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ESG Risk in Times of Crisis: Evidence from the COVID-19 Pandemic

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Abstract

This study compares the volatility of the S&P 500 ESG index and its conventional counterpart during the COVID-19 pandemic. The conditional volatility of each index is generated from an EGARCH model, with these series then used in a vector autoregression. Impulse response functions computed from the VAR show an increase in the conditional volatility of both the ESG and conventional index in response to various pandemic related shocks. However, the impact on the ESG index is significantly less than that of the conventional index, providing further evidence backing the claim that socially responsible investments are less risky than other investments during times of economic crisis.

Keywords: Conditional Volatility, COVID, ESG, Vector Autoregression
JEL Classifications: C32, G01

I. Introduction

In 2020 the CFA Institute released a study detailing the expected future of sustainable investment management.[1] Within the study are the results of a survey of investment firms regarding their motivations for incorporating ESG information into their investment process and decision making. High among the reasons put forward was client demand, the perception that sustainable investments produce superior returns, and the ability to help manage investment risks. These investment firms may be into something. While the empirical evidence regarding the performance benefits of ESG is mixed, there has been strong investor demand, and there has been both theoretical and empirical support that an ESG focus helps to mitigate investment risk.

Heinkel et al. (2001) develop a theoretical model in which the market is segmented, with traditional investors basing their investment decisions solely on expected financial performance, while socially conscious investors gain utility from both the financial and social performance of a firm. This potentially creates a larger client base for socially responsible investments, leading to excess demand for shares that drives up stock and bond prices of such companies. While this reduces expected returns for investors, it has the favorable effect of lowering the firm's cost of capital and reducing its systematic risk. The risk management hypothesis developed by Godfrey (2005), and later tested by Godfrey et al. (2009) proposes that firms can create moral capital, which improves the relationships between the firm and its stakeholders and provides insurance-like protection against various reputational risks.

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[1] Fender, R., Stammers, R., Urwin, R., and Preece, R. (2020). Future of sustainability in investment management: from ideas to reality. CFA Institute.

Early studies of socially responsible investing (SRI) in the mutual fund universe found there to be no statistical difference between the performance of ESG versus conventional funds (Hamilton et al., 1993; Statman, 2000). More recent studies have looked further into the performance of ESG versus conventional funds during recent financial crisis periods, including the 2008-2009 financial crisis and the 2020-2021 COVID-19 pandemic. The results of these studies have been mixed as to the crisis attributes of ESG oriented funds. Nofsinger and Varma (2014) find ESG funds outperform during two crisis periods that occurred from 2000-2011, while conventional funds outperform during non-crisis periods. This result is supported by Ferriani and Natoli (2021) who find that fund flows during the COVID-19 pandemic are positively correlated with ESG rating. Also looking at fund flows during the pandemic, but with opposite findings, Dottling and Kim (2022) find that funds with high sustainability ratings experience larger declines in net fund flows and have a greater likelihood of experiencing net outflows relative to conventional funds.

In a departure from the prior studies, Morales et al. (2019) test SRI indices and their conventional benchmarks or counterparts and find that the SRI indices tend to underperform during times of political uncertainty and economic crises. Unlike tests of mutual funds, indices are used to remove the bias imparted from active fund management. Capelle-Blancard et al. (2021) also test SRI and conventional indices during the COVID-19 pandemic but find that the SRI indices perform similar to the conventional indices, neither outperforming, nor exhibiting less downside risk than their conventional counterparts.

While these previous studies have looked into fund performance and fund flows, no study appears to have looked specifically at fund volatility. If the models of Heinkel et al. (2001) and Godfrey (2005) are correct, then several implications arise regarding the likely risk-related attributes of socially responsible investments during crisis periods. First, if a segment of socially conscious investors makes investment decisions predicated on more than just financial metrics, such investors should be stickier in their investment holdings when financial performance varies. Consequently, such investors should be less prone to exit their investments when financial performance is poor. Further, since insurance helps guard against tail risks, the implication is that the ESG efforts of firms should reduce their exposure to various idiosyncratic risks such as litigation, or more broad-based episodes of risk that arise during from economic crises. As such, investments seen as having higher ESG ratings should be less risky than either investments with lower ESG ratings, or even conventional investments that make no such distinction. Because this benefit should be most prevalent during periods of economic crisis, the COVID-19 pandemic provides a mechanism by which to test this prediction.

