The relationship between global economic policy uncertainty and happiness sentiment

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Abstract. This study investigates the relationship between the global economic policy uncertainty and the happiness sentiment under impacts of the Covid-19 pandemic. In which, we employ the multivariate generalized autoregressive conditional heteroskedasticity framework to examine return series of proxies derived from social media, from 01 June 2011 to 25 May 2021. We aim to explore how the global uncertainty influences economic policy and happiness in terms of return and volatility transmissions. In addition, we assess the connection between economic uncertainty and happiness sentiment before and during the unprecedented Covid-19 outbreak. We find that the relationship remains negative during the occurring outbreak, compared to the preceding period. In other words, the economic policy uncertainty and the happiness sentiment indexes are negatively correlated, regardless of the unprecedented crisis as caused by the Covid-19 pandemic. The findings suggest that policymakers should enhance the well-being of people and keep the economy under stable conditions, contemporaneously. These policies are significantly tremendous in pursuit of multiple economic and social objectives, especially in the context of the Covid-19 crisis.

Keywords: Economic policy uncertainty, Happiness sentiment, Covid-19.

1 Introduction

The novel coronavirus disease (Covid-19) pandemic has been causing enormous damages to the globe. The Covid-19 outbreak is remarked by unprecedented crises in various aspects such as economies, society, and environment. Consequences of the Covid-19 pandemic are across individuals, organizations, markets, and economies. In which, a typical impact of the pandemic on the global economy is the supply chain disruption, as reflected in demand and supply fluctuations [1]. In connection, literature has provided supportive arguments and empirical evidence on economic impacts of the Covid-19 crisis. Prominent findings comprise of an industry and sector approach [2], and multinational investigations [3]. Moreover, the Covid-19 pandemic is found to be the causation of social impacts in terms of happiness sentiment and human behavior. Indeed, the health and trust of people tend to decrease under impacts of

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the Covid-19 crisis [4]. On the other hand, the pandemic has created negative impacts on emotion [5]. This finding is supported by empirical investigations on the country level, for example, the United States [6], and China [7]. These relevant studies have revealed negative impacts of the Covid-19 pandemic on economies and individual sentiment, respectively. Following this literature, it is questioned to examine such impacts of the Covid-19 outbreak. Thus, we are supposed to investigate the relationship between economic and social consequences of the Covid-19 pandemic, in terms of policy uncertainty and happiness sentiment.

Due to the essence of a leading indicator, stock markets are straightforwardly sensitive to an unprecedented crisis as caused by the Covid-19 pandemic [8]. The outbreak has been creating complicated problems for policymakers. Despite emergent solutions, for example, the quantitative easing policy [9], impacts of the Covid-19 pandemic are considerable. The financial contagion is one of the most extreme consequences of the Covid-19 outbreak [10]. Indeed, this crisis is empirically found to transmit in multiple mechanisms, for example, international markets [11], financial sectors, [12], and developed countries [13]. More comprehensively, the socio-economic impacts of the Covid-19 pandemic has been examined in terms of the interactions between financial economies and happiness sentiment. Prior literature has provided various approaches to explain this relationship, for example, the sharing economy [14], and the mental distress [15]. Relating to the nexus between economic outcome and well-being, a prominent study indicates that the Covid-19 pandemic increases the financial volatility and decreases the happiness sentiment [16]. While the Covid-19 crisis causes unprecedented damages to both economic and social representatives, the negative relation between economic uncertainty and happiness sentiment seems to remain unchanged under impacts of the pandemic. Indeed, this fact is partly illustrated in terms of market uncertainty [17]. Intuitively, we could imagine that individual happiness is negatively correlated to the economic uncertainty regardless of the pandemic. This conjecture matches the equivalent study [18], in which the economic uncertainty is analyzed before and during the Covid-19 outbreak. Henceforth, we expect to clarify the consistent relationship between economic uncertainty and well-being under implications of the Covid-19 pandemic. In specific, we shall explore the interactions between the global economic policy uncertainty and the happiness sentiment to demonstrate our hypothesis. This consideration matches inevitable trends as caused by the Covid-19 pandemic as well as the digital era. In which, both economic uncertainty and happiness sentiment could be evaluated based on social media. Since happiness could be considered an economic terminology [19], this coincident interference lays the background for the info-demic period [20].

