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Nonlinear Cointegration and Asymmetric Adjustement between Economic policy uncertainty and Gold price: Evidence from the United States

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Abstract

The main objective of this paper is to estimate the interaction between gold price and US- EPU by using monthly data during the period span from January 1997 to September 2020. The threshold cointegration approach focus on TAR, C-TAR, M-TAR and consistent-MTAR is employed. Results indicate the evidence of asymmetry in the adjustment process to equilibrium. Unidirectional causality is reported between variables. In addition, gold price became cointegrated with economic uncertainty. The adjustment mechanism is asymmetric and the speed of adjustment to the equilibrium is different when the last equilibrium error has different signs.

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1. Introduction

The coronavirus (COVID-19) outbreak has evolved into a global problem in very short time by affecting more than 200 countries around the world. Governments have implemented a series of measures such as travel bans, business & school closures, and lockdowns to slow the spread of the pandemic. Although these measures help prevent the spread of the virus, they also affect financial markets (see, for example: Goodell, 2020; Topcu and Gulal, 2020; Zhang et al., 2020; among others). In particular, Baker et al. (2020) assert that the novel coronavirus has an unprecedented impact on stock market compared to any other infectious diseases.

Volatility, a crucial indicator reflecting the uncertainty in financial markets, has increased dramatically during the COVID-19 outbreak (Baek et al., 2020). As one of the most widely quoted stock market indices across the globe, for example, Standard & Poor's (S&P) 500 collapsed by 11,98% on March 16 which has been the biggest one-day drop since 1987.

COVID-19 or policies implemented by governments as a response to COVID-19 can affect stock market volatility in several ways (Zaremba et al., 2020). First, government interventions may trigger portfolio restructuring since they lead to a change in firms' future cash flow. Then the rapid reallocation of financial resources may increase stock market volatility. Second, the increasing uncertainty due to the worsening business cycle can cause investors to turn to safe haven assets such as sovereign bonds, gold and reserve currencies and thus capital outflows from stock markets. Third, constant flow of information regarding infections and government interventions can produce news-based volatility (Manela and Moreira, 2017).

Although the nexus between COVID-19 and stock market volatility has been investigated by previous studies (see, for example: Albulescu, 2020; Baker et al., 2020; Onali, 2020; among others), the possibility of a time-varying relationship has been ignored. The response of the market volatility to COVID-19 may differ by either stringent public health measures or economic policies adopted by governments. Thus, the structure of this relationship is not necessarily static and can vary over time. Indeed, by ignoring the possibility of time-varying nature, the results may be inconsistent and biased (Rossi and Wang, 2019). The aim of this study is therefore to examine the time-varying response of the United States (U.S) stock market volatility to the global coronavirus outbreak.

The reminder of the study is as follows: Section 2 describes model and data, Section 3 presents the methodology and empirical findings, Section 4 provides robustness check, Section 5 discusses policy implications and Section 6 gives the concluding remarks.

2. Model and Data

A large body of research on the determinants of stock market volatility describes market volatility as a function of exchange rate volatility and oil price shocks (see, for example: Basher et al., 2012; Lawal et al., 2016; among others). Following this growing literature, this study describes the US stock market volatility *(smv)* as a function of exchange rate volatility *(erv)*, oil price volatility *(opv)* and the global coronavirus outbreak *(covid)*:

$$smv = f(erv, opv, covid) \tag{1}$$

Daily data on stock market volatility, exchange rate volatility, oil price volatility, and the spread of infection were obtained for the period January 03 - October 15, 2020[1]. We use the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) procedure in measuring the volatility of stock returns, exchange rate and oil prices[2,3].

