International Review of Financial Analysis 89 (2023) 102792

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Causality between volatility and the weekly economic index during COVID-19: The predictive power of efficient markets and rational expectations

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A R T I C L E I N F O

JEL classification:
C14
C26
C32
C51
E17
O4

Keywords:
COVID-19 shocks
Volatility
Symmetric causality
Asymmetric causality
Time-varying causality of Hatemi-J
Time-varying robust granger causality

A B S T R A C T

We investigate the predictive power of the Efficient Market Hypothesis (EMH) and rational expectations (RE) during periods of economic shocks – specifically COVID-19, captured by the response of the CBOE's volatility index (*VIX*) to the newly compiled weekly economic index (*WEI*). We extend upon the literature by examining if CBOE's volatility index (*VIX*) is correctly influenced by anticipated economic activity, $\widehat{WEI}_{t+1}$. Employing the recently developed methodology of Hatemi-J (2012, 2021), and the time-varying robust Granger causality test (TVR-GC) of Rossi and Wang (2019) we investigate the symmetric and asymmetric causality – running to VIX from expected values of *WEI* in the US, in the first 42–50 weeks of the COVID-19 pandemic starting from the 3rd week of January 2020. We find evidence of asymmetric and time-varying causality between the indices after the first few weeks of the pandemic, suggesting that agents respond asymmetrically to information, providing evidence in support of the EMH and RE. The results indicate that investors do not respond rationally to news and make abnormal gains only during the first few weeks of a pandemic announcement.

1. Introduction

On the 20th of January 2020, the US reported the first confirmed case of COVID-19. This led to increased anxiety among investors in financial markets resulting in rising 'investor fear' – measured by the Chicago Board Options Exchange (CBOE) volatility index (*VIX*). The CBOE VIX put forward by Whaley (1993), is a real-time index that reflects the market's expectations of price changes of the S&P 500 Index (SPX) over the next 30 days. It measures investor risk, stress and fear when making investment decisions. *VIX* levels started soaring from the 20th of January 2020 with the onset of the pandemic to the end of March 2020, rising above the threshold level of 80. The previous peak recorded was 59, at the end of October 2008 during the global financial crisis. Historically, the *VIX* has fluctuated within a band of 10–20 with some sporadic spikes above 20. These massive spikes in *VIX* indicated abnormal trading conditions after the confirmation of a COVID-19 case in the US. By October 2020, except for two short-lived spikes, *VIX* levels started settling at the low 30s (CBOE, 2022).

Studies have examined several channels through which uncertainty affects economic activity. These include, investment (Bernanke, 1983; Bloom, 2009), consumption (Carroll, 1997), financial shocks (Caldara, Fuentes-Albero, & Gilchrist, 2016; Christiano, Motto, & Rostagno, 2014; Gilchrist, Sim, & Zakrajsek, 2014), trade (Handley and Limão, 2012) among others. More recently, studies have also investigated the effects of the pandemic on the US stock market (e.g., Baker et al., 2020; Gormsen & Koijen, 2020; Onali, 2020; Yilmazkuday, 2020). Anxiety causes investors to look to information from other sources (Gilchrist and Zakrajsek 2012), in particular, sources that are current and up to date. The Weekly Economic Index (WEI) put forward to track the swift economic changes related to the arrival of and policy response to the coronavirus in the US, is an index which offers a signal of the state of the US economy and is compiled by employing high-frequency data embodying ten different daily and weekly series covering consumer behaviour, the labour market, and production (Lewis, Mertens, & Stock,

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https://doi.org/10.1016/j.irfa.2023.102792
Received 31 October 2022; Received in revised form 28 April 2023; Accepted 11 July 2023
Available online 27 July 2023

2021; Lewis, Mertens, Stock, & Trivedi, 2021). It is updated every Thursday at 10:30 a.m. CT, using all data accessible up until 8 a.m. CT (Federal Reserve Bank of Dallas, 2022a, 2022b).

Therefore, the purpose of this study is to investigate the predictive content of the WEI, for VIX. When macroeconomic conditions are uncertain, as during the covid period, these uncertainties translate into volatilities and investor decision making. During the covid period, there was uncertainty in economic activity with pandemic-related news and reports increasing panic and investors' anxiety. Increasing anxiety among investors in financial markets resulted in rising 'investor fear' – demonstrated by the rising *VIX* levels from late January to late October 2020 (CBOE, 2022). If investor fear is driven by the postulates of rational expectations, then investor fear can be a self-fulfilling prophecy further accentuating economic disruptions (see Gangopadhyay, 2020; among others). In this regard, the forecasting accuracy of *VIX*, as a measure of stock market expectations or fear index, during a severe crisis has been explored in the extant literature. In the context of forecasting accuracy, several studies have found evidence that CBOE's uncertainty/volatility index, or *VIX*, has useful information for improving forecasting accuracy, which can benefit policy makers, market participants and regulators to stabilise volatility spillovers across markets (see Balcilar, Gupta, Kim, & Kyei, 2019; Bekaert & Hoerova, 2014; Brogaard & Detzel, 2015; Liu & Zhang, 2015; Urom, Ndubuisi, & Ozor, 2021). Rather than focusing upon the forecasting ability of *VIX* for *WEI*, we in contrast, apply the concept of efficient markets and rational expectations (RE) to test if expected future values of *WEI* have a causal relationship with the past expectations about *WEI* – embedded in the realised current values of *VIX*.

Thus, the main contribution of this paper is to evaluate the predictive power of the Efficient Market Hypothesis (EMH) and rational expectations during periods of economic shocks in the US, specifically COVID – captured by the newly compiled weekly economic index (*WEI*). We extend upon the literature in several ways. (1) we examine whether CBOE's volatility index (VIX_t) has been *correctly* influenced by anticipated economic activity, $\widehat{WEI}_{t+1}$. The Efficient Markets Hypothesis (EMH) assumes that agents have perfect knowledge of all available information in the market (Modigliani and Shiller (1973); Fama (1975, 1976); and Lucas (1978)). Accordingly, if expectations of WEI, $\widehat{WEI}_{t+1}$, are instantaneously reflected in VIX_t, other words, there is a causal relation, then the market would be efficient and expectations rational. This has not been undertaken by previous studies to the best of our knowledge. (2) we use the recently developed methodology of Hatemi-J (2012, 2021), and time-varying robust Granger causality test (TVR-GC) of Rossi and Wang (2019) to investigate the time-varying form of symmetric and asymmetric causality – running to past values of *VIX* from expected future values of *WEI* in the US, in the first 42–50 weeks of the COVID-19 pandemic starting from the 3rd week of January 2020. Hatemi-J (2012) argues that standard causality tests are restrictive as they assume that individuals react symmetrically to positive and negative news, but in fact that investors tend to react more to negative compared to positive news. Therefore, assuming the presence of asymmetric information can cause an asymmetric causal link to be found between financial markets. If there is causality from WEI_{t+1} on VIX_t., then rational expectations and the EMH would hold. We do not assume reverse causality from VIX_t to WEI_{t+1}, as investor fear does not usually lead to pandemic related economic disruptions. We seek to establish whether investors' expectations, during a turbulent time like the COVID-19 pandemic, are rational in the sense that these expectations do not systematically deviate from the realised economic outcomes as investors tend to process information efficiently (McCallum, 2009; Muth, 1961; Sargent, 1972).

Ozkan (2021) observes that markets became more speculative, financial models more unpredictable, and there was mispricing of stocks during the covid-19 pandemic increasing opportunities for abnormal returns. Similarly, Cheng (2019, 2020) argues that the mispricing of risks played an important role during the first wave of the pandemic as the increases in *VIX* future prices were consistently lower than the statistically rational forecasts of *VIX*. Crises can also create opportunities for investors. Therefore, understanding how expected weekly economic conditions during periods of uncertainty affect market volatility and whether expectations are formed rationally is of critical importance to investors and policymakers. From a policy perspective, this would enable policymakers to formulate policies that would minimize volatility in the face of uncertainty. Similarly, investors would be in a better position to reduce risk when taking investment decisions.

The rest of this paper is structured as follows. Section 2 presents the model, Section 3 discusses the empirical findings, and Section 4 concludes.

2. Methodology and data

The Efficient market hypothesis (EMH) posits that prices of financial assets fully reflect all available information (Lo, 2008). On the other hand, rational expectations, attributed to Muth (1961), is interpreted by Sargent (2008, p.1) as a concept that assumes a "unique, correct, and common model held by all relevant agents." The EMH and rational expectations equilibrium (RE) derive from the equivalence of asset prices fully reflecting all available information with agents' ability to arrive at "best" or "optimal" forecasts using all available information (see Hoover, 1988; Mishkin, 2016, p. 192).

