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RESEARCH ARTICLE

Regime-switching measure of systemic financial stress

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Abstract In this paper, I propose an approach to measuring systemic financial stress. In particular, abrupt and large changes in the volatility of financial variables that represent the dynamics of the US financial sector are modeled with a joint regime-switching process, distinguishing "low" and "high" volatility regimes. I find that the joint "high" volatility regime for the TED spread, return on the NYSE index, and capital-weighted CDS spread for large banks is closely related to periods of financial stress. This result suggests that the probability of the joint high volatility regime of these financial variables can be considered as a measure of systemic financial stress.

Keywords Financial stress · Systemic risk · Regime-switching process · SWARCH

JEL Classification C32 · G01 · G12

1 Introduction

Recently, numerous studies have analyzed causes and propagation mechanisms of systemic risk. At the same time, systemic risk continues to be a concept that is not well defined. In general, systemic risk is perceived as the risk of a negative shock, severely affecting the entire financial system and the real economy. This shock can have different causes and triggers, such as a macroeconomic shock, a shock caused

The views expressed in this paper are solely my own and do not necessarily reflect the position of the Federal Reserve Bank of Richmond or the Federal Reserve System.

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by the failure of an individual market participant that affects the entire system due to tight interconnections in the system, or a shock caused by information disruption in financial markets. Given the various causes of systemic shocks, there are also different approaches to define and measure systemic risk.

In this paper, I narrow down the definition of systemic risk to systemic financial stress. Systemic financial stress is a condition of financial markets where market participants experience increased uncertainty or change their expectations about future financial losses, fundamental value of assets, and economic activity.[1] Financial markets are the quickest to reflect this information, and it is empirically observed that the behavior of market financial variables during financial stress periods is different from calm periods. In particular, it is common that systemic shocks can cause abrupt and large changes in financial variables and can propagate systemic financial stress in the entire economy. Therefore, the volatility dynamic of financial markets is an important indicator of the impact of shocks on the financial sector that can cause systemic financial stress.

In this study, I propose a regime-switching model that captures abrupt and large changes in the volatility of financial variables by a joint Markov-switching process as an approach to measuring systemic financial stress. To do so, I extend the univariate SWARCH model, proposed in Hamilton and Susmel (1994), to a multivariate version. I use this multivariate SWARCH model to jointly describe volatility changes in financial variables representing the US financial markets, such as the TED spread, the credit default swaps (CDS) spreads of large banks, and the return on the New York Stock Exchange (NYSE) Index. In this multivariate model, the volatility regime-switching process describes the changes between "low" and "high" volatility regimes, which are assumed to be common for all considered financial variables. Presumably, this joint regime-switching process would capture large common shocks which potentially have a systemic implication. Therefore, the probability of the joint "high" volatility regime can be used as a measure of systemic financial stress.

My choice of the financial variables is motivated by different aspects of systemic risk, such as liquidity risk, credit and default risk, and interconnections between financial markets and firms. The TED spread, defined as the difference between the 3-month LIBOR and the 3-month Treasury yield, is a measure of short-term credit and liquidity risks in the banking sector. The lending banks charge interest rates (LIBOR) that are higher than the Treasury rate of the same maturity because of the risk that borrowing banks may not repay the loans. Also, if lending banks experience liquidity constraints, then there is a risk that they may not be able to convert loans into liquid assets quickly, while the Treasury bills are highly liquid assets. Therefore the TED spread contains credit and liquidity risk premia. Other studies, such as Hakkio and Keeton (2009) and Hatzius et al. (2010), also find the information in the TED spread useful for constructing their financial stress and financial condition indices. The CDS spread, another variable in the model, is a measure of default risk in the banking sector. The CDS spread is a series of payments for a contract that provides insurance to the buyer of the contract against default on a loan by a particular firm.

[1] Hakkio and Keeton (2009) provide a comprehensive review of potential causes of financial stress.

Tang and Yan (2010) find that a major proportion of the CDS spread is determined by default risk, although, as discussed in Blanco et al. (2005), it may also contain a liquidity risk premium. Given that the CDS spread is a rapidly growing and relatively liquid credit derivative, it is commonly used as a market indicator of a bank's condition. For example, Segoviano and Goodhart (2009) use information in CDS spreads to construct a measure of banking stability. The return on the NYSE index, the third variable in the model, is used to incorporate information on the effects of systemic shocks on the equity market and interconnections among firms. Many papers use information on the stock market returns to study the relationships between the financial and real sectors. For example, Estrella and Mishkin (1998) find that stock market performance is a useful recession predictor. Billio et al. (2010) use stock market returns of different types of financial institutions to analyze interconnections among financial firms and construct measures of systemic risks.

Using the multivariate SWARCH model and the selected financial variables, I find that the joint high volatility regime is closely related to financial stress periods in the considered sample of data. For example, the regime-switching process switches to the high volatility regime indicating stressful events, such as the 9–11 shock, the beginning of the "credit crunch" and the subprime mortgage crisis in 2007, and the Lehman Brothers bankruptcy in September 2008. This result suggests that the joint regime-switching process of changes in volatility of the considered financial variables can be used as one of the indicators of systemic financial stress.

