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Understanding stock market volatility: What is the role of U.S. uncertainty?

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ABSTRACT

This study investigates the spillover of U.S. economic uncertainty on the stock market volatility of six industrialized and three emerging-market countries, using a bivariate GARCH-MIDAS model. We consider three different U.S. uncertainty indices: economic policy uncertainty (EPU), financial uncertainty (FU), and news implied uncertainty (NVIX). Our results indicate that EPU is positively associated with the industrialized countries' stock market volatility; FU does not appropriately predict long-term stock market volatility; and NVIX is the more powerful predictor of market volatility, with higher NVIX leading to lower volatility. Our study highlights a new channel of market contagion and furthers our understanding of the sources of stock market volatility.

1. Introduction

Global financial market integration has received extensive attention among academics and practitioners alike (Barberis, Shleifer, & Wurgler, 2005; Bekaert and Harvey, 1995; Carrieri, Errunza, & Hogan, 2007). One of the interesting questions in the field concerns financial market contagion, which is often defined as a higher correlation of market returns or volatility across markets (Forbes & Rigobon, 2002). There is a wide variety of empirical studies that investigate this topic. Hamao, Masulis, and Ng (1990) examine the interdependence of prices and volatility across the Tokyo, London, and New York stock markets and find a volatility spillover across these markets. Solnik, Bourcrelle, and Le Fur (1996), Longin and Solnik (2001) show that international equity market correlation is usually larger in periods of bad market conditions or high volatility. Bekaert and Harvey (2003) employ a two-factor model to investigate contagion among different regions. As the U.S. has the world's largest equity market, many studies focus on the spillover from the U.S. stock market. Ashanapalli and Doukas (1993) indicate that the U.S. stock market has considerable impact on the French, German, and UK markets, showing the exact direction of the spillover. Rapach, Strauss, and Zhou (2013) find that lagged U.S. returns significantly predict market returns in non-U.S. industrialized countries. Boubaker, Jouini, and Lahiani (2016) investigate the market contagion from the U.S. on select developed and emerging market during the global financial crisis.

This study highlights a new channel of financial market contagion and a new source of stock market volatility: *uncertainty*. As we know, uncertainty is now an important factor in financial asset pricing and, as such, it influences investors' consumption and portfolio decisions, which can lead to changes in asset prices (Drechsler, 2013). King and Wadhwani (1990) indicate that contagion occurs

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when rational agents attempt to infer information from other markets. The literature describes the theory of market contagion. As the U.S. has the world's largest equity market, initial tremors in the U.S. economy and financial markets are not confined to the U.S. alone, but spread to other countries, indicating that foreign agents definitely focus on the U.S. economy and financial market conditions. The recent financial crisis in 2008 has already revealed that US stock market crash can transmit to other countries with surprising speed, and eventually evolves into a global crisis. As a source of such important market information, any economic uncertainty in the U.S. is immediately detected by foreign investors and can lead to changes in asset prices and volatility, thereby making it a channel of market contagion. Hence, it is plausible that the uncertainty of US stock market should play a critical role in international equity markets.

There are many measures of uncertainty, including economic policy uncertainty (EPU, Baker, Bloom, & Davis, 2016), financial and macro uncertainty (FU and MU, Jurado, Ludvigson, & Ng, 2015; Ludvigson, Ma, & Ng, 2018), the macroeconomic uncertainty index (MUI, Bali, Brown, & Caglayan, 2014; Asgharian, Christiansen, & Hou, 2015), news-based implied volatility (NVIX, Monela & Moreira, 2017), and global uncertainty (GU, Ozturk & Sheng, 2017). Moreover, a rich amount of empirical studies use these measures of uncertainty to examine the relationships between uncertainty and asset returns or volatility (e.g., Asgharian et al., 2015; Bams, Blanchard, Honarvar, & Lehnert, 2017; Bekiros, Gupta, & Kyer, 2016; Conrad and Loch, 2015; Su, Fang, & Yin, 2017; Yao and Sun, 2018). The empirical results of these studies are similar and straightforward and uncertainty is usually positively associated with asset volatility.

Our contribution to the literature on financial market contagion and asset pricing is threefold. First, we provide empirical evidence of U.S. uncertainty spillover on other stock markets to see if uncertainty is a new channel of market contagion. Although Klößner and Sekkel (2014) and Yin and Han (2014) confirm the spillover of EPU from the U.S. on other countries, they do not consider the impact of the spillover on financial markets and their research is limited to EPU. Furthermore, previous research usually focuses on the relationships between uncertainty and stock market volatility within a country and the international evidence of the spillover of uncertainty is quite limited. The exception is Colombo (2013), who quantified the spillover from the U.S. on Euro-area economies. Inspired by these previous studies, we look to fill the gaps in the literature by investigating the role of U.S. uncertainty in determining stock market volatility of selected developed and emerging countries to test if the U.S. affects non-U.S. financial markets through uncertainty. We select nine countries, which include six industrialized countries from the G7 group and three emerging-market countries to provide evidence of the impact of U.S. uncertainty spillover on non-U.S. financial markets directly.

