The Impact of COVID-19 on the Relative Market Efficiency and Forecasting Ability of Credit Derivative and Equity Markets

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Abstract

While there has been a significant amount of research related to COVID-19's impact on financial markets, we address the potential change in relative market efficiency and associated forecasting power for the first time. Specifically, we examine the impact of COVID-19 on previously observed predictive power of cross-market informational flow in the high yield CDS and equity markets.

Our analysis reveals that contrary to historically documented greater forecasting ability during periods of high volatility, a very significant structural break occurred with COVID-19 in which neither market demonstrated any predictive power with respect to the other. This indicates that investors reacted to the pandemic and new information coming to market very differently than in the past. Moreover, we observe that the structural break only lasted four months, which we attribute to the success of the unprecedented monetary and fiscal stimulus measures in stabilizing financial markets. Finally, we note the break was more severe in the equity than in the CDS markets, a finding consistent with the CDS market having an overall informational advantage over the equity market.

Keywords: COVID-19, market efficiency, informational flow, predictive power, structural break, CDS Indices

JEL classification: C32, C58, G14, G17

1. Introduction

With the onset and spread of the COVID-19 pandemic, financial markets were disrupted and volatility reached unprecedented levels. With this disruption, investor behavior appeared to shift from analyzing the fundamentals of economies, industries and individual firms, or the classic "top-down" approach to security analysis, to monitoring central banks and governments and the stimulus they provided in response to health-related news. This stimulus was provided initially to cushion the impact of the pandemic and then later, to buoy the economy while COVID-19 persisted beyond the initial wave. For example, in the US, investors appear to have taken their cue from extremely dovish monetary and fiscal policy, such as communications around the fed funds rate, extent of expanding the central bank's balance sheet (which increased by almost $7 trillion), stimulus checks issued by the US government, etc. While these actions contributed to higher corporate earnings, the genesis of these earnings appeared to be rooted in the amount of money circulating through the economy to counteract health related concerns as opposed to the underlying sustainable earnings power of corporations. Even later in the dovish environment, investors focus appeared to center on fed actions regarding the timing of the tapering of its asset purchases and the raising of the fed funds rate in light of the growing risk of inflation. This inflation, which was first thought to be transitory, persisted longer than the Fed had anticipated and eventually reached levels not since the 1980s. Concurrent with the foregoing investment environment and events, i.e., the shift from fundamentals to macro-policy and health news, we believe that a structural break may have occurred with respect to prior observed cross-market informational flow in the high yield CDS and equity markets and the predictive power of that flow (akin to the breaks observed by Dahler et al (2021) and Salisu & Vo (2020), respectively, within the credit and equity markets separately).

Naturally, given the unprecedented volatility and disruption, a significant amount of research has been performed examining the pandemic's impact on financial markets. For example, Salisu & Vo (2020) and Youseff et al (2021) studied its effect on equity markets while Dahler et al (2021) and Aspergis et al (2020) examined the impact on credit markets. While a few efforts have investigated the equity and credit markets jointly, such as Bystrom (2021) and Liu & Wang (2021), none have addressed the potential change in their relative market efficiency and the associated forecasting power of cross-market informational flow. In addition, given the rich, new literature stream that the pandemic spawned and the valuable insights into the economic impact provided by early research, for example Aramonte & Avalos (2020), Altavilla et al (2020) and Narayan et al (2021), most of the published studies to date have investigated the time period associated with the onset of COVID-19 and months immediately following, leaving the longer-term effects of the pandemic another rich, new area for further exploration.

Against that backdrop, we examine the impact of COVID-19 on the relative efficiency and predictive power of previously observed cross-market informational flow in the high yield CDS and equity markets. Given the unique nature of the pandemic, in order to get a comprehensive and informed view on the interactive behavior of these markets, we examine the pre-pandemic and pandemic-related time periods separately, and then compare results for heterogeneity. Therefore, building on the prior work of Procasky & Yin (2022), who analyzed the predictive power of cross-market flow in the high yield market from 2004-2019, we examine the Markit CDX North American High-Yield Index ("CDX.NA.HY") in conjunction with two systematic indices in the equity market, a closely matched portfolio from which we manually construct a high yield index, and the liquidly tradable S&P 500 index. Specifically, we investigate the predictive power of cross-market informational flow during the pre-pandemic and pandemic periods, segregating the data into pre-2020 and post 2020 "buckets," to determine if and how forecasting ability was affected. Given the widely held perception that markets decoupled from traditional drivers of value during the pandemic, we hypothesize that a significant structural break occurred in how information was captured and impounded in prices in these CDS and equity markets, and that this structural break changed the nature in which they interact with one another. In addition to drawing inferences from the juxtaposed empirical results, we perform a series of structural break tests to confirm whether in fact, a break occurred.

Historically, there have been numerous cross-market informational flow studies examining the CDS and equity markets in North America, for example, Longstaff et al. (2004), Acharya & Johnson (2007), Fung et al (2008) Han & Zhou (2011), Marsh & Wagner (2012), Narayan et al. (2014), Hilscher et al. (2015), Acharya & Johnson (2017) and Procasky (2021). However, in each case, the results were based on in-sample Granger causality analysis. Given this gap, Procasky & Yin (2022) investigated the predictive power of cross-market informational flow on an out-of-sample basis, pulling from the empirical finance literature on forecast evaluation used in market equity returns (Goyal & Welch (2008), Rapach et al. (2010), Pettenuzzo et al. (2014), Li and Tsiakas (2017) and Yin (2019)) and foreign exchange markets (Li et al. (2015), Beckmann & Schussler (2016) and Jamali & Yamani (2019)). Combining the two streams of literature, the authors utilized a battery of classic and contemporary out-of-sample methods to analyze predictive flow from each subject market to the other, and found that while each market was useful in forecasting future values of the other, predictive power was higher during periods of higher volatility, and that overall, the CDS market had an informational advantage over the equity market.

With that as context, interestingly, our analysis reveals that contrary to this documented greater forecasting ability during periods of high volatility, a very significant structural break occurred with COVID-19 in which neither market demonstrated any predictive power with respect to the other. This indicates that investors reacted to the pandemic and new information coming to market very differently than in the past, in particular during the subprime crisis. Specifically, rather than analyzing the fundamentals of the economy and companies separately in each market and capturing different types of news at different times, investors in each market looked to a common set of macro factors and news, and impounded information related to them at the same time. We attribute this asymmetry to the different geneses of these two crises, with the subprime being an endogenously driven financial related crisis while the pandemic is an exogenously driven, public health related shock (Yin et al (2022), Augustin et al (2022)). As a result of these different epicenters, investors took their cues from different types of information during each period of turmoil, focusing in both markets on a common set of news related to the public health crisis and responses to mitigate its impact in the latter. In addition, we find that the structural break only lasted four months due primarily to the success of the monetary and fiscal stimulus measures enacted by government to counteract the effects of the pandemic, and this this break was much more severe in the equity market. This difference in severity is consistent with prior documentation of the high-yield CDS market possessing an informational advantage over the equity market.

The remainder of this paper is structured as follows: Section two reviews the related literature while Section three describes the data used in our empirical analysis. 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 concludes.

2. Related Literature

2.1 Relative Market Efficiency and Structural Breaks

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 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). However, Norden & Weber (2004, 2009) and Forte & Pena (2009) examined markets internationally using non-systematic data, while Ni & Pan (2004) and Rodriguez-Moreno & 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 & Yin (2022) used CDS and equity indexes to investigate systematic flow.

Overall, the empirical results have been mixed. Interestingly, many studies such as Narayan et al. (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 & 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 & Wohar (2006) provide empirical evidence of structural breaks among predictive regressions of the U.S. stock market excess returns while Paye & 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, et al. (2010) and Yin (2019).

2.2 COVID-19 Related Literature

While there has been a lot of research examining the impact of COVID-19 on financial markets and economies, in this section, we focus on efforts related to credit (CDS, bond and bank loan) and equity markets, both separately and jointly.