My approach is an extension of the method used by González-Hermosillo and Hesse (2009), who apply an univariate SWARCH model for several financial variables to measure systemic risk.[2] Similar to the findings of González-Hermosillo and Hesse (2009), my results show that univariate models may capture the variable-specific volatility changes that are not common for all variables, in addition to common shocks. My paper contributes to the literature on systemic risk and financial stress by following the authors' suggestion in González-Hermosillo and Hesse (2009) that "future research should attempt to adopt multivariate SWARCH models that can combine various factors". While the main contribution of my paper is in modeling the joint regime-switching volatility changes, my study is also distinguished from González-Hermosillo and Hesse (2009) in several other dimensions. First, following Hamilton and Susmel (1994), I use data at the weekly frequency, in contrast to the daily data of a different set of financial variables used in González-Hermosillo and Hesse (2009). This allows my model to reduce the effects of the "noise" in high-frequency data on the identification of regimes. Second, in contrast to the three-regime model in González-Hermosillo and Hesse (2009), the weekly data allows the model to be specified with two regimes. My result suggests that the two-regime model with weekly data of the considered variables produces more persistent and more clearly identified regimes than the three-regime model with daily data.

[2] In general, regime-switching models are successfully employed in many studies of financial markets. For example, Schaller and van Norden (1997), Hess (2003), Kim et al. (2004), Milidonis and Wang (2007), Guidolin and Timmermann (2008), and Billio et al. (2010), among many others, have modeled market financial variables in the wide range of studies using a univariate Markov-switching specification.

In this paper, systemic financial stress is measured using financial markets' volatility changes. Given the potentially wide-range of causes of financial stress, this approach should be considered as a complement to other methods of measuring systemic financial stress. Many empirical studies of financial stability propose financial stress indices constructed using a combination of several financial market variables, structural variables, balance sheet data, and aggregate banking sector characteristics. The choice of variables in these studies depends on their definition of stress. For example, Vila (2000) proposes measures of banking and equity stress for the US using falling bank equity prices, aggregate deposit growth, and the degree of decline in the stock market index. Hanschel and Monnin (2005) derive a stress index for the Swiss banking system using market price data, balance sheet data, supervisory data, and other structural variables. Similarly, Illing and Liu (2006) propose an index to measure overall financial stress for Canada, combining several variables for different markets into a single index. Numerous papers propose empirical methods to measure financial stress in developing countries; however, as discussed in Illing and Liu (2006), they are not performing well for developed countries. There are also many broader financial condition indices (FCIs), which are usually constructed using a weighted-sum or a principal-components approach. Some well-known financial condition indices are: the Bloomberg FCI, the City FCI, the Deutsche Bank FCI, the Goldman Sachs FCI, the Kansas City Federal Reserve Financial Stress Index, the Macroeconomic Advisers Monetary and Financial Condition Index, and the OECD FCI. In general, given that measures of financial stress in these approaches depend on the choice of specific criteria and the methods of the combination of financial variables, performance of these financial indices is sensitive to causes of stress.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 presents the model. Section 4 reports the empirical results. Section 5 concludes.

2 Data description

In this section, I further motivate my choice of financial variables relative to other potential choices and describe the data used for the model estimation. For my analysis I use the time-series data on the TED spread, the value-weighted return on the stock market, and the capital-weighted credit default swap (CDS) spread for selected large banks.

The TED spread is constructed using the data for the 3-month Treasury yield of constant maturity series from St. Louis FRED and the 3-month LIBOR from Bloomberg. It is a measure of short-term credit and liquidity risk in the banking sector. Alternatively, the LIBOR-OIS spread, which is the difference between LIBOR and the term overnight swap (OIS) rate, can also be used to measure short-term credit and liquidity risks. Both series intend to measure the spread between a risky interbank rate and a rate with minimum risk premium and therefore they are close to each other with a correlation coefficient of 0.92. However, the Treasury rate is closer to the risk-free rate than the OIS rate, because the OIS rate contains a small portion of credit risk premium that is time varying. The data suggests that the TED spread is usually higher than the LIBOR-OIS spread and the difference between these two spreads considerably increases during volatile and stressful periods, indicating that the risk premium contained in the OIS rate increases in these periods. Therefore, the TED spread, presumably accents the risk elevation during stressful periods more strongly than the LIBOR-OIS spread. Also, while my preliminary estimation results for the univariate SWARCH model suggests that both series are successful in capturing the 2007 financial crisis, the availability of the TED spread data for a longer period allows the model to capture stressful periods in 2001, including the 9–11 shock.[3]

The time-series of the stock market returns is constructed using the value-weighted NYSE index obtained from the CRSP database. The stock market return characterizes the price dynamics of the equity market in the model. Another option for incorporating information on stock market dynamics is to focus only on the financial sector. For example, Billio et al. (2010) use equity returns of four types of financial firms to measure systemic risk and study linkages within the financial sector. To check the robustness of the results, in my preliminary analysis, I also estimate the model using the data from the financial sector equity return, instead of the overall stock market return. To measure the financial sector equity return, I use the Financial Select Sector Index (IXM) obtained from Bloomberg. The IXM index is a capital-weighted index of companies in the S&P500 that are involved in production of financial products. The time series of the overall stock market return and the financial sector return are closely correlated with a correlation coefficient of 0.87 for the sample period 2000–2010. Also, the estimated probabilities of the high volatility regime from the multivariate model, using the financial sector index return instead of the NYSE index return, are very close to those from the model with the NYSE index return with a correlation coefficient of 0.95. This analysis suggests that the equity price dynamics of the financial sector and the real sector are closely interconnected and there is a spillover effect between sectors. Therefore, to capture this interconnection among all sectors of the economy I use the overall stock market return.

