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News implied volatility and long-term foreign exchange market volatility

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ABSTRACT

We apply the GARCH-MIDAS-X component framework to investigate the effect of news uncertainty on long-term exchange rate volatility. Strong empirical results reveal that market-wide information, news implied volatility (NVIX), plays an incremental role in explaining the secular volatility of FX markets relative to specific news announcements. In addition, our analysis distinguishes five sources of NVIX: Financial Intermediation, Stock Markets, Government, Natural Disasters and War. The evidence related to the five sub-indexes suggests that news regarding Financial Intermediation, Stock Markets and Government have a more significantly positive, long-run spillover impact on the volatilities of currencies. Moreover, although natural disasters and wars are rare, the news regarding them produces highly destructive impacts on society and exerts an influence on relevant currencies.

1. Introduction

FX (foreign exchange) markets are mostly organized as OTC (over-the-counter) markets, and participants therefore have little knowledge regarding traders in the other markets (Menkhoff, Sarno, Schmeling, & Schrimpf, 2016). Although private information, at times, is important, FX markets are mainly caused by public information, which results in a high contemporaneous correlation across quotes (Covrig & Melvin, 2002; Moore & Payne, 2011). With the updating of communication technologies, mass media news disseminates different types of information to both practitioners and policy makers, which exerts a latent influence on the views and behaviors of market participants. Consequently, FX markets are expected to be affected by news, which can be regarded as incremental information (Andersen, Bollerslev, Diebold, & Vega, 2003, 2007; Bauwens, Omrane, & Giot, 2005; Chen & Zhang, 2015; Degennaro & Shrieves, 1997; Evans & Lyons, 2008; Frömmel, Mende, & Menkhoff, 2008; Kamber, Theodoridis, & Thoenissen, 2017; Manzan & Westerhoff, 2005; Omrane & Savaşer, 2017).

The existing literature focuses on specific macro news announcements, including macroeconomic fundamentals, such as GDP, CPI, M2, target federal funds and net exports (Andersen et al., 2003, 2007; Bauwens et al., 2005; Chen & Gau, 2010; Dominguez & Panthaki, 2006; Omrane & Savaşer, 2016, 2017); or monetary policies, such as interventions and interest rates (Conrad & Lamla, 2010; Fatum & Scholnick, 2008). Most likely, due to data limitations, a voluminous previous literature studied the impact of specific type of news announcements (Vlastakis & Markellos, 2012). However, such investigations and related conclusions based on specific news announcements have limitations.

Firstly, as stated by Shleifer and Summers (1990) and De Long, Shleifer, Summers, and Waldmann (1990a, 1990b), rational traders adjust their strategies based on information about macro fundamentals to stabilize the market; however, the performance of noise trades is random, due to other noisy news.[2] Bessembinder, Chan, and Seguin (1996) distinguish firm-specific and market-wide information and conclude that individual equity volume is related with firm-specific information flows, whereas equity basket volume is affected by market-wide news. Although recent theoretical and empirical work on financial markets has begun to explore the influence of both idiosyncratic and market-wide information, the effect of market-wide information still holds solidly. Vlastakis and Markellos (2012) argue that the effect of idiosyncratic news on volatility is mixed and would diminish if the indicator of market activity news is taken into consideration. Ozturk and Sheng (2017) analyze the negligible impact of idiosyncratic uncertainty shocks, while market-wide uncertainty shocks drive real economic activity significantly. In this case, attention to specific macroeconomic news announcements is not necessarily the best indicator for that currency, while information comprising market-wide

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[1] All the authors contribute equally to this paper.
[2] The theory of the crucial role of demand for information has also been well studied in Kihlstrom (1974), Grossman and Stiglitz (1980), and Allen (1990).

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information may have better predictability.

Furthermore, FX markets can be affected by news regarding, for instance, the overall statement of macro economy, financial markets, and government policy, since investors collect all news in society to adjust their behaviors. Evans and Lyons (2002) document the informational integration, specifically, the importance of information conveyed by order flow in major currencies for FX pricing and trading. With the development of information technology, such as the Internet, investors have more access to information and disseminate and consume this news (Antweiler & Frank, 2004; Barber & Odean, 2001; Rubin & Rubin, 2010). As suggested by Peng and Xiong (2006), investors tend to capture market-wide information, rather than a particular event or factor, which helps to avoid category-focused behaviors. This is not surprising, because decision-makers tend to choose the information comprising a general market instead of a specific one (Maćkowiak & Wiederholt, 2009). However, little of the literature focuses on the impact of specific and market-wide information on exchange rate volatility and whether market-wide news plays an incremental role in explaining volatility in FX markets.

Secondly, the existing FX studies have mostly unveiled the short-term impact of news announcements on exchange rates (Andersen et al., 2003, 2007; Chan, Chhagan, & Marsden, 2017; Fatum & Scholnick, 2008; Faust, Rogers, Wang, & Wright, 2007; Pearce & Solakoglu, 2007), and ignored the long-run effect. These investigations mainly lie at event analysis at intradaily or daily frequencies, since FX markets might react to macro news releases instantaneously (Bauwens et al., 2005; Degennaro & Shrieves, 1997; Omrane & Savaşer, 2016; Pearce & Solakoglu, 2007). Although the adoption of high frequency data is long-standing, it mostly focuses on specific events or macro announcements with a narrow window, and until recently it seldom explored the time-varying effects of news over a long period. However, the survey conducted by Cheung and Chinn (2001) shows that 40% of FX traders believe that the effect of announcements on exchange rates will last for six months or more. Additionally, Evans and Lyons (2005) address the fact that FX markets do not respond to news instantaneously and still absorb the news with persistent effects due to induced end-user trades. Since handling the news and forming rational expectations may take a longer time (Chen & Zhang, 2015), there also exists a question of how news alters volatilities patterns in the long term. Moreover, long-term demand-side investors in FX markets are "trend followers", who are more concerned with fundamental information (Menkhoff et al., 2016). News associated with fundamentals is more likely to change their strategies in the long run, thus affecting the variations of exchange rates.

This consideration can also be supported by theoretical evidence. Purchasing Power Parity (PPP; Cassel, 1922), one of the most important theories in international economics, is meant to characterize long-term variations of currencies rather than short-term. The seminal work of Dornbusch (1976) proposes that the overshooting behavior of currencies in the short term is ascribed to the difference in fast financial markets and slow goods market arbitrage activities. The traditional literature's view is that the basic fundamental of exchange rate changes is the behavior of imports and exports of goods and of capital flows among different countries. Kouri (1976) assumes that speculators hold long-term foresight and rule out the expectations of asset supplies. The arbitrage in the goods market will take place in the long-run, which is consistent with PPP (Hausmann, Panizza, & Rigobon, 2006). Uncovered interest parity (UIP) theory also considers that exchange rates determine interest rates on a long-term basis. Furthermore, extensive evidence indicates that the movement of currency is not a random walk and shocks to exchange rates diminish slowly over time (Froot & Rogoff, 1995). The study regarding the determinants of long-run exchange rate volatility benefits from an understanding of the behaviors of macro markets, such as trading and interest rates.

To fill this gap in the research, our paper introduces a text-based measure of news uncertainty, the news implied volatility (NVIX) proposed by Manela and Moreira (2017), to investigate the dependence between news uncertainty and volatility of different currencies during a more recent and extensive period based on GARCH-MIDAS-X models.

Our paper contributes to the present literature in four ways. First, accounting for specific news announcements, we explore whether market-wide news uncertainty, NVIX, still plays an incremental role in explaining long-run exchange rate volatility. The paper also compares the models with NVIX and without NVIX to investigate whether NVIX's addition to the regressions is essential. The empirical results further demonstrate the significant and positive impact of market-wide information on the variations of FX markets when considering U.S. or native news announcements. Moreover, models with NVIX perform better than models without NVIX.

Second, traders in FX markets collect news from abundant different sources (Dominguez & Panthaki, 2006). Our analysis distinguishes five sources of news implied volatility, including news about *Financial Intermediation*, *Stock Markets*, *Government*, *Natural Disasters*, and *War*. Government-concerned news uncertainty induces long-term exchange rate volatility, significantly accounting for corresponding news announcements. Then, since different parts of the financial market can interact with each other through capital flow or policy changes, news about financial intermediation and stock markets are plausible factors affecting currency volatility. Moreover, the present literature only focuses on the effect of news about natural disasters and wars on stock markets (Hood, Kamesaka, Nofsinger, & Tamura, 2013; Hudson & Urquhart, 2015; Kamesaka, Nofsinger, & Kawakita, 2003; Worthington & Valadkhani, 2004), while paying only slight attention to the impacts on FX markets. Our paper extends the literature by exploring the ways in which rare but destructive news about natural disasters and wars affect FX markets.

Third, since conventional methods cannot incorporate low-frequency macro variables and high-frequency exchange rate variations in a straightforward way, our paper adopts the GARCH-MIDAS-X (a novel mixed data sampling) framework (Engle, Ghysels, & Sohn, 2013; Engle & Rangel, 2008) to investigate the effects of news uncertainty at a monthly frequency on the volatility of exchange rates over a relatively long period. The GARCH-MIDAS-X model isolates currency volatility into its short- and long-term components. Furthermore, the framework can incorporate macroeconomic variables, as news uncertainty or macroeconomic news announcements, which enables us to consider the long-term impacts of news uncertainty overlooked by previous studies.

Finally, prior works have focused on certain currency markets, such as euro/dollar, dollar/yen and dollar/DM (Cai, Cheung, Lee, & Melvin, 2001; Chen & Gau, 2010; Melvin & Yin, 2000; Omrane & Savaşer, 2017). Our paper provides broad evidence of the ten most actively traded currencies, including the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Danish krone (DKK), euro (EUR), Great Britain pound (GBP), Japanese yen (JPY), Norwegian krone (NOK), New Zealand dollar (NZD), Swedish krona (SEK). These currencies cover approximately 90% of trades in the global FX market, according to the Triennial Survey of the Bank for International Settlements (Corte, Ramadorai, & Sarno, 2016). As Bodnaruk and Ostberg (2009) proposed, the relationship between uncertainty and asset returns relies on the shadow cost of incomplete information, which turns out to depend on relative market size, institutional development, propensity of herd-like behavior and overreaction and other country-specific characteristics. The international evidence provides an opportunity to examine this hypothesis, and elaborates the results of the interdependence between FX markets and news uncertainty more reliably (Ang & Bekaert, 2007). Additionally, an analysis of this sort is more likely to compare the behaviors of different currencies.

The remainder of the article proceeds as follows. Section 2 introduces the GARCH-MIDAS framework and describes the data. Section 3 explains the incremental effect of NVIX relative to news announcements. Section 4 uncovers the spillover impact of different news uncertainty on the volatility of exchange rates. Section 5 discusses the relevant issues. Section 6 presents the study's conclusions.

2. Methodology and data

2.1. GARCH-MIDAS model

In this section, we study the GARCH-MIDAS model, proposed in Engle et al. (2013), to uncover the impact of news uncertainty on long-term exchange rate volatility. Various component methods do not incorporate low-frequency data with daily volatility in a straightforward manner, such as the Spline-GARCH model. Nevertheless, the GARCH-MIDAS component model develops a novel mixed data sampling (MIDAS) approach to link low frequency data of macroeconomic variables to high frequency volatilities of currencies, which disintegrates the conditional variance into short-run and long-run components. The former is estimated by a mean-reverting unit GARCH process and a history of macroeconomic variables, such as macro news announcements and news uncertainty, with lower frequency weighted by different polynomials that can estimate long-run volatility. Engle and Rangel (2008) write the unexpected return as a two-component volatility model,

$$r_i - E_{i-1,t}(r_{i,t}) = \sqrt{\tau_t g_{i,t}}\,\varepsilon_{i,t} \tag{1}$$

where r_i is the daily log return of exchange rate. The conditional variance is disintegrated into two parts: as $g_{i,t}$, defined as short-run volatility; and τ_i, denoting long-run exchange rate volatility. Additionally, $t = 1,2,\ldots,T$ represents the month, and $i = 1,2,\ldots,N(t)$ accounts for the days of month t. Then, setting $E_{i-1,t}(r_{i,t}) = \mu$, Eq. (1) can be represented as

$$r_i = \mu + \sqrt{\tau_t g_{i,t}}\,\varepsilon_{i,t},\ \forall\ i = 1,\ 2,\ \ldots,N(t), \tag{2}$$

where $\varepsilon_{i,\ t} \sim N(0,1)$ and $g_{i,t}$ follows a mean-reverting unit GARCH(1,1) process:

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-\mu)^2}{\tau_t} + \beta \bullet g_{i-1,t} \tag{3}$$

with $\alpha > 0$, $\beta > 0$, and $\alpha + \beta < 1$. The superiority of the GARCH-MIDAS method lies in incorporating low-frequency macroeconomic time series, called GARCH-MIDAS-X. In this paper, we include macroeconomic variables, such as news announcements and the general news uncertainty index, NVIX, in the following MIDAS function as exogenous variables:

$$\log\tau_t = m + \theta_i\sum_{i=1}^{n}\sum_{k=1}^{K}\varphi_k(\omega_{i1},\omega_{i2})X_{t-k,i}, \tag{4}$$

where $X_{t-k,i}$ denotes the macroeconomic variables. The GARCH-MIDAS-X model's parameter space comprises coefficients, such as μ, α, β, m, θ, ω. The most important parameter is θ, reflecting the relationship between exchange rate volatility and macro variables. A positive θ indicates that, while macroeconomic variables increase, the fluctuations of currencies will increase, and vice versa.

In terms of the weighting scheme, we adopt an unrestricted weighting scheme and exponential Almon lag polynomial method, which are given by

$$\phi_k(\omega_1,\omega_2) = \begin{cases} \dfrac{{\omega_1}^k}{\sum_{k=1}^{K}{\omega_1}^k} & \text{Unrestricted weighting scheme} \\ \dfrac{e^{\omega_1 k+\omega_2 k^2}}{\sum_{k=1}^{K} e^{\omega_1 k+\omega_2 k^2}} & \text{Exponential Almon lag polynomial scheme} \end{cases} \tag{5}$$

The unrestricted model can engender hump-shaped or convex weights. The exponential Almon lag polynomial is more flexible than the unrestricted scheme and can take different shapes for parameters. Moreover, the sum of the weights $\sum_{k=1}^{K}\phi_k(\omega_1,\omega_2)$ should be one, and the decaying pattern for long-term volatility is warranted by each $\omega_i > 1$. Specifically, the larger ω_i is, the faster the decaying pattern (Engle et al., 2013). Moreover, we choose two MIDAS lag years (K = 24) for filtering the long-term weighted component.

