Markets contagion during financial crisis: A regime-switching approach

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Abstract

Within a Markov regime-switching VAR framework, we investigate the contagion effects among the stock market, real estate market, credit default market, and energy market covering the most recent financial crisis period when markets experience regime shifts. The results demonstrate that the watershed of regimes occurs around the start of the subprime crisis in 2007, after which the “risky” regime dominates the evolution of market chaos. During the financial crisis, excluding their own shocks, stock market shock and oil price shock are the main driving forces behind the credit default market and stock market variations, respectively. The energy market also appears to be more responsive to the stock market movements than the shocks originating from housing and credit markets. However, the impacts from the credit default market on the real estate market are not significant as expected.

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1. Introduction

The recent financial crisis provides us with an opportune backdrop to investigate the contagion effects among the stock market, credit default market, real estate market, and the energy market. In this paper, we employ a Markov regime-switching VAR framework to delve into the process and the magnitude of the impacts of certain economic shocks on different markets and how the effects spill over to the other segments of the economy.

In the early 2000s, after the high-tech bubble rocked the US stock market, the government decided to pump more funds into the real estate market to keep prices stable. As a house is usually the largest single asset of most households and its value represents an important component of the aggregate portfolio of financial intermediaries, housing policies usually have pervasive economic and social effects and attentions have been focused on the real estate price stability and mortgage affordability. Quasi-government agencies such as Fannie Mae and Freddie Mac purchased a significant amount of subprime-laden securities. As the US housing bubble peaked, a highly competitive and liquid market had made mortgage money easily available to households which otherwise would not qualify for underwriting. These low credit mortgages planted the seeds of the eventual subprime mortgage crisis.

The onset of financial crisis started after the real estate market peaked in 2006. Mortgage delinquencies and foreclosures rose sharply, which in turn caused huge losses for banks and financial institutions that held a large amount of mortgages and mortgage-backed securities. During the first half of 2007, several mortgage companies, including ResMae and New Century Financial, led for bankruptcy protection. By August 2007, Countrywide drew $11.5 billion from credit lines and Bank of America injected $2 billion of equity capital into Countrywide. Such events began to spark a widespread loss of confidence in the banking system in the
investors’ mind. As a result, banks tightened their lending standards, hence ignited another round of credit crisis. The crisis reached a critical point in September 2008 during which the Federal Housing Finance Agency placed Fannie Mae and Freddie Mac in government conservatorship, Bank of America purchased Merrill Lynch, Lehman Brothers filed for Chapter 11 protection, and the Federal Reserve Board lent $85 billion to the American International Group. Companies and financial institutions hastened to deleverage to reduce their risk exposures, hence selling massive assets at discount.

The tightening of the credit default market and liquidity, the decline of the real estate value, the rapid rising energy prices in conjunction with the tremendous loss of wealth in the stock market finally cut into economic growth, which started a domestic recession and the recession propagated into a global one. Therefore we are granted with this rare opportunity to study the dynamics of market contagion effects arising from various economic shocks. Not only this financial crisis involves the credit default swap market which was almost non-existent in the past recessions, the simultaneous collapse of the housing market and the stock market also differs from past experiences. Our analysis centers on market contagion during the financial crisis. Specifically, in this setting we study the magnitude and the process whereby certain economic shocks impact different segments of the economy. This issue not only warrants a timely study but also could be paramount to scholars and market participants.

Toward this end, we utilize a multivariate vector autoregressive (VAR) model with a Markov regime-switching feature in order to accommodate any potential regime shifts. As Dungey and Zhumabekova (2001) have shown, tests of contagion effects can be seriously affected by the size of the “crisis” and “non-crisis” periods. Our empirical results demonstrate that the watershed of regimes occurs when the subprime crisis starts in 2007, after which the “risky” regime (larger mean and high volatility) dominates the evolution of market chaos. The technical virtue of our model makes it accommodate the data and actual events sufficiently well. Subject to different market shocks, the responses of all markets exhibit regime-dependent patterns. These effects tend to be more dramatic in the “risky” regime, which corresponds to the financial crisis period. In the low volatility or “stable” regime, impulse response functions and variance decomposition analysis suggest that economic factors’ own shocks explain the lion’s share of the variations. On the other hand, the high volatility or “risky” regime finds that excluding their own shocks, stock market shock and oil price shock are the main driving forces behind the evolution of the credit default market and stock market, respectively. Contrary to general perception, however, the impacts from the credit default market and stock market on the real estate market are not significant.

The paper proceeds as follows. The next section reviews the background and related studies on the four markets in question. In Section 3, we present our econometric methodologies. Data source and preliminary analysis are provided in Section 4. We provide in detail the empirical results and their implications in Section 5. The last section summarizes the main findings.

2. Background and related studies

In this section, we discuss the possibility of contagion effects in four markets, namely housing market, stock market, credit default market, and energy market, as these markets all play essential roles in the financial crisis. We are interested in these four variables not only because these four markets are the center of focus during the financial crisis period, but also because the Federal Reserve Board on many occasions expressed its concern about the deterioration of these markets, and the situations in these markets shaped the government’s monetary and fiscal policies during the period. Our discussions focus on why these markets may be related and the ripple effects from the collapse of one market may spill over to the other markets. Financial contagion can be defined as the increase of a cross-market linkage after economic shock occurs in one market. Common to all these episodes is the fact that the turmoil originated in one market extended to a wider range of markets in a way that is beyond the changes in fundamentals. The simultaneous movement of markets, however, can be explained by common external factors, e.g., market shocks, and investor sentiments. While any of these factors could lead to what is perceived as contagious financial crises, it is crucial to identify which one of them is actually driving the market mayhem. Although the literature on financial market contagion is abundant, most of them examine cross-country contagions; fewer study cross-asset contagions. The recent financial crisis generated shocks that transmitted and/or were expected to transmit across multiple asset classes, hence provides a unique background for our study.