The capital-weighted banks' CDS spread is constructed using CDS spreads of selected banks weighted by their market capital values. This capital-weighted CDS spread is used as a measure of default risk of the banking sector.[4] This series is constructed using the data on the CDS spreads with a five-year maturity, which is the most liquid maturity, and the market capital values for eight large financial firms: Capital One Financial, Bank of America, Morgan Stanley, Citigroup Inc, Goldman Sachs, Wells Fargo, JPMorgan Chase, and American Express. The choice of the firms is based on availability of CDS prices and the capital size of the firms. The data on the CDS spreads and banks' capital data are obtained from Bloomberg. An alternative measure of default risk is a credit spread. In theory, credit spreads and CDS spreads should be close to each other because of the no-arbitrage constraint. However, many studies shows that CDS spreads may vary from credit spreads. For example, Longstaff et al. (2005), using data on CDS and credit spreads, finds that credit spreads contain the nondefault component which is related to bond market illiquidity. Blanco et al. (2005) finds that the CDS markets lead the bond markets in the price discovery process.

[3] The LIBOR-OIS spread data is available in Bloomberg from December 2001.

[4] An alternative way of weighting CDS spreads would be to use values of CDS transactions, however these data are difficult to obtain.

Therefore, the CDS spread has an advantage over the credit spread in measuring default risk and capturing financial stress periods.

For my analysis, I construct the panel of weekly time-series data on the TED spread, the value-weighted return on the stock market, and the capital-weighted credit default swap (CDS) spread for selected large banks. The raw data for all time-series are at the daily frequency. This daily data is transformed into the weekly frequency using the data on Wednesday of each week. The stock market returns are continuous growth rates of the stock index from Wednesday to Wednesday, transformed into daily returns. In this approach I follow Hamilton and Susmel (1994) who study the regime switching in the stock market return using weekly data on stock market return from Tuesday to Tuesday. I choose Wednesday because the data on this day of the week is the most available among all days of a week for the considered sample of daily data and avoids any possible effects of the beginning or end of the week. If the data on particular Wednesday is not available, the data on the day closest to Wednesday of that week is used. The effects of systemic financial stress on financial variables presumably should last longer than a week because of their systemic rather than idiosyncratic nature. Therefore, any potential drastic intra-week movements in daily data related to a systemic stress should be expected to be reflected in weekly data as well.[5] Many studies on systemic risk and financial stress are successful in detecting systemic events using monthly data (e.g., Billio et al. 2010). The choice of using weekly data is explained by a better identification of regimes due to less "noise" in the financial data at weekly frequency compared to daily data. Although the main results are estimated using the weekly data, I also estimate the model using daily data and compare results.

For the model estimation, the data transformation results in unbalanced weekly data for the TED spread and the value-weighted stock market return for the period from December 6, 2000 through September 29, 2010, which is comprised of 513 observations, and the CDS spread for the period November 10, 2004 through September 29, 2010, with 308 observations. The unbalanced data allows the model to combine a longer time-series of data with a larger number of financial variables in the panel of data for estimation of the regimes.

3 Model

It is common during periods of system-wide financial stress for all financial variables to experience large financial shocks and become highly volatile. Therefore, I assume that these periods of systemic stress are common for all variables and can be captured by a joint regime-switching process. I follow Hamilton and Susmel (1994) and describe the volatility of financial variables by the regime-switching autoregressive conditional heteroskedasticity (SWARCH) specification:

[5] In my preliminary analysis I also estimated the model using the weekly average TED spread data. While the estimated regimes are able to capture main stressful periods, the estimated regimes are more "noisy" and less clearly identified. This result can be explained by the fact that the weekly average data are smooth relative to the end of period data by construction. Also, using the end of period data rather than average data is a common approach in modeling interest rates in the finance literature.

$$y_t^i = \mu_{s_t}^i + \phi^i y_{t-1}^i + \sqrt{g_{s_t}^i} u_t^i, \tag{1}$$

$$u_t^i = h_t^i \varepsilon_t^i, \quad \varepsilon_t^i \sim N(0, 1), \tag{2}$$

$$h_t^{i\,2} = a_0^i + a_1^i u_{t-1}^{i\,2} + a_2^i u_{t-2}^{i\,2}, \tag{3}$$

where y_t^i denotes a financial variable i and s_t denotes a volatility regime.

In this specification, abrupt and large changes in volatilities of financial variables and their means are governed by an exogenous unobservable two-state first-order Markov-switching process s_t with a transition probability matrix:

$$P \equiv \begin{bmatrix} p_{11} & 1 - p_{11} \\ 1 - p_{22} & p_{22} \end{bmatrix}, \tag{4}$$

where $p_{jk} \equiv Pr[s_t = k | s_{t-1} = j]$. The model assumes that agents observe realizations of regimes up to time t; however, econometricians have to estimate the entire path of s_t given data and the model.

