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We examine the comparative efficiency of systematic investment grade CDS and equity markets using a dynamic VAR model which enables a view of cross-market informational flow along each point in the time-period under investigation by taking into account parameter instability. We obtain smoothing estimates of parameters capturing such flow between CDS and equity markets over 2004-2015 and measure the strength of flow via relative predictive gains. In contrast to prior studies employing the traditional VAR, we find a two-way interactive effect in which certain types of information are captured more efficiently in prices by each market. We also find that the dynamic VAR results in superior forecasting gains relative to models without accounting for price discovery. These results have implications for systematic investors, arbitrageurs and stakeholders who monitor systematic markets for their informational content.

***Keywords**:* *Market Efficiency, Informational Flow, Dynamic Vector Autoregression, CDS Indexes, Structural Break*

***JEL Classification**: C32, C58, G14, G17*

I. Introduction

A comprehensive examination and measure of relative market efficiency and cross-market informational flow between the credit and equity markets are of great importance to both academic researchers and financial analysts. This is because of the advantage that such knowledge gives stakeholders who monitor capital markets closely to make rapid decisions based on new information captured in asset prices. For example, with such knowledge, investors can buy and sell early to take advantage of bullish and bearish news, arbitrageurs can establish positions to capitalize on anticipated second-order movements, and risk managers can incorporate the informational content into their market forecasts and mitigation strategies.

While a significant body of historical literature has investigated whether credit default swap (CDS) or equity markets are more efficient in capturing and impounding new information into

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asset prices, including Norden and Weber (2004, Norden and Weber (2009), Fung et al. (2008), Forte and Pena (2009), Shahzad et al. (2017), and Procasky (2021), these studies have all used a vector autoregressive model (VAR) originally proposed in Sims (1980). VAR models are designed to detect and capture lead-lag relationships between two or more sets of time series variables, thereby considering informational flow between the variables. As such, 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). However, a limitation of the standard VAR model is that it assumes a stable coefficient vector throughout the time series, and consequently, any possible departure from the notion of stationarity is not captured. Because of this limitation, periods of asymmetry and/or structural breaks as well as any regime dependence during the time series remain undetected.

Given the dynamic nature of financial markets, together with the well documented empirical evidence of structural breaks or instability in financial time series (see, for example, Paye and Timmermann (2006)), this assumption of stable, static flow may lead to spurious conclusions regarding the efficiency of the subject capital markets as well as nature of any observed cross-market informational flow, especially in studies employing longer-term data. The underlying trends can also be skewed by the presence of outliers in the time series data. To address these shortcomings, we propose the introduction and use of a new form of model to this field of study, namely, a dynamic linear VAR model enabling a view and understanding of the evolution of market efficiency and informational flow along each point in the time-period under examination. Specifically, using a meticulously constructed data set, we apply this model to the systematic investment grade markets where, previously, Procasky (2021) documented that both markets capture new information efficiently, suggesting that cross-market informational flow is not present. However, given the above factors, we hypothesize that the true nature of flow may have been masked by the limitations of the standard stable vector autoregression analysis.

The dynamic VAR model we employ is a multivariate extension to the univariate dynamic linear model, which belongs to the family of state-space models. The general framework of the multivariate dynamic linear model is not only flexible enough to encompass various standard system of equations analysis, such as VARMA and SUR models, but it also allows for time-varying model coefficients, moving beyond the notion of stationarity in typical time series analysis. By employing the dynamic VAR model, we are able to obtain smoothing estimates of the coefficients which capture the cross-market informational flow between the subject equity and credit markets over the entire sample period, namely, 2004-2015, leading to a dynamic perspective on how such flow evolves over time. It is worth emphasizing that our sample period encompasses various major events, such as the maturation of the systematic credit risk index and the 2008-2009 global financial crisis; hence, we believe that it is appropriate to employ a methodology which accounts for instability in the examination of cross-market informational flow.

Moreover, since we can obtain sequences of one-step-ahead predictions of the equity and CDS returns over the entire sample period when implementing the Kalman filter to fit the dynamic VAR model to data, we are able to measure the size of the cross-market informational flow by conducting a rigorous out-of-sample analysis. Without such an analysis, a fulsome perspective on comparative efficiency and the potential for arbitrage profit opportunities is not possible. Despite this need, only one study to date in the related literature has examined cross-market informational flow on an out-of-sample basis (Procasky and Yin 2022), with the authors focusing on the high-yield systematic markets, leaving the systematic investment grade markets unexplored on an out-of-sample basis. In this regard, dynamic linear models, such as the one we employ in our study, are particularly suited to this type of analysis given that they permit time-varying model coefficients.

Unlike the typical out-of-sample analysis, such as Kolev and Karapandza (2017) in which the full sample must be arbitrarily split into a training sample for parameter estimation and a prediction sample for forecast evaluation, the implementation of the Kalman filter provides us with one-step-ahead forecasts of CDS and equity returns throughout the sample period under examination. Owing to this property, it is, therefore, not necessary to split the data into separate parts, a process which in and of itself may be susceptible to data mining and, thus, does not give a true perspective on predictive power. In conducting our out-of-sample analysis using a dynamic VAR model - which considers cross-market informational flow, we focus on its ability to forecast future movements in CDS and stock prices against a set of competing dynamic models which do not consider cross-market informational flow. Therefore, if, in fact, the true relationship between the CDS and equity markets is characterized by the presence of cross-market informational flow, then the specification which explicitly models such flow should outperform the others which do not. Moreover, while most out-of-sample analyses focus on a single market in evaluating forecasting ability, our study focuses on two separate, yet related, markets. As a result, not only are we able to evaluate the general forecasting ability of the dynamic VAR model, but we can also analyze and compare the relative ability of each market in forecasting the other. Only through such an analysis can a true understanding of the nature and strength of cross-market informational flow and predictive power emerge, and by extension, a determination as to which market captures information more efficiently.

Interestingly, we find that two-way cross-market informational flow is present in the systematic investment grade CDS and equity markets, a result that had previously not been observed in examinations using the traditional VAR model. Moreover, we find that there are instabilities in the level of flow, and that, in general, informational flow from the equity to the credit market appears to be stronger than flow in the opposite direction. This suggests that the investment grade systematic equity market is more efficient in capturing information than the CDS market, although the CDS market does capture and impound into pricing certain types of information more efficiently than the equity market. Moreover, we find that the dynamic VAR model incorporating cross-market informational flow is superior in forecasting future CDS and equity prices than a battery of other competing models not considering such flow. This indicates that the dynamic VAR is the appropriate model in capturing the dynamics of the underlying data generating process between the time series data. However, it is of interest to note that on a net basis, the dynamic VAR generally performs better in forecasting future equity returns than credit returns, suggesting that cross-market flow from the credit to the equity markets contains more information than in the opposite direction – a finding that runs counter to our initial observation and which underscores the need to engage in out-of-sample analysis when examining market efficiency. Viewed together, these results have significant implications for stakeholders who make decisions based on relative market efficiency, including index investors, arbitrageurs who buy and sell based on market movements, and risk managers who monitor systematic markets for informational content, as they indicate that only by viewing these markets from a dynamic VAR perspective is it possible to understand the true nature of cross-market informational flow.

The remainder of this paper is organized as follows: Section 2 reviews the related literature while Section 3 discusses the data. Section 4 describes the dynamic VAR methodology followed by a discussion of empirical findings in Section 5. Section 6 concludes.

II. Related Literature

As stated, there have been a significant amount of studies on price discovery and the relative efficiency of CDS and equity markets. The majority of these have involved the study of the North American market using non-systematic data, including Longstaff, Mithal, and Neis (2004), Acharya and Johnson (2007), Han and Zhou (2011), Marsh and Wagner (2012), Narayan, Sharma, and Thuraisamy (2014), and Hilscher, Pollet, and Wilson (2015) and Acharya and Johnson (2017). However, Norden and Weber (2004, Norden and Weber (2009) and Forte and Pena (2009) examined markets internationally using non-systematic data, while Ni and Pan (2020) and Rodriguez-Moreno and Pena (2013) used such data to perform sector-based analysis, focusing on the financial industry. Bystrom (2006), Fung et al. (2008), Procasky (2021), and Procasky and Yin (2022) used CDS and equity indexes to investigate systematic flow. Only Procasky and Yin (2022) have conducted out-of-sample analysis.

