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Chinese stock market volatility and the role of U.S. economic variables

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ABSTRACT

This paper investigates the effects of U.S. economic variables on the time variation of Chinese stock market volatility. We find that U.S. economic variables such as the dividend price ratio, dividend yield and industrial production strongly forecast the future monthly volatilities of the Chinese stock market. The predictability is statistically and economically significant and can be further improved when combining the information in all U.S. economic variables together. Forecast encompassing tests and regression tests show that the forecasting power of U.S. economic variables is incremental when comparing with the Chinese domestic economic variables. Our findings are robust for the out-of-sample analysis and a number of Chinese industry portfolios volatilities.

1. Introduction

Volatility forecasting is crucial to many fundamental issues in finance, including risk management, asset pricing, and asset allocation. A large body of literature documents positive evidence on stock market volatility predictability by applying different econometric models to different predictors (e.g., see Engle et al., 2013 and the references therein). In particular, Christiansen et al. (2012), Paye (2012), Corradi et al. (2013), and Engle et al. (2013) provide strong evidences that economic variables can forecast the future movements of U.S. stock market volatility. However, out of the U.S. market, little research analyzes the predictive power of economic variables. This paper adds to the international volatility predictability literature by exploring whether U.S. economic variables are useful in predicting the time variation of Chinese stock market volatility. China is of growing importance in terms of international trade, GDP, and stock market size. It has the second largest stock market in the world, valued at four trillion dollars (with the Shanghai and Shenzhen exchanges combined), and has more than two thousand public firms listed. Thus, understanding whether the Chinese stock market volatility is predictable is of great importance.

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Over the last two decades, China has been increasingly integrated to the global economy, particularly after China's admission into the WTO in the end of 2001 (Glick and Hutchison, 2013). U.S., the largest economy in the world, is China's largest trade partner. Harvey (1991) and Bekaert and Harvey (1995) show that U.S. economic conditions are highly correlated with world economic conditions. Since stock market volatility is strongly influenced by foreign factors when the stock markets are integrated (Bekaert and Harvey, 1997), U.S. economic variables therefore may have great predictive power for the Chinese stock market volatility. Rapach et al. (2013), Jordan et al. (2014), and, particularly, Goh et al. (2013) find that U.S. economic variables have significant forecasting power for Chinese stock market returns. Complementing these existing studies, we examine whether U.S. economic variables contain forecasting information for the Chinese stock market *volatility*. We also explore whether U.S. economic variables contain additional forecasting information beyond that embedded in the Chinese domestic predictors.

In our empirical analysis, we use 17 U.S. economic variables, including the book-to-market ratio (BM), treasury bill rate (TBL), long-term yield (LTY), net equity expansion (NTIS), inflation (INFL), long-term return (LTR), dividend-price ratio (DP), dividend yield (DY), earnings-price ratio (EP), dividend-payout ratio (DE), term spread (TMS), default yield spread (DFY), default return spread (DFR), commercial paper-to-treasury spread (CP), industrial production growth (IP), volatility of industrial production growth (IPVOL), and volatility of producer's price index (PPIVOL) as volatility predictors. We measure the stock market volatility as the logarithm of monthly realized volatility, which is calculated as the square root of sum squared daily returns on the aggregate Chinese stock market. In addition, while Ferson and Harvey (1999) and Ferson and Korajczyk (1995) have studied the predictability of industry portfolios returns, little research investigates the forecasting power of economic variables for the industry volatilities, which become more and more important with the increasing popularity of industry exchange-traded funds (ETFs). In this paper, we provide empirical evidence on industry portfolios volatilities forecasting beyond the market volatility forecasting. Our sample spans from January 1997 through December 2012.[1]

We regress the log realized volatility of Chinese stock market on the lagged U.S. economic variables, with controls of lagged Chinese and U.S. volatilities, since Chinese stock market volatility is fairly persistent and is negatively associated with U.S. stock market volatility (Chow and Lawler, 2003). Thus, we test whether incorporating U.S. economic variables can improve the Chinese stock market volatility forecasting compared with the benchmark autoregressive (AR) model. Our in-sample results show that five U.S. economic variables (NTIS, LTR, DP, DY, and IP) significantly forecast the Chinese stock market volatility during the full-sample period from January 1997 to December 2012, while five variables (NTIS, LTR, DP, TMS, and CP) strongly forecast the Chinese volatility during the sub-sample period from January 2002 to December 2012. The predictive regression models based on U.S. economic variables generate economically large and statistically significant ΔR^2 statistics, the increase in R^2 relative to that of the benchmark model, up to 2.18% (6.65%) during the full-sample (sub-sample) period. We next combine the forecasting information in U.S. economic variables together using the partial least square (PLS) method, following Kelly and Pruitt (2013, 2015) and Huang et al. (2015). Our results show that the combined factor strongly predicts the future Chinese stock market volatility during the full- and sub-sample periods. The predictive power is statistically and economically significant with ΔR^2 statistic of 2.17% (5.05%) for the full-sample (sub-sample), larger than most individual economic variables.