2.2. News uncertainty

To obtain estimates of the volatility of the macro economy, we use a new decomposition of the implied volatility indices, called NVIX (news implied volatility), an uncertainty proxy proposed by Manela and Moreira (2017),[3] with a monthly frequency from January 2000 to March 2016. The NVIX is constructed by extracting the titles and abstracts of front-page articles on the *Wall Street Journal* using machine learning techniques. The *Wall Street Journal*, the largest financial newspapers in the U.S., has an extensive readership among political, economic, and educational professionals, as well as financial tycoons and mangers, investors in financial markets and so on, which is sufficient to influence daily international economic activities. Moreover, changes in news information in the U.S. are intermediately unearthed by traders or investors in financial markets and spread to other markets, such as the way the U.S. financial crisis of 2008 soon contaminated other countries, evolving into a global financial crisis. The distinct feature of this text-based indicator is binding text from news coverage with aggregate risk premia, which is supposed to reflect the role of investors' attentions concerning variations in news information. Consequently, the text-based news uncertainty of the U.S. might be a plausible factor in explaining the variations in FX markets. Moreover, the NVIX index contains five types of news: Financial Intermediation (IN), Stock Markets (SM), Government (GOV), Natural Disasters (ND), and War (WAR). Thus, the NVIX covers a wide range of risks of news information, such as macroeconomic announcements, intervention by banks and portfolio positions, rare disasters and so on. Furthermore, these five sub-indexes can capture different concerns about uncertainty shocks, which can be employed to do empirical tests to explore which component drives FX markets' risk premium fluctuations more significantly. Table 1 displays the most related words of each sub-indexes.

Each NVIX component can be regarded as a different sort of news uncertainty. Fig. 1 plots the variations of NVIX and its five categories during the period of 2000:M1 to 2016:M3. We find stronger fluctuations of Financial Intermediation, Stock Markets and Government than of the other two sub-indexes. Natural Disasters vary within the scope of −0.15 to 0.05, and War changes mostly between 0 and 0.5, with the only large spike during the Iraq War.

2.3. News announcements

Following Andersen et al. (2003), our paper first uses U.S. macroeconomic announcements, as listed in Table 2, which covers the aspects of real activity, consumption, investment, government purchases, prices, and forward-looking actions of the U.S. Then, we also adopt different news announcements from Australia, Canada, Switzerland, Denmark, the European Union, the U.K., Japan, Norway, New Zealand, and Sweden, including gross domestic product, retail sales, industrial production, capacity utilization, personal income, consumer credit, unemployment rate, CPI, PPI, and m1. The details about these news announcements are represented in Appendix Table A1. All these macroeconomic news announcements data are obtained from the Thomson Reuters Datastream.

Table 2 presents the basic characteristics of news announcements in

[3] The NVIX data are obtained from Manela's website as http://apps.olin.wustl.edu/faculty/manela/data.html.

Table 1
Most related words of each sub-index (Manela & Moreira, 2017).

Sub-index	Most related words
Financial Intermediation	"Banks, financial, business, bank, credit"
Stock Markets	"Stock, market, stocks, industry, markets"
Government	"Tax, money, rates, government, plan"
Natural Disasters	"Fire, storm, aids, happening, shock"
War	"War, military, action, world war, violence"

Note: the NVIX index contains five types of news: Financial Intermediation (IN), Stock Markets (SM), Government (GOV), Natural Disasters (ND), and War (WAR).

the U.S., including sources, scheduled release times, frequency and abbreviations used in the papers. Among U.S. news announcements, most are released at 8:30 or 10:00 A.M. EST (Easter Standard Time), three announcements are released at 9:15 A.M., and the federal government budget balance, target federal funds rates, and money supply are released at 2:00 P.M., 2:15 P.M., and 4:30 P.M., respectively. Most news announcements in European countries are regularly released at 10:00 A.M. WET (Western European Time), and most Japanese news announcements are announced at 8:50 A.M. JST (Japanese Standard Time).

2.4. FX markets

We employ continuous daily exchange rates against the US dollar from January 2000 to March 2016. In our empirical exercise, our sample comprises ten currencies, including the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Danish krone (DKK), euro (EUR), Great Britain pound (GBP), Japanese yen (JPY), Norwegian krone (NOK), New Zealand dollar (NZD), and Swedish krona (SEK). These currencies cover approximately 90% of the trade in FX markets, according to the Triennial Survey of the Bank for International Settlements (2013).

Panels A and B in Table 3 provide summary statistics for the currency and uncertainty series. The means of exchange rates are at similar magnitudes with larger standard deviations. Most currencies are left-skewed, except for the AUD, GBP and NZD, and news uncertainty are mostly right-skewed, except for the ND. Overall, all these variables follow a leptokurtosis and fat-tail distribution. In terms of the Pearson correlation matrix in Panel C, we do not find that IN, SM and GOV are highly correlated with each other, whereas the correlation between ND, WAR and other indexes is lower and mostly nonsignificant.

3. Incremental effect of news implied volatility (NVIX)

3.1. Benchmark model considering unrestricted weighting scheme

In this section, we begin our analysis of the overall dependence between exchange rate volatilities with news announcements and NVIX, to explore the incremental effect of NVIX relative to news announcements. The GARCH-MIDAS-X model can divide the conditional variance into two parts, a short-term volatility with a daily frequency, and a long-term volatility component with a monthly frequency, which reflected the secular trend of the currencies, as shown in Fig. 2. We find that there are larger spikes in every estimated long-term volatility during 2008, which can affirm that the increase of news uncertainty during the global financial crisis affected most countries' FX markets, resulting in the increase of changes in long-term volatilities. Taking the Japanese yen as an example, we find that, during the 2008 global financial turmoil, long-term volatilities surged significantly, reaching 1.3E(−4), which is higher than in normal periods.

The GARCH-MIDAS-X approach combines macroeconomic variables with realized volatility to present the influence of the macro economy on the volatility of FX markets in the long run. Tables 4 and 5 illustrate the estimation results of the impact of U.S. and native news announcements, combined with NVIX, on long-term currency volatilities.

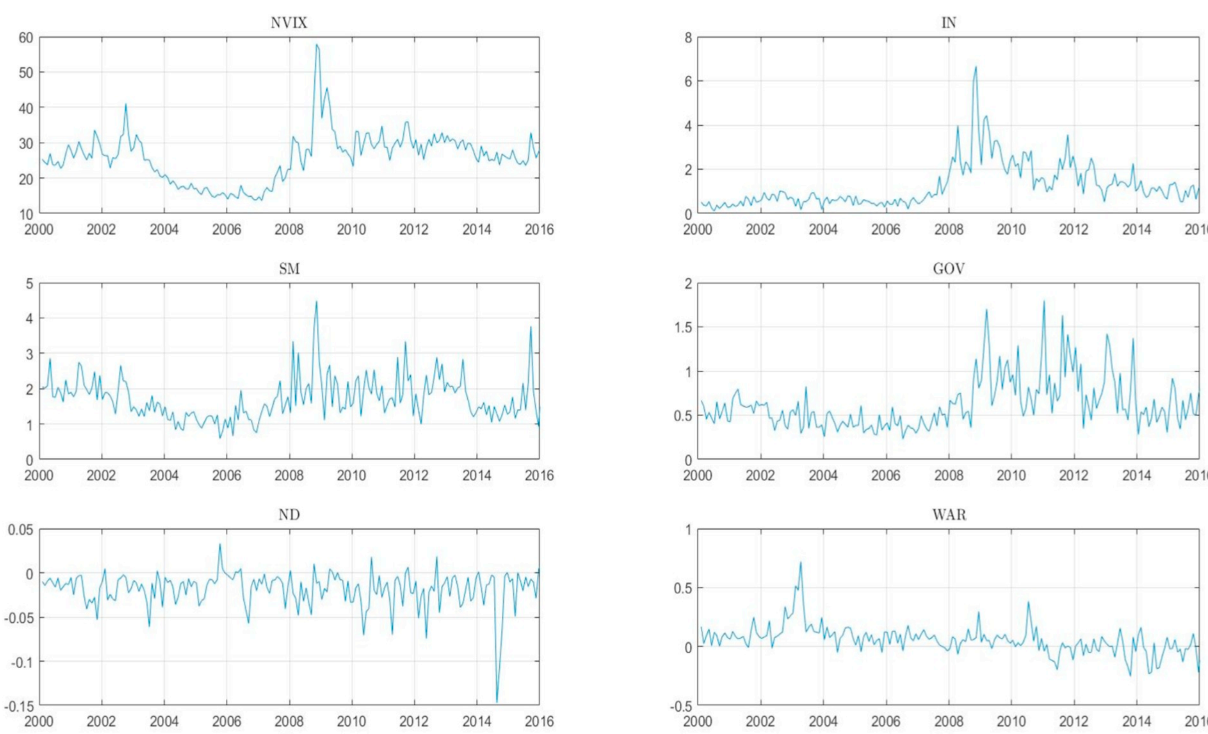


Fig. 1. News implied volatility (NVIX) and different word categories for the 1971:M1 to 2016:M3 period. The figure plots the variations of NVIX and Financial Intermediation (IN), Stock Markets (SM), Government (GOV), Natural Disasters (ND), and War (WAR) during the period of 2000:M1 to 2016:M3. We find stronger fluctuations of Financial Intermediation, Stock Markets and Government than the other two sub-indexes. Natural Disasters vary within the scope of −0.15 to 0.05, and War changes mostly between 0 and 0.5, with the only large spike during the Iraq War.

Table 2
U.S. news announcements.

Announcements	Source	Scheduled release time (EST)	Frequency	Abbreviation
GDP	BEA	8:30 A.M.	Quarterly	gdp
Personal consumption expenditures	BEA	10:00/8:30 A.M.	Monthly	percon
Retail sales	BC	8:30 A.M.	Monthly	retail
Industrial production	FRB	9:15 A.M.	Monthly	indusp
Capacity utilization	FRB	9:15 A.M.	Monthly	capu
Personal income	BEA	10:00/8:30 A.M.	Monthly	perin
Consumer credit	FRB	9:15 A.M.	Monthly	consum
New home sales	BC	10:00 A.M.	Monthly	newhome
Durable goods orders	BC	8:30/9:00/ 10:00 A.M.	Monthly	dur
Unemployment rate	ETA	8:30 A.M.	Monthly	unem
Construction expenditure	BC	10:00 A.M.	Monthly	conex
Business inventories	BC	10:00/8:30 A.M.	Monthly	busi
Federal government budget balance	FRB	2:00 P.M.	Monthly	feder
CPI (consumer confidence index)	BLS	8:30 A.M.	Monthly	cpi
Consumer confidence index	CD	10:00 A.M.	Monthly	cci
Target federal funds rates	FRB	2:15 P.M.	Six weeks	fedrate
Money supply, M1	FRB	4:30 P.M.	Monthly	m1

Note: The table lists the U.S. news announcements and their sources, scheduled release times, release frequency and abbreviations in the paper. The sources are the Bureau of the Census (BC), the Bureau of Economic Analysis (BEA), the Federal Reserve Board (FRB), the Conference Board (CB), and the Employment and Training Administration (ETA).

We adopt Akaike and Bayesian information criteria (AIC and BIC) to analyze the fit of the models. Furthermore, following the paper of Conrad and Loch (2015), we also report a variance ratio (VR) statistic to investigate how much of the long-term variance of currencies can be explained by the variations of macroeconomic variables (Engle et al., 2013). The VR is defined as

$$VR(X) = \frac{\widehat{var}(\log(\tau_t^X))}{\widehat{var}(\log(\tau_t^{RV} g_t^{RV}))}$$

which is the fraction of the log of the total expected variance estimated by the GARCH-MIDAS-RV model. The VR statistic reflects the attribution of macro variables in explaining the long-term variance of exchanges rates. Low VR does not necessarily indicate a poor fit of the model but can imply that the macroeconomic variables used move smoothly in the model when explaining long-term volatility.

First, the location-parameter (μ) is mostly significant for the exchange rates in unrestricted models. In addition, the significant results forα and β at the 1% level take the typical values, which conforms to the leverage effect. Furthermore, the sum of α and β is slightly less than one, indicating that, for all currencies estimated, the short-term volatilities of exchange rates are mean-reverting to the long-term trend.

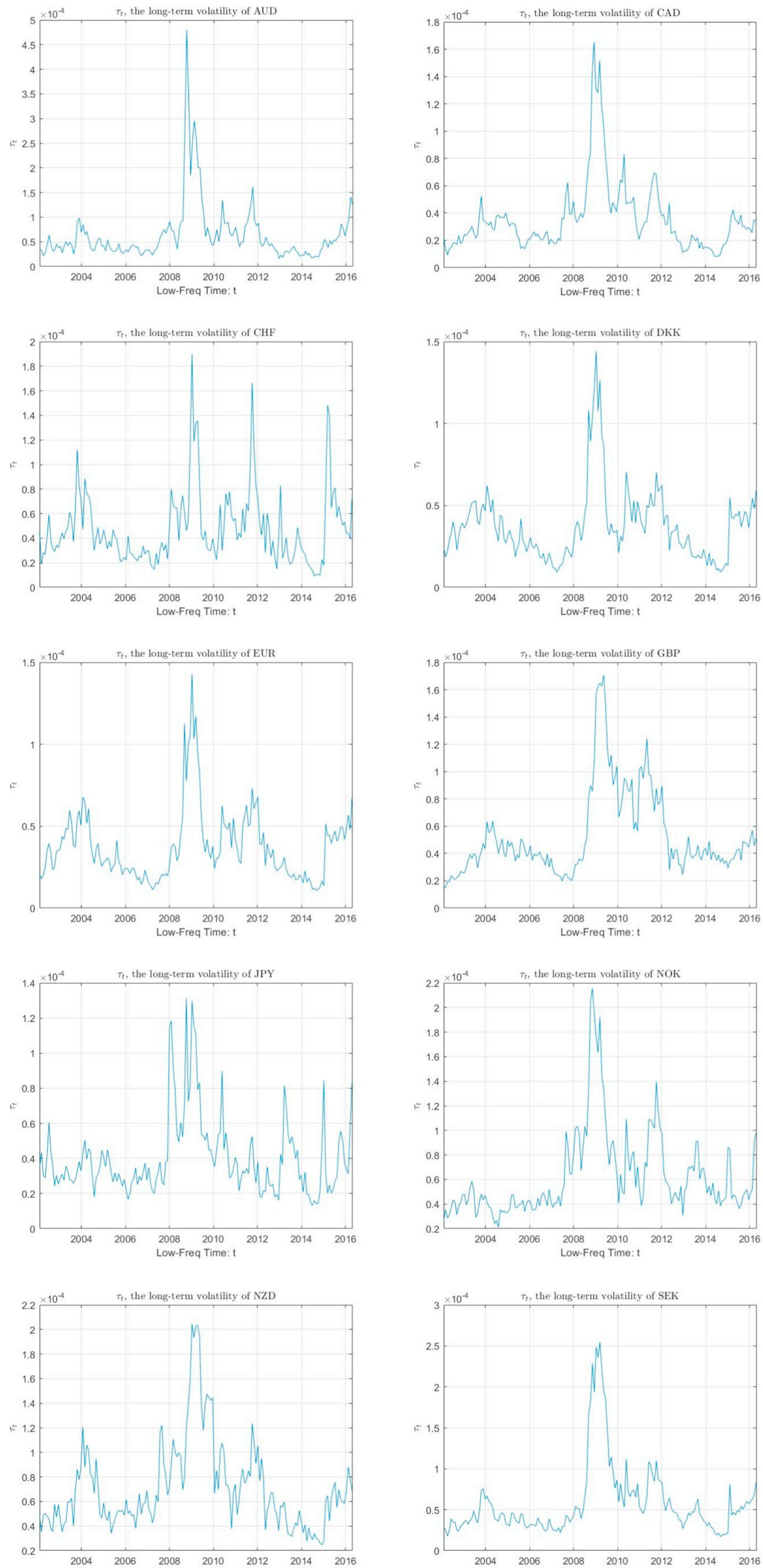
Second, we examine whether the news uncertainty proxy, NVIX, includes the additional predictive information of long-run volatility components relative to specific news announcements. The paper first considers the incremental effect of NVIX accounting for specific U.S. news information. Table 4 suggests that the parameter θ of NVIX is significant at 1% in most models when considering U.S. news announcements, except for the EUR and NOK, showing that the NVIX index engenders a highly significant incremental spillover influence on long-term exchange rate volatilities. Moreover, the estimated parameter θ of NVIX is positive in all GARCH-MIDAS-X models, which means an increase of news uncertainty will lead to an upsurge in the

Table 3
Descriptive statistics for FX markets and uncertainty data.