This study investigates the impact of pandemic related shocks on the volatility of conventional and socially responsible investments. Specifically, the conditional volatility of the S&P 500 ESG index and the more conventional S&P 500 index is estimated using an autoregressive conditional heteroskedasticity model. The two conditional volatility series are then subject to COVID-related shocks using a vector autoregression, from which generalized impulse response functions are generated.

The rest of this paper is organized as follows. Section two details the variables used to represent US ESG and conventional investments, as well as those variables related to the pandemic that may have an impact on financial markets. It also presents the EGARCH modeling of the conditional volatility of the indices, as well as the vector autoregression and impulse response function analysis. Section three provides a discussion of the results of the vector autoregressions and impulse response function analysis. Finally, section four presents concluding remarks, summarizing the findings of this study.

II. Data and Methodology

Financial time series are often characterized by periods of persistently high or low volatility, leading to heteroscedasticity in the variance of the errors. This conditional volatility tends to have the additional characteristic of asymmetry, where volatility rises more in response to bad news than it falls in response to good news. GARCH models were first proposed by Engel (1982) to model conditional volatility but fail to account for asymmetry. The EGARCH model of Nelson (1991) allows for asymmetric conditional volatility and is used here to generate the conditional volatility series for each of the S&P indices. Generalized impulse response functions are computed from a vector autoregression (VAR), where the conditional volatility of the S&P 500 and S&P 500 ESG indices are subject to direct and indirect shocks arising from the pandemic. These shocks include the direct impact of COVID-19 infections and vaccinations, and the indirect impact where these shocks affect the market through their impact on the VIX and pandemic related news.

Financial data for this study is obtained from FactSet. Daily closing prices for the S&P 500 large-cap index, the S&P 500 ESG index, and the VIX volatility index are collected for the sample period December 31, 2019, to February 28, 2022. The length of this sample is chosen to allow for the initial financial market impact of the pandemic, subsequent mutations of the virus, and the arrival of vaccines.

Data related to the pandemic comes from two sources. First, U.S. state level daily data on COVID-19 infections comes from the Centers for Disease Control and Prevention. This data is aggregated across all states to produce a daily time series at the national level, denoted as CASE. The second source of pandemic-related data includes a time series of daily vaccinations which come from Johns Hopkins, denoted as VACC.

A series reflecting market sentiment arising from pandemic related news is constructed by measuring internet searches related to the pandemic. Searches on Google Trends for the term's pandemic, coronavirus, and COVID across the sample period are used to construct the index GTRENDS. This index is scaled from 1 to 100, where 1 is a period with the minimum number of queries, and 100 is a period with the maximum number of search queries. Google Trends has been shown to be related to behavioral aspects of the market and to have power in forecasting volatility (Preis et. al., 2013; Hamid and Heiden, 2015), and has been used as an investor sentiment indicator in other empirical work on the financial effects of the pandemic (Milani, 2021).

The final variables to be used in the VAR are the conditional volatility series for each of the S&P indices. Specifically, the conditional volatility of each of the two S&P indexes is estimated using an EGARCH(1,1) model. Using Box-Jenkins techniques, an ARMA(1,1) is found to be the best fitting mean equation for each index, where the price indices have been first transformed into log returns. ARCH LM tests are then conducted and confirm the presence of ARCH effects. For the S&P500 and the S&P500ESG indices, the null hypothesis of no heteroskedasticity is rejected at the 5% level. Consequently, following Nelson (1991), the following EGARCH(1,1) model is estimated via the method of maximum likelihood:

$$(1) \qquad r_t = b_0 + b_1 r_{t-1} + b_2 \varepsilon_{t-1} + \varepsilon_t \qquad\qquad \varepsilon_t \sim \text{i.i.d.}(0, \sigma_t^2)$$

(2) $$\log(\sigma_t^2) = b_3 + b_4\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right| + b_5\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + b_6\log(\sigma_{t-1}^2)$$

where r_t is the index log return, and σ_t^2 is the conditional variance of ε_t. The parameter estimates for the EGARCH models are reported in Table 1. The coefficient for asymmetry of volatility, often referred to as leverage effects, b_5, is negative and significant at the 5% level, indicating that negative shocks have a greater impact on volatility than positive shocks. All other coefficients are significant at the 1% level

Table 1. EGARCH Parameter Estimates.

