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Toward an early warning system of financial crises: What can index futures and options tell us?

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ABSTRACT

This research develops an early warning system (EWS) for equity market crises based on multinomial logit models and variables relating to the information content of index futures and option markets. We show that the information impounded in S&P 500 futures and options is useful as leading indicators of financial crises. Results reveal that models estimated with futures and put options significantly improve the medium-term predictability of equity market crises. Variables that consistently provided information of an impending crisis include: the VIX, open interest, dollar volume, put option price, put option effective spread, and the Treasury term spread.

1. Introduction

Can the prediction of financial crises be improved? This question is addressed often in existing literature, particularly following the spike in currency crises in the late 1990s. Several authors have developed and modified 'early warning system' (EWS) models, and demonstrated success in the prediction of currency crises.[1] Surprisingly, a relatively sparse literature exists on forecasting equity market crises for the purpose of providing early signals of market declines. The current paper addresses this void in the literature. We accomplish this by exploring the information content of index futures and option markets, with the purpose of developing an EWS of financial crises.[2]

A considerable body of literature reports that option and/or futures markets tend to lead equity markets in terms of information arrival.[3] In addition, several researchers show that option/futures volumes, option/futures open interest, and implied volatility (VIX) exhibit predictive power on short-term equity price movement.[4] There are also theoretical reasons to believe that derivative markets may provide information in developing an EWS for equity markets. For example, Black (1975) argues that higher financial leverage offered by derivatives attracts greater participation by informed traders. Greater leverage implies greater risk and therefore increases the incentives for information dissemination and price discovery. Easley, O'Hara, and Srinivas (1998) and Pan and Poteshman (2006) present empirical evidence of information-based trading in option markets. The evidence in these studies indicates that derivative markets are more informative than equity markets. If an EWS model incorporates information revealed from derivative markets, it has potential to provide early signals of equity market crises.

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[1] For example, see Kaminsky et al. (1998), Berg and Pattillo (1999), Burkart and Coudert (2002), Kumar et al. (2003), and Bussiere and Fratzscher (2006).

[2] We note that the literature on the development of EWS is in contrast with the efficient market hypothesis, which says that prices follow a random walk.

[3] Please see, Manaster and Rendleman (1982), Diltz and Kim (1996), Kawaller et al. (1987), Stoll and Whaley (1990), Chan (1992), Fleming et al. (1996), Pizzi et al. (1998), and Kavussanos et al. (2008).

[4] See, Easley et al. (1998), Pan and Poteshman (2006), and Chung et al. (2011).

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The current research employs a multinomial logit model to test the forecasting power of several derivative market indicators on the probability of a financial crisis. We select variables from the two most active index derivatives in the U.S., the S&P 500 futures (SP) and the S&P 500 options (SPX), to test the predictability of financial crises from 1997 to 2009. In the multinomial logit model, we include the following variables as suggested by existing literature: open interest, dollar volume, option price, option effective spread, and the implied volatility of the S&P 500 options (VIX). This study tests several model specifications to understand the marginal contribution of each explanatory variable in the prediction of a financial crisis. Additionally, we re-estimate all models with the addition of Treasury term spread and test the robustness of the parameter estimates to an alternative definition of a financial crisis.

The empirical results support the notion that index futures and option markets lead equity markets. All models estimated successfully predict the majority of financial crisis months within the sample period.[5] Among the futures and option models, the best performing model, using put option variables, correctly identifies 85.8% of observations and 65.4% of crisis months. When the term spread is included within the model, the results improve with 94.8% of observations correctly identified and 92.3% of crisis months predicted correctly. The results of this paper demonstrate that information contained in index futures and option markets is useful as leading indicators of financial turmoil. By developing EWS models that utilize the information contained in S&P 500 futures and option markets to forecast equity market crises, this research contributes to the understanding and prediction of financial crises.

The remainder of the paper is organized as follows. Section 2 reviews literature, Section 3 describes data and methodologies, Section 4 discusses empirical results, and Section 5 concludes.

2. Literature review

The current state of predicting financial crises is much better than a 'random guess'. A number of studies have developed EWS models based on data from a variety of countries. Examples of this research include: Kaminsky, Lizondo, and Reinhart (1998), Kumar, Moorthy, and Perraudin (2003), Distinguin, Rous, and Tarazi (2006), Bussiere and Fratzscher (2006), and Coudert and Gex (2008). Kaminsky et al. (1998) propose and test a 'signals' approach which combines several macroeconomic variables as leading indicators to predict currency crises. They show that EWS models based on leading macroeconomic indicators crossing a pre-specified threshold level are useful in the prediction of currency crises.[6] Kumar et al. (2003) and Distinguin et al. (2006) employ binomial logit models to predict currency crashes and banking crises, respectively. The results of both papers argue for the use of a binomial discrete dependent variable approach to forecast financial crises. However, Bussiere and Fratzscher (2006) argue that an EWS model based on a binomial discrete dependent variable is subject to a post-crisis bias, because it does not distinguish crisis and post-crisis periods. Applying a multinomial logit model, Bussiere and Fratzscher (2006) show a significant improvement of forecasting currency crises. In a recent paper related to the current research, Coudert and Gex (2008) employ multinomial logit models using well-known risk aversion indicators. They document that the majority of these risk aversion indicators are good leading indicators of currency crises, and all have predictive power of equity market crises.

Most EWS models use macroeconomic or monetary variables as leading indicators to predict currency crises. In contrast to the majority of existing literature, the current research utilizes the information revealed in derivative markets to predict equity market crises within a multinomial logit model over a one-year forecasting horizon. To motivate our variable selection, we now briefly summarize the literature on the linkages between equity and derivative markets.

Voluminous literature examines the lead–lag relationships between option/futures prices and the underlying equity prices (returns). The preponderance of the empirical evidence demonstrates that option/futures prices (returns) lead cash index prices (returns). For example, in a comprehensive analysis of the S&P 100 and 500 futures, options, and spot markets, Fleming, Ostdiek, and Whaley (1996) find that index futures and option returns lead equity index returns. Their empirical evidence is consistent with the trading cost hypothesis that price discovery occurs first in the lowest-cost markets.[7]

The informational role of option/futures volume and open interest is also researched extensively in literature. For example, volumes and open interest are used to examine information arrival in option/futures and equity markets, to predict equity/option price movements, to predict future price volatility, and to investigate the existence of informed trading regarding corporate events. Most related to the current research are studies that use volume or order flow to examine the informativeness of options/futures relative to equity markets. A good example of this type of study is Chakravarty, Gulen, and Mayhew (2004). They document that option markets are more informative when the option volume is higher and effective spread is narrower relative to those of the stock markets. Bessembinder, Chan, and Seguin (1996) examine the relations between information, divergence of opinions, and trading activity of S&P 500 futures. They confirm a positive relationship between information flow and trading volume in the spot and futures markets.

Additional literature relevant to the current research explores the information role of option implied volatility and examines its relationship with equity returns, future realized volatility, and stock market crashes. The evidence of a positive relationship between implied volatility and equity returns is presented in Giot (2005) and Banerjee, Doran, and Peterson (2007). In an analysis of VIX and S&P 100 index, Giot (2005) documents a positive relationship between VIX and future market index returns. In a similar study, Banerjee et al. (2007) find that future portfolio returns are positively significantly related to both VIX levels and innovations for portfolios sorted by beta, size, and book-to-market equity.

Recent research has demonstrated the superior predictive power of implied volatility on future realized volatility and returns as well. In a study of the 1997 Hong Kong stock market crash, Fung (2007) finds that implied volatility performs better than volume, open interest, and arbitrage basis of index futures in forecasting the future realized volatility. Chung, Tsai, Wang, and Wang (2011) show that the information embedded in VIX options significantly improves the predictive power on the returns, volatility, and density of the S&P 500 index.

Limited research examines index derivatives market variables to predict an equity market crisis. Early research by Bates (1991) and Rappoport and White (1994) document that the equity

[5] Models estimated with index futures market variables display similar conditional probabilities to models estimated with index put option variables.

[6] Examples of leading indicators include: international reserves, the real exchange rate, domestic credit, public sector credit, domestic inflation, trade balance, exports, money growth, real GDP growth, the fiscal deficit, and equity prices.

[7] International evidence confirms that futures prices (returns) lead equity prices (returns) [e.g., Abhyankar, 1998; Kavussanos, Visvikis, & Alexakis, 2008; Ryoo & Smith, 2004; Tang, Mark, & Choi, 1992].

market crashes in 1987 and 1929 were expected. Bates (1991) reports unusually high prices of out-of-the-money (OTM) put options on the S&P 500 futures a year prior the 1987 crash. In his jump-diffusion option pricing model, the parameters implied by option prices indicate that a market crash was expected dating back to October 1986. Examining the 1929 crash, Rappoport and White (1994) treat brokers' loans as options offered to investors. They document a sharp increase in interest premium, margin requirements on brokers' loans, and implied volatility on options prior to the 1929 market crash. In a paper most related to the current research, Coudert and Gex (2008) show that risk aversion indicators, including the implied volatility of the S&P 500 options (VIX), are good leading indicators of equity market crises. Although these studies document the predictability of equity market crises using information obtained from derivative markets, they do not comprehensively examine the information impounded in index futures and option markets on the prediction of subsequent equity market crises. In the current research, we focus on the medium-term (i.e. 1-year) prediction of equity market crises using an EWS model that incorporates the information flow from index futures and options markets to equity markets.

3. Data and methodologies

3.1. Data

The Standard and Poor's 500 futures (SP) and options (SPX) are chosen as the sample for this research. The sample period selected is from January 2, 1997 to December 31, 2009. S&P 500 futures and options are the most active index derivatives traded on Chicago Mercantile Exchange (CME) and Chicago Board Options Exchange (CBOE), respectively.[8] The daily data for S&P 500 futures (SP) and options (SPX) are obtained from Norma's Historical Data and Market Data Express at CBOE, respectively. Both datasets contain closing price, expiration date, total volume, and open interest. The exercise price, and last bid and asked prices are only available for options contracts. S&P 500 index prices and the historical data on CBOE Volatility Index (VIX) are obtained from Market Data Express dataset and CBOE's website, respectively.[9] VIX measures the expected near-term stock market volatility based on the S&P 500's option prices.[10]

The following criteria are imposed to filter the options data: Options must have trading volume, open interest, closing price higher than or equal to $0.125, and at least 7 days to maturity.[11] This study excludes LEAPS (Long Term Equity AnticiPation Security) options as LEAPS often have different characteristics than standard options. The initial screen yields a total of 657,409 daily options observations, 273,030 of which are call options, while 384,379 of which are put options. We do not filter the futures data because the minimum futures price over the sample period is $668.20 and the nearest maturity of futures contracts dominate trading in each month. The sample of futures data contains 27,778 daily observations.

