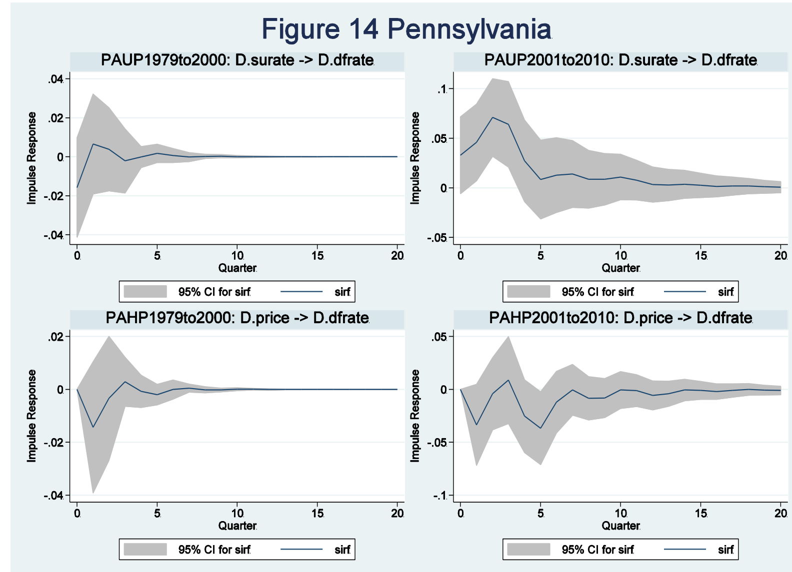


Figure 12 Michigan



Impulse Response Functions 1979 to 2000 vs. 2001 to 2010: States





2.6.3 Variance Decomposition

The variance decomposition is performed for both the 1979 to 2000 and the 2001 to 2010 periods at $h = 4\ (a\ year)$ and $h =\ 8(two\ years)$. Table 2.10 presents the results. At the state level also the unemployment and home price index shocks do not explain much of the variation in the forecast errors of the mortgage default rate for the 1979 to 2000 period. During the 2001 to 2010 period, the unemployment shocks explained more of the variation in the mortgage defaults rates than the home price index shocks at both the one and two year horizon. As Tables 2.7 and 2.8 shows, there have been significant changes in both the unemployment rates and the home price indices, but the changes in the unemployment rate on average explained more of the variation in the state mortgage default rates than the changes in the home price indices.

Policies that aim to decrease the default rates across the states should take into account the relative impact of the two shocks in explaining the variation in the mortgage default rate. If home price should dominate, then government programs that reduce the overall principal might be beneficial for that state. By contrast, if unemployment shocks dominate, reduction in payments (or subsidization mortgage payments) might be the better policy for the state.

Table 2.10

This table reports the variance decompositions, equation (17), of the states' mortgage default rates for 1979 to 2000 and 2001 to 2010 samples for $h = 4$ $(a\ year)$ and $h = 8$ $(two\ years)$. The decompositions are expressed in percentages.

States	**1979 to 2000**				**2001 to 2010**			
	Unemployment		**Price**		**Unemployment**		**Price**	
	$h = 4$	$h = 8$	$h = 4$	$h = 8$	$h = 4$	$h = 8$	$h = 4$	$h = 8$
Arizona	**1.5**	**1.5**	**2.7**	**3.6**	**53**	**57**	**19**	**18**
California	**7.0**	**7.3**	**0.8**	**0.9**	**17**	**14**	**21**	**38**
Florida	**7.6**	**7.9**	**0.9**	**1.2**	**27**	**26**	**28**	**32**
Michigan	**3.1**	**3.2**	**0.4**	**0.4**	**62**	**60**	**10**	**12**
Nevada	**4.8**	**5.1**	**0.5**	**0.6**	**54**	**43**	**10**	**22**
Pennsylvania	**1.8**	**1.8**	**1.3**	**1.3**	**40**	**37**	**4**	**9**

