Price Discovery and Cross-Market Informational Flow in High-Yield Systematic CDS and Equity Markets: Out-of-Sample Evidence

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Abstract

We contribute to the literature on the efficiency of CDS and equity markets by rigorously conducting out-of-sample analysis in order to determine the true predictive power of cross-market informational flow in the systematic high yield sector. Extant studies have been based on in-sample analysis only and reported average results across the examined time period, thereby leaving the question of true and persistent predictive power unanswered. Interestingly, we find that both markets are useful in forecasting future values of the other on an out-of-sample basis, indicating that each is more efficient in pricing in certain types of information. However, the CDS market has an informational advantage over the equity market which has increased with time, something not previously documented in the closely related literature. We attribute this finding to the development of the CDS market into more of an index based vs. a single name market as well as the relative lower level of volatility and investor fear characterizing the back end of our sample.

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1 Introduction

A significant body of historical literature such as Acharya and Johnson (2007) and Han and Zhou (2011) has investigated whether CDS or equity markets are more efficient in capturing and impounding new information into asset prices. While under the model proposed in Merton (1974), this should not occur since the same factors impact prices in both markets, i.e., they should both react the same way to the same news, in reality frictions and other market related factors give rise to inefficiencies (see Duffie (1999)). As a result, it is possible for one market to have an informational advantage over the other. In this paper we contribute to the literature by providing empirical evidence on this issue.

While most historical studies such as Narayan et al. (2014) have focused on non-systematic, or single name CDS and generally observed that the equity market has an overall advantage over the CDS (although results have been somewhat mixed), Procasky (2020) uses CDS indexes and matched equity portfolios, and observes default risk based heterogeneity in the efficiency and cross-market informational flow of systematic markets. Specifically, while neither market has an advantage in the investment grade sector, meaning they are equally efficient, a strong two-way interactive effect is observed in the high-yield market. However, while this result may have differed from historical findings, it has two methodological limitations in common with all such prior investigations, which we address for the first time in the literature with this study

First, all price discovery and cross-market informational flow results to date are based on an in-sample analysis. Accordingly, questions regarding whether the previously reported in-sample evidence of significant two-way flow as documented in Procasky (2020) can be translated into meaningful predictive content remain unanswered due to the absence of rigorous out-of-sample evaluation. As is well-known in the financial time-series forecasting literature, in-sample evidence of causality may not necessarily lead to significant out-of-sample predictability. Therefore, any robust out-of-sample evidence of the predictive content embedded in the cross-market informational flow would further strengthen the in-sample results reported in prior studies such as Procasky (2020).[1] Second, while the VAR models used in such studies are effective in detecting cross-market informational flow, traditional Granger causality tests are not very useful in quantifying the relative strength of that flow. This is due to the fact that the coefficients on lagged price variables in the endogenous system of equations do not correspond to the magnitude of subsequent price movements. As a result, researchers are left to categorize observed cross-market flow in broad statistical terms, i.e., either as "strong" or "weak", based solely on the p-values associated with these lagged terms. Thus, while the prior in-sample results suggested that the observed two-way information flow in the high yield sector is strong, there is no way to tell whether flow from

[1]The issue of disconnection between in-sample causality and out-of-sample predictability is discussed and illustrated in works such as Goyal and Welch (2008) and Rapach and Zhou (2013).

one subject market to the other may be more persistent and/or economically significant.

Accordingly, the primary purpose of this paper is to address these two open issues. Using systematic high-yield CDS index data and closely matched equity portfolio returns which we painstakingly constructed, we perform a rigorous out-of-sample analysis with VAR models to determine the true predictive power, if any, of the observed cross-market information flow. In the event the models do not work on an out-of-sample basis, then the Granger causality previously documented may be either a result of overfitting, or time varying in nature. To this end, we use a battery of classic and contemporary out-of-sample methods to analyze the relative strength of any predictive flow and to ascertain whether one market has a greater informational advantage than the other.

Interestingly, our analysis reveals that lagged values in both markets are useful in forecasting future values in the other on an out-of-sample basis, increasing the confidence in the initial in-sample findings documented in Procasky (2020) and indicating a level of persistence in the predictive power of these markets. In addition, we document that the CDS market has an informational advantage over the equity in the strength of this predictive power, with the advantage increasing over time, something not previously documented in the closely related literature and a result we attribute to two factors. The first is the increasing significance of CDS Indexes vs. single name CDS in the overall composition of the market. To illustrate, according to BIS data, CDS indexes comprised only approximately 20% of the overall market at the beginning of the time period studied, compared to 50% by the end. The second is the lower relative level of volatility and investor fear in the back end of our sample in the equity market, as evidenced by an average VIX level of 14.8 during the last three years of our sample compared to 21.3 during the first seven years. Under such conditions, we theorize that investors are not as concerned about hedging the default risk inherent in their equity and bond positions, which in turn decreases the flow of information from the equity to the CDS market associated with such activity. Viewed in tandem, these results have significant implications for investors, arbitrageurs and risk managers who monitor systematic markets for informational content.

In addition to the above contributions, our empirical results also shed light on the predictability of aggregate U.S. equity returns. With a comprehensive dataset Goyal and Welch (2008) show that the U.S. market equity premium cannot be meaningfully predicted out-of-sample against a random walk benchmark based on a number of predictors proposed in the finance literature. However, subsequent to the study, the view expressed in Goyal and Welch (2008) has been consistently challenged by researchers who document that the predictive content of those predictors can be uncovered once an appropriate model or estimation method is employed. However, most empirical results on the predictability of stock returns are based on multi-period ahead forecasts with relatively low frequency data.[2] In contrast, we examine the issue of market efficiency and return predictability with a rich

[2]See, for example, Rapach et al. (2010), Dangl and Halling (2012) and Li and Tsiakas (2017).

dataset consisting of relatively recent daily data, and show that while the predictability of equity returns attributable to cross-market informational flow does exist, it does not last beyond one trading day. Therefore, we provide new evidence of market equity return predictability based on high-frequency data with a short forecast horizon. Moreover, instead of searching for new accounting variables and estimation methodologies, we investigate the issue of equity returns predictability by looking at information flow and price discovery from a different but closely linked asset market. This new direction of research on equity returns predictability could have implications for portfolio managers who base their trading strategy on high-frequency short-horizon forecasts.[3]

Also, in contrast to prior studies such as Narayan et al. (2014) whose conclusions are based on analysis with individual name credit default swaps, in this paper we use systematic CDS index data to investigate out-of-sample predictability and cross-market informational flow. The reasons supporting the use of CDS indexes are thoroughly discussed in Procasky (2020) and Fung et al. (2008), for example, these indexes are efficiently bundled packages of diversified credit risk, thus resulting in lower transaction costs than firm-specific swaps.

The remainder of this paper is structured as follows: section two provides an overview of related literature followed by a discussion of the data in section three. Section four delves into the methodology while empirical results are discussed in section five. Further robustness checks and extensions are discussed in Section six. Section seven summarizes and discusses our empirical findings and their implications. Section eight concludes.

2 Related Literature

There is a significant amount of extant literature examining the relative efficiency of CDS and equity markets. Longstaff et al. (2004), Acharya and Johnson (2007), Han and Zhou (2011), Marsh and Wagner (2012), Narayan et al. (2014), Hilscher et al. (2015) and Acharya and Johnson (2017) broadly studied the North American market while Norden and Weber (2004), Norden and Weber (2009) and Forte and Pena (2009) examined international markets. Ni and Pan (2004) and Rodriguez-Moreno and Pena (2013) focused on the financial sector while Bystrom (2006), Fung et al. (2008) and Procasky (2020) used indexes to investigate systematic flow. Overall, the empirical results have been rather mixed. Studies such as Narayan et al. (2014) employing multivariate time series data in a vector autoregression framework have generally found that stocks lead CDS, although we also observe default risk based heterogeneity in systematic CDS and equity markets based on our full sample results. This suggests that the CDS market may be more efficient in impounding certain types of information in prices. However, these results are all based on an in-sample analysis, leaving open the question of the true predictive nature, if any, of the observed

[3]Examples of economic gains delivered by out-of-sample forecast-based trading strategies include Cenesizoglu and Timmermann (2012) and Rapach et al. (2016).

cross-market information flow.

To address this issue, we pull from the literature on VAR model out-of-sample forecast and forecast evaluation for the first time in an analysis of cross-market informational flow and price discovery, and rigorously conduct out-of-sample tests on data we constructed. West (2006) and Clark and McCracken (2013b) provide a comprehensive overview of out-of-sample forecast construction, estimation, inference and evaluation. Such tests have been widely utilized in empirical finance, in particular the field of forecasting market equity returns, for example by Goyal and Welch (2008), Rapach et al. (2010), Pettenuzzo et al. (2014), Li and Tsiakas (2017) and Yin (2019). Out-of-sample analysis has also been used extensively in examining the predictive performance of various economic fundamentals-based models in the foreign exchange markets, for example, by Li et al. (2015), Beckmann and Schussler (2016) and Jamali and Yamani (2019).

Within the out-of-sample framework, we employ a number of classic and contemporary test statistics in order to rigorously compare and evaluate CDS and equity return forecasts using lagged returns. Specifically, we first assess forecast rationality by using the forecast unbiasedness test originally proposed in Mincer and Zarnowitz (1969). Recent applications and extensions of the forecast rationality tests can be found in studies such as Gurkaynak et al. (2013). We then judge the overall quality of forecasts using a robust set of statistics which draw on insights from seminal methodological works by Diebold and Mariano (1995), Giacomini and Rossi (2009), Giacomini and Rossi (2010a), Diebold (2015) and Rossi and Sekhposyan (2016). To gain further insights into market efficiency, we also investigate separately cross-market informational flow under different investor sentiment regimes, as the importance of regime-dependent evaluation in empirical works is emphasized in studies such as Baltas and Karyampas (2018). Finally, given that the traditional Granger causality test does not provide a direct measure to quantify the observed causality, using the innovative methods proposed in Dufour et al. (2012) we measure the strength of cross-market informational flow both in-sample and out-of-sample.

3 Description of Data

3.1 Credit Default Swap

For the systematic CDS market, we use the Markit CDX North American High Yield Index ("CDX.NA.HY") comprised of 100 of the most liquidly traded, equally weighted CDS for which the reference entity is assigned a long-term credit rating below BBB- (or Baa3) by a major rating agency. As per standard practice, we use the five-year maturity since this is the most liquidly traded. Figure 1 illustrates the construction of the CDX.NA.HY.

Our data set begins on November 29th, 2004 and ends on September 18th, 2015, a time period which corresponds to series three through 24 of the CDX.NA.HY. Series are produced in sequential order as Markit adjusts the constituents of the index every six months, a process known as rebalancing. During rebalancing, companies contained in the index may be replaced according to a defined set of rules developed by Markit. Such rules include the volume of trading in its CDS, upgrades in credit rating to an investment grade level and occurrences of a credit event codified in its CDS contracts. Upon issuance of a new series, the prior one is no longer considered to be the on-the-run index, although trading in it may continue.

Between rebalancing dates, new versions of the series are issued to account for interim credit events, with such versions then becoming the on-the-run version of the index. Throughout the time period examined, our CDX.NA.HY index data corresponds to the on-the-run series and version, a critical aspect in investigating cross-market informational flow due to the fact that trading volume generally declines rapidly when a series or version is replaced as the on-the-run index. Because this drop in volume results in fewer investor views impounded in the price of this index, failure to replace the older index would bias the results.