The daily futures and options data are converted to monthly frequencies to obtain the key variables for analysis: Open interest, total dollar volume, average daily closing price of options, and average daily option effective spread. Existing literature documents that these variables contain information about future equity prices and/or contribute to price discovery. A logarithmic transformation is applied to open interest and total dollar volume following existing literature. The daily S&P 500 index prices are averaged in month t to arrive the average daily index value in monthly t (P_t). The average daily S&P 500 index value (P_t) is used to compute the $CMAX_t$ ratio and the crisis indicator CC_t as developed in Section 3.2. Please refer to Table 1 for variable definitions.

Out-of-the-money (OTM) options offer the greatest leverage to investors. Informed traders should enjoy higher profit from trading OTM options. Thus, we expect more information to be revealed from the trading of OTM options.[12] Indeed, Bates (1991) documents that the prices of OTM put options on S&P 500 futures were unusually high relative to those of OTM calls during the year prior to the 87's crisis. Motivated by this evidence, we explore the informational role of OTM puts for predicting financial crises in addition to call, put, and all options in the sample.[13]

In a study of predicting stock market bubbles, Herwatz and Kholodilin (2014) present evidence that capital valuation indicators contain more information than monetary variables for forecasting the excess equity market valuation. In light of their empirical findings, we extract the monthly frequency data of these variables for further analysis: the cyclically adjusted price-to-earnings ratio (i.e. Robert Shiller's P/E ratio), the dividend yield and earnings-to-dividend ratio for S&P 500, the growth rate of M2, term spread, and loans and leases in bank credit.[14] The P/E ratio, dividend yield, earnings-to-dividend ratio, and loans and leases in bank credit are highly correlated with the futures and options variables.[15] For model specification issues, we therefore only consider the growth rate of M2 and the Treasury term spread along with futures or option market variables.

3.2. Methodologies

Following Patel and Sarkar (1998) and Coudert and Gex (2008), we use the $CMAX_t$ ratio to identify a financial crisis month. Patel and Sarkar (1998) define $CMAX_t$ as the ratio of an index level at month t to the maximum of an index level for the period up to month t. Coudert and Gex (2008) set 24 months as a rolling period in calculating the $CMAX_t$ ratio. The current research follows Coudert and Gex's (2008) method to calculate the $CMAX_t$ as well as the corresponding crisis indicator (CC_t).

$$CMAX_t = \frac{P_t}{\max(P_t, \ldots, P_{t-24})}, \tag{1}$$

where P_t is the average daily S&P 500 index level in month t.

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8 According to the statistics released by CME and CBOE in 2011, the total trading volumes of S&P 500 futures and S&P 500 options account for 86% and 61.71% of total equity index futures and options traded on CME and CBOE, respectively.

9 The old VIX data computed using the new methodologies are also available on CBOE: http://www.cboe.com/micro/VIX/historical.aspx.

10 The original VIX was computed based on at-the-money S&P 100 index (OEX) option prices. From September 22 in 2003, CBOE changed its methodology of computing the VIX by incorporating more information of implied volatility from a wide range of strike prices. The new VIX is based on S&P 500 index option (SPX) prices.

11 Aït-Sahalia and Lo (1998) document that options with low price and low trading volume are unreliable. Sarwar (2005) also remove S&P 500 options with price less than $.125 from the sample to examine the relationship between option volume and price volatility.

12 Chakravarty et al. (2004) provide evidence that price discovery is greater for out-of-the-money options than at-the-money options.

13 Following Fleming et al. (1996), we define an out-of-the-money (OTM) put option as the ratio of its strike to spot prices less than or equal to 0.95.

14 The data of the cyclically adjusted price-to-earnings ratio, the dividend yield and earnings-to-dividend ratio for S&P 500 are available on Robert Shiller's website: http://www.econ.yale.edu/~shiller/data.htm. Because of a data subscription issue, we are not able to obtain the price-to-book ratio for S&P 500. The data of M2, term spread (10-Year Treasury Constant Maturity Rate – 3-Month Treasury Bill Rate), loans and leases in bank credit for all commercial banks can be obtained from the Federal Reserve Economic Data, which are provided by the Federal Research Bank of St. Louis (http://research.stlouisfed.org/fred2/).

15 A complete correlation matrix will be provided upon request.

A low value of $CMAX_t$ indicates a larger price decline in the index level over a 24-month period. The $CMAX_t$ ratio is capped at 100%. A $CMAX_t$ ratio of 100% indicates that the index level in that month rises to the maximum value in the rolling 24-month period.

The $CMAX_t$ ratio is then translated to an equity market crisis indicator CC_t if $CMAX_t$ is less than two and half standard deviations below its mean value.[16]

$$CC_t = \begin{cases} 1, & \text{if } CMAX_t \le \overline{CMAX_t} - 2.5\rho_t \\ 0, & \text{otherwise} \end{cases}, \tag{2}$$

where ρ is the standard deviation of $CMAX_t$.

We calculate the mean value and the standard deviation of $CMAX_t$ for the first month in the sample period (1997:01) from the period of 1995:01–1996:12, and add an additional month at a time to the sample in calculating these two statistics in each of the following months.

Bussiere and Fratzscher (2006) and Coudert and Gex (2008) document the superiority of multinomial logit models over binomial models in the prediction of financial crises. Motivated by these findings, the EWS models estimated in this research use the multinomial logit approach outlined below.

The dependent variable Y_t comprises three discrete values (0, 1, and 2) for three outcomes: the normal, pre-crisis, and post-crisis periods, respectively. The classification of the discrete values for the dependent variable Y_t is constructed based on the crisis indicator (CC_t). The pre-crisis period ($Y_t = 1$) includes 12 months before the financial crisis month (i.e. 13 months in total), while the post-crisis period ($Y_t = 2$) consists of 11 months following the crisis month.[17] Other months are considered the normal period ($Y_t = 0$).

$$Y_t = \begin{cases} 1, & \text{if } \exists k = 0, \ldots, 12 \quad \text{s.t.}\, CC_{t+k} = 1 \\ 2, & \text{if } \exists k = 1, \ldots, 11 \quad \text{s.t.}\, CC_{t-k} = 1 \\ 0, & \text{otherwise} \end{cases}, \tag{3}$$

Fig. 1 displays the $CMAX_t$ ratio over the sample period from January of 1997 to December of 2009. Consistent with the results in existing financial crisis literature, the $CMAX_t$ ratio fell sharply during the periods of the dot.com bubble and the recent subprime mortgage crisis. The periods shaded gray in Fig. 1 represent the two pre-crisis periods in the sample period: September of 2001 to September of 2002, and December of 2007 to December of 2008.

As a robustness check, we estimate all models using the heat map indicator introduced by the International Monetary Fund (IMF). The heat map identifies periods in which the equity market experiences high financial distress. The heat map is constructed using the heat index. The heat index measures the daily equity index return and the volatility of the 30-day moving average of equity index return relative to the mean and standard deviation of these two statistics in the previous 3-year period. The heat index takes the average of the *z*-scores of the daily equity index return and the standard deviation of the 30-day moving average of the equity index return, where large *z*-scores indicate large changes of the equity index. We use the average of daily heat indices in each month to obtain this measure at a monthly frequency.[18]

The sample period is mapped using the heat index with different colors: green (z-score ≤ 1), yellow ($1 < z$-score ≤ 2), orange ($2 < z$-score ≤ 3.5), and red (z-score > 3.5). We define the pre-crisis period ($Y_t = 1$) as a period coded consecutively in the order of yellow, orange, and red. The post-crisis period ($Y_t = 2$) starts after the last month coded in red and ends before the month turns green. Other months are considered the normal period.[19]

The predicted probabilities of the multinomial logit model are formulated as:

$$Prob(Y = k|\mathbf{x}) = \wedge(\mathbf{x}\beta') = \frac{e^{\mathbf{x}\beta'}}{1 + e^{\mathbf{x}\beta'}}, \quad k = 0, 1, \text{ and } 2, \tag{4}$$

where Y is the dependent variable, $\mathbf{x}$ is a matrix of explanatory variables, $\boldsymbol{\beta}'$ is the transpose of a row vector, $\boldsymbol{\beta}$, of parameters, $\wedge(\cdot)$ denotes the logistic cumulative distribution function, and $k = 1$ or 2 denotes a pre or post-crisis period, respectively.

We form various combinations of the explanatory variables in the multinomial logit models for S&P 500 futures (SP) and options (SPX), and examine their performance for predicting a financial crisis.[20] The followings are the specifications of the futures models 1–3:

$$\mathbf{x}\beta' = \alpha + \beta_k^{VIX}\mathbf{VIX} + \beta_k^{OI^F}\mathbf{ln}(\mathbf{OI^F}) \qquad \text{Futures model 1}$$

$$\mathbf{x}\beta' = \alpha + \beta_k^{VIX}\mathbf{VIX} + \beta_k^{\$Vol^F}\mathbf{ln}(\$\mathbf{Vol^F}) \qquad \text{Futures model 2}$$

$$\mathbf{x}\beta' = \alpha + \beta_k^{VIX}\mathbf{VIX} + \beta_k^{OI^F}\mathbf{ln}(\mathbf{OI^F}) + \beta_k^{\$Vol^F}\mathbf{ln}(\$\mathbf{Vol^F}) \qquad \text{Futures model 3}$$

where each element in matrix $\mathbf{x}$ is a Tx1 vector, the scalar explanatory variable at month t is defined in Table 1, and T in the current study is 156 months. Futures models 1–3 are augmented with the term spread (or with the addition of $\beta_k^{TSPD}\mathbf{TSPD}$) to form futures models 1.1–3.1.

