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What explains default risk premium during the financial crisis? Evidence from Japan

Nader Naifar*

Department of Finance and Investment, College of Economics and Administrative Sciences, Al-Imam Muhammad Ibn Saud Islamic University, PO Box 5701, Riyadh, Saudi Arabia

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ABSTRACT

As is well documented, subprime mortgage markets carried significant default risk. This paper investigates the relationship between default risk premium, stock market conditions and macroeconomic variables during the financial crisis. Using iTraxx Japan Credit Default Swap (CDS) index spreads covering the period from March 2006 to November 2009, we employ a time-varying dynamic factor model with Markov regime switching to generate regime probabilities for default risk. We analyze the sensitivity of default risk premium changes to stock market conditions and macroeconomic variables by using two-state Markov switching models: a crisis regime sparked by rising loan defaults in the sub-prime mortgage market, and a non-crisis regime. We found strong evidence that the relationship between default risk premium changes, stock market and macroeconomic variables is regime-dependent. Our results suggest that during periods of crisis, CDS indices behave as a higher-risk indicator and become more sensitive to stock market conditions and macroeconomic variables. This paper examines the effects of the financial crisis in explaining the default risk premium. Understanding the determinants of default risk premium is important for financial analysts, economic policy makers and credit risk management.

1. Introduction

The financial crisis started in 2007 with the collapse of two Bear Stearns hedge funds, the Bear Stearns High-Grade Structured Credit Fund, and the Bear Stearns High-Grade Structured Credit

* Corresponding author. Tel.: +216 97 23 01 43; fax: +216 74 879 084.
E-mail address: Nader.Naifar@fsegs.rnu.tn.

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Enhanced Leveraged Fund. With this collapse, the so-called subprime mortgage crisis became clear with an increase in mortgage delinquencies in the United States. The impact went on to create a global banking crisis and recession. Subprime mortgages are those that do not meet the underwriting guidelines of the US government agencies Freddie Mac and Fannie Mae. The main problem facing financial institutions that either originated subprime loans or purchased subprime asset-backed securities is that the decline in housing prices contributed to an increase in subprime and Alt-A mortgage defaults. House prices continue to fall because borrowers who otherwise might have sold the property or refinanced their loans when they hit a cash flow problem no longer have these options. According to the two most often cited indices (S&P/Case-Shiller Index and the Office of Federal Housing Enterprise Oversight (OFHEO) House Price Index), US national average house prices rose between 93% and 137%, over the period covering 1996–2006.[1] Falling house prices began in 2006 for the majority of the states. As of January 2008, based on the S&P/Case-Shiller repeat sales index, house prices nationally had fallen 12.5% year-over-year, with a decline of over 20% in some urban areas. At this point, the subprime mortgage segment changed from being primarily used to refinance to a significant source of home purchase financing.[2]

The share of subprime mortgage products peaked at 23.5% of all mortgages originated during 2006, approximately coincident with the peak in the housing market (Inside Mortgage Finance, 2007). With the declines in underwriting standards, the demand for housing rose in the United States and a boom in house construction followed. Borrowers with flexible-rate mortgages faced problems as they could not refinance their mortgages. Mian and Sufi (2008) show that mortgage credit-underwriting standards were relaxed from 2001 to 2005, with larger numbers of high-risk borrowers. Lower standards were associated with increased mortgage lending, rising house prices, and an increase in defaults. The decrease in personal income growth and rise in mortgage rates aggravated the problem, causing mortgage-backed securities to decline in value and resulting in large financial losses.

A growing body of work studies the causes and consequences of the recent financial crisis. Kenc and Dibooglu (2010) explain that numerous factors that have contributed to the financial crisis; of particular importance are global macroeconomic imbalances, poor risk management practices, weak financial regulations and supervision, the asymmetric distribution of investment opportunities, and the desire to accumulate official exchange reserves for precautionary purposes. Duchin, Ozbas, and Sensoy (2010) study the effect of the recent financial crisis on corporate investment. They find that corporate investment declines significantly following the onset of crisis, controlling for firm fixed effects and time-varying measures of investment opportunities. The decline is greatest for firms that are financially constrained because they have low cash reserves or high net short-term debt, or firms that operate in industries dependent on external finance. Sanders (2008) examines the relationship between housing prices and seriously delinquent mortgage rates in three states (Arizona, California and Nevada). He finds that the housing and mortgage markets were often inversely related to each other until 2005. After 2005, housing prices and higher delinquent mortgage rates were closely related. Fratzscher (2009) explains global exchange rate movements during the financial crisis. He finds that macroeconomic fundamentals and financial exposure of individual countries have played a key role in the transmission process of US shocks. Ivashina and Scharfstein (2010) show that new lending declined substantially during the financial crisis across all types of loans. They show that new loans to large borrowers fell by 47% during the peak period of the financial crisis (fourth quarter of 2008) relative to the prior quarter and by 79% relative to the peak of the credit boom (second quarter of 2007). After the failure of Lehman Brothers in September 2008, there was a freeze in inter bank liquidity, making it difficult for banks to roll over their short term debt.

The ongoing financial crisis has had dramatic effects on the financial sector and generated higher default risk. While there are a number of papers discussing how the subprime mortgages crisis slowdown can affect the economy, regulators, central banks, equity markets and exchange rates

[1] *Sources*: S&P Case-Shiller, Inside Mortgage Finance.

[2] The share of mortgages issued for non-owner-occupied homes increase to over 20% in 2006 (First American CoreLogic's LoanPerformance Prime Servicing database).

movements,[3] there has been a dearth of research explaining the default risk premium during the period of the crisis. Understanding the determinants of the default risk premium during the financial crisis is important for financial analysts, economic policy makers and credit risk management. Previously, a large body of research has used corporate bond prices or single name CDS spreads to explain the drivers of default risk premium. Longstaff, Mithal, and Neis (2005) explained that a significant part of bond spread is due to illiquidity. Elton, Gruber, Agrawal, and Mann (2001) find that the different tax behavior of corporate and government bonds have a greater effect on bond spreads than default risk. Blanco, Brennan, and Marsh (2005) show that CDS spreads are more sensitive to firm specific factors than bond spreads. Alexander and Kaeck (2008) explain that a CDS is usually quoted as a constant maturity spread, whereas bond spreads are calculated by subtracting an unknown risk-free interest rate from the bond yield, and are not directly comparable when maturities of the underlying bonds differ. In addition, single name CDS spreads are much less liquid than indices and the credit spreads that are inferred from corporate bond prices are affected by tax considerations and illiquidity. In June 2004, the iBoxx and Trac-x CDS indices merged to form the Dow Jones iTraxx index family. The iTraxx CDS index family consists of the most liquid single-name CDS in the Asian and European markets. The iTraxx CDS indexes provide liquid market prices of credit spreads of different maturities and in different economic sectors.