2.7 Conclusion

The increase in mortgage default rates over the last several years has created a renewed interest in the factors drive mortgage defaults. There has been an increase in the number of subprime loans originated after 2003, due to lax mortgage underwriting standards. This has increase the number of borrowers who are more susceptible to unemployment and negative home price shocks. These borrowers have little savings they could use to cushion them against unemployment and negative home price shocks. Studies have drawn conflicting conclusions as to which of these two factors have accounted for the most of the variation in the mortgage default rates. There is an important policy implications for how best to help home owners under water depending on which factor dominates. As Elul et al (2010) stated if negative equity dominates, then government programs that reduce the overall principal might be beneficial. By contrast, if unemployment shocks should dominate, reduction in payments (or subsidization mortgage payments) might be the better policy.

The paper uses an SVAR model to disentangle the interrelations between the home price index (which tracks housing prices) and unemployment shocks and mortgage default rates by studying the dynamics of these two shocks on mortgage default rates from 1979 to 2010 at the national, regional and state levels. The results show that, with the exception of the Pacific region, California and Florida, unemployment shocks explain more of the variation in the mortgage default rates than home price indices shock at the national, regional and state levels, especially, during the 2001 to 2010 period. These two shocks together are responsible on average for about 60% of the movement in the regional mortgage default rates.