3.2 Matching Equity Portfolio

Our primary data source for equity prices is CRSP, with quotes for only a handful of stocks taken from Yahoo Finance. All prices are adjusted for stock splits. While Canadian stock prices are translated into US Dollars at the prevailing exchange rate, the effect of exchange rate movements is negligible as such stocks represent less than 1% of the overall data set. With this data, we manually construct an equity index matching the constituents of the CDX.NA.HY and calculate its daily value on an equally weighted basis. As noted by Procasky (2020), the greater maturity of the stock market and related lower frictions in trading single name stocks enables the study of systematic informational flow using manually constructed matched equity indexes. In conjunction with the rebalancing of the CDX.NA.HY, we must rebalance the equity index every six months in order for the components to remain matched. While this process is painstaking (we rebalance the index 21 times), failure to keep the index closely matched would bias results.

We use the Bloomberg terminal to identify CDX.NA.HY constituents. Due to the fact that some companies in the index are not public, a 100% match with the manually constructed equity index is not feasible throughout the time period studied, however, the issue is not material as we achieve an average match of 90%. Rebalancing days are removed from the data set to eliminate any bias related to changes in value caused by replacement of constituents as opposed to new information impacting systematic markets.[4] However, because such days comprise fewer than 1% of all trading days, their removal does not materially impact results.

[4]This issue is especially germane for the stock index.

3.3 Summary Statistics

Descriptive statistics for the indexes are reflected in Table 1. The data set consists of days on which both the stock and CDS markets were open for trading but not when only one or the other market was open. This means that observations related to holidays on which stock markets were closed but bond markets were open, or CDX settlements were reported due to the Canadian firms are not included. However, given that volume for the open market on these days generally was light or only impacted the small number of Canadian names, little to no movement was observed in the CDX indexes and as such, removing these days has no impact on the result. During the period of study, in our raw data the mean credit spread for the CDX.NA.HY is 515 bps, with the maximum value being 1,910 bps during the height of the financial crisis.

Table 1 reports sample mean values in percentage of 0.0157 and −0.0012 for equity and CDS returns, respectively. Moreover, the equity series shows a positive skewness while the CDS series reports a negative one. Interestingly, the standard deviation in the CDX.NA.HY returns is higher than that for the equity returns, a statistical property we attribute to the relative lower liquidity driven by investor heterogeneity across the two markets. Figure 2 displays the time series plots of the equity and CDS returns in the top and bottom panels, respectively. As can be seen, overall, the return data is well-behaved without visually detectable trends, though typical high-frequency financial time series features such as volatility clustering are evident to some extent.

4 Econometric Methodology

In this section we first discuss the econometric models and out-of-sample forecasting procedure we use to carry out our empirical analysis on cross-market informational flows. We then discuss the classic and contemporary test statistics we utilize to compare and evaluate the out-of-sample forecasts.

4.1 Vector Autoregressive Regression

The primary econometric tool we employ to examine price discovery and cross-market information flow is the reduced-form vector autoregressive regression (VAR) originally proposed in Sims (1980) for application in economics.

As pointed in Elliott and Timmermann (2016), VAR models provide a coherent way to produce internally consistent out-of-sample forecasts, which take into account the concurrent and dynamic correlations across included predictive variables. As a result, they have been extensively adopted as simple yet powerful methodological tools in empirical finance. Recent examples of such studies include Longstaff et al. (2004), Rodriguez-Moreno and

Pena (2013), Fung et al. (2008), Norden and Weber (2009) and Hilscher et al. (2015).

In the context of investigating cross-market efficiencies, VAR models are designed to detect and capture lead-lag relationships between two or more sets of well-behaved time series variables. Generally, with a VAR model, variation in each time series variable is defined as a function of both its own lagged values and lagged values of the other time series variable(s), expressed as follows:

$$\begin{aligned}\Delta CDX_t &= a_1 + \sum_{j=1}^{k} b_{1j}\Delta Stock_{t-j} + \sum_{j=1}^{k} c_{1j}\Delta CDX_{t-j} + \epsilon_{1t}\\ \Delta Stock_t &= a_2 + \sum_{j=1}^{k} b_{2j}\Delta Stock_{t-j} + \sum_{j=1}^{k} c_{2j}\Delta CDX_{t-j} + \epsilon_{2t},\end{aligned} \tag{1}$$

where ΔCDX_t: contemporaneous CDS index return; $\Delta Stock_t$: contemporaneous matched stock index return; ΔCDX_{t-j}: lagged CDS index return with lag order j; $\Delta Stock_{t-j}$: lagged matched stock index return with lag order j; ϵ_{it}: innovations to the vector autoregression system.

While the model shown in Eq. (1) permits a general lag order of k, based on the results of our model selection analysis using the Schwarz-Bayesian information criterion for optimal order detection, we use the following VAR(1) model throughout our analysis:

$$\begin{aligned}\Delta CDX_t &= a_1 + b_1\Delta Stock_{t-1} + c_1\Delta CDX_{t-1} + \epsilon_{1t}\\ \Delta Stock_t &= a_2 + b_2\Delta Stock_{t-1} + c_2\Delta CDX_{t-1} + \epsilon_{2t}.\end{aligned} \tag{2}$$

Apart from the observed lag order of one selection guidance provided by the Schwarz-Bayesian information criterion, we also note that in practice, this result stands to reason. This is due to the fact that given the size and liquidity of the subject markets, it would be difficult to imagine that it would take more than one trading day for one financial market to react to news and shocks occurring in the other. Therefore, in contrast to the multi-step ahead prediction results frequently reported in stock returns forecasting literature such as Rapach et al. (2010) and Pettenuzzo et al. (2014), in the empirical sections of our paper we focus exclusively on one-period ahead out-of-sample forecasts.

4.2 Competing Benchmarks

To evaluate the practical merit of the VAR(1) model shown in Eq. (2) which takes into account cross-market informational flow, we compare the accuracy of its forecasts against various benchmarks which do not. Accordingly, as is common practice in the forecasting research of empirical finance, we first consider a natural competing alternative model consisting of two separate autoregressive regressions of order one, or AR(1) models for CDS and equity returns, respectively. Because the models only include lagged variables of their respective dependent variable, they inherently exclude the potential for cross-market flow to exist. Put differently, they assume that the CDS and equity markets contemporaneously price in new information equally efficiently, hence it would be futile for an investor to use information taken from one market to forecast the change in the other. As such, we specify this set of AR(1) models are follows:

$$\Delta CDX_t = \alpha_1 + \beta_1 \Delta CDX_{t-1} + \eta_{1t}, \tag{3}$$

for the CDS returns, and

$$\Delta Stock_t = \alpha_2 + \beta_2 \Delta Stock_{t-1} + \eta_{2t}, \tag{4}$$

for the equity returns.

In addition to the set of AR(1) models outlined above, the second model we consider is the simple yet difficult to beat random walk model specified below. Because this model assumes markets are efficient, or more specifically in our case, that past prices do not affect future ones, it is frequently used to compare the forecasting performance of new models, new predictive variables or new estimation methodologies in empirical works, for example, see Li and Tsiakas (2017). Specifically,

$$\Delta CDX_t = \alpha_1 + \eta_{1t}, \tag{5}$$

for the CDS returns, and

$$\Delta Stock_t = \alpha_2 + \eta_{2t}, \tag{6}$$

for the equity returns.

Interestingly, it is worthwhile to point out the ostensible nesting structure of the three predictive models considered in this paper: the random walk model is strictly nested within the AR(1) model, while the latter is nested within the VAR(1) model. Hence, intuitively, unless cross-market informational flow is present and persistently strong, we would not expect the VAR(1) model to outperform the two competing benchmarks in predictive accuracy since it would only involve the estimating and adding of additional parameters to the model whose population values are zero.

4.3 Out-of-Sample Forecast Construction

While there is current debate in the literature of forecast and model evaluation on whether the out-of-sample analysis framework genuinely provides better and more reliable results than traditional in-sample analysis, nevertheless, as summarized in Diebold (2015), the out-of-sample framework remains useful for certain tasks, notably for providing information about comparative forecasting performance during particular periods in the past. Possible explanations for the popularity of out-of-sample analysis in the fields of empirical finance are that it: provides an important tool for researchers or professional forecasters to detect and estimate structural change; is more closely tied to the ideal of comparing models or forecasts with the newly available data than in-sample analysis; accommodates the use of more flexible forms of loss functions other than the quadratic loss to assess forecasts; and arguably, is more robust to data mining than full-sample analysis.

In doing so, we adopt a rolling estimation window to generate out-of-sample predictions for the VAR(1) model and related competing benchmark models. Specifically, following conventional procedures documented in Clark and McCracken (2013b), we divide the full data sample of size T observations into an in-sample estimation portion of size R, and an out-of-sample forecasting portion of size P, where $P+R=T$. The size of the rolling estimation window, R, is set to equal 40% of the full sample truncated to the nearest integer, corresponding to 1069 daily observations that provide information for model estimation at each point in time when the one-step ahead forecast is made.[5] According to the rolling estimation scheme, predictive model parameters are updated via maximum likelihood estimation in each forecasting period $t=R,\dots,T$, using the most recent R observations, with the one-period ahead forecast then made based on the latest trained model. For example, we create the first set of one-step ahead out-of-sample forecasts with the first R observations according to:

$$\begin{aligned}\Delta\widehat{CDX}_{R+1} &= \widehat{a}_1^R + \widehat{b}_1^R\Delta\widehat{Stock}_R + \widehat{c}_1^R\Delta\widehat{CDX}_R\\ \Delta\widehat{Stock}_{R+1} &= \widehat{a}_2^R + \widehat{b}_2^R\Delta\widehat{Stock}_R + \widehat{c}_2^R\Delta\widehat{CDX}_R.\end{aligned}\tag{7}$$

Then, we obtain the forecast errors by taking the difference between the realized values in time period $R+1$ and the predicted values taken from Eq. (7). We proceed in this fashion until the end of the full sample, thus leading to the construction of P out-of-sample forecasts for equity and CDS returns, together with their associated forecast errors.[6]

While both the recursive and rolling estimation windows are commonly used in the out-of-sample forecasting literature, by using the rolling window we are able to take critical values from a standard normal distribution for certain test statistics that enable us to compare and rank predictive performance among competing models.[7]

[5]Generally, the rolling estimation window size is chosen arbitrary by researchers in empirical finance as long as it allows for a sufficient amount of data to obtain reliable parameter estimates. To demonstrate that our results are robust to this factor and to alleviate any concerns related to cherry-picking, at the beginning of the empirical results section of this paper we consider a wide range of estimation sample sizes.

[6]Note that the series of P out-of-sample forecast errors that are used as inputs in subsequent forecast evaluations depends on the realized value of the target variable and the in-sample parameter estimates during the forecasting period.