We also run the predictive regressions after controlling for Chinese domestic predictors, to test the incremental forecasting information contained in U.S. economic variables. We find that the U.S. economic variable's predictive power is still strong and significant. Moreover, we carry out the forecast encompassing test of Harvey et al. (1998) and the results show that none of Chinese domestic economic variables encompass the U.S. economic variables, and neither do the combined Chinese factors. It indicates that the U.S. economic variables indeed contain useful information for the predictability of Chinese stock market volatility beyond that embedded in Chinese domestic predictors.

To address concerns relating to the potential fragility of in-sample results, we study the out-of-sample performance of the U.S. economic variables.[2] This analysis is based on Campbell and Thompson (2008)'s out-of-sample R^2_{OS} statistics relative to the benchmark forecast. In our study, we consider three benchmark models: the historical average model, AR model incorporating lagged Chinese and U.S. market volatilities, and Chinese economic variable augmented AR model. The out-of-sample forecasts of Chinese stock market volatility are generated recursively only using data available through the period of forecast formation, *t*. We then calculate the R^2_{OS} statistics following Campbell and Thompson (2008).

Our results show that six U.S. economic variables (BM, NTIS, DP, DY, IP, and PPIVOL) generate positive and significant R^2_{OS} statistics in comparison with the historical average forecast, ranging from 0.16% to 16.28%. Comparing with the benchmark forecasts of AR model and Chinese variable augmented AR model, U.S. economic variables like DP, DY, and IP delivery positive R^2_{OS} statistics which are statistically significant and economically sizable. It indicates that these volatility forecasts based on U.S. economic variables produce substantially smaller mean squared forecasting errors (MSFE) than those generated by the benchmark models. This finding suggests that incorporating the U.S. economic variables helps to improve the out-of-sample forecast of Chinese stock market volatility, which is consistent with our in-sample results.

We also use the mean, median, trimmed mean methods, as well as the PLS method to generate out-of-sample combination forecasts, following Rapach et al. (2010), to incorporate information in all U.S. economic variables together. Forecasts based on these four combining methods generate positive out-of-sample R^2_{OS} statistics for all three benchmark models, ranging from 0.67% to 15.36%. Most of the R^2_{OS} statistics are statistically significant and economically large. In particular, the R^2_{OS} statistics of

[1] Our sample period for industry volatility spans from January 2002 to December 2012 due to the data availability.

[2] Welch and Goyal (2008) show that a large number of economic variables with in-sample significance generate poor out-of-sample performance. See Lettau and Ludvigson (2009) for a literature review on in-sample versus out-of-sample asset return predictability.

combination forecasts are larger than those of most individual U.S. economic variables, indicating the outperformance of combination forecast strategies.

Lastly, we investigate the forecasting power of U.S. economic variables for the volatilities of Chinese industry portfolios. Our results show that a number of U.S. economic variables (e.g., TBL, NYIS, LTR, DP, DY, TMS, CP, and IP) generate positive in-sample ΔR^2 relative to the AR model, indicating that the U.S. economic variables indeed contain useful information for the Chinese industry volatilities forecasting. In the out-of-sample analysis, the combination forecasts based on mean, median, trimmed mean, and PLS combining methods produce positive and significant R^2_{OS} for most industries, when comparing with the historical average benchmark model, the AR model, and the Chinese economic variables augmented AR model. Thus, we can conclude that the U.S. economic variables strongly forecast the industry volatilities, which is consistent with our findings for the aggregate Chinese stock market.

The remainder of this paper is organized as follows. Section 2 describes the data used in this paper. Section 3 provides empirical forecasting results. Section 4 concludes this paper.

2. Data and Summary Statistics

In this paper, we investigate the forecasting power of U.S. economic variables for the monthly Chinese stock market volatility. Following French et al. (1987), Schwert (1989), Andersen et al. (2001), Paye (2012), Christiansen et al. (2012), among many others, we focus on the log volatility denoted by *LVOL*, which is calculated as

$$LVOL_t = \ln\left(\sqrt{RV_t}\right), \tag{1}$$

where the ex post measurement of monthly variance, *RV*, is calculated as the sum of squared daily returns on Chinese stock market,

$$RV_t = \sum_{i=1}^{N_t} R_{i,t}^2. \tag{2}$$

In Eq. (2), N_t denotes the number of trading days in the t-th month and $R_{i,t}$ indicates the daily returns on the Chinese stock market on the i-th trading day of the t-th month. The log volatility *LVOL* has an approximately normal distribution, while the distribution of the raw realized volatility is right-skewed and leptokurtotic.[3]

Our sample period extends from January 1997 to December 2012.[4] To construct the log volatility *LVOL* for the Chinese market portfolio, we employ the value-weighted Chinese aggregate stock market return from RESSET. In addition, we use the daily returns on 13 Chinese industry portfolios to calculate the industry portfolios volatilities, including AGRIC (Agriculture, Forestry, and Fishing), MINES (Mining), MANUF (Manufacturing), UTILS (Electric, Gas, and Water), CNSTR (Construction), TRANS (Transportation and Storage), INFTK (Information Technology), WHTSL (Wholesale and Retail), MONEY (Finance and Insurance), PROPT (Real Estate), SRVC (Service), MEDIA (Communication and Culture), and MULTP (Conglomerate), formed on the industry classification of China Securities Regulatory Commission (CSRC). Due to the data availability, the sample period for industry portfolios extends from January 2002 to December 2012.