We also examine whether stock market volatility responds to the COVID-19 news. Following Baek et al. (2020), we use the share of recoveries and deaths as a proxy for positive news *(pnews)* and negative news *(nnews)*, respectively[4].

$$smv = f(erv, opv, pnews) \tag{2}$$

and

$$smv = f(erv, opv, nnews) \tag{3}$$

Table I.
Descriptive Statistics and Correlation Matrix

Panel A. Descriptive Statistics

	smv	erv	opv	covid	pnews	nnews
Mean	0.012	0.176	0.841	11.248	1.762	0.203
Median	0.007	0.130	0.380	6.520	1.214	0.083
Max.	0.106	0.915	27.950	38.615	9.973	1.950
Min.	0.000	0.000	0.000	0.000	0.145	0.000
Std. Dev.	0.016	0.161	2.701	11.773	1.386	0.292
Obs.	186	186	186	186	172	172

Panel B. Correlation Matrix

	smv	erv	opv	covid	pnews	nnews
smv	1	0.504	0.089	-0.321	0.162	0.295
erv	0.504	1	0.056	-0.252	0.145	0.146
opv	0.089	0.056	1	-0.136	0.086	0.166
covid	-0.321	-0.252	-0.136	1	-0.330	-0.497
pnews	0.162	0.145	0.086	-0.330	1	0.336
nnews	0.295	0.146	0.166	-0.497	0.336	1

[1] Data depends on normal business days, Monday through Friday, except holidays.

[2] The AR(1) - GARCH(1,1) model is used for stock market while the AR(2) - GARCH(1,1) models are used for exchange rate and oil prices. In order to determine the most appropriate GARCH model, we select the autoregressive parameter by BIC in the mean equation. Notice that the coefficients sum up to a number less than one and statistically significant are considered in the variance equation to select the best GARCH model.

[3] We also estimated Exponential GARCH (EGARCH) which was quite similar to the results obtained by the GARCH. They are available upon request.

[4] There are also some potential proxies (like vaccination news, variant news, etc.) to represent the COVID-19 information. Due to the time dimension of our dataset, however, we are unable to use these proxies.

Stock market volatility is measured using daily returns for S&P500[5]. Exchange rate is represented by the US dollar index while we consider West Texas crude prices in U.S. dollars per barrel in defining oil prices. COVID-19 is captured by global cumulative number of confirmed cases per million population[6]. Positive news is measured using the global number of recoveries as a share of global cumulative number of confirmed cases whereas negative news is measured using the global number of deaths as a share of global cumulative number of confirmed cases[7]. Data on stock market, the exchange rate and oil prices were obtained from Investing Database (2020) while data on COVID-19 proxies were extracted from the Johns Hopkins Coronavirus Resource Center (2020). Panel A and Panel B of Table I shows descriptive statistics of the data and correlation matrix, respectively.

3. Methodology and Results

In order to determine the integration level, we utilize the DF-GLS unit root test proposed by Elliott et al. (1996) prior to causality procedure. In the light of the test results reported in Table II, we cannot reject the null hypothesis of unit root for COVID-19 proxies whereas the null of unit root can be rejected for smv, erv, and opv.

Table II.
DF-GLS unit root results

	smv	erv	opv	covid	pnews	nnews
DF-GLS Statistic	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)

Note: Integration results are reported.
The lag length is chosen using the modified Akaike Information Criterion considering the correction by Perron and Qu (2007). The maximum number of lags is 5.Tests include a constant.

In order to examine the time-varying causality from COVID-19 to stock market volatility, we employ the recursive evolving window approach proposed by Shi et al. (2020), which based on the lag augmented vector autoregression (LA-VAR) models allowing for possibly integrated and deterministically trending time-series. The LA-VAR model for a n −dimensional vector y_t can be described as follows:

$$y_t = \sum_{i=1}^{k+d} \mathbf{A}_i y_{t-i} + \varepsilon_t \tag{4}$$

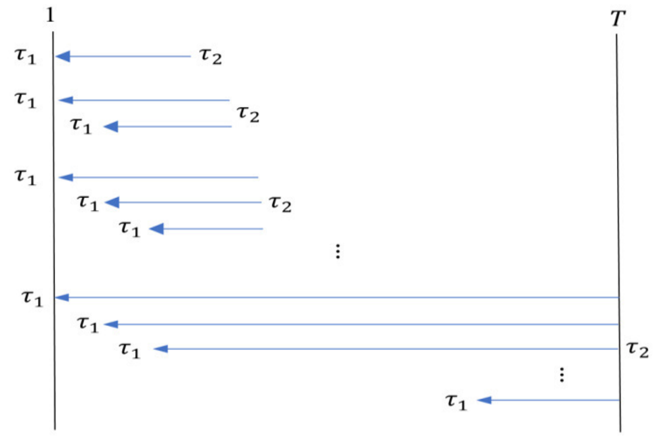
where d is the maximum integration order of $y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})'$ in the level VAR model and $t = 1,2, \ldots, T$. $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{nt})'$ is an independent white noise process with zero mean and nonsingular covariance matrix Σ_ε. One of the main advantages of the recursive evolving procedure is the applicability even when the variables are nonstationary or cointegrated, as well as allowing for multiple configurations of stationarity.

The causality approach depends on MWald statistics from subsamples of the data. Assume that f_1 and f_2 are the (fractional) starting and ending points of the estimated regression and f is the (fractional) observation of interest. Let $\tau_1 = [f_1 T]$, $\tau_2 = [f_2 T]$, while $[\cdot]$ is the integer part with interest fractional of the time dimension, T. Similarly, $\tau_w = [f_w T]$, where τ_w indicates the

[5] Note that the choice of S&P500 is not only due to its encompassing structure; but the fact that spillover effect from the US to other markets is very significant (see, for example: Fratzscher et al., 2012; Apostolou and Beirne, 2019; among others).
[6] Following the recent literature regarding the role of COVID-19 on stock markets (see, for example: Bora and Basistha, 2020; Yagli, 2020; among others), we use COVID-19 cases as a proxy of the pandemic.
[7] Given the data availability of positive and negative COVID-19 information, Model 2 and Model 3 are estimated for the period January 23 – October 15, 2020.

minimum number of observations to estimate the LA-VAR model[8]. The basic features of recursive evolving window algorithm are shown in the Figure 1.

Figure 1.
The recursive evolving window algorithm

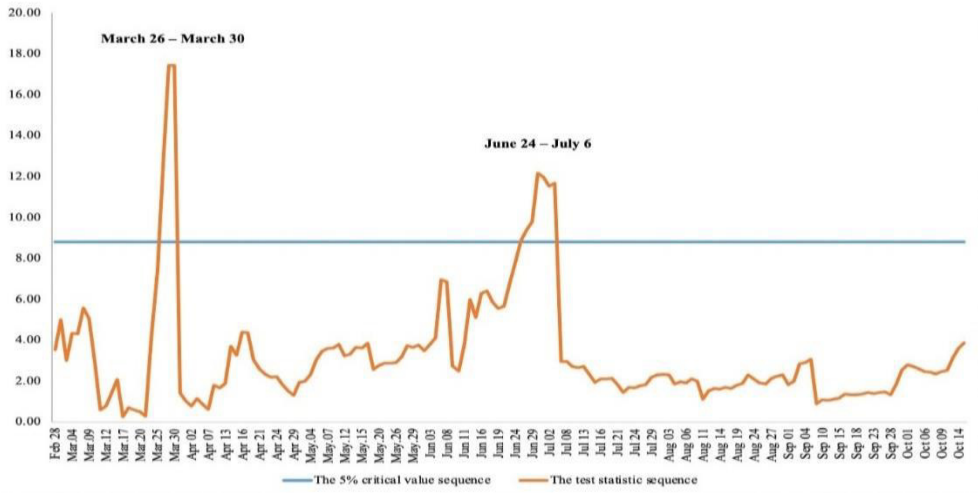


Source: Emirmahmutoglu et al. (2021).