[7]Our empirical results from a preliminary analysis under the recursive estimation window are qualitatively

4.4 Forecast Evaluation

We begin our forecast evaluation by presenting the widely adopted statistical measure of relative forecasting performance in empirical finance called the out-of-sample R^2 statistic, R^2_{OOS}, which is proposed in Campbell and Thompson (2008). Methodologically, the R^2_{OOS} compares the unconditional one-step ahead point forecasts $\bar{y}_{t+1|t}$ generated by the benchmark model denoted by a superscript of 0 to the conditional forecasts $\hat{y}_{t+1|t}$ of the VAR(1) model, and is defined as follows:

$$R^2_{OOS} = 100 \times \left(1 - \frac{\text{MSFE}}{\text{MSFE}^0}\right) = 100 \times \left(1 - \frac{\sum_{t=1}^{T-1}\left(y_{t+1} - \hat{y}_{t+1|t}\right)^2}{\sum_{t=1}^{T-1}\left(y_{t+1} - \bar{y}_{t+1|t}\right)^2}\right), \tag{8}$$

where MSFE is the abbreviated term for the mean squared forecast error, and y_{t+1} is the realized value of the forecasting target in period $t+1$.

The R^2_{OOS} statistic shown in Eq. (8) measures the percentage reduction in the MSFE for the VAR(1) model relative to the AR(1) and the random walk benchmarks. Hence, intuitively, if the R^2_{OOS} takes on a positive value, it implies better predictive performance on the part of the VAR(1) model vs. the chosen benchmark. Thus it follows that the higher the R^2_{OOS} value, the greater the predictive gains are for the VAR(1) model over the forecast evaluation time window.

While the Campbell and Thompson (2008) out-of-sample R^2_{OOS} statistic is fairly easy to understand and simple to calculate, nevertheless, it only measures the average, or global relative forecasting performance for the model under investigation. As a result, in order to better understand predictive gains related to cross-market informational flow and to gain a more dynamic perspective, we follow the empirical approach proposed in Goyal and Welch (2008). Specifically, we adopt their measure, the cumulative difference in squared forecast errors (CDSFE), and apply it to the benchmark and VAR(1) models, in order to construct a graphical device which enables us to evaluate forecasts over the entire path of out-of-sample predictions. Specifically, we create the sequence of CDSFE data according to the following:

$$\text{CDSFE}_\text{t} = \sum_{s=1}^{t}(y_{s+1} - \bar{y}_{s+1})^2 - \sum_{s=1}^{t}(y_{s+1} - \hat{y}_{s+1})^2, \tag{9}$$

where $\bar{y}_{s+1}$ is the one-step ahead forecast from the benchmark, and $\hat{y}_{s+1}$ is the one-period ahead point forecast from the VAR(1) model. At any period t, if the value of CDSFE_t is positive, it implies that the VAR(1) model outperforms the benchmark by having a smaller prediction error at that point. In other words, a positively sloped CDSFE curve would suggest better forecasting performance on the part of the VAR(1) model against the benchmark.

similar to those reported in this paper. However, the statistical procedure documented in Giacomini and White (2006) evaluating forecasts in finite sample is only valid under either a fixed or rolling window.

The time series plots of the CDSFE can be conveniently used to determine if the VAR(1) model has a lower MSFE than the benchmark for any given time period by simply comparing the heights of the curve at the beginning and end points of the segment corresponding to the period of evaluation. If the curve is higher at the end of the evaluation period relative to the starting point, then the VAR(1) model has a smaller MSFE than that of the benchmark during this particular evaluation window. As a result, a model which forecasts better than the benchmark would have a positive slope during the entire out-of-sample evaluation period.

4.4.1 Forecast Unbiasedness

Under a quadratic loss function such as the MSFE loss utilized in the construction of the R^2_{OOS} statistic, optimal forecasts should possess several statistical properties. Most importantly, they should be unbiased, and h-step ahead forecast errors should only be correlated at most at order $h-1$. Since our focus centers on evaluating one-period ahead forecasts, before comparing predictions made by our competing models, we must investigate whether the Granger causality inspired VAR(1) model generates unbiased forecasts on average over the out-of-sample evaluation period.

Specifically, our test of forecast unbiasedness falls into the family of the Mincer and Zarnowitz (1969) forecast efficiency test by regressing the one-step ahead forecast errors from the VAR(1) model on a constant term as follows:

$$y_{t+1} - \widehat{y}_{t+1} = \beta_0 + e_t. \tag{10}$$

We then test the null hypothesis that the population value of the intercept term in Eq. (10), β_0, is zero. Rejection of the null hypothesis leads to the conclusion that forecasts generated by the VAR(1) model are biased on average over the entire out-of-sample period.

4.4.2 Comparing Relative Forecasting Performance

To rigorously examine out-of-sample Granger causality associated with cross-market information flow and price discovery, we must also test whether the CDS and equity return forecasts made from the VAR(1) model are statistically better under a quadratic loss function than those from the two separate AR(1) models strictly nested within the VAR(1) model, i.e., it is not enough to draw conclusions solely based on the observed values and/or visual trends. To this end, we report statistical testing results for comparing forecasts based on the difference of the mean square forecast errors (MSFE) of these competing models using the Diebold and Mariano (1995) test statistic, together with the critical values proposed in Giacomini and White (2006).[8] Specifically, the Diebold and Mariano (1995) test statistic

[8] As concluded in Clark and McCracken (2013a), when evaluating forecasts in finite samples, the results of Giacomini and White (2006) broadly apply with VAR forecasts, as long as they are generated with either

can be calculated as:

$$\mathrm{DM} = \frac{\bar{d}_{t+1}}{sd(\bar{d}_{t+1})}, \tag{11}$$

where $\bar{d}_{t+1} = \frac{1}{P}\sum_{t=R}^{T} d_{t+1}$, $d_{t+1} = (y_{t+1} - \widehat{y}_{t+1})^2 - (y_{t+1} - \bar{y}_{t+1})^2$, and $sd(\bar{d}_{t+1})$ is the estimated standard deviation of $\bar{d}_{t+1}$ with a heteroskedasticity and autocorrelation consistent (HAC) estimator.[9]

We test the null hypothesis that both the VAR(1) and AR(1) models produce asymptotically equivalent forecasts against the one-sided alternative that the VAR(1) model delivers better forecasts in terms of smaller expected squared forecast errors. Rejection of the null hypothesis would support our finding that there is statistically significant cross-market informational flow between the equity and CDS markets. Here it is worth pointing out that, as concluded in Clark and McCracken (2013a), when evaluating forecasts in finite-samples, the results of Giacomini and White (2006) broadly apply with forecasts generated by VAR models, as long as these forecasts are constructed with either a fixed or rolling estimation window. Therefore, the adoption of the rolling estimation window provides us with the tools to rigorously test the statistical significance of the out-of-sample Granger causality.

Still, the traditional Diebold and Mariano (1995) test focuses on testing whether two competing predictive models generate equally good forecasts on average over the entire forecast evaluation period. However, as pointed out in Giacomini and Rossi (2010b), it is possible that in an unstable forecasting environment, predictive gains achieved by one model during certain periods could be offset by forecasting losses occurring in other periods, thus resulting in equal predictive performance between two competing models on average. In other words, Giacomini and Rossi (2010b) argue that looking at global or average relative forecasting performance may disguise critical information regarding the relative predictive performance of two competing models over time.

Accordingly, to keep track of the evolution of the relative forecasting performance, and to better understand the dynamics of cross-market informational flow in the context of out-of-sample Granger causality evidence, in addition to the Diebold and Mariano (1995) test discussed earlier, we also adopt the rolling window fluctuation test proposed in Giacomini and Rossi (2010b) to compare forecasts. Specifically, we construct the fluctuation test statistics as follows:

$$F_{t+1,m}^{OOS} = \hat{\sigma}^{-1} m^{-1/2} \sum_{j=t-m}^{t} \mathrm{DM}_{jt}, \quad t = m+1, \ldots, T, \tag{12}$$

a fixed or rolling estimation window approach. Since the AR(1) models are ostensibly nested within the VAR(1) model, with a rolling window we are able to take critical values from a normal distribution to conduct statistical inference.

[9]In this study, we employ a Newey and West (1987) HAC estimator with a Bartlett kernel and bandwidth automatically chosen according to Andrews (1991).

where DM_{jt} is the Diebold and Mariano (1995) statistic calculated over the evaluation window from period j to period t, and $\hat{\sigma}$ is the estimated standard deviation for DM_{jt} with a HAC estimator.[10]

Under the fluctuation test, we test the null hypothesis that both the VAR(1) and AR(1) models have the same MSFE against the one-sided alternative that the VAR(1) model performs better during at least one point in time over the forecast evaluation sample. Note that due to how the loss differential is defined in this paper, a negative value of the fluctuation test statistic indicates better performance for the VAR(1) model.

In empirical applications, the fluctuation test can be easily implemented by plotting the entire sample path of the measure of relative local performance, which in our analysis is the Diebold and Mariano (1995) statistic computed at each point in the evaluation sample, together with critical values reported in Giacomini and Rossi (2010b) which, if crossed, indicate that the VAR(1) model outperforms the AR(1) model at some point in time. In carrying out our fluctuation tests in subsequent sections, we follow Giacomini and Rossi (2010b) by setting the evaluation sample size equal to $m = R/2$.

4.4.3 Forecast Breakdown

In economic forecasting literature, it has been well documented that in-sample Granger causality may not imply meaningful out-of-sample predictive gains. When this happens, i.e., in-sample and out-of-sample results differ, a forecast breakdown is said to have occurred, a term coined by Giacomini and Rossi (2009). Empirically, factors such as structural breaks and model overfitting may help explain this disparity. As a result, in order to formally investigate whether the in-sample Granger causality between systematic CDS and equity markets can provide significant guidance with respect to out-of-sample forecasting performance, we employ the forecast breakdown test proposed in Giacomini and Rossi (2009) to examine this linkage.

The idea of the forecast breakdown test is based on a comparison of the the predictive model's in-sample performance to its out-of-sample performance using a constructed series of data termed surprise losses in Giacomini and Rossi (2009). Under this concept, surprise losses are produced by the difference between the out-of-sample squared forecast error and the historical mean squared error in each period t, $t = R, \ldots, T$. Methodologically, we begin the forecast breakdown test by first calculating a series of P out-of-sample surprise losses SL_{t+1}:

$$SL_{t+1} = \hat{\epsilon}^2_{t+1} - MSE_{t+1}, \quad \text{for} \quad t = R, \ldots, T, \tag{13}$$

[10] The fluctuation test framework is receiving growing attention in empirical finance as financial data are known to be prone to instabilities, for example, see Jamali and Yamani (2019) for its application in the FX market.

where $\hat{\epsilon}^2_{t+1}$ is the out-of-sample squared forecast error from the VAR(1) model and MSE_{t+1} is the in-sample mean squared error (MSE) of the VAR(1) model at time period t.

Next, we regress these surprise losses on a constant term in order to test the null hypothesis that the surprise losses are zero in expectation:

$$SL_{t+1} = \beta_0 + e_{t+1}. \tag{14}$$

Again, we employ the HAC estimator to estimate the sample variance of the surprise losses when constructing the forecast breakdown test statistic. The test rejects the null hypothesis at the $100\alpha\%$ confidence level whenever the test statistic is greater than the $1-\alpha$-th quantile of a standard normal distribution. If the null is rejected, i.e, surprise losses are not zero, then the predictive model under examination has experienced a forecast breakdown. Intuitively, the forecast breakdown test statistic measures the distance between the in-sample MSE and out-of-sample MSFE. If the test statistic becomes large enough to reject the null hypothesis, it indicates that the in-sample MSE provides no guidance with respect to how the out-of-sample MSFE would behave, or in other words, its predictive power has "broken down".