Statistics	Mean	Max.	Min.	Std. dev.	Skew.	Kurt.	Jarque-Bera	Obs.
Panel A: currencies								
AUD	0.0000	0.0883	−0.0670	0.0083	0.7949	14.9147	25,520.2***	4239
CAD	0.0000	0.0434	−0.0505	0.0059	−0.1196	8.3480	5061.8***	4239
CHF	−0.0001	0.0847	−0.1142	0.0071	−0.8646	27.2612	104,490.4***	4239
DKK	0.0000	0.0386	−0.0462	0.0063	−0.1573	5.4883	1111.1***	4239
EUR	0.0000	0.0384	−0.0462	0.0063	−0.1532	5.4495	1076.4***	4239
GBP	0.0000	0.0392	−0.0447	0.0058	0.0171	7.2082	3128.1***	4239
JPY	0.0000	0.0371	−0.0461	0.0064	−0.2735	6.8751	2705.1***	4239
NOK	0.0000	0.0502	−0.0646	0.0077	−0.0077	7.2452	3183.1***	4239
NZD	−0.0001	0.0665	−0.0588	0.0086	0.4008	7.9544	4448.9***	4239
SEK	0.0000	0.0354	−0.0555	0.0076	−0.1761	6.2279	1862.2***	4239
Panel B: news uncertainty								
NVIX	0.0000	0.4983	−0.4225	0.1149	0.6406	5.4764	63.2***	195
IN	0.1118	2.5107	−0.7503	0.5452	1.7035	7.0673	228.7***	195
SM	0.0560	1.5402	−0.5470	0.3740	1.3186	5.5114	107.8***	195
GOV	0.0678	1.5271	−0.6777	0.4008	0.8860	3.8059	30.8***	195
ND	−0.6058	26.0935	−71.4101	7.2796	−5.5725	53.5368	21,760.2***	195
WAR	−0.1651	34.8219	−33.6829	4.6473	0.6018	33.3523	7497.0***	195

	NVIX	IN	SM	GOV	ND	WAR
Panel C: Pearson correlation matrix						
NVIX	1					
IN	0.685***	1				
SM	0.674***	0.466***	1			
GOV	0.587***	0.589***	0.310***	1		
ND	−0.025	−0.004	0.080	0.022	1	
WAR	0.039	−0.132*	−0.021	−0.130*	0.106	1

Notes: This table reports the summary statistics and Person correlations of news uncertainty from January 2000 to March 2016. The reported statistics include the mean, the minimum (Min.) and maximum (Max.), standard deviation (Std. Dev.), Skewness (Skew.), Kurtosis (Kurt.), Jarque-Bera statistic and the number of observations (Obs.) and time spread. NVIX, IN, SM, GOV, ND, WAR represent News implied volatility, Financial Intermediation, Stock Markets, Government, Natural Disaster, and War. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.



(caption on next page)

Fig. 2. Long-run components of different currencies. The figure illustrates the long-term volatility of different currencies based on the GARCH-MIDAS-X model using daily exchange rate return data. The maximum likelihood of the model applies MIDAS beta weights of 24-month lags.

fluctuations of FX markets in long run. Taking CHF as an example, the parameter θ is 0.5746 at the 1% significance level. The first lag of NVIX with the largest weight is 0.2736 when ω is 9.3174. Hence, with the increase of one standard deviation of NVIX, the volatility of CHF rises by $e^{0.5746*0.2736}-1\approx 17.02\%$ in the next month. Furthermore, we also add both native news announcements of different countries and NVIX to the model to explore whether NVIX still plays a crucial in explaining the secular volatility of FX markets as shown in Table 5. The impact is still significant for half of the currencies, including AUD, CAD, JPY, NZD, SEK. The parameter θ of NVIX is mostly positive except for the EUR.

Finally, we compare the GARCH-MIDAS-X models that contain specific news announcements with and without market-wide information, NVIX. The estimations of models without NVIX are represented in Appendix Tables A.2 and A.3. Lower AIC and BIC indicate a better fit of the model. According to AIC and BIC, we find that models with NVIX are mostly better fits, whether considering U.S. or native news announcements. Moreover, higher VR means the improved explanation of macro variables. Models with NVIX outperform the models without

Table 4
Regression results for the impact of NVIX and U.S. news announcements on currencies based on the GARCH-MIDAS-X model.

Currencies	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
μ	−0.0002***	−0.0001***	−0.0001***	−0.0001	−0.0001***	−0.0001***	0.0000***	−0.0001***	−0.0002***	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
α	0.0334***	0.0287***	0.0167***	0.0056***	0.0093***	0.0323***	0.0206***	0.0250***	0.0360***	0.0093***
	(0.0064)	(0.0049)	(0.0063)	(0.0043)	(0.0035)	(0.0049)	(0.0066)	(0.0035)	(0.0071)	(0.0052)
β	0.9303***	0.9663***	0.8899***	0.9717***	0.9725***	0.9649***	0.9228***	0.968	0.9348	0.9401***
	(0.0129)	(0.0062)	(0.0196)	(0.0157)	(0.0083)	(0.0047)	(0.0233)	(0.0048)	(0.0155)	(0.0324)
m	−11.0443***	−10.1246	−7.735***	−9.5386	−9.4917	−9.105	−10.5142***	−9.5586	−9.0126	−10.023***
	(0.2668)	(0.2305)	(0.2953)	(0.2818)	(0.1548)	(0.6903)	(0.2156)	(0.2500)	(0.2355)	(0.2107)
θ_{usgdp}	0.4817***	0.0587**	0.2394***	−0.0401	0.0647	−0.0104	0.3566	0.0537	−0.0088	0.2539***
	(0.0735)	(0.0344)	(0.0492)	(0.1561)	(0.1822)	(0.0335)	(0.0589)	(0.0317)	(0.0154)	(0.0599)
$\theta_{uspercon}$	−1.4418**	−0.4354	−0.3298	−0.1663	−1.4184	−0.0236	4.6246	−1.4907**	−0.1994	−0.1543***
	(0.4657)	(0.1878)	(0.0562)	(0.1879)	(0.9277)	(0.0873)	(4.0837)	(1.8089)	(0.4224)	(0.0494)
$\theta_{usretail}$	1.1603***	0.0911***	−0.0491***	0.2060***	0.3909***	0.0229***	−0.1148***	0.8335	7.8501	1.2465***
	(0.5591)	(0.0755)	(0.0502)	(0.1747)	(0.8019)	(0.0232)	(0.5159)	(0.4165)	(5.2156)	(0.4214)
$\theta_{usindusp}$	−0.4313**	−0.1998***	−0.0588***	−4.5113***	−0.4780***	−0.4660**	5.4473***	1.1995	−0.0586**	−0.3168***
	(0.0620)	(0.0742)	(0.0160)	(0.5420)	(0.0703)	(0.1776)	(1.3124)	(0.6545)	(0.0845)	(0.0470)
θ_{uscapu}	0.0365	0.1923	0.3695**	4.582***	0.4429	0.3562	−7.0242	−0.8761	1.0668	0.0705**
	(0.0151)	(0.0638)	(0.0524)	(0.5780)	(0.0714)	(0.1633)	(1.2949)	(0.6306)	(0.5119)	(0.0170)
$\theta_{usperin}$	−0.0938	0.0411	0.1276***	−0.603	−0.5257	0.4072	−0.0026***	−0.011**	−0.0009***	−0.4615
	(0.0822)	(0.0616)	(0.0586)	(0.1647)	(0.2821)	(1.0086)	(0.0115)	(0.0063)	(0.0137)	(0.2216)
$\theta_{usconsum}$	0.0264	−0.0813**	−0.1142***	0.0425***	0.0282***	−0.0866**	−0.4872***	−0.1326	−0.1948	−0.3824
	(0.0943)	(0.0702)	(0.0237)	(0.1421)	(0.1523)	(0.0601)	(0.0781)	(0.0624)	(0.0644)	(0.2623)
$\theta_{usnewhome}$	−0.6609	−0.2016	0.3171***	2.0369***	0.2174	0.0694	2.4904	−0.0955	0.4562	−0.0321
	(0.4888)	(0.0923)	(0.0549)	(0.2325)	(0.0488)	(0.0327)	(0.4982)	(0.1352)	(0.359)	(0.0626)
θ_{usdur}	0.0480	0.2025	−0.1875***	−1.7587***	−0.1505	−0.0295	0.2266	0.1261	−2.679	0.0143
	(0.2165)	(0.1549)	(0.0227)	(0.6058)	(0.1263)	(0.1007)	(0.2186)	(0.2659)	(1.7541)	(0.0215)
θ_{usunem}	0.0197***	0.044	−0.1232***	2.4995***	−0.1908	0.0121	−0.0062***	0.0255	0.0271	−0.0278**
	(0.0249)	(0.0562)	(0.0283)	(0.6861)	(0.1301)	(0.1089)	(0.0214)	(0.0176)	(0.0179)	(0.0337)
$\theta_{usconex}$	−0.7523	−0.0113	−0.1769***	1.9234	0.0034	0.1019	−0.4249**	−0.0572	0.1531**	−0.2881
	(0.1654)	(0.0487)	(0.0557)	(0.3873)	(0.3614)	(0.1307)	(0.1596)	(0.0375)	(0.1742)	(0.1312)
θ_{usbusi}	−0.1527	−0.3182	0.3273***	0.3276**	0.0612***	0.0695	0.2334**	0.0875	0.8545**	−0.186***
	(0.0916)	(0.1925)	(0.0741)	(0.1764)	(0.0963)	(0.3677)	(0.1010)	(0.1080)	(0.3804)	(0.1165)
$\theta_{usfeder}$	−0.0131**	−0.0361	0.2404***	0.1059***	0.0941	0.0066	−0.1427	−0.0545	0.9588	0.3939
	(0.0363)	(0.0551)	(0.0239)	(0.0502)	(0.0184)	(0.0118)	(0.0599)	(0.0381)	(0.4124)	(0.1297)
θ_{uscpi}	−1.2723	−0.0638	−0.1431	−0.7777***	−0.6055	−0.0583	−0.0202	−0.0398	0.0190	−0.0340
	(0.5411)	(0.0412)	(0.0472)	(0.1970)	(0.3858)	(0.0808)	(0.0237)	(0.0259)	(0.0150)	(0.0283)
θ_{uscci}	−0.0917	0.0105	−0.0698	0.9751	0.0017	0.012	−0.099***	0.1899	0.9935***	−0.0222
	(0.0610)	(0.0191)	(0.0585)	(0.1699)	(0.0487)	(0.0255)	(0.0883)	(0.2586)	(0.6542)	(0.0530)
$\theta_{usfedrate}$	0.3248	−0.0134	−0.3854***	−0.4530	−0.4637**	0.8361	−1.1569	−0.1219	−1.1875***	−0.1256
	(0.3195)	(0.0404)	(0.2064)	(0.2841)	(0.3043)	(0.995)	(0.2575)	(0.1286)	(0.3576)	(0.0961)
θ_{usm1}	0.1415***	0.0559***	−0.1318***	−0.2169***	−0.2467***	−0.0108**	−0.0646***	0.1555***	−0.6698	0.0909***
	(0.0999)	(0.0565)	(0.0178)	(0.1614)	(0.1122)	(0.4770)	(0.0369)	(0.0914)	(0.2301)	(0.0716)
θ_{nvix}	0.3785***	0.3351***	0.5746***	0.2225***	0.2183	0.0396***	0.2363***	0.2397	0.0378***	0.2085***
	(0.0517)	(0.0489)	(0.1499)	(0.0639)	(0.0373)	(0.0177)	(0.0436)	(0.0459)	(0.0205)	(0.0385)
AIC	−23,528.29	−25,326.31	−24,193.83	−24,965.29	−24,948.06	−25,446.84	−24,649.01	−23,370.80	−22,806.73	−23,634.44
BIC	−23,403.57	−25,201.59	−24,075.35	−24,840.57	−24,823.34	−25,446.84	−24,524.29	−23,246.08	−22,682.01	−23,509.72
VR	1.7272	1.3171	2.1808	1.9342	1.8457	1.6392	2.2024	1.5127	1.7437	2.2425

Notes: The table reports the empirical results for the unrestricted GARCH-MIDAS-X models for different currencies. The model estimated includes 2 MIDAS lag years, as K = 24. The long-run component is defined as

$$\log\tau_t = m+\theta_i\sum_{i=1}^{n}\sum_{k=1}^{K}\phi_k(\omega_{i1}\omega_{i2})X_{t-k,i},\quad \text{(unrestricted weighting scheme)}$$

where $X_{t-k,\,i}$ denotes the macroeconomic variables, including U.S. news announcements and NVIX. AIC and BIC are the Akaike information criterion and Bayesian information criterion. The table also reports variance ratio (VR) statistics. To avoid making the table too large to include, we do not report the estimation of parameter ω.
*, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 5
Regression results for the impact of NVIX and native news announcements of different countries on corresponding currencies based on the GARCH-MIDAS-X model.