The MWald statistic, $W_{f_1}^{f_2}$, is obtained for each subsample regression with a sample size fraction of $f_w = f_2 - f_1 \geq f_0$. Then, the supremum of the MWald statistic sequence is defined as follows:

$$SW_f(f_0) = \sup_{f_2 = f, f_1 \in [0, f_2 - f_0]} W_{f_1}^{f_2} \tag{5}$$

Figure 2.
Time-varying Granger causality from COVID-19 to stock market volatility (Model 1)



The time-varying causality episodes are estimated by the origination (f_e) and termination (f_f) periods. In a single casual episode, these periods can be determined as follows:

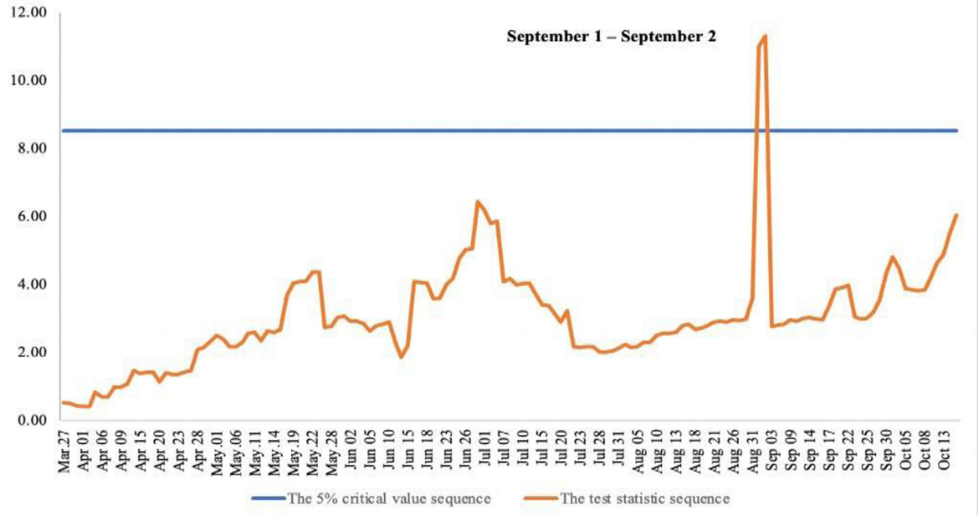
[8] Set $\tau_1 \in [1, \tau_2 - \tau_w + 1]$ and $\tau_2 = [\tau_w, T]$ and moving window size $\tau_w = \tau_2 - \tau_1 \geq \tau_0$.

$$\hat{f}_e = \inf_{f \in [f_0, 1]} \{f : SW_f(f_0) > scv\} \quad (6)$$

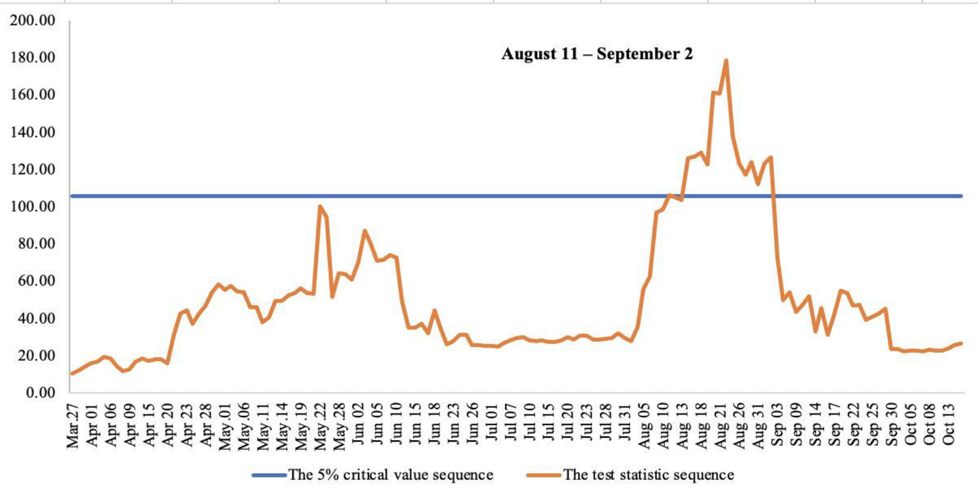
$$\hat{f}_f = \inf_{f \in [\hat{f}_e, 1]} \{f : SW_f(f_0) < scv\} \quad (7)$$