The relationships between happiness and economic factors are based on the spiral transmission from physical and mental health to well-being, and from well-being to productivity. In terms of psychology [21], health is found to have positive impacts on well-being. The individual health is significantly found to influence economic outcomes, for example, income enhancement [22], and inequality mitigation [23]. Remarkably, well-being is found to positively influence productivity [24]. This mechanism on the interactions between happiness and economic outcomes is further illustrated in various approaches. In terms of microeconomics, prior literature has found significant impacts of happiness on decision making [25], investment behavior [26], management [27], and pricing [28]. In terms of macroeconomics, happiness is found to be the key driver of consumptions [29], national income [30], and economic growth [31]. In support, the role of happiness in explaining economic behaviors is clarified in finance. This fact is demonstrated under various methodologies, for example, near-term assessments [32], and cross-sectional analysis [33]. Studies on economic impacts of happiness is developed along the innovation of well-being metrics [34]. The digital era facilitates to construct the "wordiness" technique to evaluate the global happiness based on social media platforms [35]. This prominent method is the landmark for studies regarding the relations between happiness and economic financial factors, for example, predictability of international stock markets [36]. The novelty of the "wordiness" method is the timeseries characteristic of the well-being proxy. This generates the explosion of empirical findings on the nexus between happiness sentiment and financial markets. Prior literature has affirmed that happiness significantly mitigates the volatility of stock markets [37]. Evidence is supportively found in various methodologies, for example, causality [38], quartile [39], and skewness [40]. In addition, the negative relationship between happiness and market volatility is found in alternative investments, for example, precious metals [41], crude oil [42], futures [43], and exchange-traded funds [44].

Based on related studies, we find a literature gap that the happiness sentiment has not been examined compared to the uncertainty of economic policies. Recent studies have provided partial evidence in specific markets, for example, G7 countries [45], and China [46]. The challenge is that we are supposed to construct a timeseries proxy for the global economic policy uncertainty. Fortunately, this challenge is solved by the Twitter-derived measure [47]. Accordingly, we could assess the relationship between happiness sentiment and economic policy uncertainty. Coincidently, the well-being proxy, namely Twitter's daily happiness sentiment index, is constructed based on behavior via the social media. The Twitter-based economic policy index is alternatively applied in terms of conversational uncertainty [48]. Henceforth, we shall contemporaneously investigate the relationship between these proxies under impacts of the Covid-19 pandemic. This approach suggests a specific perspective relating to enormous impacts of the Covid-19 crisis in the digital era compared to relevant literature, for example, the global industry analysis based on Google Trends search [49]. Furthermore, this study is expected to provide consistent and supportive findings compared to related literature, for example, the relationship between global wealth and happiness [50]. In which, the contemporaneous approach reveals that wealth positively influences happiness and happiness significantly mitigate the wealth volatility.

Following this introduction, Section 2 presents our modeling strategy, Section 3 preliminarily analyzes the dataset, Section 4 discusses on results, and Section 5 concludes.

2 Empirical methods

We employ the multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) framework to assess the interactions between economic uncertainty and happiness sentiment indexes. This approach matches the timeseries characteristic of proxies, which are constructed based on the social media. Considering the feasibility and flexibility of MGARCH modeling [51], we select the conditional correlation and simultaneous mechanisms. In specific, our estimations comprise of the vector autoregressive moving average (VARMA)-GARCH [52], the constant conditional correlation (CCC)-GARCH [53], the dynamic conditional correlation (DCC)-GARCH [54], and the diagonal BEKK-GARCH [55] models. These estimations shall provide results based on alternative perspectives and ensure the robustness check. In addition, our preliminary analysis on the dataset supports the efficiency of above-mentioned models as well as reveals insignificant evidence on the asymmetric effect, in terms of dynamic conditional correlation [56], and vector of simultaneous co-movements [57].

Under the MGARCH framework, we firstly estimate the s-lagged vector autoregressive (VAR) mean equation:

$$\begin{cases} r_t = \mu + \sum_{j=1}^{s} \Phi_j r_{t-j} + \epsilon_t \\ \epsilon_t = H_t^{1/2} \eta_t \\ H_t = \begin{bmatrix} h_t^u & h_t^{us} \\ h_t^{us} & h_t^s \end{bmatrix} \end{cases} \quad (1)$$

In (1), $r_t = [r_t^u \quad r_t^s]'$ is the vector of economic uncertainty and happiness sentiment return series at time t; μ is a vector of intercepts; Φ is a matrix of coefficients; ϵ_t is the error vector; H_t is the conditional covariance matrix, whose Cholesky factor is $H_t^{1/2}$; and η_t is the vector of independently and identically distributed errors. In terms of Covid-19 impact assessments, we shall respectively apply the methodology before (from 01 June 2011 to 31 December 2019) and during (from 01 January 2020 to 25 May 2021) the pandemic. Information criteria suggest that we select 6 lags in both examined periods. Following, we present the estimation of the conditional covariance matrix based on employed models.

The VARMA-GARCH model estimates the conditional variance matrix:

$$h_t = C + A\epsilon_{t-1}^2 + Bh_{t-1} \quad (2)$$

In (2), $h_t = [h_t^u \quad h_t^s]'$; C is a vector of intercepts; and A and B are coefficient matrices. Elements of H_t are therefore determined as follow:

$$\begin{cases} h_t^u = c_u + a_{11}(\epsilon_{t-1}^u)^2 + a_{12}(\epsilon_{t-1}^s)^2 + b_{11}h_{t-1}^u + b_{12}h_{t-1}^s \\ h_t^s = c_s + a_{21}(\epsilon_{t-1}^u)^2 + a_{22}(\epsilon_{t-1}^s)^2 + b_{21}h_{t-1}^u + b_{22}h_{t-1}^s \\ h_t^{us} = \rho\sqrt{h_t^u h_t^s} \end{cases} \quad (3)$$

The estimation in (3) contains specific terms of a GARCH process, those are, short-term volatility (through ϵ_{t-1}^2) and long-term volatility (through h_{t-1}). Moreover, the VARMA-GARCH model captures the return and volatility spillover effects due to full side of estimated matrices A and B. This characteristic creates the superiority of the VARMA-GARCH model in exploring past shock transmissions between return series. Besides, this estimation includes the constant conditional correlation ρ between past volatilities. This is a technical specification compared to alternative MGARCH mechanisms.