Overall, the empirical results have been mixed. Interestingly, many studies, such as Narayan, Sharma, and Thuraisamy (2014) employing multivariate time series data in a VAR framework, have found that stocks lead CDS. However, Procasky (2021) observes default risk-based heterogeneity in systematic CDS and equity markets, whereby the investment grade rated markets are equally efficient, i.e., neither leads the other, while a two-way interactive effect is documented in the non-investment grade rated markets. The latter result suggests the CDS market may be more efficient in impounding certain types of information in prices. Procasky and Yin (2022) corroborate this result in their out-of-sample analysis of the high-yield market and observe that the CDS market’s informational advantage has increased over time.

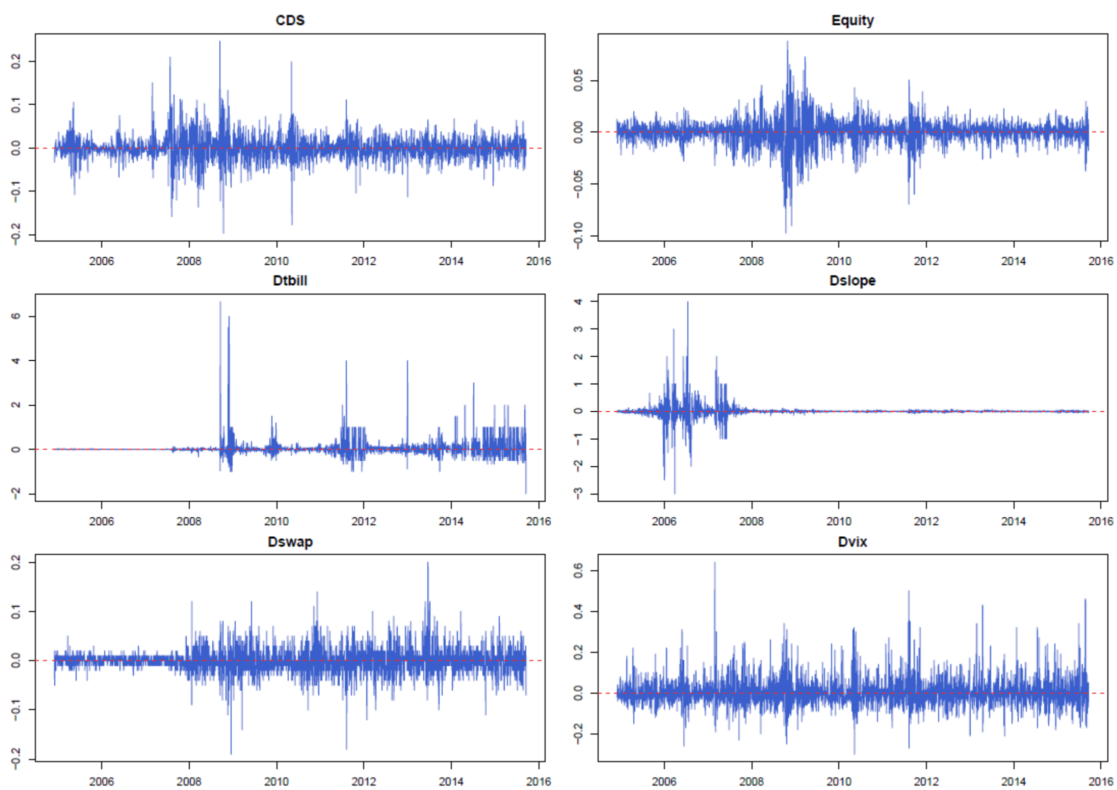
The presence of structural breaks or model instability has been well documented in the empirical finance literature. To illustrate, Rapach and Wohar (2006) provide empirical evidence of structural breaks among predictive regressions of the U.S. stock market excess returns while Paye and Timmermann (2006) find evidence of instability in international data. As a result, in recent studies, various methodologies have been proposed to better fit financial time series data in the presence of breaks or instability, see, for example, Rapach, Strauss, and Zhou (2010) and Yin (2019).

One study closely related to ours in terms of methodology is Dangl and Halling (2012). Given its flexibility, Dangl and Halling (2012) adopt the dynamic linear model to forecast the monthly U.S. market equity premium to account for the possible presence of instability. In their out-of-sample forecast evaluation results, the authors show that predictive regressions with time-varying coefficients could consistently generate more statistical and economic gains than models in which all parameters are held constant. Despite the common choice of the modeling framework, our analysis differs from Dangl and Halling (2012) in several regards. First, our primary research objective is to examine and measure the strength of cross-market informational flow in terms of price discovery in a possibly unstable environment, while Dangl and Halling (2012) focus on horse-racing in terms of predictive gains. Second, we carry out a multivariate analysis by specifying a dynamic VAR model in the family of dynamic linear models, while Dangl and Halling (2012) primarily center on Bayesian model averaging over dynamic univariate regressions with a single predictor. Last, we fit the dynamic VAR model to a rich dataset comprised of daily observations from the credit and equity markets, while Dangl and Halling (2012) use a well-known monthly dataset collected by Goyal and Welch (2008) for the equity market only.

III. Data

CDS index data was sourced from Markit. The timeframe covered is 11/29/04 - 9/18/2015, encompassing Series 3-24 of the CDX.NA.IG. Different series are produced as the index is rebalanced every six months. Constituents may be removed or replaced based on various rules governing the construction process, including but not limited to the level of trading liquidity of individual CDS or change in credit rating. New series replace the prior one as the on-the-run index. In all studies in our paper, the on-the-run series and version of the bellwether five-year index is used.

Figure 1. Time Series Plots of Data.



Note: This figure displays the time series of daily CDS and equity returns as well as four exogenous variables from November 29, 2004 to September 18, 2015.

Equity data is sourced from CRSP. Exceptions consist of a handful of stocks from Yahoo Finance. Data is adjusted for stock splits, and Canadian stocks (less than 1% of total data) are converted into US Dollars. For the matched portfolio, we must manually create an index of individual stocks and calculate daily equally weighted values from the individual stock values for all 2,680 trading days, a meticulous and time-consuming process which makes our data set unique. As with the CDX.NA.IG, we rebalance the portfolio every six months. Also, while observations related to days on which rebalancing occurs are removed to avoid bias associated with movements due to changes in constituents and not the market, such days comprise less than 1% of data. In addition to the equity and CDS return series, we also consider four exogenous variables in our empirical results. These exogeneous variables are: Dtbill, the changes in the 3-month T-bill rate; Dslope, the slope of the Treasury curve; Dswap, the lagged 5-year swap spreads; and Dvix, the lagged implied volatility of the equity market. All data for exogenous systematic variables used in robustness testing is sourced from the St. Louis Fed's FRED database. Figure 1 displays time series plots of all data described above.

Table 1 reflects descriptive statistics for the CDS and equity indices, along with the four explanatory variables considered in subsequent analysis. Observations dropped in preparing discrete indices are attributable to holidays on which equity markets were closed but bond markets were open, or CDX settlements occurred due to Canadian firms. However, given that trading was generally light or only impacted the Canadian names, little-to-no movement occurred in the CDX indices, and their removal has no impact.

Table 1. Summary Statistics.

	Mean	**Standard Deviation**	**Skewness**	**Kurtosis**	**AR(1)**	**Max**	**Min**
CDS	0.0001	0.0294	0.3597	6.8870	0.0923	0.2468	-0.1967
Equity	0.0002	0.0127	-0.6088	7.8439	-0.0696	0.0878	-0.0973
Dtbill	0.0288	0.3537	8.0087	117.2775	-0.108	6.6667	-2.0000
Dslope	0.0010	0.2360	1.3208	76.7236	-0.1154	4.0000	-3.0000
Dswap	-0.0001	0.0265	0.1105	5.1147	-0.0113	0.2000	-0.1900
Dvix	0.0027	0.0741	1.3602	6.3895	-0.0934	0.6400	-0.3000

Notes: This table presents descriptive statistics for the daily returns of the Markit CDX North American Investment Grade Index and a matching equity portfolio, together with four exogenous variables controlling for various market conditions. The dataset begins on November 29th, 2004, and ends on September 18th, 2015.

IV. Econometric Methodology

In this section we outline the dynamic vector autoregression system (DVAR) which we employ to model the bivariate time series data of the subject credit and equity markets and discuss the specification and estimation of the DVAR model.