The addition of the term spread (*TSPD*) to the models is motivated by the empirical evidence that financial and monetary variables, such as the yield spread between long-term and short-term government bonds and money supply growth, exhibit forecastability of equity market returns [e.g. Chen, Roll, & Ross, 1986; Herwatz & Kholodilin, 2014; Marathe & Shawky, 1994; Wongbangpo & Sharma, 2002, among others]. The growth rate of M2 is excluded in the model specifications because its estimate is not significant in futures and option models.[21]

[16] Patel and Sarkar (1998) document that at the beginning of a market crash, the equity price index falls to two standard deviations below the mean value of $CMAX_t$ for developed and Asian emerging markets. However, using the threshold value of two standard deviations below the mean of $CMAX_t$ produces too many trigger points of a financial crisis month in our sample period. To identify the trigger point of a crisis more accurately, we set the threshold value to two and half standard deviations below the mean of $CMAX_t$.

[17] If crisis months occur consecutively, we define the pre-crisis (post-crisis) period as 12 (11) months before (after) the last month of the crisis months.

[18] For details on the construction of the heat index, please refer to IMF (2009a, 2009b, 2010a, 2010b) and Bianconi, Yoshino, and De Sousa (2013).

[19] Using the heat map method, we obtain the pre-crisis periods: 2001:03–2002:10 and 2007:12–2009:03, and the post-crisis periods: 2002:11–2003:07 and 2009:04–2009:11.

[20] A combination which may result in multicollinearity because of high correlations among explanatory variables is avoided. The average daily futures price across futures contracts in a month, Prc_t^F, is not included in the model specification because it does not improve the estimation results. The difference between log of Prc_t^F (or Prc_t^O) and its lag is not included in the model specification for the same reason.

[21] Results of models estimated with the inclusion of the growth rate of M2 are available upon request.

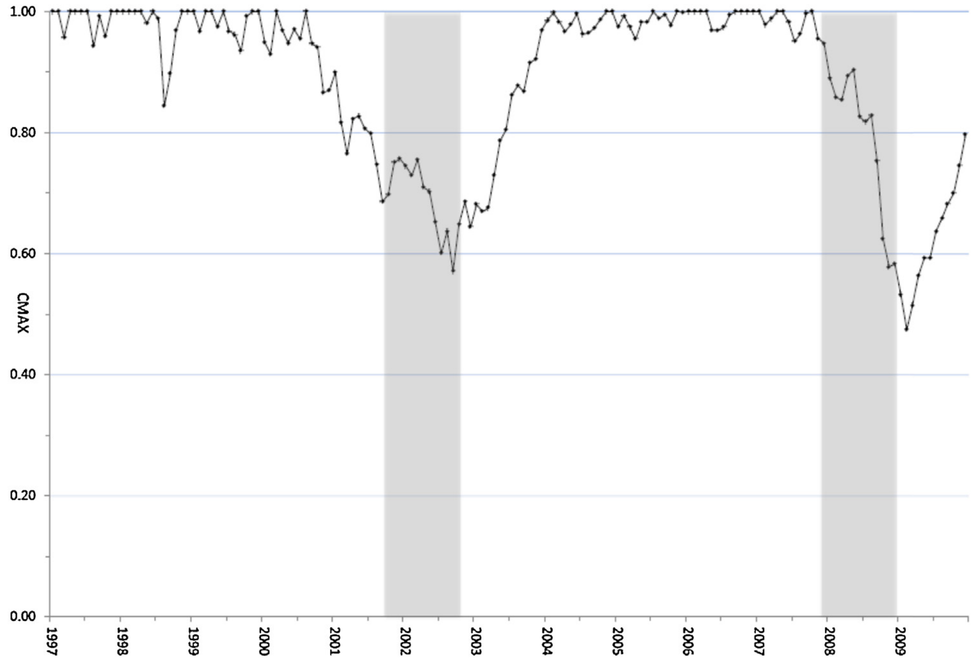

Fig. 1. The ratio of S&P 500 index levels over rolling two-year maximum levels (CMAX): 1997–2009. *Notes*: The periods shaded gray represent the pre-crisis periods: 2001:09–2002:09 and 2007:12–2008:12. The months identified as the crisis months (i.e. $CC_t = 1$) are: 2002:04–2002:09 and 2008:10–2008:12.

Option models 1–6 are specified as:

$$\mathbf{x}\beta' = \alpha + \beta_k^{VIX}\mathbf{VIX} + \beta_k^{OI^O}\mathbf{ln}(\mathbf{OI^O}) \qquad \text{Option model } 1$$

$$\mathbf{x}\beta' = \alpha + \beta_k^{VIX}\mathbf{VIX} + \beta_k^{\$Vol^O}\mathbf{ln}(\$\mathbf{Vol^O}) \qquad \text{Option model } 2$$

$$\mathbf{x}\beta' = \alpha + \beta_k^{OI^O}\mathbf{ln}(\mathbf{OI^O}) + \beta_k^{Prc^O}\boldsymbol{Prc^O} \qquad \text{Option model } 3$$

$$\mathbf{x}\beta' = \alpha + \beta_k^{\$Vol^O}\mathbf{ln}(\$\mathbf{Vol^O}) + \beta_k^{Prc^O}\boldsymbol{Prc^O} \qquad \text{Option model } 4$$

$$\mathbf{x}\beta' = \alpha + \beta_k^{OI^O}\mathbf{ln}(\mathbf{OI^O}) + \beta_k^{Esp^O}\boldsymbol{Esp^O} \qquad \text{Option model } 5$$

$$\mathbf{x}\beta' = \alpha + \beta_k^{\$Vol^O}\mathbf{ln}(\$\mathbf{Vol^O}) + \beta_k^{Esp^O}\boldsymbol{Esp^O} \qquad \text{Option model } 6$$

where each element in matrix **x** is a Tx1 vector, the scalar explanatory variable at month *t* is defined in Table 1, and T in the current study is 156 months. Identical to futures models, option models 1–6 are augmented with the term spread to form option models 1.1–6.1. Detailed variable definitions are contained in Table 1.

Prior research documents a positive relationship between implied volatility and equity market crashes [e.g. Bates, 1991; Rappoport & White, 1994; Schwert, 1990]. Therefore, the coefficient on VIX, $\beta_{k=1}^{VIX}$, is expected to be positively signed in the pre-crisis period. Existing literature does not offer a clear guidance of the relationship between a financial crisis and open interest, or volume/dollar volume. Bessembinder and Seguin (1992) report that equity volatility is negatively related to anticipated volumes and open interest, while positively related to unexpected components in futures markets. An equity market crisis is likely to be associated with higher price volatility. If the majority of the increase in the open interest or volume in options and futures is unexpected during a down market, an increase of open interest or volume will raise the chances of having a financial crisis. Thus, the coefficient on open interest or dollar volume (i.e. $\beta_{k=1}^{OI^F}$, $\beta_{k=1}^{OI^O}$, $\beta_{k=1}^{\$Vol^F}$, and $\beta_{k=1}^{\$Vol^O}$) is expected to be signed positive in the pre-crisis period. On the other hand, if an increase of open interest or dollar volume in options and futures is primarily anticipated during a market crash, the coefficient on open interest or dollar volume (i.e. $\beta_{k=1}^{OI^F}$, $\beta_{k=1}^{OI^O}$, $\beta_{k=1}^{\$Vol^F}$, and $\beta_{k=1}^{\$Vol^O}$) will be signed negative in the pre-crisis period.

Demand for a long option will pressure the price of the contract upward. In general, there is a reduction in the demand for long calls (and short puts) and an increase in demand for short calls (and long puts) during a financial crisis period. Hence, a call (put) option price tends to decline (rise) during a market downturn, which decreases (increases) the likelihood of having an equity market crisis. The coefficient on the option price, $\beta_{k=1}^{Prc^O}$, is expected to be signed negative (positive) for a call (put) option in the pre-crisis period.

Uncertainty increases and equity market liquidity decreases during times of a financial crisis. A theoretical paper by Routledge and Zin (2009) examines the relationship between model uncertainty and liquidity from a market maker's perspective. They show that liquidity crises are associated with uncertainty aversion, which limits a market maker's ability to hedge a position in derivatives. The effect of uncertainty aversion thus makes market markers raise the bid and ask prices to reduce the desirability of a derivative trade, and market liquidity declines. The theoretical argument by Routledge and Zin (2009) implies that the coefficient on the effective spread, $\beta_{k=1}^{Esp^O}$, should be signed positive in the pre-crisis period.

In a typical financial crisis, the Federal Reserve lowers the short-term interest rate to decrease the cost of short-term borrowing. This leads to an increase in the yield spread between long-term and short-term Treasuries. Due to this mechanism, we expect the coefficient on term spread ($\beta_{k=1}^{TSPD}$) to be positively signed in the pre-crisis period.

In order to evaluate the performance of the models presented above, a probability threshold must be selected. This is due to the fact that the predicted probability of a financial crisis is a continuous variable while the occurrence of a financial crisis is presented

Table 1
Variable definitions.