With respect to efforts focused on credit markets, Aramonte and Avalos (2020) observed that the pandemic initially had an unusually broad impact on lower-rated firms, threatening CLO structures, although the impact was not as much as during the bursting of the housing bubble in 2008, which undermined CDOs. Altavilla et al (2020) also focused on bank loans, studying monetary, microprudential and macroprudential policies taken in response to the outbreak and spread to support bank lending conditions. They find that absent these programs, banks' ability to supply credit would have been severely affected and led to a significantly larger decline in firms' employment. Finally, Bitar and Tarazi (2022) studied the impact on the economy and real estate market and the joint effect on bank credit risk, finding that capital and prudential COVID-19 measures were positively associated with economic growth.

Several studies have involved CDS, mostly of the sovereign nature. For example, Daehler et al (2021) investigated factors driving CDS spreads of emerging market sovereigns. Using 2014–2019 data, they estimated a model and then extrapolated the model-implied spreads for the period July 2019–June 2020. Interestingly, their model initially predicted realized spreads well but loses predictive accuracy during the COVID-19 pandemic. They also find that the cumulative COVID-19 mortality rate growth is positively associated with CDS spreads. Yin et al (2022) studied sovereign CDS prices and found that default intensities shifted from a long-range to short-range dependence regime. This suggests that historical credit performance was much less relevant in the prediction of credit risk and credit derivatives pricing during COVID-19, and that a structural break occurred. They also concluded that the credit market behaved differently during the crisis vis-à-vis the 2008 subprime mortgage crisis, with COVID-19 being a public health vs. economic issue. Finally, Augustin et al (2022) investigated the linkage between a country's fiscal capacity and economic growth shocks/sovereign default risk, and observed that financial markets penalized sovereigns with low fiscal space. Like Yin et al (2022), they concluded that the pandemic differs from the 2008 global financial crisis, which was triggered by an endogenous buildup of private and public debt whereas COVID-19 is an exogenous shock to economies. Finally, using US corporate CDS, Apergis et al (2022) documented that the magnitude of the pandemic as measured by number of COVID-19 cases and deaths both in the US and globally were positively linked to the CDS spreads. However, they also found significant heterogeneity across sectors, with banking being one of the most impacted.

Moving on to equity market focused research, Salisu and Vo (2020) examined the relevance of health-news in predicting stock returns in the 20 most impacted countries by reported cases and deaths, finding that a model incorporating a health-news related index outperforms the benchmark historical average model (with results also holding out-of-sample). Youssef et al (2021) considered dynamic connectedness between stock indices and the effect of economic policy uncertainty in eight countries where COVID-19 was most widespread over the period spanning from 01/01/2015 to 05/18/2020. While results showed that stock markets were highly connected during the entire period, dynamic spillovers reached unprecedented heights during the onset of the pandemic in Q1 2020, implying the occurrence of a structural break. Another documented structural break is Akhtaruzzaman et al (2021), where the authors studied hedge ratios in equity markets and found that most optimal hedge ratios significantly changed during the COVID–19 period, confirming that a structural break occurred on December 31, 2019 (first confirmed case reported by the WHO) with a Chow breakpoint test.

Analyzing the impact of government policies on COVID-19 related equity distress, Narayan et al (2021) demonstrated that lockdowns, travel bans, and economic stimulus packages all had a positive effect on the G7 stock markets, while Deev and Plihal (2022) analyzed the mitigating impact of announcements related to fiscal, monetary and macroprudential policies on realized stock market volatility in 23 countries. The latter document a strong "calming effect" of policy announcements and for the US in particular with macroprudential policy having the greater effect.

Finally, O'Donnell et al (2021) examined price drivers of stock market indices, using the number of confirmed COVID-19 cases as an independent variable (controlling for other factors), and index price as a dependent variable, documenting a significant and negative impact, while Samitas et al (2022) focused on volatility and contagion risk in an investigation of 51 developed and emerging stock markets, finding a significant negative relationship between daily number of COVID-19 cases and stock indices. They also documented instant financial contagion resulting from government-initiated lockdowns.

Turning our attention to the last category of research, the interaction between credit and equity markets, Bouri et al (2021) studied the structure and time-varying patterns of return connectedness across various asset classes, including global equities and bonds, finding moderate and stable dynamic total connectedness until early 2020, after which connectedness spikes (suggesting a structural break at the onset of COVID-19). In addition, using a newspaper-based index of uncertainty in financial markets related to COVID, they observed that connectedness is positively related to the index, and increases at higher levels.

Byström (2021) studied the equity market and CDS market to assess the level of credit risk impounded in pricing, and found that among US blue chip companies, it increased in tandem with the spread of the virus, with weekly ups and downs in credit risk and virus impact significantly positively correlated. However, credit risk levels and Basel II capital requirements did not rise to the level experienced during the subprime crisis. Liu and Wang (2021) also studied the equity and CDS markets, examining how the shock affected CDS spread changes and abnormal stock returns of U.S. firms with different levels of debt rollover risk very early on in the crisis, finding that it significantly increased CDS spreads and decreased shareholder value for firms facing higher rollover risk.

Li et al (2022) investigated the response of the S&P 500 to the Federal Reserve Corporate Credit Facility and Secondary Market Corporate Credit Facility programs, of which the aim was to purchase eligible corporate bonds, and found the program stabilized the return of the S&P 500 by 0.68 in variance reduction. Finally, Liu et al (2022) examined stock and bond market returns and volatility through an event study approach, focusing first on the onset of the pandemic, and then different fiscal (fiscal stimulus, open market operations, social benefits and subsidies) and monetary (rate cuts, interest rate adjustments, short-selling bans) policies. The authors found that while the pandemic had a negative impact on both markets, both also reacted positively to the economic policies and were in fact, quite sensitive to them.

Summing up the multidimensional literature stream, while the research varies in how the impact of COVID-19 on markets and economies is analyzed, some general themes emerge from the findings. As such, the main takeaways are as follows:

- Markets behaved very differently once the pandemic hit
- Health/pandemic-related news and government policies to counteract the virus impact became primary drivers of these markets
- The interconnectedness of markets increased as the pandemic spread
- The crisis was very different than the one experienced in 2008

Moreover, because many of the studies were undertaken during the beginning stages of the pandemic, and by definition, only able to examine the effects of a limited range of a data, there is an ongoing need for research investigating the continued and longer-term effects of COVID-19, which our effort addresses by investigating two full years of data. Furthermore, there has been no study of relative market efficiency across credit and equity markets.

3. 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 5-year maturity since this is the most liquidly traded.

Our data set is comprised of the daily percentage change in the CDX.NA.HY index and begins on November 29, 2004 and ends on December 31, 2021. These time periods correspond to series 3–37 of the

CDX.NA.HY. Series are produced in sequential order as Markit adjusts the constituents of the index every 6 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 correspond 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

For the matched portfolio analysis, our primary data source for equity prices is CRSP. Less than 2.5% of the data are 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, from which we then calculate the daily percentage change in the manually constructed index. As noted by Procasky (2021), 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 6 months in order for the components to remain matched. While this process is painstaking (we rebalance the index 30 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 the replacement of constituents as opposed to new information impacting systematic markets.4 However, because such days comprise less than 1% of all trading days, their removal does not materially impact results.