Second, we select several different U.S. uncertainty indices derived from three sources (policy, the financial market, and investor behavior) and empirically compare their impact on the stock market volatility of non-U.S. countries. EPU, as proposed by Baker et al. (2016), is the most popular proxy for measuring policy related uncertainty in existing literature. It is constructed of three types of underlying components: news related to economic policy uncertainty, tax code changes, and dispersion in individual forecasters' predictions about future levels of economic variables. By exploiting a data rich environment, Ludvigson et al. (2018) proposed a U.S. FU index using the same approach as Jurado et al. (2015) in constructing MU. FU is more directly correlated with financial markets and excludes components not driven by uncertainty, which means it is more accurate in measuring financial-related uncertainty. Unlike the other indices, NVIX captures investors' perceptions of future uncertainty and it is derived from the co-movement of the front-page coverage of the *Wall Street Journal* and options-implied volatility (VIX). Su et al. (2017) show that a higher NVIX leads to more volatility among U.S. financial markets. However, research on NVIX spillover is limited except for that by Fang et al. (2018), who investigate how developed markets react to NVIX. Using U.S. uncertainty derived from these three different sources, we examine the U.S. uncertainty spillover on stock market volatility of non-U.S. countries.

Third, we employ a GARCH-MIDAS model and extend it to a bivariate form. There are many studies that discuss the relationships between stock volatility and economic variables (e.g., Fama & French, 1989; Harvey, 1991; Officer, 1973; Schwert, 1989). An inevitable problem in such studies is that the dataset is unbalanced, which means stock volatility and economic variables do not have the same data frequency. For example, the gross domestic product (GDP) is released quarterly, while stock market returns and their volatility are available at a daily or even higher frequency. Thus, it is difficult to incorporate economic variables into a GARCH or realized volatility model (Pan et al., 2017). Although data frequency reduction can be applied in the empirical analysis, the reduction process may result in the loss of information. To solve this problem, Engle, Ghysels, and Sohn (2013) propose a new class of component model called GARCH-MIDAS, which extracts two components of volatility, a short-term and a secular or long-term component. The short-term volatility component uses a mean-reverting unit daily GARCH process and the secular component uses a MIDAS process (Mixed Data Sample), which applies to lower frequency variables, indicating that the GARCH-MIDAS model allows the dataset to be unbalanced. This model is now the most popular methodology for investigating the relationships between stock volatility and economic variables (Asgharian, Hou, & Javed, 2013; Conrad & Loch, 2015; Engle et al., 2013; Su et al., 2017). The economic uncertainty indices are usually constructed with macroeconomic data, which make them available in lower frequency (monthly or quarterly). Thus, it is quite appropriate to use the GARCH-MIDAS model in our analysis. We employ a bivariate GARCH-MIDAS model to accomplish our goals. Uncertainty indices are linked to long-term components through MIDAS and GU is included as a control variable to better pinpoint the real effect of U.S. uncertainty spillover.

The remainder of this paper is organized as follows. Section 2 introduces the econometric methodology, the bivariate GARCH-MIDAS model. Section 3 describes the dataset that includes daily stock market returns and monthly U.S. uncertainty indices. Section 4 illustrates our empirical results and discusses the robustness checks through subsample analysis. Section 5 concludes.

2. Methodology

We employ a bivariate GARCH-MIDAS model following Engle et al. (2013) and Conrad and Loch (2015). The model extracts two components of volatility, a short-term component, which uses a mean reverting unit daily GARCH process and a long-term component, which uses a MIDAS process applied to variables of low frequency.[2] A general version of the bivariate GARCH-MIDAS model is described below.

The stock market return $r_{i,t}$ at day $i = 1, 2, ...,N$ in period $t = 1, 2, ...,T$ is represented in the following econometric specification:

$$r_{i,t} = \mu + \sqrt{g_{i,t}\tau_t}\varepsilon_{i,t}, \tag{1}$$

where μ is the daily expected returns, $\varepsilon_{i,t}|\Phi_{i-1,t}\tilde{N}(0, 1)$ and $\Phi_{i-1,t}$ stands for the information setup on day $i-1$ of period t. Eq. (1) shows that stock market returns have two components, the short-term volatility component, $g_{i,t}$, and the long-term volatility component, τ_t.

The short-term component that accounts for daily fluctuations is assumed to be in a short period of time and follows a mean-reverting asymmetric GARCH (1,1) process:

$$g_{i,t} = (1-\alpha-\beta-\gamma/2) + (\alpha + \gamma\cdot 1_{\{r_{i-1,t}-\mu < 0\}})(r_{i-1,t}-\mu)^2/\tau_t + \beta g_{i-1,t} \tag{2}$$

with the constraints of $\alpha > 0$, $\beta > 0$, and $\alpha + \beta + \gamma/2 < 1$, the model ensures that $E[g_{i,t}] = 1$. The parameter γ contains the information of asymmetry.

In a bivariate GARCH-MIDAS model, the long-term volatility component, τ_t, is modeled as the weighted average of lagged values of two explanatory variables: USU_t and GU_t. The key explanatory variable USU_t denotes the lagged U.S. uncertainty index and GU_t is the lagged global uncertainty proposed by Ozturk and Sheng (2017). Following Engle et al. (2013) and Conrad and Loch (2015), a fixed window is used, which means the long-term component does not change within period t and we consider modeling $\log(\tau_t)$ rather than τ_t:

$$\log(\tau_t) = m + \theta^{US}\sum_{k=1}^{K}\varphi_k^{US}(\omega_1, \omega_2)USU_{t-k} + \theta^{G}\sum_{k=1}^{K}\varphi_k^{G}(\omega_3, \omega_4)GU_{t-k} \tag{3}$$

Considering the weighting scheme φ_k in Eq. (3), most empirical literature uses a Beta function in Eq. (4) directly (Asgharian et al., 2015; Conrad & Loch, 2015; Pan et al., 2017; Su et al., 2017).

$$\varphi_k(\omega_1, \omega_2) = \frac{(k/K)^{\omega_1-1}\cdot(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(j/K)^{\omega_1-1}\cdot(1-j/K)^{\omega_2-1}} \tag{4}$$

