Does NVIX matter for Volatility?——Evidence from Asia-Pacific Markets

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Cover Letter

Dear sir/Madam,

We would like to submit the enclosed manuscript entitled *Does NVIX Matter for Volatility? Evidence from Asia-Pacific Markets*, which we wish to be accepted by *European Financial Management Symposium* in Xiamen. We also wish this paper to be considered for publication in the EFM. I would like to declare on behalf of my co-authors that the work is original research that has not be published previously, or not under consideration for symposium or publication elsewhere. I hope this paper is suitable for the symposium and EFM.

We deeply appreciate your consideration of our manuscript, and we look forward to receiving messages from the symposium. If you have any queries, please contact me at the address below.

Thank you.

Yours sincerely,

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Does NVIX matter for Volatility?— Evidence from Asia-Pacific Markets

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Abstract

Using news-based implied volatility (NVIX) that measures uncertainty, we examine the impact of NVIX on the stock market volatility in both long and short-term among Asia-Pacific markets. We find that NVIX do not well explain long-term volatility variants in the full sample period using GARCH-MIDAS model, and it is positively associated with market volatility after Financial Crisis. We also conclude that impact of NVIX is more efficient in determining short-term volatility than long-term volatility, indicating that the impact of NVIX is short-lived and information that investors concern could be quickly reflected in the stock market volatilities.

Keywords: *News-based implied volatility, uncertainty, stock market returns, GARCH-MIDAS*

JEL Classification: *G*12, *G*15, *G*17

This work is supported by the National Natural Science Foundation of China (Project Number 71671193) (Project Number 71473279); key project of the National Social Science Foundation of China (Project Number 15ZDC024); the program for New Century Excellent Talents of the Ministry of Education of China (Project Number NCET-13-1055).

1. Introduction

The predictability of stock market volatilities has drawn much attention in financial asset pricing. Ample previous researches try to figure out the relations between stock market volatilities and economic fundamentals (Officer, 1973; Schwert, 1989; Schwert, 2011; Paye, 2012). However, David and Veronesi (2013) indicate that the relationships between volatilities and macroeconomic variables are very complex. Engle and Rangel (2008) show that a board of macroeconomic variables jointly explains a very small proportion of stock market volatility. Recently, empirical evidences show that macroeconomic fundamentals, including real GDP growth, industrial production growth, unemployment rates, term spread and inflations, are efficient in explaining aggregate volatilities (Engel *et al*., 2013; Corradi *et al*., 2013; Conrad and Loch, 2015; Choudhry *et al*., 2016).[1]

Previous literatures mark the disagreements of predictability by fundamentals, and we would like to provide evidences from the perspective of uncertainty following the current research.[2] Actually, uncertainty has been highlighted in financial asset pricing (Anderson *et al*. 2009, Bekaert *et al*. 2009), as Bloom (2006, 2009) brings out the uncertainty shocks on the stock market return and firms. Time variation in uncertainty influences investors' consumption and portfolio choice decisions, generating variance premium fluctuations and helping explain their power to predict stock returns (Dreschsler, 2013). Pástor and Veronesi (2012, 2013) indicate the negative relations between asset returns and policy uncertainty with general equilibrium models. More works just focus on digging the relations empirically. Bekaert *et al*. (2009) find uncertainty plays a large role in the term structure and is the driver of countercyclical volatility of asset returns. Anderson *et al*. (2009) find the similar results. Brogaard and Detzel (2015) present that economic policy

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[1] The related literatures analyze various fundamental variables. Engle et al. (2013) find the long-term volatility is driven by inflation and industrial production growth; Corradi *et al*. (2013) also use these two variables as proxies of macroeconomic conditions; Conrad and Loch (2015) indicate role of real GDP, industrial production growth, unemployment rates, term spread in anticipating long-term volatility; Choudhry *et al*. (2016) find the bidirectional relations between stock market volatility and business cycle, which is also indicated by industrial production growth.

[2] Uncertainty could be seen as changes in the conditional variance of fundamentals, which implying uncertainty as a proxy of macroeconomic fundamentals, according to David and Veronesi (2013).

uncertainty proposed by Baker et al. (2016) would positive forecast log excess market returns, implying higher uncertainty leads to higher returns. However, economic policy uncertainty would lead to negative risk premium in Fama-French 25 size-momentum portfolios. Bali *et al*. (2014) find the relations between macroeconomic uncertainty and stock market returns. Asgharian et al. (2015) presents the influences of macroeconomic uncertainty on stock and bond markets, following Bali *et al*. (2014). Segal et al. (2015) decompose uncertainty into 'good' and 'bad' components and find their different role in predicting asset prices. Gülpınar and Çanakoğlu (2017) consider impact of temperature uncertainty on portfolio. Naifar *et al*. (2017) research on the different effects of regional and global economic uncertainty on the conventional bonds and Islamic bonds. Current literatures focus on the relations between stock market and uncertainty in return levels, and find uncertainty could decrease returns in both stock and market index levels, which is consistent with the theoretical models. However, the role of uncertainty in generating asset volatilities has not been deeply found. Explorations of uncertainty in explaining market volatility would be useful complementary in the field of financial asset volatility predictability.

Ample empirical literatures actually reflect the fact of rapid developments in uncertainty measurements. Various uncertainty measurements are proposed, including Political election cycles (Mei and Guo, 2004), Economic Policy Uncertainty Index (EPU here in after, Baker *et al*., 2016; Davis, 2016), macroeconomic uncertainty index (MUI here in after, Bali *et al*., 2014; Asgharian *et al*., 2015), degree of disagreement of forecasting or expectation data (Anderson *et al*., 2009; Bachmann *et al*., 2013), common volatility from economic indicators (Peng *et al*., 2007; Jurado *et al*., 2015; Meinen and Roehe, 2017).[1] Among these uncertainty measurements, the most common used proxy of uncertainty in empirical works is EPU (Colombo, 2013; Karnizova and Li, 2014; Bernal *et al*., 2016; Beckmann and Czudaj, 2017). However, several shortcomings of EPU and uncertainty index alike are found, as they are still limited to fundamental levels, and only consider

[1] Bali *et al*. (2014) employ Principal Component Analysis (PCA) to measure macroeconomic uncertainty. Jurado *et al*. (2015) define uncertainty as common volatility in the unforecastable component of a large number of economic indicators, and provide macro and financial uncertainty through estimations. Similar to Jurado et al. (2015), Meinen and Roehe (2017) measure uncertainty by conditional volatility of unforecastable components of a broad set of time series. Peng et al. (2007) just pay attention to daily-realized volatility of 30-year Treasury bond futures.