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Appendix

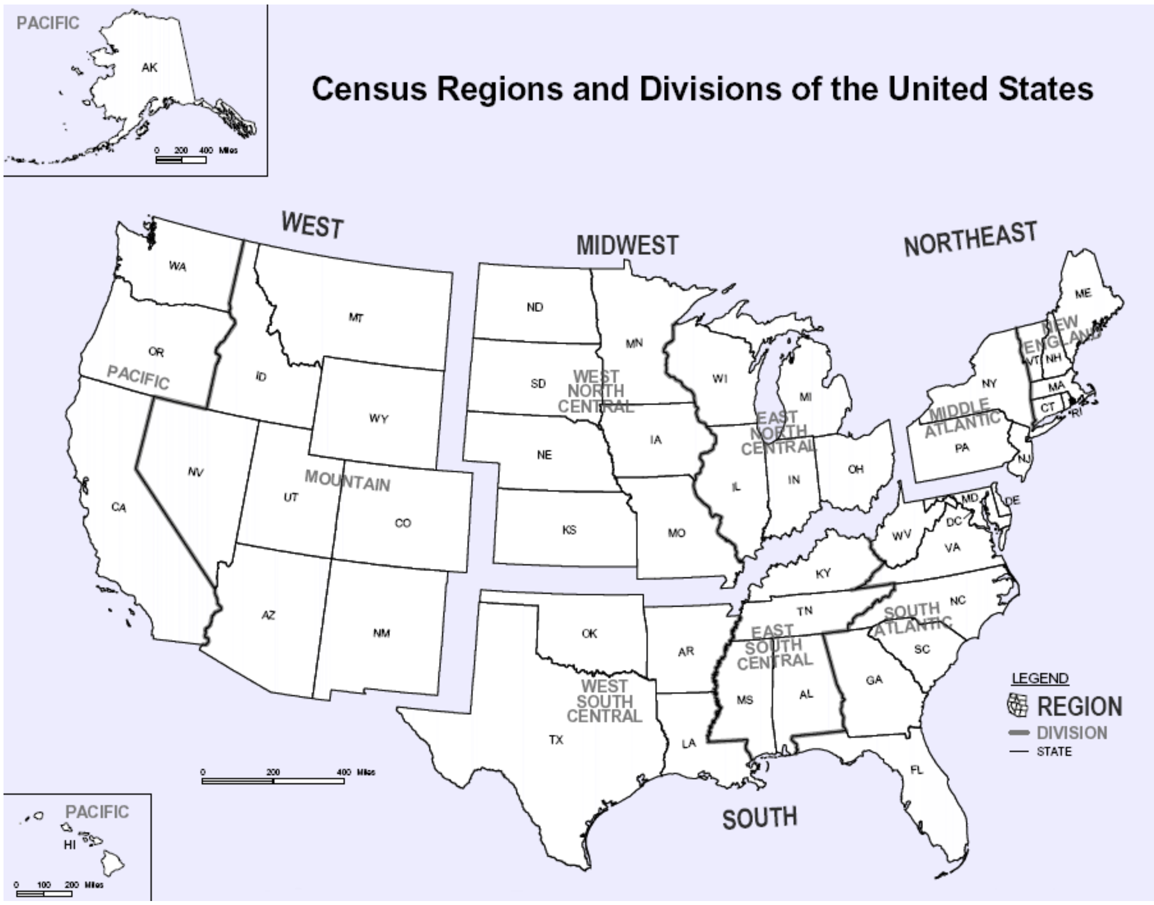
Chapter 1

A.1 Moody's Ratings

Moody's Ratings	
Aaa	AAA
Aa1, Aa2, Aa3	AA
A1, A2, A3	A
Baa1, Baa2, Baa3	BBB
Ba1, Ba2, Ba3	BB
B1, B2, B3	B
Caa	CCC
Ca	CC
C	C

Chapter 2

A.2 (Regions: US Census Bureau)



East North Central: Michigan, Wisconsin, Illinois, Indiana, Ohio
East South Central: Kentucky, Tennessee, Mississippi, Alabama
Middle Atlantic: New York, New Jersey, Pennsylvania
Mountain Census Division: Montana, Idaho, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico
New England: Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut
Pacific Census Division: Hawaii, Alaska, Washington, Oregon, California
South Atlantic: Delaware, Maryland, District of Columbia, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida
West North Central: North Dakota, South Dakota, Minnesota, Nebraska, Iowa, Kansas, Missouri
West South Central: Oklahoma, Arkansas, Texas, Louisiana

B.2 Forecasting with Estimated Process

From Lutkepohl (2005), if we denote the parameter estimators of the SVAR system, Equation (3), as $\widehat{A_1} \dots \ \widehat{A_p}$ and $\hat{\beta}$

The asymptotic estimator of the covariance matrix of the prediction error is given by:

$$(B.2.1) \qquad \Sigma_{\hat{y}}(l) = \Sigma_y(l) + \frac{1}{T}\Omega(l)$$

Where

$$(B.2.2) \qquad \Sigma_y(l) = E\{[y_{t-l} - y_t(l)][y_{t-l} - y_t(l)]^{/}\} = \textstyle\sum_{i=1}^{l-1} \widehat{\Theta}_i \hat{\Sigma}_e \widehat{\Theta}_i^{/}$$

And Θ_i is the $i - th$ coefficient of the canonical MA representation of y_t, Equation (13).

$$(\text{B}.2.3) \qquad \Omega(l) = \frac{1}{T}\sum_{t=0}^{T}\left\{\sum_{i=0}^{l-1} Z_t^{/}\left(\widehat{B^{/}}\right)^{l-1-i} \otimes \widehat{\Theta}_i\right\}\hat{\Sigma}_\beta\left\{\sum_{i=0}^{l-1} Z_t^{/}\left(\widehat{B^{/}}\right)^{l-1-i} \otimes \widehat{\Theta}_i\right\}^{/}$$

$$\hat{B} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ \hat{v} & \hat{A}_1 & \hat{A}_2 & \cdots & \hat{A}_{p-1} & \hat{A}_p \\ 0 & I_K & 0 & \dots & 0 & 0 \\ 0 & 0 & I_K & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & I_K & 0 \end{bmatrix}$$

$$Z_t = \left(1, y_t^{/}, \dots, y_{t-p-1}^{/}\right)^{/}$$

$$\widehat{\Theta}_0 = I_K$$

$$\Theta_i = \sum_{j=1}^{i} \Phi_{i-j}\hat{A}_j \qquad\qquad 1 = 1,2, \dots$$

$$\hat{A}_j = 0 \qquad for\ j > p$$

$\hat{\Sigma}_e$ is the estimate of the covariance matrix of the innovations and $\hat{\Sigma}_\beta$ is the covariance matrix of the asymptotic distribution of $\sqrt{T}(\hat{\beta} - \beta)$.