It is simple and convenient to determine φ_k with two parameters ω_1 and ω_2, and the Beta function could generate decaying, hump-shaped, or convex weights (Engle et al., 2013; Ghysels, Sinko, & Valkanov, 2007). In addition, Ghysels et al. (2007) also propose the exponential Almon function for weighting schemes with the following specification:

$$\varphi_k = \frac{e^{w_1k+w_2k^2+\cdots+w_qk^q}}{\sum_{k=1}^{K}e^{w_1k+w_2k^2+\cdots+w_qk^q}} \tag{5}$$

Ghysels et al. (2007) indicate that the exponential Almon and Beta functions have almost the same characteristics in that they all provide positive weights and various weight shapes. In their empirical analysis, the estimated weights are quite similar between the two weighting functions. However, the Beta function is the simpler and more flexible function compared to the exponential Almon function, as the Beta function is determined by two parameters. However, in the exponential Almon, the parameter q, which denotes the number of parameter w, should be pre-determined. Sometimes, different values of q may lead to different results and a larger value of q may increase the estimation's complexity. In this study, we still use the Beta function as in most previous studies.

The GARCH-MIDAS model is estimated by the quasi-maximum likelihood estimation (QLME) and $\hat{\Theta} = \{\hat{\mu}, \hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{m}, \hat{\theta}^{US}, \hat{\theta}^{G}, \hat{\omega}_1, \hat{\omega}_2\}$ denotes the estimated parameter space. The innovation of the returns is asymptotically consistent and the asymptotic standard errors are estimated consistently under the assumption of conditional normality. Robust standard error estimations are used when estimating the covariance matrix. The conditional short-term component and the long-run component are shown in Eq. (6).

$$\begin{cases} \hat{g}_{i,t} = (1-\hat{\alpha}-\hat{\beta}-\hat{\gamma}/2) + (\hat{\alpha} + \hat{\gamma}\cdot 1_{\{r_{i-1,t}-\hat{\mu} < 0\}})\frac{(r_{i-1,t}-\hat{\mu})^2}{\hat{\tau}_t} + \hat{\beta}\hat{g}_{i-1,t} \\ \log(\hat{\tau}_t) = \hat{m} + \hat{\theta}^{US}\sum_{k=1}^{K}\hat{\varphi}_k^{US}USU_{t-k} + \hat{\theta}^{G}\sum_{k=1}^{K}\hat{\varphi}_k^{G}GU_{t-k} \end{cases} \tag{6}$$

3. Data

We consider stock market returns in nine countries, including six industrialized countries of the G7 group: Germany (DAX), France (CAC40), the UK (FTSE100), Japan (N225), Italy (ITLMS), and Canada (GSPTSE); and three emerging-market countries: China (Shanghai Composite Index), India (SENSEX30), and Russia (RTS), which are the most important economies in the world. Daily stock

[2] The short-term and long-term are relative. In the GARCH-MIDAS model, the conditional variance is decomposed into two components as shown in Eq. (1), the short-term component and the long-term or secular component. The short-term component corresponds to daily volatility. The long-term component is modeled as a linear function of variables of lower frequency, indicating that the frequency of the long-term component is the same as the economic variables.

market data are obtained from Yahoo Finance, Bloomberg, and the FRED dataset at the Federal Reserve Bank of St. Louis. We take the log returns of the stock market index prices.

Three U.S. uncertainty indices derived from different sources are included: EPU, FU, and NVIX.[3] (1) EPU is constructed from the three types of underlying components. One component quantifies newspaper coverage of policy-related economic uncertainty. The second component reflects the number of federal tax code provisions set to expire in the next 10 years. The third component uses the disagreement among economic forecasters as a proxy for uncertainty. (2) FU, proposed by Ludvigson et al. (2018), measures a common component in the time-varying volatilities of h-step ahead forecast errors across a large number of financial indicators. Ludvigson et al. (2018) find that positive shocks to FU can cause a sharp and persistent decline in real activity; furthermore, FU is an exogenous impulse that causes recessions. Their research confirms that FU is appropriate for measuring financial market uncertainty. FU is available in three horizons (1, 3, and 12 months) based on estimation procedures; we choose the 3-month horizon.[4] (3) NVIX is a new proxy for measuring uncertainty. It is a text-based measure of uncertainty that captures investors' perception of future uncertainty. NVIX is estimated based on the co-movement between front-page coverage of the *Wall Street Journal* and VIX using supporting vector regression, which makes NVIX technically unique among uncertainty indices. In order to reveal the real impact of U.S. uncertainty and avoid endogeneity, we also consider GU, a measure of global macroeconomic uncertainty, as a control variable in the GARCH-MIDAS model (Ozturk and Sheng, 2017).[5] Uncertainty indices in monthly frequency are shown in Fig. 1.

The sample periods are determined by the availability of the stock market returns and uncertainty series.[6] Data for Germany, France, Canada, Japan, the UK, and India are from October 1989 to December 2015. Data for Italy are from January 2003 to December 2015. Data for China and Russia are from January 1991 to December 2015 and January 1996 to December 2015, respectively. Descriptive statistics for all variables can be found in Table 1. According to standard unit roots tests, all stock market returns and uncertainty indices can be considered as being stationary. Panel A reports descriptive statistics for daily stock market returns. Stock market returns exhibit negative skewness and excess kurtosis with a fat tail. The stock market returns of emerging-market countries apparently have higher standard deviations, which means they show more volatility than in G7 countries.

4. Empirical results

In this section, we present the results of the GARCH-MIDAS models to assess the impact of U.S. uncertainty spillover on the stock market volatility of non-U.S. countries. We include 12 MIDAS lag months of the U.S. uncertainty indices, which we determine by the Akaike information criteria (AIC).