the economic related indicators.[1] Interestingly, a different index of uncertainty called *News Implied Volatility* (NVIX for short) is proposed by Manela and Moreira (2017) recently. They construct the text-based measure of uncertainty, which focuses on investors' concerns about exact topics in *Wall Street Journal*, but not a proxy in fundamental levels. NVIX is much different from EPU in the following aspects. First, the underlying components are quite different. NVIX is estimated based on the co-movement between the front-page coverage of the *Wall Street Journal* and option-implied volatility (VIX). It is an expansion of VIX combined with information dug from unique words of business press. However, EPU contains three components, measuring uncertainty in newspapers, number of federal tax code provisions and disagreement among economic forecasters, respectively. Secondly, NVIX consider the investors' concerns or attentions on events, and we could call it attention-base uncertainty. The topics or keywords from business press capture the investor attention, which is also a key factor of asset pricing both in return level (Barber and Odean, 2008; Lou, 2009; Chemmanur and Yan, 2009; Hou *et al.*, 2008; Da *et al*, 2011, 2015), and volatility level (Andrei and Hasler, 2015), which implies uncertainty in attention level should be a key factor in expectations. On the contrary, EPU and other uncertainties are considered to be macroeconomics related, as they focus on uncertainties in economic policies and macroeconomic variables, ignoring the aspects of investor behaviors. Thirdly, NVIX is estimated through machine learning techniques, and EPU is constructed based on the number of keywords in newspapers. Considering the complexity and underlying principles of NVIX, we would provide more evidences of the relations between stock market volatility and uncertainty.

In line with the literatures focusing on the financial assets volatility and its determinants, three contributions arise from the following aspects in this paper. Firstly, this paper contributes to empirical evidence to the role of uncertainty in determining stock market volatility in both long and short-term. Most previous empirical works just focus on the long-term volatility (Engel *et al*., 2013; Conrad and Loch, 2015), few pay attention to the short-term component. It is expected that impact of uncertainty is short-lived as the related event effects would not last longer as investors

[1] EPU and the other uncertainties focus on economic policies, macroeconomic variables or series. Although some of them consider the survey data or disagreement of professional economic forecasters, the uncertainty indices are still related to current or future macroeconomic conditions.

quickly adjust their investment allocations.[1] Globalization makes information transmission in a timely manner. (Chen *et al.*, 2016). Besides, the investor behaviors including sentiments and attentions could be quickly reflected in stock market prices (Vozlyublennaia, 2014; Tantaopas et al., 2016). In this paper, we employ GARCH-MIDAS for the impact of uncertainty on the long-term volatility and OLS for the impact on the short-term volatility after filtering out the long-term component. In addition, we set the burst of Financial Crisis as the start of subsample analysis, which could more recent and accurate empirical evidence.

Secondly, we use NVIX as a proxy of uncertainty, which earns much difference from the common used EPU. It is an index that is related to investor attention, but not economic fundamentals. Previous works just conduct research on the uncertainty in fundamental levels, and no evidence of uncertainty related to investor behaviors has been found. The empirical explorations of NVIX can expand the field of investor attention in predicting volatilities, confirming the limited attention theory and making the attention-related uncertainty an efficient pricing factor (Vozlyublennaia, 2014). Besides, Manela and Moreira (2017) just pay attention to stock return levels, and it is necessary to investigate the relations between NVIX and stock market volatilities. Unlike works using fundamental uncertainty, we select lagged NVIX as predicting variable to estimate its impact on stock market volatility. Our results would provide support for the attention theory (Barber and Odean, 2008; Gwilym *et al*., 2016) and pricing effects of uncertainty.

Thirdly, researches related to uncertainty mainly focus on developed markets, especially the United States (Jurado *et al*., 2015). Works related to developing markets are focusing on the exact single market including Mainland China, Hong Kong, and Japan (Cheema and Nartea, 2014; Yang and Jiang, 2016; Li and Peng, 2017). One of the exceptions is Mei and Guo (2004), they examine the relations between political cycles and volatilities in 22 emerging markets. This paper turns to provide evidences among the emerging Asia-Pacific markets, which creates a naturally environment to test the predictions of NVIX. In less developed and efficient markets, uncertainty related to investor attentions would better test the Market Efficiency Hypothesis. We choose nine markets in Asia-Pacific area and find out the impact of NVIX on market volatility. Focusing on

[1] The attack of 911, Brexit and U.S. President Election have shown the quickly adjustments of investors, which implying the short-term impact of uncertainty.

markets out of US could also provide a viewpoint of US uncertainty spillovers (Klößner and Sekkel, 2014; Yin and Han, 2014). In particular, China nowadays is the second largest economy and has the second largest stock market valued more than eight trillion US dollars and listing two thousand public firms. Considering the reality of China, this paper could test whether the US uncertainty could affect the stock market in China. The results would be instructive for the investors both in and out of China.

The remainder of this paper is organized as follows. Section 2 introduces the GARCH-MIDAS model specifications. Section 3 describes and summarizes the dataset. Section 4 provides GARCH-MIDAS estimation results, and further evidence in short-term volatility. Robustness checks are reported in Section5. Section 6 concludes.

2. Methodology

To investigate the relations between Asia-Pacific stock market volatilities and NVIX, we rely on GARCH-MIDAS (Mixed data sampling) model following Engle *et al*. (2013). The model uses a mean-reverting unit daily GARCH process, and a MIDAS polynomial that applied to lower frequencies macroeconomic or financial variables, similar to Engle and Rangel (2008). It also assumes that the long-term volatility changes at the lower frequency that macroeconomic or financial variables are observed. In this paper, we induce NVIX series into the specification of the long-term component of daily stock market returns. And a log version of GARCH-MIDAS model is described as below.

The stock market return $r_{i,t}$ at day $i=1,\cdots,N_t$ in period $t=1,2,\cdots,T$ is represented with 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, $\varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N\left(0,1\right)$ and $\Phi_{i-1,t}$ stands for the information setup to day $i-1$ of period t. Eq. (1) presents that stock market returns has two components, the short-term volatility component $g_{i,t}$ and long-term volatility component τ_t.

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

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

with the constraints of $\alpha>0$, $\beta>0$ and $\alpha+\beta+\gamma/2<1$, the model ensures that $E\left[g_{i,t}\right]=1$. The coefficient γ contains the information about the asymmetry. According to Eq. (2) and (3), the value of $\frac{\alpha+\gamma\cdot 1_{\{r_{i-1,t}-\mu<0\}}}{e^{\theta}}\triangleq\eta$ measures the effects of NVIX on the short-term volatility component.