3.3 Summary Statistics

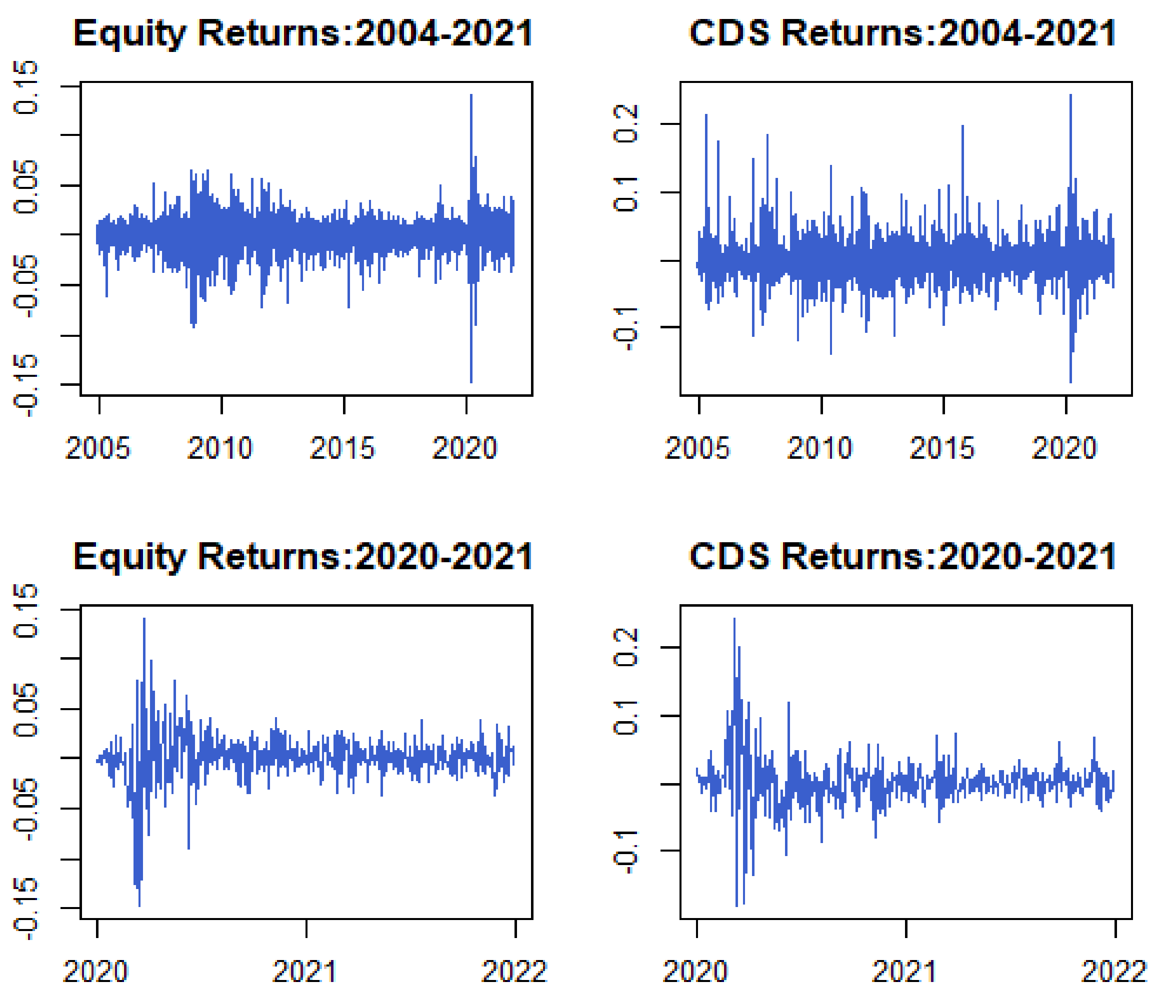
Table 1: Summary Statistics

		Mean	Standard Deviation	Maximum	Minimum	Skewness	Kurtosis
2004-2021	*Equity*	0.0220	0.0165	0.1414	-0.1482	-0.6623	8.5508
	CDS	0.0009	0.0261	0.2449	-0.1828	0.8305	9.8124

2004-2019	*Equity*	0.0106	0.0151	0.0658	-0.0912	-0.5748	4.2955
	CDS	-0.0095	0.0244	0.2134	-0.1395	0.8030	7.6434
2020-2021	*Equity*	0.1069	0.0243	0.1414	-0.1482	-0.7742	9.4744
	CDS	0.0786	0.0361	0.2449	-0.1828	0.7560	9.7607

Table 1 reports summary statistics for the equity portfolio and CDS index return series. In table 1, the top panel shows results over the full sample, while the middle and bottom panels report results for data before and the years 2020-21, respectively. Two interesting observations can be made. First, the CDS returns series are more volatile than its equity counterpart as reflected in its greater value of sample standard deviation. Second, there is a sign reversal in the CDS series as its sample mean is negative before the year 2020 while being positive after 2020. Time series plots of data are shown in Figure 1.

Figure 1: Data Time Series Plots



4. Methodology

In this section we discuss the models used in subsequent empirical analysis and the procedure in constructing out-of-sample forecasts.

4.1 Vector Autoregressive Regression

The primary econometric model we employ to examine cross-market informational flow is the reduced-form vector autoregression (VAR). Following the model specification in Procasky (2021), we adopt the following VAR(1) model throughout our analysis:

$$\Delta CDX_t = a_1 + b_1 \Delta Equity_{t-1} + c_1 \Delta CDX_{t-1} + v_{1t} \tag{1}$$

$$\Delta Equity_t = a_2 + b_2 \Delta Equity_{t-1} + c_2 \Delta CDX_{t-1} + v_{2t} \tag{2}$$

where ΔCDX_t is the contemporaneous percentage change in CDS index, $\Delta Equity_t$ the contemporaneous percentage change in the matched equity index, ΔCDX_{t-1} the lagged percentage change in CDS index with lag order 1, $\Delta Equity_{t-1}$ the lagged percentage change in matched equity index with lag order 1, and v_{it} the innovations to the vector autoregression system.

When choosing the optimal lag order of the VAR model, we base our choice on four information criteria with the maximum lag order set to 10. The information criteria are Akaike Information criterion (AIC), Schwarz–Bayesian information criterion (SBC), Hannan–Quinn information criterion (HQ), and Akaike's Final Prediction Error criterion (FPE). According to our preliminary results, both SBC and HQ suggest an optimal lag order of one while AIC and FPE recommend the lag order of six. Following the principle of parsimony and the common practice of choosing less complex models in the forecasting literature, we set the optimal lag order to one for our VAR model, which is consistent with the choice adopted in Procasky (2021).

To evaluate the practical merit of the VAR model shown above 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 consider a natural competing alternative model consisting of two separate autoregressive regressions of order one, or AR1 models for CDS and equity returns, respectively. Because the models only include lagged variables of their respective dependent variables, 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.

4.2 Forecast Construction

While there is a current debate in the literature on 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), this framework remains useful for certain tasks, notably for providing information about comparative forecasting performance during particular periods in the past. Possible explanations for this popularity 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 idea 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 in-sample analysis.

In doing so, we adopt a rolling estimation window to generate predictions for the VAR model and related competing benchmark. Specifically, following conventional procedures, we divide the full data sample of size T observations into an in-sample estimation portion of size R, and a forecasting portion of size P, where P + R = T. The size of the rolling estimation window, R, is set to equal 30% of the full sample truncated to the nearest integer, corresponding to 1266 daily observations that provide information for model estimation at each point in time when the one-step ahead forecast is made. According to the rolling estimation scheme, predictive model parameters are updated via maximum likelihood estimation in each forecasting period t = R,…,T − 1, using the most recent R observations, with the one-period ahead forecast then made based on the latest trained model. Then, we obtain the forecast errors by taking the difference between the realized values in time period R + 1 and the predicted values. 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.