4.1 The DVAR Model

The DVAR model belongs to the family of multivariate dynamic linear regression models, which are essentially state-space models under the assumptions of linearity and normality. Compared with the standard VAR model in which all model coefficients are often assumed to be constant over time, the DVAR offers a more flexible modeling choice by allowing for time-varying coefficients, thus encompassing a general breaking process underlying the data generating process.

Generally, our DVAR model takes on the following structure:

$$\begin{aligned} Y_t &= (F_t \otimes I_2)\theta_t + V_t , \\ \theta_t &= (G_t \otimes I_2)\theta_{t-1} + W_t . \end{aligned} \tag{1}$$

In the state-space model literature, the first equation in Eq. (1) is termed the observation equation while the second is called the transition equation. Defining the terms, $Y_t = \{y_{1t} , y_{2t}\}'$ is a 2×1 vector containing the bivariate time series data of the CDS and equity returns, respectively, $F_t = \{1, y_{1t-1}, \ldots, y_{1t-p}, y_{2t-1}, \ldots, y_{2t-p}\}$ is a $1 \times (2p + 1)$ vector containing lagged values of the time series data which is time-varying, p is the number of lags included, θ_t is a $2(2p + 1) \times 1$ vector of parameters of the slopes and lagged value coefficients, $\otimes$ is the Kronecker product operator, I_2 is the identity matrix of size two, G_t is a $(2p+1)\times(2p+1)$ matrix describing the evolution of the transition equation, $V_t = \{v_{1t}, v_{2t}\}'$ is a 2×1 vector of innovations to the observation equation, and W_t is a $2(2_p+1)\times1$ vector of innovations to the transition equation. We make the following distributional assumptions, $V_t \sim i.i.d\ N(0, V)$, where V is the 2×2 covariance matrix for the observation innovations, and $W_t \sim i.i.d\ N(0,W)$, where W is the $2(2p + 1) \times 2(2p + 1)$ covariance matrix for the transition innovations. We assume that V_t and W_t are independent of each other following the standard specification of dynamic linear models. The covariance matrices, V and W, comprise unknown parameters to be estimated before fitting the DVAR model to our multivariate time series data of equity and CDS returns.

In the stage of model specification, according to the information criterion results of AIC and BIC, the lag order p is set optimally to one. Hence,

$$F_t = \{1, y_{1t-1}, y_{2t-1}\}, \tag{2}$$

and $\theta_t = \{\theta_{10t}, \theta_{20t}, \theta_{11t}, \theta_{21t}, \theta_{12t} , \theta_{22t}\}'$ is a 6×1 coefficient vector describing the following system of observation equations in the DVAR model:

$$\begin{aligned} y_{1t} &= \theta_{10t} + \theta_{11t}\, y_{1t-1} + \theta_{12t}\, y_{2t-1} + v_{1t} , \\ y_{2t} &= \theta_{20t} + \theta_{21t}\, y_{1t-1} + \theta_{22t} y_{2t-1} + v_{2t} . \end{aligned} \tag{3}$$

If Y_{1t} and Y_{2t} represent the CDS and equity returns at time t, respectively, then θ_{12t} captures the cross-market informational flow from the equity market to the credit market at time period t, and θ_{21t} captures the cross-market informational flow from the CDS market to the equity market at time period t. As such, these two “theta” terms are our primary variables of interest. Note that all model coefficients in the system of observation equations are time indexed, indicating that model parameters are time-varying. Regarding the transition equation system, as there is no clear guidance on the nature of the evolution process of θ_t, typically the dynamics of θ_t are modeled as a random walk process. As a result, G_t becomes I_3, an identity matrix of size three. This choice of a random walk for model coefficients is also employed in Dangl and Halling (2012) for univariate linear predictive models for the equity premium.

4.2 Estimation

We estimate the DVAR model specified in the previous subsection via the maximum likelihood estimation. Since the focus of this study is on investigating cross-market informational flow between the credit and equity markets, to improve the quality of our parameters of interest estimates, we simplify the DVAR by imposing the restriction that the intercepts θ_{10t}, and θ_{20t} are time-invariant. As a result, the transition innovation covariance matrix can be partitioned as follows:

$$W = \begin{bmatrix} 0 & 0 \\ 0 & W_1 \end{bmatrix}, \tag{4}$$

where W_1 is a 4×4 symmetric matrix containing all possible pairs of covariance among $\{\theta_{11t}$, $\theta_{21t}, \theta_{12t}, \theta_{22t}\}$.

With the simplifications shown above, there is a total of 13 parameters to be estimated in the V and W covariance matrices for the bivariate DVAR model. In doing so, we adopt the conventional approach by first fitting the DVAR model with initial values of the 13 parameters to be estimated, and then re-estimating the model parameters in the covariance matrices via the maximum likelihood estimation. To obtain reliable initial values of model parameters, we use the univariate dynamic linear regression model to fit the CDS and equity return series separately, then take those results to estimate the V and W covariance matrices in the DVAR model.

Armed with the maximum likelihood estimates of the parameters in the V and W matrices of the DVAR model, we can then apply the algorithm of the Kalman filter to obtain smoothing and filtering estimates of θ_t, thus providing a dynamic perspective on how the cross-market informational flow evolves over time. Furthermore, since the one-step-ahead forecast of the variables in the observation system can be obtained as a byproduct of the Kalman filter, using the concept of Granger-causality, we can also measure the size or value of the cross-market informational flow in terms of predictive gains, statistical or economic. Thus, with our methodology, not only are we able to observe cross-market informational flow in the presence of instability over time, but we can also measure the strength of such flow in terms of predictive gains. For further details regarding the Kalman filter in the framework of state space models, see Hamilton (1994).

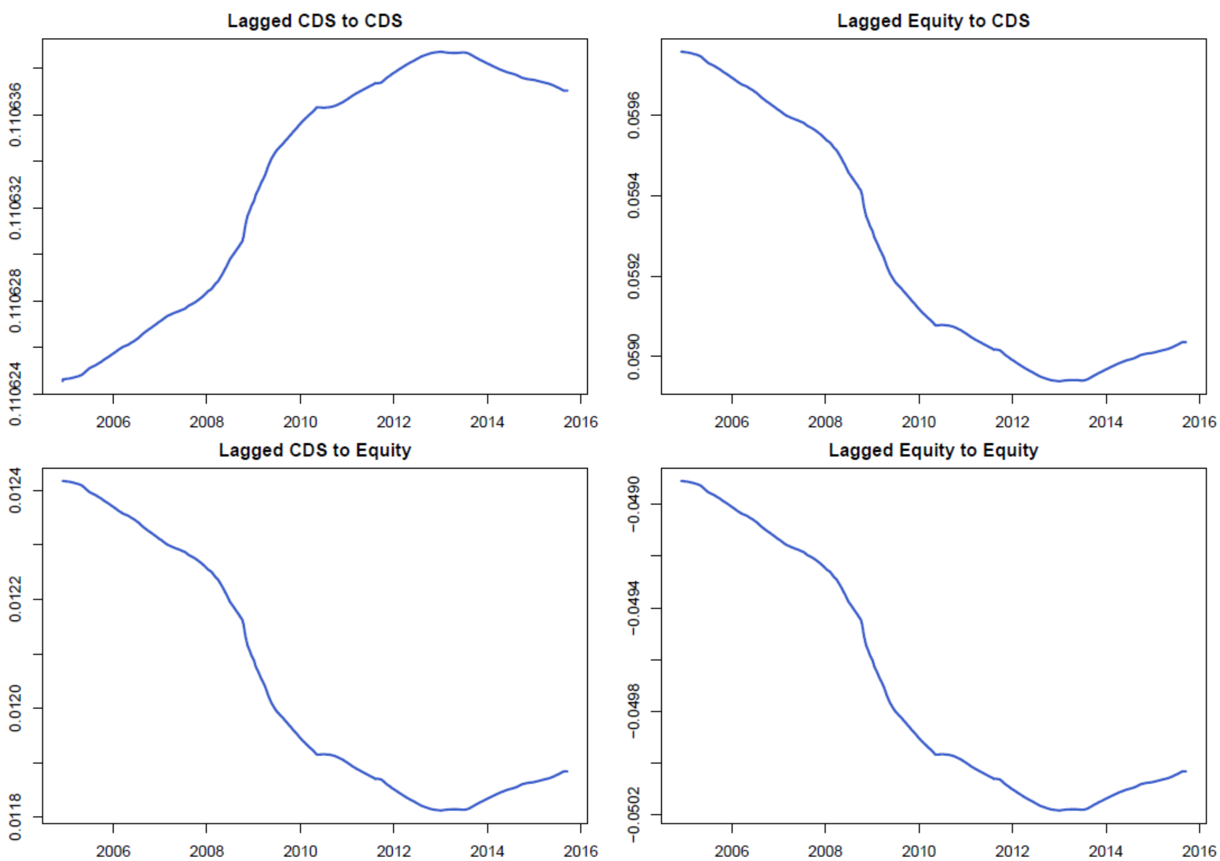
V. Empirical Results

This section presents our main results. The first subsection examines the cross-market informational flow based on the smoothing estimates of DVAR parameters. The second subsection documents further empirical evidence of structural breaks in support of the use of the DVAR model. The last subsection examines and measures the strength of the cross-market informational flow via out-of-sample predictive gains.