Currencies	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
μ	−0.0001***	−0.0001***	−0.0002	−0.0001***	−0.0001***	−0.0001***	0.0000***	−0.0001***	−0.0001***	−0.0001***
	(0.0003)	(0.0164)	(0.0076)	(0.0001)	(0.0062)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
α	0.0441***	0.0257***	0.0319***	0.0239***	0.0265***	0.0277***	0.0379***	0.0256***	0.0258***	0.0214***
	(0.0154)	(0.0071)	(0.3716)	(0.0028)	(0.0036)	(0.005)	(0.0084)	(0.0046)	(0.0041)	(0.0039)
β	0.9448***	0.9485***	0.9320	0.9748***	0.9716***	0.9654***	0.9396***	0.9664***	0.9621***	0.9716***
	(0.0308)	(0.0148)	(0.0405)	(0.003)	(0.0036)	(0.0067)	(0.0084)	(0.0063)	(0.0063)	(0.0059)
m	−9.1015***	−8.1773	−12.0206***	−10.2281	−9.1834	−10.9306***	−10.0195	−9.6618	−9.8610	−9.353***
	(0.3428)	(0.2724)	(8.7540)	(0.2932)	(0.5089)	(0.2301)	(0.3751)	(0.1732)	(0.2987)	(0.1123)
θ_{gdp}	−1.4603***	−0.2164	1.9926	−0.0394	−0.2154	−0.4767	0.1355	0.2907**	0.0861***	−1.032
	(0.0933)	(0.1623)	(0.2676)	(0.0447)	(0.1631)	(0.1333)	(0.0765)	(0.1689)	(0.0949)	(0.1268)
θ_{percon}	−0.7167	0.0502***	2.0631	0.1577**	−0.1446***	0.1469	−0.0533	−0.1439	0.1465***	−0.0693***
	(0.2406)	(0.1309)	(11.3125)	(0.2335)	(0.0875)	(0.2319)	(0.1342)	(0.0602)	(0.0385)	(0.0582)
θ_{retail}	−0.2639	−0.4540***	−0.2534**	−0.1339	−0.7185***	0.1074	−0.1675***	−0.5246	−0.9500**	−0.4680
	(0.1719)	(0.1762)	(11.4321)	(0.0656)	(0.2597)	(0.6343)	(0.1943)	(0.2966)	(0.1454)	(0.1232)
θ_{indusp}	0.0051	5.4986***	−3.0407***	−0.4746	−0.5313	−0.5459	0.3542	0.2258***	−0.1855	−0.2038***
	(0.0265)	(0.8032)	(1.5193)	(0.6138)	(0.1456)	(0.5227)	(0.1345)	(0.1957)	(0.0766)	(0.1636)
θ_{capu}	−0.0888**	1.0734***	0.6916***	−0.2365**	0.3057	−0.0423	0.263	−0.3463		0.6014**
	(0.2704)	(0.1712)	(0.2184)	(0.1791)	(0.1916)	(0.0881)	(0.1820)	(0.1127)		(0.0860)
θ_{perin}	8.3186	1.4524***	5.6739	0.1656		0.8987	−0.1121		−0.0644**	−0.0546
	(3.2334)	(0.2141)	(1.4433)	(0.0668)		(0.7670)	(0.1491)		(0.0974)	(0.0249)
θ_{consum}	−0.1181	1.3814***			−0.5430	0.5597	0.3015***	−3.6098	0.3330	
	(0.3914)	(0.0958)			(0.2391)	(0.4120)	(0.1976)	(1.7231)	(0.1300)	
θ_{unem}	−0.044***	0.6193***	0.5218	−0.322	0.0299***	0.0229	0.5045	0.0075	0.0108***	
	(0.3106)	(0.0463)	(3.2913)	(0.1990)	(0.0765)	(0.0517)	(0.0881)	(0.0126)	(0.0347)	
θ_{cpi}	−1.2001***	−5.6404	7.7901	−0.1468**	−0.3398	0.2951**	0.1339	−0.0568***	−0.1097	−0.0508***
	(0.1368)	(0.4261)	(5.9359)	(0.1571)	(0.1046)	(0.3190)	(0.1078)	(0.0374)	(0.0337)	(0.0312)
θ_{ppi}	−2.3435***	−0.1460***	−0.5026***	−0.6962	0.1438	0.1982	0.0587	0.3665	−0.1578	0.7025
	(0.5585)	(0.1061)	(3.7975)	(0.3086)	(0.0900)	(0.099)	(0.0750)	(0.1179)	(0.0996)	(0.1416)
θ_{m1}	3.4401	−2.2314***	0.4907***	0.228***	−0.4820	0.0359***	−0.0792**		0.0512***	0.0211***
	(0.5026)	(0.1861)	(0.1527)	(0.1496)	(0.2589)	(0.0374)	(0.0750)		(0.0356)	(0.0332)
θ_{nvix}	2.8336***	2.9211***	0.2217	0.1516	−0.0844	0.1950	0.1671***	2.5442	0.2645***	0.1724***
	(2.2077)	(0.4317)	(0.0845)	(0.0429)	(0.0695)	(0.0498)	(0.0674)	(0.5097)	(0.0347)	(0.0369)
AIC	−23,506.00	−25,363.31	−24,085.23	−24,949.21	−24,919.52	−25,484.50	−24,583.58	−23,408.16	−22,843.41	−23,616.50
BIC	−23,418.69	−25,276.01	−24,004.16	−24,868.14	−24,838.46	−25,397.20	−24,496.27	−23,333.33	−22,762.35	−23,541.66
VR	1.6402	1.8092	2.1044	1.5707	1.5028	1.4317	1.8143	1.5474	1.7037	1.68

Notes: The table reports the empirical results for the unrestricted GARCH-MIDAS-X models for different currencies. The model estimated includes 2 MIDAS lag years, as K = 24. The long-run component is defined as

$$\log \tau_t = m + \theta_i \sum_{i=1}^{n} \sum_{k=1}^{K} \phi_k (\omega_{i1}\omega_{i2}) X_{t-k,i}, \quad \text{(unrestricted weighting scheme)}$$

where $X_{t-k,\ i}$ denotes the macroeconomic variables, including native news announcements and NVIX. AIC and BIC are the Akaike information criterion and Bayesian information criterion. The table also reports variance ratio (VR) statistics. To avoid making the table too large to include, we do not report the estimation of parameter ω.

*, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

NVIX and have higher VR, which further confirms the impact of market-wide information. Taken together, these results provide evidence in favor of adding news uncertainty as a crucial incremental factor in explaining the fluctuations of FX markets. When the changes of uncertainty reflected in news increase, the volatilities of currencies tend to vary more severely.

3.2. Robustness checking of the exponential Almon lag polynomial scheme

In this section, we investigate whether our results are robust based on tests of the GARCH-MIDAS-X model considering the exponential Almon lag polynomial method.

The unrestricted model can engender hump-shaped or convex weights. The exponential Almon lag polynomial is more flexible than the unrestricted scheme, and allows us to get different shapes for parameters, which works well in practice (Ghysels, Sinko, & Valkanov, 2007). Hence, we employ the exponential Almon scheme to further explore whether the incremental influence of NVIX on exchange rate volatility is robust.

Table 6 reports the regression results accounting for the exponential Almon method. First, the results show some well-documented patterns: a significant location-parameter (μ), as well as α and β at the 1% level, is observed; The sum of α and β approaches one, implying a mean-reverting process of short-run volatility. Then, the θ_{nvix} is positive for all the currencies, suggesting a positive relationship between NVIX and long-run volatilities. Additionally, NVIX engenders a significant spillover impact for most exchange rate volatilities, except the AUD and GBP, relative to specific U.S. news announcements. In general, the results are robust, and do not depend on any specific methodology. NVIX does affect the long-run volatility components of the FX markets estimated, which contributes to the complementary explanation for currencies accounting for specific news information.

4. Impact of news uncertainty on long-term exchange rate volatilities

Previous results suggest that the NVIX index exposes information about the long-run volatility of exchange rates, which complements the realized volatility. To better understand the concerns driving the long-run exchange rate volatilities, we apply five sub-indexes decomposed from NVIX to quantify the impacts of different types of risk premiums on fluctuations of FX markets. Although ND and WAR are not related with other sub-indexes, IN, SM and GOV are closely associated with each other. Therefore, we added each sub-index separately in the GARCH-MIDAS-X models to the spillover effect of the five sub-indexes, as IN, SM, GOV, ND

Table 6
Regression results for the impact of NVIX and U.S. news announcements on currencies based on the GARCH-MIDAS-X model considering the Almon weighting scheme.

Currencies	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
μ	−0.0002***	−0.0001***	−0.0002***	−0.0001	−0.0001***	−0.0001***	0.0000***	−0.0001***	−0.0002***	−0.0001***
	(0.0200)	(0.0015)	(0.0198)	(0.0382)	(0.1507)	(0.0080)	(0.0032)	(0.0245)	(0.6022)	(0.0201)
α	0.0439***	0.0403***	0.0331***	0.001***	0.0116***	0.0289***	0.031***	0.026***	0.0352***	0.0278***
	(0.0045)	(0.0048)	(0.0045)	(0.003)	(0.0018)	(0.0053)	(0.0063)	(0.0036)	(0.0094)	(0.0037)
β	0.9444***	0.9538***	0.9454***	0.7651***	0.9864***	0.9632***	0.9372***	0.9551***	0.9506***	0.9659***
	(0.0052)	(0.0054)	(0.0074)	(0.1282)	(0.0016)	(0.0070)	(0.0119)	(0.0063)	(0.0099)	(0.0049)
m	−9.2003	−9.8369	−9.8126	−9.9984**	−10.0646**	−10.0903***	−9.7348***	−9.5045***	−9.1343	−9.6719
	(0.0899)	(0.1654)	(0.0682)	(0.0536)	(0.0623)	(0.1863)	(0.0768)	(0.0626)	(0.1090)	(0.1413)
θ_{usgdp}	−0.0816***	−0.0974***	0.0670	−0.1491	−0.1628	−0.2314	−0.3078***	−0.2636**	−0.072***	−0.0824**
	(0.0854)	(0.0875)	(0.0861)	(0.0726)	(0.0736)	(0.0889)	(0.0791)	(0.0744)	(0.0961)	(0.0785)
$\theta_{uspercon}$	−0.5452	−0.3448	0.1707	−0.0772**	−0.1191	0.0020	−0.3179	−0.2138	−0.5180	−0.2030
	(0.1114)	(0.1278)	(0.1061)	(0.0755)	(0.0807)	(0.1465)	(0.0951)	(0.088)	(0.1384)	(0.1002)
$\theta_{usretail}$	0.4677***	−0.0087***	−0.2642***	0.5291	0.2459**	−0.0621***	−0.4016***	−0.1477***	−0.1621**	0.1864
	(0.2921)	(0.2969)	(0.3181)	(0.2659)	(0.2716)	(0.3693)	(0.2910)	(0.2644)	(0.3131)	(0.2762)
$\theta_{usindusp}$	−0.2262***	−0.2915***	−0.1922***	−0.1841	−0.0931	−0.2779***	−0.1806***	−0.2365***	−0.1933***	−0.0644
	(0.0623)	(0.0817)	(0.0401)	(0.1043)	(0.0392)	(0.1018)	(0.0373)	(0.0363)	(0.0884)	(0.0732)
θ_{uscapu}	0.2084	0.2909***	0.1635***	0.1689	0.0790	0.2687	0.1860	0.2276	0.1852	0.0575
	(0.0652)	(0.0812)	(0.0372)	(0.1062)	(0.0471)	(0.0857)	(0.0396)	(0.0386)	(0.0406)	(0.0659)
$\theta_{usperin}$	−0.0193	−0.1115	−0.1198	−0.0824	−0.0644	−0.047	−0.0238	−0.0461	−0.0258	−0.0063
	(0.041)	(0.0343)	(0.0371)	(0.0492)	(0.0391)	(0.0457)	(0.0380)	(0.0307)	(0.0392)	(0.0391)
$\theta_{usconsum}$	0.0917***	0.0995	0.0473**	−0.0007	−0.0123	0.0638**	0.0315	0.0450	0.0565**	−0.0472**
	(0.0596)	(0.0525)	(0.0459)	(0.044)	(0.0409)	(0.0558)	(0.0551)	(0.0408)	(0.0483)	(0.0486)
$\theta_{usnewhome}$	−0.1019	−0.0434	0.0665***	−0.0161**	−0.0413	−0.0820	−0.0602	−0.0597	−0.0852	−0.0816
	(0.0334)	(0.0345)	(0.0339)	(0.2514)	(0.0313)	(0.0386)	(0.0368)	(0.0322)	(0.0374)	(0.0333)
θ_{usdur}	−0.0158	−0.0211	−0.0498	−0.0352	−0.0298	−0.0136	−0.0045	0.0118	−0.0147	−0.0053
	(0.0194)	(0.0136)	(0.0149)	(0.0173)	(0.1468)	(0.0161)	(0.0142)	(0.0146)	(0.0762)	(0.0138)
θ_{usunem}	−0.0118	0.0024	0.0263	−0.0118	−0.0133	0.0178	−0.0118**	−0.0171	−0.0195	−0.0102
	(0.0198)	(0.0141)	(0.0138)	(0.0193)	(0.015)	(0.0212)	(0.0162)	(0.0133)	(0.1133)	(0.0118)
$\theta_{usconex}$	0.4847***	0.4146***	−0.2521**	0.1685**	−0.0126**	0.2573	0.5663***	0.0125***	0.4493***	0.1678**
	(0.2769)	(0.2951)	(0.2775)	(0.1897)	(0.2276)	(0.4418)	(0.2804)	(0.2439)	(0.3061)	(0.2575)
θ_{usbusi}	−0.3941	−0.2487	−0.1631	−0.1148	−0.1345	−0.1997	−0.1693**	−0.2783**	−0.2564	−0.1457
	(0.0928)	(0.087)	(0.0695)	(0.0522)	(0.0645)	(0.1082)	(0.0619)	(0.0584)	(0.0888)	(0.0719)
$\theta_{usfeder}$	0.0419**	0.0309	0.0064***	0.0369**	0.0492	0.0273	0.0526	0.0418	0.0147	0.0434
	(0.0314)	(0.0258)	(0.0323)	(0.0449)	(0.0262)	(0.0282)	(0.0248)	(0.0192)	(0.025)	(0.0244)
θ_{uscpi}	−0.2598**	−0.1402	−0.6243***	−0.2013	−0.1367	−0.0921	0.0797	0.1314	−0.0433	0.0136
	(0.1073)	(0.1123)	(0.0996)	(0.0841)	(0.0825)	(0.1330)	(0.1023)	(0.092)	(0.1149)	(0.106)
θ_{uscci}	−0.0743	0.0047	0.0966	0.0011	0.0120	−0.0399	−0.0104	−0.0174	−0.0423	0.0198
	(0.0295)	(0.0288)	(0.0308)	(0.1873)	(0.0476)	(0.0379)	(0.0292)	(0.0275)	(0.0488)	(0.0279)
$\theta_{usfedrate}$	0.0387	0.0297	−0.0446	−0.0031	−0.0191	0.0055	0.0116	0.0065	−0.0005	−0.0161
	(0.0261)	(0.0249)	(0.0245)	(0.103)	(0.0584)	(0.0257)	(0.0253)	(0.0238)	(0.0407)	(0.0229)
θ_{usm1}	0.0202***	−0.0061**	−0.0364***	0.0620	−0.0013***	−0.0518	−0.0112	0.0091	−0.0357***	0.0375
	(0.029)	(0.0338)	(0.0293)	(0.051)	(0.0404)	(0.0339)	(0.0278)	(0.0277)	(0.0418)	(0.0271)
θ_{nvix}	0.0651	0.0501***	0.1151***	0.0114	0.3078***	0.1369	0.3061*	0.0694***	0.6437**	0.2104***
	(0.0226)	(0.0239)	(0.0234)	(0.0561)	(0.097)	(0.2482)	(0.1294)	(0.2133)	(0.2442)	(0.2114)
AIC	−25,159.85	−27,310.37	−25,753.72	−26,449.56	−26,636.83	−27,384.95	−26,330.06	−25,158.62	−24,474.45	−25,278.80
BIC	−24,974.98	−27,125.5	−25,568.85	−26,264.69	−26,461.52	−27,200.08	−26,145.20	−24,973.75	−24,289.59	−25,103.50
VR	1.2947	1.3237	1.4732	1.3486	1.1928	1.473	1.3935	1.188	1.137	1.4228