Following the recent stock market predictability literature like Welch and Goyal (2008), Paye (2012), and Christiansen et al. (2012), we consider 17 U.S. economic variables as volatility predictors:

- Book-to-market ratio, BM: ratio of book value to market value for the Dow Jones Industrial Average.[5]
- Treasury bill rate, TBL: interest rate on a three-month Treasury bill (secondary market).
- Long-term yield, LTY: long-term government bond yield.
- Net equity expansion, NTIS: ratio of a twelve-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.
- Inflation, INFL: calculated from the CPI for all urban consumers; we use lagged two-month inflation in regression to account for the delay in CPI releases.
- Long-term return, LTR: return on long-term government bonds.
- Dividend-price ratio (log), DP: log of a twelve-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index).
- Dividend yield (log), DY: log of a twelve-month moving sum of dividends minus the log of lagged stock prices.
- Earnings-price ratio (log), EP: log of a twelve-month moving sum of earnings on the S&P 500 index minus the log of stock prices.
- Dividend-payout ratio (log), DE: log of a twelve-month moving sum of dividends minus the log of a twelve-month moving sum of earnings.

[3] Consistent with Paye (2012), we find that our findings are robust when the volatility is calculated using the intraday price data.

[4] The Shanghai stock exchange was established in 1990 and the Shenzhen stock exchange was established in 1991. Since December 16, 1996, both exchanges have adopted daily price change limits of 10%. Therefore, this paper only focuses on the post-1996 sample.

[5] We use the logarithm of the book-to-market ratio in following empirical analysis.

- Term spread, TMS: long-term yield minus the Treasury bill rate.
- Default yield spread, DFY: difference between BAA- and AAA-rated corporate bond yields.
- Default return spread, DFR: long-term corporate bond return minus the long-term government bond return.
- Commercial paper-to-Treasury spread, CP: difference between the three-month commercial paper rate and the rate on three-month Treasury bills. The construction of this variable follows Paye (2012) and Lettau and Ludvigson (2009).
- Industrial production growth, IP: difference between the log of industrial production index and the log of twelve-month lagged industrial production index. The construction of this variable follows Corradi et al. (2013).
- Volatility of industrial production growth, IPVOL: sum of absolute industrial production growth rate during past twelve months divided by square root of twelve. The construction of this variable follows Mele (2008).
- Volatility of producer's price index (PPI), PPIVOL: a volatility estimate of the 12th-order autoregression for producer's price index (PPI) inflation rate. The construction of this variable follows Engle et al. (2013) and Paye (2012). This variable is a proxy for the conditional volatility of inflation growth based on PPI.

We obtain the data from the Welch and Goyal (2008)'s predictability dataset in Amit Goyal's webpage, Bradley S. Paye's volatility predictability dataset in Paye (2012), the Federal Reserve Bank of St. Louis's FRED database, and the Bureau of Labor Statistics's website.

In addition, we also analyze the incremental forecasting power of U.S. economic variables beyond the Chinese domestic economic variables. Following Jiang et al. (2011), Goh et al. (2013), Girardin and Joyeux (2013), and Cai et al. (forthcoming), we construct 14 Chinese economic variables:

- Dividend-price ratio (log), DP: difference between the logarithm of dividends and that of prices for all A-share stocks listed in Shanghai and Shenzhen stock exchanges, where dividends are measured using a one-year moving sum.
- Dividend-payout ratio (log), DE: difference between the logarithm of dividends and logarithm of earnings for A-share stocks listed in Shanghai and Shenzhen stock exchanges, where dividends and earnings are measured using a one-year moving sum.
- Dividend yield (log), DY: the difference between the logarithm of dividends and that of lagged prices, where dividends are measured using a one-year moving sum.
- Earnings-price ratio (log), EP: the difference between the logarithm of earnings and that of prices on all A-share stocks listed in Shanghai and Shenzhen stock exchanges, where earnings are measured using a one-year moving sum.
- Book-to-market ratio (log), BM: the difference between the logarithm of book value and that of market value for A-share stocks listed in Shanghai and Shenzhen stock exchanges.
- Inflation, INF: calculated according to the CPI published by China National Bureau of Statistics.
- Turnover, TO: the ratio of trading volume to total number of share outstanding for A-share stocks listed in Shanghai and Shenzhen stock exchanges.
- Changes in money supply (M0), M0G: the difference between money supply (M0) at the current month and that at the previous month.
- Changes in money supply (M1), M1G: the difference between money supply (M1) at the current month and that at the previous month.
- Changes in money supply (M2), M2G: the difference between money supply (M2) at the current month and that at the previous month.
- Industrial product growth, IP: difference between the log of industrial production index and the log of twelve-month lagged industrial production index.
- Volatility of industrial production growth, IPVOL: sum of absolute industrial production growth rate during past twelve months divided by square root of twelve.
- Volatility of producer's price index (PPI), PPIVOL: This variable is a proxy for the conditional volatility of inflation growth based on the producer's price index (PPI).
- Stock market default risk, CVI: the monthly change of corporate vulnerability index.