The model is flexible for incorporating any number of regimes. For example, Hamilton and Susmel (1994) consider more than two regimes to model strong outliers such as the October 1987 stock market crush, separately from other large shocks. However, given the objective of this study to identify periods of systemic stress, the two-regime process is easier to interpret. Also, as is shown in the Empirical Results section, the two-regime process is well identified for the considered sample of weekly data.[6]

I note that while the regimes are common for all variables, magnitudes of regime-switching volatility changes are different for each variable i and modeled by factor $\sqrt{g_{s_t}^i}$ in Eq. (1). I impose the identification constraint $\sqrt{g_1^i} < \sqrt{g_2^i}$ for all i, and therefore the two regimes are labeled as the "low" and the "high" volatility regimes. While the regime process captures large and common changes in volatility, small and gradual changes in volatility of each financial variable within each regime are modeled by the independent ARCH process described by Eqs. (2) and (3). Similar to Hamilton and Susmel (1994), who show that two lags are sufficient to model heteroskedasticity of weekly stock returns within regimes, I include two lags in Eq. (2).[7]

For identification purposes, parameters a_0, a_1, and a_2 in Eq. (3) are restricted to be positive to ensure the positiveness of h_t^2 for all sizes of shocks. In addition, these parameters are restricted to values less than unity to ensure stationarity of the process in Eq. (3). Similarly, parameters g_{s_t} and h_t in Eqs. (1) and (2) are restricted to be positive, as they represent the scaling of standard deviations. To identify g_{s_t} and the

[6] For example, González-Hermosillo and Hesse (2009) use a three-regime univariate SWARCH model to describe time-variation in several financial variables. In some instances, the middle volatility regime that they report captures a combination of relatively low volatility and high volatility observations.

[7] For simplicity, my model does not include the "leverage" term considered by Hamilton and Susmel (1994). Also, Hamilton and Susmel (1994) show that t-distribution has a better fit of the model than the Normal distribution. However, because of issues with stability of a numerical estimation for the multivariate t-distribution, I use the Normal distribution. My preliminary analysis for univariate models suggests that the regimes identified by the models with the univariate Normal distribution and the univariate t-distribution are very close to each other.

Table 1 Parameter estimates

	TED spread	Stock return	CDS spread	Joint transition probabilities
μ_1^i	0.0076	0.0512	0.0011	
	(0.0028)	(0.0119)	(0.0011)	
μ_2^i	0.0333	−0.1117	0.0820	
	(0.0259)	(0.0526)	(0.0137)	
ϕ^i	0.9593	−0.1098	0.9880	
	(0.0000)	(0.0534)	(0.0029)	
g_1^i	1.0000	1.0000	1.0000	
g_2^i	31.2316	4.1871	24.8333	
	(7.1377)	(0.9144)	(7.1369)	
a_0^i	0.0007	0.0324	0.0001	
	(0.0001)	(0.0044)	(0.0000)	
a_1^i	0.5987	0.3584	0.9999	
	(0.1168)	(0.0878)	(0.0042)	
a_2^i	0.4149	0.3481	0.6357	
	(0.0953)	(0.0739)	(0.1292)	
p_{11}				0.9493
				(0.0127)
p_{22}				0.7177
				(0.0704)

The notations of reported parameters correspond to Eqs. (1), (3), and (4). Standard errors of estimated parameters are reported in parentheses

parameters in Eq. (3), $g_{s_t=1}$ is normalized to one. Also, parameter ϕ is restricted to be less than unity in absolute value, assuming that the AR(1) process in Eq. (1) is a stationary process. I estimate the model parameters, including unobserved regimes, using the method to evaluate the likelihood function for regime-switching models developed in Hamilton (1989).

4 Results

I begin presenting my results with the analysis of key parameter estimates for the model and then I analyze the identified regimes. Table 1 reports parameter estimates for the model described in Eqs. (1), (2), and (3).[8] The point estimates of parameter g_2^i for all considered financial variables are substantially larger than g_1^i, which is normalized to one. This result suggests that the volatility of the financial variables in the high volatility regime is considerably higher than in the low volatility regime, indicating that the regime-switching process indeed captures large changes in volatility. Consistent with the notion of requiring a risk premium for increased risk during stressful periods by financial markets, the estimates of intercept term $\mu_{s_t}^i$ for the TED and CDS spreads

[8] To check the robustness of my results, I estimated the model using normalized data by subtracting sample averages and dividing by sample standard deviations to avoid potential effects of scaling of data on the identification of regimes. The two data approaches (i.e. normalized and not) produce estimates of regimes that are very close to each other. I choose to report the results for the non-normalized data.

in the high volatility regime are considerably greater than in the low volatility regime. In contrast, the point estimate of the intercept parameter for the stock index return in the high volatility regime is lower than in the low volatility regime. This result can be explained by the fact that the model captures the mean of realized returns rather than the expected return, which one theoretically should expect to increase with an increase in risk. The negative relationship between a stock volatility and return is also reported in other studies (e.g., Campbell 1987; Breen et al. 1989; Whitelaw 1994). To check the effect of the regime-switching means on the identification of the regimes, I also estimate the model with constant intercept terms. The results are robust to both specifications of the model, suggesting that the regimes are mainly identified by changes in volatility. However, the likelihood ratio test rejects constant means with a p value of 0.0001, suggesting that the model with the regime-switching intercept has a better fit. Therefore, for my analysis, I use the model specification with the regime-switching intercept terms.