5.1 Smoothing Estimates of Cross-Market Informational Flow

Given the fully specified DVAR model reflected above in Eq. (3) which considers cross-market informational flow between the CDS and equity markets, we first use the maximum likelihood estimation to estimate the unknown parameters in the covariance matrices. With these parameter estimates, we then employ the Kalman filter to obtain smoothing estimates of all lagged value coefficients in the observation equations of DVAR. Results of this process are reflected in Figure 2.

Figure 2. Smoothing Estimates of Coefficients.



Note: This figure displays the Kalman smoothing estimates of coefficients in the DVAR model over the full sample.

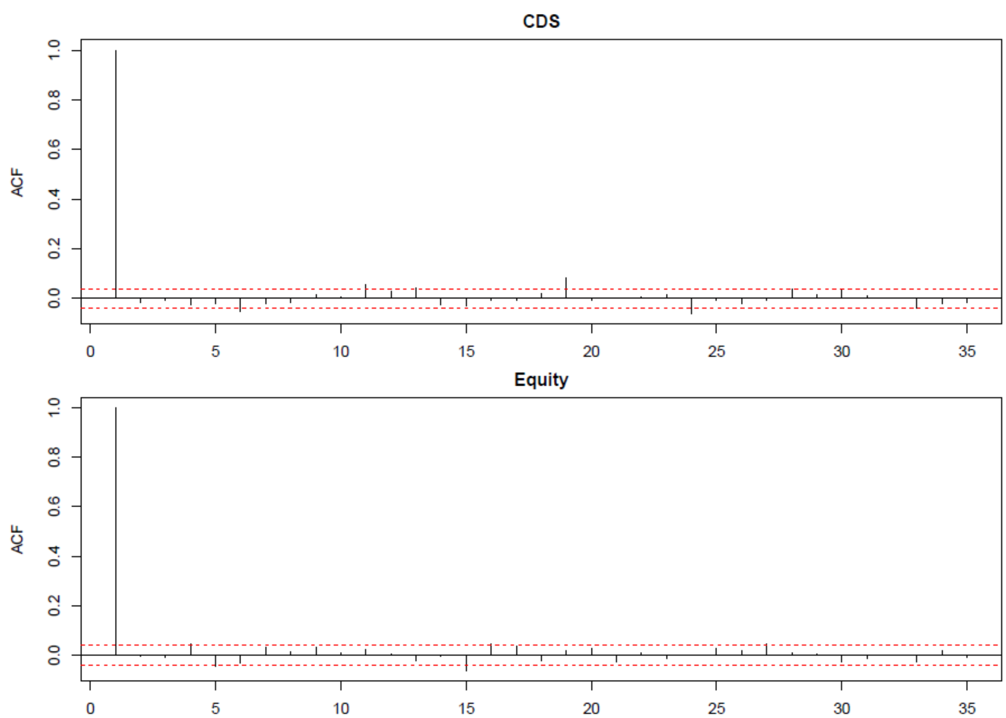
The two plots on the top present dynamic smoothing estimates of the coefficients, θ_{11t} and θ_{12t} in Eq. (3) for the credit market, over the full sample period of 2004 - 2015. Intuitively, θ_{11t} and θ_{12t} capture the strength of the informational flow from the one-period lagged CDS returns, and equity returns to the credit market, respectively. The two plots on the bottom delineate dynamic smoothing estimates of the coefficients, θ_{21t} and θ_{22t} in Eq. (3) for the equity market over the period of 2004 - 2015. Similarly, θ_{21t} and θ_{22t} are parameters capturing the strength of the informational flow from the one-period lagged CDS returns, and equity returns to the equity market, respectively.

Since the focus of this study is on cross-market informational flow, we are primarily interested in examining the patterns shown in the two plots entitled Lagged Equity to CDS and Lagged CDS to Equity as these reflect the nature of such flow, if any. Put differently, we would like to take a deeper look at the dynamic smoothing estimates of θ_{12t} and θ_{21t} in the DVAR system.

For informational flow from the equity to the credit market as represented by θ_{12t}, the upper-right plot in Figure 2 shows that the smoothing estimates of θ_{12t} remain positive over the entire sample, suggesting that CDS returns are affected by and tend to move in the same direction as the prior period's equity returns, holding other factors constant. However, the strength of that flow as measured by the absolute value of the smoothing estimates visibly declines from the beginning of the sample period until approximately 2013, after which it regains some upside momentum.

Regarding informational flow in the opposite direction, or from the credit to the equity market, as represented by θ_{21t}, a similar pattern emerges as shown in the lower-left plot in Figure 2: while the smoothing estimates of θ_{21t} remain positive over the entire 2004-2015 timeframe, its value consistently declines from 2004 to the early half of 2013 before beginning to rise again thereafter.

Figure 3. Empirical Autocorrelation Function Plot.

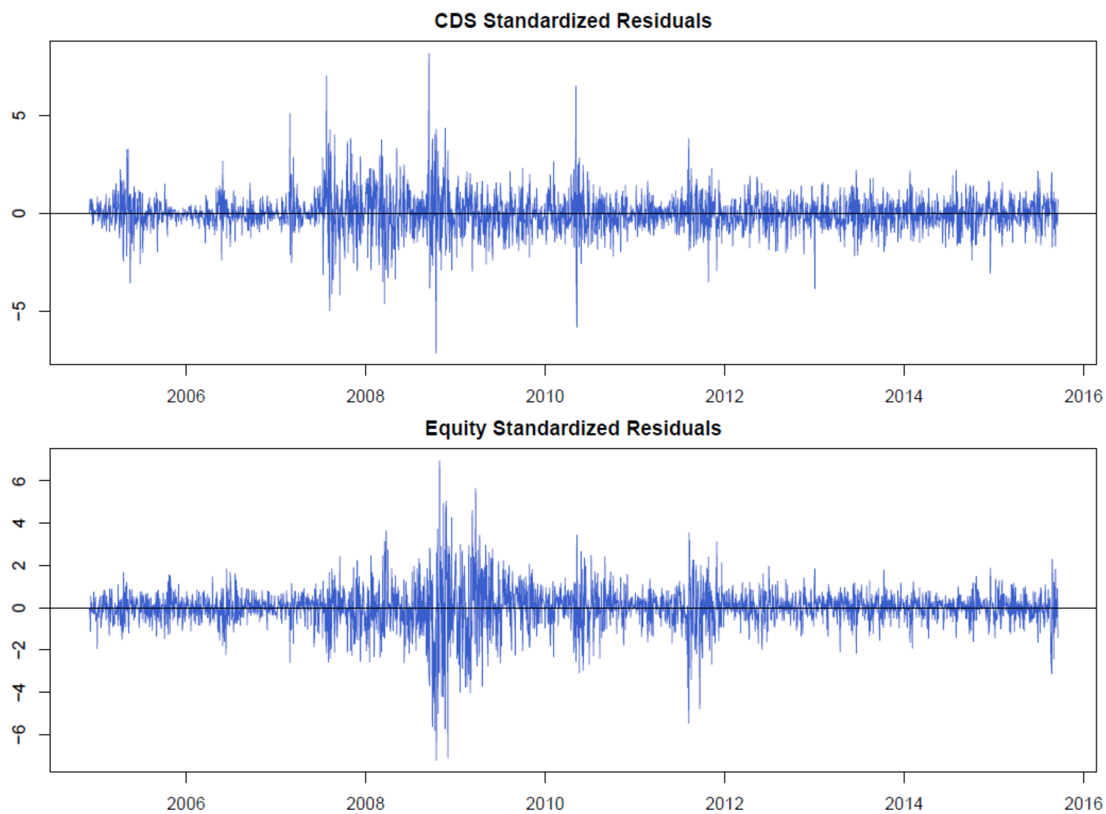


Note: This figure shows the empirical autocorrelation functions of the DVAR model residuals.