5 Empirical Results

In this section we forecast the equity and CDS returns using the VAR(1) model, then evaluate its performance against competing models. Figure 3 displays the out-of-sample forecasts of equity and CDS returns produced by the VAR(1) and the AR(1) models, in the upper and lower panels, respectively. All forecasts are generated by a rolling estimation window with window size equaling 40% of the observations of the full sample. Hence, our first forecast starts on April 23, 2009, and ends on September 18, 2015. Interestingly, a close examination of Figure 3 reveals that all forecasts have become less volatile since the first half of the year 2013, regardless of the choice of predictive model or forecasting target.

5.1 In-Sample Analysis

As a prelude to our out-of-sample analysis, we begin by examining price discovery and cross-market informational flow for the full sample. While the primary focus of this study is on exploring and evaluating forecasts, nevertheless, the full sample results presented in this section afford us the opportunity to more deeply investigate the linkage between in-sample and out-of-sample Granger causality.

Estimation results for the VAR(1) model using the full sample are depicted in Table 2. As such, several observations can be made from the information shown. First, the presence of two-way Granger causality is evident, meaning both markets capture certain types of news more quickly in prices than the other.[11] For example, the coefficient for lagged CDS returns is statistically significant at the 5% level in forecasting equity returns, while that of the lagged equity returns is significant in forecasting CDS returns at the 1% level. Second, our in-sample results suggest a negative relationship in the lead-lag relationship between equity and CDS returns, which is to be expected given that higher expected earnings result in lower default risk while lower expected earnings result in higher default risk. Third, the equity returns seem to be weakly autocorrelated even though they are constructed based on a portfolio closely matching the constituents in the systematic CDS index of the high-yield sector.

5.2 Out-of-Sample Forecasting Performance and Predictive Accuracy Ranking

We begin our out-of-sample analysis by examining the global performance of all predictive models over the entire forecast evaluation sample, on the basis of the Campbell and Thompson (2008) R^2_{OOS} statistic commonly adopted in equity return forecasting literature. Table 3 reports the statistical performance of out-of-sample forecasts of equity and CDS returns by means of the R^2_{OOS} statistic.

The R^2_{OOS} statistic measures the percentage reduction in mean squared forecast error for the VAR(1) model vis-à-vis a competing benchmark. Intuitively, a greater positive value of the R^2_{OOS} indicates that the VAR(1) model forecasts better than the competing alternative. For each predictive target, we examine the quality of forecasts produced by the VAR(1) model which incorporates cross-market informational flow against two commonly used benchmarks in the literature which do not. These two models are namely an autoregressive regression of order one, AR(1), which is nested in the VAR(1) and a simple random walk model, RW, which is nested in the AR(1) and not only ignores cross-market flow but also is grounded in the efficient market hypothesis that past prices have no effect on future ones.

As stated, to safeguard our forecast evaluation results against the possible risk created by an arbitrarily chosen sample split choice and to ensure that our predictive accuracy rankings are robust to the factor of rolling window size, we consider a sequence of choices on the rolling estimation window size, R, in percentage relative to the full sample size, when calculating the out-of-sample R^2_{OOS} statistics. The size of R ranges from 30% to 60% relative to that of the full sample in increments of 5%.[12]

A close examination of Table 3 reveals a clear ranking with respect to the forecasting performance of the three competing models. Specifically, the VAR(1) model forecasts the

[11] Procasky (2020) thoroughly investigates the cross-market information flow based on in-sample evidence.
[12] The optimal choice of the estimation sample size is rigorously examined in Pesaran and Timmermann (2007).

best while the random walk benchmark performs the worst. To illustrate, with a 40% estimation window size, the VAR(1) model reports 12% and 24% more predictive gains vs. the random walk for equity and CDS returns, respectively. Moreover, vs. the AR(1) benchmark which ignores cross-market information flow, the VAR(1) model reports 2.7% and 1.5% greater predictive gains for equity and CDS returns, respectively.[13]

Interestingly, based on the results shown in Table 3, with AR(1) being the benchmark, the VAR(1) consistently generates greater predictive gains when forecasting equity returns using lagged CDS returns vs. CDS returns using lagged equity returns. This pattern suggests that information flow from the CDS market to the equity market is stronger than in the opposite direction after controlling for the information flow within each market, something which was not evident from the in-sample analysis. Moreover, the results in Table 3 suggest that this cross-market flow dynamic exists regardless of the size of the rolling estimation window used in the construction of forecasts. As a result, in subsequent analyses, we only consider the rolling window size of 40%.

5.3 Dynamic Measure of Forecasting Performance

While the out-of-sample R^2_{OOS} is a widely adopted measure used to compare forecasts in the empirical finance literature, it only reports the average relative forecasting performance over the entire evaluation period. As a result, since financial data typically is subject to various forms of instabilities, the predictive gains shown in R^2_{OOS} could conceivably come from one particular period in the evaluation sample. Therefore, to gain a better understanding of how our forecasts evolve from a dynamic perspective, and using the graphical tool proposed in Goyal and Welch (2008), we plot the time series of the cumulative difference in squared forecast errors (CDSFE) between the VAR(1) forecasts and the two benchmark models. Because a positive value of the cumulative error difference at any given point in the evaluation window implies that the VAR(1) model forecasts better than the competing benchmark at that point, ideally, if the VAR(1) model outperforms the benchmark at all points in time, we would observe a positively sloped CDSFE curve everywhere.

Figure 4 displays the CDSFE curves for equity and CDS forecasts produced by the VAR(1) model. The top panel presents results vs. the random walk benchmark, while the bottom panel reflects those vs. the AR(1) benchmark.

Overall, the plots contained in Figure 4 confirm our forecast evaluation results based on the out-of-sample R^2_{OOS} discussed in the previous section: the VAR(1) model which takes into account cross-market informational flow dominates the two competing alternatives

[13] In the literature of forecasting stock returns, the statistical significance of the R^2_{OOS} statistic is commonly examined by the Clark and West (2007) procedure with critical values taken from a standard normal distribution. However, since in subsequent sections we deploy a battery of tests punctiliously examining not only the statistical significance of the predictive accuracy ranking, but also other issues such as forecast unbiasedness and forecast breakdown, in the interest of brevity, we do not report the Clark and West (2007) t-test results for significance in Table 3.

when forecasting both equity and CDS returns. However, one interesting pattern worth pointing out is that when using lagged equity returns to forecast CDS returns vs. the AR(1) model, the predictive power of the VAR(1) model appears to deteriorate after 2014. This suggests that the observed predictive gains in that case mainly stem from the period before the year 2014. It also suggests that once again, flow from the CDS to the equity market is stronger (or in this case, more persistent) than in the opposite direction.

5.4 Statistical Significance of Forecasts

Against the backdrop of these intriguing results, we then turn our attention to a rigorous examination of the statistical significance of the observed relative forecasting performance of the VAR(1) model in order to validate its predictive power. Table 4 reports the results of a battery of statistical tests comparing and evaluating forecasting performance. These tests can be roughly categorized into three groups: (1) the forecast efficiency test examining whether the forecasts produced by the VAR(1) model are unbiased; (2) the Diebold-Mariano and Rossi-Giacomini tests used to test the ranking of relative forecasting performance (the former examines average performance with the latter examining dynamic performance); and (3) the forecast breakdown test examining the linkage between the in-sample and out-of-sample evidence of Granger causality. The top panel in Table 4 reflects results for the equity forecasts (cross-market flow from the CDS market) while the bottom panel shows results for the CDS forecasts (cross-market flow from the equity market). The number within parentheses beneath each test statistic reports the associated p-value.

In addition to the equity returns from the matching stock portfolio constructed with the high yield data, to gain a better understanding of cross-market informational flow and the potential for heterogeneity in that flow, we also analyze and report test results using equity returns from the S&P 500 index in this section since this is a liquidly traded index used by investors.

Our forecast efficiency results show that forecasts generated by the VAR(1) model are unbiased as all test statistics fail to reject the null hypothesis of the intercept equaling zero at all conventional levels of significance (non-zero intercepts are an indication of biasedness). Moreover, both the Diebold-Mariano and Rossi-Giacomini tests reject the null hypothesis of equal predictive accuracy, favoring the one-sided alternative that the VAR(1) model forecasts better than the AR(1) model on average, or at least at one point in the evaluation window. Finally, our forecast breakdown test results show that the in-sample evidence of Granger causality for the VAR(1) model is linked with the out-of-sample evidence, as in all cases and at all conventional levels of significance, we do not reject the null hypothesis that the expected surprise loss is zero (non-zero surprise losses are an indication of forecast breakdown).

In addition to the value of the test statistic reported in Table 4, a byproduct of the Rossi-

Giacomini fluctuation test is a time series plot of the Diebold-Mariano statistic at each point during the forecast evaluation period. Figure 5 presents such fluctuation test plots for both the equity and CDS return forecasts. Confidence bands are indicated by dashed lines in Figure 5. If the fluctuation test curve falls out of the confidence bands, it rejects the null hypothesis of equal forecast accuracy between the VAR(1) model and the AR(1) model. This means that negative values of the fluctuation test curve would indicate better forecasting performance for the VAR(1) model. The top and bottom plots in Figure 5 show results for the equity and CDS forecasts, respectively.

As can be seen, Figure 5 reveals information similar to that conveyed in the CDSFE plots discussed previously: VAR(1) outperforms AR(1) in terms of equity forecasts using lagged CDS values throughout the entire forecast evaluation window; however, when it comes to forecasting CDS returns using lagged equity returns, the VAR(1) model begins to lose its dominance over the AR(1) after the second half of the year 2013. Accordingly, our fluctuation test suggests once again that information flow from the equity to the CDS market weakens toward the end of the sample while flow from the CDS to the equity market is consistent throughout the entire evaluation period.

6 Robustness and Extension

In this section we further investigate the robustness of the above findings by (i) testing whether the VAR(1) model possesses an informational advantage over the AR(1) model using forecast errors; (ii) examining if the strength of information flow varies under different market conditions; and (iii) comparing the relative strength of information flow from each market using a direct measure of the Granger causality.

6.1 Information Advantage

In this regard, we first employ the methodology used by Rossi and Sekhposyan (2016) to assess whether the VAR(1) model possesses an informational advantage over the AR(1) model. In doing so, we consider the following regression:

$$y_{i,t+1} - y^{AR}_{i,t+1|t} = \alpha + \beta y^{VAR}_{i,t+1|t} + \gamma y^{AR}_{i,t+1|t} + \epsilon_{t+1}, \tag{15}$$

where $y^{VAR}_{i,t+1|t}$ is the one-step ahead VAR(1) forecast for target variable i made in period t, $y^{AR}_{i,t+1|t}$ is the one-step ahead AR(1) forecast for target variable i made in period t, and $y_{i,t+1}$ is the realized value for target variable i at time t. The VAR(1) forecasts are useful beyond that of the AR(1) model when predicting equity or CDS returns if and only if $\beta \neq 0$. We test this hypothesis using a fluctuation-type test similar to the Giacomini and Rossi (2010b) fluctuation test in rolling regressions with a estimation window of size $R/2$. The results are reported in the upper panel of Figure 6, with the upper-left plot reflecting forecasted equity values while the upper-right plot depicts forecasted CDS values. The dashed horizontal lines in the upper panel plots of Figure 6 are appropriate critical values taken from Rossi and Sekhposyan (2016). If the fluctuation curve rises above the critical value line, the null hypothesis that the VAR(1) model possesses no informational advantage over the AR(1) is rejected.