This paper examines the link between market conditions and default risk premium inspired by recently developed structural models. We study the relationship between default risk premium (iTraxx CDS index spreads), and stock market and macroeconomic variables in the Japanese market under regime shifts (crisis and non-crisis). We use a time varying dynamic factor model with regime switching to generate regime probabilities from stock market and macroeconomic variables that can be used to signal changes in default risk premium. In particular, the Markov switching model explicitly considers the possibility of regime shift and allows the influence of explanatory variables to be state-dependent. Then, by allowing the stock market and macroeconomic variables to be time-varying and dependent upon the "state of the market", we obtain a more efficient coefficient compared to the methods which are currently being employed.

Our paper has two main goals. Our first objective is to describe, within a coherent econometric framework, the economic implications of the time-varying nature of the links between default risk, stock market and macroeconomic variables. Our second goal consists in documenting how Markov switching models may offer a useful framework within which to capture the time-varying and unstable nature of the links between stock market, macroeconomic variables and default risk premium. This study represents an investigation into explaining the default risk premium during the financial crisis.

The rest of the paper is organized as follows: The next section gives an overview of the impact of macroeconomic and stock market factors in explaining default risk premium. Next, we present the Markov switching methodology. Section 4 presents data of this study and estimation results are presented and discussed in Section 5. The article ends with a conclusion.

2. The determinants of default risk premium: background and literature

The default risk premium is an important element in financial models. The Structural approach and the reduced-form approach are two major frameworks in the literature of model default risk. The structural approach models default by a stopping time, where default is triggered when the firm value falls below some default boundary (e.g. Black and Cox, 1976; Longstaff and Schwartz, 1995; Merton, 1974). Earlier studies adopt a dynamic and continuous default boundary (e.g. Hsu et al., 2002) and stochastic interest rates (e.g. Collin-Dufresne, Goldstein, & Martin, 2001). The main drawbacks of structural models include the firm value as the sole source of uncertainty that drives default and the firm's assets are often not tradable and not observable. The reduced-form models treat default as a surprising event governed by a jump process where the default intensity process depends on some exogenously specified state variables (e.g. Duffee, 1999; Lando, 1998; Madan and Unal, 2000). Although

[3] For example the works of N'Diaye, Zhang, and Zhang (2009), Zhang, Zhang, and Han (2010), Ackermann (2008), Dooley and Hutchison (2009) and Fratzscher (2009).

numerous term structure models have been developed, there is little body of empirical evaluation on the efficiency of these models to price default risk accurately.

More substantial empirical studies have been devoted to the relationship between default risk and macroeconomic variables. Friedman and Kuttner (1998) show that both corporate bankruptcy and default rise clearly during a recession in the business cycle. Information about recession in the economy should correspond to an increase in the default risk premium, provided investors' insights about recessions are systematically correct on average. Subsequently, changes in real output can be expected to affect the default risk premium. Stokes and Neuburger (1998) provide empirical evidence that inflation influences default risk premium. In fact, Inflation affects input and output prices and therefore can influence firm performance and profitability, and future default probability. Ewing (2001) argues that monetary policy affects interest rates and aggregate demand, and is frequently used by the monetary authority to defend against future inflation pressure and may respond to the state of the economy. Tighter monetary policy would decrease the default risk premium if financial markets recognize the move as positive for the aggregate economy and, consequently, the risk of default on long term commitments should decrease. Ewing (2003) finds that monetary policy shock leads to an immediate decrease in the default risk premium but this is then followed by a rise in the risk premium. Also, unanticipated changes in economic growth are associated with a lower default risk premium as might be expected if output growth represents increases in firm profitability.

Additionally, inflation news raises the default risk premium. Estrella and Mishkin (1998) find that the yield curve can be an important indicator of future real activity. Then, a positive sloping yield curve signals higher future economic activity and a decrease in default probabilities. Tang and Yan (2006) show that incorporating a macroeconomic influence on a firm's cash flow process helps improve significantly the fit of default probabilities and credit spreads. Abid and Naifar (2006) find that macroeconomic variables have a significant effect for exploiting the determinants of credit default swap prices. Carling, Jacobson, Linde, and Roszbach (2007) find that macroeconomic variables have significant explanatory power for corporate default risk in addition to a number of common financial ratios. The output gap, the yield curve and the households' expectations about the Swedish economy are quantitatively important indicators of the evolution of default risk. Duffie, Saita, and Wang (2007) use macroeconomic variables, such as industrial production growth, to help better predict corporate default risk premium.

Other studies provide evidence that financial variables such as stock prices and interest rates explain default risk premium. Friedman and Kuttner (1992) suggest default risk as a cause for the leading behavior of the interest rate spread. Dichev (1998) explores the relationship between default risk and returns, and finds that the relationship between default risk and returns is negative and significant. Jarrow and Turnbull (2000) prove that market risk and default risk are naturally related. They argue that if the market value of the firm's assets suddenly changes (generating market risk), the probability of default becomes important. On the other hand, if the probability of default suddenly changes, the market value of the firm is affected (generating market risk). Kwark (2002) examines the relationship between the interest rate spread and default risk and how this relationship may generate the leading behavior of the interest rate spread over the business cycle within a general equilibrium model.

Huang and Kong (2003) investigate the determinants of credit spreads changes. They consider five sets of explanatory variables (default rates, interest rate variables, equity market factors, liquidity indicators, and macroeconomic indicators). They find that credit risk models may need to take into account the impact of macroeconomic variables on credit spreads. In the same way, they find that credit spreads change for high yield bonds are more closely related to interest rate and equity market conditions. Benkert (2004), Ericsson, Jacobs, and Oviedo-Helfenberger (2004) and BystrÖm (2006) find that interest rates, stock returns and implied volatility have a significant effect on CDS spreads. Pesaran, Schuermann, Treutler, and Weiner (2006) link default risk to financial market variables such as changes in equity indices and interest rates. Gharghori, Chan, and Faff (2009) examine the relationship between default risk and equity returns. They show that default probability is negatively related to returns. They decompose default probability into three components: leverage, volatility and past returns. The regression analysis does not confirm this contention; none of the underlying components seems to be able to explain the relationship between the negative returns and the default risk. Tang and Yan

(2010) examine the effect of market conditions on credit spreads. They show that the macroeconomic condition accounts for about 6% of the overall variation of credit spreads and the model-based variables such as growth rate, growth volatility, investor sentiment, and jump risk, contribute much of the explanatory power.

As the above literature attests, default risk premium may be linked to macroeconomic and stock market factors. This paper adds to the literature by providing insight into the relationship between default risk premium, stock market conditions and macroeconomic variables during the financial crisis. It examines the effects of the subprime crisis in explaining default risk premium under regime shifts with a time-varying dynamic factor model. Moreover, the majority of researches on credit risk have concentrated on the estimation of default probabilities from corporate bond data and explored the determinants and the dynamics of the term structure of credit spreads. Earlier empirical work has been done on single-name CDS products. CDSs are much less liquid than indices and the credit spreads that are inferred from corporate bond prices are affected by tax considerations and illiquidity. The iTraxx CDS indexes provide liquid market prices of credit spreads of different maturities and in different economic sectors and is considered a much better proxy for default risk premium.