As a robustness check for these preliminary results, we plot the empirical ACF estimates of the residuals for both markets in Figure 3, with the credit market on top and the equity market on the bottom. As can be seen, the information shown in Figure 3 clearly supports our lag order choice of one in specifying the DVAR system, as no materially significant spikes appear in these plots. Intuitively, this lag order also makes sense given the size and liquidity of the subject markets, i.e., information which is captured in one should flow to the other without significant delay.

Also, to examine if there exists some degree of instability underlying the cross-market informational flow, in Figure 4 we present the time series plots of the standardized residuals after fitting the DVAR model to the data. Despite their simplicity, these plots prove useful in visually detecting anomalies such as outliers and instability. In the figure, the top plot shows the standardized residuals from the equation with the CDS market as the dependent variable while the bottom plot displays the standardized residuals from the equity equation. As can be seen, all plots clearly indicate some form of instability in both markets, as their patterns discernibly deviate from that of a white noise (or random walk) process, particularly over the time period between 2008 and 2010.

Figure 4. Standardized Residuals Plot.



Note: This figure displays the standardized residuals after fitting the DVAR model to data.

Based on this robustness, we conclude that our results differ significantly from those generated by the traditional VAR model. Whereas that model does not pick up any cross-market informational flow between the two investment-grade markets, suggesting they impound information simultaneously and are equally efficient, the dynamic VAR documents a two-way interactive effect. This indicates that each market captures certain types of information more efficiently, with the information subsequently "flowing" to the other market where it is then captured in pricing – a result previously only documented in the high-yield market. This also indicates that investors trade investment-grade rated systematic risk similarly to non-investment-grade rated risk, despite the much higher probability of default associated with the high-yield systematic market. Previously, it was believed that this market reacted differently to news due to the much shorter distance to default under the Merton model and related need to delta hedge these higher risk portfolios more frequently. As such, this gave rise to comparatively greater scrutiny of new information coming to market vis-à-vis investment grade investors.

Moreover, the strength of flow originating from both markets has varied through time, suggesting there have been structural breaks or some form of instability in how these instruments have been traded. Importantly, such breaks would only be detectable with the traditional VAR model framework via the manual modeling of different temporal periods, an iterative and inefficient process that also exposes the user to the risk of missing the actual inflection points where a break occurs. However, with the dynamic VAR framework, we can visually see the development of informational flow over time and easily identify such inflection points. Specifically, in our study (and as touched on above), flow was generally stronger during the front end of the sample, gradually dissipating through the beginning of 2008, when it then decreased materially in 2009, continued its gradual dissipation again midway through 2010 until near the end of 2013, and then slowly began to increase through the remainder of the sample. Moreover, this pattern is almost the exact same in both markets, meaning that while there may have been structural breaks in the data, investors still were consistent in how they reacted to and traded around new information within those breaks. That said, it is important to note that the absolute changes in flow across the model do not appear to be particularly economically significant at first glance. To illustrate, the range of the coefficients plotted on the y-axis of the exhibit depicting cross-market informational flow from the equity to the CDS market is $0.0596 - 0.0590$, or 0.006 while for the exhibit depicting flow in the other direction, the corresponding range also is 0.006 ($0.0124 - 0.0118 = 0.006$). While this may appear to suggest that the level of flow was relatively stable throughout the examination period, it is important to keep in mind that because our data consists of daily returns, annualized over a year, the cumulative difference in coefficients results in a 1.5% movement over the sample period.[2] Moreover, when compounded daily, which matches the periodicity of our data, an investor with $1,000,000 at the beginning of our sample period and who takes advantage of cross-market flow arbitrage opportunities could potentially grow their wealth an incremental $161,829 over the sample period versus a passively managed portfolio.[3]

[2] 250 trading days/year × 0.006% = 1.5%

[3] PV = $1,000,000, I/YR = 0.006, N = 250 × 10 = 2,500, PMT = 0, FV = $1,161,829. PV: present value; I: interest rate; YR: year; N: number of periods; PMT: payments; FV: future value.

5.2 Evidence of Instability via Structural Break Tests

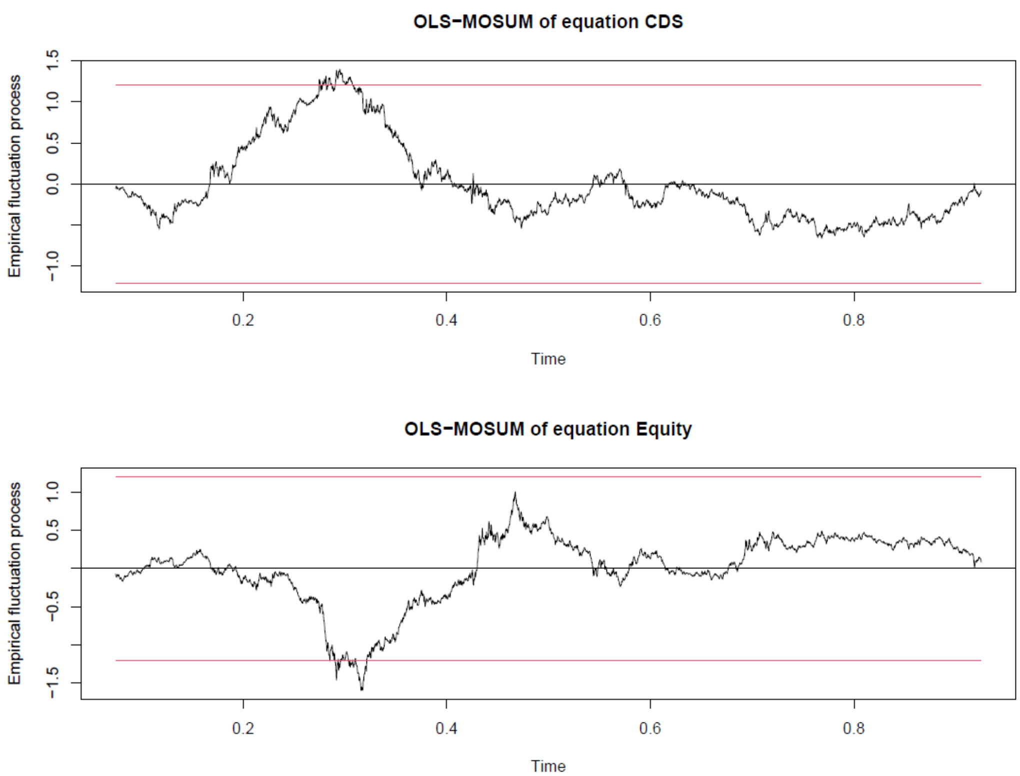
To further validate our model choice of a DVAR in investigating cross-market informational flow in the equity and credit markets, in this subsection we consider several structural break tests for evidence of instability in the lead-lag relationship between the credit and equity markets.

As such, we first use generalized fluctuation tests to fit the following predictive equations separately to data,

$$\begin{aligned} y_{1t} &= \theta_{10} + \theta_{11}\, y_{1t-1} + \theta_{12}\, y_{2t-1} + v_{1t} \\ y_{2t} &= \theta_{20} + \theta_{21}\, y_{1t-1} + \theta_{22}\, y_{2t-1} + v_{2t}\,, \end{aligned} \tag{5}$$

where y_{1t} and y_{2t} represent CDS and equity returns at time period t, respectively. We then derive empirical processes which capture the fluctuation in the residuals. The boundaries of the limiting processes for the derived empirical processes can be obtained and added to their time series plots. The null hypothesis of stability, or absence of structural breaks, can be rejected if the empirical process paths cross these boundaries as it indicates that the fluctuation of the residuals is improbably large. The crossing probability under the null hypothesis of the fluctuation test is α, which is also the significance level of the test. In our analysis, we adopt the MOSUM processes, which use the sum of a fixed number of residuals in a moving data window, to implement the fluctuation test for evidence of instability, and set α = 5%.

Figure 5: MOSUM Tests of Structural Breaks.



Note: This figure displays the MOSUM test results for evidence of structural breaks.