Financial contagion occurs through a number of channels. First, Kiyotaki and Moore (2002) propose a theoretical framework within which through a balance-sheet effect, contagion occurs when the collateral value is affected by fluctuations in asset value, and/or when the effect of default works through chains of credit. Kodres and Pritsker (2002) also posit that contagion occurs when the economic agent deleverages his/her portfolio when losses become significant in one market. For instance, hedge funds unwind their portfolios when losses occur. Such dramatic unwinding exerts downward pressure on the stock market.

We have witnessed this type of contagion during the financial crisis period. For example, Glitnir Bank of Iceland was unable to secure a line of credit when Lehman Brothers, which provided a line of credit for Glitnir, filed for bankruptcy. The collapse of the collateralized debt obligation (CDO) market is another example. Mortgage-backed securities (MBS) declined in value when

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1 Although interest rates may also be a factor to consider, we replaced interest rates with the CDS spreads for a number of reasons. First, CDS spreads play a key role during the onset of the financial crisis. Second, as CDS spreads measure the insurance cost of credit default, we expect a very high correlation between CDS spreads and various interest rates, in particular yield spreads. Indeed, during the period from January 2008 to February 2009, the simple correlations between daily CDS spreads and corresponding 3-month T-bills and 30-year Baa-rated corporate bonds are 85% and 82%, respectively; and the correlations between CDS spreads and the (Baa-AAA) yield spread and the (Baa-10-year Treasury Notes) yield spread are 80% and 91%, respectively. CDS spreads thus explain a bulk of the interest rate effect. Therefore, due to the high correlations, we include only the CDS spreads in the model to avoid multicollinearity issues. Third, the active Fed interest rate policy during the financial crisis period renders interest rates in the short maturity spectrum highly exogenous.
homeowners defaulted on their mortgages. The decline in MBS value was then transmitted to the CDO firms which often hold synthetic securities such as credit default swaps (CDS). The collapse of the CDOs then transmitted the crisis to the CDS buyers, which in turn caused a default cascade. The chain reaction was not confined in the financial sector of the economy. As the skyrocketing CDS spread caused by the uncertainty makes credit insurance very expensive, liquidity in the credit market dried up. The liquidity crunch clearly affected the real sector of the economy. As would-be consumers and homebuyers could not obtain the credit, housing market went through a free fall and manufacturers (such as GM) suffered as a result. The deterioration of expected cash flows hammered the stock market, which in turn created a negative wealth effect, and the contagion spread. Further transmission of the shock deeply concerned the Fed. In his speech, the Federal Reserve Chairman Ben Bernanke acknowledged that “… the complexity and sophistication of today’s financial institutions and instruments and the remarkable degree of global financial integration allows financial shocks to be transmitted around the world at the speed of light,” and “…the development of complex and opaque financial instruments that seems to work well during the credit boom have been shown to be fragile under stress.” Clearly, the complexity of today’s financial markets is quite different from the past, and we have evidenced the linkage among these markets which did not exist during the normal time period. To be sure, it is the potential contagion effect that prompted the Fed to bail out AIG. If AIG had collapsed, financial institutions around the world would have been forced to revalue an enormous amount of debt securities.

Second, shocks in one market can change investors’ risk-aversion, hence the equilibrium risk-premium in all risky investments. A shock in one market thus propagates into the other markets. Acharya and Pedersen (2005) argue that the shock from a distressed event may change the equilibrium risk-premia of assets in the economy. For example, the skyrocketing CDS spreads significantly increased the default risk-premium and equity risk-premium, which caused dramatic asset devaluation in the junk bond and stock markets. The changes in the equilibrium risk-premium may explain why the $500 billion loss in the mortgage market, which represents less than 3% of the $22 trillion US equity, caused a more than 50% drop in the equity value.

Finally, a third transmission mechanism for systemic risk is common shocks. Levitin (2011) contends that common shocks to sectors of the economy can result in the mass failure of individual firms, thus producing broader economic harms. The impact of 9/11 on the entire airline industry and the economy is an example. Another example is the 1973 oil price shock that resulted from the oil embargo imposed by the Organization of Arab Petroleum Exporting Countries (OAPEC). The oil price shock caused dramatic inflation, the 1973–74 stock market crash, and the 1970s recession. In the recent financial crisis, although soaring energy and commodity prices are not the direct results of the subprime mortgage crisis, historical evidence suggests that such economic shock may transmit the shock to other sectors of the economy, e.g., to the stock market due to the increase of risk-adjusted discount rates. Crude oil prices doubled from July 2007 ($74/barrel) to July 2008 ($145/barrel). Concerned about the increasing commodity prices, Fed Governor Frederic Mishkin pointed out that “…commodity prices have reached new heights, which clearly could take a toll on the US economy as well as on the economies of our major trading partners, …the latest spike up in energy and food prices has raised the upside risk to inflation and inflation expectations.” Soaring energy prices raised the inflation expectations, hence lowered equity values. Higher inflation expectations may also force the Fed to increase interest rates during a period of fragile economy, which will dampen the already troubled housing markets. On the other hand, declining stock market and housing market create a negative wealth effect, which in turn will decrease the aggregate demand and the demand for energy products. Moreover, increasing uncertainty as reflected in the CDS spreads may fuel speculation on commodity prices, notably gold and energy. Therefore, contagion occurs across markets, financial or real, through various channels during the crisis period, which may be absent in the tranquil period. It should be noted that these contagion channels are not mutually exclusive; a shock can transmit through more than one channel. The depth and the breadth of the recent financial crisis offer us an excellent environment to study this issue.