Notes: The table reports the empirical results for the GARCH-MIDAS-X models for different currencies considering the exponential Almon lag polynomial scheme. The model estimated includes 2 MIDAS lag years, as K = 24. The long-run component is defined as

$$\log \tau_t = m + \theta_i \sum_{i=1}^{n} \sum_{k=1}^{K} \phi_k (\omega_{i1} \omega_{i2}) X_{t-k,i}, \quad \text{(exponential Almon lag polynomial scheme)}$$

where $X_{t-k,\ i}$ denotes the macroeconomic variables, including U.S. news announcements and NVIX. AIC and BIC are the Akaike information criterion and Bayesian information criterion. The table also reports variance ratio (VR) statistics. To avoid marking the table too large to include, we do not report the estimation of parameter ω.
*, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

and WAR, and explore which components have a larger effect on the changes of currencies. We report the results of the unrestricted weighting schemes for the uncertainty variables in this section.

4.1. Government

Considering most news announcements are related to the GOV sub-index, we further use related U.S. and native news announcements and GOV to explore whether government-related concerns have additional explanatory ability for the long-run volatilities of different currencies, as illustrated in Tables 7 and 8.

Government-related concerns are estimated to be a significant incremental factor affecting the volatilities of different currencies in the long term. Regardless of whether you consider U.S. or native news announcements, the parameter θ is positive and significant for most currencies except the GBP, which indicates the tight and positive relation between GOV and long-term exchange rate volatility. We also take CHF as an example, and find that an increase of one standard deviation of GOV can lead to 5.40% growth in next-month volatility ($e^{0.3770*0.1395} - 1 \approx 5.40\%$). We also compare the model with and without GOV by the selection criteria AIC and BIC, and VR. Lower AIC and BIC of models with GOV imply the model is better fitted. Moreover, as indicated by higher VR statistics, models with GOV are more properly estimated. Overall, most currencies are significantly affected by

Table 7
Regression results for the impact of GOV and U.S. news announcements on currencies based on the GARCH-MIDAS-X model.

Currencies	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
μ	−0.0001***	0.0000***	−0.0001***	−0.0001***	−0.0001***	−0.0001***	0.0000***	−0.0001***	−0.0002***	−0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
α	0.053***	0.0424***	0.0251***	0.0277***	0.0276***	0.0357***	0.0383***	0.0306***	0.0387***	0.0194***
	(0.0062)	(0.0053)	(0.0049)	(0.0083)	(0.0032)	(0.0044)	(0.0056)	(0.0052)	(0.0049)	(0.0158)
β	0.9207***	0.9369***	0.9516***	0.9708***	0.9708***	0.9595***	0.9455***	0.9617***	0.946***	0.9502***
	(0.0093)	(0.0089)	(0.009)	(0.0037)	(0.0034)	(0.0052)	(0.0088)	(0.0073)	(0.0071)	(0.0290)
m	−9.6276***	−10.2894**	−7.6342***	−10.0531***	−10.0449***	−10.2299	−10.0051***	−9.7454	−9.4722	−9.926
	(0.1893)	(0.3068)	(0.1358)	(0.3247)	(0.2996)	(0.2148)	(0.1258)	(0.1653)	(0.1098)	(0.2265)
θ_{usgdp}	0.1296***	0.1119**	0.298***	0.9107	0.9210	−0.7557	0.1036	0.0366	−0.0275***	66.4932**
	(0.0283)	(0.0486)	(0.0564)	(0.1790)	(0.2729)	(0.4929)	(0.0291)	(0.0332)	(0.0900)	(34.9802)
$\theta_{uspercon}$	−0.9337**	−0.7970	−5.3584	−0.1942	−0.1945	−0.2681	−0.0248***	−0.04***	−0.3812	−17.5845
	(0.1492)	(0.3706)	(0.4845)	(0.1115)	(0.1153)	(0.1651)	(0.0198)	(0.0258)	(0.1442)	(8.5373)
$\theta_{usretail}$	0.2369	0.0545	−0.0547***	0.0473	0.0437	0.4619	−0.1158	0.7824**	0.1054***	−1.7890
	(0.1095)	(0.0611)	(0.0469)	(0.1373)	(0.0656)	(0.2634)	(0.0373)	(0.2889)	(0.0791)	(1.9292)
θ_{uscapu}	0.1041	0.1335	1.7075**	0.0646***	0.0660***	0.0709	−0.0116**	0.3388	0.3173	1.0516***
	(0.0975)	(0.0978)	(0.2414)	(0.0600)	(0.0521)	(0.0842)	(0.0070)	(0.1605)	(0.1083)	(0.8176)
$\theta_{usperin}$	−0.1230	0.0822***	0.1642***	−0.4980	−0.5060	−0.1918**	−0.3582	−0.3350***	0.0190	−0.7632
	(0.1603)	(0.0502)	(0.0653)	(0.1334)	(0.1679)	(0.2139)	(0.1748)	(0.1888)	(0.0673)	(0.249)
$\theta_{usnewhome}$	0.1956***	−1.8486	3.1459***	−0.0292	−0.0291	0.1225	0.0516	−0.1586	0.0064	3.0921
	(0.6795)	(0.6195)	(0.2914)	(0.2684)	(0.0509)	(0.0503)	(0.0455)	(0.056)	(0.0055)	(2.9346)
θ_{usdur}	−0.9438**	0.3008	−4.3087***	0.1243***	0.1206	0.2259	0.3827	0.0043	0.0132	−1.3656
	(0.2369)	(0.2137)	(0.7346)	(0.2211)	(0.1294)	(0.158)	(0.2056)	(0.0270)	(0.1253)	(1.9595)
θ_{usunem}	−0.1352	−0.0038	−0.11	−0.254**	−0.2458**	−0.9737	−0.1409***	0.192**	0.2383***	−0.6263
	(0.0637)	(0.0189)	(0.0297)	(0.0886)	(0.1454)	(0.7872)	(0.2453)	(0.1875)	(0.1252)	(1.0445)
$\theta_{usconex}$	−0.4874**	−0.1729**	−0.064***	0.7584	0.7614	0.3808	−0.0104**	−0.5795	−1.9044***	−0.3701***
	(0.2627)	(0.1156)	(0.0622)	(0.363)	(0.3188)	(0.3504)	(0.0036)	(0.2346)	(0.3831)	(0.276)
$\theta_{usfeder}$	0.0927	0.0556**	0.3384***	−0.0014	−0.0015	−0.0125	−0.1112	−0.0017	0.0770	0.0633
	(0.0403)	(0.0279)	(0.0243)	(0.0239)	(0.0052)	(0.0564)	(0.0493)	(0.0035)	(0.0246)	(0.0206)
θ_{uscpi}	−0.0964	−0.1393	−0.2353	−0.5852	−0.5860	0.1250	0.0149	−0.0343	0.0242	0.2006
	(0.1133)	(0.0699)	(0.0622)	(0.3875)	(0.3155)	(0.1257)	(0.0123)	(0.0348)	(0.0126)	(0.2737)
θ_{uscci}	−0.1013***	−0.0401	0.2777	0.0131	0.0116	0.4359	−0.0129	−0.0146	0.0145	−0.0177
	(0.0592)	(0.0685)	(0.1729)	(0.0752)	(0.0331)	(0.2787)	(0.0097)	(0.0600)	(0.0352)	(0.0809)
$\theta_{usfedrate}$	−0.5619	−0.2996	−0.0156***	−0.0331	−0.0327	0.4785	−0.5263**	0.0537***	−0.0178	−0.1319***
	(0.1762)	(0.2213)	(0.0262)	(0.1654)	(0.0256)	(0.532)	(0.2964)	(0.4233)	(0.0403)	(0.1246)
θ_{usm1}	−0.2580	−0.1573***	−0.7468***	−0.1418	−0.1523***	0.1905	−0.0769**	1.9689***	−0.0380***	0.4370***
	(0.2187)	(0.2201)	(0.0812)	(0.2611)	(0.1370)	(0.5487)	(0.0371)	(0.4537)	(0.0342)	(0.1301)
θ_{gov}	0.8836***	0.2417***	0.3770***	0.0249***	0.0250***	−0.6507**	0.4847***	0.2088***	0.7822***	4.0410
	(0.4748)	(0.0891)	(0.0945)	(0.0696)	(0.0094)	(1.0315)	(0.2153)	(0.0732)	(0.1937)	(1.4401)
AIC	−23,488.58	−25,321.64	−24,168.52	−24,921.69	−24,910.36	−25,452.9	−24,594.07	−23,364.47	−22,806.45	−23,614.33
BIC	−23,382.57	−25,215.62	−24,062.51	−24,815.68	−24,804.34	−25,346.89	−24,488.06	−23,258.46	−22,700.44	−23,508.32
VR	1.8148	1.0879	2.1419	1.7897	1.7953	1.183	1.8695	1.7132	1.6902	1.883

Notes: The table reports the empirical results for the unrestricted GARCH-MIDAS-X models for different currencies. The model estimated includes 2 MIDAS lag years, as K = 24. The long-run component is defined as

$$\log \tau_t = m + \theta_i \sum_{i=1}^{n} \sum_{k=1}^{K} \phi_k(\omega_{i1}\omega_{i2}) X_{t-k,i}, \quad \text{(unrestricted weighting scheme)}$$

where $X_{t-k,\ i}$ denotes the macroeconomic variables, including U.S. news announcements and GOV (government-concerned news uncertainty). AIC and BIC are the Akaike information criterion and Bayesian information criterion. The table also reports variance ratio (VR) statistics. To avoid marking the table too large to include, we do not report the estimation of parameter ω.
*, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

GOV accounting for U.S. or native news announcements.

Specifically, Table 9 reports the empirical results of parameter θ with respect to the other four sub-indexes to explore the long-term entanglement between distinct aspects of news uncertainty and exchange rates. The following elaborately illustrates the impact of different types of news uncertainty.

4.2. Financial Intermediation

Manela and Moreira (2017) find that Financial Intermediation does not affect the variations in stock markets. However, our results argue that the volatilities of most estimated currencies are positively and significantly affected by news about financial intermediation, as illustrated in Panel A of Table 9. The volatility of SEK is driven by the IN sub-index at the 10% significance level, while DKK, EUR and NZD are not affected by IN, and the fluctuations of other exchange rates are significant at the 1% level. The close relationship is reasonable, since FX operations have been actively led by financial institutions by dealing with bubbles or obtaining the profits perceived on fluctuating exchange rates (Aoki & Nikolov, 2015; Blanchard & Watson, 1982; Mishkin, 2017; Mun & Morgan, 2003). When financial crises happen, the potential uncertainty-inducing bankruptcies of financial institutions deteriorates the FX markets and enhances the fluctuations of currencies.[4]

[4] Thanks for the anonymous reviewer's suggestion. We further estimate the impact of the credit standards index of the U.S. Federal Reserve on the currency's long-term volatility based on GARCH-MIDAS-X models, as shown in Appendix Table A6. The indicator, representing the unwillingness of financial institutions to supply capital to fund viable projects, does not exert a significant effect on long-term volatility except for the AUD and CHF. Therefore, the variations in exchange rates might be determined by the uncertainty-inducing bankruptcies of financial institutions, rather than the unwillingness of financial institutions to supply capital.

Table 8
Regression results for the impact of GOV and native news announcements of different countries on corresponding currencies based on the GARCH-MIDAS-X model.