For forecasted equity values using lagged CDS values, the null hypothesis of no informational advantage is resoundingly rejected over the entire out-of-sample window. However, for forecasted CDS values using lagged equity values, the VAR(1) model appears to possess an informational advantage over the AR(1) model only through the middle of 2013, after which there is no advantage with the exception of a relatively short span in the middle of 2015.

The bottom panel of Figure 6 plots the coefficients on the VAR(1) forecasts, β, in Equation (15) containing the AR(1) forecasts as the additional explanatory variable in rolling regressions. Intuitively, the size of β measured in absolute value can be interpreted as a gauge of the strength of the informational advantage of the VAR(1) model. For equity forecasts, this coefficient increases rapidly at the beginning of the year 2013, then drops at the start of 2015 but is still high in value. Turning to the CDS forecasts, the coefficient values are much lower in general than for forecasted equity results and reverse signs at the beginning of 2014 and then trend toward zero. Viewed overall and as can be seen visually, the informational advantage possessed by the VAR(1) model remains strong throughout the evaluation window for equity return forecasts, and is much weaker for CDS return forecasts during the first half of the evaluation sample.

From these tests, we conclude once again that the VAR(1) model has an informational advantage over the AR(1), indicating the existence of cross-market informational flow and that flow from the CDS to the equity market is stronger than flow in the opposite direction.

6.2 Forecast Evaluation based on Risk Regimes

We then turn our attention to investigating whether the observed cross-market informational flow is different under differing risk or market fear regimes. The top panel of Figure 7 presents the time series plot of the VIX index, which we use as a proxy for risk. We separate our data sample into two distinct risk regimes according to the index: if the daily value of the VIX index associated with an observation exceeds 25, we place the observation into the high risk category; otherwise the observation is categorized as low risk. The bottom panel of Figure 7 plots the market fear regimes over time with 0 indicating low risk while 1 indicates high risk.

Table 5 reports forecast evaluation results for the VAR(1) model under the two different risk regimes. Here we consider three statistics: the out-of-sample R^2_{OOS}, the forecast efficiency test investigating forecast unbiasedness and the Diebold-Mariano test comparing the global relative forecasting performance. The number within parentheses beneath each test statistic reports the associated p-value.

All statistics reported in Table 5 indicate that the VAR(1) model dominates the AR(1) model during periods of high investor fear in both equity and CDS markets, suggesting that cross-market informational flow is particularly strong during times of turbulence. To illustrate, the CDS forecasts report a R^2_{OOS} value of 3.7484, are unbiased and are more accurate than those from the AR(1) model. However, under a low investor fear regime, only information flow from the CDS to the equity market is statistically significant, as in the other direction the forecasts are biased and less accurate than those of the AR(1) model. Interestingly, this dynamic is largely consistent with overall results as the subperiod of time near the back end of the sample, in which flow from the equity to the CDS market has been documented to decrease, is characterized by lower average VIX levels relative to the rest of the sample.

6.3 Direct Measure of Granger Causality

As a final test, we are interested in directly measuring the relative strength of the previously documented statistically significant in-sample and out-of-sample causality inherent in the VAR(1) model. While low frequency data may disguise the true causal relationship between variables, the high frequency data we use in this paper provides us with an opportunity to analyze and quantify such causal effects.

Following the methodology proposed in Dufour et al. (2012), we apply causality measures to quantify the strength of the relationships between the CDS and equity returns. A higher value of causality measure indicates stronger relative causality. We also compute the corresponding nominal 95% bootstrap confidence intervals based on the fixed-design wild bootstrap procedure described in Goncalves and Kilian (2004) and Clark and McCracken (2013a).

Table 6 shows the estimation results of causality measures for equity returns based on lagged CDS returns, and CDS returns based on lagged equity returns. Both in-sample and out-of-sample causality measures are reported. For each forecasting target, the upper row gives the point estimate of the causality measures at the one-period ahead time horizon while the bottom row reports the 95% corresponding bootstrapped confidence interval.

As can be seen, the estimates validate our earlier result that Granger causality is statistically significant both in-sample and out-of-sample. Interestingly, the out-of-sample causality measures dominate their in-sample counterparts, meaning that cross-market predictive power is greater during the out-of-sample basis. Finally, information flow from the CDS to the equity market is once again stronger than in the opposite direction.

7 Discussion

7.1 Contribution to Market Efficiency Assessment

For the first time in the literature, we test observed in-sample Granger causality results associated with cross-market informational flow between CDS and equity markets on an out-of-sample basis using indexes and a battery of established forecast evaluation techniques. This is necessary in order to understand the true nature of informational flow between these two markets. If observed in-sample results do not hold on an out-of-sample basis and/or the results are not persistent across the time period studied, then the VAR models employed do not have true predictive power.

Interestingly, we find that the observed in-sample Granger causality results hold on an out-of-sample basis, validating that both markets price in certain information more efficiently. However, we also observe that the informational advantage of the CDS market vis-à-vis the equity market has increased over time, as post 2013, cross-market flow from the CDS to the stock market remains strong while there is no observed flow in the other direction, a result not previously documented in the closely related literature. This means that only part of the observed cross-market flow is persistent and underscores the need to investigate in-sample Granger causality more deeply since it merely reports an average result.

We attribute this dynamic to two reasons. The first is the relative growth in popularity of CDS indexes vs. single name CDS during the time period studied. Along these lines, according to BIS data, indexes comprised only approximately 20% of the overall market when our sample begins compared to 50% by the end. The second and likely more material reason is the comparatively lower level of investor fear characterizing the equity market at the back end of our sample. To illustrate, the average level of the VIX during the last three years of our sample was 14.8 compared to 21.3 for the first seven years. We theorize that during such times, investors are not as concerned about hedging the default risk inherent in their equity and bond positions, which in turn decreases the flow of information from the equity to the CDS market associated with such activity. As empirical support for this theory, we reference our result in section 6.2 of this study in which flow from the CDS to the equity market was observed during both the high and low risk VIX regimes while flow in the opposite direction was only observed during the high risk regime.

The presence of heterogeneity in cross-market informational flow in the high-yield sector is also observed in Procasky (2020) based on a rigorous in-sample analysis. As a potential reason for this asymmetrical flow from the CDS market, the author cites the need for investors to delta hedge their exposure to curvilinear default risk. Because this risk is much higher in the high-yield sector, it can be implemented more efficiently with CDS than stock since CDS positions would not need to be updated as frequently (thereby resulting in lower transaction costs).

7.2 Contribution to Forecasting Equity Returns

Apart from the contributions to the efficiency of CDS and equity markets, our empirical results also shed light on the predictability of aggregate equity returns. In a seminal study utilizing a comprehensive dataset examining the forecasting of equity premiums, Goyal and Welch (2008) show that the U.S. market equity premium cannot be meaningfully predicted out-of-sample against the simple random walk benchmark based on a wide range of accounting variables and economic indicators, such as the dividend-price ratio and the inflation rate. However, the conclusion delivered in Goyal and Welch (2008) has been consistently challenged in subsequent research which argues that aggregate stock returns are predictable with the help of exogenous predictors, once a correct forecasting model or estimation methodology is employed. For example, given the extensively documented empirical evidence of instabilities in the financial markets, a number of prominent researchers have demonstrated that methods such as forecast combination (Rapach et al. (2010)), time-varying parameter model (Dangl and Halling (2012)), Beyesian estimation framework (Pettenuzzo et al. (2014)) and shrinkage estimators (Li and Tsiakas (2017)) can uncover significant predictive content embedded in previously proposed predictive variables.[14]

However, most subsequent works challenging the view expressed in Goyal and Welch (2008) have primarily centered on forecasting multi-period ahead market stock returns with low frequency data (monthly, quarterly or yearly). In contrast, we examine the issue of market efficiency and return predictability with a rich dataset consisting of relatively recent daily data. While frictions and shocks indeed occur frequently in financial markets, leading to possibly short-lived instantaneous predictability for near-future returns, given the technological advancements in the industry and maturity of financial markets, it would be difficult to argue that today's equity market changes are primarily driven by events which took place in the distant past. Our analysis confirms this by showing that while the predictability of equity returns attributable to cross-market information flow does exist, nevertheless, it does not last beyond one trading day. Therefore, we provide new evidence of market equity returns predictability based on high-frequency data with a short forecast horizon. Moreover, rather than searching for new accounting variables, sentiment indexes or estimation methodologies, we investigate the issue of equity returns predictability by taking a deep look at the price discovery and informational flow from a different but closely linked asset market. This new direction of research on equity returns predictability could have implications for portfolio managers who base their trading strategy on high-frequency short-horizon forecasts.

[14]Empirical evidence on instabilities are documented in studies such as Rapach and Wohar (2006) and Paye and Timmermann (2006). Another direction of research focuses on finding new variables or indexes which may forecast future stock returns, examples of such studies are Li et al. (2013) and Rapach et al. (2016).

8 Conclusion

We contribute to the literature on the efficiency of CDS and equity markets by rigorously conducting a battery of out-of-sample tests in order to determine the true predictive power of observed in-sample cross-market informational flow in the systematic high yield sector. Results of prior studies have been based on in-sample analysis, thereby leaving the question of true predictive power unanswered. Interestingly, we find that both markets are useful in forecasting future values of the other, indicating that each is more efficient in pricing in certain types of information. Moreover, the CDS market appears to have an informational advantage over the equity market which has increased with time, a result not previously documented in the closely related literature. We attribute this finding to the greater relative significance of CDS index trading vs. single name CDS as well as the lower level of volatility and investor fear which characterize the back end of our sample. These results have implications for high yield investors, arbitrageurs and all financial stakeholders who monitor Markit's CDX.NA.HY for informational content.

We also contribute to the literature on the predictability of aggregate equity returns. Specifically, we provide new evidence of market equity return predictability based on the study of informational flow from a closely linked asset market using high-frequency data with a short forecast horizon. Moreover, we show that such predictability does not last beyond one trading day. These results have implications for portfolio managers who base their trading strategy on such forecasts.

Table 1: Summary Statistics

	Observations	Mean (%)	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
Equity Returns	2655	0.0157	0.0164	-0.0912	0.0658	-0.5572	6.8189
CDS Returns	2655	-0.0012	0.0258	-0.1395	0.2133	0.7319	9.9177

Notes: This table presents descriptive statistics for the daily returns of the Markit CDX North American High Yield Index and a matching equity portfolio. Our data set begins on November 29th, 2004 and ends on September 18th, 2015. Details on the CDS index and the construction of the matching equity portfolio are provided in the Description of Data section of this paper.

Table 2: VAR(1) Model In-Sample Estimation Results

	CDS to Equity	Equity to CDS
intercept	0.00013	0.00004
	(0.6731)	(0.9350)
lagged equities	0.01689	-0.09878
	(0.4704)	(**0.0070**)
lagges CDS	-0.03162	0.07035
	(**0.0336**)	(**0.0025**)
R^2	0.0037	0.0139
Adjusted R^2	0.0030	0.0131

Notes: This table reports the full sample estimation results for the VAR(1) model. For "CDS to Equity", equity returns are regressed on an intercept, its own lagged values and the lagged values of CDS returns. For "Equity to CDS", CDS returns are regressed on an intercept, its own lagged values and the lagged values of equity returns. Numbers in parentheses underneath the parameter estimates report the corresponding p-values. Statistical significance at the 5% nominal level is indicated in bold.