4.1. Stock market volatility and U.S. EPU

We first analyze the spillover of the U.S. EPU on the stock market volatility of the G7 countries and the three emerging markets. The estimation results are reported in Table 2. The sum of α, β, and $\gamma/2$ are almost identical and less than one for all the countries, which means that the short-term volatility component is mean-reverting to the long-term trend. The $\alpha > 0$ and $\beta < 1$ indicate the volatility clustering in these countries.

Next, we take a closer look at the estimates of the long-run component τ_t. The parameter θ^{US} measures the impact of U.S. EPU on the stock market volatility of non-U.S. countries. The results in these countries are complex. The estimated parameters for Germany, France, the UK, Japan, and Italy are all positive, which means that higher U.S. EPU leads to higher volatility. The positive estimated parameters reveal economic policy interdependence within the G7 countries, implying that U.S. economic policy uncertainty triggers policy uncertainty in other G7 countries and that the close economic relationships make U.S. economic policy spillover easier. However, the spillover differs visibly among the G7 countries. U.S. EPU has the largest impact on the UK long-term volatility component where $\theta^{US} = 10.1696$ at a 1% significance level, implying strong policy spillover from the U.S. to the U.K. The parameter for Germany is positive but insignificant at any level; thus, the U.S. EPU would not have a significant impact on German stock market volatility. Germany is the largest European economy and leads the economy in the European Union. Thus, its economic policies should be more independent and have a very strong spillover in Euro areas (Bernal et al., 2016), which weakens the spillover of U.S. EPU. Our results are similar to Klößner and Sekkel (2014), who find that the U.S. is the largest transmitter of EPU, while Germany and Italy are the most isolated countries in terms of the spillover.

In contrast, the parameter estimates for the emerging-market economies are all negative, indicating that a higher U.S. EPU is associated with lower volatility. Unlike in G7 countries, stock markets in emerging-market countries are not well developed and the authorities always impose strong restrictions on financial market openness in order to prevent risk spillover from other countries. For

[3] EPU is available at http://www.policyuncertainty.com/; FU is available at the personal webpage of Sydney C Ludvigson; NVIX is available at the personal webpage of Asaf Manela.

[4] We also use uncertainty in the 1 and 12 month horizon and get the same results.

[5] MU constructed by Jurado et al. (2015) is a good proxy for macroeconomic uncertainty, but we do not apply it in this study. This is because EPU is actually a kind of macroeconomic uncertainty, which contains both policy and macroeconomic information, according to Su et al. (2018) and Ludvigson et al. (2018). In addition, MU is constructed from a large number of macroeconomic indicators, which may not draw as much attention as U.S. policies and financial market information among foreign policymakers and investors.

[6] Monela stopped the NVIX update at 2016M3 and GU is only available from 1989M10 to 2015M8. As we find the trend and fluctuation between GU and Global EPU (another global uncertainty measure) to be quite similar, we then estimate the values of GU from 2015M9 to 2015M12. See more details for Global EPU in Davis (2016).

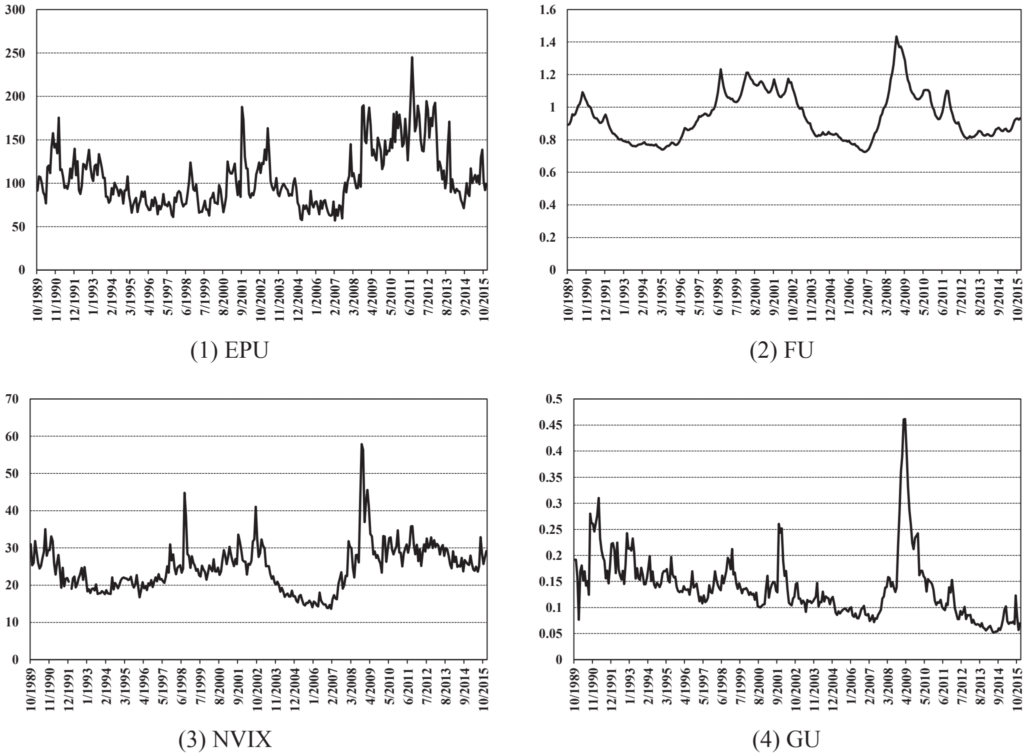

Fig. 1. U.S. uncertainty indices and Global uncertainty.