Currencies	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
μ	−0.0001***	−0.0001***	−0.0002	−0.0001	−0.0001***	−0.0001***	0.0000	−0.0001***	−0.0001***	−0.0001***
	(0.0001)	(0.0105)	(0.0029)	(0.002)	(0.0015)	(0.1082)	(0.0001)	(0.0001)	(0.0001)	(0.4607)
α	0.0568***	0.0398***	0.0335***	0.0245***	0.0251***	0.0354***	0.0349***	0.0344***	0.0368***	0.0286***
	(0.0057)	(0.0053)	(0.0259)	(0.0278)	(0.0039)	(0.0047)	(0.0209)	(0.0045)	(0.0039)	(0.0055)
β	0.9333***	0.9433***	0.9525***	0.9746***	0.9727***	0.9577***	0.9474***	0.9586***	0.9573***	0.9606***
	(0.0067)	(0.0078)	(0.1783)	(0.0575)	(0.0034)	(0.0058)	(0.0134)	(0.0056)	(0.0046)	(0.0084)
m	−9.8091***	−10.3345***	−10.2982***	−9.9872**	−9.9350	−10.6617	−10.0301**	−9.6684	−9.5513***	−9.4266**
	(0.4010)	(0.1765)	(0.3950)	(0.3387)	(0.2469)	(0.2633)	(0.2670)	(0.1228)	(0.1343)	(0.2584)
θ_{gdp}	−1.0802***	−0.3095***	−0.3965***	−0.9401	0.1024***	−0.0443**	0.3818	0.0883***	−0.1377***	−0.9908
	(0.3978)	(0.0296)	(0.1354)	(0.4550)	(0.1509)	(0.0568)	(0.1758)	(0.0505)	(0.0215)	(0.4288)
θ_{percon}	0.6022	0.2180**	0.1149	0.5631	−0.1427***	0.2783	0.0379***	−0.1422***	0.0201	−0.1156***
	(0.2079)	(0.0259)	(0.0138)	(1.1209)	(0.0162)	(0.1166)	(0.1655)	(0.0480)	(0.0072)	(0.1047)
θ_{retail}	−0.2592**	−0.1088***	−0.4999	−2.1854	−17.5918***	−0.0307	0.3792	−0.5381	0.0367	−0.6160**
	(0.1744)	(0.0509)	(2.6969)	(6.2079)	(1.5782)	(0.0608)	(0.1342)	(0.113)	(0.0219)	(0.2253)
θ_{capu}	−0.9207**	0.7149	0.4615	1.9972**	0.4465	0.0204	0.2133**	−0.0868		0.5754
	(0.4004)	(0.0881)	(1.6204)	(6.6137)	(0.1548)	(0.0454)	(0.2051)	(0.1467)		(0.2594)
θ_{perin}	−4.4656	0.0803***	0.1176***	3.2253		0.0994	−0.3294**		−0.0389	−0.1107
	(2.0159)	(0.0522)	(0.5196)	(1.4207)		(0.0893)	(0.1373)		(0.0221)	(0.1144)
θ_{unem}	0.1763**	0.1936***	1.0156	−0.3412	0.0632***	0.0313***	0.4017**	0.0040	−0.0259***	
	(0.2244)	(0.0470)	(0.1580)	(1.1996)	(0.0694)	(0.0567)	(0.1802)	(0.0139)	(0.0185)	
θ_{cpi}	−0.9577	0.2787***	0.0139	−0.2941	0.3827***	0.4354	0.1347	−0.0421	−0.073***	0.0053***
	(0.4375)	(0.0605)	(1.6946)	(1.1398)	(0.1121)	(0.1211)	(0.0622)	(0.0228)	(0.0252)	(0.1866)
θ_{ppi}	−0.9416	−0.1887	−0.3803	−0.9305	−0.0982	0.0230	0.0609**	0.0214	−0.0728***	1.0039
	(0.6221)	(0.0507)	(2.0484)	(3.2037)	(0.0183)	(0.0723)	(0.0875)	(0.0143)	(0.0205)	(0.2945)
θ_{m1}	−0.1296**	−0.0161***	0.0168	0.1986	−0.2725**	0.1627	−0.2768***		0.0793***	0.0018
	(0.1359)	(0.012)	(1.1901)	(5.9751)	(0.4343)	(0.1524)	(0.1225)		(0.0256)	(0.0646)
θ_{gov}	0.2015***	0.2167***	−0.2222***	0.1796***	0.2504***	−0.1146***	0.5324***	0.0024***	0.0031***	0.0615***
	(0.0847)	(0.0611)	(0.4376)	(1.1412)	(0.1054)	(0.1021)	(0.0991)	(0.0009)	(0.0007)	(0.105)
AIC	−23,492.47	−25,342.81	−24,023.26	−24,951.59	−24,939.71	−25,471.96	−24,604.38	−23,383.05	−22,814.91	−23,609.11
BIC	−23,423.88	−25,267.98	−23,948.43	−24,876.76	−24,871.12	−25,397.13	−24,529.55	−23,320.69	−22,746.31	−23,550.27
VR	1.5637	1.946	2.7455	1.2494	1.8279	1.3226	1.8699	1.284	1.2999	1.6298

Notes: The table reports the empirical results for the unrestricted GARCH-MIDAS-X models for different currencies. The model estimated includes 2 MIDAS lag years, as K = 24. The long-run component is defined as

$$\log \tau_t = m + \theta_i \sum_{i=1}^{n} \sum_{k=1}^{K} \phi_k(\omega_{i1}\omega_{i2}) X_{t-k,i}, \quad \text{(unrestricted weighting scheme)}$$

where $X_{t-k,\, i}$ denotes the macroeconomic variables, including native news announcements and GOV (government-concerned news uncertainty). AIC and BIC are the Akaike information criterion and Bayesian information criterion. The table also reports variance ratio (VR) statistics. To avoid marking the table too large to include, we do not report the estimation of parameter ω.
*, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

4.3. Stock Markets

The second category, Stock Markets, which explains about half of the variation in NVIX (Manela & Moreira, 2017), has much to do with FX market volatility, as presented in Panel B of Table 9. The parameter associated with the SM sub-index, θ, is significantly positive for 10 out of 12 currencies estimated under the 10% level in the long run, except for the DKK and EUR. Our results report that the long-term volatility of exchange rate estimates is significantly and positively affected by the uncertainty of security markets. In other words, the volatilities of FX markets go up when the fluctuation of stock markets increase. It appears that stock markets, being part of wealth, can positively affect foreign exchange markets through monetary expansion and a more fluctuant demand for equities (Caporale, Ali, Spagnolo, & Spagnolo, 2017; Gavin, 1989; Phylaktis & Ravazzolo, 2005). At first, the changes in news about stock prices will lead to the increase or decrease of corporate and personal wealth, thus affecting strategies for production and private consumption. These modifications trigger variations in imports and exports. Hence, while the relation between monetary supply and demand waver, exchange rates fluctuate. Moreover, as permitted by capital inflow, the changes of stock prices give rise to the flux of international hot money. The variations of both the supply and demand of currencies will arouse the volatility of FX markets. Consequently, there exists a significant and positive relationship between the news uncertainty of stock markets and the volatility of currencies in the long run.

4.4. Natural Disasters

Even though the "Natural Disasters" index occupies a negligible amount of NVIX variations, this category has a positive spillover impact on the long-run volatilities of the currencies investigated. Panel C of Table 9 illustrates that half of the currencies are significantly influenced by uncertainty of natural disasters news, such as the CHF, DKK, EUR, JPY and NOK. When the uncertainty about natural disasters increases, the long-run volatility also rises for most currencies. Although the frequency of natural disasters is low, particularly large natural disasters will strike a great blow to the economy of the affected country, and directly hurt the stabilization of the corresponding FX market. We take the earthquake in Japan on March 11, 2011 as an example, which caused Tsunami and nuclear radiation. The news about the earthquake did not cool the demand for the yen, but let speculative capital seize this opportunity to heat up the yen. In the short term, the yen against the US dollar rose sharply form 83.00 on March 10 to 76.51 on March 16, breaking the record of 79.75 in April of 1995. However, in the long term, natural disasters aggravate the development of FX markets. Double Strikes from the real economy and financial markets produce unexpected economic difficulties for the future of Japan. Because of the needs for fiscal austerity, natural disasters put a downward pressure on FX markets and increases the volatility the JPY. Therefore, Natural Disaster-related concern is a crucial factor explaining the volatility of currencies.

Table 9
Regression results for the impact of sub-indexes on currencies based on the unrestricted GARCH-MIDAS-X model.

Currencies	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
Panel A: IN										
θ_{IN}	0.2311***	0.7409***	0.4380***	0.4933	0.5044	0.7514**	0.1109***	0.2934***	0.6221	0.1035*
	(0.0662)	(0.3858)	(0.0860)	(0.3153)	(0.3175)	(0.3452)	(0.0223)	(0.0589)	(0.8282)	(0.0588)
AIC	−26,158.8	−28,169.0	−26,733.5	−10,643.5	−10,629.6	5800.75	−10,274.3	8167.28	−8304.91	−26,183.1
BIC	−26,120.7	−28,130.9	−26,695.4	−10,605.4	−10,591.5	5838.85	−10,212.5	8205.39	−8266.80	−26,145.0
VR	4.0009	1.6198	5.6087	1.2901	1.2682	2.7430	1.5429	2.1468	2.4093	2.5101
Panel B: SM										
θ_{SM}	2.4077**	0.1193*	0.7555*	0.8048	0.7963	0.1329***	0.2307***	0.2328***	0.3466***	0.1881**
	(0.9643)	(0.0682)	(0.4297)	(0.5315)	(0.5373)	(0.0474)	(0.0436)	(0.0723)	(0.0906)	(0.0784)
AIC	−26,156.5	−28,162.6	−29,487.7	−10,634.9	−10,620.8	5802.29	−10,222.9	8183.75	−8314.65	−26,275.3
BIC	−26,118.4	−28,124.5	−29,449.6	−10,596.8	−10,582.7	5840.41	−10,184.8	8221.86	−8276.54	−26,237.2
VR	3.3491	1.2091	2.9658	1.0414	1.0311	1.4916	1.7700	1.2744	1.1766	1.5544
Panel C: ND										
θ_{ND}	−0.1145	0.1500	0.1001**	0.0240*	0.0240*	−0.2617	0.1266*	0.0542***	0.0552	0.2316
	(0.0911)	(0.7752)	(0.0459)	(0.0126)	(0.0125)	(0.2429)	(0.0201)	(0.0193)	(0.0397)	(0.1627)
AIC	−26,153.1	−28,161.9	−22,920.3	−10,638.9	−10,629.8	5807.37	−10,208.0	8893.8	−8209.7	−26,273.7
BIC	−26,115.0	−28,113.8	−22,992.2	−10,597.8	−10,588.7	5845.48	−10,169.9	8855.7	−8171.6	−26,235.6
VR	6.9822	2.6174	3.2152	1.5266	1.5006	3.3545	1.4081	2.5022	1.2706	2.9981
Panel D: WAR										
θ_{WAR}	0.1138*	0.3735	0.0899	0.4510	0.4504	0.1004***	0.3693*	0.5376***	0.1287*	−0.2171
	(0.0656)	(0.4290)	(0.3119)	(0.3570)	(0.3601)	(0.0310)	(0.2013)	(0.1861)	(0.06883)	(0.4294)
AIC	−26,156.4	−28,152.6	−29,481.9	−10,634.2	−10,620.0	−10,620.2	−10,181.6	8904.16	−8308.31	−26,270.8
BIC	−26,118.2	−28,114.5	−29,443.8	−10,596.0	−10,581.9	−10,586.0	−10,119.7	8866.04	−8270.20	−26,232.7
VR	7.0169	2.6185	3.2568	1.4979	1.4732	1.4732	1.3844	2.5055	2.9263	3.3066

Notes: The table reports the empirical results of parameter θ based on different unrestricted GARCH-MIDAS-X models for ten exchange rates, to explore the long-term relationship between distinct aspects of uncertainty and FX markets. X can be replaced by four sub-indexes, IN, SM, ND and WAR. The models estimated include 2 MIDAS lag years, as K = 24. The long-run component is defined as

$$\log \tau_t = m + \theta \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{t-k}, \quad \text{(unrestricted weighting scheme).}$$

*, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

4.5. War

Finally, the estimation of the unrestricted model shown in the Panel D of Table 9 reflects that most variations in exchange rates are not significantly influenced by war-concerned news. The volatilities of the GBP and NOK are positively affected by the WAR index with a significance of 1%, and those of the AUD, JPY and NZD are at the 10% significant level. The spillover impact of WAR on other currencies is not significant. Whether wars are clearly a plausible driver of the fluctuation of some currencies largely depends on the degree of involvement in the wars. The most striking pattern in WAR, seen in Fig. 1, is the sharp spike of 0.75 in the WAR during the days of the Iraq War, which was waged by the coalition of military forces of the U.S. and U.K. against Iraq. The news about wars measured by this sub-index captures the extent of the attention to the news and predominant perspective during that time. Since the U.K. participated in the war, the volatility of the GBP is more significantly affected by the WAR index in long term than the currencies of other countries. Therefore, the impact of war-concerned news on currency fluctuations largely depends on the degree of involvement in wars, and most developed countries are far from geopolitical conflicts, so war-concerned news doesn't exert a spillover influence on these currencies.

In summary, the above results demonstrate that GOV exerts an incremental effect on long-term exchange rate volatility relative to specific news announcements. Furthermore, other components, such as IN and SM, have a stronger long-term spillover impact on the volatilities of currencies. Moreover, a substantial fraction of the times-series fluctuations in FX markets is also driven by concerns closely related to the news of rare disasters, such as natural disasters. However, the effect of war is not significant for most currencies, and depends on the degree of involvement in wars.

5. Discussions

5.1. Long-run volatility model

The existing literature compares different long-run volatility models, such as a daily realized volatility ARFIMA model, intraday GARCH and FIGARCH models (Chortareas, Jiang, & Nankervis, 2011; Pong, Shackleton, Taylor, & Xu, 2004). The long-run volatility models can take into account a long memory factor to improve the explanation of exchange rate volatility. Considering the GARCH-MIDAS-X model employing daily exchange rate data, our paper compares the ARFIMAX model (Degiannakis, 2008) with the GARCH-MDIAS-X model to explore whether the GARCH-MIDAS-X model outperforms the ARFIMAX approach when considering macroeconomic variables.

The paper first introduces the ARFIMAX model, which can be defined as

$$(1 - c(L))(1 - L)^d(\log(\sigma_t^2) - x_t'\beta) = (1 + \delta(L))\varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \tag{6}$$

where $c(L) = \sum_{i=1}^{k} c_i L^i$, $\delta(L) = \sum_{i=1}^{l} \delta_i L^i$. L is a backward-shift operator and d is the order of fractional integration $(\frac{1}{2} < d < \frac{1}{2})$, and $(1 - L)^d = \sum_{j=0}^{\infty} L^j \prod_{k=0}^{j} \frac{k-1-d}{k}$ (Degiannakis, 2008). x_t is a vector of macroeconomic variables, and β indicates the impact. We then obtain the σ_t^2 by the GARCH model, which can be shown as

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2 \tag{7}$$

Tables 10 and 11 show the regression estimation of the effect of NVIX and U.S. or native news announcements on currency volatilities

Table 10
Regression results for the impact of NVIX and U.S. news announcements on currencies based on the ARFIMAX model.

