

**The Credit Chanel of Monetary Policy: Effects on the Housing Market in the  
Time Period Preceding the Recent Financial Crisis**

by

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## Abstract

This paper investigates the effect of the broad credit channel of monetary policy on the United States' housing market during the recent financial crisis. More specifically, it explores the effects of the sharp decreases in monetary policy and increased levels of credit expansion, and their potential joint effects on increased housing market activity during the bubble period preceding the recession. The approach combines some of the literature on credit channels together with an empirical vector autoregressive model to analyze the possible consequences of the Federal Reserves' monetary policy stance and its effect on the housing market through a potential credit expansion transmission mechanism. The results indicate that while a regular interest rate transmission mechanism may have been at work, with an inverse relationship between short-term interest rates and housing market activity, it is difficult to establish the presence of a credit channel transmission mechanism operating on the housing market. Alternatively, the paper argues that other factors, most notably deregulation and financing innovations, may have separately exacerbated the effect of both credit expansion and the traditional transmission mechanism. This demonstrates the necessity for increased coordination between policy-setting bodies, with a specific focus on the potential amplification of monetary conditions through regulatory changes, and the potential interaction of both factors.

## Introduction

Explanations for the causes of the recent financial crisis have varied, with many variables hypothesized to be main drivers of the crisis. Significant amongst those in discussions are the levels of credit expansion and sharp changes in monetary policy stances that preceded the crisis. Likewise, asset price bubbles, most notably those of equity, securities and housing, are viewed as a main consequence of those adverse causal variables. Those hikes in asset prices have significantly affected economic activity and contributed to the bubble preceding the crisis, and hence to the changes in the business cycle that characterized this time period. The drivers of this growth in credit are varied, and the magnitude of explanatory power of each is debatable, varying from regulatory changes on capital requirements, changes in financial innovation, changes in financial sector infrastructure, and most importantly, monetary policy (Dokko et al. 2011, 236).

This paper aims to test the effect of the sharp monetary policy shocks which resulted in historically low short-term interest rates in the years leading up to the crisis. It will test this effect through a credit channel framework, hypothesizing that sharp and rapid decreases in interest rates by the Federal Reserve during that period may have caused a surge in credit expansion by potentially resulting change in the external finance premium of borrowers due to financial market imperfections (Bernanke & Gertler 1995, 28). In other words, historically low interest-rate may have affected borrowers' ability to obtain credit and lenders' ability to lend, allowing for increased credit provision levels. This, together with the conventional workings of interest rate, in turn, had a significant impact on economic activity, most notably that of the housing market, viewed to be a very sensitive component of aggregate demand to interest rates (Bernanke & Gertler 1995,28).

Alternatively, non-monetary causes of credit expansion may have also experienced sharp changes during this period; and as such, a final section of the paper will offer a short discussion of the relevant regulatory and financial market changes that accompanied this time period and may have contributed largely to these appreciations. More importantly, these changes may have acted as an amplifier to the expansionary monetary policy at the time (Iacoviello & Minetti 2003, 20), inducing individuals to demand more loans and lenders to extend more housing credit in response to the blend of low interest rates and low regulation environment.

### **Approach and Motivation**

The paper will start by discussing the theoretical and economic aspects of monetary policy and credit channels. With the exception of a few studies, such as Iacovelli and Minetti's (2008), most credit channel literature focuses on the effects of the channel on general economic activity. Thus, the first section will discuss the relevance and potential application of this mechanism to the housing market during the recent financial crisis.

The next section will present the vector autoregressive model, which aims to search for a relationship between monetary policies and housing through both, a standard interest rate channel, and an intermediate credit channel. The variables used are grouped into three categories representing monetary policy stance, a credit channel indicator, and a housing market indicator. The model will attempt to investigate the following: whether a traditional interest rate channel was present and whether it was accompanied by a magnifying credit channel. The results of each VAR will be reported, most importantly through Granger-causality Wald tests, which illustrate whether each variable and its lags

plays a role in explaining the other, and whether the whole equation for each variable is statistically significant (Stock & Watson 2001, 104). Accompanying those tests are impulse response functions for our variables of interest, which demonstrate the effect of a one unit (or one standard error) shock to one variable on another variable over time (Gregory, Chapter 7, 15). A robustness sub-section will follow, with tests of modification to the benchmark model that involve changing the variable for the credit channel category, extending the time period, or accounting for omitted variable bias to investigate whether the initially deduced results would hold otherwise.

The rest of the paper will include a qualitative discussion on the potential role of other, non-monetary factors, such as regulation measures and requirements which also experienced notable changes during the period of study, and their relation to the empirical results.

### **Theoretical Background and Relevance to the Recent Financial Crisis**

The theoretical understanding of credit channels used in this paper is mainly derived through Bernanke and Gertler's (1995) work on the transmission mechanisms of monetary policy. This is accompanied by other discussions such as Bernanke and Blinder (1988), and empirical applications of credit channels such as that of Italiano (2000). The description of a credit channel is best captured by Bernanke et al. (1995, 28) as an "enhancement mechanism" that accompanies the traditional transmission mechanism in transferring the effects of monetary policy. The channel works through changes in the external finance premium, described as the difference between the cost of funds raised internally and externally, and that is caused by credit market imperfections (Ibid 28,

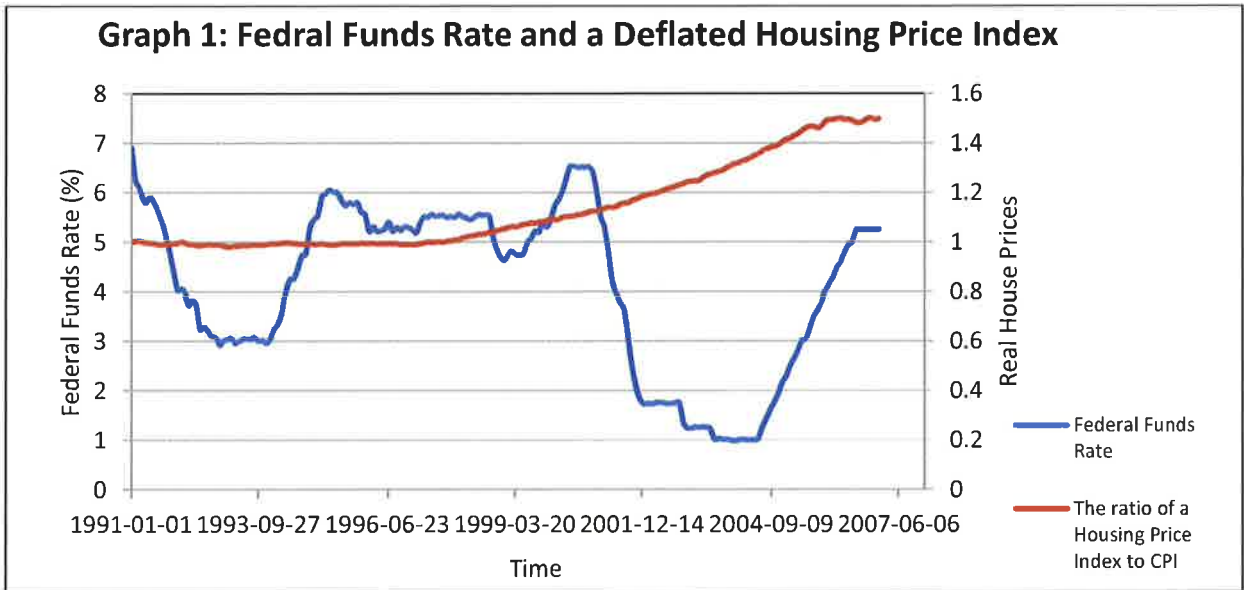
1995; Iacoviello et al. 2008, 2). Consequently, they argue that changes in monetary policy will affect this premium in the same direction as that of monetary policy (Ibid 28, 1995). This, in turn, implies that an expansionary monetary policy shock which decreases interest rates may also decrease the external finance premium for individuals. Thus, a distinction is drawn between the traditional interest rate mechanism which affects the opportunity cost of capital for individuals through wealth and substitution effects, and a supplementary mechanism which induces credit changes, rather than money changes in the economy. This broad credit channel is also divided into a narrower bank lending channel and balancer sheet channel, where monetary policy shocks affect the supply of loans by banks in the first, and the financial position and hence net worth of borrowers in the later (Ibid 29). For the purposes of this paper, the focus will be on a broad credit channel. This is standard in many papers which seek to investigate a broad role for credit rather than the specific channels that manifest it. As Bernanke and Gertler (1995, 45) note, housing demand can be very responsive to changes in balance sheets. Thus, there might be an interesting interrelationship between monetary policy, credit, and housing market, all of which experienced sharp changes preceding the crisis.