Following the work of McCallum (2009), we posit that the dynamic economic modelling of the VIX_t and WEI_{t+1} can be best understood by a simplified equation based on the rational expectations equilibrium:

$$\mathrm{VIX}_t - \alpha \mathrm{WEI}_{t+1} = 0 \tag{1a}$$

(1a) implies that agents' current expectations of future values of a variable (WEI_{t+1}) influence the realization of the current value of VIX_t.

2.1. Methodology

We apply the Hatemi-J test to establish time-varying and asymmetric Granger causality running from $\widehat{WEI}_{t+1}$ to VIX_t. Following Hatemi-J (2021) we instigate an $m \times 1$ vector y_t in which each element is integrated of degree one with drift and trend[1]:

$$y_t = a + bt + y_{t-1} + \varepsilon_t, \tag{2a}$$

Note that y_t is a vector, b is the time trend, t denotes the t_{th} week and the error term is given by ε_t. The positive and negative shocks of each element is defined, by Hatemi-J (2021), in a cumulative and asymmetric form as:

$$y_t^+ = \frac{a_t + \left[\frac{t(t-1)}{2}\right] b + y_0}{2} + \sum_{i=1}^{t} \varepsilon_i^+ \tag{2b}$$

and

$$y_t^- = \frac{a_t + \left[\frac{t(t-1)}{2}\right] b + y_0}{2} + \sum_{i=1}^{t} \varepsilon_i^- \tag{2c}$$

Hence, y_t is defined as

$$y_t = y_t^+ + y_t^- \tag{2d}$$

Applying the aforementioned asymmetric decompositions for the variable *WEI*, one can write the time-varying asymmetric causality model for *WEI* as the following:

[1] Asymmetric causality testing is also implemented for stationary variables. In that case, positive or negative changes are used instead of the cumulative sums (see Hatemi-J Atri et al., 2021).

$$WEI_t^+ = \frac{a_t + \left[\frac{t(t+1)}{2}\right]b + WEI_0}{2} + \sum_{i=1}^{t} \varepsilon_{1i}^+ \tag{3a}$$

$$WEI_t^- = \frac{a_t + \left[\frac{t(t+1)}{2}\right]b + WEI_0}{2} + \sum_{i=1}^{t} \varepsilon_{1i}^- \tag{3b}$$

Hence,

$$WEI_t = WEI_t^- + WEI_t^+ \tag{3c}$$

Note that WEI_t^+ is the positive partial sum of positive changes in *WEI* until date t and WEI_t^- is the negative partial sum of negative changes in *WEI* until date t. For the expected value of WEI_{t+1}, given by $\widehat{WEI}_{t+1}$we can express the decomposition of the time-varying asymmetric model as:

$$\widehat{WEI}_{t+1} = \widehat{WEI}_{t+1^+} + \widehat{WEI}_{t+1}^- \tag{3d}$$

Applying the same decomposition, we write the asymmetric causality model for VIX_{t-1} as:

$$VIX_{t-1}^+ = \frac{c_{t-1} + \left[\frac{t(t-1)}{2}\right]d + VIX_0}{2} + \sum_{i=1}^{t-1} \varepsilon_{2i}^+ \tag{4a}$$

$$VIX_{t-1}^- = \frac{c_t + \left[\frac{t(t-1)}{2}\right]d + WEA_0}{2} + \sum_{i=1}^{t-1} \varepsilon_{2i}^- \tag{4b}$$

Hence

$$VIX_{t-1} = VIX_{t-1}^+ + VIX_{t-1}^- \tag{4c}$$

Note that VIX_{t-1}^+ is the positive partial sum of positive changes in *VIX* until date (t-1) and VIX_{t-1}^- is the negative partial sum of negative changes in *VIX* until date (t-1). In Section 3, we present the results and briefly discuss the significance of our findings. Further details of the econometric results are available in the appendix.

We have further employed the time-varying robust Granger causality method of Rossi and Wang (2019) as a robustness check for the Hatemi-J model.

2.1.1. Robustness checks: time-varying robust granger causality method (TVR-GC)

To investigate the direction of causality between *VIX* and *WEI* over the study period, we will implement the time-varying robust Granger causality method (TVR-GC) of Rossi and Wang (2019). This method (TVR-GC) is more efficient than the conventional and time-invariant Granger causality test in the presence of fluctuations, or instabilities, in the causal variables. As the method of Hatemi-J (2021), the TVR-GC methodology can separate the periods when Granger causality occurs or breaks down in the data. In particular, we consider a VAR model with time-varying parameters as follows:

$$Z_t = \sum_{i=1}^{p} \alpha_{1,i} Z_{t-i} + \varepsilon_t \tag{4d}$$

Where Z_t $[=Z_{1t}, Z_{2t}, \ldots, Z_{nt}]$ is an **nx1** vector and $\alpha_{1,i}$ *for* $i = 1\ldots p$ are functions of time-varying coefficient matrix, and εt is idiosyncratic shocks – postulated to be to be heteroscedastic and serially correlated. By iteration (4d) can be projected on the linear space spanned by (Z_{t-1}, Z_{t-2}, …Z_{t-p}) from the following equation:

$$Z_{t+h} \sum_{i=1}^{p} \alpha_{1,i} Z_{t-i} + \varepsilon_{t+h} \tag{4e}$$

The null hypothesis is that variable Z_1 does not Granger cause variable Z_j for j = 2,3…p.

The exposition of the results and their implications are best understood by slightly reformulating the condition for symmetric, or asymmetric, impacts of one variable (say, Z_1) on another variable (say, Z_2) of Hatemi-J (2021). Hatemi-J (2021) showed that Z_1 causes Z_2 if:

$$TV_P > CV \tag{5a}$$

Where TV_P is the extracted test value from the Hatemi-J procedure and *CV* is the bootstrap critical value at either 5% or10% levels of significance. The inequality (5a) holds if and only if TV_PCV, defined as the ratio of TV_p and *CV*, exceeds one (1):

$$TV_pCV = [(TV_P)/(CV)]\rangle 1 \tag{5b}$$

Inequality (5b) allows us to confirm graphically, from the time profile of TV_pCV and the threshold (1) if there exists causality running from variable Z_1 to Z_2 and also to determine, from the time dynamics, when causality starts and when it ceases to exist. We explore, bilateral, symmetric, and asymmetric causality between our variables of interest.

In Section 3, we present the results and briefly discuss the significance of our findings and compare the implications of the time-varying method of Hatemi-J with that of TVR-GC.

Table 1
Test results for multivariate normality and multivariate ARCH in the VAR model.

Variables in the Model	The *P*-value of the Multivariate Normality Test	The P-value of the Multivariate ARCH test
$[VIX_t, \widehat{WEI}_{t+1}]$	0.0555	0.012
$[(VIX_t)^+, (\widehat{WEI}_{t+1})^+]$	0.0000	0.284
$[(VIX_t)^+, (\widehat{WEI}_{t+1})^-]$	0.0000	0.305
$[((VIX_t)^-, (\widehat{WEI}_{t+1})^+]$	0.0000	0.306

1. VIX_t is the (natural) logarithmic transformation of the stock market volatility index and $\widehat{WEI}_{t+1}$ is the expected value of WEI_t, *which* is the (natural) logarithmic transformation of the weekly economic activity index of US economy during the first 50 weeks from the announcement of COVID-19 as the pandemic.
2. The vector $[(VIX_t)^+, (WEI_t)^+]$ denotes the cumulative partial sum of the positive changes and the vector $[(VIX_t)^-, (WEI_t)^-]$ indicates the cumulative partial sum of the negative changes. In a similar fashion we define $[(VIX_t)^-, (WEI_{t+1})^+]$
3. The multivariate test of Doornik and Hansen (2008) was implemented for testing the null hypothesis of multivariate normality in the residuals in each VAR model.
4. The multivariate test of Hacker and Hatemi-J (2005) was conducted for testing the null hypothesis of no multivariate ARCH (1).