The CCC-GARCH model is a special case of the VARMA-GARCH model, in which matrices A and B are imposed to be diagonal. The conditional covariance matrix is therefore estimated:

$$\begin{cases} h_t^u = c_u + a_{11}(\epsilon_{t-1}^u)^2 + b_{11}h_{t-1}^u \\ h_t^s = c_s + a_{22}(\epsilon_{t-1}^s)^2 + b_{22}h_{t-1}^s \\ h_t^{us} = \rho\sqrt{h_t^u h_t^s} \end{cases} \quad (4)$$

To ensure the stationarity of estimators, the VARMA-GARCH and the CCC-GARCH models via (4) require finding eigenvalues λ of matrix $(A + B)$ inside the unit circle.

Approaching alternatively, the DCC-GARCH model assumes that the conditional correlation ρ is dynamic and decomposes the conditional correlation matrix:

$$H_t = D_t P_t D_t = \begin{bmatrix} \sqrt{h_t^u} & 0 \\ 0 & \sqrt{h_t^s} \end{bmatrix} \begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_t^u} & 0 \\ 0 & \sqrt{h_t^s} \end{bmatrix} \quad (5)$$

In details, the dynamic conditional correlation in (5) is estimated as:

$$\begin{cases} P_t = (Q_t^*)^{-1/2} Q_t (Q_t^*)^{-1/2} \\ Q_t = \begin{bmatrix} q_t^u & q_t^{us} \\ q_t^{us} & q_t^s \end{bmatrix} = (1 - \alpha - \beta)\bar{Q} + \alpha\eta_{t-1}\eta'_{t-1} + \beta Q_{t-1} \\ Q_t \succ 0 \quad Q_t^* = diag(Q_t) \quad \bar{Q} = E(\eta_t\eta'_t) \end{cases} \quad (6)$$

In (6), Q_t is a symmetric positive definite matrix; α and β are non-negative scalars such that $\alpha + \beta < 1$; and $\bar{Q}$ is the matrix of unconditional correlations between standardized errors η_t.

On the other hand, the diagonal BEKK-GARCH model suggests a contemporaneous estimation for the conditional covariance matrix:

$$H_t = C'C + A'\epsilon_{t-1}\epsilon'_{t-1}A + B'H_{t-1}B \quad (7)$$

In (7), C is an upper-triangular matrix of intercepts; and A and B are diagonal matrices of parameters. Under this process, the conditional covariance matrix is simultaneously estimated:

$$\begin{cases} h_t^u = c_u + a_u^2(\epsilon_{t-1}^u)^2 + b_u^2 h_{t-1}^u \\ h_t^{us} = c_{us} + a_u a_s \epsilon_{t-1}^u \epsilon_{t-1}^s + b_u b_s h_{t-1}^{us} \\ h_t^s = c_s + a_s^2(\epsilon_{t-1}^s)^2 + b_s^2 h_{t-1}^s \end{cases} \quad (8)$$

Accordingly, the diagonal BEKK-GARCH model contains imposed restrictions compared to the conditional correlation mechanism. Relating to stationary conditions, the diagonal BEKK-GARCH requires that $d_u = a_u^2 + b_u^2 < 1$, $d_{us} = |a_u a_s + b_u b_s| < 1$, and $d_s = a_s^2 + b_s^2 < 1$.

Regarding empirical findings, the MGARCH methodology is found to be efficient in terms of investigating the nexus between timeseries proxies. The efficiency of conditional correlation and simultaneous MGARCH models has been demonstrated in various research fields, for example, commodity markets [58], stock-gold nexus [59], stock-bond co-movements [60], macro news [61], air quality [62], and metaphysical finance [50]. Therefore, the MGARCH approach is expected to provide significant evidence on the persistent relationship between the global economic policy uncertainty and the happiness sentiment under impacts of the Covid-19 pandemic.

3 Data and preliminary analyses

We employ the dataset of the global economic policy uncertainty index[1] [47] and the Twitter's daily happiness sentiment index[2] from 01 June 2011 to 25 May 2021 to investigate the hypothesis of this study. The intimate relationship between these proxies is that they are constructed based on the social media platform. To clarify impacts of the Covid-19 pandemic to the relationship between economic uncertainty and happiness sentiment, we respectively consider this nexus before the crisis (from 01 June 2011 to 31 December 2019) and during the crisis (from 01 January 2020 to 25 May 2021). Fig. 1 and Fig. 2 illustrate the index series during the studied period. Both series tend to harmonize in the long term. In which, the economic policy uncertainty index has a higher range of volatility compared to the happiness sentiment index. The economic uncertainty index hits its peak in the beginning of the Covid-19 period. These patterns reflect the fact that the economic uncertainty depends on various factors, while the happiness index mostly relates to the human behavior and sentiment.