3. Explaining default risk premium during the financial crisis

In this section, we develop a model to explain the relationship between default risk premium, stock market conditions and macroeconomic variables during the financial crisis. CDS index spreads have become a preferred proxy for default risk premium rather than bond spreads.[4] The aim of the model is to generate regime probabilities from stock market and macroeconomic variables that can be used to signal changes in default risk premium. This model allows the variance of default risk premium to switch across different regimes, and the regime at any given date is presumed to be the outcome of a Markov chain. We consider the following model with Markov-switching heteroskedasticity and time varying parameters:

$$\Delta \mathrm{DRP}_t = X_t \beta_{S_t} + e_t \tag{1}$$

$$\beta_{S_t} = \beta_{S_{t-1}} + \nu_t \tag{2}$$

$$e_t \sim iid \cdot N(0, \sigma^2_{S_t})$$

$$\nu_t \sim iid \cdot N(0, Q)$$

where $\Delta \mathrm{DPR}_t$ is the default risk premium changes, X_t is the matrix of explanatory variables and β_{S_t} is the vector of time varying coefficients and Q is a positive definite matrix.

The variance $\sigma^2_{S_t}$ is defined as:

$$\sigma^2_{S_t} = \sigma^2_0(1 - S_t) + \sigma^2_1 S_t \tag{3}$$

The vector β_{S_t} is defined as:

$$\beta_{S_t} = \beta_{0t}(1 - S_t) + \beta_{1t} S_t \tag{4}$$

Let us assume that there are two regimes (crisis and non-crisis), represented by an unobservable process denoted as S_t. Let S_t takes the values 0 or 1, depending on the prevailing regime. Then, $S_t \in \{0, 1\}$ is the unobserved two-state Markov Switching variable that evolves according to the transition probabilities given as follows:

$$p = \begin{Bmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{Bmatrix} \tag{5}$$

[4] e.g. BystrÖm (2006), Alexander and Kaeck (2008), Tang and Yan (2010).

where:

$$\begin{cases} P_{00} = Pr[S_t = 0 \,|S_{t-1} = 0\,] \\ P_{01} = Pr[S_t = 0 \,|S_{t-1} = 1\,] \\ P_{10} = Pr[S_t = 1 \,|S_{t-1} = 0\,] \\ P_{11} = Pr[S_t = 1 \,|S_{t-1} = 1\,] \end{cases} \tag{6}$$

and

$$\begin{cases} P_{00} + P_{10} = 1 \\ P_{01} + P_{11} = 1 \end{cases} \tag{7}$$

Following Hamilton (1989), we assume that S is a first-order Markov-process, which means that the current regime S_t depends only on the regime in the preceding period S_t. This model is completed by defining the transition probabilities of moving from one regime to another. The probability that default risk premium changes and volatility is either in state 0 or 1 at time t is a function of the earlier state in $t-1$. State 0 of the Markov model implies a situation of low volatility (tranquil or non-crisis regime), whereas state 1 implies high volatility (volatile or crisis regime). Notice that, since $P_{01} = 1 - P_{00}$ and $P_{10} = 1 - P_{11}$, the transition probabilities are completely defined by P_{00} and P_{11}. According to the model defined by Eqs. (1)–(7), if we define $S_t = 0$ as the tranquil regime and $S_t = 1$ as the volatile regime, we can conclude that $\beta_{S_t} = \beta_{0t}$ and $\sigma^2_{S_t} = \sigma^2_0$ in the tranquil regime; and $\beta_{S_t} = \beta_{1t}$ and $\sigma^2_{S_t} = \sigma^2_1$ in the volatile regime.

The relationship between default risk premium and stock market conditions under regime shifts is presented in model 1 (Eq. (8)). The relationship between default risk and equity markets is determined by economic agents' expectations regarding company default risk, which impacts the value of their debt and equity prices, as shown by Merton (1974). Recent studies on single-regime models have investigated relationships between the CDSs and equity markets. Abid and Naifar (2005) study the impact of equity return volatility of reference entities on CDS rates from the Japanese market. Acharya and Johnson (2007) find that there is information flow from the CDS markets to equity. Fung, Gregory, Sierra Yau, and Zhang (2009) investigate the market relationship between the stock and CDS markets using daily index data. Dupuis, Jacquier, Papageorgiou, and Rémillard (2009) analyze the daily prices of 5-year-maturity CDSs of three different portfolios and show that the dependence structures between CDSs and equity returns can be statistically very different.

Model 1:

$$\Delta \mathrm{CDSI}_t = \beta_{0t,S_t} + \beta_{1t,S_t}\Delta IR_t + \beta_{2t,S_t}\Delta \mathrm{IRV}_t + e_t \tag{8}$$

$$\beta_{it,S_t} = \beta_{it,S_{t-1}} + \nu_t$$

$$\beta_{it,S_t} = \beta_{it,0}(1 - S_t) + \beta_{it,1}S_t$$

$$e_t \sim iid \cdot N(0, \sigma^2_{S_t})$$

$$\nu_{it} \sim iid \cdot N(0, \sigma^2_{\nu i}), \quad i = 0, 1, 2.$$

where $\Delta\mathrm{CDSI}_t$ is the CDS index spreads changes from $t-1$ to t (in basis points). Following Gatfaoui (2009), we consider the daily changes of CDS index spreads as the first order difference between t and $t-1$ ($\Delta\mathrm{CDSI}_t = \mathrm{CDSI}_t - \mathrm{CDSI}_{t-1}$). $\Delta\mathrm{IR}_t$ is the stock market index returns changes, $\Delta\mathrm{IRV}_t$ is the stock market index returns volatilities with GARCH (1,1),[5] β_{it,S_t} is the time-varying coefficient following

[5] The most popular approach for modelling conditional volatility is the GARCH family of models as introduced by Engle (1982) and generalised by Bollerslev (1986) and Nelson (1991). GARCH models are appealing because of their simplicity, ease of estimation and empirical success in modelling time-varying volatility in a variety of contexts.

a Markov-switching process for $i=0, 1, 2$, ν_{it} is the error term for $i=0, 1, 2$, and $S_t \in \{0, 1\}$ are the unobserved two states Markov Switching variable.

The relationship between macroeconomic variables is presented in model 2.

Model 2:

$$\Delta \mathrm{CDSI}_t = \beta_{0t,S_t} + \beta_{1t,S_t}\Delta \mathrm{CPI}_t + \beta_{2t,S_t}\Delta \mathrm{IPI}_t + e_t \tag{9}$$

$$\beta_{it,S_t} = \beta_{it,S_{t-1}} + \nu_t$$

$$\beta_{it,S_t} = \beta_{it,0}(1 - S_t) + \beta_{it,1}S_t$$

$$e_t \sim iid \cdot N(0, \sigma^2_{S_t})$$

$$\nu_{it} \sim iid \cdot N(0, \sigma^2_{\nu i}), \quad i = 0, 1, 2.$$

where $\Delta \mathrm{CPI}_t$ is the consumer price index changes and $\Delta \mathrm{IPI}_t$ is the changes in industrial production index.