5. Empirical Results

5.1 In-sample Analysis

Table 2: In-Sample VAR Model Estimation Results

	2004-2019		**2020-2021**		**2004-2021**	
	Equity	CDS	Equity	CDS	Equity	CDS
Intercept	0.0001	-0.0001	0.0011	0.0006	0.0002	0.0000
	(0.6879)	(0.8438)	(0.3160	(0.7040)	(0.3867)	(0.9620)
Lagged equity	0.0138	**-0.0765**	-0.0366	0.0868	-0.0037	-0.0358
	(0.4998)	(0.0200)	(0.6260	(0.4370)	(0.8549)	(0.2615)
Lagged CDS	**-0.0330**	**0.0598**	0.0198	0.0394	**-0.0218**	**0.0518**
	(0.0089)	(0.0033)	(0.6950	(0.6010)	(0.0863)	(0.0100)
R2	0.0039	0.0092	0.0039	0.0013	0.0010	0.0047
Adj R2	0.0034	0.0086	-0.0001	-0.0028	0.0006	0.0042

Table 2 shows the VAR(1) model estimation results over 2004-2021, along with two subsamples before and after the year 2020. Columns titled Equity report estimation results for the equation with matching equity portfolio returns as the dependent variable, and columns titled CDS display results for the equation with CDS returns as the dependent variable. Both lagged equity and lagged CDS represent the lag order of one in the VAR system, which is selected according to the Bayesian information criterion. The numbers in parentheses under model parameter estimates are the associated p-values. Statistically significant coefficient estimates at least at the 10% level are denoted in bold.

We make the following observations from Table 2. The in-sample estimation results before the year 2020 are broadly consistent with those reported in Procasky (2021) and Procasky & Yin (2022), in which the cross-market informational flow represented by the lagged coefficients are all statistically significant at least at the 5% level. However, such significant flow seem to have disappeared over the 2020-2021 subsample, as all model parameter estimates become insignificant, demonstrating the material impact of the COVID pandemic and related subsequent policy responses on the cross-market informational flow. Turning to the full sample estimation results, the flow from the credit market to the equity market remains significant while the flow in the other direction becomes insignificant. Taken together, the in-sample estimation results suggest that the cross-market informational flow from the credit market to the equity market in the systematic high-yield sector is stronger, albeit the impact brought about by the COVID pandemic.

Why does the standard VAR model not fit the data well post 2020? To ascertain the possible cause of the discrepancy in the VAR model fit, we carry out stability analysis based on the OLS-CUSUM fluctuation tests, as the deterioration in predictive relationship is often attributed to structural breaks or model instability (see, for example, Rossi (2013)). Figures 2 and 3 display the empirical fluctuation test results for VAR model stability for 2004-2019 and 2020-2021, respectively. In both figures, the top panel show results for the equity equation in the VAR system while the bottom panel displays results for the CDS equation. Time is normalized to a unit internal in the plots. In all figures, if the empirical process represented by the fluctuating series in black crosses the red-colored confidence bands either from above or below at any moment over the unit time interval, it would indicate the occurrence of model instability. Figure 2 clearly shows that the VAR model is stable over 2004-2019, as both empirical processes representing equity and CDS remain inside the confidence bands. However, the VAR model fails the stability test during the 2020-2021 time window as both empirical processes representing equity and CDS cross the confidence bands multiple times during the first half of the year 2020 as shown in Figure 3, suggesting that the onset of the COVID pandemic has caused instability in the predictive relationship embedded in the VAR system.

The foregoing model stability analysis based on the empirical processes provides us with a visual tool for the existence of structural breaks. In the following, we formally test for the presence of instability employing a battery of classic and contemporary hypothesis tests. Broadly speaking, we consider two families of break tests. The first group comprises the SupW, AveW and ExpW test statistics proposed in the seminal paper of Andrews (1993) testing for the null hypothesis of no structural breaks. A rejection of any of the three tests indicates the presence of parameter instability. The second group consists of the QLR, Exp-Wald and Mean-Wald test statistics proposed in Rossi (2005), which jointly test the composite null hypothesis that there is no break in model parameters together with the absence of Granger causality.

Table 3: Structural Break Test over 2020-2021

	CDS to Equity		**Equity to CDS**	
	statistic	**p-value**	**statistic**	**p-value**
SupW	35.5080	0.0000	24.8370	0.0002
AveW	7.7507	0.0366	5.6960	0.1053
ExpW	12.1890	0.0000	7.0111	0.0033
	statistic	**critical value**	**statistic**	**critical value**
QLR	14.6885	14.2250	68.7093	14.2250
Exp-Wald	16.0922	5.0150	66.1558	5.0150
Mean-Wald	0.4920	8.7430	3.0204	8.7430

Table 3 reports all structural break test results over the period 2020-2021, with Andrews' tests shown on top while Rossi's tests are on the bottom. Columns entitled Equity report results for the equation with matching equity portfolio returns as the dependent variable, and columns entitled CDS display results for the equation with CDS returns as the dependent variable. We report the associated p-values for all Andrews' test statistics, and critical values at the 5% level associated with Rossi's test statistics, which are taken from Rossi (2005) since these test statistics asymptotically follow non-standard distributions.

Consistent with the results from our model stability analysis, the majority of the instability tests support the presence of structural breaks in the lead-lag relationship between the equity and CDS returns over 2020-2021. For the equity equation, five out of six tests are statistically significant, rejecting the null hypothesis of stability. For the CDS equation, four out of six tests support the existence of breaks.

Viewed in tandem, our in-sample estimation results and structural break tests suggest that the onset of the COVID global pandemic and the subsequent policy responses may have caused a substantial impact on the cross-market informational flow between the equity and credit markets in the systematic high-yield sector. Nonetheless, as the in-sample evidence of Granger-causality arising from the cross-market informational flow is not necessarily linked to the out-of-sample forecasting performance, see, for example, Rossi (2013), in the next section we examine the impact on the cross-market informational flow brought about by the COVID pandemic from an out-of-sample perspective.