(1) $$r_t = b_0 + b_1 r_{t-1} + b_2\varepsilon_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim \text{i.i.d.}(0, \sigma_t^2)$$

(2) $$\log(\sigma_t^2) = b_3 + b_4\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right| + b_5\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + b_6\log(\sigma_{t-1}^2)$$

	SP500ESG	SP500
b_0	0.001584**	0.001414**
b_1	0.594106**	0.610676**
b_2	-0.692510**	-0.696273**
b_3	-0.773451**	-0.866311**
b_4	0.398507**	0.447496**
b_5	-0.080183*	-0.100687*
b_6	0.947788**	0.942143**
Log likelihood	1399.820	1408.148

Notes: ** indicates significance at the 1% level, and * indicates significance at the 5% level.

The empirical impact of the pandemic on the two conditional volatility series is estimated using a vector autoregression model (VAR) and computing the corresponding generalized impulse response functions from the VAR (Koop et. al., 1996; Pesaran and Shin, 1998). Because the VAR model used in this study assumes that each variable is stationary, unit root tests are conducted on each variable. Augmented Dickey-Fuller tests confirm that the VIX and the two conditional volatility series estimated from the EGARCH(1,1) model are stationary, rejecting the hypothesis of a unit root at the 5% level. Unit roots tests of CASE, VACC, and GTRENDS fail to reject the hypothesis of a unit root at the 5% level. To obtain stationarity, each of these series is transformed by taking the first difference of the logarithm of the series. Descriptive statistics for all variables used in the VARs and impulse response functions are presented in Table 2.

Table 2. Descriptive Statistics

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
SP500ESG	0.00027	0.00010	0.00638	0.00002	0.00060	5.7905	44.2349
SP500	0.00027	0.00009	0.00714	0.00002	0.00064	6.1103	49.4654
CASE	0.02665	0.00870	0.72920	0.00035	0.06751	6.1058	50.1720
VACC	0.04229	0.00623	1.13708	0.00152	0.12855	6.2818	46.7448
GTRENDS	0.00816	0.00181	0.11672	0.00069	0.01852	3.3226	13.7837
VIX	0.00390	-0.01200	0.61640	-0.23370	0.09349	2.0990	11.7667

Notes: Descriptive statistics are reported for all variables used in the vector autoregressions. The first difference log transformation is used for CASE, VACC, and GTRENDS. SP500ESG and SP500 are the conditional volatility series estimated from the EGARCH(1,1) model. All data is daily. Observations for VACC span December 14, 2020 to February, 28, 2022, while all other variables start in December 31, 2019.

The Akaike information criteria is used to determine the optimal order of the VARs. Based on this measure, each VAR is estimated with eight lags.[2] The estimated VARs are then used to compute the related impulse response functions. Generalized impulse response functions are computed rather than the more common Cholesky decomposition to trace out the effects of shocks from CASE, VACC, GTRENDS, and VIX.[3]