We obtain the stock market related data from RESSET, the CPI from China National Bureau of Statistics, the money supply (M0, M1, and M2) from People's Bank of China, the industrial product growth from CEIC, and the CVI from the Risk Management Institute (RMI) at the National University of Singapore.[6]

Table 1 reports the summary statistics of the Chinese stock market volatility and the U.S. economic variables. The average log volatility for the Chinese stock market is −2.63, which is larger than −3.27 (−3.22) for the U.S. stock market over the period from 1926 to 2010 (1983 to 2010), as reported in Christiansen et al. (2012). Thus, the Chinese stock market on average displays high volatility over our sample period. According to the reported skewness (0.16) and kurtosis (2.67), the Chinese log volatility shows an approximately Gaussian distribution, consistent with Andersen et al. (2001). It is well known that volatility is highly persistent in the U.S. stock market, and we find similar patterns for the Chinese stock market volatility measure, indicated by the large first-order autocorrelation coefficient of 0.58.

Fig. 1 plots the time series of Chinese stock market volatility over the period from January 1997 to December 2012. The anecdotal evidence shows that the time variation of Chinese stock market volatility appears to be related to U.S. economic conditions.

[6] Girardin and Joyeux (2013) use the Chinese bank credit data, but we consider the default risk for the aggregate stock market which is measured by the aggregated corporate vulnerability index.

Table 1
Summary statistics.
This table reports the mean, standard deviation (Std. Dev.), skewness (Skew.), kurtosis (Kurt.), minimum (Min.), maximum (Max.), and first-order autocorrelation coefficient (ρ_1) of the monthly log volatility for the Chinese aggregate stock market (*LVOL*) and 17 U.S. economic variables used in this paper. The sample period extends from January 1997 through December 2012.

	Mean	Std. Dev.	Skew.	Kurt.	Min.	Max.	ρ_1
LVOL	−2.63	0.43	0.16	2.67	−3.73	−1.60	0.58
BM	−1.41	0.33	−0.39	2.03	−2.12	−0.82	0.96
TBL	0.03	0.02	0.11	1.42	0.00	0.06	0.99
LTY	0.05	0.01	−0.51	3.14	0.02	0.07	0.95
NTIS	0.00	0.02	−1.14	3.87	−0.06	0.03	0.96
INFL	0.00	0.00	−1.03	7.84	−0.02	0.01	0.47
LTR	0.01	0.03	0.01	5.75	−0.11	0.14	−0.03
DP	−4.06	0.23	0.45	3.91	−4.52	−3.28	0.97
DY	−4.06	0.23	0.35	3.76	−4.53	−3.29	0.97
EP	−3.20	0.43	−1.64	6.51	−4.84	−2.57	0.97
DE	−0.86	0.51	2.84	11.32	−1.24	1.38	0.98
TMS	0.02	0.01	−0.11	1.69	0.00	0.05	0.98
DFY	0.01	0.00	2.72	11.94	0.01	0.03	0.96
DFR	0.00	0.02	−0.38	8.42	−0.10	0.07	0.02
CP	0.00	0.00	1.57	5.37	0.00	0.01	0.82
IP	0.02	0.05	−1.84	6.65	−0.16	0.08	0.97
IPVOL	0.15	0.09	1.60	5.79	0.03	0.45	0.99
PPIVOL	0.18	0.09	0.34	2.23	0.03	0.39	0.98

For example, we observe persistently high volatility spikes during the collapse of "technology bubble" in 2002 and the recent financial crisis in 2008.

Table 1 also presents the summary statistics of the U.S. economic variables. The mean values range from −4.06 (the DP and DY ratios) to 0.18 (the volatility of PPI, PPIVOL). Consistent with the literature, economic predictors are highly persistent based on the first-order autocorrelation coefficients, except for the long-term return (LTR) and default return spread (DFR).

3. Empirical results

3.1. Forecasting ability of U.S. economic variables

In this section, we investigate whether the U.S. economic variables can improve the Chinese stock market volatility forecasting. We first test the forecasting power of each individual U.S. economic variables using the predictive regression framework,

$$LVOL_t = \alpha + \beta X_{t-1} + \rho_1 LVOL_{t-1} + \rho_2 LVOL_{t-2} + \varphi LVOL_{t-1}^{US} + \varepsilon_t, \tag{3}$$

where *LVOL* denotes the log volatility for Chinese stock market, measured as in Eq. (1), $LVOL^{US}$ is the logarithm of U.S. stock market volatility, and *X* represents one of the 17 standardized U.S. economic variables used in this paper. We include two lags of Chinese stock market volatility in model (3), since realized volatility is fairly persistent. We also control for the lagged U.S. market volatility, since Chow and Lawler (2003) show that the volatility measures of Shanghai and New York Stock Exchange composite price indices are significantly negatively correlated. The number of lags for Chinese and U.S. stock market volatilities are determined according to Schwarz information criterion (SIC). Hence, we analyze whether the U.S. economic variables improve the Chinese volatility forecasting beyond the information in lagged Chinese and U.S. stock market volatilities.