Figure 2: VAR Stability over 2004-2019

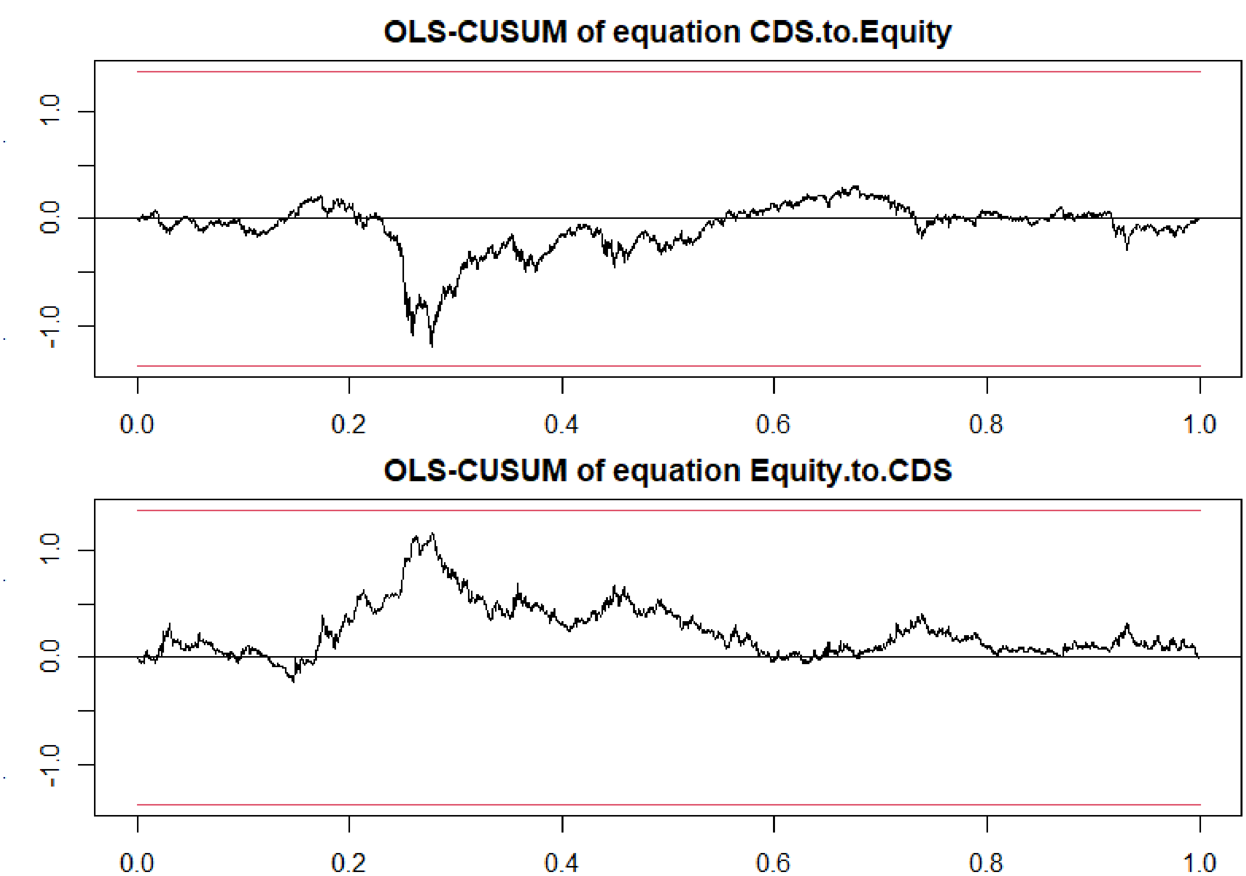
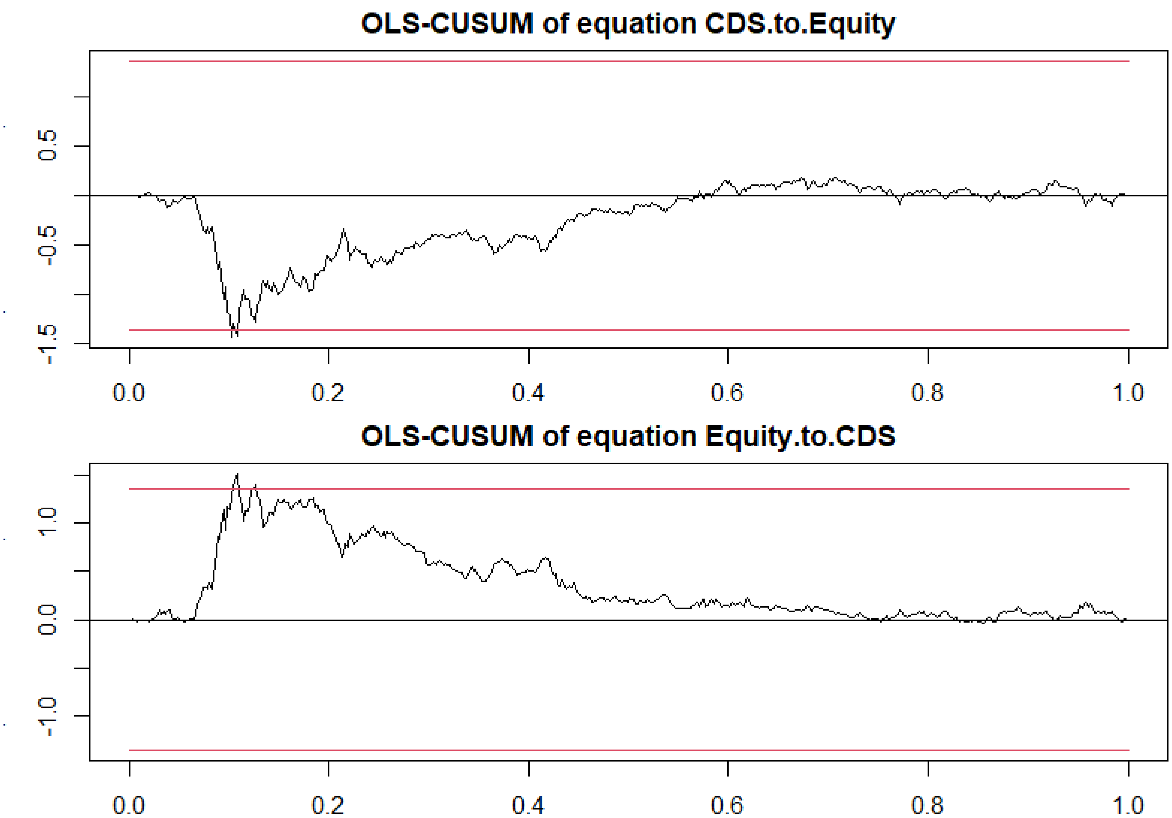


Figure 3: VAR Stability over 2020-2021



5.2 Out-of-Sample Analysis

In this section we employ a battery of econometric tools to investigate the impact of the COVID pandemic on the predictive performance of the VAR model which accounts for the presence of cross-market informational flow. We first report forecast evaluation results based on commonly used metrics in the economic forecasting literature comparing model performances before and after the pandemic. Then, we execute a variety of hypothesis tests to gain further insights into the impact on the forecasting ability.

Table 4: Out-of-Sample Forecast Evaluation

2010-2021	**Equity**		**CDS**	
	VAR	AR1	VAR	AR1
RMSFE	0.0155	0.0155	0.0243	0.0242
MAD	0.0103	0.0104	0.0162	0.0163
Theil's U	0.9764	0.9805	0.9355	0.9333
OOS-R2	0.8364		-0.4601	

2010-2019	Equity		CDS	
	VAR	AR1	VAR	AR1
RMSFE	0.0128	0.0129	0.0210	0.0211
MAD	0.0092	0.0092	0.0150	0.0151
Theil's U	0.9473	0.9567	0.9012	0.9044
OOS-R2	1.9478		0.6938	

2020-2021	Equity		CDS	
	VAR	AR1	VAR	AR1
RMSFE	0.0248	0.0247	0.0362	0.0358
MAD	0.0162	0.0161	0.0222	0.0221
Theil's U	1.0189	1.0156	1.0018	0.9899
OOS-R2	-0.6574		-2.4305	

In carrying out the out-of-sample analysis, we reserve the first 30% of the observations in the full sample as the initial training sample to estimate model parameters to make one-step ahead forecasts. As a result, our series of predictions for both CDS and equity returns start with February 19, 2010 and end with December 31, 2021, for a total of 2957 forecasts. We adopt the rolling estimation window to estimate model parameters at each stage of making forecasts, because the rolling window arguably tends to be more robust to structural breaks and is widely adopted in the financial and economic forecasting literature (see, for example, Elliott & Timmermann (2016)).To measure the predictive gains owing to the presence of the cross-market informational flow embedded in the VAR model, we select the system of the autoregressive regression of order one (AR1) as the benchmark model against which to compare the VAR forecasting performance. It is worth pointing out that the AR1 benchmark differs from the VAR model solely in that it ignores the presence of the cross-market informational flow between the credit and equity markets in the systematic high-yield sector. Thus, we expect the VAR model to outperform the AR1 model in terms of predictive gains if the cross-market informational flow is significant over the evaluation period. Otherwise, the noise arising from estimating extra parameters whose population values are zero would result in an inferior forecasting performance of the VAR model relative to the simpler AR1 model.

We consider four metrics evaluation forecasts: the root mean squared forecast error (RMSFE), the mean absolute deviation (MAD), Theil's U statistic, and out-of-sample R-square proposed in Campbell & Thompson (2008). For the RMSFE and MAD, a smaller value would indicate lower forecast error rate over the evaluation sample. Theil's U statistic compares a model's predictive performance with the no-change model of the predictive target. A value less than one would indicate that the model under examination forecasts better than the no-change model over the evaluation sample. The out-of-sample R-square is also a relative forecasting performance measure which compares the average forecast error rate of the VAR model with that of the AR1 benchmark. A positive out-of-sample R-square value would indicate better performance for the VAR model relative to the AR1 model. The higher the value of the out-of-sample R-square is, the more predictive gains there are for the VAR model relative to the AR1, suggesting a higher degree of strength of the cross-market informational flow.