Table 3: Out-of-Sample Forecasting Performance Measured by R^2_{OOS} (%)

	CDS to Equity		Equity to CDS	
Window Size	AR(1)	RW	AR(1)	RW
30%	1.2235	10.1218	0.9566	23.0616
35%	1.7336	11.8112	1.0890	23.6047
40%	2.6759	12.2939	1.4501	24.2991
45%	2.8538	12.0077	1.1252	23.8379
50%	2.5303	11.5659	0.9559	23.3636
55%	2.2287	10.9972	0.7713	23.1104
60%	2.6263	11.7455	0.5032	22.8893

Notes: This table reports the out-of-sample R^2_{OOS} for various values of the training sample size measured in percentage relative to the full sample size. The R^2_{OOS} measures the percent reduction in mean squared forecast error for the VAR(1) model relative to two different benchmarks: the AR(1) and the Random Walk (RW) models. The higher the value of the R^2_{OOS}, the better predictive performance for the VAR(1) model against the competing benchmark. "CDS to Equity" indicates forecasted equity returns based on potential information flow from the CDS to the equity market, while "Equity to CDS" denotes forecasted CDS returns based on possible information flow from the equity to the CDS market.

Table 4: Forecast Evaluation Tests

CDS to Equity				
	Forecast Efficiency	Diebold-Mariano	Rossi-Giacomini	Forecast Breakdown
High Yield	0.0005	-8.3927	9.7442	-0.2937
	(0.204)	(0.000)	(0.003)	(0.385)
SP500	0.0004	-9.2646	11.6930	-0.2269
	(0.220)	(0.000)	(0.003)	(0.410)
Equity to CDS				
	Forecast Efficiency	Diebold-Mariano	Rossi-Giacomini	Forecast Breakdown
High Yield	-0.0006	-3.266	6.0143	-0.1804
	(0.262)	(0.001)	(0.003)	(0.428)
SP500	-0.0006	-3.0626	3.1295	-0.1593
	(0.296)	(0.001)	(0.003)	(0.437)

Notes: This table reports the results of various out-of-sample tests which evaluate and compare forecasts. Forecast efficiency tests for the null hypothesis of forecast unbiasedness. The Diebold-Mariano statistic tests for the null of equal predictive accuracy against the one-sided alternative that the VAR(1) outperforms the AR(1) model on average over the evaluation sample. The Rossi-Giacomini statistic tests for the null of equal predictive accuracy against the one-sided alternative that VAR(1) outperforms the AR(1) model at least once over the evaluation sample. Forecast breakdown tests for the null of zero distance between the in-sample MSE and the out-of-sample MSFE against the one-sided alternative that the MSFE is larger than MSE. "High Yield" indicates use of the closely matched equity portfolio consisting of all names in the high-yield CDS index for equity returns while "SP500" denotes use of the S&P500 index returns for equity returns in our out-of-sample analysis. Numbers in parentheses underneath the test statistics report the corresponding p-values. "CDS to Equity" indicates forecasted equity returns based on potential information flow from the CDS to the equity market, while "Equity to CDS" denotes forecasted CDS returns based on possible information flow from the equity to the CDS market.

Table 5: Forecast Evaluation Based on Market Fear Regime

	High Fear		Low Fear	
	Equity	CDS	Equity	CDS
R^2_{OOS}	2.5714	3.5907	2.7612	0.2598
Forecast Efficiency	-0.0012	0.0009	0.0008	-0.0009
	(0.415)	(0.657)	(0.014)	(0.086)
Diebold-Mariano	-4.7362	-3.403	-7.5997	-0.74311
	(0.000)	(0.000)	(0.000)	(0.229)

Notes: This table reports the results of various out-of-sample tests evaluating and comparing forecasts based on VIX implied market fear regimes. We choose a VIX value of 25 to separate the high and low market fear regimes. The R^2_{OOS} measures the percent reduction in mean squared forecast error for the VAR(1) model relative to the AR(1) benchmark. The higher the value of the R^2_{OOS}, the better the predictive performance for the VAR(1) model against the competing benchmark. Forecast efficiency tests for the null hypothesis of forecast unbiasedness. The Diebold-Mariano statistic tests for the null of equal predictive accuracy against the one-sided alternative that the VAR(1) outperforms the AR(1) model on average over the evaluation sample. Numbers in parentheses underneath the reported test statistics show the corresponding p-values. "Equity" indicates forecasted equity returns based on potential information flow from the CDS to the equity market, while "CDS" denotes forecasted CDS returns based on possible information flow from the equity to the CDS market.

Table 6: Causality Measure

		In-Sample	Out-of-Sample
CDS to Equity			
	Point Estimate of Causality	0.0746	2.7124
	95% Bootstrap Interval	[0.0000, 0.2569]	[0.000, 3.2188]
Equity to CDS			
	Point Estimate of Causality	0.2039	1.4607
	95% Bootstrap Interval	[0.0000, 0.2161]	[0.000, 1.6418]

Notes: This table reports the Dufour et al. (2012) Granger Causality measures for the lead-lag relationship between the CDS and equity markets. For each direction of information flow, we report the point estimate of the Granger causality and its associated 95% bootstrap confidence interval. Both in-sample and out-of-sample results are reported. "CDS to Equity" indicates forecasted equity returns based on possible informational flow from the CDS to the equity market, while "Equity to CDS" consists of forecasted CDS returns based on possible informational flow from the equity to the CDS market.

Figure 1: Construction of High Yield CDS Index. This figure illustrates the construction of the high-yield systematic CDS index consisting of 100 single name CDS.

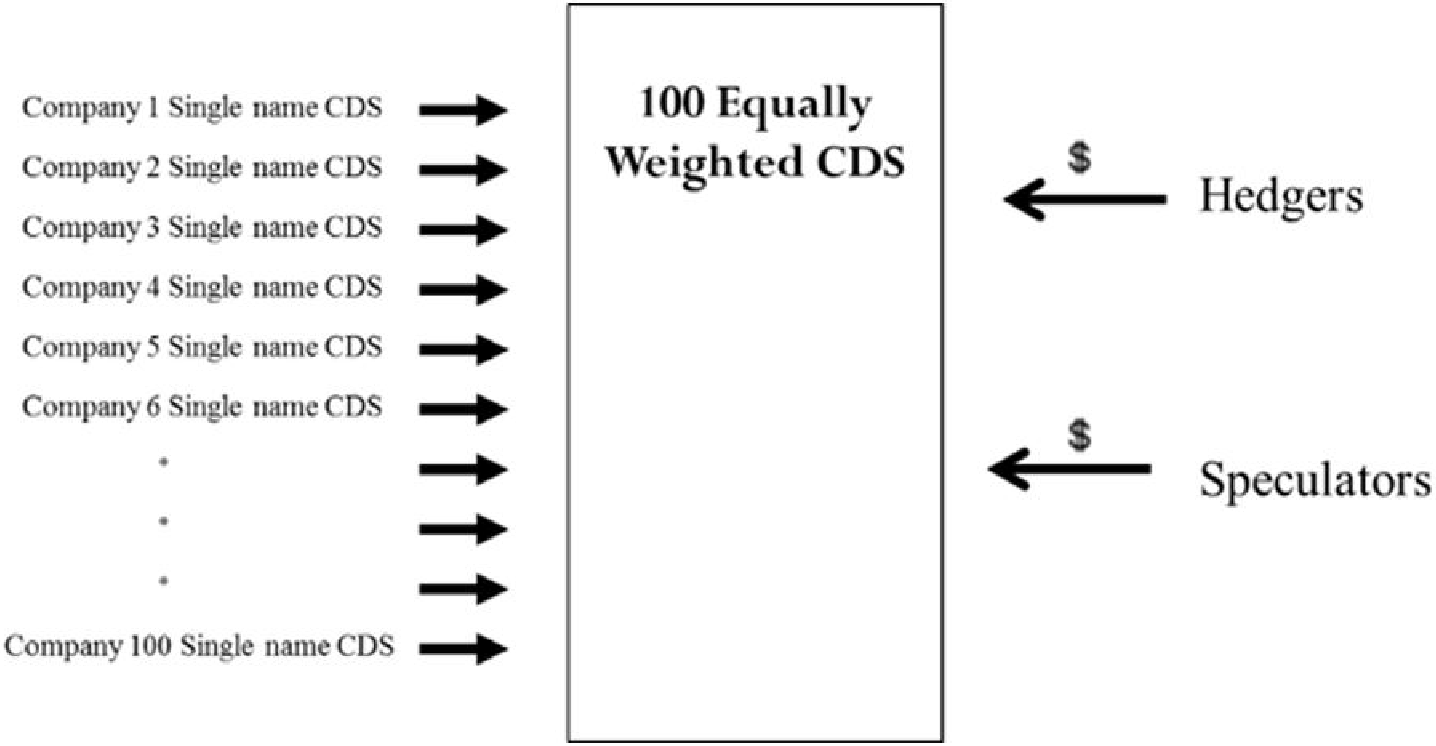


Figure 2: Time Series Plot of Equity and CDS Returns. This figure plots the time series of the high-yield systematic CDS index returns and the matching equity portfolio returns.