For a simulation with R repetitions, this algorithm is used[54]:

1. Fit the model and save the estimated coefficients. Only data up to T is used for the estimation.

2. Use the estimated coefficients to calculate the residuals.

3. Repeat steps 3a–3c R times.

3a. Draw a simple random sample with replacement of size T +h from the residuals. When the tth observation is drawn, all K residuals are selected, preserving any contemporaneous correlation among the residuals.

3b. Use the sampled residuals, p initial values of the endogenous variables, any exogenous variables, and the estimated coefficients to construct a new sample dataset.

3c. Save the simulated endogenous variables for the h forecast periods in the bootstrapped dataset.

[54] StataCorp, 2011, Time Series Reference Manual p. 151

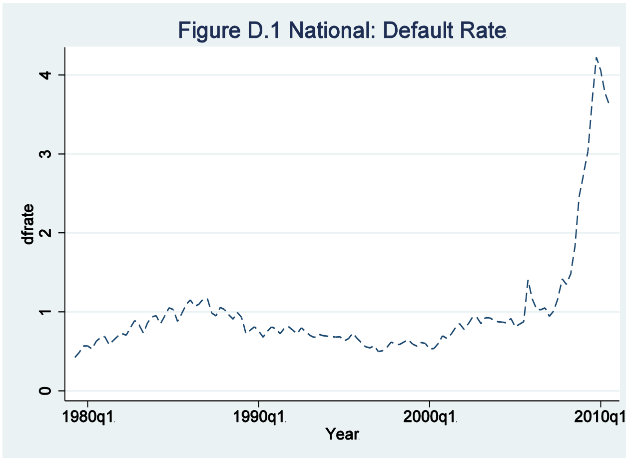
C.2 Individual structural test

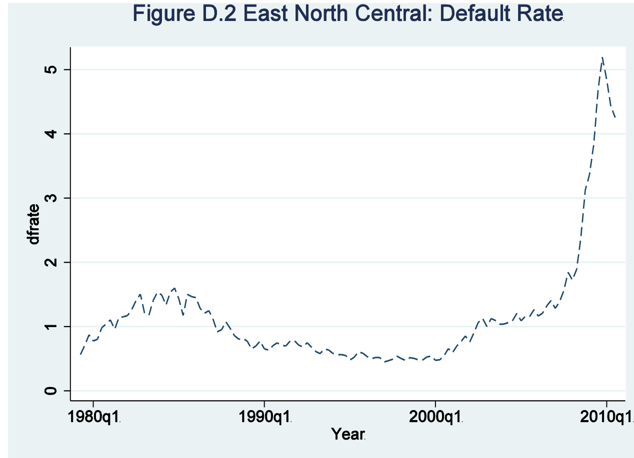
Table C.2.1

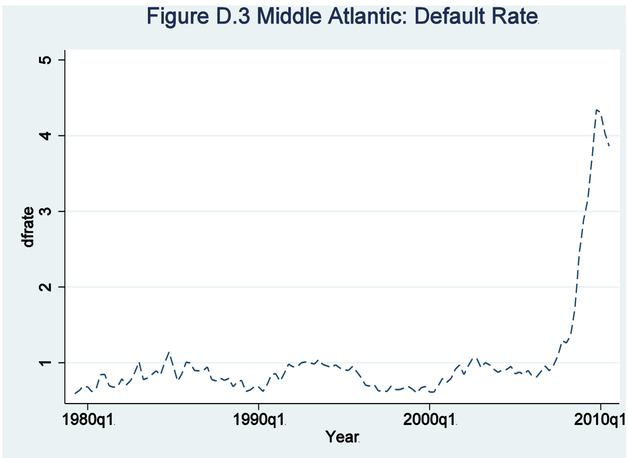
This table reports the optimal lag for estimating equation (16) for the full sample (1979 to 2010) and the 1979 to 2007 sample. Akaike's information criterion (AIC) was used in selecting the optimal lags