A look at some of the trends illustrates why this mechanism may be particularly relevant to the recent financial crisis. For example, many observers have criticized monetary policy for being too loose before the crisis (Dokko et al. 2011, 236). This is illustrated in Graph 1<sup>1</sup> below, which demonstrates a time series of the federal funds rate and the ratio of a housing price index to a consumer price index. The ratio appears to be consistent until the mid-1990s, where it starts to pick up. However, the surge follows the 2001

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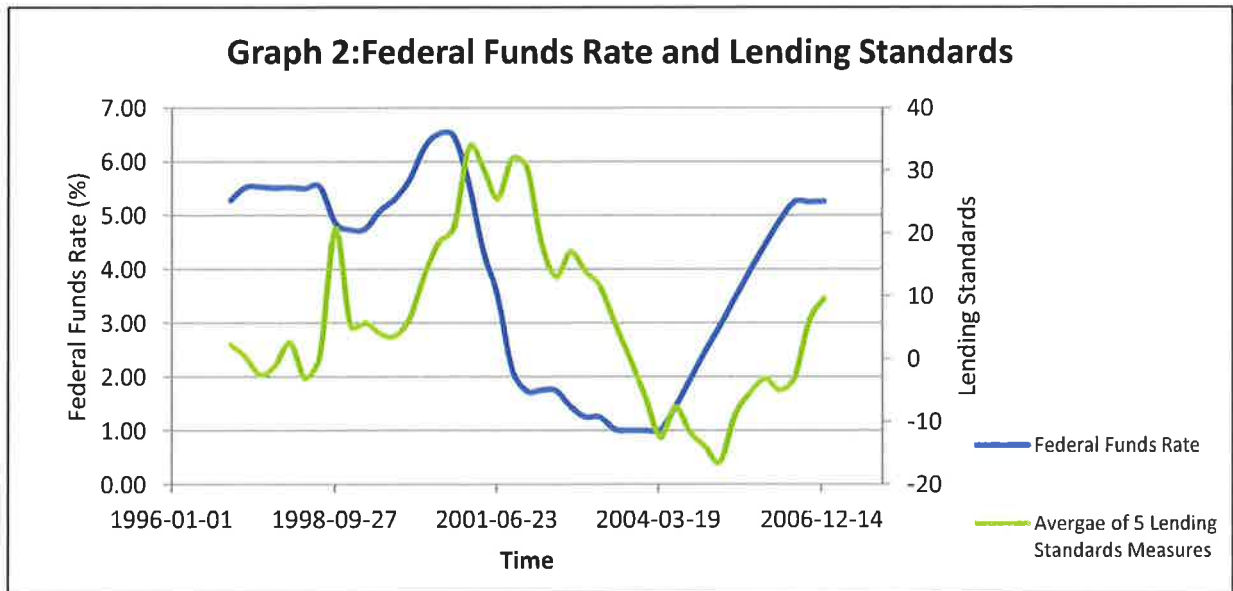
<sup>1</sup> Source: Graph: Own calculations. Raw data for federal funds rate, CPI, and a purchase only housing price index gathered through Federal Reserve Bank of St. Louis (FRED)

expansionary shock. Historically, upward movement in house prices was not as evident, as can be derived from the earlier shocks that were accompanied by mild or insignificant changes in housing market activity.



It will be apparent that the period was also characterized by increased levels of credit.

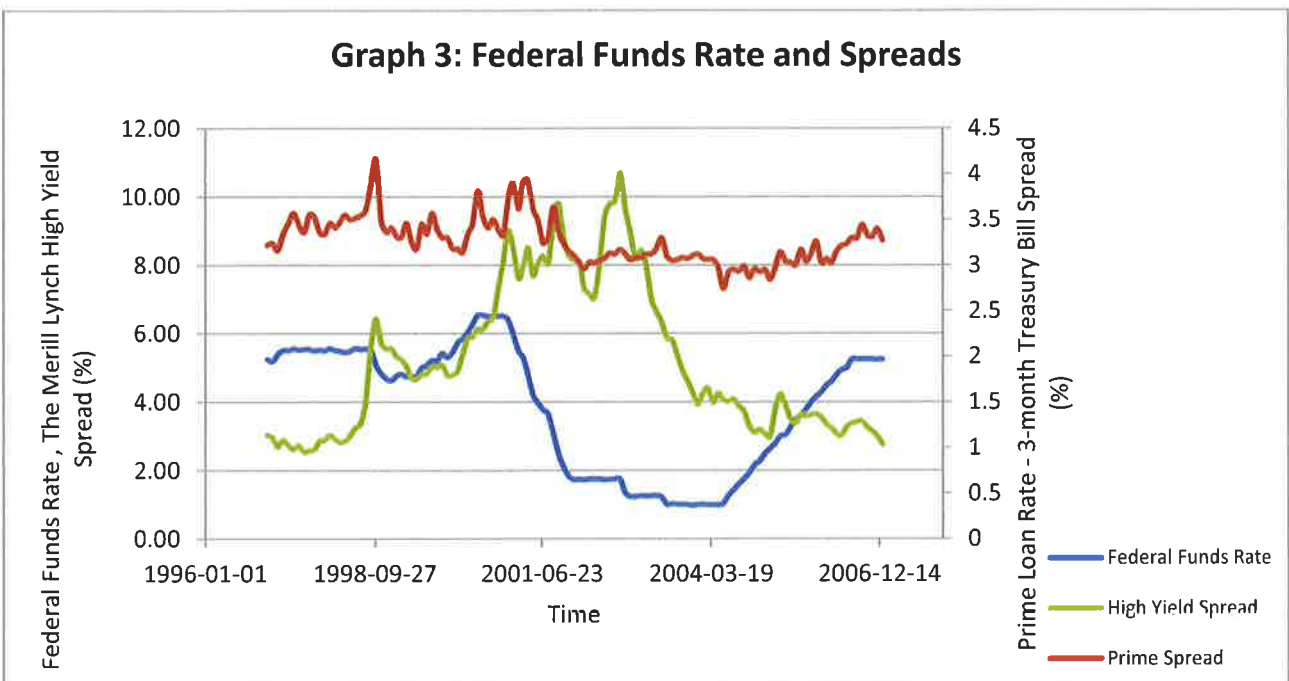
This can be shown, for example, through changes in lending standards, illustrated below<sup>2</sup>



<sup>2</sup> Source: Graph: Own Calculations. Raw data on Federal Funds Rate gathered from Federal Reserve Bank of St. Louis (FRED) and Lending Standards Survey from the Federal Reserve Board Senior Loan Officer Opinion Survey



The lending standards measure is an average of 5 lending standards measures provided by the Senior Loan Officer Survey<sup>3</sup> (Swiston 2008, 9). A look at the graph demonstrates a loosening in lending standards that follows decreases in interest rates, with a lag. Similarly, spreads between bank rates, or corporate bonds, and treasury bills, or treasury spot curves, respectively, are expected to narrow following decreases in interest rates, with a lag, as illustrated below. Moreover, a comparison of Graph 2 and Graph 3<sup>4</sup> may show that Spreads and lending standards are very highly correlated. As Iacovelli and Minetti (2006, 74) note, changes in the magnitude of the spread between a non-government rate and a riskless rate may indicate a change in the external finance premium in the same direction. Likewise, many VAR analyses of credit channels include different interest rate spreads as a variable that accounts for a credit channel.