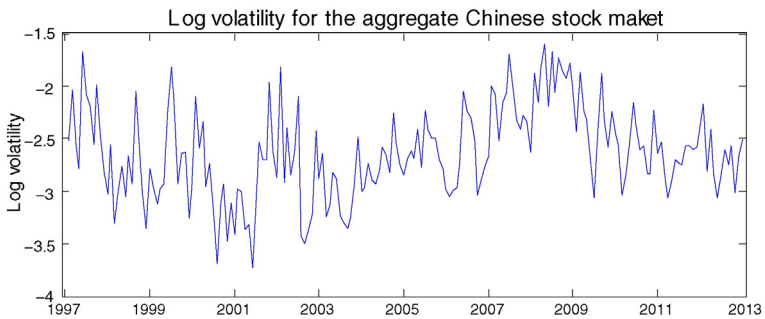

Fig. 1. Chinese stock market volatility. This figure plots the monthly log volatility for the Chinese aggregate stock market over the period from January 1997 through December 2012.

Table 2
In-sample forecasting results.
Panel A presents results for in-sample predictive regressions for the log Chinese aggregate stock market volatility using U.S. economic variables over the full-sample period from January 1997 through December 2012. Panel B shows results for the sub-sample period from January 2002 through December 2012. The table reports results from predictive regressions,
$LVOL_t = \alpha + \beta X_{t-1} + \rho_1 LVOL_{t-1} + \rho_2 LVOL_{t-2} + \varphi LVOL^{US}_{t-1} + \varepsilon_t$,
where *LVOL* is the logarithm of Chinese aggregate stock market volatility, $LVOL^{US}$ is the logarithm of US stock market volatility, and *X* represents one of the 17 U.S. economic variables. In the last row, we also report the results for the U.S. economic factor (US) estimated from all the 17 U.S. economic variables using the partial least square (PLS) method. For each U.S. economic variable, the table presents the estimated slope coefficients (β), Newey and West (1987) *t*-statistics (NW-*t*), and the increase in R^2 value (ΔR^2) relative to a benchmark model (under the assumption that $\beta = 0$). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on wild bootstrapped *p*-values. To save space, we do not report the intercept and estimated slope coefficients for the lagged volatilities in regressions.

	β	NW-*t*	ΔR^2 (%)	β	NW-*t*	ΔR^2 (%)
	Panel A: Full-sample period			Panel B: Sub-sample period		
BM	0.02	1.04	−0.07	0.01	0.56	−0.35
TBL	−0.01	−0.63	−0.24	0.04	1.38	0.24
LTY	−0.01	−0.51	−0.29	0.00	−0.16	−0.46
NTIS	−0.08***	−2.69	2.18	−0.13***	−3.61	6.56
INFL	−0.01	−0.53	−0.26	0.01	0.55	−0.37
LTR	−0.05**	−2.05	0.76	−0.05**	−2.05	1.22
DP	0.07***	2.66	1.67	0.06*	1.67	0.95
DY	0.07**	2.43	1.50	0.06	1.50	0.99
EP	0.00	−0.16	−0.34	0.02	0.49	−0.35
DE	0.04	1.29	0.16	0.00	0.02	−0.47
TMS	0.01	0.55	−0.26	−0.05*	−1.85	0.68
DFY	0.04	1.39	0.19	0.00	−0.01	−0.47
DFR	−0.01	−0.46	−0.29	0.00	−0.01	−0.47
CP	0.02	0.72	−0.12	0.09***	2.94	3.20
IP	−0.05**	−1.99	0.78	−0.02	−0.71	−0.21
IPVOL	−0.01	−0.34	−0.31	0.00	−0.17	−0.46
PPIVOL	0.03	1.35	0.18	0.03	0.99	0.08
US	0.07***	2.79	2.17	0.18***	2.95	5.05

The in-sample predictability is tested by inspecting the Newey and West (1987) *t*-statistic corresponding to β, the regression estimate of β in model (3). The null hypothesis is that the U.S. economic variables have no predictability for the future Chinese stock market volatility, i.e., $\beta = 0$. Under the alternative hypothesis, β is significantly different from zero, and that is to say, the U.S. economic predictors contain additional forecasting information beyond that in the lagged Chinese and U.S. market volatilities.

Panel A of Table 2 reports in-sample results for the period from January 1997 to December 2012. We report the estimated regression slope coefficients (β) for U.S. economic variables, the Newey and West (1987) *t*-statistics, and the ΔR^2 which measures the increases in R^2 values relative to the benchmark predictive regression ($\beta = 0$ in Eq. (3)).[7] The estimated coefficients (β) for the net equity expansion (NTIS), the long-term return (LTR), and the industrial production growth (IP) are negative and statistically significant at the 5% level at least, while the β estimates for the dividend price ratio (DP) and the dividend yield (DY) are positive and statistically significant at the 5% or better levels. Hence, an increase in the U.S. dividend price ratio or the dividend yield will lead to higher Chinese future stock market volatility, and an increase in the U.S. net equity expansion, the long-term Treasury bond return, or the industrial production growth will lead to lower the Chinese market volatility, with statistical significance. The absolute values of regression coefficient estimates β for these four variables range from 0.05 to 0.08, thus a one standard deviation shock to the U.S. economic predictors can forecast about 5% to 8% changes in the Chinese stock market log volatility for the next month, which is about 20% of the standard deviation of the Chinese stock market log volatility, as exhibited in Table 1, indicating strong economic significance of the forecasting power of these U.S. predictors.