Table 1
Descriptive statistics of stock returns and U.S. uncertainty indices. This table reports descriptive statistics for daily stock returns and monthly U.S. uncertainty indices, including number of observations (Obs.), minimum (Min.), maximum (Max.), mean, standard deviation (Std.Dev.), skewness and kurtosis. J-B statistics refer to the statistics of the Jarque-Beta test for normality. Stock market returns are in percentage.

Panel A: Daily Stock Market Returns								
Country	Obs.	Min.	Max.	Mean.	Std.Dev.	Skewness	Kurtosis	J-B Statistics
Germany	6636	−13.71	10.80	0.03	1.45	−0.22	8.46	8292.34***
France	6655	−9.47	10.59	0.01	1.40	−0.05	7.44	5468.95***
UK	6634	−9.27	9.38	0.02	1.12	−0.14	9.00	9973.06***
Japan	6645	−12.11	13.23	0.01	1.53	−0.13	8.33	7656.39***
Canada	6609	−9.79	9.37	0.01	1.01	−0.73	13.70	32108.28***
Italy	3306	−8.56	10.66	0.01	1.44	−0.11	7.97	3410.17***
China	6116	−17.91	10.05	0.01	2.39	5.26	148.57	55024.00***
India	6289	−13.66	15.99	0.06	1.71	−0.06	8.98	9386.07***
Rrussia	4995	−21.20	20.20	0.04	2.62	−0.36	10.51	11850.46***
Panel B: U.S. uncertainty indices								
Variable	Obs.	Min.	Max.	Mean	Std.Dev.	Skewness	Kurtosis	J-B Statistics
EPU	315	57.20	245.13	106.40	33.73	1.05	3.75	65.70***
FU	315	0.72	1.43	0.94	0.15	0.72	2.93	26.91***
NVIX	315	13.62	57.90	24.77	6.35	1.15	6.78	256.24***

** Indicates significance at 5% level.
* Indicates significance at 10% level.
*** Indicates significance at 1% level.

example, China has a series of capital market control policies to keep its financial system stable and avoid financial crisis. In addition, a higher U.S. EPU has negative impacts on the U.S. macroeconomy and financial markets, which can be seen as "good news" for emerging-market economies. Investors in China, India, and Russia, who obtain such "good news," may have positive attitudes toward their domestic stock markets and this may lead to lower market volatility.

Table 2
GARCH-MIDAS estimation with U.S. EPU and GU.

	GER	FRA	UK	JPN	CAN	ITA	CHN	IND	RUS
μ	0.0346**	0.0108	0.0083	−0.0016	0.0352***	0.0225	−0.0440	0.0604***	0.1016***
	(0.0135)	(0.0137)	(0.0105)	(0.0164)	(0.0087)	(0.0177)	(0.0523)	(0.0170)	(0.0386)
α	0.0199***	0.0045	0.0065	0.0341***	0.0337***	0.0059	0.1816**	0.0795***	0.0693***
	(0.0075)	(0.0067)	(0.0066)	(0.0101)	(0.0092)	(0.0077)	(0.0915)	(0.0113)	(0.0201)
β	0.9049***	0.9221***	0.9102***	0.8857***	0.9120**	0.9252***	0.8791***	0.8858***	0.9248***
	(0.0117)	(0.0124)	(0.0111)	(0.0114)	(0.0155)	(0.0138)	(0.0362)	(0.0154)	(0.0158)
γ	0.1141***	0.1117***	0.1308***	0.1178***	0.0798***	0.1145***	−0.0314	0.0567***	0.0302**
	(0.0182)	(0.0167)	(0.0171)	(0.0208)	(0.0176)	(0.0224)	(0.0591)	(0.0175)	(0.0121)
m	0.5367***	0.5099***	0.0731	0.8976***	−0.3818**	0.1380	−3.7078***	1.6695*	−1.0409*
	(0.1470)	(0.1144)	(0.1562)	(0.2214)	(0.1851)	(0.2543)	(0.7309)	(0.9638)	(0.6103)
θ^{US}	0.0164	1.3300*	10.1696***	3.1418*	−0.7171**	3.8992	−3.9508	−1.3621	−5.9866*
	(0.0273)	(0.7988)	(2.8612)	(1.8007)	(0.3650)	(3.5013)	(5.2007)	(1.2420)	(3.0558)
ω_1	4.7489**	12.4344	2.3623***	6.9374*	47.4097***	11.5608	2.2886**	2.3112	3.9130***
	(2.4068)	(7.9768)	(0.4386)	(4.0645)	(0.9093)	(8.7010)	(1.1174)	(1.5855)	(0.9745)
ω_2	5.4324*	26.5816*	2.1876***	5.1117	371.9663***	6.5499**	8.2224	11.0378**	8.1390***
	(3.2731)	(14.3563)	(0.4567)	(3.6051)	(0.5734)	(3.3329)	(7.3507)	(4.7133)	(2.5757)
θ^{G}	−0.0241	−3.1713**	−1.7389	−1.2124**	−1.0307***	−4.5280	−2.7588	−0.8012	−1.0464
	(0.0152)	(1.4641)	(1.2898)	(0.6184)	(0.3816)	(4.0961)	(3.4076)	(0.7486)	(0.8138)
ω_3	3.8050***	2.8033***	3.7172*	11.0537***	47.6630***	1.7464	2.6752**	16.4265	15.7700***
	(1.0922)	(0.6663)	(2.0761)	(2.2333)	(1.4333)	(1.2634)	(1.2461)	(18.0638)	(4.1578)
ω_4	10.4862**	9.9299***	11.2611	39.4229***	205.5648***	3.8499	10.3534	59.6987	41.0041***
	(4.0801)	(3.4625)	(8.6983)	(7.5288)	(0.5341)	(4.3625)	(10.0915)	(74.1874)	(6.9077)
LLF	−10264.60	−10343.78	−8590.64	−10693.22	−7600.18	−4850.77	−11922.33	−10856.15	−10326.80

Notes: The numbers in parentheses are standard errors. *LLF* is the value of maximum likelihood function.
*** Indicates significance at 1% level.
** Indicates significance at 5% level.
* Indicates significance at 10% level.