<sup>3</sup> The method of averaging out different lending standards is borrowed from Swiston (2008)

<sup>4</sup> Graph Source: Own Calculations. Raw Data for federal funds rate and the Merrill Lynch High Yield Spread gathered from the Federal Reserve Bank of St. Louis (FRED). Data for Lending Standards gathered from the Senior Loan Officer Opinion Survey on Bank Lending Practices, Federal Reserve Board of Directors Website.

However, plots of these trends do not necessarily indicate a conclusive relationship between the three groups of variables. Thus, the next section provides a vector autoregressive model that attempts to further address the question.

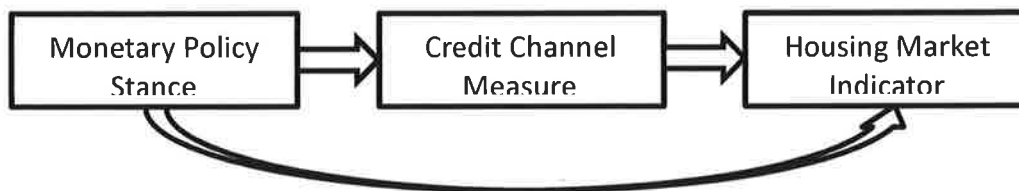
### A Vector Autoregressive Model

#### - I - Benchmark Model:

##### Data Description:

Variables in both the benchmark and robustness models will be divided into three categories, following the categorization scheme used by Italiano (2001, 10), where he groups those variables into a monetary policy stance, credit channel variables, and economic activity variables. Applying this categorization scheme to this paper, economic activity variables are replaced with the main response variables of question, housing market indicators. Detailed descriptions of each variable's frequency and source are represented in Appendix 1 tables.

Thus, a simple diagrammatic illustration of the relationship being investigated is as follows:



- 1) **Monetary Policy Stance:** While a variety of short-term rates and monetary quantities can be used for this, the Federal Funds Rate, denoted *fedf*, will be

adopted in this paper as the indicator of monetary policy. This follows from Bernanke et al's argument that the federal funds rate is the most suitable indicator of monetary policy that is "most closely controlled" (through open market operations) by monetary authorities (Bernanke & Gertler 1995, 28; Bernanke & Blinder 1992, 905)

- 2) **Credit Channel Variables:** There is no consensus in literature on the suitable measure of credit expansion, or credit channel indicator. Most works use a variety of spreads, lending standards, or financing mixes and ratios for individuals and business. For simplicity, the main variable of interest will be a spread between the prime loan rate and a short-term government bond, denoted *pspread*. This is amongst the variables identified by Bernanke & Gertler (1995, 43). Swiston describes how spreads can indicate borrowing levels (Swiston 2008, 3). However, given the uncertainty of the variable's representativeness of credit, robustness tests will ensure the model is modified to test if it gives the same relation with other measures of credit channels.
- 3) **Housing Market Indicators:** The ratio of a purchase-only housing price index to a consumer price index is used, denoted *hindex*, following Dokko et al's. method (2011, 250). This is done to create some measure of real prices for houses and account for corresponding increases in price levels. Housing prices could be more useful in illustrating short term changes as opposed to quantities (Iacoviello & Minetti 2006, 76). Alternatively, one can use housing quantities, such as residential investment or housing starts, to test a similar relationship that may differ in terms of magnitude, statistical significance, or lag length.

The time interval for the benchmark model goes back to the first month of 1997 and up to the first month of 2007. The use follows evidence that nominal house prices began to pick up during the late 1990s (Dokko et al 239), and the evidence of changes in real house prices shown in the time series graphs presented above. Extending the time period a few years backwards will be one form of further test to investigate whether the benchmark relationship was unique to the period identified.

Model specification:

The benchmark model is outlined as follows:

$$y_t = u + \phi_1 y_{t-1} + \dots + \phi_3 y_{t-3}$$

In matrix form, this is represented as:

$$\begin{matrix} dfedf_t \\ pspread_t \\ hindex_t \end{matrix} = \begin{pmatrix} u_1 \\ u_2 \\ u_3 \end{pmatrix} + \begin{pmatrix} \phi^1_{ff} & \dots & \phi^1_{fh} \\ \vdots & \ddots & \vdots \\ \phi^1_{hf} & \dots & \phi^1_{hh} \end{pmatrix} \begin{pmatrix} fedf_{t-1} \\ pspread_{t-1} \\ hindex_{t-1} \end{pmatrix} + \dots + \begin{pmatrix} \phi^3_{ff} & \dots & \phi^3_{fh} \\ \vdots & \ddots & \vdots \\ \phi^3_{hf} & \dots & \phi^3_{hh} \end{pmatrix} \begin{pmatrix} fedf_{t-3} \\ pspread_{t-3} \\ hindex_{t-3} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix}$$

The left hand side represents the system of equations for each variable of interest. The right hand side represents the interaction coefficients for each variable with its own lags and the lagged values of others, with each matrix representing the coefficients for the  $i^{th}$  lag. For example,  $\phi^1_{hf}$  represents the coefficient of the federal funds rate's effect on *hindex* in the first lag. The last term,  $\varepsilon$ , represents the error term for each equation. The matrix form can alternatively be represented as a separate equation for each variable, with each line representing an equation for the respective variable. In the benchmark model, the optimal lag length was determined to be 3 months using a varsoc command which establishes the significance of lags using different criteria. The results of the varsoc

command are represented in Appendix 3<sup>5</sup>. As illustrated in the equation, the lag length chosen for the benchmark model is 3 months (3 lags). Plotting the autocorrelation functions for all three variables indicates that the first differences must be taken for *fedf* and *hindex*. This prevents any variables correlated with their lags from distorting the model, and thus ensures the variables satisfy the stationary requirement. All models are tested to verify they meet stability condition using a *varstable* command.

Results<sup>6</sup>:

It is important to start with granger-causality tests, which test the relevance of each lagged variable in the prediction or explanation of another (Stock & Watson 2001, 104). In other words, the test determines whether the equation of interest is relevant at the chosen significance level. The table below represents the granger-causality Wald test for the benchmark model. Our equation of interest that of the housing market index, is significant at the 1% level. Both *dfedf* and *pspread* are shown to granger-cause *dhindex* at the 5% significance level, and jointly at the 1% level. Another relation of interest is the effect of *dfedf* on *pspread*, shown to be significant at the 5% level.

**Table 1: Benchmark Granger-Causality Wald Test:**

<u>Equation</u>	<u>Excluded</u>	<u>Chi<sup>2</sup></u>	<u>Df (lags)</u>	<u>P-value</u>
dfedf	pspread	50.8	3	0.000
dfedf	hindex	0.9291	3	0.818
dfedf	All	57.731	6	0.000
pspread	dfedf	8.276	3	0.041
pspread	dhindex	11.07	3	0.012

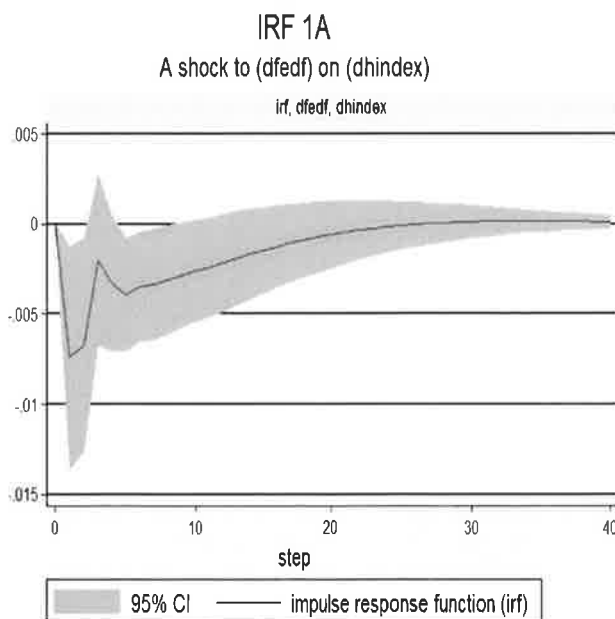
<sup>5</sup> In the case of different lag lengths determined by different selection criteria, the longer lag was chosen

<sup>6</sup> It should be noted that most VAR analyses and literature focus on Granger causality, impulse responses and/or forecast error variance decompositions. Thus, regression outputs, mostly not used in credit channel VAR analyses, were excluded from the analysis and included as supplementary tables in Appendix 3.