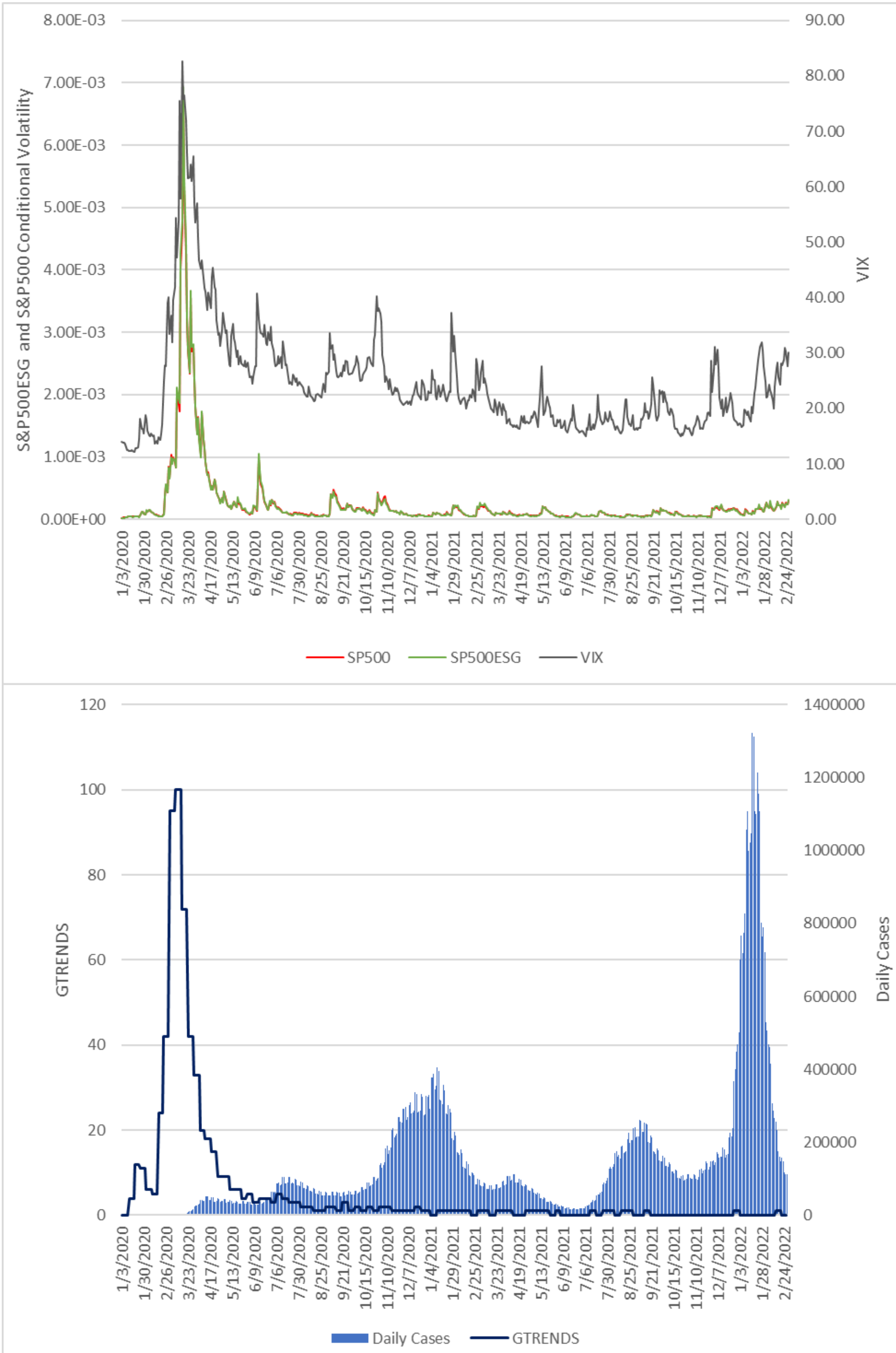
III. Empirical Results

Before analyzing the results of the VARs and associated impulse response function analysis, it is worth discussing several features that present themselves in the time series charts shown in Figure 1. Both S&P conditional volatility series reached their pandemic maximum on March 17, 2020, and the VIX on March 16. In the first week of that same month, Google Trends searches seeking pandemic related information hit their peak. However, while COVID-19 infections surged, they didn't hit their peak until January 18, 2022. Yet, even with the omicron variant of the virus producing the largest numbers of daily infections recorded in the US, the impact on the market indexes, and pandemic information seeking as measured by Google Trends, was minimal. As the chart shows, the behavioral impact of the virus as proxied by Google Trends seems to be visually much more closely aligned with the increase in the market's conditional volatility. Finally, there appears to be no relationship between vaccinations and the conditional volatility of either index.

The impact of shocks on the conditional volatility of the S&P500ESG index and the S&P500 conventional index are shown in Figure 2. The graphs show the response to a one standard deviation increase each in COVID-19 infections (CASE), vaccinations (VACC), Google

