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Forecasting Large Price Declines of the Nikkei Using the S&P 500 Implied Volatility

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Abstract

Using several quantile regression models, this study experimentally investigates the predictive potential of the prior day's US implied volatility for big drops of the Nikkei. Our data suggests that big declines in the Nikkei 225 may be predicted using the implied volatility of the S&P 500 on the day before. Our evidence of the S&P 500 implied volatility's predictive power for the Nikkei's downside risk is very robust because we rigorously tested the several left tail risks in price changes of the Nikkei and also tested by using some different versions of quantile regression models.

Keywords: terms such as "tail risk," "downside risk," "implied volatility," "Nikkei 225," and "quantile regression model"

1. Introduction

Academic and professional interest in stock market connections has increased against the backdrop of globalization of international financial markets. Researchers face a variety of challenges as a result of the globalization of financial markets. Emerging financial markets and financial instruments (e.g., Riasi, 2015), interconnected financial markets (e.g., Fratzscher, 2002), and financial risk overflows (e.g., Zhu, 2014) are all areas where this concept has been investigated. While numerous studies have been undertaken for certain market circumstances, such as bull, bear, and normal market conditions (e.g., Diebold and Yilmaz, 2009; Baumöhl and Lyócsa, 2014), we point out that these studies are not exhaustive. In this article, we take a fresh look at the interconnections across global stock markets, but this time from the perspective of a bearish market.

Using multiple variants of quantile regression models, this study experimentally investigates the predictive value of the previous day's US S&P 500 implied volatility for big drops of the Japanese Nikkei 225 stock price index. The following is some new evidence gleaned from our examinations of American and Japanese data. First, (1) our basic univariate quantile regression model's estimate findings reveal statistically substantial evidence that the movement of the previous day's US implied volatility has predictive capacity for major decreases in the Japanese Nikkei price. The second (2) piece of evidence is that the estimate findings of our autoregressive (AR) (3)-quantile regression model likewise statistically imply that US implied volatility from the day before has predictive value for substantial Nikkei falls. Finally (3) our quantile regression model with additional control variables provides statistically significant evidence that the previous day's US implied volatility has predictive value for substantial Nikkei price decreases in Japan. The study's contributions consist of the novel results obtained using our novel analytical lens.

Section 2 gives a review of the relevant literature, Section 3 details the data and variables we collected and analyzed, Section 4 explains the procedures we used to perform the tests, Section 5 details the statistical findings, and Section 6 draws the appropriate conclusions.

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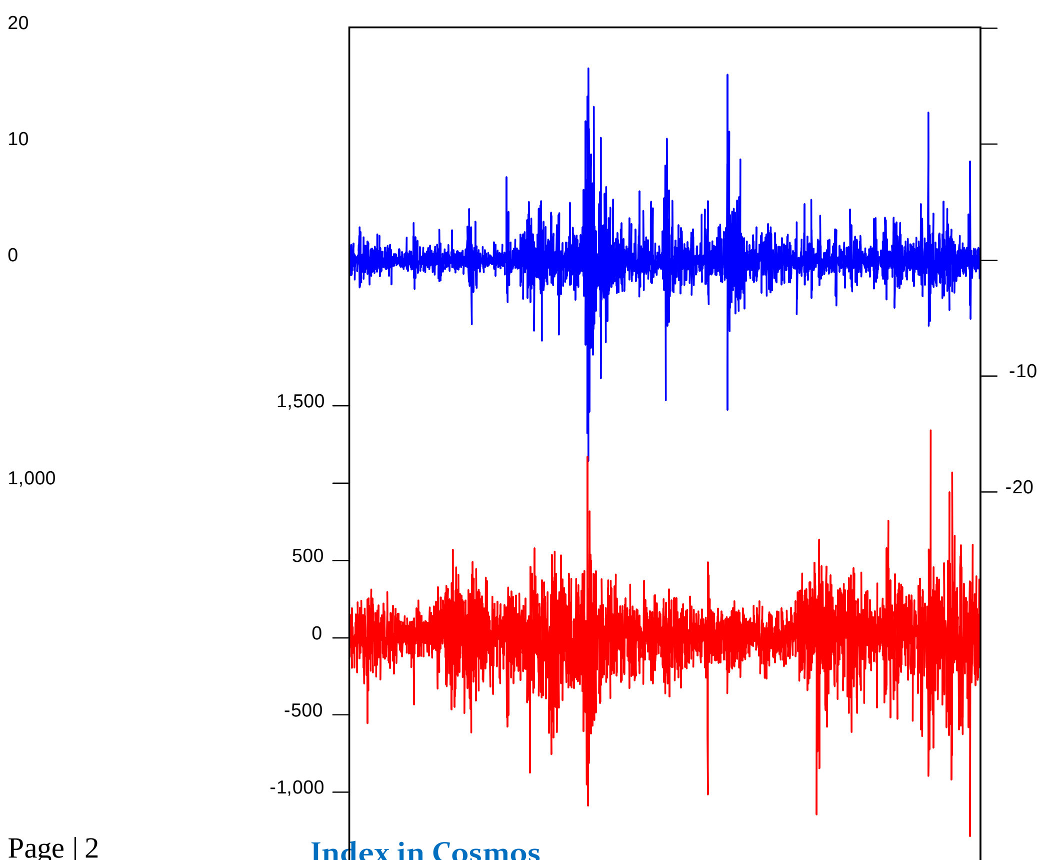
1. Literature Review