Figure 5 reports the results of our MOSUM fluctuation tests. The top plot illustrates results for the CDS as the dependent variable equation in the DVAR system while the bottom panel reports results for the equity equation. Time is represented as a unit interval over 2004–2015 on the horizontal axis. Boundaries are represented as two parallel, red-colored solid lines in each plot. As can be seen, the information shown in Figure 5 clearly indicates the presence of instability as both MOSUM processes cross boundaries multiple times in the first half of the sample. For the CDS equation, the empirical fluctuation processes frequently cross the upper boundary around the 30th percentile of observations, suggesting instability or the occurrence of structural breaks during the 2008 financial crisis. A similar pattern holds for the equity equation with the empirical fluctuation processes crossing the lower boundary multiple times between the 30th and 35th percentile of the observations, indicating frequent occurrences of structural breaks over the period of 2008–2009.

In addition to the empirical processes, we examine for evidence of instability by conducting formal instability tests of breaks using the SupW statistic of Andrews (1993). Specifically, we apply the SupW test separately to the same set of predictive equations as in the fluctuation tests with the trimming parameter set at 15% following the level used in related literature.

As can be seen in Table 2, the results clearly indicate the presence of structural breaks in both the CDS and equity predictive equations. The null hypothesis of stability is rejected at the 5% level for both equations given the p-values reported, a finding consistent with that of the fluctuation tests. Based on the cumulative results of these structural break tests, we conclude that our choice of a DVAR model capable of capturing dynamic predictive relationships in the presence of structural breaks is the correct form of model for our data set.

Table 2. Structural Break Test Results.

	CDS	**Equity**
SupW Statistic	15.654	14.232
p-value	0.024	0.043

Notes: This table reports structural break test results according to the SupW statistic in Andrews (1993) for CDS and equity returns. Current CDS and equity returns are regressed on previous period CDS and equity returns in univariate models when detecting breaks. The trimming parameter is set at 15% of sample.

So, what are the potential sources of the structural break(s) in our data? We attribute our result to a multitude of factors. First and foremost, we cite the general development of the CDS market. Specifically, when the market was first incepted in 1994, only single name CDS were traded, and it took until 2004 for there to be adequate volume and breadth in the market to construct multi-name CDS such as indexes which were liquidly tradable. However, even as these were launched, trading in them remained thin relative to the overall market as investors still preferred single-name CDS, and they did not begin to comprise a large part of it until after the housing crisis began. As a result, the market was initially relatively inefficient due to its illiquidity, resulting in a high level of informational flow, with efficiency then gradually increasing as trading in the indices began to take hold. Then, with the onset of the housing crisis, this process accelerated as investors began favoring indices over single-name CDS as these provided more protection against the risk of non-performance on the part of the underwriter, or seller of the CDS since indices represent diversified and efficiently bundled packages of credit risk. Accordingly, with this shift, cross-market informational flow decreased, initially dropping off sharply, then continuing its gradual decline as indices became more and more mature and informational inefficiencies, less and less exploitable with the increase in trading. Concurrent with the maturation, flow naturally normalized/stabilized for a period, and while it did begin to increase slightly thereafter, it remained well below the historical level observed in the early part of the sample. We attribute this modest uptick in cross-market informational flow at the back end of our sample to the lower volatility characterizing the time from the end of 2013 through 2015, as evidenced by an average VIX level of 14.7 during that time compared to the rest of the sample of 21.3. Attendant with these lower levels of fear, investors did not monitor cross-market developments and news quite as closely, as the risk of default was much lower. In turn, this lower level of concern/monitoring of risk resulted in greater potential for market inefficiencies, albeit at a much lower level than had been documented at the front end of the sample when the CDS market was much less mature.[4]

5.3 Measure of the Cross-Market Informational Flow via Predictive Gains

We now turn our attention to the second of our primary research objectives in this paper, namely the measuring of the value of the DVAR in terms of the predictive gains it generates relative to other models. That is, if the cross-market informational flow inherent in the model exists and is significant, then forecasts of asset returns which consider the presence of this cross-market informational flow should be more accurate on average than those ignoring its presence. The more accurate the forecasts are, the stronger the magnitude is of the cross-market informational flow. To this end, we consider three measures of predictive accuracy, the mean absolute deviation (MAD), the mean squared error (MSE), and Theil's U statistic which compares the MSE of the model under examination with the MSE of the no-change, or random walk model that predicts the subsequent value of the variable of interest as the current one. Specifically,

$$MAD = \frac{1}{T}\sum_{t=1}^{T}|e_t|, \tag{6}$$

$$MSE = \frac{1}{T}\sum_{t=1}^{T}e_t^2, \tag{7}$$

$$U = \sqrt{\frac{\sum_{t=2}^{T}(y_t - f_t)^2}{\sum_{t=2}^{T}(y_t - y_{t-1})^2}}, \tag{8}$$

where f_t is the one-step-ahead forecast for y_t made at time-period $t - 1$ from a predictive model, and $e_t = y_t - f_t$ is the one-step-ahead forecast error. Note that for the U statistic, a value of less

[4] Please note the foregoing discussion assumed multiple potential structural breaks in the data where visible points of inflection occurred in Figure 2.

than one indicates that the predictive model under investigation produces more accurate forecasts than the random walk benchmark model.

In testing the value of the DVAR, we consider seven alternative models in forecasting the CDS and equity returns. These models are the SDAR, the system of dynamic linear autoregressive models of order one; DTRATE, the dynamic linear regression model with the changes in the 3-month T-bill rate as the sole regressor; DSLOPE, the dynamic linear model with the slope of the Treasury curve as the sole regressor; DSWAP, the dynamic linear regression model with the lagged 5-year swap spreads as the sole regressor; DVIX, the dynamic linear regression model with the lagged implied volatility of the equity market as the sole regressor; EXO, the dynamic linear regression model including all four variables used in DTRATE, DSLOPE, DSWAP, and DVIX; and AREXO, the autoregressive model of order one plus all four variables used in DTRATE, DSLOPE, DSWAP, and DVIX. Note that the SDAR model provides us with the opportunity to directly measure the value of the cross-market informational flow, as it differs from the DVAR model only in the absence of the cross-market lagged values. From this, it follows that, for the DVAR to demonstrate the superior predictive capability necessary to leverage cross-market arbitrage opportunities, it must generate smaller forecast errors than the SDAR without cross-market flow.

Table 3 reports the results of predictive gains from the various models in terms of statistical performance. The top panel in Table 3 displays results for forecasts of CDS returns, while the bottom panel shows results for forecasts of equity returns. In each panel, model names are shown in the first column. Columns 2, 4, and 6 reflect values of the MAD, MSE, and Theil's U statistic, respectively. Columns 3, 5, and 7 report the percentage predictive gains of the DVAR model relative to the competing alternatives in terms of the MAD, MSE, and Theil's U statistic (hence, the first value in the column is 0.000% as the DVAR is competing against itself). For example, in the top panel of Table 3 for the credit market, SDAR has a value of 1.4456 in the column of Theil's U Gain (%), indicating that the DVAR model outperforms the SDAR model in terms of further reducing the value of the U statistic by 1.4456% (hence, positive values in the Theil's U Gain (%) column indicate superior predictive performance on the part of the DVAR model relative to the particular alternative). Also, in this particular instance, the comparison between the DVAR and SDAR models in Table 3 provides a direct measure of the value of cross-market informational flow in terms of statistical predictive gains.

Against that backdrop, as can be seen in the bottom panel of Table 3, the DVAR also outperforms the SDAR in predicting equity returns with respect to the Theil's U statistic; however, the magnitude of the outperformance, 0.5802%, is less than that in predicting CDS returns. However, in viewing Columns 3 and 5, the predictive gains generated by the DVAR relative to the SDAR using the MAD and MSE are much greater than with the Theil's U statistic. Specifically, in the top panel, the DVAR generates incremental predictive gains of 3.1369% and 33.8462% over the SDAR based on the MAD and MSE, respectively, while in the bottom panel, the corresponding gains are even larger at 4.561% and 69.8113%, respectively. Moreover, on a net basis using all three statistics, predictive gains are greater in the bottom panel, indicating that informational flow is stronger from the CDS to the equity market, as opposed to in our initial analysis which suggested that such flow was stronger in the opposite direction. This dynamic underscores the need to perform out-of-sample analysis in order to gain the most complete perspective on relative market efficiency. Our results also suggest that while there exists significant informational flow between credit and equity markets, the answer to which market leads in the price discovery process to a great extent depends on the measure of forecast evaluation in the framework of out-of-sample analysis. When we use relative measures such as the Theil's U statistic, our results indicate that the equity market leads the credit market in terms of price discovery, while the opposite holds when stand-alone measures such as MAD or MSE are used evaluating forecasts.