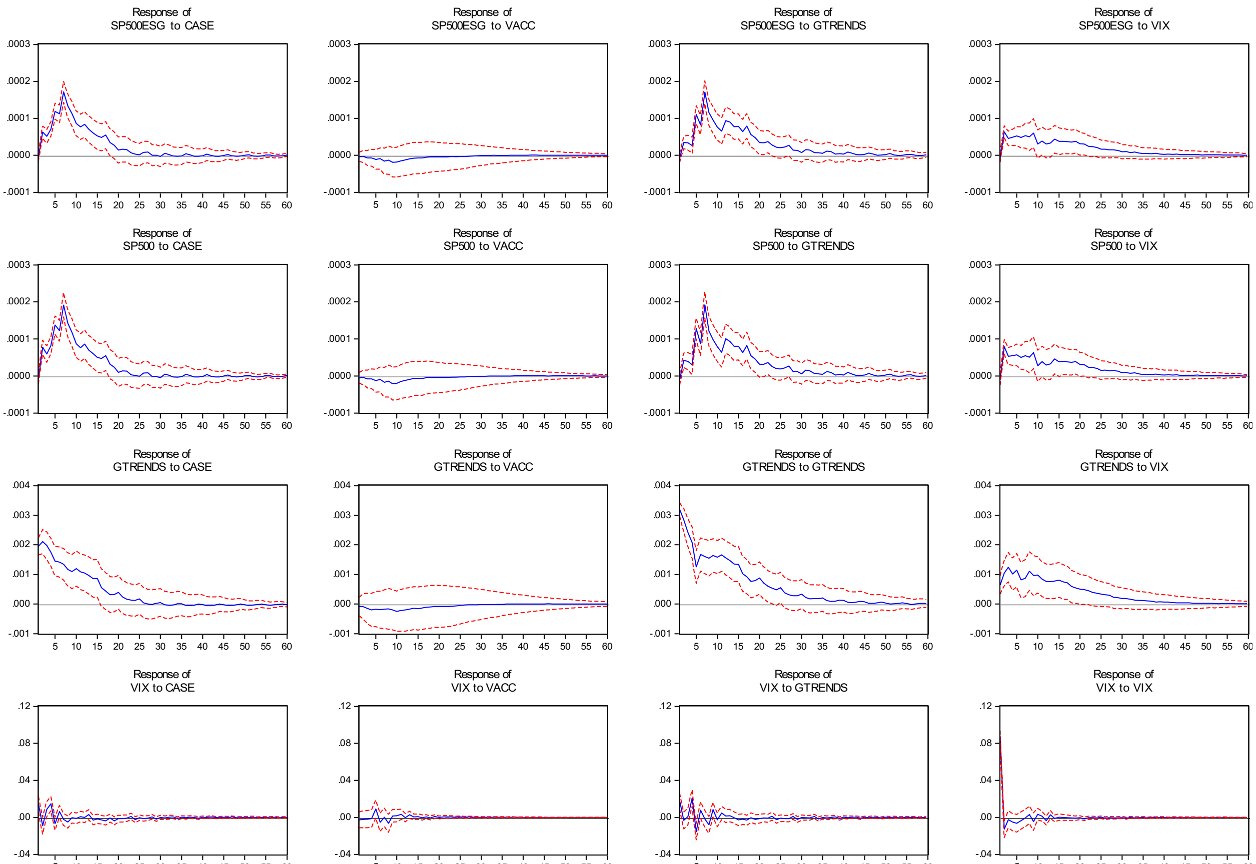
[2] Impulse response standard errors are valid only if the VAR is stable. This requires all roots to have a modulus less than one, a result confirmed for each estimated VAR.
[3] The traditional orthogonalized impulse response employs a Cholesky decomposition from the covariance matrix, whereas the generalized version does not impose this restriction. Unlike the Cholesky decomposition, the generalized impulse responses do not depend on the ordering of the variables in the VAR.

Figure 1.



Notes: S&P500ESG and S&P500 Conditional Volatility, VIX, COVID Infections, Vaccinations, and Google Trends Searches during sample period December 31, 2019 to February 28, 2022.

Figure 2. Impulse Response Functions for Shocks applied to Conditional Volatility Series



Notes: Impulse Response Functions from a six variable VAR with the variables SP500ESG, SP500, CASE, VACC, GTRENDS, and VIX. Each graph shows the effects of a one standard deviation shock. 95% confidence interval represented by the dashed lines.

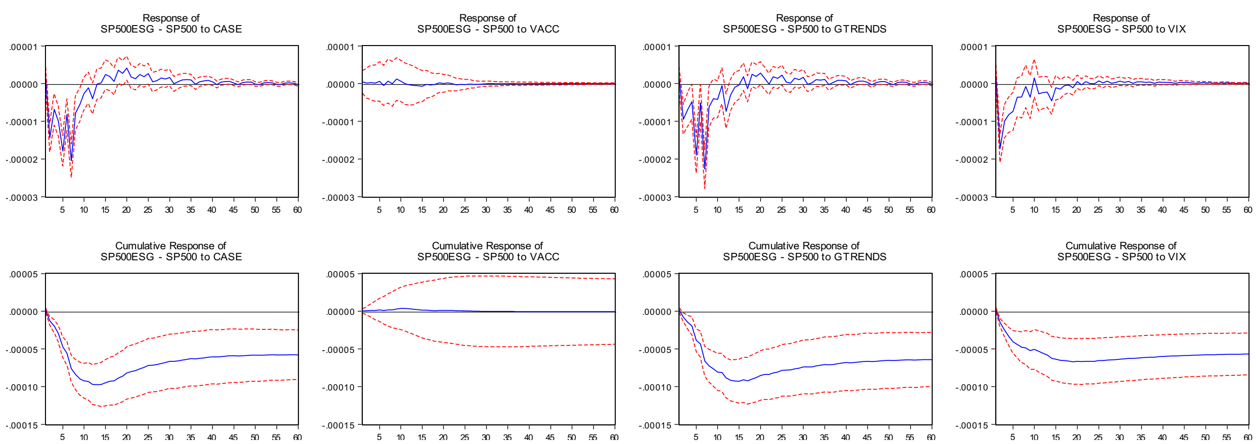
Trends pandemic searches (GTRENDS), and the VIX volatility index, with the dashed lines representing a 95 percent confidence interval around each shock. The conditional volatility of the S&P 500 ESG and S&P 500 indices increases by a statistically significant amount in direct response to shocks from CASE, GTRENDS, and VIX. The impact of these shocks is also quite persistent, with significant impact continuing for up to 18 days for CASE, to as many as 23 days in response to GTRENDS.