4. Data and preliminary statistics

4.1. Data description

We use iTraxx Japan CDS index spreads as a proxy for default risk premium. The iTraxx CDS index family consists of the most liquid single-name CDSs in the European and Asian markets.[6] We choose the most representative type of CDS, the 5-year CDS, because they are the most liquid. The data consists of daily closing quotes (the mid-points between quoted bid and ask quotes) for the iTraxx CDS Japanese index. The data are obtained from Markit Group Limited covering the period from March 2006 to November 2009. The Markit Group Limited provides Markit iTraxx Japanese index which comprises 50 investment grades rated Japanese entities. The second data sets consist of Japanese stock market index returns for the same period, obtained from the Tokyo Stock Exchange (TSE). The stock market index return is considered a proxy for the overall state of the stock market. The Nikkei 225 is the most widely quoted stock market index of the TSE. It is calculated daily and reviewed once a year by the Nihon Keizai Shimbun (NIKKEI) newspaper using a price-weighted average. Equal weighting is given to all stocks based on a par value of 50 yen per share. The daily stock index returns are computed as follows: $\ln(SI_t/SI_{t-1})$. We use daily observations and we estimate daily stock return index volatility with GARCH (1,1). The most popular approach for modeling conditional volatility is the GARCH family of models as introduced by Engle (1982) and generalized by Bollerslev (1986) and Nelson (1991). The GARCH (1,1) model is defined as:

$$\sigma_i^2 = \omega + \alpha r_{i-1}^2 + \beta\sigma_{i-1}^2, \quad \omega > 0 \text{ and } \alpha, \beta \geq 0 \tag{10}$$

where α is the weight assigned to the lagged squared returns, β is the weight assigned to the lagged variances and ω is a constant. GARCH models are appealing because of their simplicity, ease of estimation and empirical success in modeling time-varying volatility in a variety of contexts. The GARCH model is to be preferred for short term horizons because it is mean reverted.

For macroeconomic variables, we use monthly data for the important economic indicators: the changes in consumer price index (CPI) and the changes in industrial production index (IPI).[7] The first variable is commonly used as the proxy for unobserved inflation. The second variable is used as the

[6] In June 2004, the iBoxx and Trac-x CDS indices merged to form the Dow Jones iTraxx index family.

[7] Xie, Shi and Wu (2008) explain the determinants of corporate bond yields with S&P 500 return, the rate of changes in consumer price index and the growth rate of industrial production index.

Table 1
Preliminary statistics.

Stock market and macroeconomic data	Mean	SD	Max	Min	Skewness	Kurtosis
Daily data						
5-Year iTraxx CDS Index levels (bp)	112.11	117.95	565.835	16.03	1.60	2.23
NIKKEI 225 index returns	−0.00043	0.019	0.141	−0.114	0.024	7.520
Monthly data						
Consumer price index (CPI)	100.691	0.748	02.500	99.600	1.055	0.257
Industrial production index (IPI)	99.116	12.222	110.100	69.500	−1.169	−0.080

Fig. 1. iTraxx Japan CDS level and stock index level.

proxy of economic growth.[8] The data are obtained from the Cabinet Office of Japan and the Portal Site of Official Statistics of Japan.[9] Table 1 summarizes the preliminary statistics of the data.

We notice that the standard deviation for 5-Year iTraxx CDS Index is important. The CDS series also exhibits a positive skewness, indicating that the returns are not normally distributed. Also, Table 1 shows a positive excess kurtosis for NIKKEI 225 Index, underlining a leptokurtic feature (i.e. a peaked probability distribution relative to the Gaussian one).

4.2. Identification of the crisis period

We examine our data over two periods: a period before, and a period during the subprime crisis. As a first investigation, we plot in Fig. 1 the daily 5-Year Japan iTraxx CDS index level, and the NIKKEI 225 index level. Both series are normalized and cover the period from 20 March 2006 to 30 November 2009.

[8] The most intuitive proxy for economic growth is the real GDP growth rate. We employed the growth rate of industrial production because monthly data on GDP is not available.

[9] http://www.cao.go.jp/index-e.html.

For the stock market index, we observe that the NIKKEI 225 fell sharply from August 2007. CDS index spreads widened and plunged sharply in three phases. The first phase was after August 9, 2007, when the subsidiaries of BNP Paribas suspended the liquidation of assets from two hedge funds. This date marks the start of the crisis in the CDS market. The beginning of 2008 marks the second phase. The spreads for the iTraxx Japan CDS index hit 250 basis points in mid-March 2008 (however, in March 2006, the spreads were at 28 basis points). The third phase was after September 15, 2008 when Lehman Brothers went bankrupt. The CDS market response to the stock market was very prompt. We notice also a negative relationship between CDS spread levels and stock price valuations. Stock prices clearly have a tendency to increase when CDS spreads decrease and vice versa. Usually, a rise in a CDS premium is linked to the firm's financial difficulties and should therefore go with a decline in its stock price.

Financial crises are generally characterized by a rise in volatility. Therefore we measure the variations in the volatility of iTraxx CDS index changes in order to identify the crisis period more accurately. We use Exponentially Weighted Moving Average volatility (EWMA) which is defined as the weighted sum of quadratic yields with exponentially decreasing weightings over time. The EWMA model is widely used to identifying crisis period (Coudert & Gex, 2010). The model is defined by:

$$\sigma_i^2 = (1-\lambda)r_{i-1}^2 + \lambda\sigma_{i-1}^2, \quad \lambda > 0 \tag{11}$$

where λ is the weight assigned to the lagged variances. The EWMA is a particular case of a GARCH model (Eq. (10)) where $\omega = 0$, $\alpha = 1-\lambda$ and $\beta = \lambda$. One of the main differences between these two models is that the GARCH model incorporates mean reversion while the EWMA does not. This feature allows us to identifying the sudden increase in the volatility. The results are plotted in Fig. 2.

From Fig. 2, we observe a sudden increase in volatility in August 2007. We consider that the crisis period corresponds to this period of pronounced volatility. Table 2 illustrates the beginning of the crisis period by computing monthly EWMA volatility of CDS market (from March 2006 to November 2009).

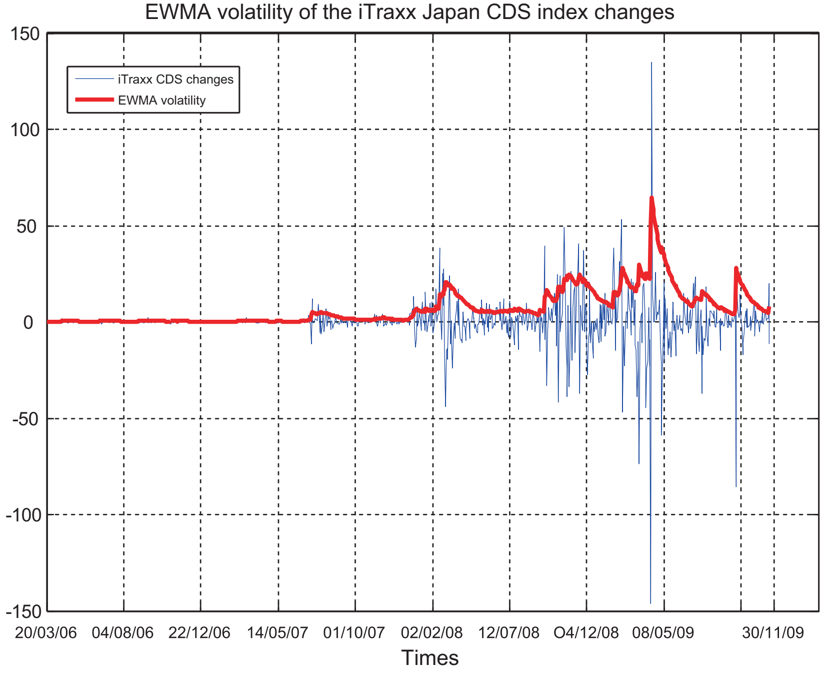

Fig. 2. Exponentially Weighted Moving Average (EWMA) volatility.