The long-term volatility component τ_t is modeled as the weighted average of the lagged values of one explanatory variable X_t , which is NVIX series from different sources in this paper, following Engel 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. As in Engle et al. (2013) and Conrad and Loch (2015), we consider modeling $\log\left(\tau_t\right)$ rather than τ_t:

$$\log\left(\tau_t\right)=m+\theta\sum_{k=1}^{K=12}\varphi_k\left(\omega_1,\omega_2\right)X_{t-k} \tag{3}$$

here the weighting scheme which called Beta weighting scheme in Eq. (3), $\varphi_k\left(\omega_1,\omega_2\right)$ follows such specification:

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

Where $K=24$ in our paper.[1] Beta weighting scheme attached to past NVIX series depend on the coefficients of ω_1 and ω_2. For $\omega_1=\omega_2=1$, the weights will be $\varphi_k=1/K$ for all k. With ω_1 and ω_2, this weighting scheme could generate hump-shaped or convex weights, as mentioned by Ghysels et al. (2006). If we restrict $\omega_1=1$, the weighting scheme guarantees a decay pattern where the rate of decay is determined by ω_2. A large value of ω_2 means a rapid decaying pattern and a small value means a slow decaying pattern. Then we have Eq. (5) and

1 The lag length is determined by AIC and BIC.

restricted Beta weighting scheme Eq. (6). The coefficient θ measures the effects of NVIX on the long-term volatility.

$$\log\left(\tau_t\right) = m + \theta \sum_{k=1}^{K=12} \varphi_k\left(\omega_2\right) X_{t-k} \tag{5}$$

$$\varphi_k\left(\omega_2\right) = \frac{\left(1 - k/K\right)^{\omega_2 - 1}}{\sum_{j=1}^{K}\left(1 - j/K\right)^{\omega_2 - 1}} \tag{6}$$

Eq. (1)-(4) are GARCH-MIDAS model with unrestricted weighting scheme, and Eq. (1)-(2), (5)-(6) are model with restricted weighting scheme. We refer to these models as GARCH-MIDAS-X. In our cases, we mainly investigate the impact of NVIX series on the stock market volatilities among Asia-Pacific markets.

3. Data

We consider nine Asia-Pacific markets including China, South Korea, Singapore, Malaysia, Thailand, Philippine, Vietnam, Mexico and Indonesia. The daily stock market data are obtained from Yahoo Finance and Bloomberg. We take log returns of the index prices. In addition, we calculate the monthly realized volatility by the daily market returns.

With respect to the NVIX series constructed by Manela and Moreira (2017), it is a text-based measure of uncertainty. The time-variation in the topics covered by the business press is the proxy for the evolution of investors' concerns regarding these topics. Relying on machine learning techniques, Manela and Moreira (2017) estimate NVIX index based on the co-movement between the front-page coverage of the *Wall Street Journal* and options-implied volatility. NVIX data are available from Manela's personal website.[1]

The sample period for each market is determined by the availability of stock market data and NVIX. The end of the sample period is 2016.3.31. The start of the sample period is determined by the availability of index prices. The period starts from 1981M1 for South Korea and Malaysia, 1987M1 for Thailand and Philippine, 1988M1 for Singapore, 1984M1 for Indonesia, 1992M1 for Mexico, 1991M1 for China and 2000M1 for Vietnam. The descriptive statistics for these data are reported in Table 1. The stock market returns are not subject to normal distribution at 1%

[1] NVIX is available at: http://apps.olin.wustl.edu/faculty/manela/mm/nvix/nvix_interactive.html

significant as verified by Jarque-Beta test. The standard deviation is higher for China, indicating market of China is less unstable than the other markets. All the variables are stationary according to unit root test.

[Insert Table 1 Here]

4. Empirical Analysis

In section 4.1, we first investigate the impact of NVIX on the stock market volatilities using GARCH-MIDAS model with unrestricted weighting schemes in full sample period. We also provide further evidences in a subsample period, which is after Financial Crisis in 2008.

4.1 *Full sample analysis*

We estimate the GARCH-MIDAS-X model for the Asia-Pacific markets. Following AIC and BIC, we include two MIDAS lag years of NVIX, which is long enough for estimating procedures. The estimation results are presented in Table 2. For the GARCH-MIDAS coefficients, the estimated α are β are all positive and significant. The coefficient γ are all significantly positive except for Vietnam (-0.0125) and Indonesia (-0.0286). The sums of α, β and $\gamma/2$ are almost identical and less than one, indicating the short-term volatility component is mean-reverting to the long-term trend.

[Insert Table 2 Here]

This paper focuses on the estimations of coefficient θ, which measure the effects of NVIX on the stock market volatilities. The results are consistent that all the estimations are negative except for Indonesia, indicating that higher NVIX would lead to lower volatility. The estimated θ are significantly negative for China, Singapore, and Mexico. The full sample estimations are quite counterfactual as NVIX is a measure of uncertainty which captures the disaster concerns of the average investor, and it is positively related to stock market volatilities, based on the results of Manela and Moreira (2017).

Figure 1 plots the unrestricted weighting schemes. The largest weights are on the first lagged NVIX for most markets, indicating impact of NVIX on the market volatilities are short-lived. The NVIX after five months have no effects on stock market volatilities. The weighting schemes of China, South Korea, and Malaysia are the exceptions. The largest weight on the NVIX is at the

14^{th} lag for China, 5^{th} lag for South Korea, and 15^{th} lag for Malaysia. The news-based information after several months can be reflected in the stock market volatility, which implies the less efficient of these markets.

[Insert Figure 1 Here]

4.2 *Subsample Analysis*

It is noted that the estimated θ are negative for the most markets in the full sample among the Asia-Pacific markets, which is contrary to the effects of volatilities including realized volatility and VIX. In fact, it is anticipated that NVIX should positively forecast the stock market volatilities, based on its constructions. In this section, we try to present further evidences with a subsample period which is after Financial Crisis.

[Insert Table 3 Here]

The GARCH-MIDAS coefficients can still indicate the mean-reverting component. We just pay attention to the coefficient θ reported in Table 3. Considering the estimated θ, they range from -0.3509 (China) to 0.3067 (Mexico). The estimations are positive and significant, except for China and Thailand, which means higher NVIX leads to higher long-term volatilities. With respect to the weighting schemes, we take Malaysia as an example. The estimated coefficient for Malaysia is 0.1206 at 1% significant level, and ω_1 and ω_2 put the maximum weight of 0.3638 on the third lagged NVIX. A NVIX shock at current month would lead to a size of 0.0439 increase in the long-term component, which means a size of 0.5289 in the long-term volatility. The results are improved significantly when estimated with the subsample data. NVIX has significant and positive effects on the stock market volatilities among most of the Asia-Pacific markets, which is consistent with the results in return level, proposed by Manela and Moreira (2017), and the results imply the NVIX is more efficient in predicting stock market volatilities after Financial Crisis. The reason may lie at the fact that burst of Financial Crisis drives the investors to pay more attention to information related to events including uncertainty policies, disasters, and wars. In addition, NVIX would not have positive effects on the market volatilities of China, no matter in the full sample or subsample period.