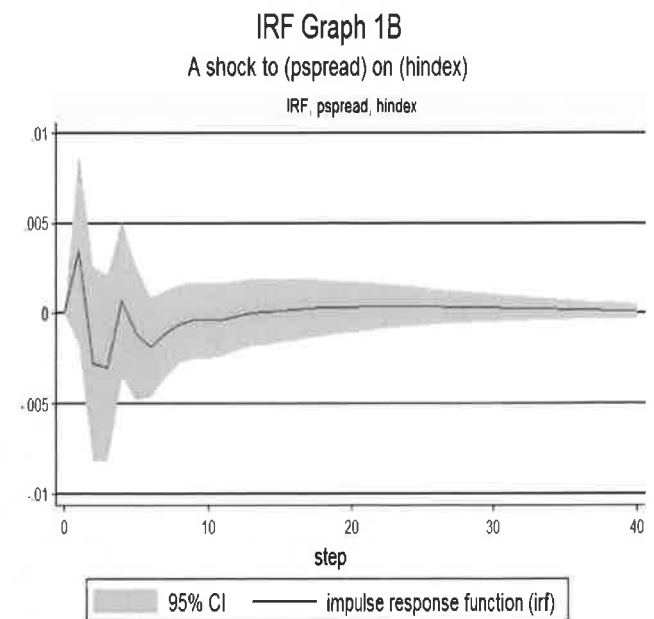
pspread	All	22.02	6	0.001
hindex	dfedf	9.2396	3	0.026
hindex	pspread	16.96	3	0.001
hindex	All	17.527	6	0.008

Whilst providing evidence that the variables of interest granger-cause each other, or in other words, may hold some explanatory power with respect to other variables, Granger-causality tests are not sufficient within themselves to establish a relationship. In essence, they are sufficient to reject the hypothesis that these variables don't cause each other.

Following this, impulse response functions must be used to trace out the relationship between the variables. As illustrated by IRF 1A, a positive shock to *dfedf* results in a mostly negative response from *dhindex*. Given that impulse response functions are symmetric in both directions, it confirms our hypothesis that a negative shock to *dfedf* results in a positive effect on *dhindex*. The 95% confidence interval must lie below zero for this inverse effect to be statistically significant at the 5% level. As illustrated the effect is significant at this level for the first two steps, which indicate the lag period (in this case months), and then from the fifth to the eighth lag. The magnitude of the effect



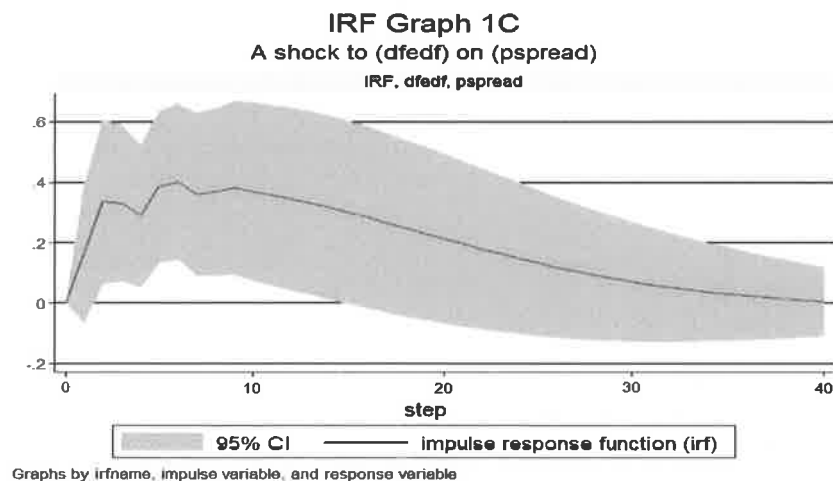
Graphs by irfname, impulse variable, and response variable



Graphs by irfname, impulse variable, and response variable

can be described as a one unit change in the first differences of  $fedf$  ( $fedf_t - fedf_{t-1} = \Delta fedf$ ) which results in a negative change on the first differences of the housing index to CPI ratio ( $hindex_t - hindex_{t-1} = \Delta hindex$ ) by the amount on the vertical axis scale. The shock of  $pspread$  on  $hindex$  is not as statistically significant. However, one can only expect a shock to a controlled variable ( $dfedf$ ) to have a more notable effect.

A closer look, however, at the shocks of monetary policy on the spread, hence the credit channel indicator shows a positive relationship, indicating that the measure of credit in this case does move in tandem with monetary policy. The overall equation for the housing market indicator thus shows that there may be a traditional transmission mechanism, and a weaker credit channel at work, inversely affecting the housing market, and producing the relationship seen preceding the crisis, during the bubble years. Finally, the impulse response functions demonstrate that the shocks all converge to zero in the long run, consistent with neutrality and the temporary aspect of shocks that are expected in IRF functions with stationary data (Gregory).



## II- Robustness Tests:

### Model 2: Using a Longer Time Interval:

A separate VAR was run as a robustness experiment to test whether this relationship would hold if the time interval was extended. Data was extended back to 1991, given limitations regarding the use of the same housing market index, hence adding 6 more years (66 additional time-series observations). Below is the Granger-Causality table for this regression:

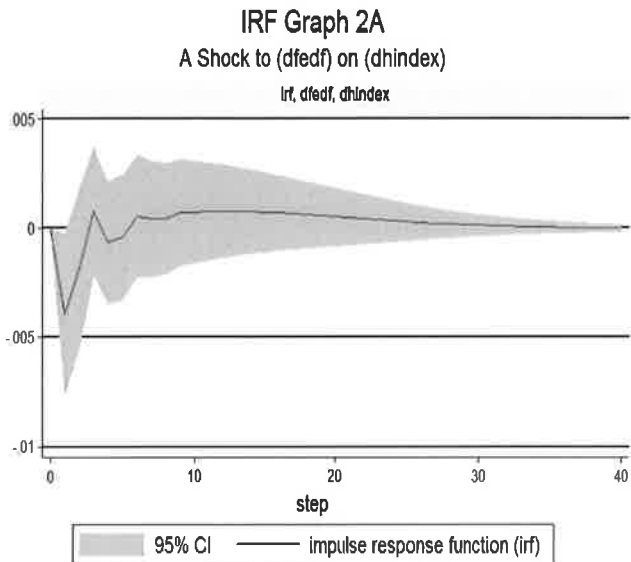
**Table 2: Model 2 Granger-Causality Wald Test:**

<u>Equation</u>	<u>Variable</u>	<u>Chi<sup>2</sup></u>	<u>Df (lags)</u>	<u>P-value</u>
dfedf	pspread	47.354	3	0.000
dfedf	hindex	2.2548	3	0.521
dfedf	All	53.574	6	0.000
pspread	dfedf	16.893	3	0.001
pspread	dhindex	10.048	3	0.018
pspread	All	26.474	6	0.000
hindex	dfedf	4.8939	3	0.180
hindex	pspread	4.0507	3	0.256
hindex	All	7.7771	6	0.255

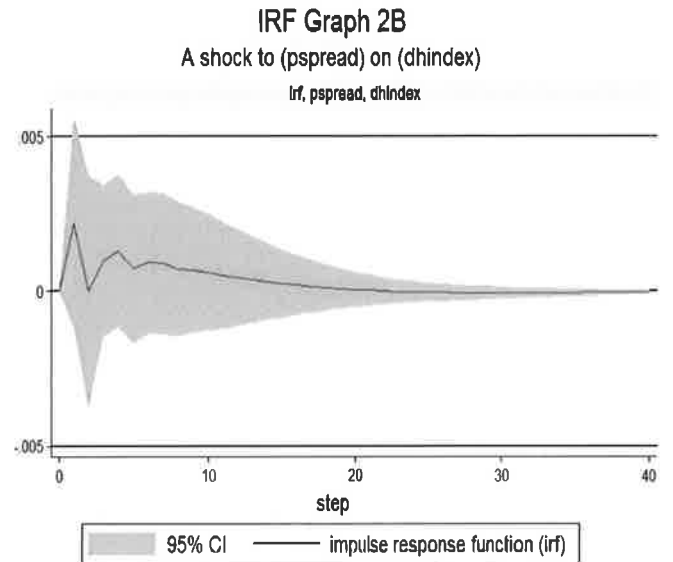
The results show a fading out of the significance of the relationship, as the variables of interest do not granger-cause another within a 95% or a 90% confidence interval. What this implies is that the relationship was unique, or more pronounced during the benchmark model period. For example, *dfedf* is shown to Granger-Cause *dhindex* within a 82% confidence interval. Hence, the hypothesis that *dfedf* does not granger-cause *dhindex* cannot be rejected at the 5, 10, or 15% significance level.