Table 2
Monthly EWMA volatility.

	January	February	March	April	May	June	July	August	September	October	November	December
2006			00 64%	01.58%	00.47%	01.31%	00.77%	00.11%	03.87%	00.49%	01.83%	00.27%
2007	0.51%	0.86%	04.88%	01.61%	01.57%	02.10%	29.84%	**83.71%**	10.66%	06.23%	17.06%	02.80%
2008	40.39%	42.41%	96.33%	36.34%	19.96%	23.36%	14.23%	07.81%	45.21%	56.27%	42.59%	14.48%
2009	8.18%	14.85%	14.05%	20.49%	45.91%	15.01%	35.01%	05.50%	45.96%	19.80%	06.82%	

Notes: The Exponentially Weighted Moving Average (EWMA) introduces lambda (λ), which is called the smoothing parameter. λ must be less than one. We use a lambda of 0.94, or 94% (according to RiskMetrics™, a financial risk management company).

Table 3
Estimation results for the Japanese market.

Parameters (model 1)	Estimates	Standard errors	p-Values
p_{00}	0.668406***	0.024623	0.000000
P_{11}	0.651466***	0.149473	0.000031
σ_0	0.04369**	0.055091	0.042794
σ_1	0.361534***	0.063457	0.000000
Var (constant)	0.182600	0.000001	0.999976
Var (index returns)	0.011328	0.000001	0.999976
Var (index returns volatilities)	0.012018***	0.000292	0.000037
Log-likelihood	−185.9633		
Parameters (model 2)	**Estimates**	**Standard Errors**	**p-Values**
p_{00}	0.921025***	0.038637	0.000000
P_{11}	0.592908*	0.404426	0.0753704
σ_0	0.783529***	0.189333	0.000053
σ_1	4.571314**	2.064614	0.028016
Var (constant)	0.199336	0.127339	0.119162
Var (CPI)	3.164023	3.049351	0.300779
Var (IPI)	0.848494***	0.098387	0.000000
Log-likelihood	−316.6291		

Notes: Estimation is by maximum likelihood. Heteroskedastic-consistent standard errors according to White (1980) are shown. For convergence, we use 100 times the data matrix. We use the first 60 observations (for model 1) and the first 12 observations (for model 2) in order to get the initial parameter values and the remaining observations in order to get the results in this table.
* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

From Table 2, we observe that the crisis period started on August 2007 when the volatility of CDS spread index had already notably increased (jumping from 29.84% on July 2007 to 83.71% on August 2007). It is possible to identify two sub-periods: a pre-crisis period when iTraxx CDS spreads volatilities were particularly low (from March 2006 to July 2007) and the crisis period (from August 2007 to November 2009). For the first period, CDS premium were particularly low and stable (23 bp on average). During this period, default rates were low and investors' risk appetite was high. However, during the crisis period, CDS premiums exhibited a sharp increase, reaching 565.83 bp on March 2009.

5. Empirical results and discussion

5.1. Parameters estimation

The estimation results of Eqs. (8) and (9) for the Japanese market are given in Table 3 (for model 1 we use daily data and for model 2 we use monthly data).[10]

Estimation results for model 1 (Table 3) show that the volatility level of regime 0 (variance of tranquil regime, σ_0), is different from the volatility level of regime 1 (variance of volatility regime, σ_1) and statistically significant. Furthermore, the probability ($p = P_{00}$) of staying in a tranquil regime at time (t), given that the market is in the same state at time ($t-1$), is 0.668406. The probability ($q = P_{11}$) of being in a crisis regime in time (t) given that the market was in the volatility regime at time ($t-1$) is 0.651466. These high probabilities indicate that if the market is in either a high volatility or a tranquil

[10] For the estimation, we have modified the MATLAB codes in the Econometrics Toolbox produced by James P. LeSage. For more details you can visit the following links: For the estimation, we have modified the MATLAB codes in the Econometrics Toolbox produced by James P. LeSage. For more details you can visit the following links: For the estimation, we have modified the MATLAB codes in the Econometrics Toolbox produced by James P. LeSage. For more details you can visit the following links: http://www.spatial-econometrics.com/.

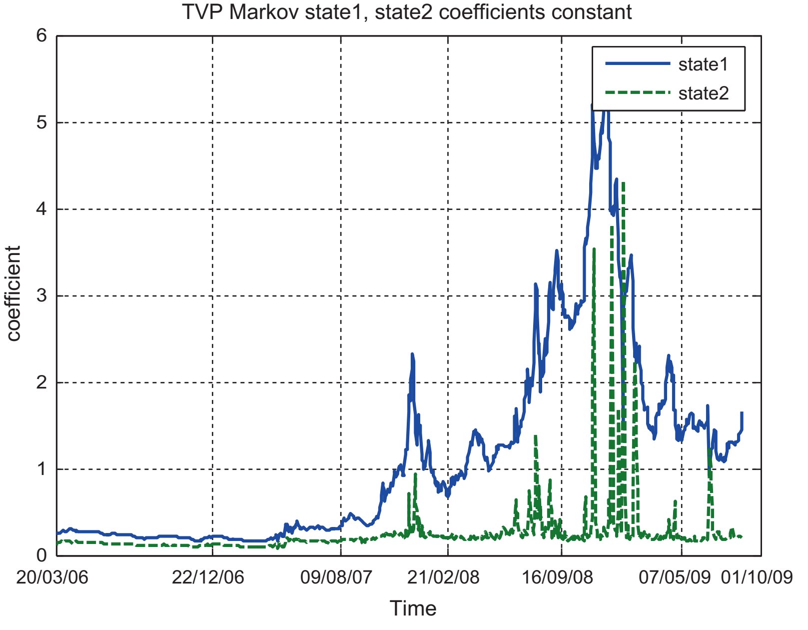

Fig. 3. The estimate of time-varying constant under regime shifts.

regime, it is likely to remain in such a regime. In addition, Table 3 shows that the variance of the index returns volatilities is statistically significant at the 1% level (0.012018) but the variance of the index return is not significant (0.011328). The findings show that the relationship between default risk premium and stock market conditions during the financial crisis is regime-dependent. During the financial crisis, the iTraxx CDS index spreads became highly sensitive to stock index return volatility. The estimated values for the time-varying parameters, namely the constant, the coefficient of stock market index returns ΔIR_t ($\beta_{1t,0}$ and $\beta_{1t,1}$) and the coefficient of stock market index returns volatilities ΔIRV_t ($\beta_{2t,0}$ and $\beta_{2t,1}$) are plotted in Figs. 3–5, respectively. Since these parameters follow a Markov-switching process, in the figure, there are two plots for each parameter: one for state 1 (crisis regime) and the other for state 2 (non-crisis regime). In each figure, the vertical axis represents the value of the parameter and the horizontal axis represents observations.