Table 4 reports forecast evaluation results. The top panel in table 4 shows results for the entire forecast evaluation sample of 2010-2021, while the middle and bottom panels display subsample results for 2010-2019, and 2020-2021, respectively. Several observations can be made after a thorough inspection of Table 4. First, for forecasts made before the year 2020, the VAR model outperforms the AR1 model in terms of forecasting both CDS and equity returns across all evaluation metrics, indicating strong and persistent cross-market information flow between the credit and equity markets. This finding is also reported in Procasky (2021) and Procasky & Yin (2022). However, for the 2020-2021 subsample, there is reversal in the ranking of forecasting performance, with the AR1 model outperforming the VAR model across all metrics. This performance reversal suggests that there are structural breaks in the predictive relationship established in the VAR system, possibly due to the impact arising from the COVID pandemic and the subsequent policy responses. Put differently, structural breaks have occurred in the cross-market informational flow between the credit and equity markets, possibly owing to the investors' fear and subsequent changes in investment behavior during the pandemic period. Finally, turning to the full evaluation window, we observe that the VAR model forecasts better than the AR1 in predicting equity returns while the opposite holds for forecasting CDS returns, indicating that the flow from the credit market to the equity market is stronger on average than that in the opposite direction over the past 12 years.

While the results reported in Table 4 shed light on the impact of the COVID pandemic on the cross-market information flow, several important empirical questions are still left unanswered in the context of out-of-sample analysis. Do forecasts from the VAR model contain additional informational content due to the presence of cross-market flow beyond those in the AR1 model? Are the performance rankings shown in Table 4 statistically significant? Are in-sample results reported in the previous subsection indicative of the out-of-sample performance? To address these, we carry out additional hypothesis tests further investigating the impact of the COVID pandemic on the strength of the cross-market informational flow.

Our tests can be categorized into three categories. The first group comprises three forecast encompassing tests from Clark & McCracken (2001): ENC-T, ENC-REG, and ENC-NEW. All forecast encompassing tests test the null hypothesis that the AR1 model encompasses the VAR model in terms of the predictive content. A rejection of the null hypothesis would indicate that the forecasts from the VAR model contain additional useful information beyond those in the AR1 forecasts. Put differently, a rejection of the null hypothesis of any of the encompassing tests would indicate the presence of cross-market informational flow between the credit and equity markets. The second group consists of tests testing for the statistical significance of the ranking of predictive models: the Diebold-Mariano test (DM) test from Diebold and Mariano (1995), the Clarke-West test (CW) proposed in Clark & West (2007), and the Giacomini-Rossi fluctuation test (GR) proposed in Giacomini & Rossi (2010). Both the DM and CW tests test the null hypothesis that the VAR and AR1 models forecast equally well against the one-sided alternative that the VAR model outperforms the AR1 model. Thus, a rejection of either test would support the existence of cross-market informational flow. The DM test takes forecasts from competing models as primitives in constructing the test statistic in a model-free environment, while the CW takes into account the nesting structure between the two competing models. Both DM and CW tests essentially test for the average performance over the evaluation sample. In contrast, the GR tests provides us with a dynamic perspective on the ranking of predictive models by testing the null hypothesis of equal predictive ability against the alternative that the VAR model forecasts better than the AR1 at least once in time in the evaluation sample. The forecast break-down test (FB) proposed in Giacomini & Rossi (2009) tests for the linkage between a model's in-sample and out-of-sample performances, with the null hypothesis being no forecast breakdown.

Table 5 reports all hypothesis test results, with the top and bottom panels showing results for two subsamples 2010-2019 and 2020-2021, respectively. In each panel, the header CDS to Equity indicates results for forecasting equity returns based on the flow from the credit market to the equity market, while the header Equity to CDS indicates results for predicting CDS returns on the basis of the flow from the equity market to the credit market.

Test results shown in the 2010-2019 subsample strongly support the presence of the cross-market informational flow, as all null hypotheses are resoundingly rejected at the 1% level with the exception of the FB test, in which non-rejection suggests that in-sample performance is consistent with its out-of-sample counterpart. Again, these findings are consistent with those reported in Procasky (2021) and Procasky & Yin (2022).

However, our test results are mixed in the 2020-2021 subsample as shown in Table 5, reflecting the impact on the cross-market informational flow brought about by the COVID pandemic. For the encompassing tests, the null hypothesis is not rejected across all tests for forecasting equity returns. However, for forecasting CDS returns, the null hypothesis is resoundingly rejected by two tests, and is rejected at the 10% level according to the ENC-T test. Turning to model rankings, both DM and CW tests suggest equal predictive performance between the VAR and AR1 models on average over the COVID pandemic period, but the GR test indicates that the VAR model has outperformed the AR1 model at least once during the COVID pandemic period. Again, there is no evidence of forecast breakdown according to the FB test.

Table 5: Out-of-Sample Hypothesis Test Results

Forecast Evaluation Period: 2010-2019

CDS to Equity

	ENC-T	**ENC-REG**	**ENC-NEW**	**DM**	**CW**	**GR**	**FB**
Statistic	6.2136	9.6648	28.9771	-5.2281	6.2136	7.1103	-0.2644
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0013	0.3957

Equity to CDS

	ENC-T	**ENC-REG**	**ENC-NEW**	**DM**	**CW**	**GR**	**FB**
Statistic	2.7311	5.2196	10.6874	-2.1975	2.7311	6.5161	-0.1430
p-value	0.0063	0.0000	0.0000	0.0140	0.0032	0.0013	0.4431

Forecast Evaluation Period: 2020-2021

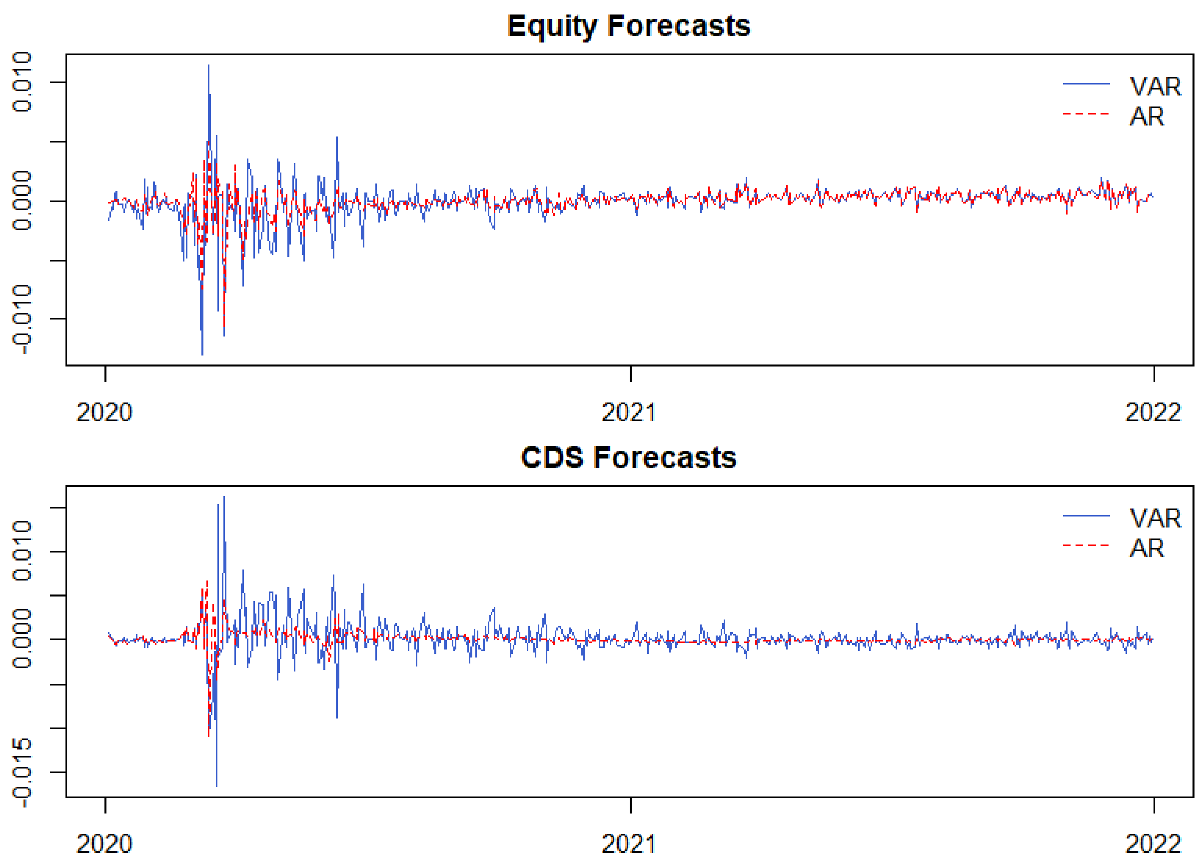
CDS to Equity

	ENC-T	**ENC-REG**	**ENC-NEW**	**DM**	**CW**	**GR**	**FB**
Statistic	-0.6204	-1.4268	-1.2473	0.8156	-0.6204	2.9314	0.1687
p-value	0.5350	0.1537	0.2123	0.7924	0.7325	0.0013	0.5670