Previous researches examining the relation between aforementioned markets are scant and focus exclusively on bi-lateral relations. Moreover, those studies investigate the inter-market relation during tranquil periods, where the relation uncovered is due to fundamentals, not contagions. For example, the relationship between the CDS and stock markets is investigated in Longstaff, Mithal and Neis (2005), where both markets are found to lead the bond market. However, no clear lead–lag relationship is found between the stock market and the CDS market. Norden and Weber (2007) suggest that stock returns usually lead the CDS market and the CDS market is more sensitive to the stock market than the bond market.

Others have examined the roles played by oil price or stock returns in the real estate market. For example, Quan and Titman (1999) find significant positive relations between real estate values and stock returns in 17 countries, given that both variables are affected by the level of economic activity and interest rates. Ling and Naranio (1999) support the hypothesis that the market for exchange-traded real estate companies is integrated with the market for exchange-traded stocks in the US market. Moreover, the degree of integration between markets has significantly increased during the 1990s. At the same time, it is important to recognize that higher oil prices may add to inflationary pressures in an economy and reduce household real income, leading to reduced demand for real estates. For example, Hamilton (1996) and Hooker (2002) show that increases in oil price can affect a large national economy, impacting output and domestic price level and resulting in reduced consumer demand for goods.

Based upon the above discussions, we contribute to the literature in twofold. First, we investigate the less-studied cross-market contagions; second, we examine the multi-lateral relations between four market sectors in both tranquil and turmoil periods.

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3. Methodology

The focus of our study is to investigate the impact of various shocks on different markets within the economic system. To this end, a vector autoregressive model (VAR) is appropriate. However, the effects of shocks are not expected to be stable over time, which may be subject to occasional regime shifts. In the wake of financial crisis, a VAR model with regime shift feature seems more appropriate for our analytical purpose. Following Krolzig (1997), we expand Hamilton’s (1989) MS-AR model to a multivariate Markov switching vector autoregressive (MS-VAR) framework with two regimes that allow the mean and the variance to shift simultaneously. The innovation accounting exercise of the MS-VAR model admits various dynamic structures, depending on the value of the state variable, $s_t$, which controls the switching mechanism between various states. Consider the MS-VAR process in its most general form:

$$ y_t = v(s_t) + A_1(s_t)y_{t-1} + \ldots + A_p(s_t)y_{t-p} + e_t $$

where $y_t = (y_{1t}, \ldots, y_{nt})$ is an $n$ dimensional time series vector, including returns of oil price ($ROP$), stock price ($RSP$), credit default swap index ($RCDs$) and housing price ($RHP$); $v$ is a $4 \times 4$ matrix of intercepts; $A_1, \ldots, A_p$ are matrices containing the autoregressive parameters and $e_t$ is a white noise vector such that $e_t|s_t \sim \text{NID}(0, \Sigma(s_t))$. In Eq. (1), $s_t$ is a random variable that triggers the behavior of $y_t$ to change from one regime to another. Therefore, the simplest time series model that can describe a discrete value random variable, such as the unobserved regime variable $s_t$, is the Markov chain. Generally, $s_t$ follows a first-order Markov-process, where it implies that the current regime $s_t$ depends on the regime one period ago, $s_{t-1}$ and is denoted as

$$ P(s_t = j | s_{t-1} = i, s_{t-2} = k, \ldots) = P(s_t = j | s_{t-1} = i) = p_{ij} $$

where $p_{ij}$ gives the transition probability from one regime to another. For $m$ regimes, these transition probabilities can be collected in an $(m \times m)$ transition matrix denoted as $P$.

$$ P = \begin{bmatrix}
    p_{11} & p_{12} & \cdots & p_{1m} \\
p_{21} & p_{22} & \cdots & p_{2m} \\
    \vdots & \vdots & \ddots & \vdots \\
p_{m1} & p_{m2} & \cdots & p_{mm}
\end{bmatrix} $$

with

$$ \sum_{j=1}^{m} p_{ij} = 1 \text{ where } i = 1, 2, \ldots, m \text{ and } 0 \leq p_{ij} \leq 1 $$

The transition probabilities also provide us with the expected duration the system is going to stay in a certain regime:

$$ E(D_j) = \frac{1}{1-p_{ij}} \cdot j = 1, 2, \ldots m $$

where $D_j$ denotes the duration of regime $j$.

In this study, two discrete states $(s_1, s_2)$ representing (a) a larger mean, high volatility regime and (b) a smaller mean, low volatility regime are sufficient to capture the dynamics of the data series for our purposes. The higher the values of $p_{11}$ and $p_{22}$ are, the more likely that the null hypothesis of no regime shift would be rejected. Following Hamilton’s (1989), we estimate the population parameters including the joint probability density of unobserved states and then probabilistic inferences about the unobserved states are made by using a nonlinear filter and smoother. “Filtered” probabilities $P(s_t = j | \psi_t)$ are inferences about $s_t$ conditional on the information up to time $t$, while “smoothed” probabilities $P(s_t = j | \psi_T)$ use all the information in the data where $t = 1, 2, \ldots, T$.

Maximum likelihood estimation of Eq. (1) is based on the Expectation Maximization (EM) algorithm (Dempster, Laird and Rubin, 1977), which starts with the initial estimates of the hidden data and iteratively produces a new joint distribution that increases the nonlinear probability of observed data. If the Hamilton’s Markov regime-switching test shows that the system displays shifting regimes, it would be more informative if we could further investigate the different market performances in the “risky” regime (corresponding to larger means and higher volatilities) as well as in the “stable” regime (associated with smaller means and lower volatilities). We expect asymmetrical effects in market performances including sign reversals or differential speeds of adjustment to the economic shocks.