Estimation results for model 2 show that the volatility of regime 0 is different from the volatility of regime 1 and is statistically significant. The findings show that the relationship between default risk premium and macroeconomic variables during the financial crisis is regime-dependent. However, only the industrial production index is statistically significant at the 1% level (0.848494), while the consumer price index is not significant. The estimated values for the time-varying parameters are plotted at Figs. 6–8.

Table 3 and Figs. 3–8 show that the relationship between default risk premium changes, the stock market level and macroeconomic variables are regime dependent. Fig. 4 shows that the effect of stock returns on CDS spreads changes under a regime shift is not obvious. We do not observe the impact of stock returns index changes on the CDS spreads changes before and during the crisis. However, according to the results in Table 3 and Fig. 5, we can confirm that stock return volatility explain CDS spreads changes under regime shifts.

5.2. Identification of switching behavior

Once the parameters of the model have been estimated, we look at the daily closing value of the CDS spreads alongside the estimated probability of that day having been a high variance regime day.

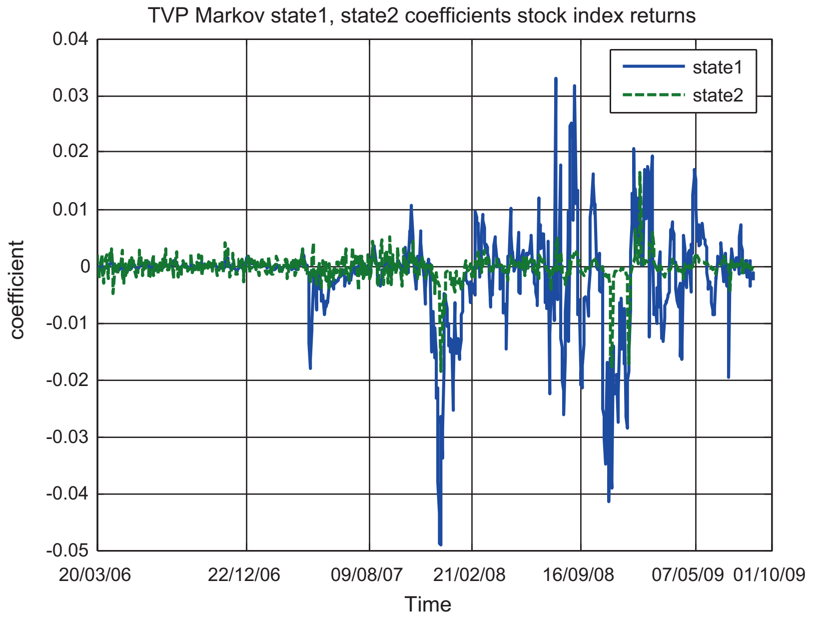

Fig. 4. The estimate of time-varying coefficient of ΔIR_t under regime shifts.

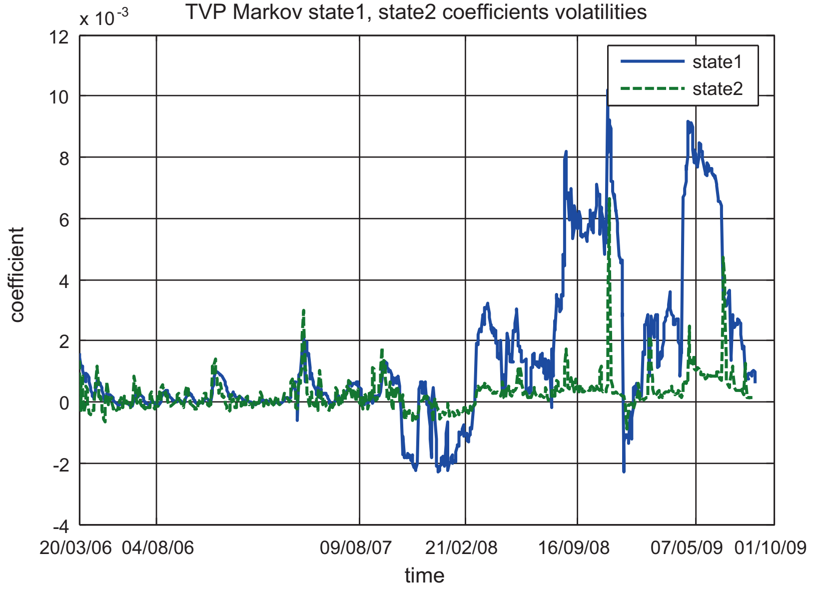

Fig. 5. The estimate of time-varying coefficient of ΔIRV_t under regime shifts.

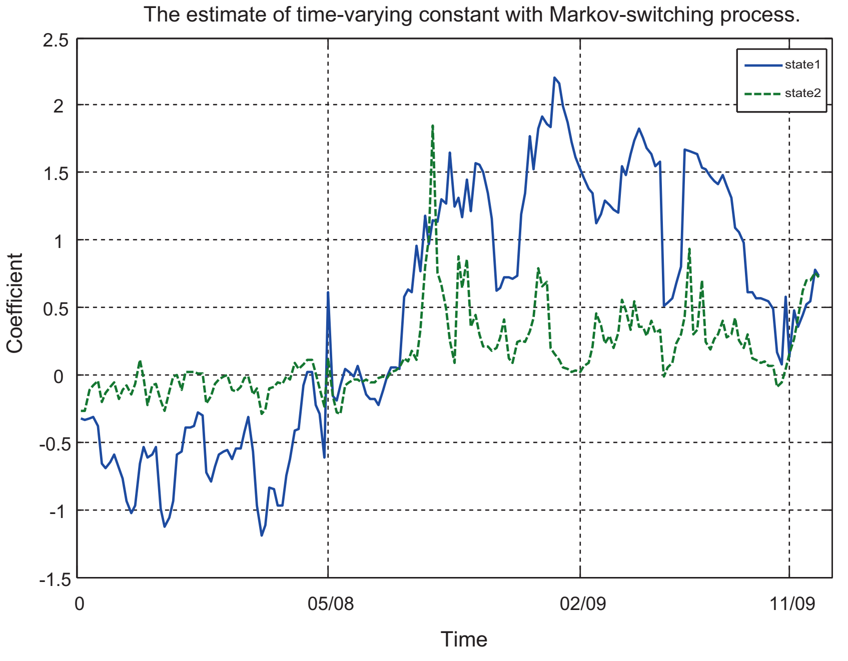

Fig. 6. The estimate of time-varying constant under regime shifts.