4.2. Stock market volatility and U.S. financial uncertainty

The GARCH-MIDAS model estimation results with U.S. FU are reported in Table 3. We strictly focus on the parameter θ^{US}, which measures the impact of U.S. FU on stock market volatility of non-U.S. countries. It is interesting to note that the estimation parameters are insignificant for most countries except Canada, India, and Russia. In addition, we find that the directions of the impact are not identical among these countries. Our empirical results show that U.S. FU is not an appropriate variable in anticipating the long-term stock market volatility of non-U.S. countries and the spillover of the U.S. financial market is not significant.

We also investigate the impact of U.S. FU on the S&P 500 long-term volatility and find that a higher U.S. FU is significantly associated with higher stock market volatility, even when considering GU as a control variable.[7] This provides novel evidence that the U.S. FU measure is only useful in anticipating long-term volatility in the U.S. The reason for this may be that the FU index is constructed of a large number of financial market indicators, which means that FU information may not be readily obtained directly by foreign investors. Thus, the stock market volatility of non-U.S. countries does not respond significantly to changes in the U.S. FU.

Besides, Ludvigson et al. (2018) find that FU is an exogenous source of business cycles, which makes it a good proxy for U.S. macroeconomic activities. As the U.S. is the world's largest economy, its macro uncertainty is highly correlated with global macroeconomic uncertainty and the impact of U.S. FU is already contained in the impact of global macroeconomic uncertainty. To the best of our knowledge, there are no empirical studies considering the impact of U.S. FU on stock market volatility. However, these results seem difficult to explain and thus, further research is needed.

4.3. Stock market volatility and U.S. NVIX

In this section, we turn to the impact of U.S. NVIX on stock market volatility in non-U.S. countries. The bivariate GARCH-MIDAS estimation results are reported in Table 4. We find that the results are interesting and unexpected. The parameter estimates are all negative, ranging from −12.8630 (Russia) to −0.0457 (Germany). The estimated θ^{US} values are all significant for non-U.S. G7 countries. In contrast, the estimated parameters are statistically significant only for Russia among the emerging-market countries.

As we mention above, NVIX is a text-based proxy for measuring uncertainty, which captures U.S. investors' perception of future

[7] The results are available upon request.

Table 3
GARCH-MIDAS estimation with U.S. FU and GU.

	GER	FRA	UK	JPN	CAN	ITA	CHN	IND	RUS
μ	0.0346**	0.0119	0.0077	−0.0020	0.0360***	0.0239	−0.0451	0.0644***	0.1019***
	(0.0136)	(0.0137)	(0.0109)	(0.0162)	(0.0087)	(0.0178)	(0.0507)	(0.0169)	(0.0384)
α	0.0202**	0.0056	0.0132**	0.0351***	0.0333***	0.0063	0.1868**	0.0807***	0.0647***
	(0.0079)	(0.0062)	(0.0064)	(0.0097)	(0.0091)	(0.0075)	(0.0893)	(0.0111)	(0.0209)
β	0.9038***	0.9236***	0.9160***	0.8890***	0.9171***	0.9235***	0.8781***	0.8759***	0.9289***
	(0.0107)	(0.0123)	(0.0111)	(0.0115)	(0.0185)	(0.0153)	(0.0338)	(0.0157)	(0.0170)
γ	0.1160***	0.1086***	0.1195***	0.1128***	0.0710***	0.1158***	−0.0388	0.0576***	0.0295**
	(0.0175)	(0.0164)	(0.0168)	(0.0203)	(0.0199)	(0.0238)	(0.0619)	(0.0177)	(0.0123)
m	0.5471***	0.5215***	0.2299	0.9116***	−0.3842**	0.1196	−3.7575***	1.2002***	−0.9457
	(0.1540)	(0.1184)	(0.3076)	(0.2290)	(0.1735)	(0.2512)	(0.7010)	(0.3013)	(0.6264)
θ^{US}	−0.0532	4.0843	−1.8012	1.9104	13.5792*	7.4579	0.6069	12.3684***	8.6971*
	(0.0431)	(2.9075)	(2.2447)	(3.0349)	(7.1926)	(4.8070)	(5.6914)	(4.4472)	(5.1691)
ω_1	234.0337***	68.0819***	66.3861***	29.0377***	1.0126	102.0890***	−7.8099	742.9857***	4.6001
	(8.2503)	(6.2734)	(1.3440)	(8.4350)	(1.5930)	(12.3276)	(29.5264)	(13.8934)	(3.7615)
ω_2	447.9644***	271.5847***	377.1784***	125.8254***	3.1535**	46.1150***	143.1558***	388.6007***	22.9805
	(1.4339)	(1.8460)	(1.0663)	(4.9002)	(3.4361)	(8.9367)	(1.2086)	(11.6041)	(16.9344)
θ^{G}	−0.0032	−2.6092*	−1.3667	−1.2771**	−1.2000**	−4.0524**	−10.9324**	0.4053	−1.6996
	(0.0023)	(1.4923)	(0.8934)	(0.6008)	(0.6009)	(1.9224)	(0.8257)	(0.4769)	(1.1993)
ω_3	60.2390***	2.6627***	5.0155**	11.3014***	7.5742***	1.7648	34.6159***	25.2517***	8.3469*
	(0.5613)	(0.7908)	(2.4773)	(2.6349)	(2.8496)	(1.1015)	(0.8549)	(2.1487)	(4.6246)
ω_4	365.5225***	10.5937**	18.1563**	41.9651***	37.4555***	5.5724	264.5673***	195.2537***	24.5093**
	(1.2785)	(5.3716)	(8.1597)	(8.8639)	(12.8858)	(4.2533)	(2.5988)	(11.6921)	(11.3990)
LLF	−10262.69	−10346.17	−8599.22	−10696.37	−7600.12	−4852.68	−11923.51	−10849.88	−10334.77

Notes: The numbers in parentheses are standard errors. *LLF* is the value of maximum likelihood function.