The estimates of the ARCH terms a_1^i and a_2^i for all financial variables are statistically significant, suggesting the importance of capturing the time-variation in volatility within each regime. The point estimates of these parameters indicate that the volatility variations within regimes are relatively persistent.

The probabilities of staying in the low and high volatility regimes are estimated at 95 and 72 %, respectively, indicating higher persistence of the low volatility regime relative to the high volatility regime. These estimates of the probabilities imply that, on average, the low and high volatility regimes are expected to last about 20 and 4 weeks, respectively.

To analyze the role of each financial variable for the identification of the joint volatility regimes, I first estimate the univariate SWARCH model for each financial variable separately from the other variables.

Graphs (1) through (3) of Fig. 1 illustrate that the high volatility regimes from the separate univariate SWARCH models for the financial variables capture the main stressful events reasonably well, such as i) the aftermath of the dot-com bubble burst in late 2000 and beginning 2001, prior to the 2001 recession, ii) the 9–11 shock, iii) the beginning of the "credit crunch" and the subprime mortgage crisis in 2007, and iv) the Lehman Brothers bankruptcy and AIG seeking an emergency loan in September 2008. In addition to these common systemic stressful periods, the variables experience higher volatility periods which are variable specific. For example, the high volatility regime for the TED spread also captures a few short-term spikes in late 2002 and 2005. The spike in the TED spread in November 2002 is explained by an unexpected drop in the federal fund target rate by 50 basis points against a market-priced decrease by about 25 basis points. The increase in the TED spread's volatility in December 2005 captures the timing lag between market-priced interest rate increases and gradual increases in the Federal Fund rate. Similarly, the high volatility regime for the return on the NYSE index in 2002–2003 and 2010 captures an equity market specific increase in volatility in the stock market. In particular, the volatile stock market in 2002–2003 reflects the low faith of investors in the stock market related to low earning announcements and fears about the Iraq War. In the period from May-August 2010, fears of implications of the debt crisis in Greece resulted in an increase in the volatility of the stock market.

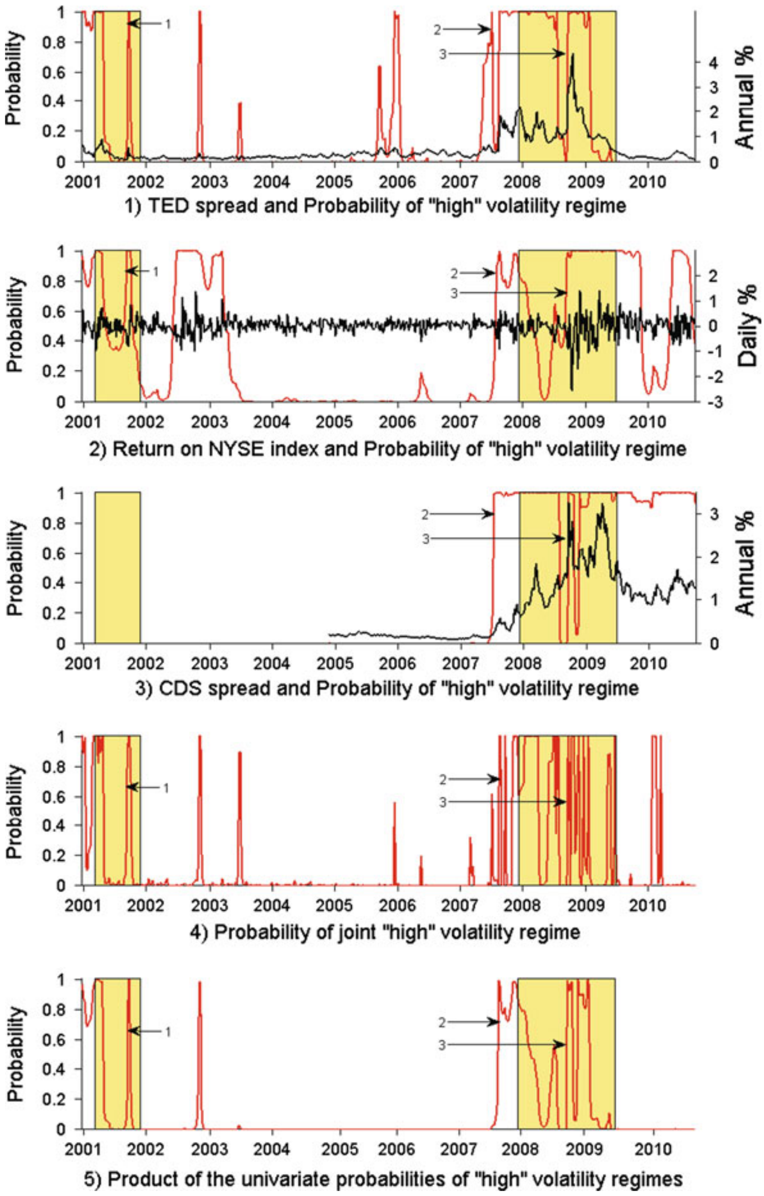

Fig. 1 TED spread, Return on NYSE index, CDS spread and "high" volatility regimes; weekly data. Graphs (1), (2), and (3) display the time series of the weekly data together with probabilities of "high" volatility regimes from their respective univariate SWARCH models. Graph (4) displays the probabilities of the joint "high" volatility regime from the multivariate SWARCH model. Graph (5) displays the product of probabilities from the univariate SWARCH models. *Shaded areas* correspond to NBER recession dates. The *numbers with arrows* indicate specific stressful events: *1*—September-11; *2*—beginning of "credit crunch" and subprime crisis; *3*—Lehman Brothers bankruptcy