Variable	Definition
$CMAX_t$	A variable used to detect extreme changes of price levels over a 24-month rolling period, $CMAX_t = \frac{P_t}{\max(P_t,\ldots,P_{t-24})}$, where P_t is the S&P 500 index level in month t.
CC_t	The crisis indicator in month t, $CC_t = \begin{cases} 1 & \text{if } CMAX_t \le \overline{CMAX_t} - 2.5\rho_t \\ 0 & \text{otherwise} \end{cases}$, where ρ_t is the standard deviation of $CMAX_t$ in the sample period.
Y_t	$Y_t = \begin{cases} 1 & \text{if } \exists k = 0,\ldots,12 \text{ s.t. } CC_{t+k} = 1 \\ 2 & \text{if } \exists k = 1,\ldots,11 \text{ s.t. } CC_{t-k} = 1 \\ 0 & \text{otherwise} \end{cases}$, where Y_t = 0, 1, and 2 denotes a normal, pre-crisis, and post-crisis period, respectively.
VIX_t	The average daily CBOE S&P 500 volatility index in month t.
$\mathrm{Ln}(OI_t^F)$	Log of total open interest of S&P 500 futures contracts at the end of month t.
$\mathrm{Ln}(\$Vol_t^F)$	Log of total dollar volume of S&P futures contracts in month t. The daily dollar volume is approximated by daily futures price times daily total volume.
$\mathrm{Ln}(OI_t^O)$	Log of total open interest of S&P 500 option contracts at the end of month t.
$\mathrm{Ln}(\$Vol_t^O)$	Log of total dollar volume of S&P 500 option contracts in month t. The daily dollar volume is approximated by daily closing option price times daily total volume.
Prc_t^O	The average daily closing price of S&P 500 option contracts in month t.
Esp_t^O	The average daily effective spread of S&P 500 option contracts in month t, $esp_t^O = \left[\sum_{d=1}^{D} 2 \times \lvert prc_{j,d,t}^O - ((ask_{j,d,t}^O + bid_{j,d,t}^O)/2)\rvert\right]/D$, where $prc_{j,d,t}^O$ is the closing price of S&P 500 option contract j in day d of month t, $ask_{j,d,t}^O$ and $bid_{j,d,t}^O$ are last asked and bid prices of option contract j in day d of month t, and D is the total number of valid trading days in month t.
$TSPD_t$	The average daily term spread (in percent) in month t = 10-Year Treasury Constant Maturity Rate – 3-Month Treasury Bill Rate.

by a discrete value in the dependent variable. Following existing literature, a 20% probability threshold is selected.[22] The model predicts a crisis if the estimated probability is above the threshold value in each month. We compute the following conditional probabilities to evaluate goodness of fit of models: the percentage of observations correctly called, the percentage of pre-crisis periods correctly called, the percentage of false alarms of total alarms, the percentage of probabilities of crisis given an alarm, and the percentage of probabilities of crisis given no alarm.[23] Table 8 presents conditional probabilities for each model.

Following Coudert and Gex (2008), the present study conducts in-sample tests, rather than out-of-sample test, to evaluate the performance of models because the sample size is small. Inoue and Kilian (2005) document that out-of-sample analysis based on sample-splitting results in loss of information and lowers their reliablity in small samples. Kilian and Taylor (2003) also show that out-of-sample tests in small samples have considerably lower power than in-sample tests. We compute two statistics to analyze the accuracy of predicted probabilities with the actual occurrence of the crises: the quadratic probability score (QPS) and the log probability score (LPS).[24] The results of in-sample performance for all models are presented in Table 8.

Quadratic probability score is calculated as follows:

$$QPS = 1/T\sum_{t=1}^{T} 2(Pr_t - R_t)^2 \quad (5)$$

where Pr_t is the estimated probability of pre-crisis periods, R_t is set to 1 for pre-crisis periods, and set to zero otherwise. Quadratic probability score (QPS) ranges from 0 to 2, with a zero for a perfect forecast.

Log probability score is calculated as follows:

$$LPS = -1/T\sum_{t=1}^{T} [(1 - R_t)\ln(1 - Pr_t) + R_t \ln(Pr_t)] \quad (6)$$

Log probability score (LPS) ranges from 0 to infinity, with a zero for a perfect forecast.

4. Empirical results

The empirical evidence of this research is presented in the following manner: Section 4.1 briefly describes the data; Section 4.2 presents the main results of futures models 1–3 and option models 1–6, in Section 4.3 we estimate all models with the inclusion of term spread, and Section 4.4 presents the performance characteristics of selected EWS models.

[22] The 20% probability threshold is used in Bussiere and Fratzscher (2006), and Coudert and Gex (2008).

[23] To form the conditional probabilities, we compare months predicted as the normal, pre, or post-crisis period (Y_t = 0, 1, or 2) with the months that are actually normal, pre, or post-crisis period. Following Bussiere and Fratzscher (2006), we define these conditional probabilities as follows: *the percentage of observations correctly called* is equal to the number of observations in the normal and pre-crisis periods correctly predicted divided by the total number of observations in normal and pre-crisis periods; *the percentage of pre-crisis periods correctly called* is equal to the number of observations in pre-crisis period correctly predicted divided by the number of observations in the pre-crisis period; *the percentage of false alarms of total alarms* is equal to the number of observations in the normal period incorrectly predicted as a pre-crisis period divided by the number of observations in normal and pre-crisis periods predicted as a pre-crisis period; *the percentage of probabilities of crisis given an alarm* is equal to the number of observations in the pre-crisis period correctly predicted divided by the number of observations in the normal and pre-crisis periods predicted as a pre-crisis period; *the percentage of probabilities of crisis given no alarm* is equal to the number of observations in the pre-crisis period wrongly predicted as the normal period divided by the number of observations in normal and pre-crisis periods predicted as a normal period.

[24] The quadratic probability score (QPS) and log probability score (LPS) are commonly employed in several recent studies [e.g., Chen, 2009; Kaminsky, 2000; Kumar et al., 2003].

Table 2
Mean values and comparisons of mean values for key variables.

	Normal periods	Pre-crisis periods	Post-crisis periods	Normal vs. pre-crisis periods		Normal vs. post-crisis periods	
	Mean (1)	Mean (2)	Mean (3)	Mean difference (1) – (2)	t-stat	Mean difference (1) – (3)	t-stat
VIX_t	19.569 (5.883)	29.757 (12.370)	29.491 (7.298)	−10.188***	−4.091	−9.922***	−5.873
$\mathrm{Ln}(OI_t^F)$	13.074 (0.372)	13.223 (0.077)	13.132 (0.233)	−0.148***	−3.834	−0.058	−0.932
$\mathrm{Ln}(\$Vol_t^F)$	21.287 (0.500)	21.151 (0.465)	20.694 (0.695)	0.135	1.315	0.593***	3.727
$\mathrm{Ln}(OI_t^O)$	14.540 (0.690)	14.880 (1.005)	15.075 (0.789)	−0.340	−1.635	−0.535***	−2.901
$\mathrm{Ln}(\$Vol_t^O)$	17.956 (0.603)	18.723 (1.222)	18.740 (0.791)	−0.767***	−3.110	−0.784***	−4.309
Prc_t^O	37.367 (10.136)	50.424 (13.012)	45.038 (8.693)	−13.057***	−4.782	−7.670***	−3.599
Esp_t^O	3.082 (1.459)	5.069 (3.135)	2.911 (0.926)	−1.987***	−3.151	0.170	0.693
$TSPD_t$	1.049 (1.060)	2.595 (0.701)	2.926 (0.385)	−1.546***	−7.063	−1.877***	−8.175
NOB	109	26	21				

Notes: Please refer to Table 1 for variable definitions. The sample period covers from 1997:01 to 2009:12, which includes 109 normal months, 26 pre-crisis months, and 21 post-crisis months. Standard deviations are reported in parentheses.
*** Significant at 1%.

Table 3
Correlation matrix of key variables.

	Y_t	VIX_t	$\mathrm{Ln}(OI_t^F)$	$\mathrm{Ln}(\$Vol_t^F)$	$\mathrm{Ln}(OI_t^O)$	$\mathrm{Ln}(\$Vol_t^O)$	Prc_t^O	Esp_t^O	$TSPD_t$
Y_t	1								
VIX_t	0.474***	1							
$\mathrm{Ln}(OI_t^F)$	0.155*	−0.167**	1						
$\mathrm{Ln}(\$Vol_t^F)$	−0.377***	0.025	−0.187**	1					
$\mathrm{Ln}(OI_t^O)$	0.259***	−0.004	0.458***	−0.514***	1				
$\mathrm{Ln}(\$Vol_t^O)$	0.389***	0.392***	0.286***	−0.266***	0.851***	1			
Prc_t^O	0.322***	0.809***	−0.014	0.317***	−0.205***	0.247***	1		
Esp_t^O	0.106	0.748***	−0.068	0.234***	−0.046	0.334***	0.808***	1	
$TSPD_t$	0.622***	0.281***	0.089	−0.345***	0.057	0.104	0.155*	0.010	1

Notes: This table reports Pearson correlation coefficients of key variables. Please refer to Table 1 for variable definitions. The sample period covers from 1997:01 to 2009:12.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

4.1. Summary statistics

Table 2 reports the mean values and standard deviations of key variables used in this study. Statistics are presented separately for three segmented periods (i.e. normal, pre-crisis, and post-crisis periods) from 1997 to 2009.

As the world has witnessed over the past two decades, equity markets are characterized by increased levels of volatility in periods surrounding financial crises. Our data confirm the statistically significant difference in the mean value of the VIX between normal and pre/post-crisis periods. In normal months the average VIX is 19.6%, whereas the VIX spikes to 29.8% and 29.5% for pre and post-crisis periods, respectively. Examination of variables related to the S&P 500 futures and options reveals significant differences in the behavior of selected variables surrounding financial crisis months. We document that the mean of futures open interest is statistically higher during the pre-crisis period, while the mean open interest of options is statistically higher in the post-crisis period.

The average futures dollar volume is statistically lower in the post-crisis period than that in the normal period. Different from the reported futures dollar volume, the mean value of options dollar volume is statistically higher during the pre/post-crisis period than that in the normal period.[25] The different patterns of dollar volume in futures and options markets indicate that on average there is less (more) trading of futures (options) contracts in the pre/post-crisis period than that in the normal period. A possible explanation for higher dollar value of options trading volume surrounding times of market turmoil is associated higher equity price volatility. The higher equity price volatility makes options more valuable, consequently inducing more options trading. Futures traders may switch to trade options during times of a financial crisis.

Table 2 also reports the mean value of the average daily closing price and the effective spread for S&P 500 options. It is noted that the average daily option price is significantly higher in pre and post-crisis months. Since option prices are positively associated with volatility, our data confirm that the option prices increase in

[25] The total volume of futures/options is examined, and its results are similar to those of total dollar volume. To conserve space, this paper does not report the statistics of total volume and its estimates in the multinomial models. These statistics and estimates are available upon request.