2.2. Data

As discussed above, we use weekly data on *VIX* for the first 42–50 weeks of the COVID-19 pandemic starting from the 3rd week of January 2020 to October 2020. The data for VIX are taken from the Chicago Board Options Exchange (CBOE) webpage (https://www.cboe.com/tradable_products/vix/). To capture economic disruptions and shocks in the US economy during the same time period, we use the weekly economic index (*WEI*). The *WEI* data are from the Federal Reserve Bank of New York (https://www.newyorkfed.org/research/policy/weekly-economic-index#/) website. CBOE's *VIX* Index is widely used as a metric by financial professionals to measure stability for 30 days ahead, which tracks the S&P 500's basket of stocks and utilises trends in options trading for estimating problems in futures trading.

3. Empirical results

3.1. Hatemi-J's time varying asymmetric causality models

The *p* values for the multivariate normality tests and multivariate ARCH tests are presented in Table 1. The results of the diagnostic tests

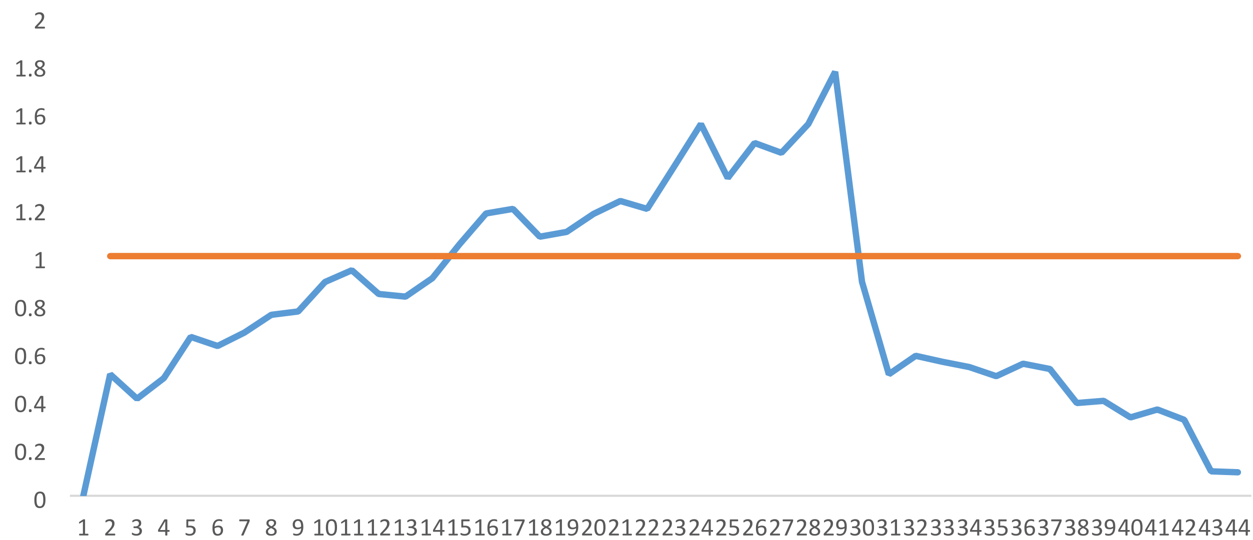


Fig. 1. Time plot for dynamic symmetric causality test results at the 5% significance level.
(H0: Expectation of WEI_{t+1} Does Not Cause VIX_t)
Note: Expectation of $WEI_{t+1}=\widehat{WEI}_{t+1.}$
The blue line plots the values of the left-hand side of inequality (5b) - extracted from the Hatemi-J procedure. The orange line is the right-hand side of inequality (5b).

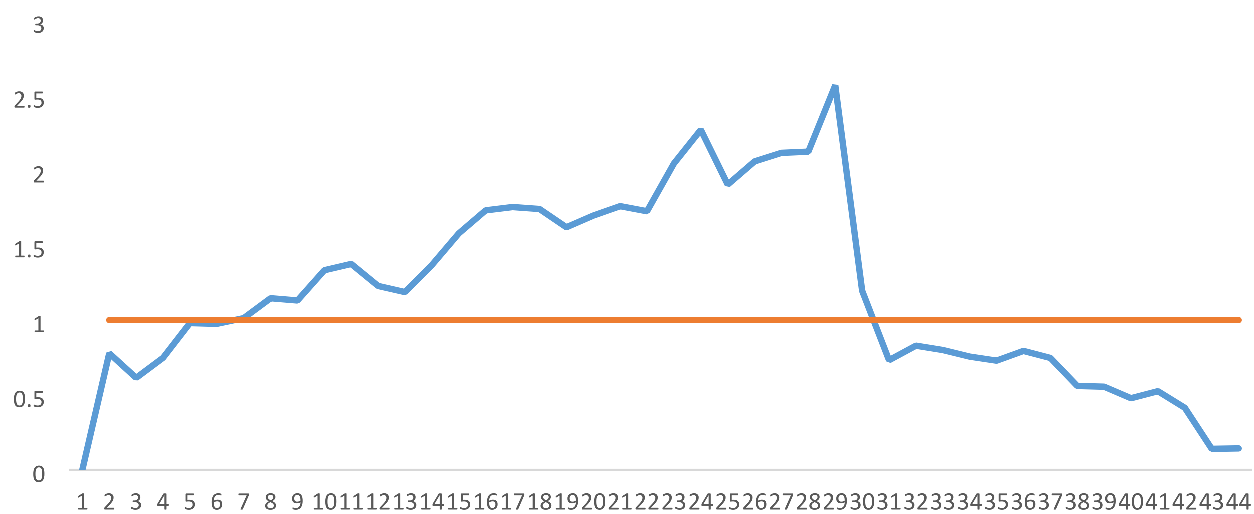


Fig. 2. Time plot for dynamic symmetric causality test results at the 10% significance level.
(H0: Expectation of WEI_{t+1} Does Not Cause VIX_t)
Note: Expectation of $WEI_{t+1}=\widehat{WEI}_{t+1}$
The blue line plots the values of the left-hand side of inequality (5b) - extracted from the Hatemi-J procedure. The orange line is the right-hand side of inequality (5b).

show that the underlying residuals in the VAR models are non-normal in all cases and multivariate ARCH (1) effects prevail in all asymmetric cases. The bootstrap simulation approach of Hatemi-J with leverage adjustment, therefore, is used to produce critical values that are robust to non-normality and time-varying volatility that illustrate our data (Atri, Kouki, & Gallali, 2021; Hatemi-J, 2012). Hence, we can safely utilise T bootstrap simulations with leverage adjustments for implementing more accurate critical values for asymmetric causality tests for symmetric and time-varying causality. The bootstrapped causality test results are presented in Tables 1A–6A of the Appendix. The results are summarised in Figs. 1 to 5.

Figures 1-2 plot the dynamic symmetric causality results from $\widehat{WEI}_{t+1}$ to VIX_t. The horizontal axis gives time (week) and the vertical axis gives the ratio of Test Value-to- the Bootstrap Critical Value. The blue curve is the ratio of Test Value and the Bootstrap Critical Value at either 10% or 5% level of significance. Thus, the blue curve is $TV_pCV =$ $[(TV_P)/(CV)]$ and represents the left-hand-side of inequality (5b). The orange (horizontal) line is the right-hand-side of inequality (5b), which is equal to unity (1). The null hypothesis of "no Granger causality" is rejected when the blue line is above the yellow line. Note that time-varying causality holds only when the left-hand side (LHS) of the inequality (5b) exceeds the value of unity. The LHS has been extracted from the Hatemi-J procedure and plotted as a blue line in Fig. 1. The right-hand side (RHS) of the inequality (5b) is plotted as an orange line in Fig. 1. If the blue line exceeds the orange line, then (time-varying) causality runs from WEI_{t+1} to VIX_t.