Plotting the impulse response functions to the shocks of interest shows the same expected inverse relationship between *dfedf* and *dhindex*. However, given the confidence interval lies above zero for most of the steps (with the exception of the first lag), the relationship is seen as mostly statistically insignificant at the 5% level.



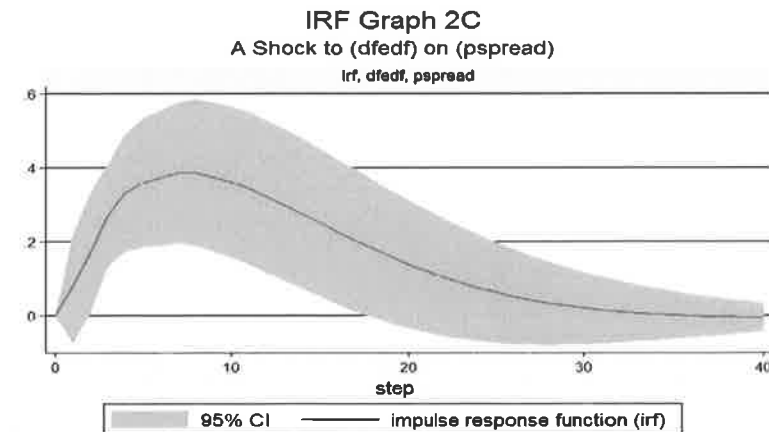
Graphs by irfname, impulse variable, and response variable



Graphs by irfname, impulse variable, and response variable

A shock to monetary policy still positively affects the credit channel measure (As hypothesized) with a statistically significant relationship, as illustrated in IRF 2C.

However, the overall equation for the housing market indicator shows that neither does



Graphs by irfname, impulse variable, and response variable

this credit effect, nor the interest effect, reach the housing market prices at a statistically

The results for this robustness test have important implications for the hypothesis of this paper. They show that the relationship expected does hold during a shorter time-span close to the financial crisis, and one which starts around the time housing prices start to pick up. However, this relationship is not statistically significant if the time period is extended. This is expected, especially if one looks at the time-series plot of federal funds rate and the ratio of housing market prices to CPI in Graph 1, which shows that monetary policy shocks were only negatively affecting housing during the shorter time span, and that a relationship was almost non-existent during the early 1990s (or perhaps less evident if using a more volatile indicator of housing prices). This suggests that perhaps, there was another factor at play with monetary policy during the period of interest which was magnifying expected interest rate effects on housing.

### Model 3: Changing the Credit Channel Measure<sup>7</sup>:

The credit channel category variables will be changed from a spread between the prime loan rate and a government security, to the average lending standards measure discussed earlier. The Senior Loan Officer Opinion survey reports the net percentage of respondents from 60 domestic banks and 24 foreign branches who answered that they tightened lending standards for the specific quarter (Bassett et al. 2012, 5). Those include C&I loans for large firms, C&I loans for small business, residential mortgages, commercial real estate loans, and consumer loans. The method of averaging out all 5 standards is borrowed from Bassett et al. (2012, 9). This might be useful, especially given

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<sup>7</sup> Lag length used changed to 1, given it is quarterly data. This is shown in the varsoc command in Appendix 3

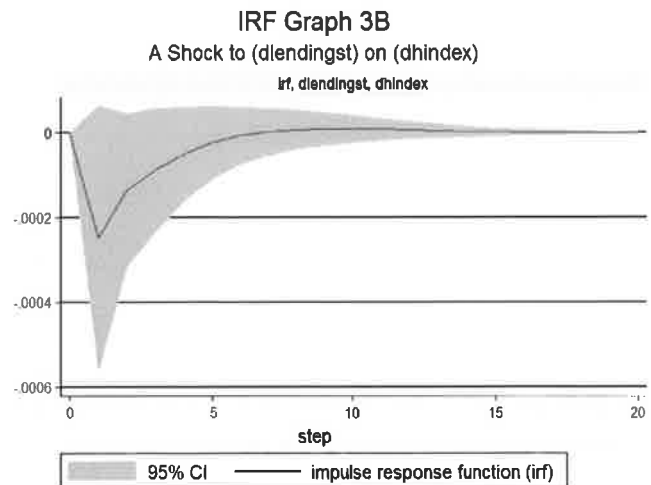
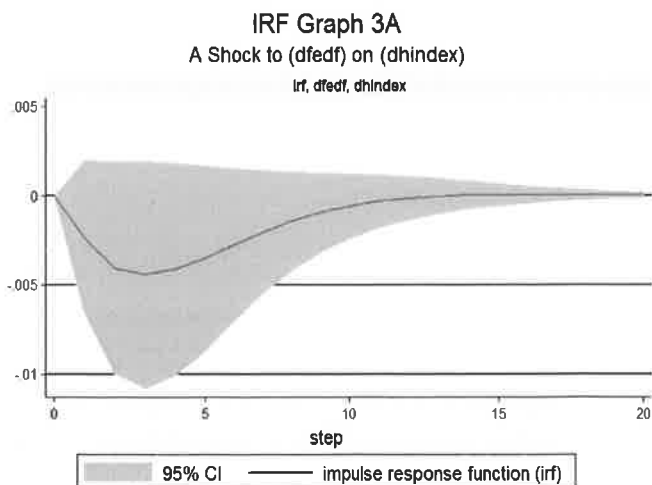
that the residential mortgage category has shown huge fluctuations, and was discontinued following the crisis, hinting that it may not have been very indicative. The lending standards measure, thus, may be helpful in providing an overall indication of credit conditions in the economy.

The results represented in Table 3 show, once more, a less statistically significant relationship between the variables of interest.

**Table 3: Model 3 Granger-Causality Wald Test:**

<u>Equation</u>	<u>Variable</u>	<u>Chi<sup>2</sup></u>	<u>Df (lags)</u>	<u>P-value</u>
dfedf	plendingst	0.00645	1	0.936
dfedf	dhindex	2.6978	1	0.100
dfedf	All	2.7156	2	0.257
dlendingst	dfedf	3.8168	1	0.051
dlendingst	dhindex	3.3679	1	0.066
dlendingst	All	7.3586	2	0.025
dhindex	dfedf	1.1132	1	0.291
dhindex	dlendingst	2.4066	1	0.121
dhindex	All	3.2035	2	0.202

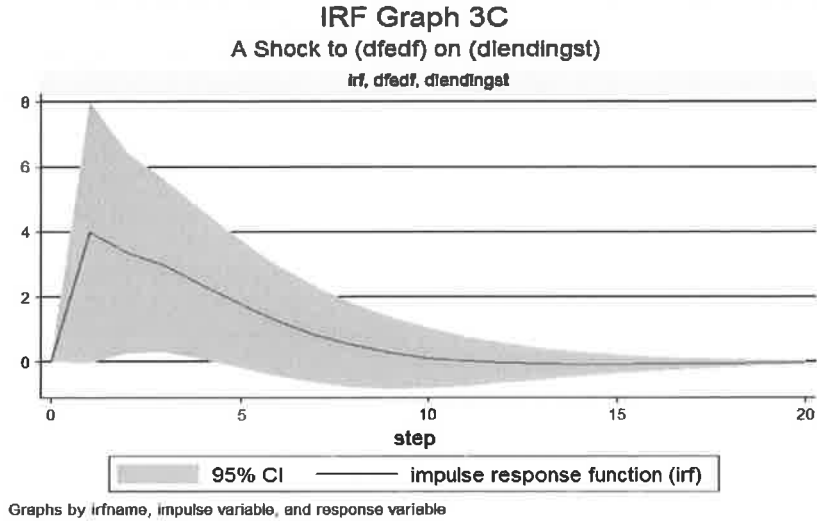
Plotting the impulse response functions still provide a relationship direction that matches the one hypothesized, with *dfedf* inversely affecting *dhindex* in IRF Graph 3A, and



Graphs by irfname, impulse variable, and response variable

Graphs by irfname, impulse variable, and response variable

positively affecting the credit measure, *dlendingst*, in IRF Graph 3C, but one that is mostly not statically significant at the 5% level.