Given that the separate univariate SWARCH models can indicate an increase in volatility which does not have a systemic nature, I propose the multivariate SWARCH model with the joint volatility regime, which is a key distinction of my model from the approach in González-Hermosillo and Hesse (2009). Presumably, this joint regime should capture the high volatility periods, which are common for all financial markets and the banking sector. Graph (4) of Fig. 1 displays the probability of the joint high volatility regime from the multivariate SWARCH model. The graph suggests that the joint regime indicates the common systemic stressful periods listed earlier in my analysis. For example, the probability of the joint high volatility regime becomes dominantly high during the entire recession period of 2007–2009, starting from the beginning of the subprime crisis in 2007. At the same time, the joint model assigns a smaller probability to the TED-spread-specific spikes in late 2005 because the other two financial variables did not have high volatility in this period due to the predictable nature of the changes in the TED spread in that episode. In contrast, the unexpected move in the TED spread in November 2002 complemented by sharp changes in the stock market index resulted in the joint high volatility regime in this period. Another interesting episode is early 2010, identified as the joint high volatility regime when the TED spread and stock market return remain in the low volatility regimes and the CDS spread is in the high volatility regime. However, the CDS spread and the stock return show signs of volatility increase, which the joint regime captures as the high volatility regime. As soon as these financial variables do not experience further dramatic increase in volatility, the joint regime returns to the low volatility regime.

Following Billio et al. (2010), I also estimate the joint probabilities of the high volatility regime as the product of the probabilities from the univariate models as an alternative to the joint volatility regime from the multivariate model. As discussed in Billio et al. (2010), the product of probabilities is the low bound of the joint probability that should under-estimate the true joint probabilities, because the product of probabilities implicitly assume independence of random variables. The product of the probabilities is displayed on graph (5) of Fig. 1. Comparing the joint probabilities of the high volatility regime from both approaches, one can observe that both models are able to capture the main stressful periods. The difference appears mainly in periods when one of the variables shows low probability while other variables have high probabilities of being in the high volatility regime. In these periods, the products of probabilities have low magnitudes by construction. In contrast, the multivariate model still can produce a high joint probability, because the model is estimated simultaneously with all variables. An example of such a case is the period of early 2010, when the stock market return and the CDS spread show signs of elevated volatilities, while the TED spread is relatively stable. The product of probabilities confirms that the high volatility regimes of the selected variables are capturing all key stressful periods in the sample.

As briefly discussed in the Introduction, my approach to a univariate SWARCH model is distinguished from the one used in González-Hermosillo and Hesse (2009) in several dimensions. First, I use weekly data in contrast to daily data, which is used in González-Hermosillo and Hesse (2009).[9] This allows a Markov-switching model

[9] González-Hermosillo and Hesse (2009) focus their study on global financial conditions and consider the TED spread, the VIX index, and the euro-US dollar forex swap.

to reduce negative effects of the "noise" in high-frequency data on the identification of regimes. Second, in González-Hermosillo and Hesse (2009), the time series of data are transformed in first differences. I model the interest rates (i.e., the TED spread and CDS spread) in levels, which is a common approach to modeling interest rates in macro-finance literature (e.g., Ang and Piazzesi 2003; Ang et al. 2006; Diebold and Li 2006; Rudebusch and Wu 2008).[10] The frequency of data has a considerable effect on the identification of regimes. As displayed on graphs (1) through (3) of Fig. 1, the identified regimes in my approach are mostly persistent and relatively well identified (e.g., in most cases the probabilities of regimes are close to 1 or 0). Third, in contrast to the three-regime model in González-Hermosillo and Hesse (2009), the weekly data allows the model to be specified with two regimes. My preliminary analysis also suggests that the regimes in the two-regime model are not well identified at the daily frequency. In the three-regime model, the "high" volatility regime captures strong outliers in the data, leaving other volatile observations to be captured by the "medium" volatility regime. Therefore, as González-Hermosillo and Hesse (2009) show, while the "high" volatility regime captures mainly the extreme movements in financial variables, the "medium" volatility regime captures some stressful periods, as well as periods with moderate elevations in volatility. The two-regime model with weekly data has the advantage over the three-regime process in interpreting the regimes because of the binary nature of the regime process with the high volatility regime responsible for capturing all stressful observations.[11] To demonstrate these points and to complement the approach which is based on weekly data, I also estimate the univariate and multivariate models with daily data.