4.3 *Impact on the market volatility with OLS estimations in full sample*

Results of section 4.1 are quite counterfactual comparing with previous literatures. The reason may be that this paper does not consider more control variables, which would vitally influence the estimation results. Traditionally, realized volatility (RV) is a key variable that should be included into the model, following Conrad and Loch (2015). Considering the lag length in the model which could lower the estimation efficiencies, we first filter the long-term and short-term volatility with RV using GARCH-MIDAS, contrary to GARCH-MIDAS-X-Y model proposed by Conrad and Loch (2015), and then employ OLS to estimate the impact of NVIX on the market volatilities in Eq. (7) and Eq. (8), where Vol_t^L and Vol_t^S denote the long-term and short-term volatility, respectively

$$Vol_t^L = \alpha + \beta NVIX_{t-1} + \varepsilon_t$$

(7)

$$Vol_t^S = \alpha + \beta NVIX_{t-1} + \varepsilon_t$$

(8)

The estimation results of Eq. (7) are reported in Table 4. The coefficients of NVIX are positive for the most markets except for Malaysia and China, implying that higher NVIX would bring higher long-term volatilities, and NVIX could better anticipate long-term volatility among the Asia-Pacific markets. All the markets except for Malaysia have R^2 statistics above 1%. However, the estimated β is -0.0046, significant at 1% level with a *t*-value of 0.0004, which indicate that higher NVIX would lead to lower market volatilities for China. The OLS results for China is similar to that of GARCH-MIDAS, the direction and statistical significance of the impact of NVIX are quite different from the Asia-Pacific markets, which indicates the particularity of China market.

[Insert Table 4 Here]

As for the estimations results of Eq. (8) presented in Table 5, the coefficients on lagged NVIX are all positive and highly significant at 1% level except for China. All markets have R^2 statistics above 1%, and the statistics for Malaysia turns from 0.01% to 2.33%. The coefficient for South Korea is 0.0072, significant at 1% level with a *t*-value of 0.002, which is the largest estimation. Conversely, the coefficient for Vietnam is 0.0027 with a *t*-value of 0.003 at 1% significant level. The other estimated coefficients are between 0.0027 and 0.0072. The coefficient for China is -0.0041, significant at 1% level with a *t*-value of 0.0004, and the R^2 statistics is 1.74% which is smaller than the other markets.

[Insert Table 5 Here]

Next we consider models with lagged volatility as control variable in Eq. (9) and Eq. (10). We also present the estimations for the long-term and short-term volatility, respectively.

$$Vol_t^L = \alpha + \beta NVIX_{t-1} + \gamma Vol_{t-1}^L + \varepsilon_t \tag{9}$$

$$Vol_t^S = \alpha + \beta NVIX_{t-1} + \gamma Vol_{t-1}^S + \varepsilon_t \tag{10}$$

Considering the impact of lagged NVIX on the long-term volatilities reported in Table 6, it is showed that the coefficients on the NVIX series are positive and significant for South Korea, Singapore, Philippine and Mexico. The estimated β for South Korea is 0.0004, significant at 1% level with a *t*-value of 0.0001. The coefficients for Singapore, Philippine and Mexico are significant at 5% level. The results indicate that NVIX could positively predict future long-term stock market volatilities when considering lagged market volatilities. The coefficients are negative for Malaysia (-0.0001) and Vietnam (-0.0001), and insignificant for Thailand (0.0004) and Indonesia (0.0002). As for China, the coefficient is 0.0001 with a *t*-value of 0.0004 implying higher NVIX leads to higher volatility, and it is not significant at any levels, indicating that NVIX could not significantly forecast market volatilities.

[Insert Table 6 Here]

Considering the coefficient β in Eq. (10) that measures the impact of NVIX on the short-term stock market volatility as reported in Table 7, the estimated β are positive and highly significant at 1% level for all the Asia-Pacific markets except for China and Vietnam, when including lagged volatility in OLS estimations. NVIX still have positively significant effects on the future short-term volatilities among the Asia-Pacific markets, which could be regarded as a spillover of uncertainty of US. The coefficients for South Korea, Singapore, Malaysia, Thailand, Philippine, Mexico and Indonesia are 0.0002, 0.0003, 0.0002, 0.0002, 0.0002, 0.0002, 0.0003, respectively. The estimated β is -0.001 with a *t*-value of 0.0001 for China, and it is not significant at any levels, which implies NVIX could not significantly anticipate the short-term volatilities in China.

[Insert Table 7 Here]

In summary, it is interesting to find that lagged NVIX could significantly forecast market volatilities among the Asia-Pacific markets in the full sample period with OLS. When considering lagged volatilities as control variable, NVIX still have significant power in predictability of long-term and short-term volatilities. Moreover, NVIX could better explain variants in the short-term volatilities than the long-term volatilities, implying the impact of NVIX is short-lived and the information concerning uncertainty could be quickly reflected in the market volatilities, thus confirming the limited attention theory (Vozlyublennaia, 2014). However, the result for China is counterfactual that higher NVIX lead to lower market volatilities. It is positive when considering control variables, but insignificant. As mentioned above, NVIX is a news-based uncertainty index from *Wall Street Journal*, it mainly reflects the attention uncertainty of US, and uncertainty for US may be "good news" for China, which leads to lower market volatilities.

4.4 *Impact on the market volatilities in subsample period*

In this section, we provide regressions to measure the impact of NVIX on the long-term and short-term volatility in subsample period. We focus on Eq. (9) and Eq. (10) using OLS estimations. The results of Eq. (9) are reported in Table 8. For most markets, the coefficients are positive, implying that higher NVIX associate with higher long-term volatilities. However, the coefficients are negative, ranging from 0.0002 (China) and 0.0015 (Singapore), except for Malaysia, Philippine and Vietnam. It is highlighted that the estimated β is 0.0002 for China, 5% significant with a *t*-value of 0.0001, which indicates that NVIX is positively related to future long-term market volatilities after Financial Crisis. Considering the long-term volatilities, NVIX becomes efficient in forecasting stock market volatilities for China. The news-based uncertainty from US becomes to play an important role in determining the future long-term volatility in China.

[Insert Table 8 Here]

Next we turn to the estimations results for Eq. (10) in Table 9. The coefficients on lagged NVIX are all positive and significant, when including lagged volatilities. For example, the estimated coefficient is 0.0011, 1% significant with a *t*-value of 0.0002. The coefficient for China is 0.0002 at 10% significant level, indicating NVIX positively associated with market volatilities. US uncertainty shadows significant spillovers on China stock market after Financial Crisis, confirming the devastating impact of the crisis.

[Insert Table 9 Here]

The findings in Table 7 and Table 8 indicate that NVIX could better anticipate long and short-term volatilities after Financial Crisis. Although NVIX could not draw significant effects for the full sample period on China stock market, it is more efficient in subsample period. After Financial Crisis, uncertainty from US becomes an important role in determining stock market volatility in China stock market, which reflects the consistency of market volatilities among the Asia-Pacific markets. Moreover, NVIX performs better in predicting short-term volatilities among the stock markets other than the long-term volatilities, and this evidence complements previous literatures that conclude impact of NVIX is short-lived and confirms uncertainty related pricing factors are quite efficient in volatility level.

5. Robustness Checks

This section we provide robustness checks with respect to GARCH-MIDAS with restricted weighting schemes. The restricted weighting schemes guarantee a decay pattern of the weights on the lagged NVIX and the most recent NVIX has higher weights on the stock market volatilities.