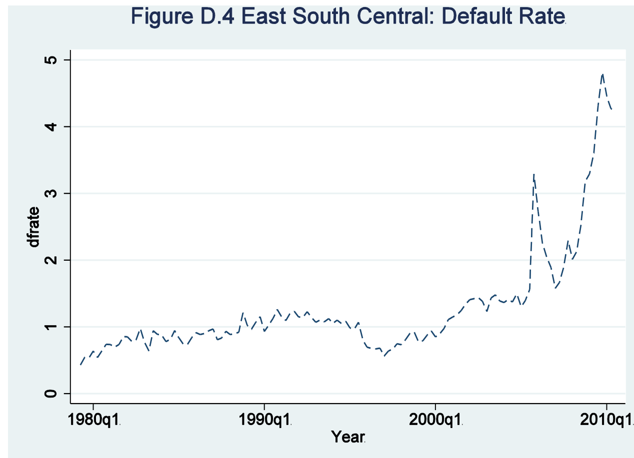
National and Regions	ARMA	Degrees of Freedom
National	(6,2)	F(11,107)
East North Central	(4,2)	F(11,109)
East South Central	(6,2)	F(11,107)
Middle Atlantic	(3,2)	F(11,110)
Mountain	(4,2)	F(11,109)
New England	(3,1)	F(11,111)
Pacific	(5,2)	F(11,108)
South Atlantic	(2,2)	F(11,111)
West North Central	(5,2)	F(11,108)
West South Central	(3,2)	F(11,110)

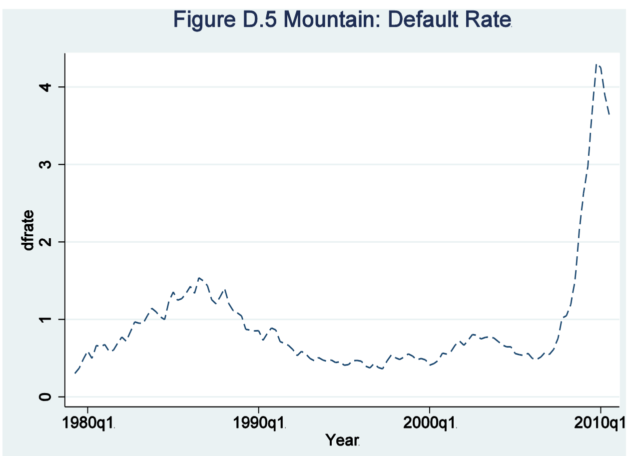
D.2 Graphs of National and Regional Mortgage Default Rate