Table 1 presents descriptive statistics and stochastic properties of daily returns of the index series. In terms of mean, a preliminary analysis reveals that the global economic policy becomes more uncertain, and the happiness sentiment decreases under implications of the Covid-19 outbreak. This performance is supportively affirmed to be robust in terms of standard deviation. Besides, the skewness of both series transforms from positive before the Covid-19 event to negative during the crisis. Interestingly, both index series turn from platykurtic to leptokurtic under impacts of the Covid-19 pandemic. These significant statistics confirm that our data splitting is reasonable. Stochastic properties indicate that return series are normally distributed, autocorrelated, heteroskedastic, and stationary. Accordingly, it is implied that the MGRACH approach is suitable for proxies with such timeseries characteristics. Significant stochastic properties are prerequisites for further investigation in terms past shock and volatility transmissions between return series.

[1] Retrieved from https://www.policyuncertainty.com/.
[2] Retrieved from https://www.hedonometer.org/timeseries/en_all/.

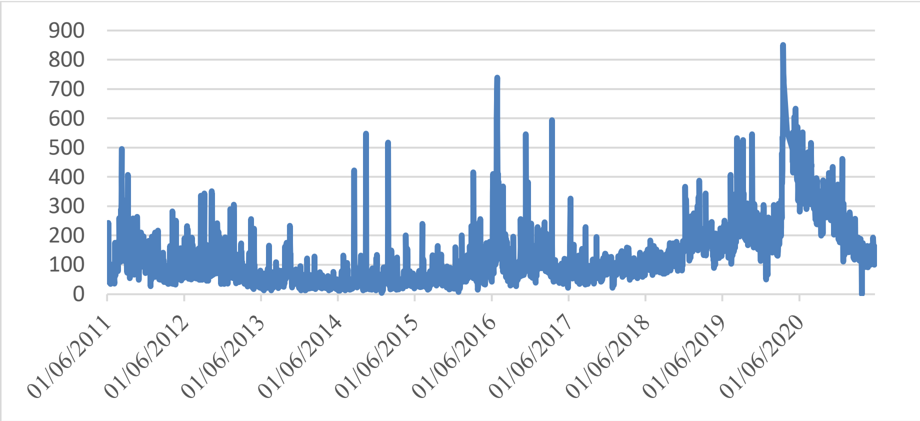

Fig. 1. The global economic policy uncertainty index (GEPU)

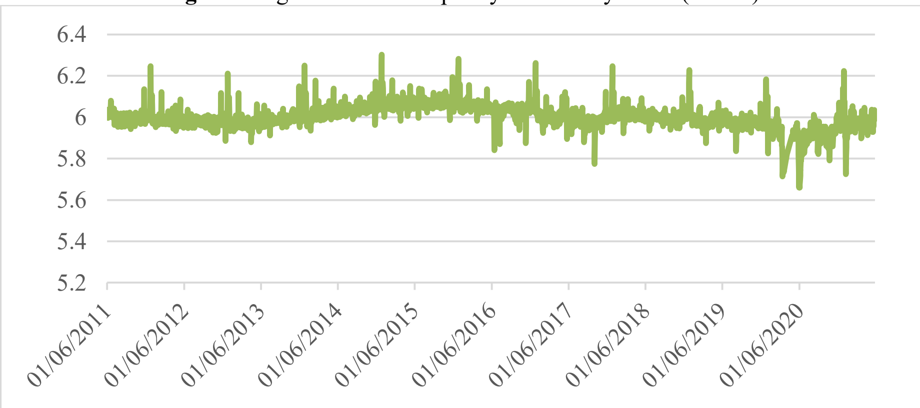

Fig. 2. The Twitter's daily happiness sentiment index (DHS)

Table 1. Summary statistics for returns of GEPU and DHS

	GEPU 2011-2019	**GEPU** 2020-2021	**DHS** 2011-2019	**DHS** 2020-2021
Observation	3113	464	3113	464
Mean	-0.06%	0.04%	0.00%	-0.01%
Std deviation	0.4716	0.2217	0.0048	0.0069
Skewness	0.4133***	0.2772**	-0.8030***	-0.3476***
Kurtosis	1.8195***	1.5528***	9.9489***	11.2698***
Jarque-Bera	518.03***	52.5591***	13173.17***	2464.85***
Ljung-Box	471.08***	120.87***	614.15***	60.4136***
McLeod-Li	405.92***	57.0141***	396.91***	162.77**
ARCH	269.71***	44.5770***	374.48***	149.48***
Dickey-Fuller	-81.2537***	-32.5131***	-60.9139***	-27.7736***
Phillips-Perron	-100.57***	-37.7454***	-67.9867***	-29.8267***

Notes: *, **, and *** indicate statistical significance of 10%, 5%, and 1%, respectively. Descriptive statistics include number of observations, mean, standard deviation, skewness, and kurtosis. Stochastic properties include normality with the Jarque-Bera test, the autocorrelation effect with 15-lagged Ljung-Box and McLeod-Li tests, heteroskedasticity with a 15-lagged ARCH test, and stationary conditions with Dickey-Fuller and Phillips-Perron unit root tests.