Equity to CDS

	ENC-T	ENC-REG	ENC-NEW	DM	CW	GR	FB
Statistic	-1.7240	-4.8522	-5.2948	1.9105	-1.7240	3.5773	0.1314
p-value	0.0847	0.0000	0.0000	0.9717	0.9576	0.0013	0.5523

Figure 4: Out-of-Sample Forecasts over 2020-2021



It should not be surprising to see the stark differences between the two subsamples, as our stability tests shown previously in Table 3 have provided evidence of the presence or occurrence of structural breaks in the cross-market informational flow during the COVID pandemic period. Figure 4 displays out-of-sample forecasts of CDS and equity returns for both VAR and AR1 models over 2020-2021. In Figure 4, the top and bottom panels show equity and CDS forecasts, respectively, with the solid blue line representing VAR predictions while the dashed red line for AR1 forecasts. Figure 2 clearly shows that the VAR forecasts are more volatile that its AR1 counterparts during the period of February 2020 – July 2020, which overlaps with the period of unprecedented turbulence in financial markets due to the fear of COVID pandemic. Nonetheless, all forecasts become less volatile afterwards with the AR1 model producing more smooth predictions. Combined with the time series plots of data in Figure 1, we conjecture that the VAR model should forecast better during the first half of the year 2020 because the volatility pattern in its forecasts is largely consistent with the pattern in the realized series.

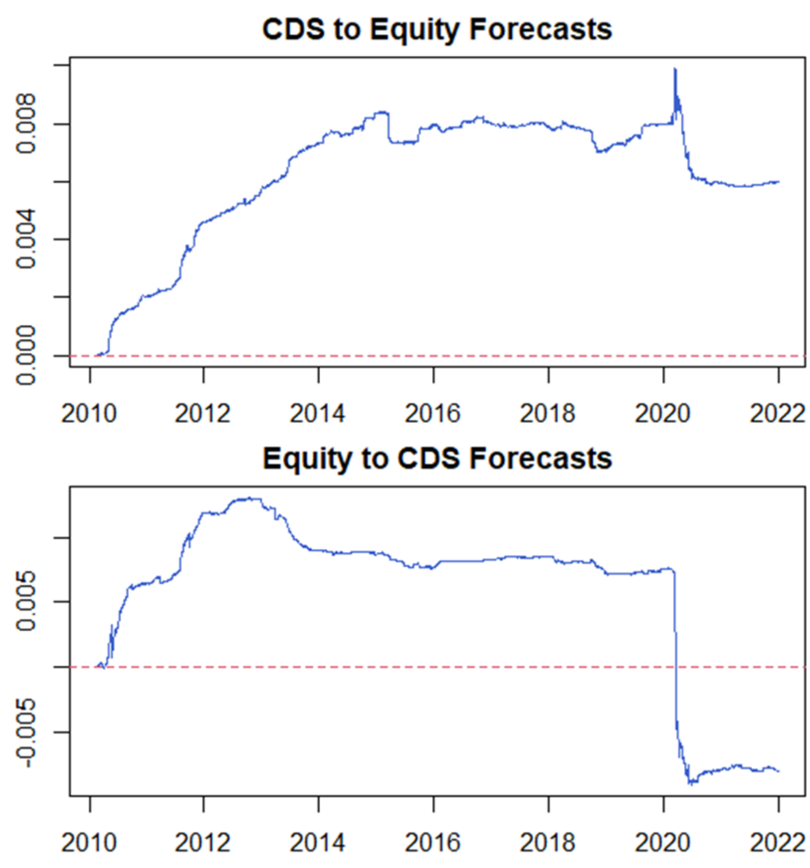
To gain further insights into the impact on cross-market informational flow from a dynamic perspective, in the next section we create a graphical device monitoring the changes in predictive gains owing to the flow throughout the entire evaluation window.

6. How does the COVID pandemic affect forecasts?

To gain a better understanding of how our forecasts evolve from a dynamic perspective, using the graphical tool proposed in Goyal & Welch (2008), we plot the time series of the cumulative differences in squared forecast errors (CDSFE) between the VAR forecasts against the AR1 predictions. Figure 5 depicts the CDSFE curves for forecasting power related to cross-market informational flow from the CDS to the equity market and equity to the CDS market in the top and bottom panels, respectively. Figure 6 reproduces the results shown in Figure 5 over the 2020-2021 subsample, highlighting the changes during the COVID pandemic period.

The slope of the curve reflects/determines the relative performance of the model incorporating cross-market informational flow vis-a-vis the one ignoring such flow. As a result, if cross-market informational flow contains predictive power, we would expect the slope to be positive, indicating that the model incorporating such flow outperforms the model that does not. A negative slope would indicate that the model containing the cross-market flow variable underperforms the simple auto-regressive one while a flat curve, or zero slope, implies that neither model outperforms the other, suggesting a period of relative market efficiency in which news is captured at the same time in each market.

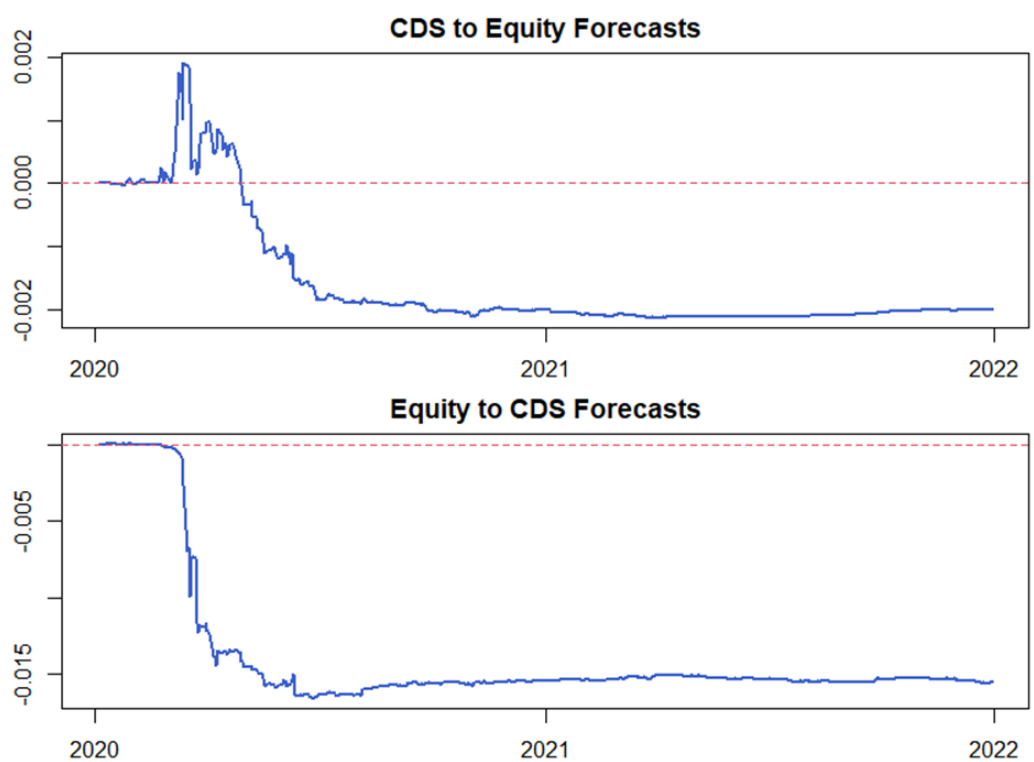
Figure 5: Dynamic Forecasting Performance of VAR against AR1 over 2010-2021