This may be due to several reasons. First, lending standard surveys are subjective and not definitive, and may thus not represent a very accurate or true indicator of real credit conditions. Second, these surveys are conducted on a quarterly basis, which means that there may not be enough observations to establish a statistically significant relationship (41 observations against 121 observations under a monthly VAR for the same time-span). Alternatively, the *pspread* variable used in the benchmark regression may not be a very accurate indicator of credit channels, or may be highly correlated with monetary policy in general. Yet, it is important to note that the shape of the relationship remains the same; that the effect of *dfedf* on lending standards is still a statistically significant, positive one, and that perhaps lowering the confidence interval for the IRF functions may show an existing relationship during some of the lags.

#### Model 4: Accounting for the Potentiality of Omitted Variable Bias:

A final robustness test was done to account for the potentiality of any omitted variable bias that may affect both  $dfedf$  and  $dhindex$  concurrently (Gregory, 14). A fourth, economic activity variable was added to the benchmark model. Given that our benchmark model uses monthly data, a change in the industrial production index, denoted  $dindp$  was the closest to this category, since GDP levels are only reported quarterly. The results confirm the same relationship outlined in the benchmark model. The specific granger-causality results are reported, in Appendix 2, given their irrelevance to the hypothesis of the paper

#### Discussion

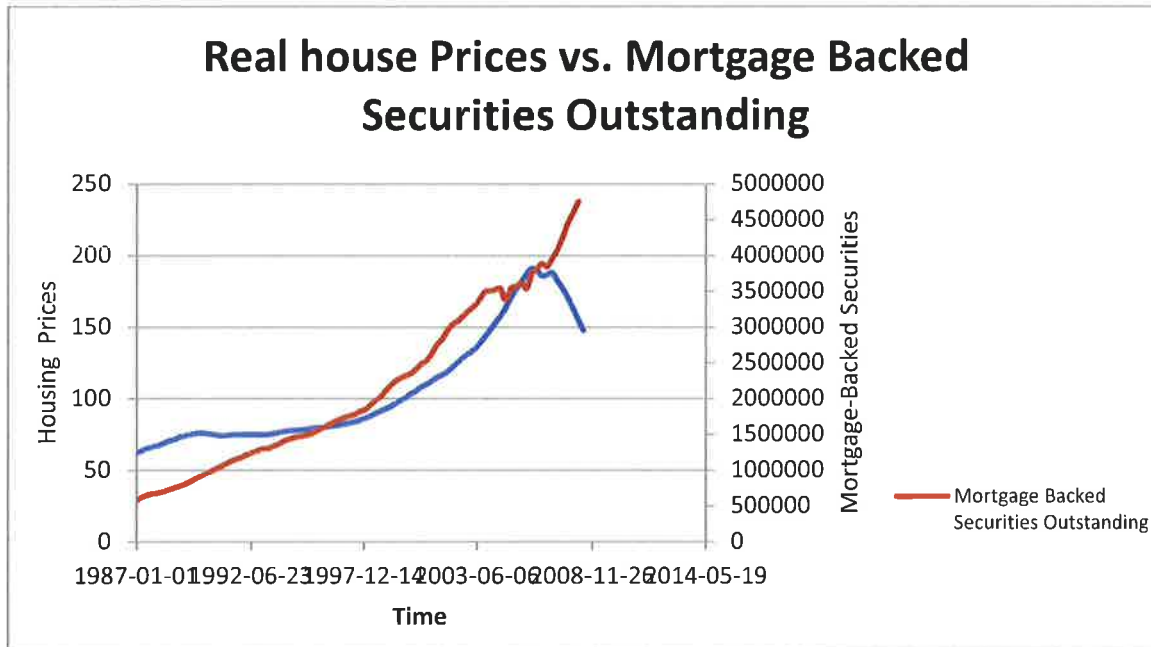
The benchmark model produced results that are, to a certain extent, consistent with the initial hypothesis, showing an inverse relationship between monetary policy stances and housing market activity. Additionally, it demonstrated a positive relationship between monetary policy and the credit measure used. Robustness tests produced similar relationships in terms of direction, but with less statistical significance. This section presents an analysis of those results combined with some extrapolation as to which other factors may have had a significant impact on housing market activity during the crisis, such as securitization.

Keys et al. define securitization as an "act of converting illiquid loans into liquid securities", and hypothesize that such practices may have led to bad lending standards. (Keys et al. 2009, 701) In essence, such a structure distorts the risk-bearing and information in the market and induces lenders to take riskier loans given their ability to

shift the risk to other parties, hence creating a situation of moral hazard (Ibid 701). Thus, an alternative explanation or continuation to the hypothesis may be that a traditional interest rate mechanism was amplified by exogenous regulatory changes in the economy. These regulatory changes also affected credit availability and ease of lending and borrowing, hence potential creating credit expansion that is exogenous to monetary policy and potentially undermining the credit channel of monetary policy. Some studies have offered some explanations for the regulatory changes occurring at this period. For example, as Dokko et al. note, changes in mortgage standards may have amplified monetary policy effects on the housing market (Dokko et 2011, al.259). Shiller also describes how both monetary policy and housing market activity are unrelated (Ibid 2011, 260), which conflicts with this paper's hypothesis and findings, but hints that monetary policy is not exclusive in determining housing market activity. Dokko et al. also note how the housing market saw "rapid and unusual changes" during the boom period (Ibid 2011, 262). For example, they discuss how there may have been a "feedback loop" with high house prices resulting in increased demand for easy mortgage financing, which in turn raises prices more due to increased demand (Ibid 2011, 262). Such combinations of factors imply that a traditional transmission mechanism at least facilitated these increases. A simple plot<sup>8</sup>, for example, of mortgage backed securities against real house prices shows that they have both been increasing dramatically, and in the same direction. This is one example of financial innovation and regulation changes altering risk for lending institutions through securitization, and hence potentially allowing for increased lending and lower credit standards.

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<sup>8</sup> Graph plotted using raw data for house prices from the Case-Schiller Index downloaded from the Standard and Poors Website. The number of mortgage backed securities downloaded from Securities Industry and Financial Markets Association (SIFMA)



### Conclusion

The paper's initial hypothesis stated that increases in housing prices during the recent financial crisis were partly caused by monetary policy and a credit channel effect. The results indicate that while there may have been a traditional transmission mechanism at work, with sharp decreases in interest rates affecting consumer's cost of capital and hence their demand for housing, a credit channel may be difficult to disentangle. The benchmark model was accompanied by robustness exercises to ensure no false conclusions are met, and left us with a hint that a traditional transmission mechanism may be at work. Alternatively, the discussion section briefly presents some alternative explanations for factors that may have exacerbated this traditional mechanism and caused dramatic increases in housing prices, explaining why this relationship may have held at this time, and not during other expansionary periods, all other factors constant. In

essence, the blend and combination of dramatically low interest rates, accompanied by decreased regulation, easier lending standards, and risk-shifting, may have induced both lenders and buyers to increase their demand and supply of housing loans, respectively, resulting in those hikes. Thus, an important implication is the need for coordination amongst policy-setting bodies to ensure that monetary and regulatory factors' potential interconnectedness and tendency to reinforce each other is analyzed before implementing dramatic policy changes.

Finally, some potential strategies for investigating this combined effect of monetary policy and regulatory changes may involve running VARs for periods of financial deregulation and periods without, and comparing the impulse responses (Iacoveillo & Minetti 2003, 29), which is similar to the first robustness test carried in this paper.