4 Findings

Table 2 and Table 3 present our results on the relationship between return series of the economic policy uncertainty and the happiness sentiment indexes under the MGARCH modeling. The estimations include VARMA-GARCH, CCC-GARCH, DCC-GARCH, and diagonal BEKK-GARCH models for separate period, that is, before and during the Covid-19 pandemic. In each model, the estimation captures the VAR mean equation and the conditional covariance matrix. On the other hand, each estimation is considered based on model selection information and diagnostic tests.

Before the Covid-19 pandemic, the DCC-GARCH model provides the best-suited estimation, in terms of log likelihood and information criteria. In the vector autoregressive mean equation, all models provide statistically significant evidence that past returns of economic policy and happiness sentiment negatively affects to each other. These estimations indicate the negative relationship between return series and therefore matches our conjecture. In common sense, it is popularly perceived that stable economic conditions positively influence happiness as well as the well-being facilitates to mitigate the uncertainty. Our finding based on the MGARCH approach is consistent to prior literature on the relationship between economic uncertainty and happiness sentiment, for example, the role of happiness in financial markets [36], and the relationship between wealth and happiness [50]. The results are strongly supported by lagged terms of return series. This implies that economic uncertainty and happiness sentiment are interchangeably accumulated. In addition, the conditional covariance matrix estimations reveal further information on the nexus between return series. Accordingly, the MGARCH process provides detailed explanation on the interactions between return series. Indeed, selected models demonstrate the past shock and volatility transmission effect between economic uncertainty and happiness sentiment indexes, in which significant estimations are found in both short-term and long-term coefficients. Interestingly, each model provides a significant perspective based on their own mechanisms, those are, the constant conditional correlation of VARMA-GARCH and CCC-GARCH models, the dynamic terms under the DCC-GARCH model, and the simultaneous estimation under the diagonal BEKK-GARCH model. The appropriateness of the MGARCH modeling is supportively confirmed by diagnostic tests, in which residuals are checked with normally distributed, autocorrelated, heteroskedastic, and stationary properties. Thus, we find that economic policy uncertainty and happiness sentiment are negatively correlated under stable conditions, as determined from 01 June 2011 to 31 December 2019.

During the occurring Covid-19 outbreak, the VARMA-GARCH model gains advantage compared to others, in terms of log likelihood and information criteria. We find significant evidence that the negative relationship between economic uncertainty and happiness remain unchanged under impacts of the Covid-19, in terms of mean equation. This finding matches our hypothesis that uncertainty and well-being are negatively correlated regardless of the crisis. The nexus is further supported by various specifications, those are, lag coefficients, conditional correlations under alternative perspectives, and stochastic properties of residual series. An interesting point is that the VARMA-GARCH model captures the return and volatility spillovers between economic uncertainty and happiness sentiment indexes. This finding is supportive evidence compared to the economic uncertainty assessments before and during the Covid-19 pandemic [18]. Henceforth, the relationship between economic uncertainty and happiness sentiment remains negative during the Covid-19 period, as determined from 01 January 2020 to 25 May 2021. In other words, this relationship is consistent under impacts of the unprecedented crisis caused by the Covid-19 pandemic. Our findings imply that there is still anticipation during unprecedented events. The important thing is that we are supposed to prepare feasible policies in case of difficult periods, for example, the Covid-19 crisis. These empirical findings reflect the VUCA context, which includes volatility, uncertainty, complexity, and ambiguity following the pandemic.