Only the most current research on the topic are briefly discussed here. Baumöhl and Lyócsa (2014) recently analyzed the conditional volatilities and time-varying correlations of 32 international developing and frontier stock markets and the MSCI World stock market index. Using dynamic Markov Regime Switching Copula (MRS-Copula) models, Changqing et al. (2015) looked at the Chinese stock market and others across the world in an effort to gauge the spread of financial market risk contagion. Sriananthakumar and Narayan (2015) used a Dynamic Conditional Correlation (DCC) model to look at the relationships between the stock markets of Sri Lanka and India.

USA, Singapore, Malaysia, Pakistan, India, and China.

Further, applying a panel vector autoregressive model to 34 OECD country data, Pradhan et al. (2015) examined their cointegration relations and Granger causality nexuses with regard to economic growth, inflation, and stock market developments. Chuluun (2016) examined global portfolio investment networks and stock market comovements in 49 international countries using network analysis. Boubaker et al. (2016) attempted to assess the contagion between the US stock market and 10 selected developed and emerging equity markets by particularly focusing on the contagion risk that the subprime crisis caused. Moreover, Tsuji (2016) recently rigorously revealed the superior predict power of volatility forecasts from several generalized autoregressive conditional heteroskedasticity (GARCH) models in the US stock market (The journal's web site supplies this paper for free.). However, as far as we know, there is no existing study that analyzed the predict power of US implied volatility for large Japanese stock market declines.



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04 05 06 07 08 09 10 11 12 13 14 15 16

S&P 500 implied volatility changes (right scale)
Nikkei 225 price changes (left scale)

Figure 1. Time-series evolution of the daily changes in the S&P 500 implied volatility and the Nikkei 225

2. Data and Variables

Our study's informational resources and factors are outlined below. To begin, DNK is shorthand for the first day's change in the value of the Nikkei 225 index of stocks in Japan. Second, DSPX refers to the US S&P 500's implied volatility's initial divergence. Additionally, we do our studies using DTERM and DEX as controls. DTERM is for the yield gap between the benchmark 10-year Japanese government bond yield and the 3-month Japanese interbank offered rate, and DEX stands for the initial difference in the value of the Japanese yen relative to the US dollar.

All samples are daily and the sample period we test in this study spans January 2, 2004 to September 5, 2016. All data used in this study are from Thomson Reuters. Figure 1 displays the time-series of DSPX and DNK for the above sample period. From this figure, we understand that the two series show similar movements for our sample period.

Table 1. Forecast power of the US implied volatility for large Nikkei declines: Results of univariate quantile regressions

Panel A. 6% left tail			Panel B. 5% left tail		
	Coefficient	*p*-value		Coefficient	*p*-value
Const.	−249.7521***	0.0000	Const.	−272.5929***	0.0000
DSPX(−1)	−48.4030***	0.0000	DSPX(−1)	−46.8985***	0.0000
Adj.R^2	0.094147		*Adj.*R^2	0.092318	
Panel C. 4% left tail			Panel D. 3% left tail		
	Coefficient	*p*-value		Coefficient	*p*-value
Const.	−297.6566***	0.0000	Const.	−350.2519***	0.0000
DSPX(−1)	−47.7182***	0.0000	DSPX(−1)	−42.7658***	0.0000
Adj.R^2	0.08879		*Adj.*R^2	0.082563	
Panel E. 2% left tail			Panel F. 1% left tail		
	Coefficient	*p*-value		Coefficient	*p*-value
Const.	−425.4153***	0.0000	Const.	−511.7494***	0.0000
DSPX(−1)	−46.9975***	0.0000	DSPX(−1)	−43.1272***	0.0000
Adj.R^2	0.079022		*Adj.*R^2	0.069778	

Notes: DSPX(−1) denotes the first lag variable of the first difference of the S&P 500 implied volatility in the US. *Adj.*R^2 means the adjusted *R*-squared value. *** denotes the statistical significance at the 1% level.

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3. Testing Methods

This section explains the testing methods we employ in this study. We use three kinds of quantile regression models to test the predictability of the US implied volatility for large price declines in the Nikkei 225 in Japan. We emphasize that our multiple tests with below three models are effective for robustness checks.