Table 3. Measure of the Informational Flow via Predictive Gains.

CDS Market	MAD	MAD GAIN (%)	MSE	MSE GAIN (%)	THEIL'S U	THEIL'S U GAIN (%)
DVAR	0.02038	0.0000	0.00086	0.0000	0.7431	0.0000
SDAR	0.02104	3.1369	0.00130	33.8462	0.7540	1.4456
DTRATE	0.02257	9.7031	0.00178	51.6854	0.9387	20.8373
DSLOPE	0.02118	3.7771	0.00135	36.2963	0.7610	2.3522
DSWAP	0.02092	2.5813	0.00128	32.8125	0.7507	1.0124
DVIX	0.02138	4.6773	0.00132	34.8485	0.7680	3.2422
EXO	0.02396	14.9416	0.00219	60.7306	1.0546	29.5373
AREXO	0.02412	15.5058	0.00211	59.2417	1.0282	27.7281
Equity Market	MAD	MAD GAIN (%)	MSE	MSE GAIN (%)	THEIL'S U	THEIL'S U GAIN (%)
DVAR	0.00837	0.0000	0.00016	0.0000	0.6854	0.0000
SDAR	0.00877	4.5610	0.00053	69.8113	0.6894	0.5802
DTRATE	0.00956	12.4477	0.00070	77.1429	0.9832	30.2889
DSLOPE	0.00895	6.4804	0.00058	72.4138	0.6981	1.8192
DSWAP	0.00882	5.1020	0.00053	69.8113	0.6946	1.3245
DVIX	0.00888	5.7432	0.00054	70.3704	0.6992	1.9737
EXO	0.01008	16.9643	0.00080	80.0000	1.0664	35.7277
AREXO	0.01011	17.2107	0.00080	80.2469	1.0755	36.2715

Notes: This table reports the out-of-sample predictive gains forecasting the one-step-ahead CDS and equity returns. The top panel shows results for the CDS market while the bottom panel displays results for the equity market. Predictive gains are measured according to mean absolute deviation (MAD), mean squared error (MSE), and the Theil's U statistic, with smaller values indicating better forecasting performance. The DVAR model is chosen as the benchmark when computing relative predictive gains in percentage, so higher values of gains in percentage indicate better performance of the DVAR model against alternative models under examination.

Armed with this result, we then test its strength and robustness by comparing the predictive performance of the DVAR model using lagged CDS and equity values with those of the suite of systematic exogenous variables discussed above to ascertain whether any of those variables outperform the DVAR. These variables have been chosen based on the work of Fung et al. (2008), Norden and Weber (2009), and Procasky (2021) in their robustness checks, who in turn based their variables on factors identified by Collin-Dufresne, Goldstein, and Martin (2001) as determinants of credit spreads. The results are also reflected in Table 3.

Once again, we focus our attention on Columns 3, 5, and 7 in both tables, which reflects the percentage gain in predictive power produced by the DVAR model versus the other competing models. As can be seen, the DVAR significantly outperforms all the other models in both panels, as in each case the value is materially positive (again, a negative value would indicate the competing model outperformed the DVAR). In fact, the closest competing model in terms of being the least loss of predictive power relative to the DVAR is the DSWAP (the lagged change in the five-year swap spread). Specifically, this model is only outperformed by the DVAR by 2.5813% and 1.0124% in terms of the MSE and U statistic, respectively, with respect to predicting future CDS market returns, and 5.102% and 1.3245%, respectively, in forecasting equity market returns. Also, the other lagged systematic factor models consistently underperform even the previously examined SDAR, or dynamic autoregressive model which does not account for cross-market informational flow, although the result is mixed with the DSWAP. Moreover, and perhaps most interestingly, the DVAR decisively outperforms the "kitchen-sink" model consisting of the full suite of systematic factors covering a broad spectrum of macroeconomic indicators (EXO) by 14.9416% (16.9643%), 60.7306% (80%), and 29.5373% (35.7277%), for the MSE, MAD, and Theil's U, respectively, in predicting credit (equity) returns. Based on the totality of these results, we conclude that the superior performance of the DVAR model in predicting future CDS and equity returns is very robust to the inclusion of systematic economic factors in the set of competing models, and that models which consider cross-market informational flow have greater predictive capability than those which do not. In addition, cross-market informational flow from the equity to the CDS market is stronger than in the opposite direction when measured by the Theil's U statistic while the opposite holds when gauged via the MAD or MSE. However, when comparing DVAR with models based exogenous factors, the credit market leads as it leads to greater predictive gains for the equity returns.

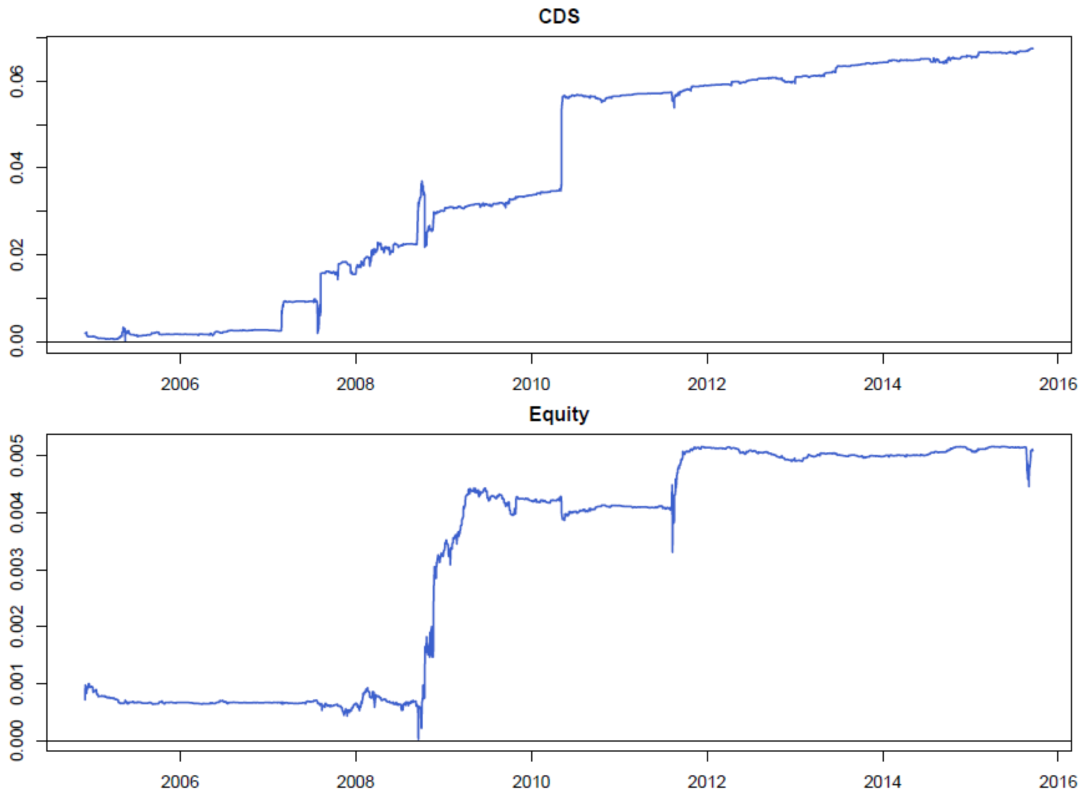
While the statistical measures such as MAD, MSE, and Theil's U statistic help measure the strength of cross-market informational flow in terms of predictive gains, it is important to keep in mind that they only report and rank the average forecasting performance of competing models over the entire forecast evaluation period. To further investigate predictive gains at a more granular level, we employ a graphical device first utilized by Goyal and Welch (2008) in their comparison of predictive models for the equity premium.[5] Specifically, we construct and plot the time series of the cumulative differences of the squared forecast errors between the SDAR and DVAR models (CDSFE) over the entire forecast evaluation sample, paying attention to the slope of these CDSFE curves. A positive slope of the CDSFE curve indicates better forecasting performance on the part of the DVAR model relative to the SDAR model for the particular time period under examination. Put differently, the cross-market informational flow embedded in the DVAR model translates into predictive gains against the SDAR model where the slope is positive.