Table 2. Empirical results under constant conditional correlation MGARCH models

	VARMA-GARCH		**CCC-GARCH**	
	2011-2019	2020-2021	2011-2019	2020-2021
r_t^u				
μ^u	0.0096	0.0048***	0.0030	-0.0030
	(0.0071)	(0.0003)	(0.0068)	(0.0083)
r_{t-1}^u	-0.5971***	-0.5266***	-0.5997***	-0.5848**
	(0.0143)	(0.0153)	(0.0144)	(0.0483)
r_{t-1}^s	-6.5898***	-1.4272	-5.6188***	-0.2961
	(1.4599)	(1.2652)	(1.4795)	(1.3691)
r_{t-2}^u	-0.4919***	-0.4089***	-0.4979***	-0.4198**
	(0.0145)	(0.0034)	(0.0147)	(0.0525)
r_{t-2}^s	0.8859	-0.9102	0.1097	0.2329
	(1.4952)	(1.1515)	(1.5377)	(1.4565)
r_{t-3}^u	-0.3564***	-0.3382***	-0.3760***	-0.3252**
	(0.0140)	(0.0314)	(0.0146)	(0.0564)
r_{t-3}^s	2.3264	-3.1994***	0.1049	-2.1037
	(1.6176)	(1.1730)	(1.4714)	(1.4483)
r_{t-4}^u	-0.2719***	-0.1864***	-0.2885***	-0.2102**
	(0.0144)	(0.0383)	(0.0151)	(0.0569)
r_{t-4}^s	2.0371	-2.8425**	1.0639	-1.7815
	(1.5313)	(1.2182)	(1.2866)	(1.4863)
r_{t-5}^u	-0.2108***	-0.2236***	-0.2271***	-0.2688**
	(0.0138)	(0.0345)	(0.0143)	(0.0525)
r_{t-5}^s	3.8419***	-3.4100***	1.5460	-2.0266
	(1.3402)	(1.1130)	(1.2944)	(1.3982)
r_{t-6}^u	-0.1309***	-0.1785***	-0.1287***	-0.1975**
	(0.0137)	(0.0022)	(0.0139)	(0.0446)
r_{t-6}^s	5.3426***	-1.1641	3.6873**	-1.0183
	(1.4667)	(1.2129)	(1.5716)	(1.3172)
r_t^s				
μ^s	-0.0001	0.0003	-0.0001*	0.0002

	VARMA-GARCH		CCC-GARCH	
	2011-2019	2020-2021	2011-2019	2020-2021
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
r^u_{t-1}	-0.0002	0.0009	-0.0002*	0.0001
	(0.0001)	(0.0013)	(0.0001)	(0.0013)
r^s_{t-1}	-0.3194***	-0.2553***	-0.3191***	-0.2627**
	(0.0163)	(0.0459)	(0.0233)	(0.0486)
r^u_{t-2}	-0.0002*	-0.0020	-0.0003**	-0.0029*
	(0.0001)	(0.0014)	(0.0001)	(0.0015)
r^s_{t-2}	-0.4293***	-0.3110***	-0.4085***	-0.3158**
	(0.0166)	(0.0516)	(0.0170)	(0.0527)
r^u_{t-3}	-0.0003*	-0.0053***	-0.0001	-0.0065**
	(0.0001)	(0.0013)	(0.0001)	(0.0015)
r^s_{t-3}	-0.3882***	-0.1198***	-0.3907***	-0.1265**
	(0.0181)	(0.0420)	(0.0177)	(0.0509)
r^u_{t-4}	-0.0001	-0.0041***	-0.0001	-0.0055**
	(0.0001)	(0.0012)	(0.0001)	(0.0014)
r^s_{t-4}	-0.3574***	-0.0935***	-0.3673***	-0.0951**
	(0.0168)	(0.0353)	(0.0165)	(0.0446)
r^u_{t-5}	0.0001	-0.0002	0.0002*	-0.0014
	(0.0001)	(0.0014)	(0.0001)	(0.0014)
r^s_{t-5}	-0.3339***	0.0205	-0.3541***	-0.0052
	(0.0153)	(0.0303)	(0.0166)	(0.0435)
r^u_{t-6}	-0.0001	-0.0002	0.0000	-0.0015
	(0.0002)	(0.0012)	(0.0001)	(0.0013)
r^s_{t-6}	-0.1460***	0.0000	-0.1680***	-0.0133
	(0.0138)	(0.0371)	(0.0167)	(0.0400)
H_t				
c_u	0.0539***	0.0205***	0.0001	0.0021
	(0.0025)	(0.0009)	(0.0001)	(0.0015)
c_s	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
a_{11}	0.2374***	-0.0620***	0.0130***	0.0434*
	(0.0131)	(0.0012)	(0.0001)	(0.0224)
a_{12}	407.40***	56.9281***		
	(47.0986)	(6.8312)		
a_{21}	0.0000**	0.0001***		
	(0.0000)	(0.0000)		
a_{22}	0.6410***	0.1755***	0.7300***	0.3085***
	(0.0508)	(0.0410)	(0.0556)	(0.0630)
b_{11}	0.4335***	0.3309***	0.9864***	0.8929***
	(0.0096)	(0.0288)	(0.0006)	(0.0595)
b_{12}	-269.00***	57.6807***		
	(76.5678)	(1.7584)		
b_{21}	0.0000***	-0.0003***		
	(0.0000)	(0.0000)		