Figure 2 also points to several indirect channels through which COVID-19 infections affects the conditional volatility of the indices. Specifically, an increase in infections leads to increases in GTRENDS and the VIX, which, in turn, have a direct impact on the conditional volatility of the indices.

Lastly, vaccinations are shown to have no impact on either conditional volatility series. Intuition would suggest that market conditional volatility would decrease due to the vaccine, as might investor anxiety towards the pandemic as proxied by GTRENDS, and overall market volatility as measured by the VIX. However, none of this happens. The vaccine didn't become available until mid-December of 2020. This suggests that by the time the vaccine appeared, the impact of COVID on the market had passed. Thus, while COVID had a dramatic impact on market volatility, this impact appears to have been largely relegated to the early months of the pandemic. By the end of 2020, other factors outside the realm of this study were largely affecting markets.

From the time series charts in Figure 1 and the impulse responses in Figure 2, it appears that both the S&P 500 ESG and the S&P 500 had highly similar conditional volatility, even at their peak in mid-March at the start of the pandemic. To test if the conditional volatility of the ESG index responds to shocks by a magnitude statistically different than that of the conventional index, the difference between these two conditional volatility series is subject to the same shocks as before. From the results of the shocks applied to the individual conditional volatility series as shown in Figure 2, the two volatility series display near identical responses to the shocks. However, applying the same shocks to the difference in the conditional volatility series provides a different result. As shown in Figure 3, the difference in the conditional volatility series decreases in response to shocks from CASE, GTRENDS, and VIX, while it is unaffected by shocks from VACC. Because this variable is constructed as SP500ESG less SP500, a decrease indicates that the conditional volatility of the ESG index responds less than the conditional volatility of the conventional index. Thus, while both conditional volatility series increase in response to pandemic-related shocks, the ESG index is less affected. This is perhaps the most important result from the perspective of ESG advocates, as it supports the claim that socially responsible or high ESG investments are less volatile than conventional or low ESG investments during times of market crisis.

Figure 3. Impulse Response Functions and Cumulative Impulse Response Functions for Shocks applied to Difference in Conditional Volatility Series



Notes: Impulse Response Functions and Cumulative Impulse Response Functions from a five variable VAR with the variables SP500, CASE, VACC, GTRENDS, VIX, and the difference of the two conditional volatility series constructed as SP500ESG less SP500. Each graph shows the effects of a one standard deviation shock. 95% confidence interval represented by the dashed lines.

IV. Concluding Remarks

This study looks at the impact of the COVID-19 pandemic on the conditional volatility of the S&P 500 ESG index and its conventional counterpart, the S&P 500. The VAR and impulse response function analysis shows that the conditional volatility of each of the indices increases in direct response to an increase in infections. Indirectly, increases in infections produce to heightened market volatility as measured by the VIX, and increased interest or concern about the virus as measured by Google Trends searches related to the pandemic. In turn, increases in the VIX and Google Trends searches corresponds to increased conditional volatility in the indices. On the other hand, while COVID-19 infections have a significant and negative impact on the volatility of these indices, vaccinations have no impact.

A central question of this study was whether the conditional volatility of the ESG index behaves differently than that of the conventional index. While the empirical evidence from prior studies is mixed, advocates of ESG have long contended that sustainable investments tend to have lower risk, especially during periods of extreme market volatility. The results of this study support this claim. While the conditional volatility of both the S&P 500 ESG index and the S&P 500 increased in response to the pandemic, the sustainable index increased to a lesser extent than did its conventional counterpart, indicating favorable tail risk properties of the S&P 500 ESG index.

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