Table 4
Estimation results of multinomial logit models: S&P 500 futures.

Dependent variable	Futures model 1		Futures model 2		Futures model 3	
	Y_{CMAX} Estimate	$Y_{Heat\ Map}$ Estimate	Y_{CMAX} Estimate	$Y_{Heat\ Map}$ Estimate	Y_{CMAX} Estimate	$Y_{Heat\ Map}$ Estimate
Pre-crisis period						
Constant	−80.531[a]	−78.227[a]	28.801[b]	21.549[c]	−63.389[b]	−60.718[b]
	(−6.083)	(−7.160)	(0.838)	(0.856)	(−6.592)	(−7.014)
VIX_t	0.267[a]	0.298[a]	0.274[a]	0.276[a]	0.328[a]	0.336[a]
	(0.017)	(0.025)	(0.021)	(0.027)	(0.020)	(0.027)
Ln(OI_t^F)	5.549[a]	5.354[a]			5.708[a]	5.203[a]
	(0.425)	(0.496)			(0.433)	(0.480)
Ln($\$Vol_t^F$)			−1.721[b]	−1.364[b]	−0.973	−0.771
			(−0.066)	(−0.073)	(0.017)	(0.001)
Post-crisis period						
Constant	−60.392[a]	−53.502[a]	68.597[a]	56.443[a]	12.931	8.508
	(−2.673)	(−1.684)	(4.499)	(3.474)	(3.254)	(2.672)
VIX_t	0.261[a]	0.257[a]	0.272[a]	0.236[a]	0.322[a]	0.292[a]
	(0.015)	(0.011)	(0.012)	(0.008)	(0.013)	(0.010)
Ln(OI_t^F)	4.022[a]	3.508[b]			3.340[c]	2.829[c]
	(0.170)	(0.101)			(0.055)	(0.027)
Ln($\$Vol_t^F$)			−3.627[a]	−3.014[a]	−3.120[a]	−2.558[a]
			(−0.231)	(−0.178)	(−0.207)	(−0.158)
LOGL	−93.773	−95.065	−86.953	−92.976	−77.799	−83.467
Pseudo R^2	0.414	0.438	0.483	0.459	0.570	0.550
NOB	156	156	156	156	156	156

Notes: Please refer to Table 1 for variable definitions. The sample period covers from 1997:01 to 2009:12. The predicted probabilities of the multinomial logit model are: $Prob(Y = k|\mathbf{x}) = \wedge(\mathbf{x}\beta') = e^{\mathbf{x}\beta'}/(1 + e^{\mathbf{x}\beta'})$, $k = 0$, 1 and 2, where Y is the dependent variable, $\mathbf{x}$ is a matrix of explanatory variables, $\boldsymbol{\beta}'$ is the transpose of a row vector, $\boldsymbol{\beta}$, of parameters, $\wedge(\cdot)$ denotes the logistic cumulative distribution function, and $k = 1$ or 2 denotes a pre or post-crisis period, respectively. The dependent variable is translated from the CMAX or the heat map crisis indicator. Marginal effects are reported in parentheses. The superscripts, a, b, and c, denote significance at 1%, 5%, and 10% level, respectively. LOGL denotes the log of likelihood function.

Table 5
Estimation results of multinomial logit models: S&P 500 put options.

Dependent variable	Option model 1		Option model 2		Option model 3		Option model 4		Option model 5		Option model 6	
	Y_{CMAX} Estimate	$Y_{Heat\ Map}$ Estimate	Y_{CMAX} Estimate	$Y_{Heat\ Map}$ Estimate	Y_{CMAX} Estimate	$Y_{Heat\ Map}$ Estimate	Y_{CMAX} Estimate	$Y_{Heat\ Map}$ Estimate	Y_{CMAX} Estimate	$Y_{Heat\ Map}$ Estimate	Y_{CMAX} Estimate	$Y_{Heat\ Map}$ Estimate
Pre-crisis period												
Constant	−20.013[a]	−13.754[a]	−24.092[a]	−18.734[a]	−28.190[a]	−27.336[a]	−25.544[a]	−23.483[a]	−13.265[a]	−8.796[b]	−18.213[a]	−13.985[a]
	(−1.329)	(−1.102)	(−1.813)	(−1.734)	(−1.466)	(−1.507)	(−1.467)	(−1.429)	(−1.037)	(−0.882)	(−1.279)	(−1.302)
VIX_t	0.229[a]	0.239[a]	0.172[a]	0.201[a]								
	(0.017)	(0.024)	(0.011)	(0.020)								
Ln(OI_t^O)	0.936[a]	0.505[c]			1.506[a]	1.344[a]			0.670[b]	0.362		
	(0.060)	(0.032)			(0.075)	(0.070)			(0.049)	(0.033)		
Ln($\$Vol_t^O$)			1.059[a]	0.739[a]			1.146[a]	0.945[a]			0.854[a]	0.609[b]
			(0.082)	(0.069)			(0.064)	(0.055)			(0.056)	(0.053)
Prc_t^O					0.136[a]	0.189[a]	0.099[a]	0.150[a]				
					(0.008)	(0.012)	(0.006)	(0.011)				
Esp_t^O									0.645[a]	0.750[a]	0.476[a]	0.637[a]
									(0.062)	(0.091)	(0.050)	(0.081)
Post-crisis period												
Constant	−22.758[a]	−19.296[a]	−20.514[a]	−17.980[a]	−27.559[a]	−27.175[a]	−23.227[a]	−21.581[a]	−14.323[a]	−11.003[b]	−22.789[a]	−19.735[a]
	(−1.473)	(−1.208)	(−1.131)	(−0.912)	(−1.694)	(−1.364)	(−1.458)	(−1.098)	(−1.365)	(−0.880)	(−2.031)	(−1.501)
VIX_t	0.225[a]	0.198[a]	0.180[a]	0.167[a]								
	(0.013)	(0.009)	(0.012)	(0.007)								
Ln(OI_t^O)	1.123[a]	0.918[a]			1.538[a]	1.449[a]			0.854[a]	0.645[c]		
	(0.075)	(0.063)			(0.097)	(0.077)			(0.084)	(0.054)		
Ln($\$Vol_t^O$)			0.839[a]	0.709[b]			1.079[a]	0.939[a]			1.214[a]	1.055[a]
			(0.043)	(0.036)			(0.069)	(0.051)			(0.111)	(0.083)
Prc_t^O					0.112[a]	0.139[a]	0.074[a]	0.098[a]				
					(0.006)	(0.005)	(0.004)	(0.003)				
Esp_t^O									0.182	−0.017	−0.081	−0.256
									(0.007)	(−0.014)	(−0.021)	(−0.035)
LOGL	−98.121	−102.906	−97.666	−102.224	−88.375	−81.544	−91.473	−84.624	−108.919	−108.640	−103.499	−104.395
Pseudo R^2	0.368	0.357	0.373	0.364	0.469	0.568	0.437	0.539	0.249	0.294	0.310	0.341
NOB	156	156	156	156	156	156	156	156	156	156	156	156

Notes: Please refer to Table 1 for variable definitions. The sample period covers from 1997:01 to 2009:12. The predicted probabilities of the multinomial logit model are: $Prob(Y = k|\mathbf{x}) = \wedge(\mathbf{x}\beta') = e^{\mathbf{x}\beta'}/(1 + e^{\mathbf{x}\beta'})$, $k = 0$, 1 and 2, where Y is the dependent variable, $\mathbf{x}$ is a matrix of explanatory variables, $\boldsymbol{\beta}'$ is the transpose of a row vector, $\boldsymbol{\beta}$, of parameters, $\wedge(\cdot)$ denotes the logistic cumulative distribution function, and $k = 1$ or 2 denotes a pre or post-crisis period, respectively. The dependent variable is translated from the CMAX or the heat map crisis indicator. Marginal effects are reported in parentheses. The superscripts, a, b, and c, denote significance at 1%, 5%, and 10% level, respectively. LOGL denotes the log of likelihood function.

periods characterized by spikes in volatility, consistent with the prediction by standard option pricing theories. In addition, the mean effective spread on S&P 500 options widens in the pre-crisis period. The summary statistics demonstrate that variables relating to the information content of S&P 500 futures and options are often dissimilar surrounding times of market turmoil when compared to relatively normal periods. It is one of the objectives of this research to use these differences to develop EWS models of impending market downturns.

Table 3 presents the correlations of key variables used in this study. Examination of the correlations between the discrete dependent variable (Y_t) and selected explanatory variables reveals a positive significant correlation with the VIX. This indicates that higher volatilities are associated with periods outside of normal. One interesting result is the contrast in the correlations between dollar volume and the discrete dependent variable (Y_t) in futures and options markets. The correlation between dollar value of volume and the discrete dependent variable (Y_t) is negative in the futures market, but is positive in the options market, both statistically significant. We also observe a statistically negative correlation of dollar volume between options and futures markets. These findings may indicate that investors, when anticipating a period outside of normal, increase (decrease) their trading in options (futures) markets.[26]

Finally worth noting is the statistically positive correlation between the VIX, effective spread, and option price. Routledge and Zin (2009) argue that because of the uncertainty aversion effect during a financial crisis, market makers raise spreads to reduce derivative trading. Our data appear to confirm this theory.

4.2. Empirical results: S&P 500 futures and option models

Tables 4 and 5 concisely summarize the estimation results from three and six multinomial logit models for S&P 500 futures and option models, respectively.[27] One of the attractive features of a multinomial logit model is that the model not only provides an EWS of a potential financial crisis, but also provides clues as to when a market may be returning to normal. For example, an exceptionally high VIX may signal the potential for a financial crisis, but in the post-crisis period a declining VIX may signal the return to a normal market period. For this reason, coefficient estimates and marginal impacts are reported separately for pre and post-crisis months. The first column for each model presents the results when a financial crisis month is defined using the CMAX ratio and the second column summarizes the results when a financial crisis month is defined using the IMF heat map methodology as a robustness check. We discuss the results in the first column for each model first.