Currencies	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
β_{usgdp}	−0.0063	−0.7349***	−0.5867*	−0.3537	−0.3848	−0.3718**	0.7743**	−0.0126	−0.0393	−0.0994
	(0.0522)	(0.2213)	(0.3531)	(0.2544)	(0.2606)	(0.1679)	(0.3059)	(0.0146)	(0.0411)	(0.0649)
$\beta_{uspercon}$	−0.1842**	−0.5284	−0.9512**	−0.3927	−0.3707	0.0288	−0.5757	−0.0316	−0.0430	−0.1690*
	(0.0850)	(0.3666)	(0.4607)	(0.3258)	(0.3338)	(0.2247)	(0.3886)	(0.0239)	(0.0661)	(0.0916)
$\beta_{usretail}$	−0.0161	−0.0896	−0.0641	−0.0135	0.0115	0.0447	0.0270	−0.0025	0.0129	−0.0188
	(0.0138)	(0.0581)	(0.1291)	(0.1050)	(0.1074)	(0.0586)	(0.1103)	(0.0040)	(0.0112)	(0.0272)
$\beta_{usindusp}$	0.4230	−0.5423	0.4804	0.4465	0.4463	0.1739	1.9461	0.1807	0.2183	0.2341
	(0.7237)	(4.5941)	(1.5491)	(1.0508)	(1.0800)	(0.8023)	(1.2817)	(0.2068)	(0.3804)	(0.3575)
β_{uscapu}	−0.3315	0.9758	0.1444	−0.1118	−0.1247	−0.0489	−1.6774	−0.1601	−0.2008	−0.0920
	(0.7228)	(4.5891)	(1.5252)	(1.0291)	(1.0581)	(0.7927)	(1.2545)	(0.2066)	(0.3793)	(0.3575)
$\beta_{usperin}$	−0.0093	−0.0607	−0.0570	−0.0919	−0.1093	0.0631	−0.0137	−0.0082	−0.0214	−0.0224
	(0.0203)	(0.0858)	(0.1806)	(0.1417)	(0.1451)	(0.0809)	(0.1538)	(0.0058)	(0.0164)	(0.0360)
$\beta_{usconsum}$	−0.0307	0.0196	0.1991	0.0736	0.0775	−0.1046	0.1556	−0.0096	−0.0204	−0.0049
	(0.0282)	(0.1188)	(0.2622)	(0.2066)	(0.2115)	(0.1181)	(0.2239)	(0.0080)	(0.0230)	(0.0527)
$\beta_{usnewhome}$	0.0001	−0.0139*	−0.0059	0.0034	0.0021	−0.0059	−0.0155	−0.0002	−0.0012	0.0015
	(0.0017)	(0.0071)	(0.0166)	(0.0136)	(0.0140)	(0.0074)	(0.0141)	(0.0005)	(0.0014)	(0.0035)
β_{usdur}	0.0104*	0.0061	−0.0262	−0.0369	−0.0449	−0.0316	−0.1025**	0.0006	0.0013	−0.0038
	(0.0059)	(0.0247)	(0.0567)	(0.0468)	(0.0479)	(0.0254)	(0.0484)	(0.0017)	(0.0048)	(0.0120)
β_{usunem}	0.0080	−0.0090	0.0531	0.0177	0.0175	−0.0010	0.0725	0.0009	0.0050	0.0082
	(0.0059)	(0.0246)	(0.0545)	(0.0441)	(0.0452)	(0.0247)	(0.0462)	(0.0017)	(0.0048)	(0.0114)
$\beta_{usconex}$	0.0186	0.0258	0.0659	0.0359	0.0330	−0.0477	−0.0861	0.0036	−0.0113	0.0247
	(0.0161)	(0.0679)	(0.1237)	(0.0933)	(0.0956)	(0.0581)	(0.1081)	(0.0044)	(0.0128)	(0.0243)
β_{usbusi}	−0.1160**	−0.2961	−0.6824**	−0.5436**	−0.5450**	−0.0481	−0.2893	−0.0317**	−0.0462	−0.1496**
	(0.0522)	(0.2205)	(0.3238)	(0.2331)	(0.2388)	(0.1653)	(0.2799)	(0.0148)	(0.0410)	(0.0632)
$\beta_{usfeder}$	−0.0000	0.0000	0.0001	0.0000	0.0000	0.0001	0.0000	−0.0000	−0.0000	0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
β_{uscpi}	−0.0408	−0.4243	−1.0661**	−0.5170	−0.4986	0.0563	−0.3854	0.0128	−0.0492	0.0444
	(0.0637)	(0.2769)	(0.5257)	(0.3853)	(0.3947)	(0.2320)	(0.4285)	(0.0183)	(0.0519)	(0.0992)
β_{uscci}	−0.0053***	−0.0291***	−0.0266*	−0.0272**	−0.0259**	−0.0101	0.0159	−0.0009**	−0.0016	−0.0066**
	(0.0015)	(0.0063)	(0.0137)	(0.0110)	(0.0112)	(0.0062)	(0.0117)	(0.0004)	(0.0012)	(0.0028)
$\beta_{usfedrate}$	−0.0012	−0.0011	0.0072	−0.0147	−0.0150	−0.0019	0.0002	−0.0002	0.0002	−0.0028
	(0.0012)	(0.0049)	(0.0115)	(0.0091)	(0.0093)	(0.0050)	(0.0096)	(0.0003)	(0.0010)	(0.0023)
β_{usm1}	−0.0208	−0.1060	0.0984	−0.1164	−0.1149	0.0118	0.2359**	0.0017	0.0070	−0.0583**
	(0.0157)	(0.0663)	(0.1397)	(0.1137)	(0.1162)	(0.0635)	(0.1177)	(0.0045)	(0.0130)	(0.0294)
β_{nvix}	−0.0010	−0.0047	−0.0073	−0.0014	−0.0011	−0.0042	0.0003	−0.0006*	−0.0000	0.0026
	(0.0011)	(0.0048)	(0.0107)	(0.0086)	(0.0088)	(0.0048)	(0.0092)	(0.0003)	(0.0010)	(0.0022)
AR(1)	0.8587***	0.9549***	0.3495	−0.1486	−0.1725	0.4256*	0.7334***	0.3351	0.5415*	0.9602***
	(0.1498)	(0.0308)	(0.2519)	(0.3901)	(0.3954)	(0.2253)	(0.2377)	(0.3154)	(0.2790)	(0.1099)
MA(1)	0.2379	0.2983***		0.2821	0.3026	−0.0520	−0.0685	0.2220	0.1834	−0.9762***
	(0.1517)	(0.1002)		(0.3350)	(0.3408)	(0.1858)	(0.2004)	(0.1419)	(0.1193)	(0.0889)
d	−0.1594	−0.2130**	−0.0470	0.0288	0.0329	−0.0023	−0.3724	0.3551	0.1225	0.1857*
	(0.2873)	(0.1025)	(0.2236)	(0.1164)	(0.1142)	(0.1233)	(0.4128)	(0.2367)	(0.2792)	(0.1011)
Constant	0.0081***	0.0458***	0.0609***	0.0511***	0.0513***	0.0279***	0.0495***	0.0059***	0.0080***	0.0084***
	(0.0011)	(0.0092)	(0.0031)	(0.0023)	(0.0024)	(0.0017)	(0.0023)	(0.0008)	(0.0008)	(0.0008)
Observations	195	195	195	195	195	195	195	195	195	195

Notes: The table shows the regression estimation of the effect of NVIX and U.S. news announcements on currency volatilities based on ARFIMA(1,d,1) model, which can be defined as

$$(1 - c(L))(1 - L)^d(\log(\sigma_t^2) - x_t'\beta) = (1 + \delta(L))\varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$$

We can obtain the σ_t^2 by the GARCH model as

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2$$

*, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

based on the ARFIMAX(1,d,1) model. The results in Table 10 suggests that nearly all macroeconomic variables, including NVIX, do not exert a significant spillover impact on long-term exchange rate volatilities when only considering monthly exchange rate data. Only 3 out of 18 news announcements about GDP, business inventories and the consumer confidence index affect some currencies. Compared with the results in Table 4, we find that most macro variables significantly explain long-run volatilities; particularly, NVIX influences the volatilities significantly and positively. As for Table 11, although long-run volatilities of some currencies respond to some native news announcements based on the ARFIMAX model, the impacts are not more significant than those reflected in Table 5. It is possible that the GARCH-MIDAS-X model develops novel mixed data sampling to link daily exchange rate data to monthly macroeconomic variables, and thus takes high-frequency information of currencies into consideration to obtain long-run components of volatility. Instead, considering the monthly exchange rate volatility, ARFIMAX loses some information of daily variations, and thus the impact is not significant. Consequently, the MIDAS method provides the advantage of containing more high-frequency information to estimate the impact of macroeconomic variables.

5.2. Endogeneity issue

Although a model containing different news announcements can

Table 11
Regression results for the impact of NVIX and native news announcements on corresponding currencies based on the ARFIMAX model.

Currencies	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
β_{gdp}	−0.1466**	−0.6330	−0.6665	0.0395	0.3900	0.0002	0.1974	−0.0295***	−0.0481	−0.1769***
	(0.0585)	(0.4970)	(0.4996)	(0.2037)	(0.9999)	(0.1612)	(0.1685)	(0.0110)	(0.0815)	(0.0416)
β_{percon}	0.0154	−0.9340***	−0.9675***	−0.4177***	−0.1899	−0.0572	−0.0600	0.0303	0.0014	0.0481
	(0.0560)	(0.3325)	(0.3330)	(0.1415)	(0.2166)	(0.1453)	(0.1831)	(0.0210)	(0.0567)	(0.0465)
β_{retail}	0.0117	0.0129	0.0386	0.1601	−0.1266	0.0374	0.0101	−0.0006	−0.0918**	−0.0037
	(0.0109)	(0.0665)	(0.0643)	(0.1955)	(0.1525)	(0.0544)	(0.0233)	(0.0062)	(0.0394)	(0.0242)
β_{indusp}	−0.0280	0.1121	0.1233	0.0233	−0.2366**	−0.0115	−0.0349	0.0016	0.1172*	0.0029
	(0.0733)	(0.0752)	(0.0754)	(0.0382)	(0.1024)	(0.0487)	(0.0512)	(0.0039)	(0.0641)	(0.0116)
β_{capu}	−0.0110	−0.3940**	−0.4038**	−0.1012	−0.1687**	−0.0701*	−0.0685	−0.0869***	0.0106	−0.0284
	(0.0161)	(0.1938)	(0.1949)	(0.0675)	(0.0822)	(0.0389)	(0.3408)	(0.0264)	(0.0202)	(0.0236)
β_{perin}	–	−0.0110	−0.0001	−0.0761**		−0.1428**	−0.0492**	−0.0033	0.0102	−0.0022
		(0.1235)	(0.1245)	(0.0360)		(0.0689)	(0.0236)	(0.0032)	(0.1424)	(0.0019)
β_{consum}	0.0067	0.3013*	0.3064*	−0.0406	−0.1007	−0.0713	0.0417*	0.0113	−0.0075	−0.0140
	(0.0091)	(0.1753)	(0.1772)	(0.0430)	(0.1234)	(0.0823)	(0.0245)	(0.0288)	(0.0136)	(0.0148)
β_{unem}	−0.0050	−0.0158	−0.0157	0.0873**	0.2441	0.0394	0.0041	−0.0024	−0.0002	0.0012
	(0.0055)	(0.0322)	(0.0325)	(0.0375)	(0.1623)	(0.0387)	(0.0367)	(0.0025)	(0.0142)	(0.0065)
β_{cpi}	−0.0891	−0.5647**	−0.4529*	0.6126	−0.2109	−0.2407	−0.0664	−0.0080	−0.5450***	0.0083
	(0.1710)	(0.2621)	(0.2509)	(0.6926)	(1.0823)	(0.1573)	(0.4627)	(0.0161)	(0.1944)	(0.0710)
β_{ppi}	−0.3148*	0.1766	–	−0.1162	−0.1581	0.1839	0.0047	0.0032	−0.0337	−0.0554
	(0.1621)	(0.1306)		(0.2007)	(0.4653)	(0.2189)	(0.1613)	(0.0030)	(0.0688)	(0.0473)
β_{m1}	−0.0024	0.0684	0.1178	0.0657	0.4868***	−0.0218	0.1781*	0.0004	0.0275	0.0118
	(0.0086)	(0.1369)	(0.1334)	(0.0560)	(0.1524)	(0.0529)	(0.0993)	(0.0013)	(0.0242)	(0.0139)
β_{nvix}	0.2420***	−0.0106*	−0.0105*	0.0047	−0.0020	−0.0045	0.2736	−0.0006	−0.0018	0.0055**
	(0.0597)	(0.0054)	(0.0055)	(0.0102)	(0.0088)	(0.0048)	(0.1920)	(0.0005)	(0.0014)	(0.0024)
AR(1)	0.8659***	0.3795*	0.3875*		0.4146	0.5705*	0.7603***	0.8892***	0.7009***	0.2436
	(0.1739)	(0.2085)	(0.2156)		(0.9030)	(0.3351)	(0.2095)	(0.1068)	(0.2061)	(0.2399)
MA(1)	0.0244	0.0922	0.0750	0.2386**	−0.2393	−0.0032	−0.0701	0.2763*	−0.1450	−0.4556
	(0.2347)	(0.1954)	(0.2018)	(0.1046)	(0.6151)	(0.1358)	(0.1924)	(0.1601)	(0.1948)	(0.3083)
d	−0.1332	0.4641***	0.4627***	−0.1400	−0.1169	−0.2272	−0.4139	−0.3083	0.1493	0.1729
	(0.3981)	(0.0530)	(0.0553)	(0.1141)	(0.3678)	(0.3856)	(0.3808)	(0.2330)	(0.3218)	(0.2495)
Constant	0.0022	0.0415	0.0413	0.0464***	0.0429***	0.0278***	0.0435***	0.0058***	0.0093***	0.0074***
	(0.0020)	(0.0379)	(0.0370)	(0.0012)	(0.0020)	(0.0010)	(0.0051)	(0.0003)	(0.0014)	(0.0006)
Observations	195	195	195	159	195	195	195	99	93	172

Notes: The table shows the regression estimation of the effect of NVIX and native news announcements on currency volatilities based on ARFIMA(1,d,1) model, which can be defined as

$$(1 - c(L))(1 - L)^d(\log(\sigma_t^2) - x_t{}'\beta) = (1 + \delta(L))\varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$$

