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The role of news-based implied volatility among US financial markets

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HIGHLIGHTS

- News-based implied volatility is a new measure of uncertainty for capturing investors' perceptions.
- We investigate the impact of news-based implied volatility on long-term market volatilities from a GARCH-MIDAS model.
- News-based implied volatility performs well in predicting long-term market volatilities.
- The predictive power of news-based implied volatility is decreasing through a subsample analysis.

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ABSTRACT

We investigate the role of uncertainty measured by news-based implied volatility in anticipating US long-term market volatilities from a GARCH-MIDAS model. We find that news-based implied volatility performs well in predicting long-term aggregate market volatilities. A subsample analysis provides that the predictive power of news-based implied volatility is decreasing.

1. Introduction

The impact of uncertainty on asset pricing has drawn much attention among academics and practitioners. Measurement of uncertainty is a challenge in empirical finance explorations. Several uncertainty proxies are constructed, including conditional variance of fundamentals (Bekaert et al., 2009), common variant (Strobel, 2015; Jurado et al., 2015), and newspaper coverage frequency (Baker et al., 2016). Various uncertainty indices lead to ample empirical works on the relations between uncertainty and asset pricing (Brogaard and Detzel, 2015; Ko and Lee, 2015).

These uncertainties actually just focus on macroeconomic conditions, ignoring the vital role of public media and investor attentions, which is more flexible and timely than the economic data. How to extract the underlying uncertainty information? Manela and Moreira (2017) proposed a solution called news-based implied volatility (NVIX) from news coverage and the implied volatility.[1] Unlike the similar indices like Economic Policy Uncertainty, NVIX captures people's perception on future uncertainty, and it is decomposed into five categories that perform well in predicting returns.[2] The natural disasters component also expands the literature on the uncertainty concerning disasters (Kaplanski and Levy, 2009; Strobl, 2011).

Our contribution to the literature on uncertainty and asset pricing is threefold. First, we provide the empirical evidence on the relationships between NVIX and market volatilities from a GARCH-MIDAS model, which enables us to mainly focus on the impact on the long-term volatility. Second, we deeply investigate the US financial markets including stock, exchange, bond and commodity markets, and confirm the positive and significant impact. Third, we further uncover the fact that the predictive power of NVIX is declining estimated by a subsample period.

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[1] They consider VIX and VXO index reported by CBOE.

[2] The five categories include War, Financial Intermediation, Government, Stock Markets and Natural Disasters. See Manela and Moreira (2017).

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Table 1
Summary statistics.

	Mean	Max	Min	Std	Skewness	Kurtosis
S&P 500	0.0003	0.1096	−0.2290	0.0117	−1.2607	30.2617
USD	−0.0001	0.0216	−0.0411	0.0045	−0.2326	5.9448
Long-term bond	−0.0002	0.0892	−0.1850	0.0148	−0.0925	10.0262
Short-term bond	−0.0004	2.0369	−3.3322	0.1452	−0.9525	78.1646
S&P GSCI	0.0001	0.0760	−0.1843	0.0123	−0.5807	12.6277
NVIX	24.1631	57.8977	13.6225	5.7448	1.4127	8.1153

Table 2
GARCH-MIDAS model estimation with unrestricted weighing schemes from 1985 to 2016.

Coefficients	μ	α	β	γ	m	θ	ω_1	ω_2
S&P 500	0.0288***	0.0009	0.8885***	0.1604***	−1.1383***	0.0473***	4.9140	6.9827
	(0.0095)	(0.0066)	(0.0250)	(0.0350)	(0.3532)	(0.0136)	(8.0789)	(5.5407)
USD	0.0027	0.0448***	0.9586***	−0.0085*	−0.9153	0.0272***	26.2177***	210.9378***
	(0.0043)	(0.0048)	(0.0039)	(0.0049)	(0.5790)	(0.0087)	(3.4133)	(25.0350)
Long-term bond	−0.0245**	0.0344***	0.9538***	0.0160**	−0.3095	0.0324**	−0.3081	3.0772
	(0.0110)	(0.0063)	(0.0055)	(0.0073)	(0.5987)	(0.0136)	(2.0612)	(10.6546)
Short-term bond	4.0657***	0.6214***	0.3811***	−0.0700*	0.9947	0.0485**	12.7747***	97.6744***
	(0.1038)	(0.0446)	(0.0430)	(0.0416)	(0.8680)	(0.0245)	(3.5805)	(8.1396)
S&P GSCI	0.0232**	0.0507***	0.9422***	0.0053	−0.3880	0.0290***	22.0872***	177.2025***
	(0.0095)	(0.0046)	(0.0042)	(0.0053)	(0.2884)	(0.0097)	(3.1931)	(23.2533)

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

2. Methodology

The GARCH-MIDAS model proposed by Engle et al. (2013) specifies the conditional variance of daily asset returns as the product of a short-term and a long-term component, which allows us to combine daily returns with a long-term volatility component that is driven by low-frequency endogenous variables. We induce monthly NVIX series into the specification in the log version of the long-term component. Considering the stock market return $r_{i,t}$ at day $i = 1, 2, \ldots, N_t$ in month $t = 1, 2, \ldots, T$, we assume the daily return follows the specification:

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

where μ is daily expected returns, $\varepsilon_{i,t}|\Phi_{i-1,t} \sim N(0, 1)$ and $\Phi_{i-1,t}$ stands for the information setup to day $i-1$ of month t. $g_{i,t}$ and τ_t denote the short-term and long-term component conditional variance, respectively. The short-term component follows a mean-reverting asymmetric GARCH(1,1) process:

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

with constraints of $\alpha > 0, \beta > 0$ and $\alpha + \beta + \gamma/2 < 1$. The parameter γ contains the information about the asymmetry. The long-term component is driven by the weighted average of the lagged endogenous variable X_t:

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

where the unrestricted Beta weighting scheme $\varphi_k(\omega_1, \omega_2)$ follows such specification:

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

The Beta weighting schemes generate hump-shaped or convex weights. As ω_1 is restricted to 1, the weighting schemes guarantee a decay pattern where the rate of decaying is determined by parameter ω_2.[3] The restricted weighting schemes are as follows in Eq. (5),

$$\varphi_k(\omega_2) = \frac{(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K} (1-j/K)^{\omega_2-1}}. \tag{5}$$

We employ GARCH-MIDAS model to investigate the impact of NVIX on the long-term volatilities among US financial markets.

3. Data

We consider daily stock market returns for S&P 500, USD index returns, long-/short-term government bond yields, and returns for S&P GSCI. The sample period is from January 1985 to December 2016. The monthly NVIX is a text-based uncertainty constructed by Manela and Moreira (2017), for measuring public perception on future uncertainty. Manela and Moreira (2017) follow the idea that time variation in the topics covered by business press is a good proxy for investor concerns, and they estimate NVIX based on the co-movement between the front-page coverage of the *Wall Street Journal* and options-implied volatility.[4] The stock market index for S&P 500, USD index, the long-/short-term government bond yields and S&P GSCI index are obtained from FRED database, DataStream and Bloomberg. The descriptive statistics are reported in Table 1.

4. Empirical results

4.1. NVIX and long-term volatility

In this section, we investigate the relationships between NVIX and the long-term components for S&P 500, USD, long-/short-term government yields and commodity index from January 1985 to December 2016. We start with the GARCH-MIDAS model with

[3] The values of ω_2 determine the rate of decaying, whereby large values of ω_2 generate a rapid decaying pattern. See Engle et al. (2013) and Conrad and Loch (2015) for more details.

[4] NVIX is available at Manela's personal website.