	VARMA-GARCH		CCC-GARCH	
	2011-2019	2020-2021	2011-2019	2020-2021
b_{22}	0.1762***	0.6929***	-0.0010	0.5498***
	(0.0312)	(0.0248)	(0.0069)	(0.0594)
ρ	-0.1297***	-0.0852*	-0.1254***	-0.0878*
	(0.0156)	(0.0473)	(0.0162)	(0.0477)
Information				
Observation	3107	458	3107	458
LOGL	11585.55	1906.79	11745.31	1896.52
AIC	-7.4340	-8.1650	-7.5390	-8.1380
SBC	-7.3620	-7.8320	-7.4750	-7.8400
HQ	-7.4080	-8.0340	-7.5160	-8.0210
LFPE	-7.4340	-8.1650	-7.5390	-8.1370
Tests				
Jarque-Bera	1600.66***	15.60***	680.30***	15.26***
	11850***	46.67***	9902.37***	105.19***
Ljung-Box	54.6681***	18.1673	52.5126***	19.3136
	70.3222***	17.0558	68.9811***	17.8471
McLeod-Li	41.3069***	16.9551	17.6962	14.5988
	17.7628	19.4929	15.9726	25.3055**
ARCH	42.4090***	14.1190	17.3070	14.5180
	17.0200	18.4430	15.1130	22.3200*
λ_1	-0.6709	-0.3099	-0.7290	-0.8583
λ_2	-0.8172	-0.8274	-0.9994	-0.9363

Notes: Standard errors are in parentheses. *, **, and *** indicate statistical significance of 10%, 5%, and 1%, respectively. LOGL = Log likelihood. Information criteria include Akaike (AIC), Schwarz-Bayes (SBC), Hannan-Quinn (HQ), and logarithm of the final prediction error (LFPE). The Jarque-Bera test is for normality of residuals. The autocorrelation effect is checked with 15-lagged Ljung-Box and McLeod-Li tests. The heteroskedasticity effect is checked with a 15-lagged ARCH test.

Table 3. Empirical results under competing MGARCH models

	DCC-GARCH		DBEKK-GARCH	
	2011-2019	2020-2021	2011-2019	2020-2021
r_t^u				
μ^u	0.0029	-0.0035	0.0021	-0.0025
	(0.0065)	(0.0079)	(0.0071)	(0.0082)
r_{t-1}^u	-0.6006***	-0.5914**	-0.6025***	-0.5847**
	(0.0172)	(0.0465)	(0.0169)	(0.0451)
r_{t-1}^s	-5.5272***	-0.5999	-5.7085***	-0.4449
	(1.4482)	(1.2652)	(1.4402)	(1.1157)
r_{t-2}^u	-0.4983***	-0.4132**	-0.5014***	-0.4152**
	(0.0204)	(0.0504)	(0.0199)	(0.0502)
r_{t-2}^s	0.1083	0.2375	0.1000	-0.0875
	(1.4993)	(1.3256)	(1.4841)	(1.2466)
r_{t-3}^u	-0.3788***	-0.3457**	-0.3828***	-0.3337**
	(0.0215)	(0.0551)	(0.0208)	(0.0495)

	DCC-GARCH		DBEKK-GARCH	
	2011-2019	2020-2021	2011-2019	2020-2021
r_{t-3}^s	0.0211	-2.1023	-0.0855	-2.5505**
	(1.6422)	(1.3802)	(1.5186)	(1.2672)
r_{t-4}^u	-0.2903***	-0.2268**	-0.2956***	-0.2123**
	(0.0214)	(0.0540)	(0.0205)	(0.0510)
r_{t-4}^s	1.1630	-1.7838	0.9313	-2.0053
	(1.6265)	(1.4032)	(1.5407)	(1.3404)
r_{t-5}^u	-0.2278***	-0.2647**	-0.2298***	-0.2703**
	(0.0204)	(0.0484)	(0.0188)	(0.0463)
r_{t-5}^s	1.3653	-2.0354	1.3601	-2.1734
	(1.5006)	(1.2996)	(1.4757)	(1.3739)
r_{t-6}^u	-0.1298***	-0.2041**	-0.1309***	-0.2043**
	(0.0176)	(0.0418)	(0.0161)	(0.0421)
r_{t-6}^s	3.7684**	-1.4419	3.7638**	-1.3656
	(1.5441)	(1.1976)	(1.5137)	(1.2637)
r_t^s				
μ^s	-0.0001*	0.0002	-0.0001*	0.0003
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
r_{t-1}^u	-0.0002*	-0.0003	-0.0002	0.0001
	(0.0001)	(0.0014)	(0.0001)	(0.0013)
r_{t-1}^s	-0.3211***	-0.2715**	-0.3186***	-0.2871**
	(0.0229)	(0.0544)	(0.0223)	(0.0553)
r_{t-2}^u	-0.0003*	-0.0037**	-0.0002	-0.0030**
	(0.0001)	(0.0015)	(0.0002)	(0.0015)
r_{t-2}^s	-0.4076***	-0.3080**	-0.4103***	-0.3197**
	(0.0157)	(0.0519)	(0.0167)	(0.0530)
r_{t-3}^u	-0.0001	-0.0066**	-0.0001	-0.0063**
	(0.0002)	(0.0014)	(0.0002)	(0.0015)
r_{t-3}^s	-0.3891***	-0.1153**	-0.3924***	-0.1335**
	(0.0170)	(0.0542)	(0.0172)	(0.0524)
r_{t-4}^u	-0.0001	-0.0055**	-0.0001	-0.0054**
	(0.0002)	(0.0014)	(0.0002)	(0.0014)
r_{t-4}^s	-0.3657***	-0.1082**	-0.3680***	-0.1112**
	(0.0161)	(0.0464)	(0.0160)	(0.0454)
r_{t-5}^u	0.0002	-0.0012	0.0002	-0.0014
	(0.0001)	(0.0014)	(0.0001)	(0.0015)
r_{t-5}^s	-0.3534***	0.0037	-0.3558***	-0.0040
	(0.0173)	(0.0404)	(0.0173)	(0.0410)
r_{t-6}^u	0.0000	-0.0014	0.0000	-0.0014
	(0.0001)	(0.0013)	(0.0001)	(0.0013)
r_{t-6}^s	-0.1653***	-0.0186	-0.1684***	-0.0284
	(0.0161)	(0.0412)	(0.0159)	(0.0446)
H_t				
c_u	0.0001	0.0023	0.0128***	0.0468**
	(0.0001)	(0.0017)	(0.0029)	(0.0194)