In the next step, we conduct impulse response function analysis to quantify and trace the time paths of the effects of a typical shock on the economic system. A perturbation in one innovation in the system sets up a chain reaction over time in all the variables, but the conventional method without estimating structural changes could present a potential pitfall. Hence, we employ the regime-dependent impulse response functions, which analogously describe the relationship between endogenous variables and fundamental disturbances within each Markov-switching regime. Our impulse response functions are conditional on a given
Following Ehrmann, Ellison and Valla (2003), we use oil price to represent the impact of the energy market shock contemporaneous and ensuing impacts from the oil market, stock market, real estate market and credit default market in two distinct regimes.

We define the generalized impulse response function (GIRF) of variable i for an arbitrary shock to variable j denoted by $\varepsilon_i = \delta_j$ and shock history $w_{t-1}$ as:

$$GIRF(N, \delta_j, w_{t-1}) = E(Y_{it+N} | \varepsilon_i = \delta_j, w_{t-1}) - E(Y_{it} + N | w_{t-1})$$

Estimates of the response vectors can be derived by combining the parameter estimates of the Markov-switching unrestricted vector autoregression with the estimate of regime-dependent residuals in Eq. (1). A key feature of GIRF is that the generalized impulse response function allows for meaningful interpretation of the initial response of each variable to shocks originating from any of the other variables. Thus, we are able to detect the contemporaneous and ensuing impacts from the oil market, stock market, real estate market and credit default market in two distinct regimes.

4. Data and preliminary analysis

We obtain weekly observations on oil price ($R_{OP}$), stock price ($R_{SP}$), CDS index ($R_{CDS}$) and housing price index ($R_{HP}$) from October 2003 to March 2009 for the postulated framework. We use oil price to represent the impact of the energy market shock partially because oil price plays an important role in the most recent financial crisis and the economic recession. Using weekly data allows us to better capture the fluctuations in these four markets without incorporating too much noisy information often found in daily data. On the other hand, monthly data produces too few data points for the VAR analysis, hence not used in our analysis.

The CDS data is retrieved from Bloomberg covering the period from October 2003 through March 2009, which constitutes the longest recent time period in a study on CDS. Similar to the way a stock index is created as a portfolio of individual stocks, a CDS index is essentially a portfolio of single-name credit default swaps. As a popular credit derivative instrument, a credit default swap index can be used for hedging in risk management or to take a position on a basket of credit entities for speculation or arbitraging purposes. The five-year maturity CDX IG generic index, which is the most actively traded credit default swap index based upon North American reference entities, is used in the paper.

The S&P/Case–Shiller Home Price Indices are a benchmark of residential real estate prices to track the prices of single-family homes in different geographical areas. In the paper, we adopt the most-widely cited index, the S&P 20 Metropolitan area (MSA) Index. However, since the Case–Shiller 20 MSA housing index is available only in monthly intervals, we use the cubic spline process, which is a non-parametric polynomial interpolation method, to convert the index into weekly observations.

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4 Daily data for the oil price, stock price, and CDS index is available for analysis. However, weekly data is employed for the VAR analysis because daily data contains too much noisy information, which tends to produce less powerful results.

5 Since first differences instead of levels are used in the VAR model, weekly returns for the stock index, CDS index, and oil price are constructed based upon each Wednesday’s prices.

6 As opposed to a credit default swap, a CDS index is a standardized and liquid credit security, trading at a smaller bid-ask spread of $\frac{1}{2}$ to $\frac{1}{4}$ of a basis point with high volumes. Therefore it is usually cheaper to hedge a portfolio of bonds with a CDS index than using many CDS contracts to achieve a similar result.

7 The index is made up of 125 of the most liquid investment grade credits and the composition is determined by Dow Jones and the member banks, which is intended to reflect multiple industry sectors and provide a broad exposure to the credit risk of North American investment grade firms.

8 McCulloch (1975) uses cubic spline method and states that this approach performs at least as satisfactorily as other interpolation methods. Similarly, Adams and Van Deventer (1994) illustrate using the technique to obtain maximum smoothness for forward curves. Although the approach can lead to smooth shapes for the housing price index, it is an accessible method and one that gives reasonable accuracy.
Summary statistics of our sample are reported in Table 1. ROP is the return on oil price; RSP is the return on stock price; RCDS is the return on CDS index; and RHP is the return on housing price. Returns are calculated by taking the natural log of price ratios. Both ROP and RCDS show positive weekly returns, while RSP and RHP have negative returns. Table 1 also indicates that, over the sample period, all the series evidence significant skewness and kurtosis. Jarque–Bera tests show that all four series depart from normality.

Prior to the identification of possible long-term relations of the variables specified in the MS-VAR system, it is necessary to verify that all variables are stationary since lack thereof can make any empirical results deceptive. Table 2 presents the stationarity results for all the variables, based upon the Augmented Dickey–Fuller unit root test as well as the Phillips–Perron test, which corrects any possible presence of autocorrelation in the standard ADF test in a non-parametric way. We find that all series are $I(0)$ with the exception of housing price index return, but the tests display that $RHP_t$ exhibit stationarity in the first difference. Hence, it is appropriate to include the change of housing price index return in the analysis of the MS-VAR model consisting of $ROP_t$, $RSP_t$, $RCDS_t$, and $\Delta RHP_t$. There is no need to further extend the model into a multivariate cointegrating framework with an autoregression maximum likelihood approach.