The increase in R^2, ΔR^2, measures the incremental predictive power of incorporating each U.S. economic variable into the benchmark model, and it provides another metric to assess the economic significance of Chinese volatility predictability. For economic variables of NTIS, LTR, DP, DY, and IP, the ΔR^2 statistics range from 0.76% to 2.18%, indicating that these U.S. economic variables are able to explain about an additional 0.76% to 2.18% larger proportion of total variations of the Chinese stock market volatility relative to the benchmark model. These U.S. economic variables' ΔR^2 for the Chinese stock market volatility forecasting are as large as their ΔR^2 for the U.S. stock market volatility forecasting, as in Paye (2012) which shows that the ΔR^2 for most economic variables in the U.S. market range from 0.00% up to 2.01% at the monthly sampling frequency. This again indicates the large economic significance of Chinese stock market volatility predictability of U.S. economic variables.

Our results are consistent with many studies on volatility predictability for the U.S. market. Mele (2007) argues that the countercyclical return volatility is endogenously induced by rational fluctuations of the price dividend ratio. He shows that the return volatility increases on the downside, because the price-dividend ratio is an increasing and concave function of variables tracking

[7] To save space, we do not report the estimates of coefficients for lagged Chinese and U.S. market volatilities. The estimates for lagged Chinese volatilities are statistically significant, whereas the φ estimate for lagged U.S. stock market volatility is insignificant and negatively signed, which is consistent with the results in Chow and Lawler (2003).

the business cycle conditions. Baskin (1989) advances four basic models which relate the dividend yield to common stock volatility, i.e., the duration effect, the rate of return effect, the arbitrage pricing effect, and the informational effect. Larrain and Varas (2013) suggest that changes in risk (i.e., changes in rational discount rates) constitute the main source of return volatility and therefore for the connection between volatility, returns, and issuance decisions. Paye (2012) finds that the industrial production growth is negatively related to the future market volatility.

In Panel B of Table 2, we report the in-sample results for U.S. economic variables during the post-WTO sub-sample period from January 2002 to December 2012. Goh et al. (2013) find that the U.S. economic variables have significant predictive power for the Chinese stock returns after China joined the World Trade Organization (WTO) in the end of 2001. Our results show that the NTIS, LTR, DP, and TMS significantly forecast the Chinese stock market volatility during the sub-sample period. Moreover, we find that the estimated β for the commercial paper-to-treasury spread (CP) is positive and statistically significant at the 1% level. The corresponding ΔR^2 is 3.20%, indicating a strong economic significance. Paye (2012) also finds strong volatility predictability of CP in the U.S. stock market.

In addition, we test the performance of combined U.S. economic variables. As suggested by Rapach et al. (2010), model uncertainty and parameter instability surrounding the data-generating process seriously impair the forecasting ability of individual predictive regression models. In addition, while some individual predictors may generate good forecasting performance over certain sample periods, research aiming to identify the "best" individual predictor may subject to survival bias in that ex ante the investor cannot know which one of the predictors to use and the best model may change over time due to parameter instability. Thus, we extract one common economic factor from the 17 U.S. economic variables, using the partial least square (PLS) method. The PLS combining method extracts a common factor from the individual predictors that is relevant for forecasting volatility according to the covariance with economic variables and future stock volatilities. This method is also used in Kelly and Pruitt (2013, 2015) and Huang et al. (2015). Then, we test the forecasting power of the U.S. economic PLS factor using the standard predictive regression model (3) again.

In the last row of Table 2, we can see that, during the full sample period, the estimate of β for the combined PLS factor is statistically significant at the 1% level and the ΔR^2 of combination forecast is 2.17% which is larger than most individual variables. It indicates that the PLS combined U.S. economic factor has superior forecasting power and outperforms most individual economic variables. Our finding is robust to the sub-sample from January 2002 to December 2012.

3.2. Comparison with Chinese Economic Variables

Next, we test whether the U.S. predictor contains additional forecasting information for the Chinese stock market volatility beyond that embedded in the Chinese domestic economic variables.[8] To assess the incremental information in U.S. economic variables, we carry out a forecast encompassing test. Harvey et al. (1998) develop a statistic for testing the null hypothesis whether a given forecast contains all of the relevant information found in a competing forecast (i.e., the given forecast encompasses the competitor) against the alternative that the competing forecast contains relevant information beyond that in the given forecast.

Table 3 reports p-values of the test. None of the individual Chinese economic variables as well as the PLS combined Chinese factor encompass the U.S. PLS factor extracted from 17 economic variables, indicating the potential information gains associated with U.S. economic variables to make better forecasts. On the other hand, the U.S. PLS factor does not encompass the Chinese economic variables neither. That is to say, both Chinese and U.S. economic variables are useful in explaining the Chinese stock market volatility.