[Insert Table 10 Here]

The estimation results for GARCH-MIDAS model with restricted weighting schemes in full sample period are reported in Table 10. The coefficients on lagged NVIX are all negative except for Malaysia and Indonesia, however the coefficients for these two markets are not statistical significant. Through the full sample period, news-based uncertainty does not positively associated with stock market volatilities among Asia-Pacific markets, consistent with the unrestricted weighting schemes models.

[Insert Table 11 Here]

As for the subsample analysis, the results are reported in Table 11. The coefficients are positive and significant for most of the markets except for China, Thailand, Vietnam and Indonesia. The estimated θ is -0.0458 for Thailand and -0.6078 for Vietnam. It is noted that the coefficient for China is 0.0206, implying the positive relations between NVIX and market volatilities. Actually, the results for the most markets are similar to the results in Table 3, indicating higher NVIX would bring higher future volatilities. No matter what are the weighting schemes, the results are proved robustness. Besides, we also filter the long-term and short-term volatilities with RV using GARCH-MIDAS models with restricted weighting schemes, the OLS estimation results also confirm the predictability power of NVIX series.[1]

6. Conclusions

In this paper, we investigate the impact of NVIX on the stock market volatilities among the Asia-Pacific markets. NVIX is news-based implied volatility index proposed by Manela and Moreira (2017), which measures uncertainty and disaster concerns. Through GARCH-MIDAS estimations, we focus on the impact of NVIX on the long-term market volatilities. We find that NVIX seems to be inefficient in predicting the long-term stock market volatilities among the Asia-Pacific markets, and the results are counterfactual based on the previous literatures. After we pay attention to the subsample period starting from the burst of Financial Crisis, NVIX is positively associated with the long-term market volatilities and it could significantly anticipate the market volatilities. China is an exception, as NVIX is not significant in both full sample and subsample period.

Based on the GARCH-MIDAS estimation results, we filter the market volatilities by RV and employ OLS to estimate the impact of NVIX on the long and short-term market volatilities, in order to filter the information that influences the results. The OLS estimations results show that the lagged NVIX is positively leading to the long-term and short-term market volatilities for most of the Asia-Pacific markets. The subsample analyses are consistent with the results estimated with full sample data. In the subsample estimations, NVIX could significantly predict market volatilities for China, which confirms the spillover effects of US uncertainty. Moreover, it is interesting to find that NVIX performs better in predicting short-term volatilities, which indicates the news-based uncertainty has short-lived impacts. This paper provides evidences among the Asia-Pacific markets, and it reflects the spillover effects of US uncertainty. As the more efficiency after Financial Crisis, the investors in Asia-Pacific markets pay more attentions to US, which drives uncertainty in US a better factors in determining market volatilities.

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[1] The results are available upon requests.

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Table 1

Descriptive Statistics of stock market returns and NVIX series

This table reports the descriptive statistics of daily stock market returns and monthly NVIX. The sample spans vary from different markets. The sample of NVIX spans from 1981M1 to 2016M3. Descriptive statistics includes minimum (Min.), maximum (Max.), mean, standard deviation (Std.Dev.), skewness and kurtosis. J-B statistics refers to the statistics of Jarque-Beta test for normality. Stock market returns are in percentage.

	Min.	**Max.**	**Mean.**	**Std.Dev.**	**Skewness**	**Kurtosis**	**J-B Statistics**
China	-10.0000	9.9900	0.0243	2.1650	0.8945	21.0819	76101.18***
South Korea	-12.8047	11.2844	0.0333	1.6258	-0.1484	8.5762	10678.41***
Singapore	-9.1535	12.8738	0.0100	1.2681	0.0324	10.5783	15531.49***
Malaysia	-0.2560	0.2082	0.0002	0.0138	-0.7901	54.3423	897209.60***
Thailand	-17.3884	27.0909	0.0074	1.6849	0.5981	22.8767	107108.60***
Philippine	-13.0887	21.3525	0.0323	1.5248	0.4394	16.7220	52583.72****
Vietnam	-19.9180	19.9030	0.0309	1.5913	-0.1415	20.1590	41417.60***
Mexico	-15.4575	16.1161	0.0522	1.5493	0.0537	12.7198	21621.71***
Indonesia	-22.5301	40.3095	0.0590	1.6455	2.1628	74.2133	1540587***
NVIX	13.6225	57.8977	24.1631	5.7448	1.4127	8.1153	601.8890***

Table 2

GARCH-MIDAS estimations with unrestricted weighting schemes in full sample

This table reports GARCH-MIDAS estimations with unrestricted weighting schemes among the Asia-Pacific markets in full sample period. The estimated coefficient θ measures the impact of lagged NVIX on the long-term component. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively.

Coefficients	μ	α	β	γ	m	θ	ω_1	ω_2
China	0.0084	0.0558***	0.9155***	0.0447***	3.8479***	-0.0815**	18.8503***	15.4220***
	(0.0214)	(0.0140)	(0.0175)	(0.0152)	(1.0160)	(0.0341)	(6.4957)	(5.4955)
South Korea	0.0319**	0.0523***	0.9113***	0.0586***	1.5295***	-0.0228	29.4481***	109.8294***
	(0.0130)	(0.0083)	(0.0117)	(0.0123)	(0.4370)	(0.0177)	(6.6125)	(1.6392)
Singapore	0.0175	0.0633***	0.8803***	0.0926***	1.4459***	-0.0300**	-19.7259***	6.9788***
	(0.0113)	(0.0123)	(0.0175)	(0.0180)	(0.4493)	(0.0121)	(0.1329)	(0.0781)
Malaysia	0.0294***	0.1016***	0.8607***	0.0566**	2.3968	-0.0584	676.0459***	433.7679***
	(0.0097)	(0.0262)	(0.0364)	(0.0243)	(2.3153)	(0.0989)	(0.0648)	(0.0648)
Thailand	0.0611***	0.0887***	0.8567***	0.0844***	3.2922**	-0.0730	0.9625	20.8264***
	(0.0158)	(0.0134)	(0.0181)	(0.0253)	(1.3714)	(0.0504)	(2.1803)	(7.0152)
Philippine	0.0355**	0.0700***	0.8666***	0.0845***	1.5506***	-0.0192	-13.6604***	28.8823***
	(0.0157)	(0.0237)	(0.0314)	(0.0176)	(0.5297)	(0.0180)	(0.6693)	(0.3934)
Vietnam	-0.0170	0.1705**	0.8204***	-0.0125	1.8057*	-0.0164	-19.1707***	13.1010***
	(0.0271)	(0.0699)	(0.0939)	(0.0335)	(1.0465)	(0.0367)	(0.4399)	(1.2176)
Mexico	0.0619***	0.0327***	0.8879***	0.1414***	2.3580***	-0.0401***	-16.9502***	14.2348***
	(0.0167)	(0.0092)	(0.0126)	(0.0250)	(0.4489)	(0.0108)	(0.1508)	(0.2575)
Indonesia	0.0502***	0.1471***	0.8571***	-0.0286***	-0.3005	0.0706***	169.0118***	1318.1374***
	(0.0122)	(0.0084)	(0.0067)	(0.0087)	(0.2576)	(0.0071)	(13.6600)	(13.8970)