*** Indicates significance at 1% level.

** Indicates significance at 5% level.

* Indicates significance at 10% level.

uncertainty. It is a totally different uncertainty index from EPU. Klößner and Sekkel (2014) find strong spillover of U.S. EPU on other developed countries. Economic policy interdependency means that investors in non-U.S. G7 countries can acquire information regarding their country's uncertainty from the U.S. EPU, which indicates that a higher U.S. EPU will trigger higher stock market volatility in other G7 countries, especially in the UK, France, and Japan.

However, NVIX is a proxy for measuring uncertainty derived from investor attention. Su et al. (2017) provide evidence that a higher NVIX leads to higher volatility among U.S. financial markets and is a good index for predicting future market risk or volatility. Investors in the U.S. forecast future uncertainty through mass media information and try to find a safer market to avoid upcoming risks in U.S. markets. As the stock markets in emerging-market countries are not well developed yet and always experience high volatility, moving to other developed markets is a good choice; it is representative of the "flight to quality" phenomenon. In addition, investors are more sensitive to information obtained from the business press than from economic policy changes or macroeconomic indicators, which makes NVIX the most efficient index in anticipating stock market volatility in non-U.S. countries.

In terms of the results, the estimated parameters for China and India are not significant at any level. This is consistent with the results from Su, Fang, and Yin (2018) who also find that NVIX does not have a significant impact on Chinese stock markets. The reasons for this may be as follows. (1) In China, there are more individual investors than institutional investors and these non-professional investors, who only care about short-term profits, will never seek out information from the U.S. (2) The Chinese government has imposed strong controls on financial markets and capital accounts, making the Chinese stock market relatively isolated from other markets; thus, U.S. uncertainty will have hardly any spillover effect on China. The estimation results for the U.S. EPU and the FU confirm the second reason.

4.4. Subsample analysis and robustness checks

In this section, we review our subsample analysis and detail the robustness checks for our results. The financial crisis in 2008 apparently led to higher U.S. uncertainty and severe financial market volatility. We consider two subsamples to exclude the crisis period: pre-crisis and post-crisis. Based on the National Bureau of Economic Research (NBER) business cycle data, the pre-crisis period ends December 2007 and the post-crisis period starts June 2009. The results in the subsample analysis are reported in Table 5; we only present the estimates of the key coefficient. We find that U.S. EPU and FU do not effectively anticipate long-term volatility in non-U.S. countries in the two subsamples. The results of the pre-crisis and post-crisis periods are quite different, implying a significant

Table 4
GARCH-MIDAS estimation with U.S. NVIX and GU.

	GER	FRA	UK	JPN	CAN	ITA	CHN	IND	RUS
μ	0.0334**	0.0109	0.0078	−0.0033	0.0353***	0.0273	−0.0453	0.0596***	0.1082***
	(0.0135)	(0.0141)	(0.0110)	(0.0159)	(0.0087)	(0.0171)	(0.0547)	(0.0170)	(0.0408)
α	0.0199***	0.0059	0.0120*	0.0348***	0.0330***	0.0053	0.1696**	0.0796***	0.0645***
	(0.0053)	(0.0043)	(0.0064)	(0.0047)	(0.0069)	(0.0067)	(0.0827)	(0.0115)	(0.0234)
β	0.8992***	0.9162***	0.9145***	0.8874***	0.9111***	0.9291***	0.8879***	0.8814***	0.9264***
	(0.0063)	(0.0056)	(0.0103)	(0.0071)	(0.0077)	(0.0085)	(0.0331)	(0.0154)	(0.0193)
γ	0.1274***	0.1220***	0.1254***	0.1157***	0.0822***	0.1089***	−0.0352	0.0622***	0.0350**
	(0.0087)	(0.0083)	(0.0168)	(0.0077)	(0.0109)	(0.0127)	(0.0553)	(0.0178)	(0.0141)
m	0.5757***	0.5474***	0.2601	0.9083***	−0.3830***	0.0388	−3.8920***	1.5406**	−0.9417
	(0.1040)	(0.1006)	(0.3326)	(0.0990)	(0.1246)	(0.1852)	(0.7589)	(0.7585)	(0.7106)
θ^{US}	−0.0457**	−2.4068**	−1.4014*	−3.8528**	−0.6428*	−0.8811*	−0.8627	−4.7407	−12.8630***
	(0.0210)	(1.0076)	(0.7413)	(1.8270)	(0.3774)	(0.4929)	(0.7258)	(4.1082)	(4.4786)
ω_1	1.4497**	2.6070**	4.4428***	5.2922***	20.5611***	64.1002***	34.2678***	1.5902	2.3196
	(0.6465)	(1.0828)	(1.6103)	(1.9544)	(2.9268)	(9.4764)	(5.2410)	(1.0691)	(1.5743)
ω_2	5.5607	12.6706	25.4418**	10.1854**	157.8200***	271.1095***	127.7152***	4.6367**	3.3674*
	(4.3216)	(7.7068)	(10.7831)	(4.3418)	(21.8093)	(39.4555)	(2.6497)	(2.1755)	(1.9208)
θ^{G}	−0.0161*	−2.7203***	−1.5470*	0.4292	−1.1669***	−3.4030**	−1.1632	−0.7269	−1.0588
	(0.0088)	(0.8069)	(0.9380)	(0.4482)	(0.4368)	(1.3270)	(0.7975)	(0.5703)	(1.0909)
ω_3	4.4427*	2.9066***	5.1671*	17.9543***	9.2505**	2.8288*	259.2815***	17.7635***	12.3853**
	(2.3503)	(0.9508)	(2.7269)	(5.5906)	(5.3524)	(1.4598)	(7.2094)	(2.2731)	(5.6585)
ω_4	14.8025	10.0925**	19.1888*	158.0007***	43.7418***	8.8808*	507.6744***	65.3104***	36.4882***
	(9.3061)	(4.6030)	(10.0313)	(3.5747)	(25.4832)	(4.9585)	(10.3406)	(3.7190)	(13.7155)
LLF	−10254.66	−10342.07	−8596.60	−10696.33	−7602.18	−4853.76	−11923.02	−10854.11	−10331.01