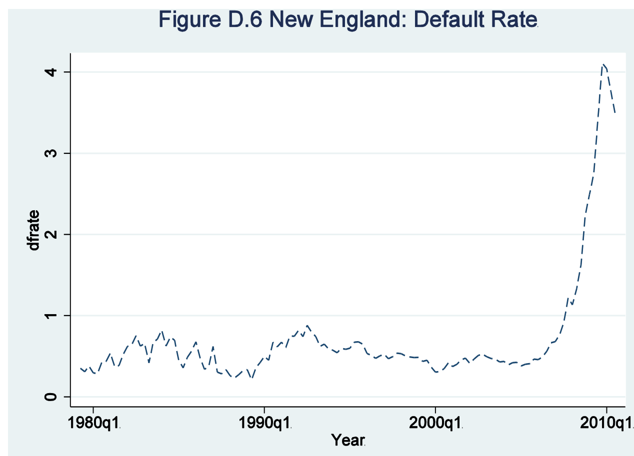












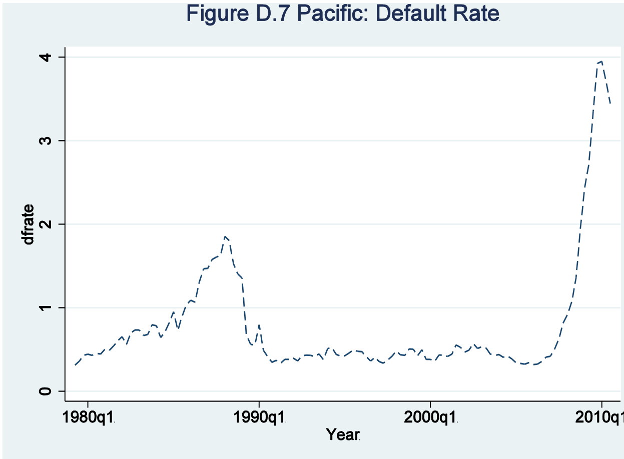


Figure D.7 Pacific: Default Rate
dfrate
0
1
2
3
4
1980q1
1990q1
2000q1
2010q1
Year

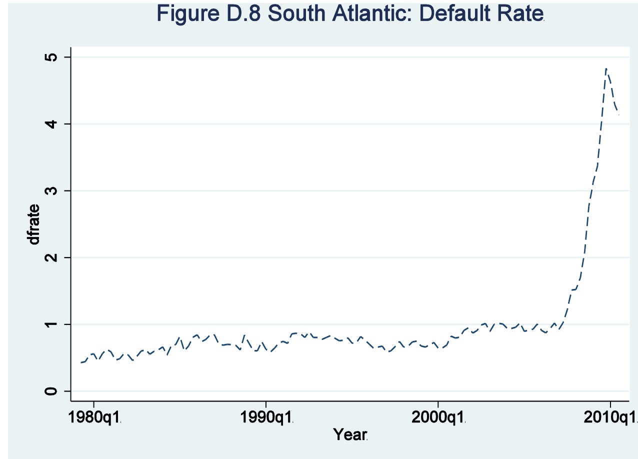


Figure D.8 South Atlantic: Default Rate
dfrate
0
1
2
3
4
5
1980q1
1990q1
2000q1
2010q1
Year

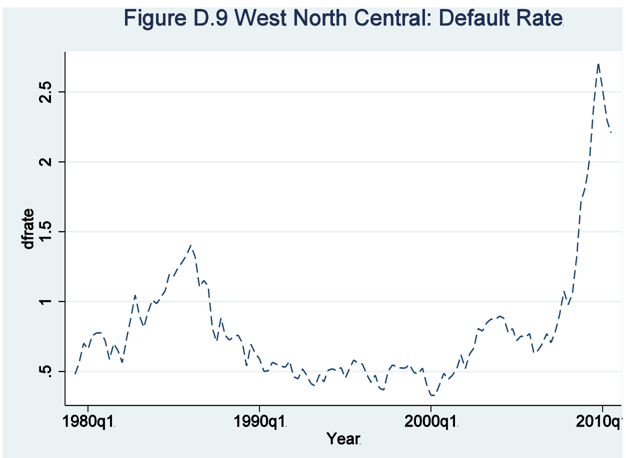


Figure D.9 West North Central: Default Rate
dfrate
.5
1
1.5
2
2.5
1980q1
1990q1
2000q1
2010q1
Year

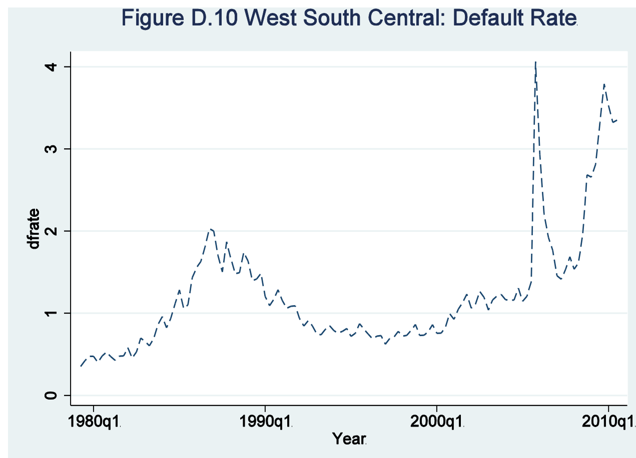


Figure D.10 West South Central: Default Rate
dfrate
0
1
2
3
4
1980q1
1990q1
2000q1
2010q1
Year