We begin by the following simple univariate quantile regression model (1):

$$DNK_t^{j\%} = \rho_0^{j\%} + \rho_1^{j\%} DSPX_{t-1} + \varepsilon_t^{j\%}, \quad (1)$$

where $DNK^{j\%}$ means the *j*-percentile point of the distribution of the Nikkei 225 price changes and *j* takes one of the values of 6, 5, 4, 3, 2, and 1 in our analyses (hereinafter the same). Thus, all our model estimations test the forecast power of the US S&P 500 implied volatility for the downside tail risk in the Nikkei 225 in Japan.

Our next model is the following AR(3)-quantile regression model (2):

$$DNK_t^{j\%} = \eta_0^{j\%} + \eta_1^{j\%} DSPX_{t-1} + \sum_{k=1}^{3} \eta_{k+1}^{j\%} DNK_{t-k} + \nu_t^{j\%}. \quad (2)$$

As shown, the above model includes three AR terms as control variables.

Further, our third test is conducted by the following multiple quantile regression model (3):

$$DNK^{j\%} = \xi^{j\%} + \xi^{j\%} DSPX \quad + \xi^{j\%} DNK$$

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Table 2. Forecast power of the US implied volatility for large Nikkei declines: Results of AR(3)-quantile regressions

Panel A. 6% left tail			Panel B. 5% left tail		
	Coefficient	*p*-value		Coefficient	*p*-value
Const.	−250.3194***	0.0000	Const.	−276.2992***	0.0000
DSPX(−1)	−47.8477***	0.0000	DSPX(−1)	−51.0474***	0.0000
DNK(−1)	0.0747**	0.0455	DNK(−1)	0.0610	0.1052
DNK(−2)	0.1349***	0.0016	DNK(−2)	0.1843***	0.0000
DNK(−3)	0.1541***	0.0000	DNK(−3)	0.1684***	0.0000
$Adj.R^2$	0.108571		$Adj.R^2$	0.110616	
Panel C. 4% left tail			Panel D. 3% left tail		
	Coefficient	*p*-value		Coefficient	*p*-value
Const.	−304.2882***	0.0000	Const.	−337.1443***	0.0000
DSPX(−1)	−48.1343***	0.0000	DSPX(−1)	−49.1860***	0.0000
DNK(−1)	0.0434	0.3276	DNK(−1)	0.0001	0.9979
DNK(−2)	0.1840***	0.0000	DNK(−2)	0.1872***	0.0000
DNK(−3)	0.1593***	0.0007	DNK(−3)	0.1901***	0.0000
$Adj.R^2$	0.112307		$Adj.R^2$	0.107849	
Panel E. 2% left tail			Panel F. 1% left tail		
	Coefficient	*p*-value		Coefficient	*p*-value
Const.	−401.9958***	0.0000	Const.	−512.5970***	0.0000
DSPX(−1)	−45.6727***	0.0000	DSPX(−1)	−45.8613***	0.0000
DNK(−1)	0.0344	0.2135	DNK(−1)	0.0282	0.8883
DNK(−2)	0.1448***	0.0000	DNK(−2)	0.0583	0.2791
DNK(−3)	0.1240**	0.0297	DNK(−3)	0.0585	0.7316
$Adj.R^2$	0.098527		$Adj.R^2$	0.074453	

Notes: DSPX(−1) denotes the first lag variable of the first difference of the S&P 500 implied volatility in the US. DNK(−*k*) denotes the *k*th lag variable of the first difference of the Nikkei 225 stock index price in Japan. $Adj.R^2$ means the adjusted *R*-squared value. *** (**) denotes the statistical significance at the 1% (5%) level.

4. Results of Analyses

The estimate outcomes of the basic univariate quantile regression model (1) are first explained. The outcomes are shown in Table 1. Table 1 shows that all of the DSPX(1) coefficients have negative significance at the 1% level (panels A-F). According to the data, big drops in the Nikkei may be predicted based on the implied volatility of the S&P 500 in the United States the day before.

The AR(3)-quantile regression model (2) estimation results are then shown. All panels A-F in Table 2 show that,

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once again, all coefficients of DSPX(-1) are statistically significant at the 1% level with negative signs. Table 2 shows that even with three AR variables included in the testing model, the previous day's implied volatility for the US S&P 500 still has predictive value for big declines in the Nikkei.