Our results of time-varying causality seek to establish whether expected future economic shocks are aligned with forthcoming US economic shocks during the early phase of the pandemic. The EMH holds only when a time-varying causal relationship exists between WEI_{t+1} to VIX_t. When there is no causal, $\widehat{WEI}_{t+1}$ does not hold predictive content for VIX_t. One plausible source of the failure of the EMH is the irrational

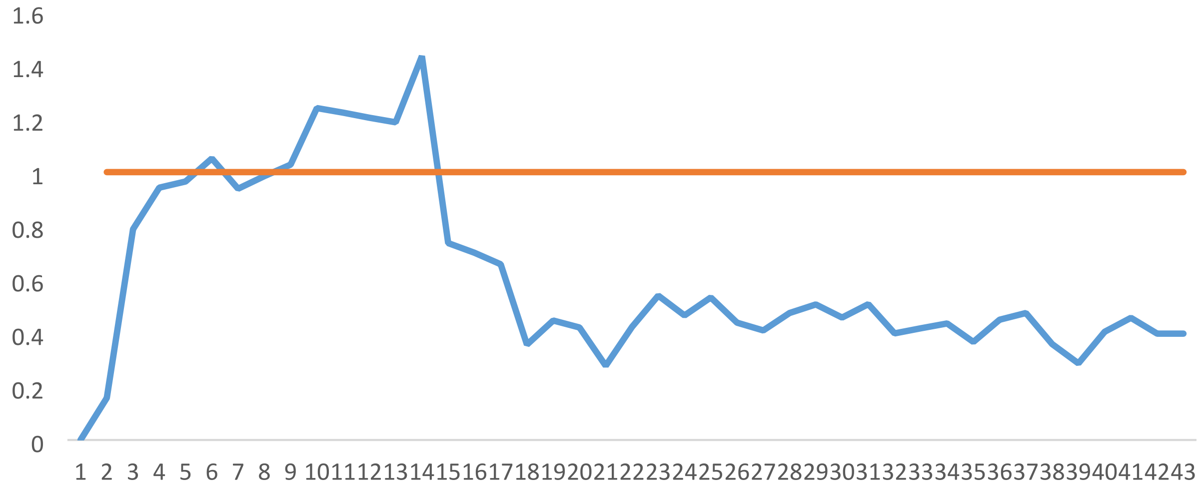


Fig. 3. Time plot for dynamic symmetric causality test results at the 5% significance level.
(H0: A Decrease in Expectation of WEI_{t+1} Does Not Cause an Increase in VIX_t

Note: A Decrease in the Expectation of $WEI_{t+1}=(\widehat{WEI}_{t+1})^{-}$
The blue line plots the values of the left-hand side of inequality (5b) - extracted from the Hatemi-J procedure. The orange line is the right-hand side of inequality (5b).

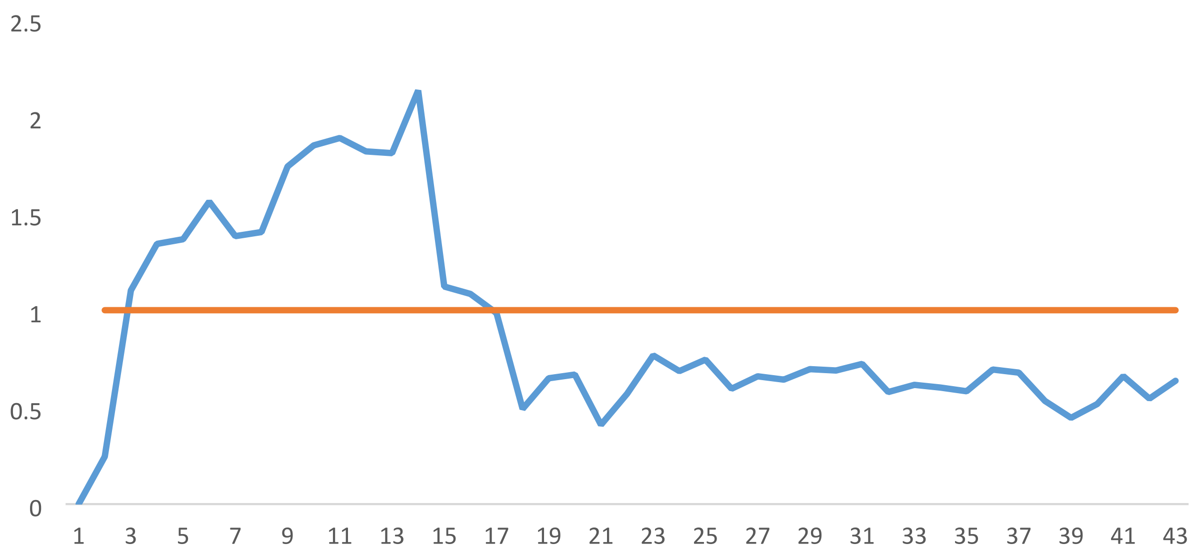


Fig. 4. Time plot for dynamic symmetric causality test results at the 10% significance level.
(H0: A Decrease in Expectation of WEI_{t+1} Does Not Cause an Increase in VIX_t)

Note: An increase in the Expectation of $WEI_{t+1}=(\widehat{WEI}_{t+1})^{+}$
The blue line is the value of the left-hand side of inequality (5b) - extracted from the Hatemi-J procedure. The orange line is the right-hand side of inequality (5b).

panic element characterising investor behaviour during the pandemic. As it has been argued by several authors (Apergis & Apergis, 2021; Atri et al., 2021; Baker et al., 2020; Gangopadhyay, 2020; Kirman, 2014; Vives, 1996), the pandemic impacted markets and sent shockwaves through the economy, causing investor fear to rise.

Figure 1 shows the symmetric causal relationship from $\widehat{WEI}_{t+1}$ to VIX_t at the 5% level of significance. The standard test results for the symmetric and time-varying causality show that there is a causal relationship running from $\widehat{WEI}_{t+1}$ to VIX_t (see Fig. 1) at 5% level of significance from Week 14 to Week 30. After Week 30, there is no evidence of causality. At the 10% level of significance, as shown by Fig. 2, the causality runs from $\widehat{WEI}_{t+1}$to VIX_t from Week 6 to Week 30, and after Week 30 there is an alignment of $\widehat{WEI}_{t+1}$to VIX_t. Based on the symmetric and time-varying causality result, one might like to conclude that predictions of WEI_{t+1} at date t, $\widehat{WEI}_{t+1}$, had a causal effect on VIX_t for some weeks until Week 30 after which the rational expectations equilibrium breaks down. However, from the diagnostics outlined in Table 1, we find that the Hatemi-J methodology is not suitable for symmetric and time-varying cointegration. This is because the *p*-values of the multivariable normality test and the multivariate ARCH test do not support the use of this methodology. Hence, we do not attach much credence to the results of the symmetric and time-varying cointegration tests and explore the asymmetric cases.

For the asymmetric and time-varying cointegration tests, the Hatemi-J methodology is suitable as can be seen from Table 1. Table 1 shows

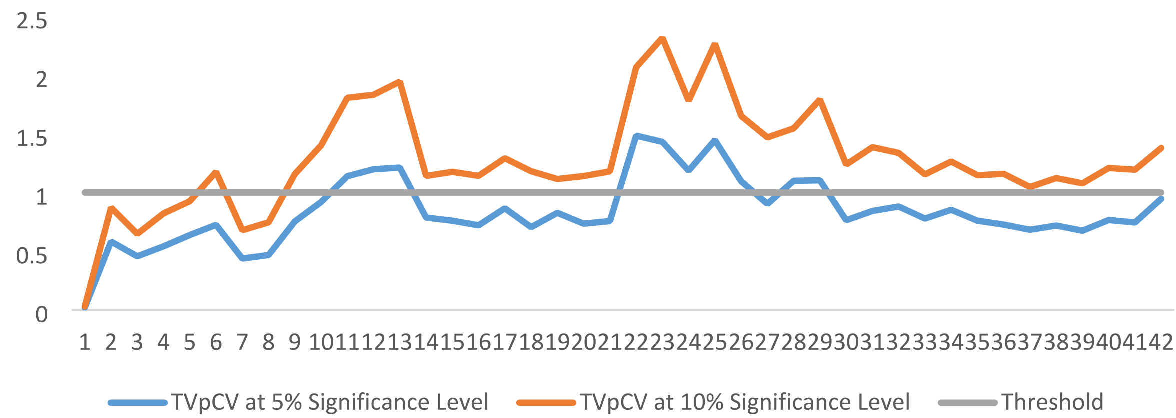


Fig. 5. Time plot for dynamic symmetric causality test results at the 5% & 10% significance level.
(H0: An Increase in Expectation of WEI_{t+1} Does Not Cause a Decrease in VIX_t)
Note: An Increase in the Expectation of $WEI_{t+1}=(\widehat{WEI}_{t+1})^{+}$
The blue line is the value of the left-hand side of inequality (5b) - extracted from the Hatemi-J procedure. The orange line is the right-hand side of inequality (5b).

that there is evidence of hidden cointegration.[2] During a crisis such as the pandemic, Park and Hahn (1999) argue that structural changes can cause potential decoupling of the cointegrating relationship. The methodology of Hatemi-J (see Hatemi-J (2021)) can handle both time varying and hidden (or, asymmetric) cointegration. Once we consider asymmetric causality, a very interesting pictures emerges. Fig. 3 shows how a decrease in the expectation of $\widehat{WEI}_{t+1}$ affects *VIXt*.Fig. 3 shows that a decreases in VIX_t, or a reduction in investor fear or uncertainty in the previous week - given by VIX_{t-1}^{-} - is determined by the predicted fall in WEI_{t+1}, given by $(\widehat{WEI}_{t+1})^{-}$, from Week 9 to Week 14 at the 5% level of significance. At the 10% level of significance, we find from Fig. 4, the predicted fall WEI_{t+1} in week t, given by $(\widehat{WEI}_{t+1})^{-}$, determines increases in VIX_t (or investor fear) from Week 3 to Week 17. After Week 17, the rational expectations equilibrium breaks down.