Alternatively, one can compare the effects of monetary policy transmission mechanism on housing quantities and prices as potential related research. Further robustness tests could include using more sophisticated criteria for the selection of a credit channel variable, or the use of several housing market indices and comparing the results.



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**Appendix 1: Detailed Data Description:**

**Benchmark Model (1997M1-2007M1)**

<b>Variable</b>	<b>Source</b>	<b>Description</b>	<b>Frequency</b>	<b>Observations</b>
<i>fedf</i>	Federal Reserve Bank of St. Louise (FRED)	The Federal Funds Rate	(Monthly)	121
<i>hindex</i>	Federal Reserve Bank of St. Louise (FRED)	The ratio of a Purchase-Only Housing Price Index (gathered from FRED) to a Consumer Price Index (gathered from FRED)	Monthly	121
<i>dfedf</i>	Computed from <i>fedf</i>	The first differences of the federal funds rate. The first differences were taken after plotting the autocorrelation function of <i>fedf</i> .	Monthly	120
<i>pspread</i>	Federal Reserve Bank of St. Louise (FRED)	The spread between the prime loan rate (gathered from FRED) and a 3-month treasury bill secondary market rate (gathered from FRED).	Monthly	121
<i>dhindex</i>	Computed from <i>hindex</i>	The first differences of <i>hindex</i>	Monthly	120

**Model 2 (1991M1 – 2007M1):**

- Data is identical to benchmark model data description represented above.

However, time span extends back to January 1991. Hence, the frequency is monthly from 1991M1 to 2007M1.

**Model 3 (1997Q1-2007Q1):**

<b>Variable</b>	<b>Source</b>	<b>Description</b>	<b>Frequency</b>	<b>Observations</b>
<i>fedf</i>	Federal Reserve Bank of St. Louise (FRED)	The Federal Funds Rate	Quarterly	41
<i>hindex</i>	Federal Reserve Bank of St. Louise (FRED)	The ratio of a Purchase-Only Housing Price Index (gathered from FRED) to a Consumer Price Index (gathered from FRED)	Quarterly	41
<i>dfedf</i>	Computed from <i>fedf</i>	The first differences of the federal funds rate. The first differences were taken after plotting the autocorrelation function of <i>fedf</i> .	Quarterly	40
<i>lendingst</i>	Senior Loan Officer Survey – Federal Reserve Board of Directors	The average of five lending standards measures discussed previously.	Quarterly	41
<i>dlendingst</i>	Computed from <i>lendingst</i>	The first differences of <i>lendingst</i>	Quarterly	40
<i>dhindex</i>	Computed from <i>hindex</i>	The first differences of <i>hindex</i>	Quarterly	40



0	522.281				2.6e-08	-8.95311	-8.9242	-8.8819
1	637.834	231.11	9	0.000	4.1e-09	-10.7902	-10.6746	-10.5054
2	660.296	44.925	9	0.000	3.3e-09	-11.0223	-10.82*	-10.5230*
3	670.001	19.411*	9	0.022	3.2e-09*	-11.0345*	-10.7454	-10.3224
4	675.494	10.986	9	0.277	3.5e-09	-10.974	-10.5982	-10.0483

**Model 2 Varsoc:**

Selection-order criteria  
Sample: 1991m6 - 2007m1  
Number of obs = 188

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	813.354				3.6e-08	-8.62079	-8.59987	-8.56915
1	1010.63	394.56	9	0.000	4.9e-09	-10.6238	-10.5401	-10.4172*
2	1032.03	42.792	9	0.000	4.3e-09	-10.7556	-10.6092	-10.3941
3	1054.81	45.565	9	0.000	3.7e-09	-10.9023	-10.693*	-10.3858
4	1065.24	20.859*	9	0.013	3.6e-09*	-10.9175*	-10.6454	-10.2461

**Model 3 Varsoc:**

Selection-order criteria  
Sample: 1998q2 - 2007q1  
Number of obs = 36

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-85.5735				.02752	4.92075	4.96681	5.05271
1	14.0315	199.21	9	0.000	.00018*	-.11286*	.071371*	.41498*
2	22.4569	16.851	9	0.051	.000188	-.080939	.241464	.842781
3	28.0682	11.223	9	0.261	.000234	.107324	.5679	1.42692
4	37.6575	19.179*	9	0.024	.00024	.074582	.67333	1.79006

**Benchmark Model Regression:**

Sample: 1997m5 - 2007m1  
 Log likelihood = 677.0721  
 FPE = 3.16e-09  
 Det(Sigma\_ml) = 1.89e-09

No. of obs = 117  
 AIC = -11.06106  
 HQIC = -10.77352  
 SBIC = -10.35281

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dfedf	10	.107167	0.6812	249.9579	0.0000
pspread	10	.133819	0.7523	355.2642	0.0000
dhindex	10	.003666	0.2633	41.8083	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
<b>dfedf</b>						
dfedf						
L1.	.4222109	.0922427	4.58	0.000	.2414185	.6030033
L2.	.2067088	.0965247	2.14	0.032	.0175238	.3958937
L3.	.1392073	.0792061	1.76	0.079	-.0160338	.2944484
<b>pspread</b>						
pspread						
L1.	-.5073919	.0734102	-6.91	0.000	-.6512732	-.3635106
L2.	.2858629	.1007526	2.84	0.005	.0883915	.4833343
L3.	.0450893	.0879739	0.51	0.608	-.1273364	.2175149
<b>dhindex</b>						
dhindex						
L1.	-1.256315	2.796739	-0.45	0.653	-6.737823	4.225193
L2.	-1.425949	2.97932	-0.48	0.632	-7.265309	4.413411
L3.	-1.01717	2.878926	-0.35	0.724	-6.659761	4.625422
_cons	.5921083	.201333	2.94	0.003	.1975029	.9867137
<b>pspread</b>						
pspread						
dfedf						
L1.	.1391461	.1151833	1.21	0.227	-.0866091	.3649013
L2.	.153392	.1205302	1.27	0.203	-.0828429	.3896269
L3.	-.0275625	.0989045	-0.28	0.780	-.2214118	.1662868
pspread						
L1.	.734591	.0916672	8.01	0.000	.5549267	.9142554
L2.	-.0362143	.1258096	-0.29	0.773	-.2827965	.210368
L3.	.2502046	.1098528	2.28	0.023	.034897	.4655122
dhindex						
L1.	5.606577	3.492283	1.61	0.108	-1.238172	12.45133
L2.	-3.748636	3.720271	-1.01	0.314	-11.04023	3.542962
L3.	-7.538345	3.59491	-2.10	0.036	-14.58424	-.4924513
_cons	.1935916	.2514041	0.77	0.441	-.2991514	.6863347
<b>dhindex</b>						
dhindex						
dfedf						
L1.	-.0073643	.0031557	-2.33	0.020	-.0135493	-.0011793
L2.	-.0012622	.0033022	-0.38	0.702	-.0077343	.00521
L3.	.0023867	.0027097	0.88	0.378	-.0029242	.0076976
pspread						
L1.	.0026481	.0025114	1.05	0.292	-.0022741	.0075704
L2.	-.0109721	.0034468	-3.18	0.001	-.0177277	-.0042165
L3.	.0024265	.0030096	0.81	0.420	-.0034722	.0083253
dhindex						
L1.	.3702496	.0956779	3.87	0.000	.1827243	.5577749
L2.	-.2475822	.1019241	-2.43	0.015	-.4473498	-.0478147
L3.	.1059117	.0984896	1.08	0.282	-.0871244	.2989477

_cons	.0226253	.0068877	3.28	0.001	.0091256	.0361249
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**Model 2 Regression:**

Sample: 1991m5 - 2007m1	No. of obs	=	189
Log likelihood = 1059.5	AIC	=	-10.89418
FPE = 3.73e-09	HQIC	=	-10.68572
Det(Sigma_ml) = 2.71e-09	SBIC	=	-10.37962