We can obtain the $\sigma_t{}^2$by the GARCH model as

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2$$

*, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

diminish omitted variables bias, the causal inference between news uncertainty and exchange rate volatility is also troubled by a possible reverse effect, as NVIX contains different types of news uncertainty, such as stock markets, financial intermediations, and governments, which can also be affected by the FX markets. Therefore, following Ghysels (2016), we adopt a general Vector Autoregressive (VAR) model embedded in the MIDAS structure to eliminate the impact of endogeneity. The existing MF-VAR (mixed-frequency VAR) suffers from the curse of dimensionality, but the MIDAS scheme uses weighted polynomials to estimate related parameters in the model (Kuzin, Marcellino, & Schumacher, 2011). The paper starts with a $K_L + m \times K_H$ dimensional VAR-MIDAS model with P lags represented in a stacked vector as

$$\begin{bmatrix} x_H(\tau_L, 1) \\ \vdots \\ x_H(\tau_L, m) \\ x_L(\tau_L) \end{bmatrix} = A_0 + \sum_{j=1}^{P} A_j \begin{bmatrix} x_H(\tau_L - j, 1) \\ \vdots \\ x_H(\tau_L - j, m) \\ x_L(\tau_L - j) \end{bmatrix} + \underline{\varepsilon}(\tau_L), \tag{8}$$

where x_H and x_L indicate the high-frequency and low-frequency data, referring to daily exchange rate volatility estimated by the GARCH(1,1) process and monthly news uncertainty data in the paper. Then, we set $K_L = K_H = 1$ and all the variables are assumed to have a mean of zero. Eq. (8) can be rewritten as a $m + 1$ dimensional VAR model with P lags as

$$\begin{bmatrix} x_H(\tau_L, 1) \\ \vdots \\ x_H(\tau_L, m) \\ x_L(\tau_L) \end{bmatrix} = \sum_{j=1}^{P} \begin{bmatrix} A_j^{1,1} & \cdots & A_j^{1,m} & A_j^{1,m+1} \\ \vdots & \cdots & \vdots & \vdots \\ A_j^{m,1} & \cdots & A_j^{m,m} & A_j^{m,m+1} \\ A_j^{m+1,1} & \cdots & A_j^{m+1,m} & A_j^{m+1,m+1} \end{bmatrix} \times \begin{bmatrix} x_H(\tau_L - j, 1) \\ \vdots \\ x_H(\tau_L - j, m) \\ x_L(\tau_L - j) \end{bmatrix} + \underline{\varepsilon}(\tau_L), \tag{9}$$

As suggested in the paper of Ghysels (2016), the impact of monthly NVIX series is constant over the sample period, and the daily currency volatility follows an ARX(1) process; thus, we get

$$\begin{bmatrix} x_H(\tau_L,1) \\ \vdots \\ x_H(\tau_L,m) \\ x_L(\tau_L) \end{bmatrix} = \begin{bmatrix} 0 & \cdots & \rho & a \\ \vdots & \cdots & \vdots & \vdots \\ 0 & \cdots\cdots & \rho^m & a\left(1+\sum_{j=0}^{m-1}\rho^j\right) \\ \omega(\gamma)_m & & \omega(\gamma)_1 & \alpha_1 \end{bmatrix} \times \begin{bmatrix} x_H(\tau_L-1,1) \\ \vdots \\ x_H(\tau_L-1,m) \\ x_L(\tau_L-1) \end{bmatrix} + \sum_{j=2}^{P} \begin{bmatrix} 0 & \cdots & 0 & 0 \\ \vdots & \cdots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 \\ \omega(\gamma)_{jm} & \cdots & \omega(\gamma)_{(j-1)m+1} & \alpha_j \end{bmatrix} \times \begin{bmatrix} x_H(\tau_L-j,1) \\ \vdots \\ x_H(\tau_L-j,m) \\ x_L(\tau_L-j) \end{bmatrix} + \underline{\varepsilon}(\tau_L). \tag{10}$$

The parameters ρ and a involved in the regression of high-frequency series indicate the impact of the low-frequency variables of high-frequency data. Therefore, we mainly report the estimation of the two parameters. The equation also includes another P parameter, α_j, and the low dimensional MIDAS polynomial coefficient γ. Moreover, the MIDAS weigh,

$$[A_1^{m+1,1} \ \cdots \ A_1^{m+1,m} \ \ A_2^{m+1,1} \ \cdots \ A_p^{m+1,m}] = \left[\sum_{i=1}^{K_H\times m\times P} (\omega(\gamma)_i)\right] \otimes B, \tag{11}$$

where B is a $K_L \times K_H$ matrix and $\left[\sum_{i=1}^{K_H\times m\times P} (\omega(\gamma)_i)\right] = 1$. We adopt the unrestricted weighted scheme to investigate the relationships.

Table 12 reports the estimations of ρ and a, which demonstrate whether NVIX still affects the long-run volatility of currencies when considering the endogeneity issue based on VAR-MIDAS models. Observing parameter a, we find that 9 out of 10 exchange rate volatilities are positively affected by NVIX, and half of them significantly respond to changes of NVIX. The results are generally consistent with those based on the GARCH-MIDAS-X model. In sum, as the impacts are generally positive and substantial, we conclude that NVIX, market-wide information, is an important factor in explaining long-run exchange rate volatility.

5.3. Cross-currency contagion

There still exists a concern about whether market-wide news uncertainty affects the currencies directly or whether only one or a few currencies respond to NVIX and then affect others by cross-currency contagion. That is, investors place greater attention on market-wide information, and they will adjust their views and strategies on multiple currencies simultaneously when a given piece of market-wide news uncertainty changes, even if NVIX is actually only applicable to one or only a few currencies. Therefore, our paper introduces the DCC-MIDAS (Dynamic Conditional Correlation) method to address this concern (Colacito, Engle, & Ghysels, 2011). The DCC-MIDAS approach disintegrates the conditional covariance matrix into the conditional variance component and the correlation matrix. The conditional variance has been calculated by the GARCH-MIDAS method, which was introduced in Section 2.1, and the parameters were then estimated with the standardized residuals. Dynamic q_{ijt}, an element in a quasi-correlation matrix Q_t, can be measured by

$$q_{ijt} = \rho_{ijt}(1-a-b) + a\varepsilon_{i,t-1}\varepsilon_{j,t-1} + bq_{ij,t-1}, \tag{12}$$

where $\varepsilon_{i,t-1}$ is the standardized residuals, and thus q_{ijt} can be regarded as a GARCH(1,1)-like dynamic. ρ_{ijt} is the long-run components and can be estimated by the MIDAS weighting scheme-based sample correlation matrix c_{t-k} as

$$\rho_t = \sum_{k=1}^{K} \psi_k(\omega)c_{t-k}. \tag{13}$$

Thus, we can collect the correlations in Eq. (12), which yield the

Table 12
Regression results for the impact of NVIX on currencies based on the VAR-MIDAS model.

Currencies	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
a	0.964	0.108***	0.039**	0,096*	−0.139	0.161	0.044***	0.098*	0.445	0.398
	(0.709)	(0.010)	(0.002)	(0.024)	(0.226)	(0.167)	(0.001)	(0.083)	(0.947)	(0.172)
ρ	0.964	0.9610	0.996	0.989	0.988	0.983	0.998	0.990	0.966	0.988*
	(0.680)	(0.445)	(0.592)	(0.530)	(0.528)	(0.523)	(0.469)	(0.479)	(0.886)	(0.162)
R^2	0.327	0.366	0.274	0.373	0.375	0.360	0.300	0.354	0.364	0.352

Notes: The table reports the estimations of ρand a, which demonstrate whether NVIX affects the long-run volatility of currencies when considering the endogeneity issue based on the VAR-MIDAS model. As suggested in the paper of Ghysels (2016), the impact of monthly NVIX series is constant over the sample period and the daily currency volatility follows an ARX(1) process; thus, the VAR-MIDAS can be written as

$$\begin{bmatrix} x_H(\tau_L,1) \\ \vdots \\ x_H(\tau_L,m) \\ x_L(\tau_L) \end{bmatrix} = \begin{bmatrix} 0 & \cdots & \rho & a \\ \vdots & \cdots & \vdots & \vdots \\ 0 & \cdots\cdots & \rho^m & a\left(1+\sum_{j=0}^{m-1}\rho^j\right) \\ \omega(\gamma)_m & & \omega(\gamma)_1 & \alpha_1 \end{bmatrix} \times \begin{bmatrix} x_H(\tau_L-1,1) \\ \vdots \\ x_H(\tau_L-1,m) \\ x_L(\tau_L-1) \end{bmatrix} + \sum_{j=2}^{P} \begin{bmatrix} 0 & \cdots & 0 & 0 \\ \vdots & \cdots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 \\ \omega(\gamma)_{jm} & \cdots & \omega(\gamma)_{(j-1)m+1} & \alpha_j \end{bmatrix} \times \begin{bmatrix} x_H(\tau_L-j,1) \\ \vdots \\ x_H(\tau_L-j,m) \\ x_L(\tau_L-j) \end{bmatrix} + \underline{\varepsilon}(\tau_L).$$

The parameters ρand ainvolved in the regression of high-frequency series indicate the impact of the low-frequency variables of high-frequency data. The equation also includes other P parameter, α_j, and low dimensional MIDAS polynomial coefficient, γ.
*, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

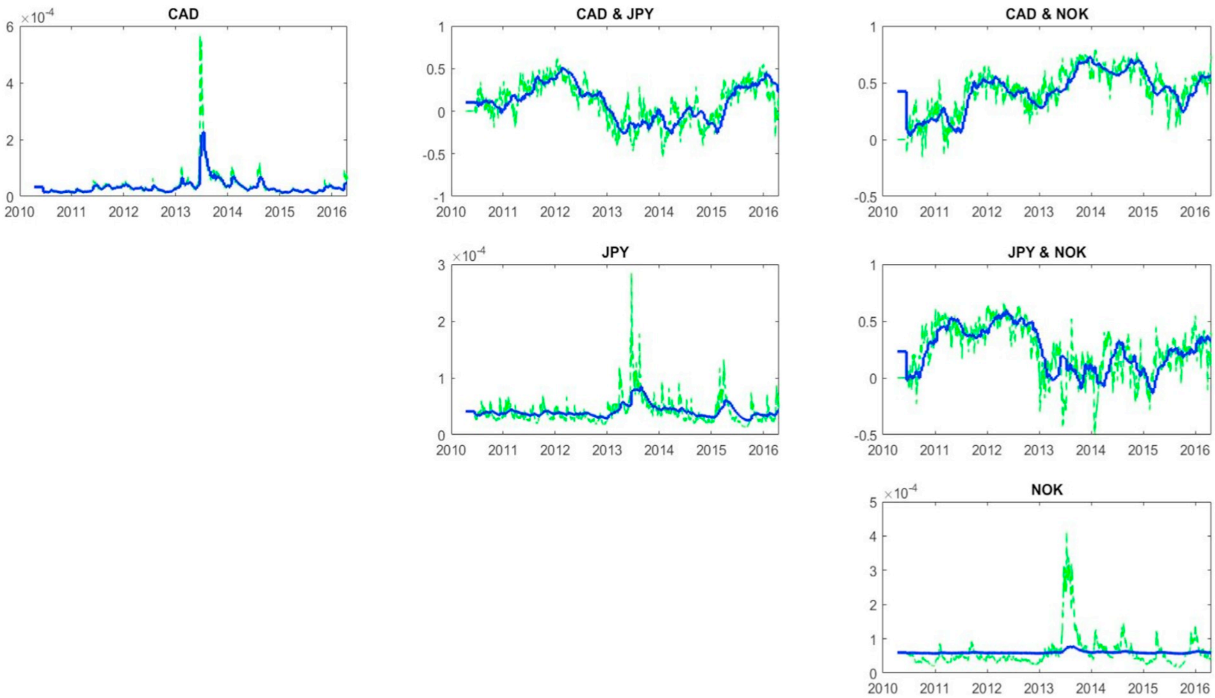


Fig. 3. Estimated volatilities and correlation for CAD, JPY and NOK. The figure illustrates a DCC-MIDAS example using the three currencies: the volatility of JPY and CAD is closely related with NVIX, and NZD is not related with NVIX. The model is fitted by maximum likelihood with MIADS Beta weights. The solid blue line of the diagonal panel is the long-term volatility and the dashed green line of the diagonal panel refers to short-term volatility. In the off-diagonal panel, the solid blue line represents the long-term correlation and the dashed green line is the total correlation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

correlation matrix as a quasi-correlation matrix:

$$R_t = diag(Q_t)^{-1/2} Q_t \, diag(Q_t)^{-1/2}. \tag{14}$$

We adopt three typical currencies to examine the correlation of volatilities: JPY (the effect of NVIX is significant for JPY in nearly every model), CAD (the effect is significant and Canada is a non-European country), and NOK (the impact is not significant). From Fig. 3, we find that the long-run correlation between CAD and NOK fluctuates by nearly 0.5, and the correlation of JPY and NOK is between 0 and 0.5 In other words, there exists a relatively high correlation between NOK with JPY and CAD, which indicates that the volatility of JPY and CAD can infect the variation of NOK. However, although the variations of other currencies can spread to NOK, NVIX does not exert a significant effect on NOK, but influences other currencies significantly. Hence, the plausible explanation is that NVIX affects currency volatilities directly, rather than by cross-currency contagion channels.

6. Conclusions

In this paper, we apply the GARCH-MIDAS-X component framework to investigate the dependence between long-run exchange rate volatilities and macroeconomic variables, including news announcements and news uncertainty. In general, our results strongly confirm that changes in NVIX can positively and significantly affect the fluctuations of most currencies estimated. Furthermore, relative to specific news, such as U.S. or native news announcements, market-wide information, or NVIX, contains incremental information that explains the variations in FX markets. Models with NVIX perform better than models without NVIX.

Next, the MIDAS weighting scheme uses weighting polynomials for the parameter to solve the curse of dimensionality. The approach also links the low frequency data of macroeconomic variables to high frequency FX market data to explore the long-term impact, and decomposes the short-run and long-run volatilities that contain more high-frequency information, which provides an additional advantage over other long-run volatility models, such as ARFIMA.

Finally, the evidence with respect to the five sub-indexes suggests that these long-term volatilities are driven by variations in different types of news concerning Financial Intermediation (IN), Natural Disasters (ND), Stock Markets (SM), Government (GOV), and War (WAR). First, the GOV plays a crucial role in explaining long-term exchange rate volatility accounting for specific information. Second, news uncertainty associated with financial intermediation and stock markets as the leading components is tightly and positively related to the long-term volatilities of ten currencies. The increase of uncertainty with respect to IN and SM increases the volatilities of exchange rates. It is reasonable that news about financial institutions and stock markets acts as the most relevant and influential factor for FX markets globally. Third, although the natural disasters index accounts for a negligible amount of NVIX variation, the long-run volatilities are driven by the information related to rare natural disasters. Finally, the spillover impact of war-concerned news on FX markets is related to the degree of involvement in wars. Most developed economies are far from geopolitical conflicts; thus, war-concerned news does not exert an influence on their currencies.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2018.10.005.

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