where scv is the corresponding critical value of the SW_f. For multiple episodes, these periods can be obtained by a similar procedure[9]. According to Shi et al. (2020), SW_f statistic follows a nonstandard asymptotic distribution.

Figure 3.
Time-varying Granger causality from COVID-19 news to stock market volatility
Panel A. Causality from positive news to stock market volatility (Model 2)



Panel B. Causality from negative news to stock market volatility (Model 3)



The results obtained from the time-varying causality[10] are illustrated in Figure 2 and Figure 3. Figure 2 displays that the algorithm identifies an episode in the late March around when the

[9] The empirical methodology summarized herein is heavily based on Emirmahmutoglu et al. (2021).
[10] The 5% bootstrapped critical values are obtained with 1000 repetitions and controlled over a five-days period. For the minimum window size, 49 observations are considered for Model 1 while 46 observations are considered for Model 2 and Model 3. Lag orders are assumed to be constant and selected using Bayesian Information Criterion (BIC) with a maximum length of 8 for each model.

outcomes of the quantitative easing policy kicked in following the Federal Reserve's (FED) "whatever it takes" announcement and an episode which lasted for eight business days from June 24 following the update announcement for Secondary Market Corporate Credit Facility to support market liquidity[11].

Figure 3 illustrates the time-varying causality results when the response of the pandemic is proxied by COVID-19 information. The recursive evolving algorithm locates one short episode in the early September, as illustrated in Panel A of Figure 3. On the other hand, the algorithm detects an episode[12] from August 11 to September 2 during when negative COVID-19 news Granger causes volatility, as displayed in Panel B of Figure 3. These findings prove that positive COVID-19 news is not as significant as negative COVID-19 news in predicting the stock market volatility, which is consistent with the findings by Baek et al. (2020).

For comparison purposes, we also employ a conventional Granger causality approach proposed by Toda and Yamamoto (1995). Empirical results presented in Table III reveal that negative COVID-19 news Granger causes volatility whereas neither total coronavirus figures nor positive news Granger causes volatility.

Table III.
Toda-Yamamoto causality results

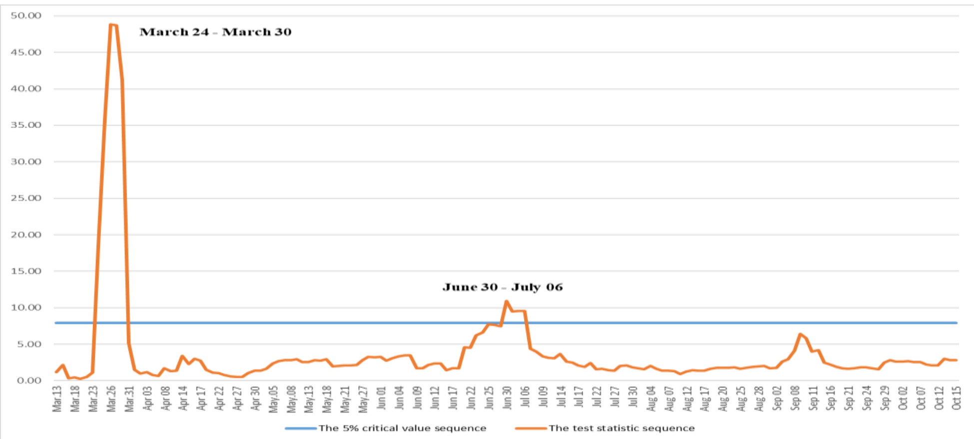
Model	Null Hypothesis	MWALD
Model 1	covid does not cause smv	0.006
Model 2	pnews does not cause smv	2.202
Model 3	nnews does not cause smv	11.741[b]

Note: The order of VAR model is selected by BIC, with a maximum length of 8.
All findings are not reported. They are available upon request.
[b] indicates significance at 5%.