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dfedf	10	.126001	0.5427	224.3396	0.0000
pspread	10	.135935	0.7552	583.1525	0.0000
dhindex	10	.003357	0.3450	99.5631	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
dfedf						
dfedf						
L1.	.2789707	.0699608	3.99	0.000	.1418501	.4160913
L2.	.2821854	.0705941	4.00	0.000	.1438235	.4205472
L3.	.2221548	.0630947	3.52	0.000	.0984915	.3458181
pspread						
L1.	-.3985186	.0649377	-6.14	0.000	-.5257941	-.2712431
L2.	.1144937	.0861669	1.33	0.184	-.0543902	.2833777
L3.	.1655508	.070231	2.36	0.018	.0279005	.3032011
dhindex						
L1.	2.493453	2.688962	0.93	0.354	-2.776815	7.763722
L2.	-3.006701	3.144901	-0.96	0.339	-9.170593	3.157191
L3.	3.20454	2.718794	1.18	0.239	-2.124198	8.533279
_cons	.373261	.1251615	2.98	0.003	.127949	.6185729

pspread						
dfedf						
L1.	.0763253	.0754766	1.01	0.312	-.0716061	.2242566
L2.	.1170029	.0761598	1.54	0.124	-.0322676	.2662734
L3.	.0910235	.0680692	1.34	0.181	-.0423896	.2244366
pspread						
L1.	.7256401	.0700575	10.36	0.000	.58833	.8629502
L2.	-.0294788	.0929604	-0.32	0.751	-.2116778	.1527203
L3.	.2437537	.0757682	3.22	0.001	.0952508	.3922566
dhindex						
L1.	6.173624	2.900964	2.13	0.033	.4878387	11.85941
L2.	-3.309769	3.39285	-0.98	0.329	-9.959633	3.340094
L3.	-5.776238	2.933148	-1.97	0.049	-11.5251	-.0273733
_cons	.2017704	.1350294	1.49	0.135	-.0628824	.4664231

dhindex						
dfedf						
L1.	-.0039407	.0018642	-2.11	0.035	-.0075945	-.000287

L2.	.0011145	.0018811	0.59	0.554	-.0025723	.0048013
L3.	.0022579	.0016812	1.34	0.179	-.0010373	.005553
pspread						
L1.	.0022116	.0017303	1.28	0.201	-.0011798	.005603
L2.	-.0043087	.002296	-1.88	0.061	-.0088088	.0001914
L3.	.0026047	.0018714	1.39	0.164	-.0010632	.0062725
dhindex						
L1.	.5139682	.0716504	7.17	0.000	.3735361	.6544003
L2.	-.0960472	.0837993	-1.15	0.252	-.2602909	.0681965
L3.	.2445351	.0724453	3.38	0.001	.102545	.3865252
_cons	-.0007065	.0033351	-0.21	0.832	-.0072431	.0058301

### Model 3 Regression:

Sample: 1997q3 - 2007q1  
 Log likelihood = 14.36653  
 FPE = .0001782  
 Det(Sigma\_ml) = .0000961

No. of obs = 39  
 AIC = -.1213603  
 HQIC = .0622925  
 SBIC = .3905049

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dfedf	4	.31385	0.5932	56.87936	0.0000
dlendingst	4	6.25163	0.1598	7.416275	0.0597
dhindex	4	.006685	0.3801	23.9086	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
dfedf						
dfedf L1.	.7515343	.1023758	7.34	0.000	.5508815	.9521871
dlendingst						
dlendingst L1.	.0006012	.0074888	0.08	0.936	-.0140765	.015279
dhindex						
dhindex L1.	10.3421	6.296554	1.64	0.100	-1.998917	22.68312
_cons	-.141512	.0952611	-1.49	0.137	-.3282204	.0451964
dlendingst						
dfedf L1.	3.983981	2.039238	1.95	0.051	-.0128522	7.980814
dlendingst L1.	-.0394369	.1491703	-0.26	0.791	-.3310053	.2529316
dhindex L1.	-230.1716	125.422	-1.84	0.066	-475.9942	15.65095
_cons	3.256535	1.897521	1.72	0.086	-.4625371	6.975608
dhindex						
dfedf L1.	-.0023008	.0021807	-1.06	0.291	-.0065749	.0019732



dlendingst							
L1.	-.0002475	.0001595	-1.55	0.121	-.0005601	.0000652	
dhindex							
L1.	.577055	.1341206	4.30	0.000	.3141835	.8399265	
_cons	.0052857	.0020291	2.60	0.009	.0013087	.0092627	

**Model 4 Regression:**

Sample: 1997m4 - 2007m1  
 Log likelihood = 574.1211  
 FPE = 1.29e-09  
 Det (Sigma\_ml) = 6.98e-10

No. of obs = 118  
 AIC = -9.120697  
 HQIC = -8.777483  
 SBIC = -8.275403

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dindpr	9	.620182	0.1092	14.46901	0.0703
dfedf	9	.105502	0.6864	258.3003	0.0000
pspread	9	.140054	0.7237	309.1296	0.0000
dhindex	9	.003615	0.2728	44.25761	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
dindpr						
dindpr						
L1.	-.0857452	.0929991	-0.92	0.357	-.26802	.0965296
L2.	.1246465	.0954533	1.31	0.192	-.0624384	.3117315
dfedf						
L1.	.98341	.4937651	1.99	0.046	.0156482	1.951172
L2.	-.2140645	.444735	-0.48	0.630	-1.085729	.6576001
pspread						
L1.	-.1489504	.4119954	-0.36	0.718	-.9564465	.6585457
L2.	-.0128856	.4624848	-0.03	0.978	-.9193391	.8935679
dhindex						
L1.	-3.30343	15.52263	-0.21	0.831	-33.72723	27.12037
L2.	-12.00276	16.02533	-0.75	0.454	-43.41184	19.40631
_cons	.800147	1.03462	0.77	0.439	-1.227672	2.827966
dfedf						
dindpr						
L1.	.034486	.0158205	2.18	0.029	.0034783	.0654937
L2.	-.0038648	.016238	-0.24	0.812	-.0356908	.0279611
dfedf						
L1.	.4553011	.0839969	5.42	0.000	.2906702	.6199319
L2.	.2441233	.0756561	3.23	0.001	.09584	.3924065
pspread						
L1.	-.5006771	.0700866	-7.14	0.000	-.6380443	-.3633098
L2.	.3309301	.0786756	4.21	0.000	.1767288	.4851315

dhindex							
L1.	-1.513624	2.640634	-0.57	0.567	-6.68917	3.661923	
L2.	-1.497323	2.72615	-0.55	0.583	-6.84048	3.845833	
_cons	.560227	.1760045	3.18	0.001	.2152645	.9051894	
-----							
pspread							
dindpr							
L1.	-.0233243	.0210017	-1.11	0.267	-.0644869	.0178383	
L2.	.0008307	.021556	0.04	0.969	-.0414182	.0430796	
dfedf							
L1.	.3047582	.1115057	2.73	0.006	.0862111	.5233053	
L2.	-.0472867	.1004333	-0.47	0.638	-.2441324	.149559	
pspread							
L1.	.8180173	.0930398	8.79	0.000	.6356626	1.000372	
L2.	.1186162	.1044417	1.14	0.256	-.0860858	.3233182	
dhindex							
L1.	5.660284	3.505435	1.61	0.106	-1.210243	12.53081	
L2.	-6.62078	3.618958	-1.83	0.067	-13.71381	.4722486	
_cons	.2177484	.2336456	0.93	0.351	-.2401885	.6756853	
-----							
dhindex							
dindpr							
L1.	.000195	.0005422	0.36	0.719	-.0008676	.0012576	
L2.	-.0009672	.0005565	-1.74	0.082	-.0020579	.0001234	
dfedf							
L1.	-.0058314	.0028785	-2.03	0.043	-.0114732	-.0001897	
L2.	-.0003135	.0025927	-0.12	0.904	-.005395	.0047681	
pspread							
L1.	.0019685	.0024018	0.82	0.412	-.002739	.0066759	
L2.	-.0083526	.0026961	-3.10	0.002	-.013637	-.0030683	
dhindex							
L1.	.34311	.0904923	3.79	0.000	.1657484	.5204715	
L2.	-.1877615	.0934228	-2.01	0.044	-.3708669	-.0046561	
_cons	.0246915	.0060315	4.09	0.000	.0128699	.0365131	