The encompassing test suggests that U.S. economic variables contain incremental information beyond that embedded in the Chinese domestic variables. We further investigate this issue using the standard predictive regression framework, which gives us a quantitative estimation. More specifically, we test the forecasting power of the U.S. economic PLS factor and the Chinese domestic economic variables (both the individual variables and PLS combined factor) using the regressive model,

$$LVOL_t = \alpha + \beta^{US} X_{t-1}^{US} + \beta^{CN} X_{t-1}^{CN} + \rho_1 LVOL_{t-1} + \rho_2 LVOL_{t-2} + \varphi LVOL_{t-1}^{US} + \varepsilon_t, \tag{4}$$

where $LVOL$ is the logarithm of Chinese stock market volatility, $LVOL^{US}$ is the logarithm of U.S. stock market volatility, X^{US} is the lagged U.S. economic factor estimated from all the 17 U.S. economic variables using the partial least square (PLS) method, and X^{CN} is one of the 14 Chinese economic variables or PLS combined Chinese variable.

Panel A and Panel B of Table 4 report the regression results for Eq. (4) during the full-sample and post-WTO sub-sample periods, respectively. As is shown, the forecasting power of U.S. economic variable is statistically significant at the 5% level at least according to the Newey and West (1987) t-statistics, after controlling for the Chinese domestic variables. The ΔR^2 statistics range from 1.23% to 5.09% during the full sample period and from 3.84% to 7.05% during the sub-sample period. It suggests that the U.S. economic PLS factor can explain additional 7.05% larger proportion of total variations of the Chinese stock market volatility in comparison to using the lagged Chinese domestic variables and Chinese and U.S. market volatilities as benchmark forecast. In the last row of Table 3, we regress the Chinese stock market volatility on the combined PLS factors for U.S. and Chinese economic variables plus lagged volatilities. The results show that estimates of both PLS factors are statistically significant at the 1% level, and the combination forecasts generate ΔR^2 of 4.42% and 5.86% during the full- and sub-sample, respectively. Again, it indicates that

[8] Cai et al. (forthcoming) investigate the forecasting power of individual Chinese economic variables.

Table 3
Forecast encompassing tests.
This table reports the *p*-values of the Harvey et al. (1998) statistics for the 14 Chinese economic variables, the combined Chinese economic factor (CN), and the combined U.S. economic factor (US). The statistic corresponds to a one-sided (upper-tail) test of the null hypothesis that the predictive regression forecast for Chinese stock market volatility based on one of the predictors given in the row heading encompasses the forecast based on one of the predictors given in the column heading, against the alternative hypothesis that the forecast given in the row heading does not encompass the forecast given in the column heading. The CN and US economic factors are estimated from the 14 Chinese economic variables and 17 U.S. economic variables, respectively, using the partial least square (PLS) method.

	$M0^{CN}$	$M1^{CN}$	$M2^{CN}$	DP^{CN}	DY^{CN}	DE^{CN}	BM^{CN}	EP^{CN}	INF^{CN}	TO^{CN}	$PPIVOL^{CN}$	$IPVOL^{CN}$	IP^{CN}	CVI^{CN}	CN	US
$M0^{CN}$		0.18	0.16	0.00	0.00	0.01	0.29	0.00	0.00	0.00	0.10	0.00	0.18	0.04	0.00	0.00
$M1^{CN}$	0.25		0.22	0.00	0.00	0.01	0.20	0.00	0.00	0.00	0.08	0.00	0.12	0.03	0.00	0.00
$M2^{CN}$	0.10	0.11		0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.05	0.00	0.05	0.01	0.00	0.00
DP^{CN}	0.85	0.72	0.60		0.32	1.00	0.86	0.02	0.00	0.05	0.82	0.28	0.90	0.34	0.05	0.00
DY^{CN}	0.75	0.63	0.51	0.45		0.99	0.79	0.02	0.00	0.04	0.82	0.26	0.85	0.25	0.05	0.00
DE^{CN}	0.28	0.17	0.14	0.00	0.00		0.19	0.00	0.00	0.00	0.33	0.01	0.47	0.05	0.00	0.00
BM^{CN}	0.04	0.03	0.04	0.00	0.00	0.00		0.00	0.00	0.00	0.06	0.00	0.02	0.01	0.00	0.00
EP^{CN}	0.01	0.01	0.01	0.00	0.00	0.00	0.06		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
INF^{CN}	0.36	0.22	0.22	0.00	0.00	0.03	0.20	0.06		0.00	0.11	0.01	0.22	0.18	0.00	0.00
TTO^{CN}	0.17	0.17	0.13	0.00	0.00	0.02	0.41	0.09	0.00		0.13	0.00	0.15	0.02	0.00	0.00
$PPIVOL^{CN}$	0.01	0.01	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00		0.01	0.02	0.01	0.00	0.00
$IPVOL^{CN}$	0.05	0.03	0.02	0.00	0.00	0.02	0.05	0.00	0.00	0.00	0.28		0.44	0.01	0.00	0.00
IP^{CN}	0.02	0.01	0.02	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.10	0.00		0.01	0.00	0.00
CVI^{CN}	0.48	0.26	0.20	0.00	0.00	0.02	0.29	0.00	0.00	0.00	0.11	0.00	0.35		0.00	0.00
CN	0.43	0.24	0.19	0.12	0.11	0.75	0.37	0.01	0.00	0.03	0.73	0.38	0.64	0.21		0.00
US	0.05	0.04	0.04	0.00	0.00	0.00	0.04	0.02	0.00	0.00	0.00	0.00	0.04	0.03	0.00	

the U.S. economic variables contain substantially additional information beyond that embedded in the Chinese local economic variables in forecasting the future Chinese stock market volatility.