4. Robustness Check

Although a large body of research has employed COVID-related figures in order to examine the impact of the pandemic, another set of covariates such as pressure over the health system, distancing measures, web search for COVID-19 symptoms are also better able to monitor the panic environment caused by the outbreak. For robustness purposes, we control whether our results remain same once COVID-19 is proxied by these variables.

Figure 4.
Time-varying Granger causality from web search for covid symptoms to stock market volatility



[11] Policy announcement schedule can be found from the FED's Press Releases (FED, 2020).
[12] Although the signal turns on and off in the beginning of the identified period.

Figure 4 illustrates the time-varying causality results once COVID-19 is measured using web search for COVID-19 symptoms[13]. The episodes detected in Figure 4 follow roughly the same pattern with those in Figure 2, indicating that the results are robust to COVID-19 proxy[14].

5. Policy Discussions

The time-varying framework in this study detects two episodes when the FED announced stimulus policies to combat COVID-19. The first episode is identified soon after emergency actions to stave off a depression while the second episode is detected following the new step in the efforts to keep credit flowing freely. The timeline of these episodes indicates that policies in response to COVID-19 outweighs the uncertainty caused by COVID-19. This finding reveals that investor expectations are more responsive to monetary policy actions than the ongoing transmission of COVID-19, suggesting an indirect volatility response.

This study also shows that market volatility is sensitive to information type, though negative news is more pronounced. The negativity bias associated with the sparking fear addresses to the importance of policy announcement timing in dealing with the uncertainty environment.

The comparison of the results produced by the conventional approach with those by the time-varying framework provides some prospective technical insights. First, it is worth noting that the response time proposed by a conventional method does not necessarily dominate the whole sample period. This result verifies that the nature of the relationship is not static and the ability of COVID-19 to predict the volatility in the US stock market may vary across episodes. Second, forecasting market volatility without a time-varying framework may lead to mis-estimation of financial risk, which, in turn, decreases the effectiveness of policies designed to deal with the economic and financial aftermath of the pandemic. The ignorance of the time-varying framework may also lead to an inconsistency in financial risk assessment.

6. Conclusion

Uncertainty about COVID-19 has triggered fear sentiment of investors and led to an increase in market volatility. Although previous literature has examined the nexus between COVID-19 and volatility, we still do not know whether the response of stock market volatility to COVID-19 is time-varying. Therefore, the goal of this study is to investigate the causality between COVID-19 and US stock market volatility over the period January 03 – October 15, 2020. Causality results obtained from Toda-Yamamoto procedure does not indicate evidence of Granger causality from COVID-19 to stock market volatility. However, the time-varying framework detects the late March episode as well as the late June-early July episode, both of which coincide soon after the FED's interventions. The timeline of these episodes demonstrates an indirect response of market volatility to the coronavirus outbreak. This finding also confirms the time-varying nature of the relationship. Furthermore, we find that market volatility is sensitive to both positive and negative COVID-19 news, though the response to negative information is relatively longer, suggesting a negativity bias.

Because the regional impact of the pandemic is highly heterogeneous, an attempt with more regional statistics is likely to bring extra prediction ability. Thus, future research could be devoted to regional analysis.

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[13] The data for web search for COVID-19 symptoms were obtained from Google Trends (2021).

[14] Note that web search for COVID-19 symptoms is I(1) and Toda-Yamamoto results indicate no causality from this variable to smv.

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