Model 1 for futures and put options includes the VIX and the log of open interest as independent variables. Giot (2005) shows that the VIX has superior predictive power on future market returns. In addition, Bessembinder et al. (1996) document that open interest of futures contracts is positively related to increase in information flow between markets. We find that both variables positively forecast the likelihood of entering into a pre-crisis or post-crisis period. Estimates for futures and option model 1 show a strong

Table 6
Estimation results of multinomial logit models: S&P 500 futures with the term spread.

	Futures model 1.1 Dependent variable: Y_{CMAX}	Futures model 2.1	Futures model 3.1
	Estimate	Estimate	Estimate
Pre-crisis period			
Constant	−116.891[a]	−7.157	−117.999[a]
	(−5.954)	(−2.110)	(−7.067)
VIX_t	0.473[a]	0.372[a]	0.482[a]
	(0.017)	(0.016)	(0.018)
$\mathrm{Ln}(OI_t^F)$	7.653[a]		7.622[a]
	(0.418)		(0.349)
$\mathrm{Ln}(\$Vol_t^F)$		−0.327	0.054
		(0.074)	(0.091)
$TSPD_t$	1.962[a]	2.041[a]	1.984[a]
	(0.029)	(0.080)	(0.060)
Post-crisis period			
Constant	−86.681[b]	33.339[a]	−54.555
	(−0.474)	(2.645)	(1.551)
VIX_t	0.481[a]	0.366[a]	0.476[a]
	(0.013)	(0.009)	(0.011)
$\mathrm{Ln}(OI_t^F)$	5.177[b]		5.911[b]
	(−0.010)		(0.064)
$\mathrm{Ln}(\$Vol_t^F)$		−2.276[b]	−1.925[b]
		(−0.144)	(−0.135)
$TSPD_t$	2.690[a]	2.165[a]	2.222[a]
	(0.110)	(0.060)	(0.064)
LOGL	−61.304	−60.838	−55.586
Pseudo R^2	0.710	0.714	0.754
NOB	156	156	156

Notes: Please refer to Table 1 for variable definitions. The sample period covers from 1997:01 to 2009:12. The predicted probabilities of the multinomial logit model are: $Prob(Y = k|\mathbf{x}) = \wedge(\mathbf{x}\boldsymbol{\beta}') = e^{\mathbf{x}\boldsymbol{\beta}'}/(1 + e^{\mathbf{x}\boldsymbol{\beta}'})$, k = 0, 1 and 2, where Y is the dependent variable, $\mathbf{x}$ is a matrix of explanatory variables, $\boldsymbol{\beta}'$ is the transpose of a row vector, $\boldsymbol{\beta}$, of parameters, $\wedge(\cdot)$ denotes the logistic cumulative distribution function, and k = 1 or 2 denotes a pre or post-crisis period, respectively. The dependent variable is translated from the CMAX or the heat map crisis indicator. Marginal effects are reported in parentheses. The superscripts, a, b, and c, denote significance at 1%, 5%, and 10% level, respectively. LOGL denotes the log of likelihood function.

positive marginal impact of open interest in the pre-crisis period. This indicates that spikes in the number of futures/option contracts outstanding are indicative of an increased probability of entering into a pre-crisis period. The marginal impact of the VIX is relatively stable in all segmented periods for both futures and option models. For example in futures model 1, a 1% increase in the VIX increases the probability of entering a pre-crisis (post-crisis) period by 1.7% (1.5%).

Existing literature shows that increases in volume are generally related to greater information flows. Model 2 for futures and put options investigates whether an increase in dollar volume of futures/option contracts improves information dissemination and therefore functions as a leading indicator of financial turmoil beyond the information contained in the VIX. In futures model 2, we find that a 1% increase in contract dollar volume marginally impacts the probability of a pre-crisis period by −6.6%. For the post-crisis period, the impact of the dollar volume of futures contracts remains statistically significant and is even greater than that in the pre-crisis period. The results provide key insights about the nature of trading in futures surrounding financial crises. Consider the futures market to be made up of two sets of players, hedgers and speculators. In times of financial uncertainty, hedgers will take the short position and increase the number of contracts initiated. Therefore, we should see an increase in open interest. Speculators, on the other hand, will time the market, wait for the market to rebound, and thus reduce the volume of trades in times of financial uncertainty. So while the number of contracts outstanding increases during times

[26] Open interest and dollar value of volume in the options market are highly correlated. Due to the strong positive correlation between open interest and dollar volume in the options market, option open interest and dollar volume are not simultaneously included in a given model specification.

[27] Due to the large number of results, only the major findings are presented in the current paper. To conserve space, we do not report the results for OTM put options because they are similar to those for put options. All option models were also estimated with call options and all options. A complete discussion of results is available upon request.

Table 7
Estimation results of multinomial logit models: S&P 500 put options with the term spread.

	Option model 1.1 Dependent variable: Y_{CMAX}	Option model 2.1	Option model 3.1	Option model 4.1	Option model 5.1	Option model 6.1
	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Pre-crisis period						
Constant	−40.123[a]	−45.574[a]	−41.055[a]	−43.028[a]	−27.233[a]	−31.895[a]
	(−1.098)	(−1.465)	(−0.986)	(−1.074)	(−0.803)	(−0.781)
VIX_t	0.422[a]	0.349[a]				
	(0.014)	(0.010)				
$\mathrm{Ln}(OI_t^O)$	1.709[a]		1.987[a]		1.048[b]	
	(0.048)		(0.048)		(0.022)	
$\mathrm{Ln}(\$Vol_t^O)$		1.762[a]		1.785[a]		1.176[a]
		(0.066)		(0.045)		(0.020)
Prc_t^O			0.183[a]	0.140[a]		
			(0.006)	(0.005)		
Esp_t^O					1.571[a]	1.271[a]
					(0.076)	(0.068)
$TSPD_t$	2.379[a]	2.492[a]	1.989[a]	2.156[a]	2.697[a]	2.609[a]
	(0.039)	(0.036)	(0.023)	(0.027)	(0.091)	(0.081)
Post-crisis period						
Constant	−45.130[a]	−44.938[a]	−43.662[a]	−44.225[a]	−30.067[a]	−38.279[a]
	(−1.331)	(−0.974)	(−1.348)	(−1.295)	(−1.288)	(−1.595)
VIX_t	0.426[a]	0.365[a]				
	(0.010)	(0.009)				
$\mathrm{Ln}(OI_t^O)$	1.895[a]		2.116[a]		1.370[a]	
	(0.055)		(0.065)		(0.067)	
$\mathrm{Ln}(\$Vol_t^O)$		1.585[a]		1.822[a]		1.628[a]
		(0.025)		(0.053)		(0.076)
Prc_t^O			0.163[a]	0.119[a]		
			(0.003)	(0.002)		
Esp_t^O					1.042[a]	0.669[c]
					(0.018)	(−0.003)
$TSPD_t$	3.110[a]	3.191[a]	2.565[a]	2.690[a]	2.703[a]	2.729[a]
	(0.115)	(0.114)	(0.103)	(0.105)	(0.105)	(0.099)
LOGL	−60.509	−58.700	−58.566	−58.262	−62.544	−59.918
Pseudo R^2	0.717	0.731	0.732	0.734	0.701	0.721
NOB	156	156	156	156	156	156

Notes: Please refer to Table 1 for variable definitions. The sample period covers from 1997:01 to 2009:12. The predicted probabilities of the multinomial logit model are: $Prob(Y = k|\mathbf{x}) = \wedge(\mathbf{x}\boldsymbol{\beta}') = e^{\mathbf{x}\boldsymbol{\beta}'}/(1 + e^{\mathbf{x}\boldsymbol{\beta}'})$, k = 0, 1 and 2, where Y is the dependent variable, $\mathbf{x}$ is a matrix of explanatory variables, $\boldsymbol{\beta}'$ is the transpose of a row vector, $\boldsymbol{\beta}$, of parameters, $\wedge(\cdot)$ denotes the logistic cumulative distribution function, and k = 1 or 2 denotes a pre or post-crisis period, respectively. The dependent variable is translated from the CMAX or the heat map crisis indicator. Marginal effects are reported in parentheses. The superscripts, a, b, and c, denote significance at 1%, 5%, and 10% level, respectively. LOGL denotes the log of likelihood function.

of financial crisis, the trading of futures contracts is reduced. When markets are returning to normal, speculators return to the market and trading volume increases.

Results for option model 2 demonstrate that dollar volume positively impacts the probability of entering into a pre or post-crisis period. For example, a 1% increase in the dollar volume is associated with an 8.2% (4.3%) increase in the probability of entering into a pre-crisis (post-crisis) period. In option model 3, the average daily closing price of put options is included along with the log of open interest. It is noted that due to the high correlation between the VIX and average daily option price (0.809), the VIX is excluded from models containing average daily option prices to avoid problems of multicollinearity.[28] As expected, an increase in the prices of put options signals an increase in the probability of entering a pre or post-crisis period. It is observed that the marginal impact of the average option price is much lower than that of other variables tested to this point.

Option model 4 is estimated with inclusion of log of dollar volume and the average of put option price. We report that higher dollar volume increases the probability of entering a pre or post-crisis period. The results are very economically significant, where a 1% increase in dollar volume increases the probability of entering a pre-crisis period by 6.4%. The estimates of the marginal contribution of option prices remain stable and similar to model 3.

In option models 5 and 6, we repeat the estimations of models 3 and 4, substituting the effective spread for the put option price. In model 5, our results show that if the effective spread is raised by $1, the probability of entering into a pre-crisis period will increase by 6.2%. However, the signaling ability of effective spread is limited to the pre-crisis period as its parameter estimate is insignificant in the post-crisis period. Our finding of the positive significant impact of effective spread on the prediction of a pre-crisis period is consistent with a recent theoretical paper by Routledge and Zin (2009) that in times of lower liquidity, market makers increase their spread.

Prior to formal assessment of model performance, we test the robustness of parameter estimates to an alternative definition of a financial crisis. The second column for each model in Tables 4 and 5 contains the estimates for futures and put options models when the heat map method is used to define a crisis. A careful comparison of the parameter estimates in the first and second columns for each model in Tables 4 and 5 reveals that parameter estimations remain stable and significant under both methods to identify a crisis.