Finally, Fig. 5 shows how a predicted increase in WEA_{t+1} affects VIX_t. For predicted increases in WEA_{t+1} in Week t, given by $(\widehat{WEI}_{t+1})^{+}$, leads to decreases in VIX_t (investor fear in Week t) in Week 11-to-Week 13 and Week 21-to-Week 26 at 5% level of significance. After Week 26, the rational expectations equilibrium breaks down. At the 10% level of significance $(\widehat{WEI}_{t+1})^{+}$, predicted increases in WEI_{t+1}, in Week t influences VIX_t from Week 8 onwards. Except for the first seven (7) weeks, the rational expectations equilibrium is operational.

3.2. Robustness checks: Rossi and Wang estimation

In this subsection we present results for the time-varying Granger causality method (TVR-GC), developed by Rossi and Wang (2019), as a robustness check for our findings from the Hatemi-J procedure to test time-varying Granger causality. The TVR-GC procedure also treats estimated parameters as functions of time. As in the Hatemi-J procedure, TVR-GC overcomes estimation challenges created by nonlinearities, nonstationarities, regime shifts and parameter instabilities over time. In what follows, we find that the TVR-GC procedure also confirms our findings from the Hatemi-J tests. Thus, both TVR-GC and Hatemi-J procedures confirm causality between *VIX and WEI*. The TVR-GC results show that the symmetric and asymmetric impact WEI on VIX during the period under study varies from week to week.

Table 2
Wald tests results on time varying granger causality.

Direction of Causality	Max Wald FE	Max Wald RO	Max Wald RE
$LnVIX_t$ caused by $ExpWEI_{t+1}$	24.789	0.000	9.657e+18
	(3.056e+17)	(2.750e+17)	(3.056e+17)
	[1.404e+19]	[1.264e+19]	[1.404e+19]
$LnVIX_t\_pos$ caused by $ExpWEI_{t+1}\_pos$	6.032	0.000	2.020e+21
	(2.686e+17)	(2.418e+17)	(2.686e+17)
	[1.110e+19]	[9.986e+18]	[1.110e+19]
$LnVIX_t\_pos$ caused by $ExpWEI_{t+1}\_neg$	132.296	0.000	7.469e+21
	(1.748e+18)	(1.573e+18)	(1.748e+18)
	[2.423e+19]	[2.180e+19]	[2.423e+19]
$LnVIX_t\_neg$ caused by $ExpWEI_{t+1}\_pos$	8.481	0.000	8.922e+20
	(9.982e+16)	(9.982e+16)	(9.982e+16)
	[4.738e+19]	[4.264e+19]	[4.738e+19]

The 95th and 99th percentiles of the empirical distribution of the bootstrap statistics are in parentheses and brackets, respectively.

The endogenous variables in the TVR-GC model vector Z_t include *LnVIX* and the expectation of *WEI (ExpWEI)*. Given our theoretical models (4d) - (4e), we test the null hypothesis that the lags of *LnVIX* do not Granger cause *ExpWEI*. Our initial estimation considers several test statistics by taking into account the possibility of parameter instabilities. More importantly, we consider the possibility that relevant parameters undergo changes at an unknown time point. The coefficient estimates change after the possible (unknown) structural break. Hence, the null hypothesis posits that there is no Granger causality for each time point under investigation. The mean Wald test statistics are reported in Table 2. The lag length of the VAR model is selected using the Schwarz Information Criterion (SIC). Moreover, we choose the standard trimming parameter 0.10 in an effort to cover as much data as possible. Based on the extant structural break literature, the potential break dates are usually trimmed to omit the beginning and end of the sample period. From Table 2, we find evidence of time-varying Granger causality under alternative simulations.

In each of the panels in the following Figs. 6–9, time-varying robust Granger causality requires the solid line to be above the dotted line for causality to hold. For any date if the dotted line is above the solid line, there is no evidence of time-varying robust Granger causality. Fig. 6 reports symmetric Granger causality from $ExpWEI_{t+1}$ to $LnVIX_t$. In the first panel of Fig. 6, the solid line is not above the dotted line in all weeks, which implies that there is no time-varying robust Granger causality running from $ExpWEI_{t+1}$ to $LnVIX_t$. The same finding holds under the rolling (RO) Wald test results outlined in the second panel. The results suggest no alignment between investor fear and economic shocks under the symmetric time-varying robust Granger causality test.

[2] Structural changes during crises can decouple the cointegrating relationship, which leads to the possibility of time-varying cointegration advanced by Park and Hahn (1999). Time is used as a proxy for unobserved variables that impact the long-term relationship. During crises, hidden cointegration highlights the impacts of positive and negative shocks (see Granger and Yoon, 2002).

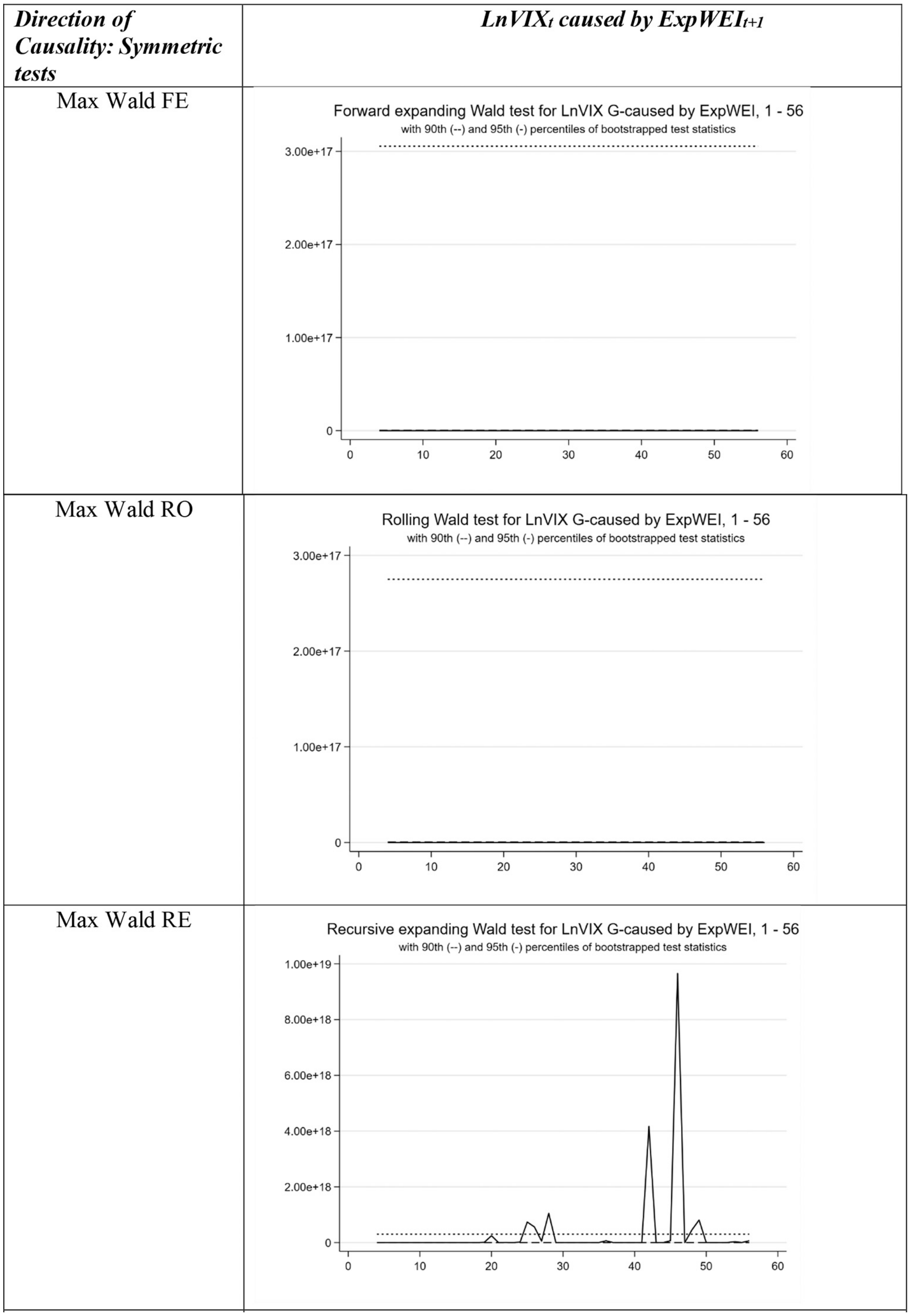


Fig. 6. $LnVIX_t$ caused by $ExpWEI_{t+1}$.