5. Empirical results

In this section, we report the empirical results including Markov regime-switching VAR, impulse response functions, and variance decompositions analysis.

Table 2
Tests for stationarity. This table presents the results of unit root tests for all the variables. $ROP_t$ is the weekly return of oil price; $RSP_t$ is the weekly return of stock price; $RCDS_t$ is the weekly return of credit default swap index; and $RHP_t$ is the weekly return of housing price index. *** denotes the rejection of the unit root hypothesis at the 1% level of significance.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Augmented Dickey-Fuller</th>
<th></th>
<th>Phillips–Perron</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Returns</td>
<td>Differences in returns</td>
<td>Returns</td>
<td>Differences in returns</td>
</tr>
<tr>
<td>$ROP_t$</td>
<td>-15.25***</td>
<td>-12.11***</td>
<td>-15.34***</td>
<td>-94.91***</td>
</tr>
<tr>
<td>$RSP_t$</td>
<td>-17.92***</td>
<td>-14.99***</td>
<td>-17.90***</td>
<td>-76.30***</td>
</tr>
<tr>
<td>$RCDS_t$</td>
<td>-13.22***</td>
<td>-13.07***</td>
<td>-13.21***</td>
<td>-91.22***</td>
</tr>
<tr>
<td>$RHP_t$</td>
<td>-0.99</td>
<td>-4.55***</td>
<td>-0.82</td>
<td>-3.68***</td>
</tr>
</tbody>
</table>

5.1. Empirical results

In this section, we report the empirical results including Markov regime-switching VAR, impulse response functions, and variance decompositions analysis.

Table 3
Maximum likelihood estimates from the Markov regime-switching model. In this table, we report the estimates of autoregressive parameters, regime transition probabilities, and durations of regimes from a Markov regime-switching model. $ROP_t$ is the weekly return of oil price; $RSP_t$ is the weekly return of stock price; $RCDS_t$ is the weekly return of credit default swap index; and $\Delta RHP_t$ is the change in weekly return of housing price index. *** denotes 5% significance level. The numbers in parentheses are standard errors.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$ROP_t$</th>
<th>$RSP_t$</th>
<th>$RCDS_t$</th>
<th>$\Delta RHP_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic, $t(1,1)$</td>
<td>4.953</td>
<td>4.947</td>
<td>3.837</td>
<td>4.953</td>
</tr>
<tr>
<td>Logistic, $t(1,2)$</td>
<td>-4.493</td>
<td>-4.806</td>
<td>-3.021</td>
<td>-4.953</td>
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<tr>
<td>$p_{1,1}$</td>
<td>0.993**</td>
<td>0.993**</td>
<td>0.979**</td>
<td>0.993**</td>
</tr>
<tr>
<td>$p_{2,2}$</td>
<td>0.988**</td>
<td>0.992**</td>
<td>0.954**</td>
<td>0.991**</td>
</tr>
<tr>
<td>Mean ($\mu_i$), regime 1</td>
<td>0.302</td>
<td>2.528</td>
<td>-0.112</td>
<td>0.406</td>
</tr>
<tr>
<td>Mean ($\mu_i$), regime 2</td>
<td>-0.928</td>
<td>-8.857</td>
<td>3.124</td>
<td>-0.478</td>
</tr>
<tr>
<td>Variance ($\sigma^2_i$), Regime 1</td>
<td>2.007</td>
<td>17.218</td>
<td>1.758</td>
<td>0.494</td>
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<tr>
<td>Variance ($\sigma^2_i$), Regime 2</td>
<td>5.624</td>
<td>44.633</td>
<td>13.166</td>
<td>0.529</td>
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<tr>
<td>Expected duration of “stable” regime</td>
<td>142.86</td>
<td>142.86</td>
<td>47.62</td>
<td>142.86</td>
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<tr>
<td>Expected duration of “risky” regime</td>
<td>83.33</td>
<td>125.0</td>
<td>21.74</td>
<td>111.11</td>
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</table>

MS-VAR System

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$ROP_t$</th>
<th>$RSP_t$</th>
<th>$RCDS_t$</th>
<th>$\Delta RHP_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic, $t(1,1)$</td>
<td>4.69 (0.84)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Logistic, $t(1,2)$</td>
<td>-4.13 (0.93)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_{1,1}$</td>
<td>0.991**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_{2,2}$</td>
<td>0.984**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_{1,2}$</td>
<td>0.016</td>
<td></td>
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<td></td>
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<tr>
<td>$p_{2,1}$</td>
<td>0.009</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected duration of “stable” regime</td>
<td>110.25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected duration of “risky” regime</td>
<td>63.21</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-2099.7</td>
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<td>Schwarz Criterion</td>
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5.1. Markov regime-switching VAR

In this subsection, we explore the relationships of \([ROP, RSP, RCDS, \Delta RHP]\) within a Markov regime-switching VAR framework, which allows the influence of explanatory variables to be state-dependent.

We first turn our attention to the regime-switching analysis on the generating processes of each individual series to see if they can be characterized by nonlinearity with varied turning points at different time periods. Using the step-down procedure of Campbell and Perron (1991), we find that the appropriate lag length is six in the MS-VAR model. Only two states are assumed, where state one corresponds to a smaller mean, low variance state or the “stable” regime, whereas state two is a larger mean, high variance state or the “risky” regime. The transition between states is characterized by a first order Markov chain and duration independency is also assumed.