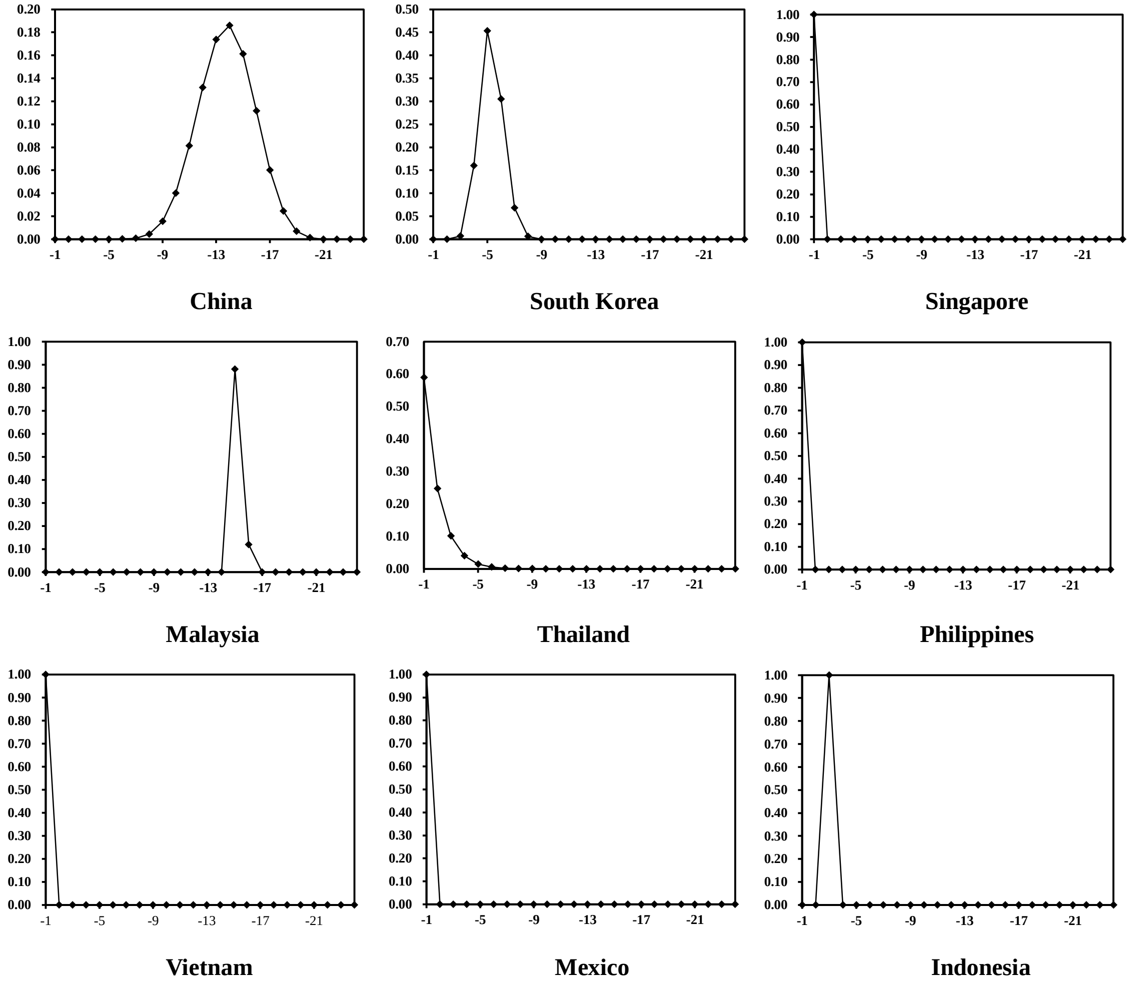

Fig. 3. Unrestricted weighting schemes patterns among Asia-Pacific markets

Table 3

GARCH-MIDAS estimations with unrestricted weighting schemes in subsample

This table reports GARCH-MIDAS estimations with unrestricted weighting schemes among the Asia-Pacific markets in subsample period. The estimated coefficient θ measures the impact of lagged NVIX on the long-term component. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively.

Coefficients	μ	α	β	γ	m	θ	ω_1	ω_2
China	-0.0050	0.0265	0.9173***	0.0273	10.7522***	-0.3509***	6.2890	5.7423
	(0.0352)	(0.0255)	(0.0309)	(0.0410)	(2.2757)	(0.0770)	(4.5473)	(6.0094)
South Korea	-0.0041	-0.0230*	0.9200***	0.1435***	-2.2449**	0.0694*	23.3863**	106.1007***
	(0.0217)	(0.0134)	(0.0189)	(0.0324)	(1.0785)	(0.0371)	(11.6721)	(36.3735)
Singapore	-0.0181	-0.0078	0.9434***	0.1072***	-3.9492**	0.1227*	8.4213	19.8260**
	(0.0213)	(0.0166)	(0.0181)	(0.0195)	(1.9499)	(0.0639)	(5.6284)	(7.7764)
Malaysia	0.0254*	0.0517*	0.8398***	0.1053***	-4.5446***	0.1206***	8.3162	51.6195
	(0.0130)	(0.0278)	(0.0488)	(0.0357)	(1.3596)	(0.0468)	(8.6007)	(54.4828)
Thailand	0.0569**	0.0537***	0.8512***	0.1387***	1.5754*	-0.0459*	-24.3028***	7.6429
	(0.0245)	(0.0165)	(0.0207)	(0.0290)	(0.8604)	(0.0278)	(2.3655)	(6.1580)
Philippine	0.0338	-0.0344	0.8626***	0.2028***	-3.3245*	0.1158**	11.5503**	29.8323***
	(0.0246)	(0.0281)	(0.0650)	(0.0485)	(1.7266)	(0.0579)	(4.4952)	(10.1192)
Vietnam	0.0363	0.0991***	0.5827***	0.1516***	-5.8411**	0.2177***	363.4962***	843.5507***
	(0.0307)	(0.0363)	(0.0864)	(0.0587)	(2.3351)	(0.0840)	(0.0001)	(0.0001)
Mexico	0.0315	0.0412***	0.8635***	0.1171***	-8.7729***	0.3067***	102.8687	238.2916
	(0.0236)	(0.0119)	(0.0212)	(0.0259)	(2.5559)	(0.0880)	(144.6487)	(338.2671)
Indonesia	0.0385	0.0346	0.8849***	0.0878***	-2.3977**	0.0870**	404.3752***	722.3045***
	(0.0248)	(0.0287)	(0.0347)	(0.0337)	(1.1487)	(0.0397)	(0.0063)	(0.0076)

Table 4

OLS estimations of NVIX and long-term volatility

This table reports OLS estimations of NVIX and long-term market volatility in full sample period, following Eq.(7). The estimated coefficient β measures the impact of lagged NVIX on the long-term market volatility. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively.