6.1 CDS to Equity Market

Turning our attention to the first panel in Figure 5, there are several distinct slope patterns that emerge. First, from 2010 through the beginning of 2015, there is a very steep, positively sloped curve, indicating that CDS movements in the high yield market are useful in predicting next day equity returns. Next, beginning in 2015, this predictive power reduces and then from there, essentially levels off for three years through midway 2018, when it once again drops for an approximate six-month period. Then, near the start of 2019, forecasting ability picks up again and remains relatively strong through the end of the year, although it is important to note that cumulatively, total predictive gains never surpass the level achieved through the end of 2015. As a result, on the whole, we conclude that neither model consistently outperforms the other from 2015-2019.

Figure 6: Dynamic Forecasting Performance of VAR against AR1 over 2020-2021



However, beginning in February 2020, predictive power once again picks up significantly, followed by a very sudden and significant drop off in power beginning in April 2020 and extending through July 2020, as evident in the steeply negatively sloped curve during this time period. In fact, the depth and extent of this negative slope is not observed during any other time period under examination and strongly suggests the presence of a structural break, as for the first time in our analysis, the model incorporating cross-market informational flow is very significantly and consistently outperformed. Interestingly, though, after this four-month period of tumult, the structural break appears to end and the pattern observed largely returns to that documented during the 2015-2019 timeframe in which neither model exhibits superior forecasting ability. This would appear to indicate that fiscal and monetary policies designed to stabilize the economy, or in statistical terms, address the structural break, were successful in restoring a sense of normalcy relatively quickly.

6.2 Equity to CDS market

With respect to the second panel in Figure 5 depicting forecasting power associated with flow from the equity to the CDS market, the pattern which emerges reflects some similarities and then some very stark differences vis-à-vis the first panel. Specifically, while predictive power also is observed at the beginning of the forecasting period and in fact, exceeds that in the opposite direction based on the steeper positive slope, this forecasting ability only lasts through the end of 2012, after which it declines continually through 2013 and from 2014 through the beginning of 2020, levels off into a random walk. Thus, the predictive power of cross-market informational flow from the equity to the CDS market lasts a full two years shorter than in the opposite direction and in addition, does not pick up in the months leading up to the pandemic as with the curve in the first panel.

Moreover, concurrent with the onset of the effects of the pandemic in March 2020, there is a very distinct cliff-like drop-off in performance of the model as the slope of the CDSFE curve is almost vertical. While this again indicates a significant structural break vis-à-vis the rest of the sample period as in Figure 5, as nowhere else is this pattern evident, it also suggests that the break was a much deeper break than in the opposite direction. Also, as with the forecasting power of the CDS market, the drop-off in performance continues through July 2020, after which the curve once again levels off to a pattern in which neither model demonstrates consistent forecasting ability.

However, unlike the cumulative predictive power of the model documented in the top panel in Figure 5, whereby after the loss of predictive power resulting from the structural break, total gains eventually stabilize at a level still reflective of significant cumulative ability over the sample period, gains related to cross-market informational flow from the equity to the CDS market are completely wiped out. In fact, on a cumulative basis, the model now significantly underperforms the basic autoregressive model omitting such flow. Therefore, on the whole, in comparing the two CDSFEs, we conclude that the CDS market has an informational advantage over the equity market in terms of relative market efficiency and predictive power, and perhaps because of this, it did not experience as severe a structural break as the equity market related to the pandemic.

6.3 Underlying Drivers

What factors explain the above patterns? Consistent with Procasky & Yin's (2022) observations, we attribute the initial, front end of the pattern to the greater relative significance of CDS index trading versus single name CDS trading beginning with reforms enacted after the housing and financial crisis. 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 with over 59% by the end. With investors increasingly using these instruments, more default related information was impounded in the high-yield systematic CDS market, resulting in the observed predictive power through 2015. Further supporting the observed pattern up until 2015 is Procasky's (2021) documented in-sample two-way flow between these markets in which they both capture certain types of information more efficiently.

In addition, we attribute the subsequent drop-off in predictive power and ensuing apparent "random walk" from 2015-2019 to the significantly lower level of volatility and fear in this portion of our sample, as evidenced by an average VIX level of 14.7x during this timeframe compared to 20x during the period before. As support, we cite Procasky & Yin's (2022) analysis of predictive performance during high and low investor fear regimes as reflected in the level of VIX, and conclude that in low fear environments, 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 associated with such activity.

Naturally, the very apparent structural break that occurs near the end of February 2020 is due to the onset of the pandemic. With this, investors heightened and completely shifted their focus away from traditional, financial market related news (earnings, default risk, etc.) to health-related news (number of cases, spread, etc.), with both the CDS and equity markets consuming the same type of news at the same time. As a natural consequence of this change in behavior, cross-market informational flow came to an abrupt halt. This reduction/reversal in predictive power, or in statistical terms, underperformance of the VAR vs. the simple auto-regressive model, continued steadily through July 2020, as governments responded to the spread and number of cases, hospitalizations, deaths, etc., with multiple announcements/measures related to massive fiscal and monetary stimulus designed to stabilize economic activity.

These actions gradually resulted in the stabilization of financial markets and as a result of the amount of liquidity injected into the financial system and restoration of confidence, markets returned to their pre-pandemic pattern of a random walk driven by the now much lower level of investor fear (as evidenced by a decrease in the VIX from 38x from March-July 2020 to 21x thereafter, a 45% reduction). Interestingly, through our CDSFE analysis, we able to determine that the structural break – while severe in nature – was relatively short-lived as it only lasted four months. We attribute this relatively short time span vis-à-vis the ongoing, extended timeframe associated with the pandemic to the unprecedented level of government support, as well as the optimistic health-related news associated with the prospects for development of a COVID-19 vaccination (thus presenting a biological solution to a biological problem). Moreover, we document that this structural break was much more severe in the equity than the CDS market, which is largely consistent with the finding/notion that, viewed in totality, the CDS market has an informational advantage over the equity market.

7. Conclusion

The COVID-19 pandemic resulted in extreme disruption and unprecedented volatility in financial markets. With this disruption, investor behavior appeared to shift from analyzing the fundamentals of economies, industries and individual firms to monitoring health-related news and central banks and governments' stimulus responses to this news. While there has been a significant amount of research related to pandemic's impact on financial markets, we address the potential change in relative market efficiency and associated forecasting power for the first time. Specifically, we examine the impact of COVID-19 on the previously observed predictive power of cross-market informational flow in the high yield CDS and equity markets.

Our analysis reveals that contrary to historically documented greater forecasting ability during periods of high volatility, a very significant structural break occurred with COVID-19 in which neither market demonstrated any predictive power with respect to the other. This indicates that investors reacted to the pandemic and new information coming to market very differently than in the past. Moreover, through a series of empirical tests, we observed that the structural break only lasted four months, which we attribute to the success of the unprecedented stimulus measures in stabilizing financial markets. Finally, we note the break was more severe in the equity than in the CDS markets, a finding consistent with the CDS market overall having an informational advantage over the equity market.

These results have implications for investors and government policy makers as they show that exogenous shocks like the pandemic affect markets much differently than endogenously driven shocks, and that monetary and fiscal stimulus measures can be effective in restoring confidence to markets, at least in the short to intermediate term.

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