However, there is a possibility of asymmetric causality, which is tested in subsequent panels. The recursive expanding Wald test results, in the third panel, shows the presence of causal impacts between the variables during 20th week, 25th to 30th week and 41 to 50th week. For these weeks, investor fear is aligned with expected economic shocks. For other weeks, this alignment breaks down. However, these results are based on symmetric causality tests. We pay more attention to the asymmetric test results. In what follows, we examine the asymmetric causality running from increases, or decreases, in WEI_{T+1} and decreases, or increases, in VIX_t .

The picture of asymmetric causality offers a different story: first, from Fig. 7, when increases in *LnVIX* are caused by increases in *ExpWEI*, both FE and RO Wald test results show that there is no asymmetric causality. However,the recursive expanding Wald test result shows that after 22 weeks there is steady causality between the variables. Fig. 8 illustrates an increase in *LnVIX* caused by a decrease in *ExpWEI*. The results suggest similar findings. The RE results exhibit a highly significant causal relationship during 40 to 41 weeks. Third, when assessing the causality as a decrease in *LnVIX* caused by an increase in *ExpWEI*, the recursive expanding test results show highly significant causality during 18 to 20 weeks and 43 to 50 weeks. In other words, these asymmetric causality test results show that the EMH holds for these weeks 18–20 and

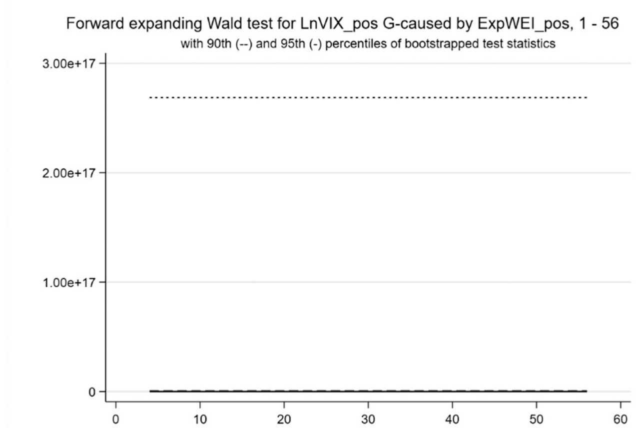
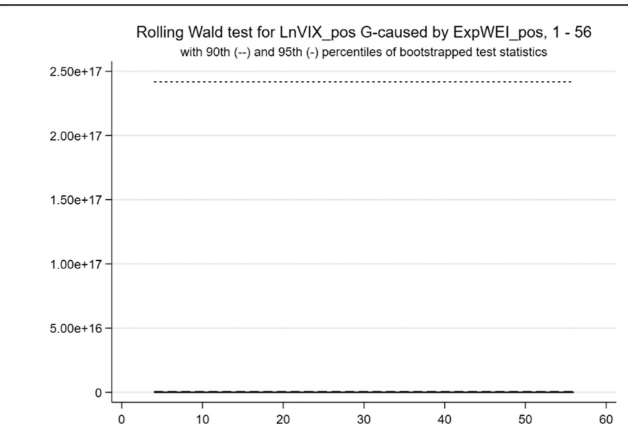
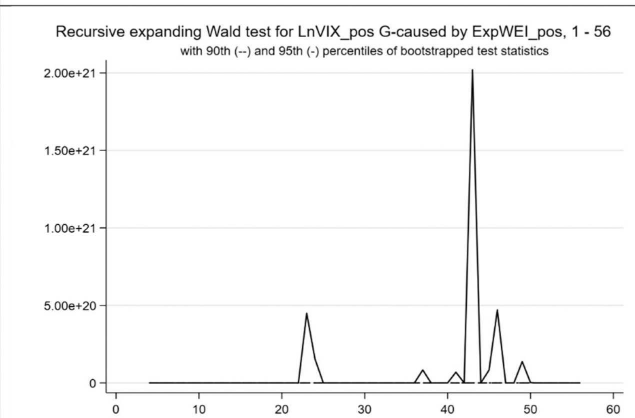
Direction of Causality: Asymmetric Tests	***$LnVIX_t$_pos caused by $ExpWEI_{t+1}$_pos***
Max Wald FE	
Max Wald RO	
Max Wald RE	

Fig. 7. $LnVIX_t$_pos caused by $ExpWEI_{t+1}$_pos.

43–50, indicating that investor fear is based upon rational forecasts. For other weeks, this alignment disappears. This disappearance suggests that the rational foundation of forecasts are replaced by panic elements caused by the pandemic. This is supported by the reaction to COVID-19 which was unprecedented (Apergis & Apergis, 2021; Atri et al., 2021; Baker et al., 2020 among others).

4. Conclusion

This study investigates whether $\widehat{WEI}_{t+1}$ has predictive content for VIX_t during the COVID period. Our study investigates the most turbulent phase of the pandemic in the US starting from the 20th of January 2020 for 42–50 weeks. The rationality of expectations implies that the expected value of WEI_{t+1} in Week t, $\widehat{WEI}_{t+1}$, cannot systematically deviate from the realised value of WEI_{t+1}. In the presence of rational expectations, $\widehat{WEI}_{t+1}$ as a predictor of investor fear in week t will drive, or cause, VIX_t. In other words, the causality running from $\widehat{WEI}_{t+1}$ to VIX_t is used to test the effectiveness of the rational expectations equilibrium during a crisis. Our study leads to several conclusions.

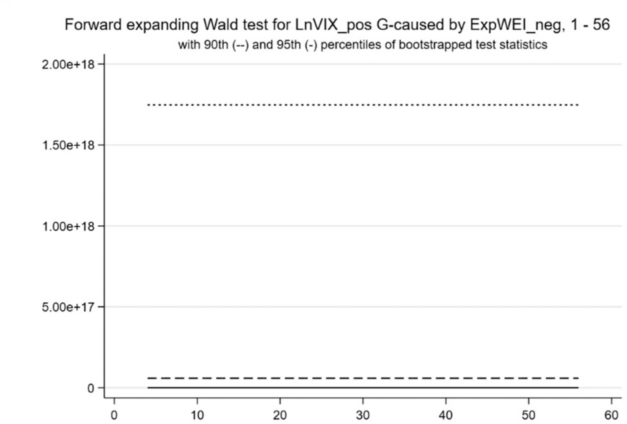
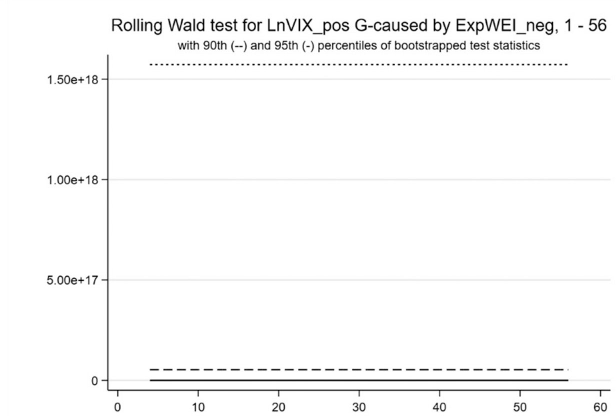
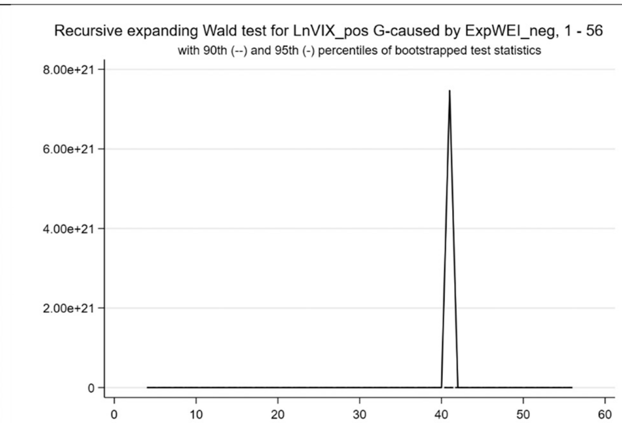
<table>
<tr><th>Direction of Causality</th><th>$LnVIX_t\_pos$ caused by $ExpWEI_{t+1}\_neg$</th></tr>
<tr><td>Max Wald FE</td><td>
</td></tr>
<tr><td>Max Wald RO</td><td>
</td></tr>
<tr><td>Max Wald RE</td><td>
</td></tr>
</table>

Fig. 8. $LnVIX_t\_pos$ caused by $ExpWEI_{t+1}\_neg$.