Markets	**China**	**South Korea**	**Singapore**	**Malaysia**	**Thailand**
α	0.4367***	0.1372***	0.1054***	0.2752***	0.2345***
	(0.0387)	(0.0233)	(0.0143)	(0.0276)	(0.0159)
β	-0.0046***	0.0046***	0.0036***	-0.0001	0.0018***
	(0.0015)	(0.0009)	(0.0006)	(0.0011)	(0.0006)
R^2	0.0331	0.0576	0.1187	0.0001	0.0253
AIC	-0.7473	-1.5909	-2.7027	-1.2459	-2.4708
Markets	**Philippine**	**Vietnam**	**Mexico**	**Indonesia**	
α	0.2373***	0.2685***	0.2345***	0.2119***	
	(0.0106)	(0.0149)	(0.0138)	(0.0341)	
β	0.0010**	0.0021***	0.0014**	0.0035***	
	(0.0004)	(0.0006)	(0.0005)	(0.0014)	
R^2	0.0186	0.0803	0.0248	0.0185	
AIC	-3.2694	-2.9931	-2.8803	-0.8730	

Table 5

OLS estimations of NVIX and short-term volatility in full sample period

This table reports OLS estimations of NVIX and short-term market volatility in full sample period, following Eq.(8). The estimated coefficient β measures the impact of lagged NVIX on the long-term market volatility. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively.

Markets	**China**	**South Korea**	**Singapore**	**Malaysia**	**Thailand**
α	0.4087***	0.0597***	0.0264***	0.0927***	0.1415***
	(0.0106)	(0.0054)	(0.0042)	(0.0064)	(0.0057)
β	-0.0041***	0.0072***	0.0063***	0.0036***	0.0043***
	(0.0004)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
R^2	0.0174	0.1165	0.1917	0.0233	0.0524
AIC	-0.3648	-1.4732	-2.1521	-1.1497	-1.4893
Markets	**Philippine**	**Vietnam**	**Mexico**	**Indonesia**	
α	0.1264***	0.1625***	0.1045***	0.0652***	
	(0.0047)	(0.0075)	(0.0054)	(0.0075)	
β	0.0041***	0.0027***	0.0049***	0.0064***	
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	
R^2	0.0706	0.0264	0.0906	0.0596	
AIC	-1.9088	-1.3565	-1.7137	-0.9183	

Table 6

OLS estimations of NVIX and long-term volatility in full sample period

This table reports OLS estimations of NVIX and long-term market volatility in full sample period, following Eq.(9) that considers lagged volatility. The estimated coefficient β measures the impact of lagged NVIX on the long-term market volatility. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively.

Markets	**China**	**South Korea**	**Singapore**	**Malaysia**	**Thailand**
α	0.0298**	-0.0075***	-0.0023	-0.2589***	0.0324***
	(0.0120)	(0.0022)	(0.0032)	(0.0307)	(0.0110)
β	0.0001	0.0004***	0.0003**	-0.0001	0.0004
	(0.0004)	(0.0001)	(0.0001)	(0.0011)	(0.0003)
γ	0.8880***	0.9919***	0.9718***	0.0606	0.8467***
	(0.0143)	(0.0044)	(0.0117)	(0.0502)	(0.0299)
R^2	0.9354	0.9926	0.9636	0.0037	0.7274
AIC	-3.4466	-6.4362	-5.8828	1.2446	-3.7383
Markets	**Philippine**	**Vietnam**	**Mexico**	**Indonesia**	
α	0.0160**	0.0095	0.0025	0.0108	
	(0.0071)	(0.0064)	(0.0051)	(0.0116)	
β	0.0003**	-0.0001	0.0003**	0.0002	
	(0.0002)	(0.0001)	(0.0001)	(0.0004)	
γ	0.9067***	0.9749***	0.9642***	0.9461***	
	(0.0230)	(0.0198)	(0.0156)	(0.0170)	
R^2	0.8315	0.9431	0.9375	0.8976	
AIC	-5.0252	-5.7637	-5.6202	-3.1279	

Table 7

OLS estimations of NVIX and short-term volatility in full sample period

This table reports OLS estimations of NVIX and short-term market volatility in full sample period, following Eq.(10) that considers lagged volatility. The estimated coefficient β measures the impact of lagged NVIX on the short-term market volatility. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively.

Markets	**China**	**South Korea**	**Singapore**	**Malaysia**	**Thailand**
α	0.0106***	-0.0002	-0.0008	0.0008	0.0058***
	(0.0019)	(0.0011)	(0.0010)	(0.0015)	(0.0018)
β	-0.0001	0.0002***	0.0003***	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
γ	0.9684***	0.9801***	0.9694***	0.9718***	0.9512***
	(0.0021)	(0.0021)	(0.0030)	(0.0026)	(0.0038)
R^2	0.9758	0.9669	0.9553	0.9468	0.9111
AIC	-4.0694	-4.7570	-5.0475	-4.0588	-3.8549
Markets	**Philippine**	**Vietnam**	**Mexico**	**Indonesia**	
α	0.0041***	0.0085***	0.0024	0.0018	
	(0.0014)	(0.0025)	(0.0015)	(0.0022)	
β	0.0002***	0.0001	0.0002***	0.0003***	
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
γ	0.9560***	0.9489***	0.9626***	0.9578***	
	(0.0035)	(0.0054)	(0.0036)	(0.0034)	
R^2	0.9221	0.9038	0.9354	0.9231	
AIC	-4.3874	-3.6707	-4.3583	-3.4216	

Table 8

OLS estimations of NVIX and long-term volatility in subsample period

This table reports OLS estimations of NVIX and long-term market volatility in subsample period, following Eq.(9) that considers lagged volatility. The estimated coefficient β measures the impact of lagged NVIX on the long-term market volatility. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively.

Markets	**China**	**South Korea**	**Singapore**	**Malaysia**	**Thailand**
α	-0.0051	-0.0265***	-0.0343***	0.2062***	0.0144
	(0.0056)	(0.0037)	(0.0071)	(0.0268)	(0.0182)
β	0.0002**	0.0012***	0.0015***	0.0002	0.0009**
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0004)
γ	0.9972***	0.9593***	0.9431***	0.1774*	0.8377***
	(0.0230)	(0.0110)	(0.0185)	(0.1041)	(0.0550)
R^2	0.9680	0.9905	0.9728	0.0479	0.7365
AIC	-7.9116	-7.2878	-5.8735	-6.9724	-4.6472
Markets	**Philippine**	**Vietnam**	**Mexico**	**Indonesia**	
α	0.0200	0.0031	-0.0206**	-0.0051	
	(0.0167)	(0.0104)	(0.0098)	(0.0070)	
β	0.0003	0.0004	0.0011***	0.0007***	
	(0.0004)	(0.0003)	(0.0003)	(0.0002)	
γ	0.8823***	0.9507***	0.9432***	0.9422***	
	(0.0499)	(0.0286)	(0.0261)	(0.0235)	
R^2	0.7817	0.9394	0.9433	0.9552	
AIC	-4.8873	-5.4372	-5.4705	-6.5122	

Table 9

OLS estimations of NVIX and short-term volatility in subsample period

This table reports OLS estimations of NVIX and short-term market volatility in subsample period, following Eq.(10) that considers lagged volatility. The estimated coefficient β measures the impact of lagged NVIX on the short-term market volatility. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively.