As I note above, the two-regime model is not well-identified with daily data, therefore, following González-Hermosillo and Hesse (2009), I estimate the models with three regimes labeled "low", "medium", and "high" volatility regimes.[12] The daily data has an advantage in capturing a timely reaction of the variables to systemic shocks. However, the advantage of this approach comes with a cost from the "noise" in high-frequency data.

Figures 2 and 3 display the estimated probabilities of the "high" and "medium" volatility regimes, respectively. Graphs of the "high" and the "medium" volatility regimes from the univariate models show that the identified regimes capture numerous episodes in the middle of the sample that appear unrelated to systemic stress.

[10] The ADF tests reject that the daily data on the TED and CDS spreads have a unit root at the 5 % confidence level. The CDS spread is tested for a unit root separately for two subsamples covering the periods of 2004 through mid-2007 and mid-2007 through 2010. These are two periods where the CDS spread remains predominantly in one regime.

[11] I do not claim that the two-regime model has a statistically better fit than the three-regime model at weekly frequency of data. However, given the focus of my study to propose a measure of systemic financial stress, I believe the two-regime process suits my objective better than more complicated specifications. Also, as discussed in Hamilton and Susmel (1994), the three-regime model requires imposing additional identification restrictions on the transition probabilities given estimation difficulties.

[12] I present results for the daily data in levels. To check the robustness of the results, I also estimated the model with the daily data in first differences, which is the approach in González-Hermosillo and Hesse (2009). The estimated regimes from both approaches with daily data are very close to each other with the correlation coefficients between probabilities of joint volatility regimes of 0.99 and 0.98 for the "medium" and "high" volatility regimes, respectively.

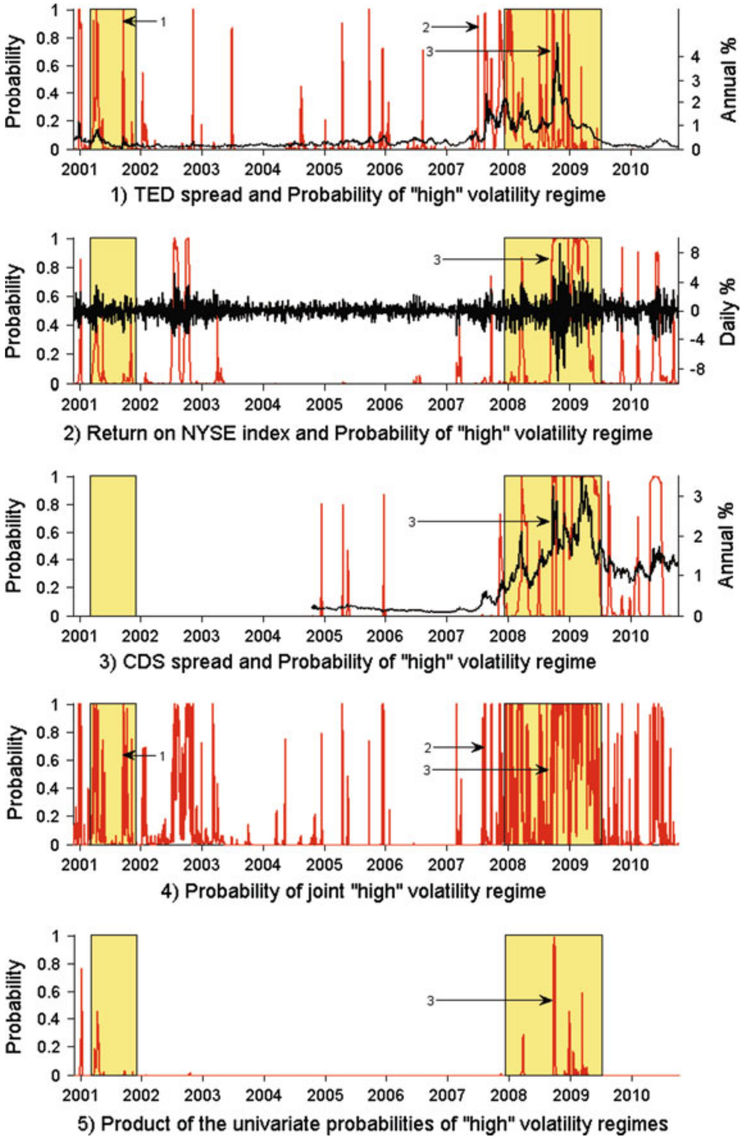

Fig. 2 TED spread, Return on NYSE index, CDS spread and "high" volatility regimes; daily data. Graphs (1), (2), and (3) display the time series of the daily data together with probabilities of "high" volatility regimes from their respective univariate SWARCH models. Graph (4) displays the probabilities of the joint "high" volatility regime from the multivariate SWARCH model. Graph (5) displays the product of probabilities from the univariate SWARCH models. *Shaded areas* correspond to NBER recession dates. The *numbers with arrows* indicate specific stressful events: *1*—September-11; *2*—beginning of "credit crunch" and subprime crisis; *3*—Lehman Brothers bankruptcy