Table 3 reports the estimates of autoregressive parameters and regime transition probabilities, \(p_{11}\) and \(p_{22}\). It is clear that there is strong evidence of regime-switching behavior in all the series, since the null hypothesis of only one regime can be rejected at 5% significance level with all the transition probabilities \(p_{11}\) and \(p_{22}\) larger than 0.95. This demonstrates that there is a strong tendency for all variables to switch from the first state to the second state. In addition, the probability of staying in regime 1 is higher than the probability of staying in regime 2, suggesting that regime 1 \((St_1 = 1)\) is more persistent than regime 2 \((St_2 = 2)\). What’s more, the first regime \((St_1 = 1)\) indicates that all the variables in a “stable” market have smaller averages, \(\mu_1\) \((St_1 = 1)\) in absolute terms and lower volatilities, \(\sigma^2_1\) \((St_1 = 1)\). Conversely, the second regime captures features of a “risky” market with higher absolute averages \(\mu_2\) \((St_2 = 2)\) as well as higher volatilities \(\sigma^2_2\) \((St_2 = 2)\). For example, RCDS has a volatility measure of 1.758% in the stable regime, but the volatility increases dramatically to 13.17% in the risky regime.

Using Eq. (4), we thus obtain the average expected durations for all series in Table 3. It is found that all the series stay longer in regime 1 than in regime 2. For example, one may expect that the “stable” regime for credit default swap index will last close to 48 weeks before the next regime arrives, and the “risky” regime would end in about 22 weeks. The real estate market’s transition probability of “risky” regime is 0.991, which implies an expected average duration of 111 weeks in the “risky” regime.

In the lower panel of Table 3 the results for the entire MS-VAR system consisting of \([ROP, RSP, RCDS, \Delta RHP]\) are reported. Two regimes are clearly identified, as the null hypothesis of only one regime can be rejected at 5% significance level with the transition probabilities \(p_{11} = 0.991\) and \(p_{22} = 0.984\), respectively. Moreover, the calculations from transition probabilities point out an expected duration of 110 weeks for the “stable” regime and 63 weeks for the “risky” regime. In other words, the duration of a “stable” market is about twice longer than that of a “risky” market. This finding is consistent with the empirical observation of market performances in the past that the durations of economic booms tend to be longer than those of economic slumps.

The smoothed regime probabilities depicted in Fig. 1 reveals that the watershed of two regimes for the markets occurs in the beginning of 2007, after which the “risky” regime dominates the evolution of the markets as manifested by the economic upheavals and financial chaos we have undergone.

5.2. Regime-dependent impulse response functions

In this subsection, we trace the time paths of the invoked responses of various markets after economic shocks are imposed on the system. This exercise allows us to identify the sign of association between the variables and the respective market response paths over time, as they explicitly reveal the interaction between these markets and the dynamic process of the interaction. To achieve this objective, we apply the regime-dependent impulse response function suggested in Ehrmann et al. (2003), which analogously describes the relationship between endogenous variables and fundamental disturbances within each Markov-switching regime. Since impulse responses trace the paths of different variables when they return to equilibriums after a shock is
5.2.3. Responses of the housing market

Market shocks invoke more tangible responses in the stock market in regime 2. Approximately half the impact of the stock market’s own shock. Fig. 3(a) and (b) demonstrates that both oil price and housing regime shown in Fig. 3(b), a positive stock market’s own shock invokes a more than 4% response in the stock market. The effect shocks than regime 1 does. In fact, in the high volatility regime (regime 2). While the response of CDS index to the real estate market shock in both regimes are significant but short-lived (ranging from 2 to 3 weeks). Nevertheless, with the exception of CDS own shock, the stock market shocks play the most important role in the CDS market variations.

In a similar fashion, the impulse responses of CDS index to the real estate market shock (HP shock) in two regimes are presented in Fig. 2(a) and (b). Results also display a higher degree of negative linkage between the CDS and real estate markets in the high volatility regime (regime 2). While the response of CDS index to the real estate market shock in the first regime is almost negligible, an instant and negative response of CDS index is observed after the imposition of a shock from the real estate market in the second regime. In regime 2, the magnitude of the CDS index response gets close to 1% in the first week, after which the effect wears off with a downward trend to its long-run equilibrium level.

The impact of oil price shocks on the CDS index in the first regime is trivial. Following an expansionary oil price shock in regime 2, CDS index decreases approximately 1% below its baseline in the first week. The magnitude of the response, however, is very small and the standard error bands are quite wide, indicating the limited impact of oil prices on the CDS market.

5.2.1. Responses of the credit default market

The impulse responses of CDS index to various shocks imposed are presented in Fig. 2(a) and (b) for the low and high volatility regimes, respectively. Some dissimilarities between regimes stand out. Overall, credit default swap index is more responsive to economic shocks in the “risky” regime (regime 2). For instance, as shown in Fig. 2(a), in response to its own shock, CDS index jumps to its peak at approximately 5% above its baseline in the first week in the “stable” regime (regime 1), followed by a correction to the baseline level within 3 weeks. By comparison, due to its own shock, CDS index shoots up instantaneously by some 9% in the “risky” regime in Fig. 2(b).

Initial negative responses in CDS index are found due to a shock emanating from the stock market. Reactions of CDS index to the stock market shock are stronger in the second (“risky”) regime than in the first (“stable”). In the first regime, the negative response of CDS index maxes out at 2% below the baseline in the first week after a positive shock originating from the stock market is applied and the impact dies down in about 3 weeks. By contrast, following a positive SP shock in the second regime, the CDS index instantaneously decreases by 4%, about twice the magnitude in the first regime, and then it trails off after 2 weeks. The reactions of CDS index to the stock market shock in both regimes are significant but short-lived (ranging from 2 to 3 weeks). Nevertheless, with the exception of CDS own shock, the stock market shocks play the most important role in the CDS market variations.