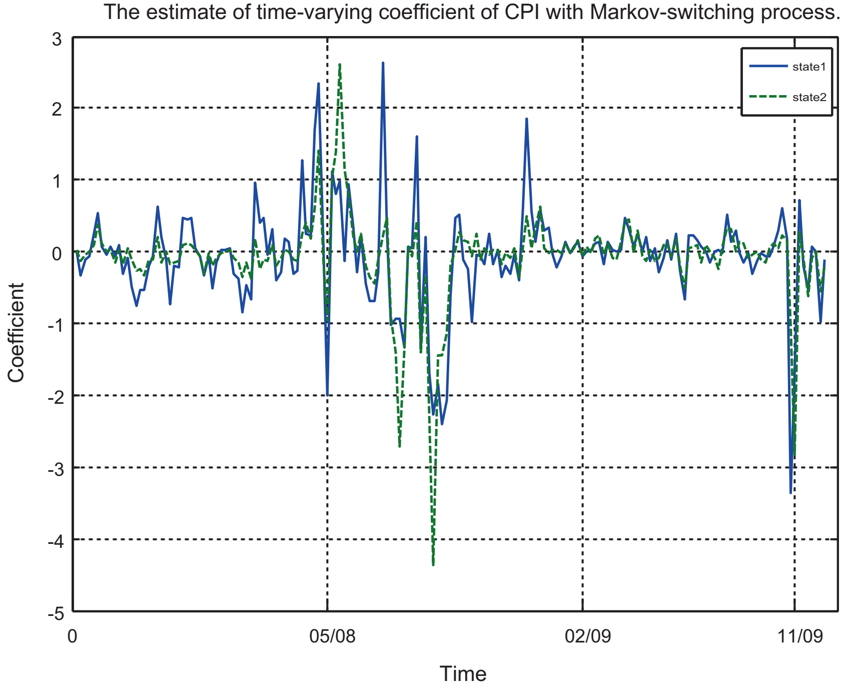

Fig. 7. The estimate of time-varying coefficient of ΔCPI_t under regime shifts.

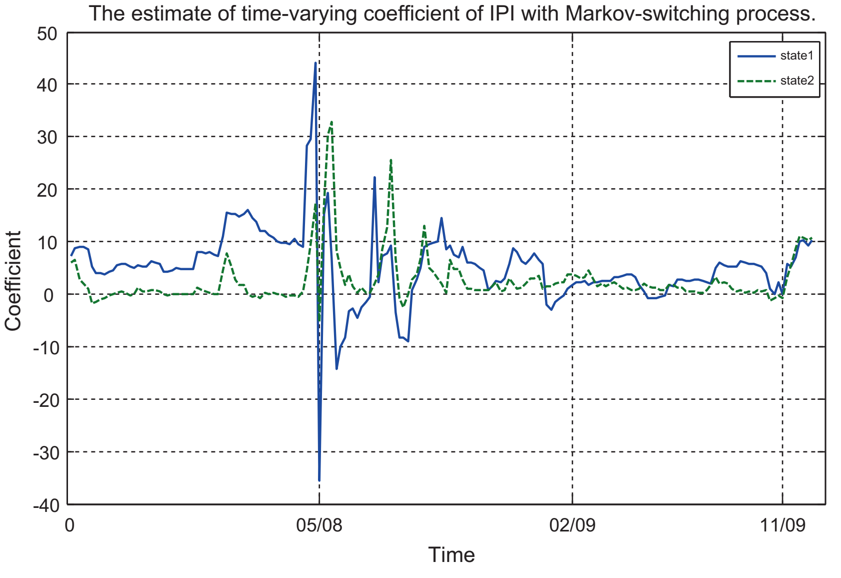

Fig. 8. The estimate of time-varying coefficient of ΔIPI_t under regime shifts.

These probabilities are the so-called smoothed probabilities, computed by taking into account the whole sample of observations.[11] As an illustration of switching behavior, Fig. 9 plots the smoothed probability to be in a high volatility regime (given that at time $t-1$ the market was in the high volatility regime).

The smoothed probabilities shown in Fig. 9 provide insights into the timing of each regime. Visual inspection of these graphs shows that the periods of high volatility, which are represented by the jumps in the solid line in Fig. 9, match with the impact of the subprime crisis on the Japanese CDS market. Also, the graph displays sharp spikes at irregular intervals after March 2008, suggesting that the transition from the low to the high volatility regime occurs in a short period of time.

The impact of the subprime loan crisis on the CDS market has changed since March 2008. There are numerous structural and technical factors behind the impact of the financial crisis in the Japanese CDS market and the sudden widening in CDS index prices, including the following:

- Policy makers have been frightened by the rise in CDS prices because they are worried that sellers of protection may not have enough reserves to pay future claims and that default by one party could lead to a cascade of failures throughout the financial system.
- When the mortgage-backed securities that were protected by CDS began to lose value in 2007, investors began to fear that the CDS market could suddenly face large liabilities.
- The collateralised debt obligation (CDO) market has weakened notably since summer 2009, leading to a fall in demand for protection sales connected with synthetic CDOs and related products.
- CDS market investors buy and sell insurance protection against defaults in the bond markets. The cost of the protection (spread) rises when investors grow more concerned about the viability of companies.
- Losses on structured products such as *n*th to default swaps, which are CDS composed of multiple corporate credits. These products are used frequently in recent years, but now losses on them have increased demand for credit protection, needed for hedging and unwinding through reverse transactions.

[11] In Appendix, we present the major steps necessary to explain the regime inference and the construction of switching behavior chronology.

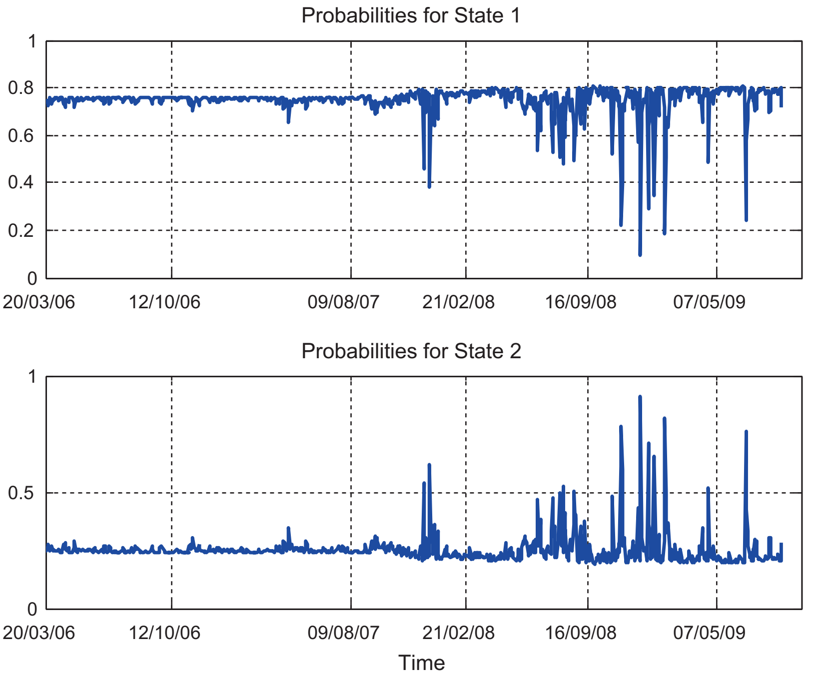

Fig. 9. Filtered probabilities under regime shifts.