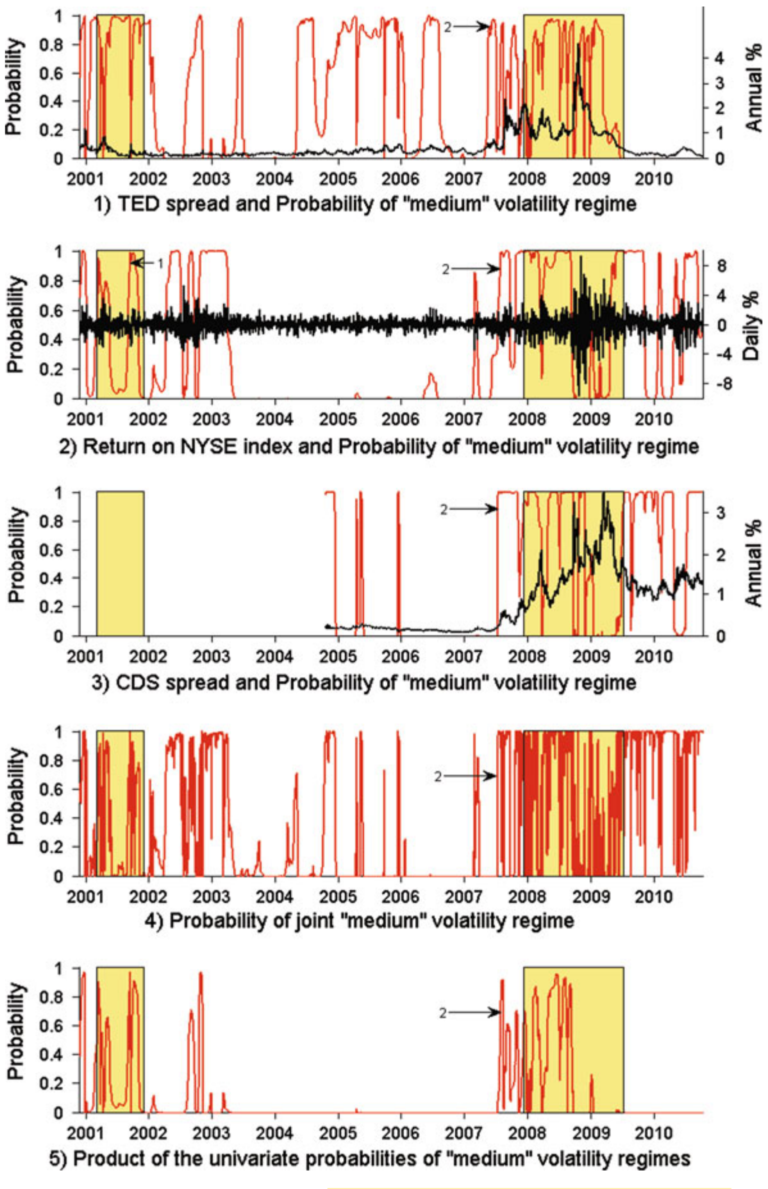

Fig. 3 TED spread, Return on NYSE index, CDS spread and "medium" volatility regimes; daily data. Graphs (1), (2), and (3) display the time series of the daily data together with probabilities of "medium" volatility regimes from their respective univariate SWARCH models. Graph (4) displays the probabilities of the joint "medium" volatility regime from the multivariate SWARCH model. Graph (5) displays the product of probabilities from the univariate SWARCH models. *Shaded areas* correspond to NBER recession dates. The *numbers with arrows* indicate specific stressful events: *1*—September-11; *2*—beginning of "credit crunch" and subprime crisis; *3*—Lehman Brothers bankruptcy

In addition, different variables identify the same stressful events differently by the "high" and "medium" volatility regimes. For example, the "high" volatility regime of the TED spread from the univariate model identifies all key stressful events in the sample, such as September-11, beginning of "credit crunch" and subprime crisis, and Lehman Brothers bankruptcy. At the same time, the "high" volatility regime of the stock market return identifies only Lehman Brothers bankruptcy and the other two stressful events are captured by the "medium" volatility regimes. A similar result is observed for the regimes of the CDS spread. As a result of these distributions between the "high" and "medium" volatility regimes and short durations of regimes, the products of the probabilities, displayed on graphs (5) of Figs. 2 and 3, are not always able to indicate stressful periods. Meanwhile, the joint "high" volatility regime from the multivariate model is able to identify all three stressful events. Comparing the estimated regimes from the models with daily and weekly data, one can observe that the identified regimes with weekly data are more persistent and better identified.

Thus, the probability of the joint high volatility regime from the multivariate SWARCH model can indicate systemic financial stress periods. This model can be used as a warning signal of the beginning of financial stress as well as an exit from the stress period. The latter is indicated by the model if the joint regime switches and persistently remains in the low volatility regime for an extended period of time. At the same time, it is important to analyze the underlying reasons for the joint regime model capturing a particular period as a high volatility regime.

5 Conclusion

In this study, I propose a multivariate regime-switching model as a potential way of measuring systemic financial stress. In particular, I model large and abrupt volatility changes of financial variables such as the TED spread, the stock market return, and the CDS spread of large banks by the joint volatility regime-switching process, which is common for all financial variables. My results suggest that the probability of the joint "high" volatility regime captures stressful episodes in the considered sample of data reasonably well. At the same time, given a potentially wide-range of causes of systemic shocks, I propose this model as a complement to other approaches, which can provide insights to causes of systemic shocks.

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