[28] Futures model 3 includes the VIX, log of open interest, and log of dollar volume as explanatory variables. The results are similar to futures models 1 and 2, but the coefficient on log of dollar volume is insignificant in the pre-crisis period.

Table 8
In-sample performance of multinomial logit models for S&P 500 futures, put options, and the term spread.

Panel A. S&P 500 futures

Futures model	% of observations correctly called	% of pre-crisis periods correctly called	% of false alarms of total alarms	% probabilities of crisis given an alarm	% probabilities of crisis given no alarm	QPS	LPS
1	82.836%	57.692%	44.444%	55.556%	10.280%	0.2304	0.3583
2	78.358%	57.692%	54.546%	45.455%	10.891%	0.2426	0.3855
3	82.836%	57.692%	44.444%	55.556%	10.280%	0.2250	0.3499

Panel B. S&P 500 put options

Option model	% of observations correctly called	% of pre-crisis periods correctly called	% of false alarms of total alarms	% probabilities of crisis given an alarm	% probabilities of crisis given no alarm	QPS	LPS
1	83.582%	65.385%	43.333%	56.667%	8.654%	0.2407	0.3860
2	85.075%	69.231%	40.000%	60.000%	7.692%	0.2293	0.3703
3	87.313%	69.231%	33.333%	66.667%	7.477%	0.2041	0.3227
4	85.821%	65.385%	37.037%	62.963%	8.411%	0.2025	0.3181
5	79.851%	53.846%	51.724%	48.276%	11.429%	0.2107	0.3470
6	81.343%	57.692%	48.276%	51.724%	10.476%	0.2084	0.3429

Panel C. S&P 500 futures with the term spread

Futures model	% of observations correctly called	% of pre-crisis periods correctly called	% of false alarms of total alarms	% probabilities of crisis given an alarm	% probabilities of crisis given no alarm	QPS	LPS
1.1	88.806%	84.615%	33.333%	66.667%	3.960%	0.2098	0.3132
2.1	87.313%	73.077%	34.483%	65.517%	6.667%	0.1838	0.2921
3.1	89.552%	80.769%	30.000%	70.000%	4.808%	0.1803	0.2797

Panel D. S&P 500 put options with the term spread

Option model	% of observations correctly called	% of pre-crisis periods correctly called	% of false alarms of total alarms	% probabilities of crisis given an alarm	% probabilities of crisis given no alarm	QPS	LPS
1.1	91.045%	92.308%	29.412%	70.588%	2.000%	0.1879	0.2746
2.1	92.537%	96.154%	26.471%	73.529%	1.000%	0.1825	0.2655
3.1	93.284%	88.462%	20.690%	79.310%	2.857%	0.1762	0.2628
4.1	94.776%	92.308%	17.241%	82.759%	1.905%	0.1734	0.2568
5.1	92.537%	84.615%	21.429%	78.571%	3.774%	0.1452	0.2297
6.1	92.537%	84.615%	21.429%	78.571%	3.774%	0.1419	0.2218

Notes: The sample period covers from 1997:01 to 2009:12. The multinomial logit models use the dependent variable that is translated from the CMAX crisis indicator. Two statistics are used to evaluate the in-sample performance: quadratic probability score (QPS) and log probability score (LPS). Quadratic probability score (QPS) = $1/T\sum_{t=1}^{T}2(Pr_t - R_t)^2$, where Pr_t is the estimated probability of pre-crisis periods, R_t is set to 1 for pre-crisis periods, and set to zero otherwise. Quadratic probability score (QPS) ranges from 0 to 2, with a zero for a perfect forecast. Log probability score (LPS) = $-1/T\sum_{t=1}^{T}[(1-R_t)\ln(1-Pr_t) + R_t \ln(Pr_t)]$. Log probability score (LPS) ranges from 0 to infinity, with a zero for a perfect forecast.

4.3. Empirical results: S&P 500 futures/options with the term spread

The frequency of our index derivative data allows for the inclusion of Treasury term spread within the selected empirical framework. Table 6 reports the results for futures models with the inclusion of Treasury term spread. In all three models the parameters on variables relating to S&P 500 futures remain similar to the original estimates, demonstrating the importance of these variables in the development of EWS models. In all models the coefficient on term spread is significant, consistently signed and positive in both the pre and post-crisis periods. For example in model 3.1, a 1% larger spread increases the probability of entering a pre (post) crisis period by 6% (6.4%).

Table 7 reports the estimates for all put options models with the inclusion of term spread. In all option models, an increase in term spread positively and consistently increases the probability of entering a pre or post-crisis period. Similar to futures models estimated with term spread, the inclusion of this financial variable does not significantly change the significance or marginal impacts of the variables relating to S&P 500 options on the prediction of a financial crisis.

Overall, our results demonstrate a strong role for variables relating to the information content of S&P 500 futures and option markets as signals of a financial crisis. The parameter estimates as well as marginal impacts are stable when the term spread is included.

4.4. Assessing the performance of the models

Table 8 presents the conditional probabilities of a crisis (i.e. $Y_t = 1$) within one year and the in-sample performance statistics. We consider an alarm to be issued when the estimated probability of a crisis is above the threshold level of 20%. The estimated futures and put options models correctly indentify most observations. Spefically, 78.4–82.8% and 79.9–87.3% of months are correctly called in models estimated for futures and put options, respectively. It is noted that 57.7% of crisis months are correctly indentified by futures models, and between 53.8% and 69.2% of crises are correctly identified in put options models. With the 20% cut-off, 44.4–54.6% of alarms are false for futures models and 33.3–51.7% for put options models. Although the fitting characteristics of these models are good for observations and crisis months correctly called, we must be aware of incorrectly identifying too many crises as this may undermine the confidence in an EWS.

Alternatively, we are interested in knowing how frequently an alarm is actually followed by a crisis within 12 months. If an alarm is issued by futures models, the probability of a crisis actually

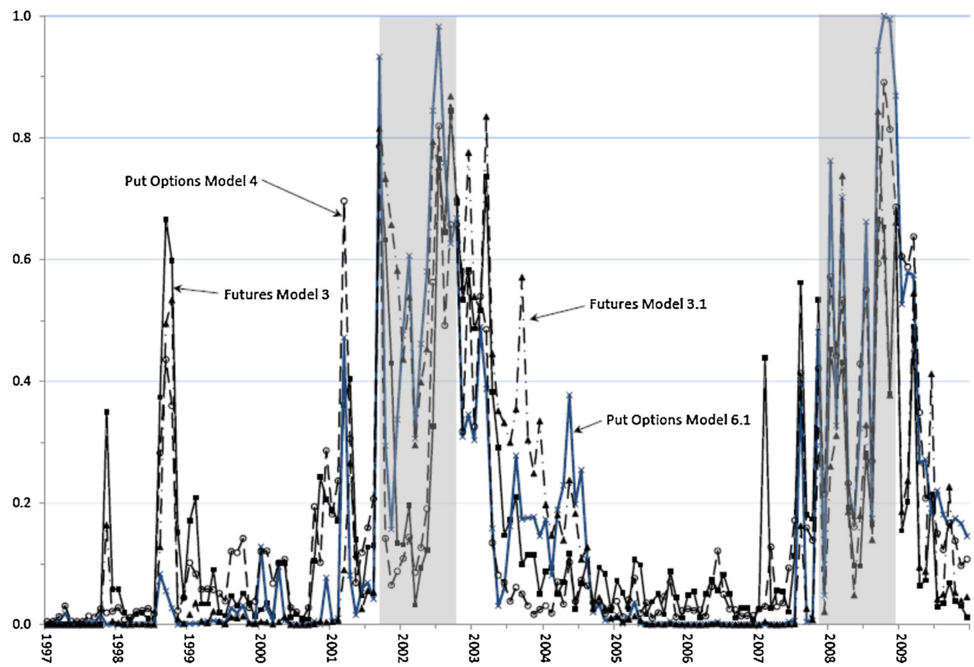

Fig. 2. In-sample predicted probabilities of futures and put options with the term spread for $Y_t = 1$. *Notes*: The periods shaded gray represent the pre-crisis periods: 2001:09–2002:09 and 2007:12–2008:12.

occuring within 12 months is between 45.5% and 55.6%. For option models, this probability is between 48.3% and 66.7%.[29] However, this is much better than the unconditional probability of a crisis of 16.7% in the sample period. If no alarm is issued, the likelihood that a crisis actually occurs is 10.3–10.9% for futures models and 7.5–11.4% for option model.[30]

Evaluation of in-sample performance of futures and option models is conducted by comparing the quadratic probability score (QPS) and the log probability score (LPS). For futures models, we find that the lowest value of QPS and LPS is reported for futures model 3, which includes the VIX, log of open interest, and log of dollar volume.

Among the six option models, model 4 performs the best as it reports the lowest value of QPS and LPS.[31] This model includes log of dollar volume and average daily put option price. Inspection of the conditional probabilities of this option model shows that 85.9% of observations are correctly identified and 65.4% of crisis months are called correctly. When an alarm is issued, there is a 63% probability that a pre-crisis period will follow and a 37% probability that the alarm will be false. Additionally, if no alarm is given, there is a 8.4% probability that a pre-crisis period will follow. We note that the performance of put option model 3 is very similar and has slightly better fit characteristics than put option model 4.

Panels C and D of Table 8 present the conditional probablities of a crisis and in-sample performance of futures and option models with the inclusion of term spread. In general, the inclusion of term spread improves both the fit characteristics and in-sample performance of all models. QPS and LPS indicate that the best performing models are futures model 3.1 and put option model 6.1, respectively. Option model 6.1 is the best overall performing model based on LPS and QPS, while the model with the best fit characteristics is option model 4.1 with 94.8% of months correctly indentified and 92.3% of pre-crisis months correctly called. It is noted that for all models the inclusion of term spread greatly reduces the percentage of false alarms and the percentage of a crisis given no alarm.

Fig. 2 presents predicted probabilities (for $Y_t = 1$) of the top performing futures and option models based on the calculated QPS and LPS. The predicted probabilties in these four top performing models are very volatile, and rise during the outbreak of the Asian currency crisis in July 1997 and the Russian Ruble crisis in August 1998. This illustrates the predictive power of these index derivatives models. Fig. 2 demonstrates that these EWS models correctly call both pre-crisis periods and in fact the spikes in predicted probabilities for some models are highest prior to or during the two pre-crisis periods.