First, assuming symmetric and time-varying causality, VIX_t is not caused by anticipated, or expected levels of WEI_{t+1}, or $\widehat{WEI}_{t+1}$, in the first five weeks or so of the pandemic, the rational expectations equilibrium fails to materialise. This failure could be due to the panic and unknown elements in the dynamics of the pandemic. However, from week 6 to week 30, causality is established between expectations of future *WEI* ($\widehat{WEI}_{t+1}$) and current *VIX* (VIX_t), which indicates the affirmation of the rational expectations hypothesis. Interestingly, after Week 30, the rational expectations equilibrium breaks down and there is no causality running from the expected value of $\widehat{WEI}_{t+1}$to VIX_t. At a tighter level of significance (5%), the window during which causality holds is reduced to Week 15-Week 30. After Week 30, the predictive power of rational expectations, based on informational efficiency, breaks down.

Secondly, when we consider asymmetric and time varying causality at the 5% level of significance, the window during which the rational expectations hypothesis holds shrinks to a window of Week 9 to Week 15 when expected decreases in WEI_{t+1}, given by $(\widehat{WEI}_{t+1})^{-}$, affects VIX_t. In other weeks, we find no evidence of asymmetric and time-varying causality for other weeks. For the 10% level of significance, time-varying (asymmetric) causality is noted from Week 2 to Week 15. Thus, after Week 15, the rational foundation of *VIX* seems to have been compromised by the pandemic.

Finally, when we consider expectations of improvements in WEI_{t+1},

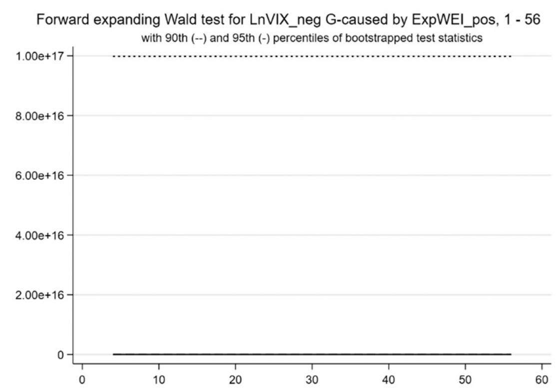
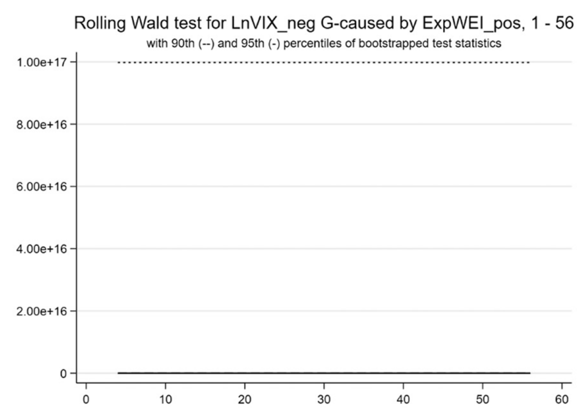
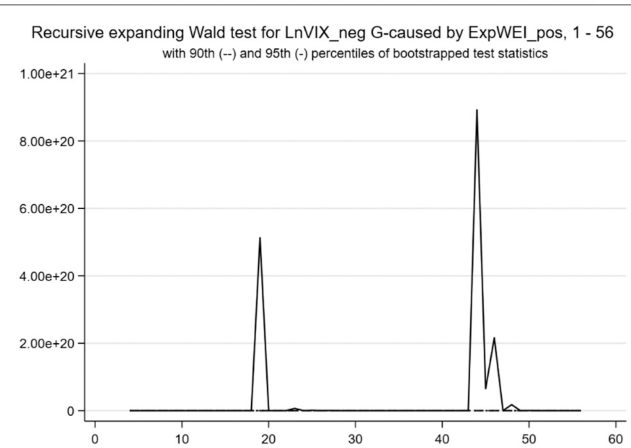
Direction of Causality	***$LnVIX_t$_neg caused by $ExpWEI_{t+1}$_pos***
Max Wald FE	
Max Wald RO	
Max Wald RE	

Fig. 9. $LnVIX_t$_neg caused by $ExpWEI_{t+1}$_pos.

or $(\widehat{WEI}_{t+1})^+$, investor fear showed more rational foundations. At the 10% level of significance, decreases in investor fear (VIX_t) after Week 7 appear to be caused by forthcoming improvements in economic conditions, or $(\widehat{WEI}_{t+1})^+$. However, at the 5% level of significance, the time-varying and symmetric causality have an uneven path. Using time-varying robust Ganger causality tests, we find evidence in support of the findings from the Hatemi-J's methodology of time-varying causality. During the early phase of the pandemic, our results show that the fluctuations in the investor fear, or VIX, have been correctly aligned with anticipated (forthcoming) economic shocks disruptions for some weeks. For these weeks, the EMH functions smoothly. For other weeks, this alignment breaks down and the EMH fails to hold. One plausible rationale behind the breakdown of the alignment, or failure of the EMH, is the case of irrational fear and panic which dominate investor behaviour in some weeks.

Our results, therefore, provide evidence in support of the efficient market hypothesis and rational expectations after the first few weeks of the announcement of a pandemic. In the first few weeks of a crisis, investors are ablet o make abnormal gain. However, there is no likelihood of gaining systematic abnormal profits, after the first few weeks of a pandemic. This fading away suggests that the rational foundation of forecasts is replaced by social learning caused by the pandemic (see Cornell, 1987; Vives, 1996).

Data availability

Data will be made available on request.

Acknowledgements

We wish to thank an anonymous reviewer and the editor for valuable comments.

Appendix A. Appendix

Table 1A: Dynamic symmetric causality test results at the 5% significance level. (H0: WEI_{t+1} Does Not Cause VIX_t).

SSP	Test Value	5% Bootstrap CV	TVpCV
1	2.676	5.277	0.507
2	2.112	5.216	0.405
3	2.576	5.244	0.491
4	3.04	4.582	0.663
5	2.927	4.687	0.625
6	3.218	4.726	0.681
7	3.474	4.601	0.755
8	3.653	4.75	0.769
9	4.114	4.611	0.892
10	4.238	4.503	0.941
11	3.709	4.405	0.842
12	3.782	4.552	0.831
13	3.946	4.347	0.908
14	4.553	4.343	1.048
15	4.755	4.036	1.178
16	4.906	4.098	1.197
17	4.928	4.56	1.081
18	5.126	4.656	1.101
19	5.226	4.445	1.176
20	5.54	4.503	1.23
21	5.645	4.717	1.197
22	6.276	4.571	1.373
23	6.623	4.27	1.551
24	6.315	4.764	1.326
25	6.495	4.414	1.472
26	5.992	4.188	1.431
27	6.219	4.01	1.551
28	7.755	4.384	1.769
29	3.588	4.018	0.893
30	2.31	4.556	0.507
31	2.349	4.02	0.584
32	2.306	4.13	0.559
33	2.142	3.989	0.537
34	2.223	4.459	0.499
35	2.345	4.252	0.551
36	2.268	4.284	0.529
37	1.696	4.385	0.387
38	1.578	3.987	0.396
39	1.349	4.122	0.327
40	1.437	3.991	0.36
41	1.2	3.782	0.317
42	0.371	3.654	0.102
43	0.353	3.595	0.098

Table 2A: Dynamic symmetric causality test results at the 10% significance Level. (H0: WEI_{t+1} Does Not Cause VIX_t.)