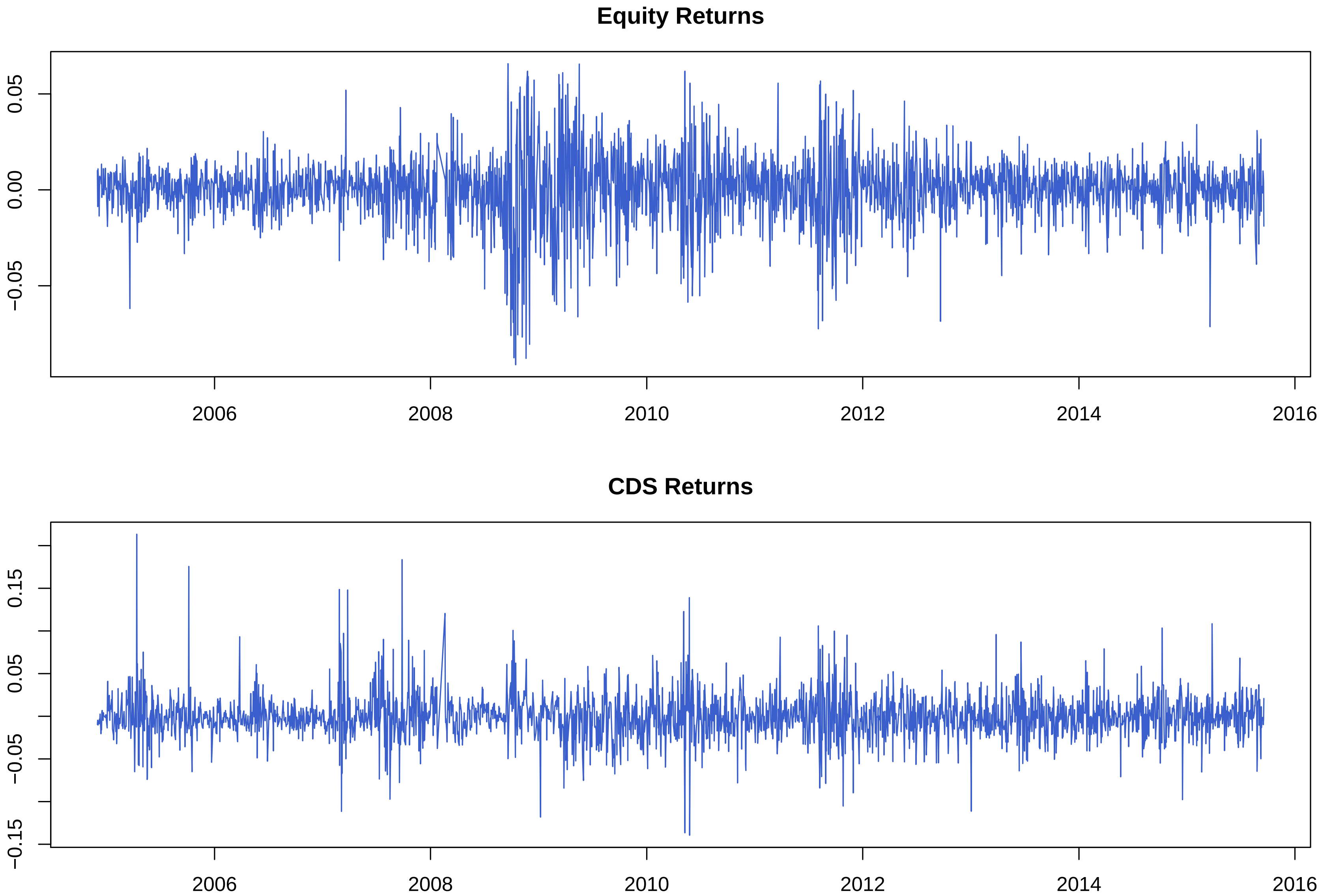


Figure 3: Out-of-Sample Forecasts of Equity and CDS Returns. This figure plots the out-of-sample forecasts of the high-yield systematic CDS index returns and matching equity portfolio returns from the VAR(1) and AR(1) models. Forecasts run from April 23, 2009 to September 18, 2015.

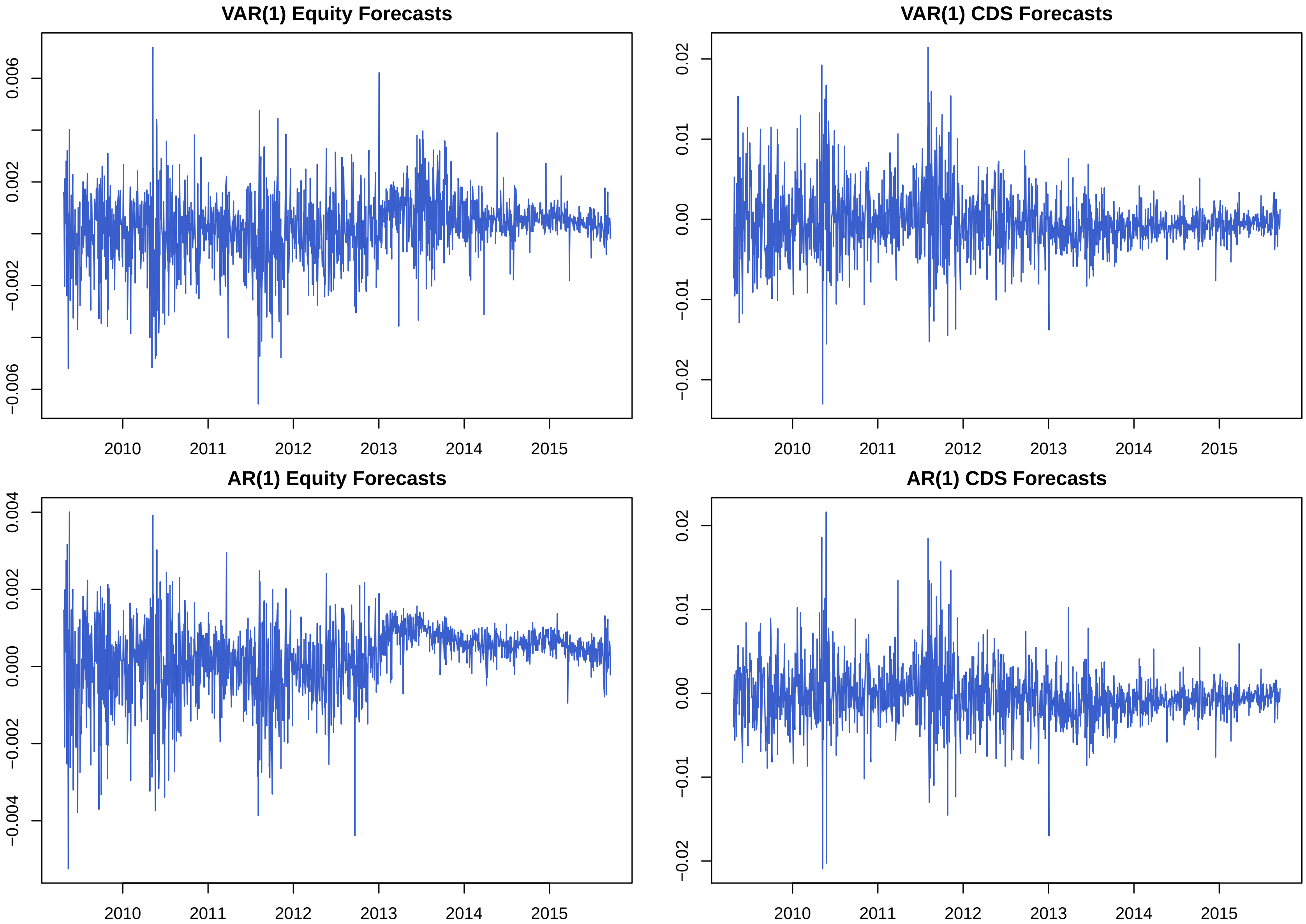


Figure 4: Cumulative differences in squared forecast error (CDSFE) for VAR(1) forecasts against two benchmarks: AR(1) and Random Walk (RW). We plot the constructed CDSFE series following the guidance proposed in Goyal and Welch (2008). If the CDSFE curve moves up, it indicates better forecasting performance for the VAR(1) model than the benchmark for a particular forecasting target.

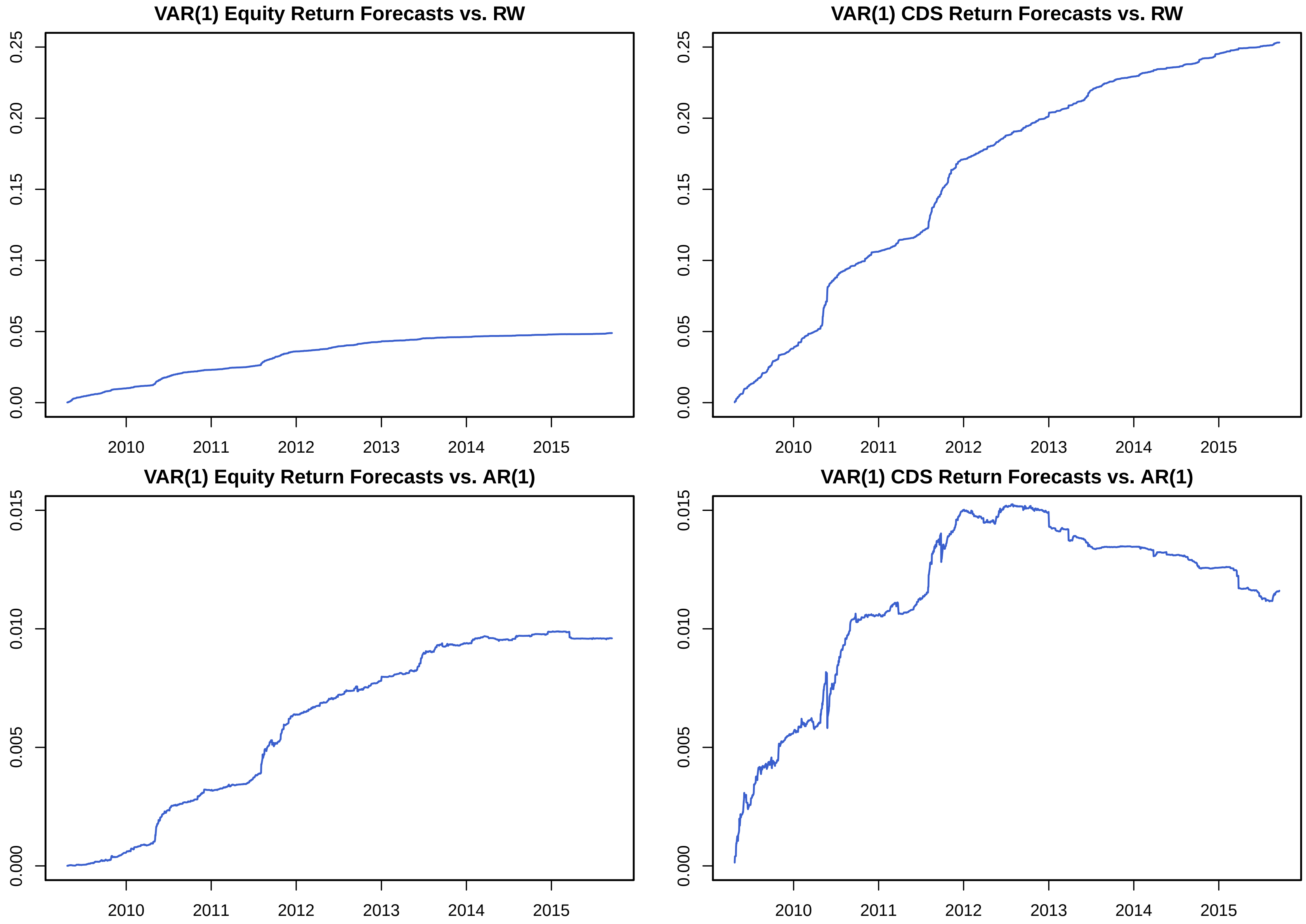


Figure 5: Rossi-Giacomini Fluctuation Tests. We plot the time series of the Giacomini and Rossi (2010b) fluctuation test statistics for CDS and equity return forecasts. For each forecasting target, if the curve falls below the confidence bands, it implies that the VAR(1) model forecasts better than AR(1) at least once during the entire forecast evaluation period.