In summary, the parameter estimates, the conditional probabilities, and the in-sample model performance statistics demonstrate the success of our index futures and option models with inclusion of term spread in predicting a financial crisis.

5. Conclusions

Derivatives play an important role in price discovery. However, a relatively sparse literature examines the medium-term (one-year) predictability of equity market crises using variables relating to index futures and option markets. In this research, we develop an early warning system (EWS) of financial crises using variables relating to S&P 500 futures and options within a multinomial logit model. We document that the following variables are good leading indicators of an equity market crisis: the VIX, open interest, dollar volume, put option price, and put option effective spread. Our empirial results show that models estimated with futures and put options successfully predict the majority of equtiy market crisis months from 1997 to 2009.

[29] We note that the conditional probabilities for option models display a high degree of volatility.

[30] Models estimated with put options have the best fit characteristics overall.

[31] In models with options or futures, the results of QPS and LPS are not always consistent with the fit characteristics. Inconsistency between fit characteristics and QPS and LPS is possible. As Greene (2003) points out, the likelihood estimator in a logit model is not selected to maximize a fitting criterion based on prediction of the dependent variable as it is in classical regression (i.e. to maximize R squared). It is rather selected to maximize the joint density of the observed dependent variables.

In-sample statistics show that model 4 estimated with put options is the best performing model. The fit characteristics indicate that this model correctly identifies 85.8% of observations and correctly calls 65.4% of crisis months. When the model is augmented to include term spread, the performance of this model improves with 94.8% of observations correctly called and 92.3% of pre-crisis months correctly indentified. It should be stressed that the EWS models developed in this paper are certainly not comprehensive. However, this paper makes an important contribution to existing literature by using the important information linkage between index derivatives and equity markets to predict financial crises in an EWS framework over a medium-term forcasting horizon.

The past two decades have witnessed several financial crises with many spreading contagiously around the world. The empirical findings provided in this research are useful to both investors and policy makers. From an investor's perspective, a reliable EWS provides time for the reallocation of portfolios prior to a crisis. Such reallocation will serve to protect mutual and pension fund assets. From a policy perspective, a reliable EWS will allow policy makers to take pre-emptive actions to mitigate the consequences of a significant downturn in equity markets. Overall, the results presented in this paper are an important step in understanding and predicting equity market crises.

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References

Abhyankar, A. H. (1998). Linear and nonlinear Granger causality: Evidence from the UK stock index futures market. *Journal of Futures Markets*, *18*, 519–540.

Aït-Sahalia, Y., & Lo, A. W. (1998). Nonparametric estimation of state-price densities implicit in financial asset prices. *Journal of Finance*, *53*, 499–547.

Banerjee, P. S., Doran, J. S., & Peterson, D. R. (2007). Implied volatility and future portfolio returns. *Journal of Banking and Finance*, *31*, 3183–3199.

Bates, D. S. (1991). The crash of '87: Was it expected? The evidence from options markets. *Journal of Finance*, *46*, 1009–1044.

Berg, A., & Pattillo, C. (1999). Predicting currency crises: The indicators approach and an alternative. *Journal of International Money and Finance*, *18*, 561–586.

Bessembinder, H., Chan, K., & Seguin, P. J. (1996). An empirical examination of information, differences of opinion, and trading activity. *Journal of Financial Economics*, *40*, 105–134.

Bessembinder, H., & Seguin, P. J. (1992). Futures-trading activity and stock price volatility. *Journal of Finance*, *47*, 2015–2033.

Bianconi, M., Yoshino, J. A., & De Sousa, M. O. M. (2013). BRIC and the U.S. financial crisis: An empirical investigation of stock and bond markets. *Emerging Markets Review*, *14*, 76–109.

Black, F. (1975). Fact and fantasy in the use of options. *Financial Analysts Journal*, *31*, 36–41.

Burkart, O., & Coudert, V. (2002). Leading indicators of currency crises for emerging countries. *Emerging Markets Review*, *3*, 107–133.

Bussiere, M., & Fratzscher, M. (2006). Towards a new early warning system of financial crises. *Journal of International Money and Finance*, *25*, 953–973.

Chakravarty, S., Gulen, H., & Mayhew, S. (2004). The informed trading in stock and option markets. *Journal of Finance*, *59*, 1235–1257.

Chan, K. (1992). A further analysis of the lead–lag relationship between the cash market and stock index futures market. *Review of Financial Studies*, *5*, 123–152.

Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, *59*, 383–403.

Chen, S. S. (2009). Predicting the bear stock market: Macroeconomic variables as leading indicators. *Journal of Banking and Finance*, *33*, 211–223.

Chung, S. L., Tsai, W. C., Wang, Y. H., & Wang, P. S. (2011). The information content of the S&P 500 index and VIX options on the dynamics of the S&P 500 index. *Journal of Futures Markets*, *31*(12), 1170–1201.

Coudert, V., & Gex, M. (2008). Does risk aversion drive financial crises? Testing the predictive power of empirical indicators. *Journal of Empirical Finance*, *15*, 167–184.

Diltz, J. D., & Kim, S. (1996). The relationship between stock and option price changes. *Financial Review*, *31*, 499–519.

Distinguin, I., Rous, P., & Tarazi, A. (2006). Market discipline and the use of stock market data to predict bank financial distress. *Journal of Financial Service Research*, *30*, 151–176.

Easley, D., O'Hara, M., & Srinivas, P. S. (1998). Option volume and stock prices: Evidence on where informed traders trade. *Journal of Finance*, *53*, 431–465.

Fleming, J., Ostdiek, B., & Whaley, R. E. (1996). Trading costs and the relative rates of price discovery in stock, futures, and option markets. *Journal of Futures Markets*, *16*, 353–387.

Fung, J. K. W. (2007). The information content of option implied volatility surrounding the 1997 Hong Kong stock market crash. *Journal of Futures Markets*, *27*(6), 555–574.

Giot, P. (2005). Relationships between implied volatility indexes and stock index returns. *Journal of Portfolio Management*, *26*, 92–100.

Greene, W. H. (2003). *Econometric analysis* (fifth ed.). United States of America: Prentice Hall.

Herwatz, H., & Kholodilin, K. A. (2014). In-sample and out-of-sample prediction of stock market bubbles: Cross-sectional evidence. *Journal of Forecasting*, *33*, 15–31.

IMF. (2009a). *Global financial stability report: Responding to the financial crisis and measuring systemic risk*. Washington, DC.

IMF. (2009b). *Global financial stability report: Navigating the financial challenges ahead*. Washington, DC.

IMF. (2010a). *Global financial stability report: Meeting the new challenges to stability and building a safer system*. Washington, DC.

IMF (2010b). *Global financial stability report: Sovereigns, funding and systemic liquidity*. Washington, DC.

Inoue, A., & Kilian, L. (2005). In-sample or out-of-sample tests of predictability: Which one should we use? *Econometric Review*, *23*(4), 371–402.

Kaminsky, G. (2000). *Currency and banking crises: The early warnings of distress*. IMF Working Paper, 99/178.

Kaminsky, G., Lizondo, S., & Reinhart, C. M. (1998). Leading indicator of currency crises. *IMF Staff Papers*, *45*, 1–48.

Kavussanos, M. G., Visvikis, I. D., & Alexakis, P. D. (2008). The lead–lag relationship between cash and stock index futures in a new market. *European Financial Management*, *14*, 1007–1025.

Kawaller, I. G., Koch, P. D., & Koch, T. W. (1987). The temporal price relationship between S&P 500 futures and the S&P 500 index. *Journal of Finance*, *42*, 1309–1329.

Kilian, L., & Taylor, M. P. (2003). Why is it so difficult to beat the random walk forecast of exchange rate? *Journal of International Economics*, *60*, 85–107.

Kumar, M., Moorthy, U., & Perraudin, W. (2003). Predicting emerging market currency crashes. *Journal of Empirical Finance*, *10*, 427–454.

Manaster, S., & Rendleman, R. T., Jr. (1982). Option prices as predictor of equilibrium stock prices. *Journal of Finance*, *37*, 1043–1057.

Marathe, A., & Shawky, H. (1994). Predictability of stock returns and output. *Quarterly Review of Economics and Finance*, *34*, 317–331.

Pan, J., & Poteshman, A. M. (2006). The information in option volume for future stock prices. *Review of Financial Studies*, *19*, 871–908.

Patel, S., & Sarkar, A. (1998). Crises in developed and emerging stock markets. *Financial Analyst Journal*, *54*, 50–59.

Pizzi, M., Economopoulos, A. J., & O'Neill, H. M. (1998). An examination of the relationship between stock index cash and futures markets: A cointegration approach. *Journal of Futures Markets*, *18*, 297–305.

Rappoport, P., & White, E. (1994). Was the crash of 1929 expected? *American Economic Review*, *84*, 271–281.

Routledge, B. R., & Zin, S. E. (2009). Model uncertainty and liquidity. *Review of Economic Dynamics*, *12*, 543–566.

Ryoo, H. J., & Smith, G. (2004). The impact of stock index futures on the Korean stock market. *Applied Financial Economics*, *14*, 243–251.

Sarwar, G. (2005). The informational role of option trading volume in equity index options markets. *Review of Quantitative Finance and Accounting*, *24*, 159–176.

Schwert, G. W. (1990). Stock volatility and the crash of '87. *Review of Financial Studies*, *3*, 77–102.

Stoll, H. R., & Whaley, R. E. (1990). The dynamics of stock index and stock index futures returns. *Journal of Financial and Quantitative Analysis*, *25*, 441–468.

Tang, G. Y. N., Mark, S. C., & Choi, D. F. S. (1992). The casual relationship between stock index futures and cash index prices in Hong Kong. *Applied Financial Economics*, *2*, 187–190.

Wongbangpo, P., & Sharma, S. (2002). Stock market and macroeconomic fundamentals dynamic interaction: ASEAN-5 countries. *Journal of Asian Economics*, *13*, 27–51.