	DCC-GARCH		DBEKK-GARCH	
	2011-2019	2020-2021	2011-2019	2020-2021
c_{us}			-0.0028***	-0.0003
			(0.0001)	(0.0002)
c_s	0.0000***	0.0000***	0.0000	0.0024***
	(0.0000)	(0.0000)	(0.0011)	(0.0003)
a_{11}	0.0131***	0.0458*	0.1167***	0.1755***
	(0.0024)	(0.0242)	(0.0096)	(0.0529)
a_{22}	0.7287***	0.3116***	0.8488***	0.5632***
	(0.0557)	(0.0615)	(0.0311)	(0.0626)
b_{11}	0.9864***	0.8851***	0.9925***	0.9499***
	(0.0024)	(0.0646)	(0.0012)	(0.0345)
b_{22}	-0.0011	0.5493***	0.0583	0.7319***
	(0.0077)	(0.0563)	(0.0576)	(0.0488)
α	0.0218	0.1566**		
	(0.0139)	(0.0734)		
β	0.8113***	0.2949*		
	(0.1085)	(0.1517)		
Information				
Observation	3107	458	3107	458
LOGL	11747.09	1898.63	11729.89	1895.58
AIC	-7.5400	-8.1430	-7.5290	-8.1340
SBC	-7.4740	-7.8360	-7.4650	-7.8360
HQ	-7.5160	-8.0220	-7.5060	-8.0160
LFPE	-7.5400	-8.1420	-7.5290	-8.1330
Tests				
Jarque-Bera	680.74***	16.44***	687.20***	16.05***
	9657.64***	115.04***	9938.88***	115.19***
Ljung-Box	52.8028***	19.5657	53.6484***	19.1463
	69.3660***	16.6997	69.6908***	18.4435
McLeod-Li	17.6716	14.3899	17.5079	16.1644
	16.2348	26.1232**	16.0871	27.8182**
ARCH	17.2790	14.4740	17.0740	15.9310
	15.3500	23.3350*	15.2260	24.4060*
$\alpha+\beta$	0.8331	0.4515		
d_u			0.9987	0.9331
d_{us}			0.1569	0.7941
d_s			0.7239	0.8529

Notes: Standard errors are in parentheses. *, **, and *** indicate statistical significance of 10%, 5%, and 1%, respectively. LOGL = Log likelihood. Information criteria include Akaike (AIC), Schwarz-Bayes (SBC), Hannan-Quinn (HQ), and logarithm of the final prediction error (LFPE). The Jarque-Bera test is for normality of residuals. The autocorrelation effect is checked with 15-lagged Ljung-Box and McLeod-Li tests. The heteroskedasticity effect is checked with a 15-lagged ARCH test.

5 Conclusion

We have investigated the relationship between economic policy uncertainty and happiness sentiment before and during the occurring Covid-19 crisis and find that it remains negative under impacts of the pandemic. In support, our MGARCH methodology clarifies that the vector autoregressive moving average explains provides the best-suited explanations during the crisis compared to the dynamic conditional correlation before the crisis. The persistent relationship between economic uncertainty and happiness sentiment is further investigated in terms various coefficients, those are, lagged returns, past shock and volatility transmissions, and stochastic residuals. As an unprecedented event, the Covid-19 pandemic has been causing extreme social and economic consequences. However, there is still a consistence under impacts of the Covid-19 crisis. In which, one of anticipated things is the nexus between the global economic policy uncertainty and the happiness sentiment.

This study has investigated interactions between economic uncertainty and happiness on the global scale based on technical instruments derived from the social media platform. The findings imply that policymakers shall enhance the well-being of people and mitigate the economic uncertainty, regardless of the Covid-19 crisis. The consonance of related social and economic policies is the tremendous means in pursuit of multiple objectives, especially in the context of the Covid-19 outbreak. In connection, future studies on this topic are recommended to approach on the country level. This perspective is expected to suggest specific policy implications depending on economic, social, and geopolitical conditions of each country.

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