In a similar fashion, the impulse responses of CDS index to the real estate market shock (HP shock) in two regimes are presented in Fig. 2(a) and (b). Results also display a higher degree of negative linkage between the CDS and real estate markets in the high volatility regime (regime 2). While the response of CDS index to the real estate market shock in the first regime is almost negligible, an instant and negative response of CDS index is observed after the imposition of a shock from the real estate market in the second regime. In regime 2, the magnitude of the CDS index response gets close to 1% in the first week, after which the effect wears off with a downward trend to its long-run equilibrium level.

The impact of oil price shocks on the CDS index in the first regime is trivial. Following an expansionary oil price shock in regime 2, CDS index decreases approximately 1% below its baseline in the first week. The magnitude of the response, however, is very small and the standard error bands are quite wide, indicating the limited impact of oil prices on the CDS market.

5.2.2. Responses of the stock market

Fig. 3(a) and (b) shows the impulse responses of stock price invoked by various economic shocks. A few observations are worth noting. Consistent with the findings in Fig. 2(a) and (b), regime 2 exhibits greater responses of the relevant variable to economic shocks than regime 1 does. In fact, in the first regime, the stock market responds predominately to its own shock. In the risky regime shown in Fig. 3(b), a positive stock market’s own shock invokes a more than 4% response in the stock market. The effect diminishes, however, by the end of the second week. The stock market responds negatively to the CDS market shock — a one standard deviation shock of the CDS residual causes a 2% decrease in the stock return in the first week after the shock is initiated, approximately half the impact of the stock market’s own shock. Fig. 3(a) and (b) also demonstrates that both oil price and housing market shocks invoke more tangible responses in the stock market in regime 2.

5.2.3. Responses of the housing market

Fig. 4(a) and (b) illustrates the impulse responses of the housing price index in response to various economic shocks. Again, it is noted that the housing market is more responsive to economic shocks when the high volatility regime dominates, and negligible responses are uncovered in the low volatility regime. The strongest response in the housing price index is aroused by a shock coming from the real estate market itself in both regimes. Specifically, a shock of one standard deviation of the housing market equation residual initially invokes approximately a 1% response in the housing market in regime 1, and a 2% response in regime 2. In both regimes, the impact of the shock peaks in the second week after the initiation of the shock, but the equilibrium in the housing market is not restored until 6 weeks afterwards.

For the stock market shock in regime 2, there is an initial positive reaction in the housing price index that lasts for approximately 2 weeks. Positive relations between real estate values and stock returns have been previously reported, such as Quan and Titman (1999), which attribute the finding to the fact that both markets are affected by economic activities and interest rates. Other studies, such as Tsatsaronis and Zhu (2004), Guo and Huang (2010) also reveal co-movements and causalities in the two markets.

With regard to the impulse response of the housing market invoked by a positive CDS shock in the second regime, the result in Fig. 4(b) suggests a negative response of the real estate market. The effect diminishes and moves toward its long-run equilibrium within 4 weeks. Conversely, the low volatility regime (Fig. 4(a)) witnesses a rather diminutive reaction of housing price index to a credit default market shock.
Fig. 2. Each graph shows the response of credit default swap index to standardized structural shocks over a forecast horizon of 12 weeks. Estimations are made by the Monte Carlo method with 1000 replications. Plus/minus two standard error bands (dashed lines) are displayed along with the impulse responses.
Fig. 3. Each graph shows the response of stock price to standardized structural shocks over a forecast horizon of 12 weeks. Estimations are made by the Monte Carlo method with 1000 replications. Plus/minus two standard error bands (dashed lines) are displayed along with the impulse responses.
Fig. 4. Each graph shows the response of housing price index to standardized structural shocks over a forecast horizon of 12 weeks. Estimations are made by the Monte Carlo method with 1000 replications. Plus/minus two standard error bands (dashed lines) are displayed along with the impulse responses.
5.2.4. Responses of the energy market

Fig. 5(a) and (b) documents the impulse responses of oil price invoked by various economic shocks under two regimes. The potential impacts of the stock market shock, housing market shock and credit default market shock on the energy market can be derived from the effect of these shocks on the expected economic conditions. For example, as the stock market deteriorates, investors' wealth declines, which causes decreases in aggregate demand in the economic system, hence lower economic activities. Lower economic activities are supposed to reduce the demand for energy products and result in lower energy prices.

Similar to the impulse response functions shown in some of the other figures, oil price responds only to its own shock in the first regime. The effects of other economic shocks on oil price are lacking in this low volatility regime, yet the responses of oil price to economic shocks are detected to be stronger in the second regime. It can be seen that oil price responds to its own shock twice as strong in this “risky” regime compared with the “stable” regime. Although the responses of oil price to the other economic shocks are stronger in the second regime, the effects are mixed. For example, the initial response of oil price to a stock market shock is positive, declining to the baseline in the second week, but becomes positive again in week 3 before it settles down to the equilibrium value in week 4. The intuitive explanation of the initial positive response in oil price is that a stronger stock market signals improving economy, which pushes up the expected energy consumption and enhances energy prices.

5.3. Sources of variations — variance decomposition analysis

Last, we analyze the variables’ forecast error variance decompositions, which aim to assess the relative strengths of various shocks to the innovations of the variables in the economic system. To gauge how the forecast error variances of the variables evolve over time, we report the results pertaining to two regimes in Table 4 based on the Markov regime-switching model.