6. Conclusion

The ongoing financial crisis has had dramatic effects on the financial markets. Global economic growth has decelerated due to the banking crisis and ongoing squeeze in credit. This paper has examined the effects of the subprime crisis on the default risk premium. We used a time-varying dynamic factor model with regime switching to construct and estimate the leading indicators of the default risk premium during the financial crisis. We examined regime-switching behavior in the default risk premium changes in the Japanese market over the period from March 2006 to November 2009, and examined the specific characteristics of each regime by utilizing Markov-switching models.

We analyzed the sensitivity of default risk premium changes to stock market conditions and macroeconomic variables by using two state Markov switching models: crisis regime sparked by rising loan defaults in the sub-prime mortgage market and non-crisis regime. We used iTraxx CDS index spreads as proxy for default risk premium and found that CDS index spreads displayed pronounced regime specific behavior. A Markov switching model of the determinants of changes in the iTraxx Japan CDS index demonstrated that they were sensitive to stock index volatility and the industrial production index during the financial crisis. A combined look at the results of the two models has important policy implications in the sense that the default risk premium during the financial crisis can be explained by the condition and volatility of the stock market, and macroeconomic variables.

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Appendix A. Regime inference and identification of switching behavior

In the following, we give a brief calculation of the filtered and smoothed regime probabilities, which are essential for the regime inference and the construction of switching behavior chronology.

- *Filtering*: The aim of the filtering algorithm (usually associated to Hamilton, 1989) is to infer the probability distribution of the unobserved regime variable (s_t) given the currently available information set (Y_t).

Let $p(y_t/s_t, Y_{t-1})$ denote the probability density of observing (y_t) conditional on the regime variable (s_t). $\Pr(s_t/s_{t-1})$ refers to the transition probabilities from regime (s_{t-1}) to (s_t). Using the law of Bayes, the probability $\Pr(s_t/Y_t)$ of the regime variable (s_t) conditional the currently available information set (Y_t) is given by:

$$Pr\left(\frac{s_t}{Y_t}\right) = Pr\left(\frac{s_t}{y_t}, Y_{t-1}\right) = \frac{Pr(s_t/Y_{t-1}) \times p(y_t/s_t, Y_{t-1})}{p(y_t/\Upsilon_{t-1})} \tag{12}$$

where $\Pr(s_t/Y_{t-1})$ is the probability of the regime variable (s_t) conditional the previous available information set (Y_{t-1}) and $p(y_t/Y_{t-1})$ is the marginal density of observing (y_t) conditional on the information set (Y_{t-1}).

Using Eq. (12), the filtered regime probabilities for a sample $Y_t = (y_T, \ldots, y_1)$ can be computed by a forward recursion for $t = 1, \ldots, T$ initialized by some estimate of the initial value (s_0) of the regime variable. In this study when one regime represents “low volatility” or pre-crisis period and the other “high volatility” or crisis period, the filter recursion in Eq. (12) can be simplified to the following ratio of the regimes:

$$\frac{Pr(\text{“low volatility” at time } t/Y_t)}{Pr(\text{“high volatility” at time } t/Y_t)} = \frac{p(y_t/\text{“low volatility”})}{p(y_t/\text{“high volatility”})} \times \frac{Pr(\text{“low volatility” at time } t/Y_{t-1})}{Pr(\text{“high volatility” at time } t/Y_{t-1})}$$

- *Smoothing*: The regime inference can be improved by using future observations of (y_t), in which case the regime probabilities $\Pr(s_t/Y_s)$, $s > t$, are called smoothed probability. This probability gives the best estimate of the unobservable state at any point within the sample. Thus, it gives the most informative answer to the question which regime the process was likely in at time t. The smoothing algorithm proposed by Kim (1994) can be explained as a backward filter that start at the end point, $t = T$ of the previously filter. The full sample smoothed probabilities $\Pr(s_t/Y_T)$ are found by starting from the last output of the filter $\Pr(s_T/Y_T)$, by iterating backward from $t = T - 1$ to $t = 1$:

$$Pr\left(\frac{s_t}{Y_T}\right) = \sum_{s_{t+1}} Pr\left(s_t, \frac{s_{t+1}}{Y_T}\right) = \sum_{s_{t+1}} Pr\left(\frac{s_t}{s_{t+1}}, Y_T\right) \times Pr\left(\frac{s_{t+1}}{Y_T}\right) \tag{13}$$

In the case of two regimes, the recursion is initialized with the final filtered probability vector:

$$Pr\left(\frac{s_t}{Y_T}\right) = \sum_{s_{t+1}=1}^{2} \frac{Pr(s_{t+1}/s_t) \times Pr(s_t/Y_t)}{Pr(s_{t+1}/Y_t)} \times Pr\left(\frac{s_{t+1}}{Y_T}\right) \tag{14}$$

Recursion (14) explains how the additional information to improve the inference on the unobserved state (s_t):

$$\frac{Pr(s_t/Y_T)}{Pr(s_t/Y_t)} = \sum_{s_{t+1}=1}^{2} Pr\left(\frac{s_{t+1}}{s_t}\right) \times \frac{Pr(s_{t+1}/Y_T)}{Pr(s_{t+1}/Y_t)} \tag{15}$$

In this study when one regime represents low volatility ($s_t = 0$) and the other represents high volatility ($s_t = 1$):

$$\frac{Pr(\text{“low volatility” at time } t/Y_T)}{Pr(\text{“low volatility” at time } t/Y_t)} = p_{00} \frac{p(\text{“low volatility” at time } t+1/Y_T)}{p(\text{“low volatility” at time } t+1/Y_t)} + p_{01} \frac{Pr(\text{“high volatility” at time } t+1/Y_T)}{Pr(\text{“high volatility” at time } t/Y_t)}$$

$$\frac{Pr(\text{"low volatility" at time } t/Y_T)}{Pr(\text{"low volatility" at time } t/Y_t)} = p_{00}\frac{p(\text{"low volatility" at time } t+1/Y_T)}{p(\text{"low volatility" at time } t+1/Y_t)} + (1-p_{00})\frac{1-Pr(\text{"low volatility" at time } t+1/Y_T)}{1-Pr(\text{"low volatility" at time } t+1/Y_t)}$$

- *Identification of switching behavior*: The classification of every observation y_t to a regime $s_t \in \{0, 1\}$ is done according to the highest smoothed probability:

$$s_t = arg \max_{0,1} Pr\left(\frac{s_t}{Y_T}\right) \tag{16}$$

According to Hamilton (1989), the classification of regimes simplifies to assigning the observation to the first regime if $\Pr(s_t = 0/Y_T) > 0.5$ and the second if $\Pr(s_t = 0/Y_T) < 0.5$.

The regime classification allows the identification of switching behavior. The peak date denotes the period t just before the beginning of a low volatility, i.e. Pr(" low volatility " at time $t/Y_T) < 0.5$ and Pr(" low volatility " at time $t+1/Y_T) > 0.5$; the trough is the last period of the "low volatility".

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