Markets	**China**	**South Korea**	**Singapore**	**Malaysia**	**Thailand**
α	0.0017	-0.0202***	-0.0128***	-0.0028**	-0.0099***
	(0.0028)	(0.0028)	(0.0023)	(0.0013)	(0.0033)
β	0.0002*	0.0010***	0.0007***	0.0003***	0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
γ	0.9720***	0.9424***	0.9557***	0.9424***	0.9323***
	(0.0053)	(0.0063)	(0.0058)	(0.0074)	(0.0080)
R^2	0.9544	0.9720	0.9749	0.9409	0.9273
AIC	-4.7306	-5.1495	-5.4990	-6.2122	-4.4506
Markets	**Philippine**	**Vietnam**	**Mexico**	**Indonesia**	
α	-0.0107***	-0.0003	-0.0135***	-0.0149***	
	(0.0030)	(0.0052)	(0.0036)	(0.0040)	
β	0.0008***	0.0005***	0.0009***	0.0011***	
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	
γ	0.9312***	0.9334***	0.9392***	0.9189***	
	(0.0079)	(0.0083)	(0.0078)	(0.0087)	
R^2	0.9304	0.8884	0.9425	0.9129	
AIC	-4.6094	-3.4809	-4.4241	-4.1140	

Table 10

GARCH-MIDAS estimations with restricted weighting schemes in full sample period

This table reports GARCH-MIDAS estimations with restricted weighting schemes among the Asia-Pacific markets in full sample period. The estimated coefficient θ measures the impact of lagged NVIX on the long-term component. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively.

Coefficients	μ	α	β	γ	m	θ	ω_2
China	0.0075	0.0546***	0.9190***	0.0440***	3.3776***	-0.0546**	5.0525
	(0.0216)	(0.0152)	(0.0184)	(0.0147)	(0.7355)	(0.0223)	(3.8166)
South Korea	0.0317**	0.0532***	0.9084***	0.0621***	1.4242***	-0.0177	74.1062***
	(0.0131)	(0.0077)	(0.0108)	(0.0126)	(0.3604)	(0.0122)	(0.1096)
Singapore	0.0175	0.0633***	0.8803***	0.0926***	1.4459***	-0.0300**	135.5424***
	(0.0113)	(0.0123)	(0.0175)	(0.0180)	(0.4492)	(0.0121)	(0.1038)
Malaysia	0.0268**	0.1005***	0.8740***	0.0389	1.0941**	0.0033	103.1668***
	(0.0136)	(0.0262)	(0.0297)	(0.0293)	(0.4909)	(0.0166)	(0.1444)
Thailand	0.0611***	0.0888***	0.8569***	0.0839***	3.3129**	-0.0738	10.1185
	(0.0158)	(0.0135)	(0.0179)	(0.0251)	(1.3198)	(0.0483)	(6.4386)
Philippine	0.0355**	0.0700***	0.8666***	0.0845***	1.5506***	-0.0192	117.9502***
	(0.0157)	(0.0237)	(0.0314)	(0.0176)	(0.5298)	(0.0180)	(0.0959)
Vietnam	-0.0170	0.1705**	0.8204***	-0.0125	1.8057*	-0.0164	114.7602***
	(0.0271)	(0.0699)	(0.0939)	(0.0335)	(1.0463)	(0.0367)	(0.5430)
Mexico	0.0619***	0.0327***	0.8879***	0.1414***	2.3580***	-0.0401***	122.0403***
	(0.0167)	(0.0092)	(0.0126)	(0.0250)	(0.4488)	(0.0108)	(0.1357)
Indonesia	0.0495***	0.1406***	0.8666***	-0.0347	0.2170	0.0473	7.2493***
	(0.0137)	(0.0382)	(0.0394)	(0.0242)	(0.8495)	(0.0312)	(2.3026)

Table 11

GARCH-MIDAS estimations with restricted weighting schemes in subsample period

This table reports GARCH-MIDAS estimations with restricted weighting schemes among the Asia-Pacific markets in subsample period. The estimated coefficient θ measures the impact of lagged NVIX on the long-term component. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively.

Coefficients	μ	α	β	γ	m	θ	ω_2
China	0.0054	0.0482***	0.9478***	-0.0086	0.0436	0.0206	132.2639***
	(0.0346)	(0.0156)	(0.0214)	(0.0158)	(0.8370)	(0.0271)	(0.9930)
South Korea	-0.0050	-0.0220**	0.9199***	0.1425***	-2.1535*	0.0665*	1.1492
	(0.0218)	(0.0112)	(0.0142)	(0.0245)	(1.1680)	(0.0404)	(1.8411)
Singapore	-0.0167	-0.0041	0.9392***	0.1062***	-3.3357**	0.1013*	1.5043
	(0.0182)	(0.0117)	(0.0107)	(0.0156)	(1.6520)	(0.0561)	(1.4814)
Malaysia	0.0259**	0.0525*	0.8357***	0.1061***	-4.4420***	0.1170**	3.4855***
	(0.0131)	(0.0284)	(0.0530)	(0.0374)	(1.5323)	(0.0525)	(1.0702)
Thailand	0.0560**	0.0526	0.8525***	0.1370***	1.5476	-0.0458	125.8294***
	(0.0249)	(0.0343)	(0.0347)	(0.0386)	(1.2869)	(0.0380)	(0.7303)
Philippine	0.0365	-0.0241	0.8457***	0.2068***	-2.4184**	0.0853**	1.4682**
	(0.0253)	(0.0153)	(0.0290)	(0.0314)	(1.0793)	(0.0372)	(0.5755)
Vietnam	0.0140	0.0615**	0.9463***	-0.0172	18.1227*	-0.6078*	4.0925***
	(0.0312)	(0.0245)	(0.0257)	(0.0138)	(10.0928)	(0.3409)	(0.9155)
Mexico	0.0346	0.0352*	0.8679***	0.1570***	3.4082	0.0981***	176.3093***
	(0.0236)	(0.0195)	(0.0157)	(0.0325)	(2.7940)	(0.0120)	(0.2094)
Indonesia	0.0390	0.0349	0.8851***	0.0850***	-0.0969	0.0068	8.6009
	(0.0249)	(0.0253)	(0.0346)	(0.0323)	(1.6427)	(0.0569)	(10.3789)