Table 3. Forecast power of the US implied volatility for large Nikkei declines: Results of quantile regressions with control variables

Panel A. 6% left tail			Panel B. 5% left tail		
	Coefficient	*p*-value		Coefficient	*p*-value
Const.	−249.6399***	0.0000	Const.	−275.7074***	0.0000
DSPX(−1)	−48.7715***	0.0000	DSPX(−1)	−48.4701***	0.0000
DNK(−1)	−0.0364	0.4812	DNK(−1)	−0.0391	0.4780
DTERM(−1)	89.3092	0.7351	DTERM(−1)	−54.7192	0.8591
DEX(−1)	16.8357	0.2805	DEX(−1)	26.2650*	0.0608
$Adj.R^2$	0.094714		$Adj.R^2$	0.093845	
Panel C. 4% left tail			Panel D. 3% left tail		
	Coefficient	*p*-value		Coefficient	*p*-value
Const.	−301.0762***	0.0000	Const.	−347.6548***	0.0000
DSPX(−1)	−47.2295***	0.0000	DSPX(−1)	−45.6444***	0.0000
DNK(−1)	−0.0130	0.8117	DNK(−1)	0.0419	0.6292
DTERM(−1)	−90.1175	0.8748	DTERM(−1)	−1066.5310	0.1065
DEX(−1)	29.7127*	0.0907	DEX(−1)	29.6416	0.1237
$Adj.R^2$	0.090959		$Adj.R^2$	0.085221	
Panel E. 2% left tail			Panel F. 1% left tail		
	Coefficient	*p*-value		Coefficient	*p*-value
Const.	−418.7015***	0.0000	Const.	−535.0660***	0.0000
DSPX(−1)	−44.4865***	0.0000	DSPX(−1)	−37.6213***	0.0000
DNK(−1)	0.0465	0.6112	DNK(−1)	0.0785***	0.0086
DTERM(−1)	−732.0405	0.4721	DTERM(−1)	−1407.2790**	0.0300
DEX(−1)	37.6263	0.3054	DEX(−1)	21.9822	0.5373
$Adj.R^2$	0.081927		$Adj.R^2$	0.078741	

Notes: DSPX(−1) denotes the first lag variable of the first difference of the S&P 500 implied volatility in the US. In addition, DNK(−*k*) denotes the *k*th lag variable of the first difference of the Nikkei 225 stock index price in Japan. Moreover, DTERM(−1) denotes the first lag variable of the first difference of the Japanese term spread and DEX(−1) represents the first lag variable of the first difference of the Japanese yen exchange rate to the US dollar. Further, $Adj.R^2$ means the adjusted *R*-squared value. ***, **, and * denote the statistical significance at the 1%, 5%, and 10%

levels, respectively.

Finally, we explain the estimation results of our final quantile regression model (3), which includes the control variables of DNK(−1), DTERM(−1), and DEX(−1). Table 3 presents the results and again, all panels from A to F of Table 3 show that all coefficients of DSPX(−1) are statistically significant at the 1% level with negative signs. Therefore, the results in Table 3 again suggest that the previous day's US implied volatility has forecast power for large Nikkei declines even though different control variables are included in our testing model.

As above, we examined six left tail risks of one to six percent downside risks in the distribution of the Nikkei 225 price changes by using three versions of quantile regression models (1) to (3). All results evidenced that the previous day's US S&P 500 implied volatility has forecast power for large Nikkei price declines in Japan.

5. Interpretations and Conclusions

In this study, we empirically test three different quantile regression models' ability to predict big daily drops in the Nikkei based on the prior day's US implied volatility. The following new findings emerged from our examinations of data from the United States and Japan. First, (1) the estimate results of our basic univariate quantile regression model showed statistically substantially that the change in US implied volatility from the previous day had predictive capacity for major drops in the Nikkei price in Japan. Second (2), our AR(3)-quantile regression model's estimate findings also statistically substantially confirmed that US implied volatility from the day before is a reliable predictor of huge Nikkei drops. Finally (3) our quantile regression model with additional control variables provided further statistically significant evidence that the previous day's US implied volatility had predictive ability for substantial Nikkei price decreases in Japan. The most significant contributions of this research are the novel results from our novel analytical perspective, worldwide stock market connections by concentrating on the bearish equity market scenario.

As we have shown above, the implied volatility of the S&P 500 index from the previous trading day is a reliable predictor of big drops in the Nikkei 225 index in Japan. Our findings may be taken at face value since (1) we examined three alternative quantile regression models and (2) we consistently assessed multiple tail risks including one to six percent left tails in price fluctuations of the Nikkei.

Our findings further suggest that (1) negative risks in the US and Japanese stock markets are interdependent (commove), and (2) downside risks in the US stock market spill over into the Japanese stock market (overflow). We stress that these are fresh and engaging ways of thinking about the interconnections between stock markets throughout the world. The results of this study are promising for further investigation, as we have noted. One of our next duties will be to do advanced research based on the results of this investigation. We also think the data gathered here is relevant for real-world applications of asset and risk management in the financial sector. For instance, the findings of this research could inform the practices of asset management and financial risk management by professionals such as fund managers and corporate leaders.

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