Figure 6 presents the CDSFE time series plots with the top panel reflecting informational flow to the credit market while the bottom panel represents flow to the equity market. While Figure 6 largely reveals that forecasts of both CDS and equity returns from the DVAR model outperform those from the SDAR model ignoring cross-market informational flow, several further observations can be made. First, the predictive gains in the credit market largely arise from a few

[5] For the sake of brevity, we limit this part of our analysis to the SDAR; the model outperformed the least in the prior examination.

discrete jumps as revealed in the CDS plot. These jumps occur roughly during 2007, late 2008, and the middle of 2010. Second, while the DVAR model continues to lead the SDAR model in forecasting CDS returns following the largest jump in the middle of 2010, the gains are of a smaller magnitude as the slope of the CDSFE curve remains close to being flat. Third, for the equity market, the predictive gains for the DVAR model mainly come from two discrete jumps in the CDSFE curve, with the one occurring around late 2008 to early 2009 particularly evident. Finally, there appear to be no predictive gains generated by cross-market informational flow in the equity market after 2012, as the equity CDSFE curve remains roughly flat and even occasionally turns downward-sloping.

Figure 6. Cumulative Differences in Squared Forecast Errors.



Note: This figure shows the time series plots of the cumulative squared forecast error differentials for forecasts of the CDS and equity returns from the DVAR model against those from the SDAR model over the full sample. A positive slope of the curve indicates better forecasting performance of the DVAR model.

Based on these results, we conclude that the DVAR model continues to outperform the SDAR, although the level of that outperformance varies greatly over the period under examination, and much of the outperformance occurs during the period associated with the financial crisis. Moreover, while the presence of informational flow generally results in predictive gains, flow from the equity to the credit market appears to generate greater gains than in the opposite direction.

VI. Conclusion

We contribute to the literature by examining the relative efficiency of systematic CDS and equity markets using a dynamic VAR model. Unlike traditional VAR models in which all model coefficients are assumed constant throughout the time-period studied, dynamic VAR models which permit time-varying coefficients enable a view and understanding of market efficiency and informational flow along each point in the time-period under examination. In addition, we investigate the strength of the cross-market informational flow by conducting a rigorous out-of-sample analysis against a competing set of models. To date, only one study in the related literature has conducted such an analysis (Procasky and Yin (2022)); however, the examination of cross-market informational flow on an out-of-sample basis is necessary to understand the true nature of relative market efficiency.

Interestingly, we find that there is a two-way interactive effect in the systematic investment grade CDS and equity markets, with information flowing in each direction, a result not previously observed using the traditional VAR model. Moreover, we find that there are structural breaks in the level of flow and that, in general, informational flow from the equity to the credit market is stronger than flow in the opposite direction. We also find that the dynamic VAR model is superior in forecasting future CDS and equity prices than a battery of other competing dynamic linear models that do not consider cross-market informational flow. While to a great extent, the strength of the flow depends on the measure used in forecast evaluation, on a net basis, we document that the dynamic VAR generally performs better in forecasting future equity returns than credit returns, suggesting that cross-market flow from the credit to the equity markets may contain more information than in the opposite direction. While this result runs counter to our initial finding, it also underscores the need for out-of-sample analysis when examining market efficiency.

Overall, our findings have implications for stakeholders who make decisions based on relative market efficiency, including index investors, arbitrageurs, and risk managers who monitor systematic markets for informational content. Only through the inclusion of a dynamic VAR perspective can the true nature of cross-market informational flow be understood.

References

Acharya, V. V., and T. C. Johnson. 2007. “Insider trading in credit derivatives.” *Journal of Financial Economics* 84 (1): 110–141.

Acharya, V. V., and T. C. Johnson. 2017. “The economic significance of CDS price discovery.” *Review of Quantitative Finance and Accounting* 48 (1): 1–30.

Andrews, D. W. 1993. “Tests for parameter instability and structural change with unknown change point.” *Econometrica* 61 (4): 821–856.

Bystrom, H. 2006. “CreditGrades and the iTraxx CDS Index Market.” *Financial Analysts Journal* 62 (6): 65–76.

Collin-Dufresne, P., R. S. Goldstein, and J. S. Martin. 2001. “The determinants of credit spread changes.” *The Journal of Finance* 56 (6): 2177–2207.

Dangl, T., and M. Halling. 2012. “Predictive regressions with time-varying coefficients.” *Journal of Financial Economics* 106 (1): 157–181.

Forte, S., and J. I. Pena. 2009. "Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS." *Journal of Banking and Finance* 33 (11): 2013–2025.

Fung, H.-G., G. E. Sierra, J. Yau, and G. Zhang. 2008. "Are the U.S. Stock Market and Credit Default Swap Market Related? Evidence from the CDX Indices." *Journal of Alternative Investments* 11 (1): 43-61.

Goyal, A., and I. Welch. 2008. "A comprehensive look at the empirical performance of equity premium prediction." *Review of Financial Studies* 21 (4): 1455–1508.

Hamilton, J. D. 1994. *Time Series Analysis*. Princeton, New Jersey: Princeton University Press.

Han, B., and Y. Zhou. 2011. "Term structure of credit default swap spreads and cross-section of stock returns." *McCombs Research Paper Series No. FIN-01-11*, Red McCombs School of Business, The University of Texas at Austin.

Hilscher, J., J. M. Pollet, and M. Wilson. 2015. "Are credit default swaps a sideshow? Evidence that information flows from equity to CDS markets." *Journal of Financial and Quantitative Analysis* 50 (3): 543–567.

Kolev, G., and R. Karapandza. 2017. "Out-of-sample equity premium predictability and sample-split invariant inference." *Journal of Banking and Finance* 84: 188–201.

Longstaff, F. A., S. Mithal, and E. Neis. 2004. "Corporate yield spreads: Default risk or liquidity? New evidence from the credit-default swap market." Working Paper, University of California at Los Angeles.

Marsh, I. W., and W. Wagner. 2012. "Why is price discovery in credit default swap markets news-specific?" *European Banking Center Discussion Paper No. 2012-004*, Tilburg University, The Netherlands.

Narayan, P. K., S. S. Sharma, and K. S. Thuraisamy. 2014. "An analysis of price discovery from panel data models of CDS and equity returns." *Journal of Banking and Finance* 41: 167– 177.

Ni, S. X., and J. Pan. 2020. "Trading options and CDS on stocks under the short sale ban." Unpublished Manuscript.

Norden, L., and M. Weber. 2004. "Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements." *Journal of Banking and Finance* 28 (11): 2813–2843.

Norden, L., and M. Weber. 2009. "The co-movement of credit default swap, bond and stock markets: An empirical analysis." *European Financial Management* 15 (3): 529–562.

Paye, B., and A. Timmermann. 2006. "Instability of return prediction models." *Journal of Empirical Finance* 13 (3): 274–315.

Procasky, W. J. 2021. "Price discovery in CDS and equity markets: Default risk-based heterogeneity in the systematic investment grade and high yield sectors." *Journal of Financial Markets* 54: 100581.

Procasky, W. J., and Yin A. 2022. "Forecasting high yield equity and CDS index returns: Does observed cross-market informational flow have predictive power?" *Journal of Futures Markets* forthcoming. https://doi.org/10.1002/fut.22342

Rapach, D., J. Strauss, and G. Zhou. 2010. "Out-of-sample equity premium prediction: Combination forecasts and links to the real economy." *The Review of Financial Studies* 23 (2): 821–862.

Rapach, D. E., and M. E. Wohar. 2006. "Structural breaks and predictive regression models of aggregate U.S. stock returns." *Journal of Financial Econometrics* 4 (2): 238–274.

Rodriguez-Moreno, M., and J. I. Pena. 2013. "Systemic risk measures: The simpler the better?" *Journal of Banking and Finance* 37 (6): 1817–1831.

Shahzad, S. J. H., S. M. Nor, R. Ferrer, and S. Hammoudeh. 2017. “Asymmetric determinants of CDS spreads: U.S. industry-level evidence through the NARDL approach.” *Economic Modelling* 60: 211–230.

Sims, C. 1980. “Macroeconomics and reality.” *Econometrica* 48 (1): 1–48.

Yin, A. 2019. “Out-of-sample equity premium prediction in the presence of structural breaks.” *International Review of Financial Analysis* 65: 101385.