SSP	Test Value	10% Bootstrap CV	TVpCV
1	2.676	3.438	0.778
2	2.112	3.437	0.614
3	2.576	3.445	0.748
4	3.04	3.1	0.98
5	2.927	3.002	0.975
6	3.218	3.178	1.013
7	3.474	3.031	1.146
8	3.653	3.23	1.131
9	4.114	3.086	1.333
10	4.238	3.083	1.375
11	3.709	3.02	1.228
12	3.782	3.187	1.187
13	3.946	2.884	1.368

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SSP	Test Value	10% Bootstrap CV	TVpCV
14	4.553	2.883	1.579
15	4.755	2.743	1.733
16	4.906	2.796	1.755
17	4.928	2.829	1.742
18	5.126	3.164	1.62
19	5.226	3.078	1.698
20	5.54	3.146	1.761
21	5.645	3.269	1.727
22	6.276	3.067	2.046
23	6.623	2.916	2.271
24	6.315	3.315	1.905
25	6.495	3.154	2.06
26	5.992	2.831	2.117
27	6.219	2.927	2.125
28	7.755	3.02	2.568
29	3.588	3	1.196
30	2.31	3.156	0.732
31	2.349	2.833	0.829
32	2.306	2.882	0.8
33	2.142	2.833	0.756
34	2.223	3.05	0.729
35	2.345	2.953	0.794
36	2.268	3.035	0.747
37	1.696	3.028	0.56
38	1.578	2.843	0.555
39	1.349	2.82	0.478
40	1.437	2.74	0.525
41	1.2	2.895	0.414
42	0.371	2.643	0.14
43	0.353	2.476	0.143

Table 3A: dynamic symmetric causality test results at the 5% significance Level. (H0: An Increase in WEI_{t+1} Does Not Cause a Decrease in VIX_t.)

SSP	Test Value	5% Bootstrap CV	TVpCV
1	0.111	5.665	0.02
2	2.856	4.9	0.583
3	1.784	3.902	0.457
4	2.62	4.832	0.542
5	3.048	4.779	0.638
6	3.391	4.675	0.725
7	2.012	4.595	0.438
8	2.287	4.886	0.468
9	3.515	4.663	0.754
10	4.283	4.66	0.919
11	4.866	4.272	1.139
12	5.373	4.484	1.198
13	5.768	4.76	1.212
14	3.406	4.326	0.787
15	3.312	4.357	0.76
16	3.339	4.633	0.721
17	3.684	4.255	0.866
18	3.184	4.514	0.705
19	3.148	3.806	0.827
20	3.17	4.314	0.735
21	3.22	4.255	0.757
22	6.077	4.097	1.484
23	6.281	4.389	1.431
24	5.342	4.505	1.186
25	5.488	3.796	1.446
26	3.912	3.571	1.096
27	3.984	4.41	0.903
28	4.427	4.023	1.1
29	4.68	4.241	1.104
30	3.5	4.58	0.764
31	3.571	4.234	0.843
32	3.861	4.383	0.881
33	3.144	4.039	0.778
34	3.238	3.795	0.853
35	3.131	4.118	0.76
36	3.339	4.594	0.727
37	2.803	4.104	0.683

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SSP	Test Value	5% Bootstrap CV	TVpCV
38	2.853	3.971	0.719
39	3.047	4.513	0.675
40	3.321	4.337	0.766
41	3.416	4.587	0.745
42	3.635	3.838	0.947

Table 4A: Dynamic symmetric causality test results at the 10% significance Level. (H0: An Increase in WEI_{t+1} Does Not Cause a Decrease in VIX_t)

SSP	Test Value	5% Bootstrap CV	TVpCV
1	0.111	3.628	0.03
2	2.856	3.276	0.872
3	1.784	2.755	0.648
4	2.62	3.186	0.822
5	3.048	3.292	0.926
6	3.391	2.882	1.176
7	2.012	2.962	0.679
8	2.287	3.065	0.746
9	3.515	3.038	1.157
10	4.283	3.056	1.401
11	4.866	2.695	1.806
12	5.373	2.933	1.832
13	5.768	2.967	1.944
14	3.406	2.985	1.141
15	3.312	2.815	1.176
16	3.339	2.923	1.142
17	3.684	2.851	1.292
18	3.184	2.697	1.181
19	3.148	2.822	1.115
20	3.17	2.779	1.14
21	3.22	2.728	1.18
22	6.077	2.942	2.066
23	6.281	2.711	2.317
24	5.342	2.999	1.781
25	5.488	2.421	2.267
26	3.912	2.369	1.652
27	3.984	2.713	1.469
28	4.427	2.863	1.546
29	4.68	2.611	1.792
30	3.5	2.828	1.238
31	3.571	2.576	1.386
32	3.861	2.887	1.337
33	3.144	2.724	1.154
34	3.238	2.562	1.264
35	3.131	2.729	1.147
36	3.339	2.882	1.159
37	2.803	2.677	1.047
38	2.853	2.541	1.123
39	3.047	2.826	1.078
40	3.321	2.746	1.209
41	3.416	2.86	1.194
42	3.635	2.636	1.379

Table 5A: Dynamic asymmetric causality test results at the 5% significance Level. (H0: A Decrease in WEI_{t+1} Does Not Cause an increase in VIX_t)

SSP	Test Value	5% Bootstrap CV	TVpCV
1	0.832	5.294	0.157
2	3.956	5.03	0.787
3	4.774	5.069	0.942
4	4.538	4.705	0.965
5	4.94	4.701	1.051
6	4.404	4.696	0.938
7	4.83	4.904	0.985
8	5.414	5.267	1.028
9	5.589	4.51	1.239
10	5.394	4.415	1.222
11	5.762	4.79	1.203
12	5.384	4.541	1.186

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SSP	Test Value	5% Bootstrap CV	TVpCV
13	6.253	4.363	1.433
14	3.37	4.585	0.735
15	3.228	4.62	0.699
16	3.141	4.789	0.656
17	1.614	4.534	0.356
18	1.9	4.266	0.446
19	1.944	4.628	0.42
20	1.282	4.62	0.277
21	1.628	3.854	0.422
22	2.422	4.49	0.539
23	2.009	4.316	0.465
24	2.006	3.77	0.532
25	1.748	3.99	0.438
26	1.771	4.325	0.409
27	1.961	4.134	0.474
28	1.88	3.718	0.506
29	1.888	4.129	0.457
30	2.049	4.041	0.507
31	1.85	4.654	0.398
32	1.844	4.421	0.417
33	1.634	3.753	0.435
34	1.646	4.495	0.366
35	1.861	4.145	0.449
36	1.821	3.844	0.474
37	1.566	4.373	0.358
38	1.261	4.408	0.286
39	1.418	3.51	0.404
40	1.747	3.829	0.456
41	1.622	4.084	0.397
42	1.799	4.532	0.397

Table 6A: Dynamic asymmetric causality test results at the 10% significance level. (H0: A Decrease in WEI_{t+1} Does Not Cause an increase in VIX_t)

SSP	Test Value	5% Bootstrap CV	TVpCV
1	0.832	3.399	0.245
2	3.956	3.591	1.102
3	4.774	3.556	1.342
4	4.538	3.322	1.366
5	4.94	3.168	1.56
6	4.404	3.186	1.382
7	4.83	3.443	1.403
8	5.414	3.109	1.741
9	5.589	3.021	1.85
10	5.394	2.856	1.888
11	5.762	3.167	1.819
12	5.384	2.975	1.81
13	6.253	2.931	2.133
14	3.37	3.004	1.122
15	3.228	2.979	1.084
16	3.141	3.19	0.985
17	1.614	3.289	0.491
18	1.9	2.929	0.649
19	1.944	2.91	0.668
20	1.282	3.132	0.409
21	1.628	2.862	0.569
22	2.422	3.157	0.767
23	2.009	2.93	0.686
24	2.006	2.691	0.745
25	1.748	2.938	0.595
26	1.771	2.689	0.659
27	1.961	3.053	0.642
28	1.88	2.703	0.696
29	1.888	2.738	0.689
30	2.049	2.836	0.723
31	1.85	3.204	0.578
32	1.844	2.998	0.615
33	1.634	2.718	0.601
34	1.646	2.83	0.582
35	1.861	2.68	0.694
36	1.821	2.687	0.678
37	1.566	2.944	0.532

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SSP	Test Value	5% Bootstrap CV	TVpCV
38	1.261	2.835	0.445
39	1.418	2.747	0.516
40	1.747	2.648	0.66
41	1.622	2.979	0.544
42	1.799	2.83	0.636

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