Notes: The numbers in parentheses are standard errors. *LLF* is the value of maximum likelihood function.
*** Indicates significance at 1% level.
** Indicates significance at 5% level.
* Indicates significance at 10% level.

Table 5
Subsample analysis.

		GER	FRA	UK	JPN	CAN	ITA	CHN	IND	RUS
EPU	pre-crisis	−0.0088	0.9316**	−0.2098	−1.4055	−6.4835*	−1.5342*	−10.2857	−0.7824	−1.4235
		(0.0162)	(0.4185)	(0.2159)	(0.9046)	(3.7508)	(0.8919)	(7.5631)	(0.6053)	(0.8794)
	post-crisis	0.0085	2.1516	14.5416***	−5.0190*	−1.5311	1.5623	0.7294	−0.8918	−0.9291
		(0.0066)	(2.5361)	(3.1498)	(2.8616)	(0.9564)	(1.2511)	(3.4750)	(0.8780)	(0.8082)
FU	pre-crisis	0.0329	−3.7948	3.4251	−2.5270	5.4921*	−16.9543***	−11.4245	14.5791**	7.7081*
		(0.0576)	(2.8309)	(2.8581)	(3.1055)	(3.2594)	(5.3969)	(12.8027)	(6.9959)	(4.4768)
	post-crisis	−0.1053*	6.9663	−9.5124	14.0216**	−12.0277**	−2.3996	15.3886***	−11.8764**	−12.6276**
		(0.0606)	(5.4682)	(6.6134)	(6.1813)	(5.9066)	(2.9626)	(5.4307)	(4.8801)	(6.0923)
NVIX	pre-crisis	0.0195	−0.7369	−0.7480	−7.8692**	−1.6849	−1.7793	−0.0773	−0.5911	−3.7707
		(0.0228)	(0.7033)	(0.6851)	(3.1096)	(1.3959)	(1.4675)	(0.6676)	(1.4032)	(4.4160)
	post-crisis	−0.0832*	−2.1328**	−4.2730	−2.7510***	−2.0511***	2.5560*	12.3125	−8.8498**	1.0865
		(0.0438)	(1.0184)	(2.8386)	(1.0090)	(0.7958)	(1.3548)	(8.3721)	(3.4659)	(1.4135)

Notes: The numbers in parentheses are standard errors.
*** Indicates significance at 1% level.
** Indicates significance at 5% level.
* Indicates significance at 10% level.

influence of the financial crisis on global financial markets.

The results for U.S. NVIX are quite interesting. The estimates for the coefficients show that NVIX has a higher impact on the stock market volatility among G7 countries after the financial crisis, while it still does not have a stable impact on emerging markets. Although NVIX does not perform well in predicting U.S. financial market volatility (Su et al., 2017), the spillover to other G7 countries is much larger after the financial crisis. Mclean and Pontiff (2016) conclude that reveals of risk factors decrease return predictability, and Su et al. (2017) provide evidence of this in U.S. financial markets. However, our study provides contrary results from an international spillover perspective. Although U.S. investors pay less attention to news-based uncertainty, foreign investors pay more attention to information derived from U.S. news and mass media to identify future uncertainty, an inevitable consequence of the financial crisis.

5. Conclusion

This study investigates the impact of U.S. uncertainty on the stock market volatility of nine selected countries through a bivariate GARCH-MIDAS model. We consider three uncertainty indices: EPU, FU, and NVIX, which represent three different sources of uncertainty. Thus, the study contributes to market contagion and asset pricing literature from the perspective of uncertainty.

We clearly find that U.S. uncertainty proxies perform differently in anticipating long-term stock market volatility. First, U.S. EPU is positively associated with the stock market volatility of non-U.S. G7 countries, which underscores the economic policy interdependency among the G7 countries. U.S. EPU has the largest spillover effects on the UK and Japan. Second, FU is not an appropriate variable in predicting the stock market volatility of non-U.S. countries, as it does not have a significant impact on most countries. Third, in contrast to U.S. EPU, NVIX is negatively associated with stock market volatility and it is a more powerful measure of uncertainty in predicting stock market volatility in non-U.S. G7 countries. The insensitivity of emerging markets to NVIX comes from strong local market constraints and the proportion of professional investors in these markets. Our study implications can be useful to financial investors and hedgers who are continually looking to adjust their asset allocations while enhancing their understanding of U.S. uncertainty spillover.

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