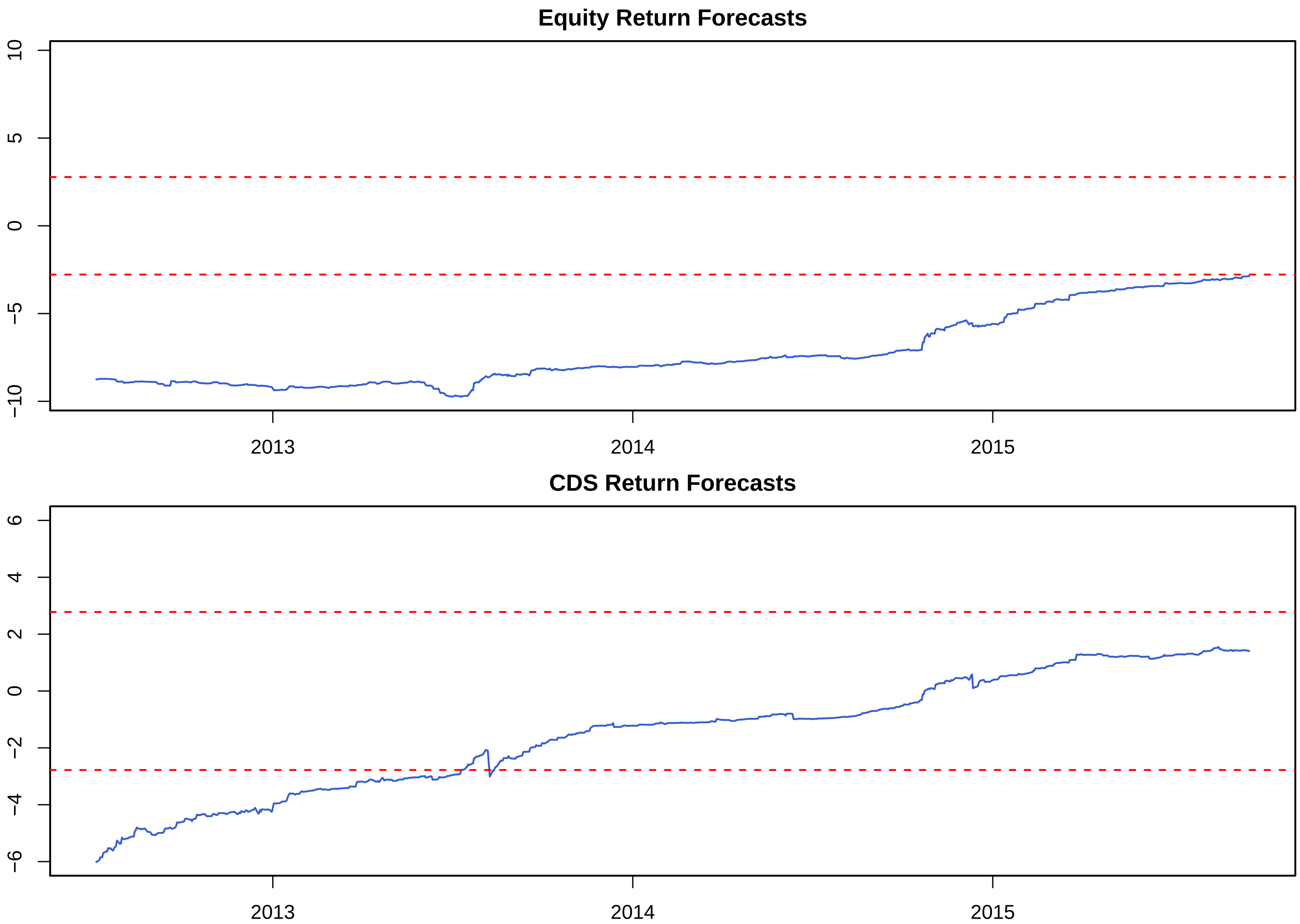


Figure 6: Information Advantage. The top panel plots the fluctuations test statistics testing the existence of an informational advantage of the VAR(1) model over the AR(1) benchmark following Rossi and Sekhposyan (2016) for equity and CDS return forecasts. If the curve stays above the critical band, it implies that the cross-market informational flow results in a VAR(1) informational advantage over the AR(1) model. The bottom panel plots the time series of the estimated coefficients for VAR(1) in the informational advantage tests for equity and CDS returns forecasts. At any time point, a larger absolute value of the estimated coefficient suggests greater informational strength for the VAR(1) model over its AR(1) competitor.

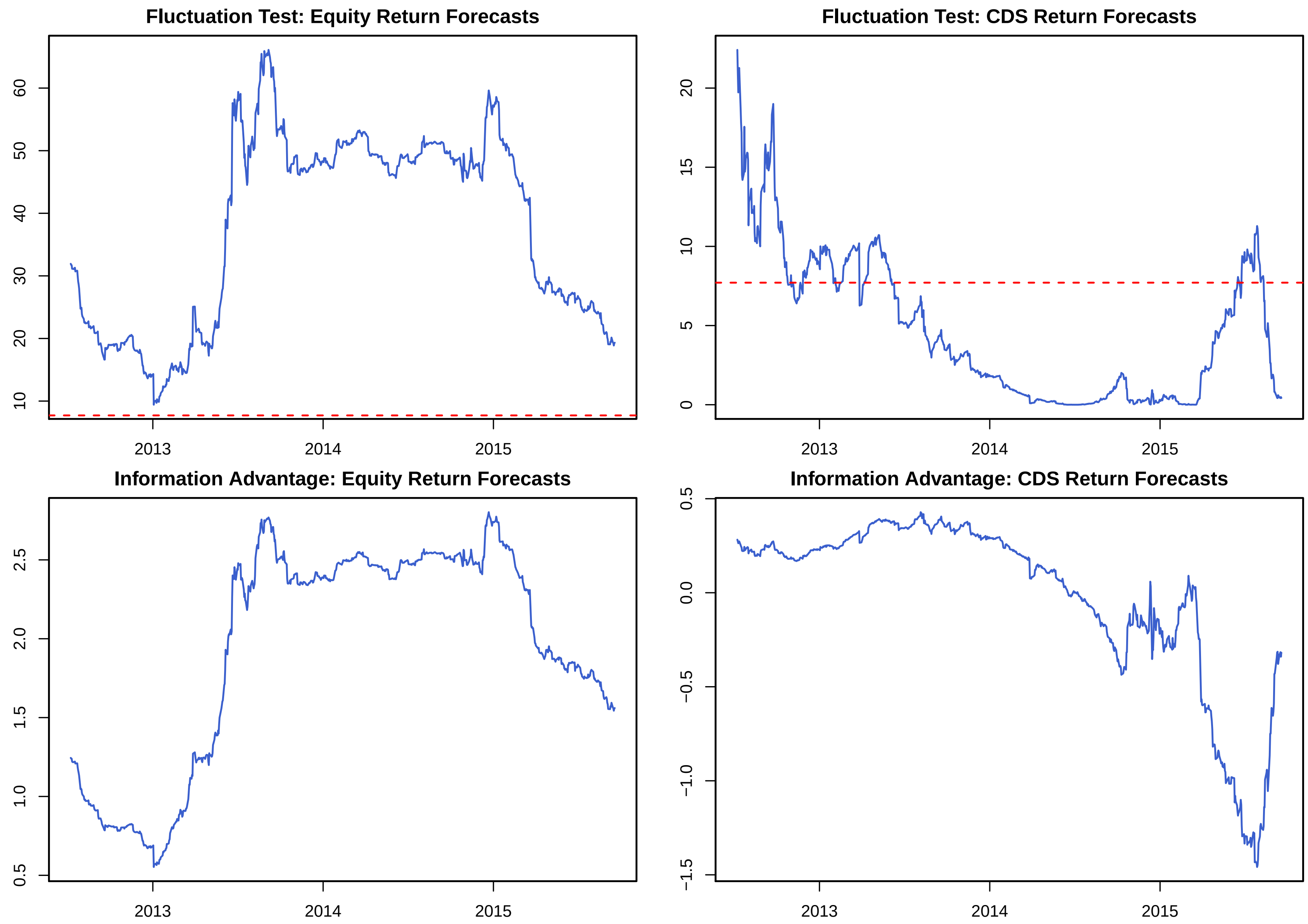
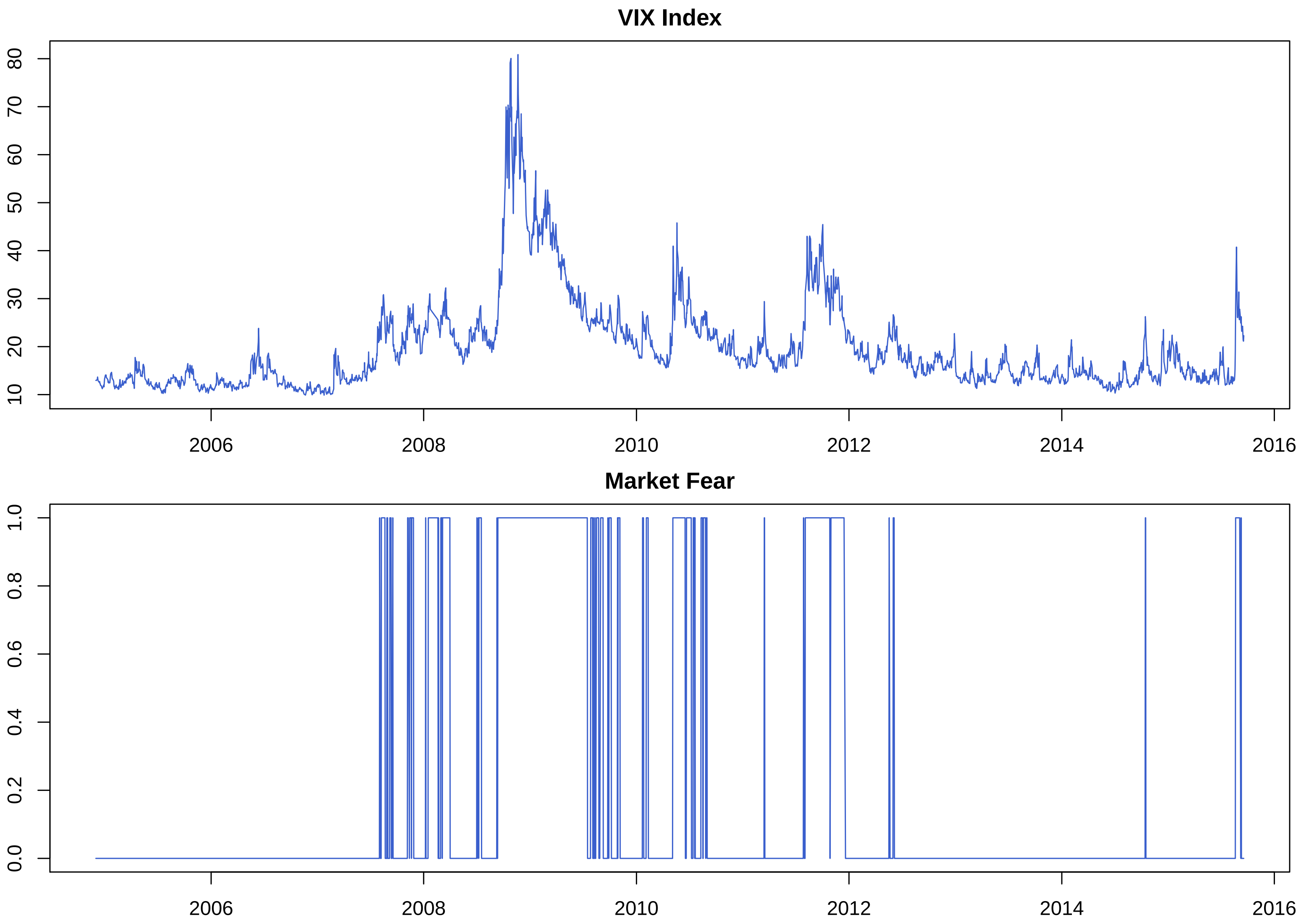


Figure 7: Market Fear Regimes Based on VIX Index. The top panel plots the time series of the VIX index, while the bottom panel presents the market fear regimes. Market fear being 0 implies a low risk regime while 1 indicates a high risk regime. The threshold value of the VIX separating the data into high and low risk regimes is 25. Our data set begins on November 29th, 2004 and ends on September 18th, 2015.



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