Overall, the results presented in Table 4 are consistent with the prevailing finding from the impulse response functions discussed in the above subsection. For credit default swap index, its own shock is the main driving force irrelevant of the regime, accounting for 81% of the forecast error variance in CDS index 3 weeks after the shock in regime 1, and 75% of the variation in regime 2. We find the shock from stock market ranks as the second largest contributor in the decomposition of the forecast error variance of CDS index. In the high volatility regime, where the market undergoes greater variations, the proportion explained by stock returns accounts for nearly 23% of the CDS index variance in the third week and a prominent 22% in 12 weeks. Even in the low volatility regime, stock return shocks can explain up to 17% of the variation in the CDS market in the long run. These results correspond to the impulse response function findings in Fig. 2, and are more consistent with the findings in Bystrom (2005) and Norden and Weber (2007) that the stock market and CDS market are correlated. In contrast, shocks originating from the oil and real estate markets explain a limited proportion of the forecast error variance in CDS index, although the magnitudes of influence are both slightly larger in the “risky” regime than in the “stable” regime.

For the stock market returns, the impact of its own shock plays the most dominant role in both regimes. In regime 2, the stock market’s own shock still explains almost 90% of the forecast error variance 12 weeks ahead after the shock. Other than its own shock, in regime 1 the housing market shock accounts for roughly 5% of the stock price variation in 12 weeks, while in regime 2 oil price shock takes the second spot, accounting for 6% of the stock price variation in 12 weeks. In regime 2, i.e., the financial crisis period, although the CDS index and CDS market gain most of the public attention, they account for only 2% and 1.5% of the forecast error variance in the stock market weeks after the initial shock, respectively. This suggests that the stock market specific factors are mainly in play and deterministic in the development of the stock market during this financial crisis period, while the CDS and housing markets have played a fairly indirect role.

In terms of the housing price index, the shock from the real estate market itself plays the predominant role in illuminating its forecast error variations and the impacts stay significant throughout the whole forecast period in both regimes. This is particularly true for regime 1, where the housing price index’s own shock explains almost 99% of its forecast error variance in 12 weeks. In regime 2, this statistic drops slightly to 94%, allowing the other three shocks to explain a little more of the forecast error variance in the housing price index.

For the oil price, the explanatory power of its own shock drops from 95% in regime 1 to 86% in the second regime in 12 weeks. In the high volatility regime, therefore, the other three shocks tend to explain more of the forecast error variance in oil price as opposed to the low volatility regime. For example, the housing market shock is the second largest long-run factor (2.7%) in driving the energy market activity in the “stable” regime, but it falls to the third place (4%) in the “risky” regime. In contrast, the long-run contribution from the stock market shock overtakes the housing market shock increasing to 7% in regime 2, making it the second largest contributor under the “risky” regime. Evidence from the stock market and the energy market thus shows that these two markets are highly correlated during the financial crisis period.

6. Conclusions

The subprime mortgage meltdown, the massive default in the credit default swap market, the crash of the stock market and the skyrocketing oil prices are factors believed to have played complex roles in the recent financial turmoil and recession. However, relatively little information is known as to what extent the four markets interact and contribute to the catastrophic economic meltdown. In this paper, we model the nonlinear relationships of these risk factors within a four-dimensional Markov switching VAR model. Using weekly data of oil price, stock index, CDS index and housing price index from October 2003 through March 2009, we investigate the key issue mentioned above and several important conclusions have been derived from our analysis.
a. Impulse Responses of Oil Price to Various Shocks in Regime 1

b. Impulse Responses of Oil Price to Various Shocks in Regime 2

Fig. 5. Each graph shows the response of oil price to standardized structural shocks over a forecast horizon of 12 weeks. Estimations are made by the Monte Carlo method with 1000 replications. Plus/minus two standard error bands (dashed lines) are displayed along with the impulse responses.
The results from a Markov switching specification reveal that the contagion effects among these markets are characterized by nonlinearity with two distinct regimes. The watershed of the two regimes within the MS-VAR framework occurs around the start of the subprime crisis in 2007, after which the “risky” regime (larger mean and high volatility) dominates the evolution of the market chaos. In addition, the duration of a “stable” market is found to be about twice longer than that of a “risky” market. This finding is consistent with the empirical observation that the durations of economic booms tend to be longer than those of economic slumps. The technical virtue of our model makes it accommodate the data and actual events sufficiently well.

Assessment of the relations of the economic variables utilizing regime-dependent impulse response functions reveals that all market indicators respond more significantly to various economic shocks when the “risky” regime is dominant. That is, the contagion effects among markets are more prominent during the financial crisis. Specifically, we observe that the stock market activities generate higher volatilities in the CDS market. The contagion effects between stock and energy markets also appear to be larger in the “risky” regime. However, the impacts from the credit default market on the real estate market are not significant as expected. Similar conclusions emerge from the variance decomposition analysis.

This study also uncovers a few findings that may differ from the general public postulations but are worth noting. First, credit default market shows strong reactions to the stock market fluctuations, but obviously is much less responsive to the housing market shock in the “risky” regime. Second, although the real estate market shock is an important factor in explaining the variation in the stock market in the “stable” regime, its influence diminishes during the financial crisis period, after the oil and CDS market shocks. Finally, we find that the stock market ranks as the second largest contributor in the fluctuations of the variation in the energy market—only after its own shock during the financial crisis. Interestingly, the impact on the stock market from itself subsides rapidly in the “risky” regime, while the other factors gain momentum in their influences over the longer horizon.

Our findings have important implications for policymakers regarding the amplified contagion effects among the markets during financial crisis, so as to avoid any reckless lack of oversight. In particular, they should carefully examine and uncover the underlying primary driving forces behind the crisis, and take precautions against the potential risk factors in making future policy decisions. It is critical for policymakers to guide investors to pay special attention to those unexpected factors arising from various markets.

References