Comparing the results in Table 2 with those in Table 4, we find that the U.S. and Chinese economic variables seem to be complementary. Relative to the AR benckmark model, the ΔR^2 of regression based on the U.S. economic PLS factor is 2.17% during the full-sample period in Table 2. This value nearly doubles (4.42%) in Table 4, relative to the AR benchmark model augmented with Chinese variables. For individual Chinese variables in Table 4, some ΔR^2 values are unchanged or slightly reduced, but some are increased sharply even up to 5.09% (DE ratio). It indicates that some Chinese economic variables are complementary to U.S. economic predictors. They help to remove some irrelevant noise from the U.S. economic variables.

In summary, our analyses show that the U.S. economic variables strongly improve the Chinese stock market volatility forecasting, and contains substantially additional forecasting information beyond that embedded in the Chinese domestic economic

Table 4
Comparison with Chinese economic variables.
This table compares the in-sample performance of U.S. economic variables with Chinese economic variables. Panel A shows results for the full-sample period from January 1997 through December 2012 and Panel B displays results for the sub-sample period from January 2002 through December 2012. The table reports results for predictive regressions
$LVOL_t = \alpha + \beta^{US} X_{t-1}^{US} + \beta^{CN} X_{t-1}^{CN} + \rho_1 LVOL_{t-1} + \rho_2 LVOL_{t-2} + \varphi LVOL_{t-1}^{US} + \varepsilon_t$,
where *LVOL* is the logarithm of Chinese stock market volatility, $LVOL^{US}$ is the logarithm of U.S. stock market volatility, X^{US} is the lagged U.S. economic factor estimated from all the 17 U.S. economic variable using the partial least square (PLS) method (denoted as US), X^{CN} is one of the 14 Chinese economic variables given in the first column. In the last row, we also compare the PLS U.S. economic factor with the Chinese PLS economic factor (CN) estimated from the 14 Chinese economic variables. The table presents the estimated slope coefficients (β^{US} and β^{CN}) for the U.S. and Chinese economic predictors, the Newey and West (1987) *t*-statistics (NW-*t*), and the increase in R^2 value (ΔR^2) relative to a benchmark model (under the assumption that $\beta^{US} = 0$). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on wild bootstrapped *p*-values. To save space, we do not report the intercept and estimated coefficients for the lagged volatilities in the regressions.

	Panel A: Full-sample period					Panel B: Sub-sample period				
	β^{US}	NW-*t*	β^{CN}	NW-*t*	ΔR^2 (%)	β^{US}	NW-*t*	β^{CN}	NW-*t*	ΔR^2 (%)
US + $M0^{CN}$	0.07***	2.77	−0.02	−0.68	2.15	0.18***	2.94	−0.04*	−1.85	5.07
US + $M1^{CN}$	0.07**	2.55	0.05**	2.27	1.95	0.18***	2.83	0.01	0.49	4.79
US + $M2^{CN}$	0.07**	2.49	0.03	1.05	1.80	0.19***	3.14	−0.03	−1.55	5.53
US + DP^{CN}	0.09***	3.28	0.08***	4.02	3.21	0.16**	2.61	0.06***	2.84	3.84
US + DY^{CN}	0.09***	3.38	0.09***	4.29	3.34	0.16**	2.61	0.06***	2.92	3.84
US + DE^{CN}	0.12***	4.27	0.10***	4.50	5.09	0.19***	3.09	0.06***	2.75	5.56
US + BM^{CN}	0.12***	4.26	−0.09***	−2.88	4.20	0.23***	3.88	−0.07**	−2.52	7.05
US + EP^{CN}	0.11***	3.09	−0.06	−1.58	2.71	0.22***	3.38	−0.04	−1.24	5.63
US + INF^{CN}	0.06**	2.32	0.06**	2.28	1.23	0.20***	3.55	0.09***	3.35	6.02
US + TO^{CN}	0.07**	2.50	0.05	1.56	1.81	0.17***	2.65	0.03	1.04	3.84
US + $PPIVOL^{CN}$	0.11***	3.58	−0.06**	−2.19	3.64	0.20***	3.15	−0.04	−1.25	5.83
US + $IPVOL^{CN}$	0.07**	2.62	0.01	0.35	1.61	0.19***	3.18	0.06**	2.24	5.54
US + IP^{CN}	0.07***	2.83	−0.01	−0.50	2.26	0.21***	3.21	0.04	1.37	5.90
US + CVI^{CN}	0.08***	3.06	0.04*	1.73	2.50	0.19***	3.19	0.05**	2.27	5.43
US + CN	0.10***	4.12	0.10***	4.74	4.42	0.20***	3.41	0.14***	4.60	5.86

variables. Hence, we can conclude that the U.S. economic conditions drive the Chinese stock market volatility. Bad U.S. economic conditions tend to result in higher volatility and thus higher market risk in the Chinese stock market.

3.3. Out-of-Sample Predictability

The extensive stock market predictability literature shows that, although the in-sample analysis provides more efficient parameter estimates and thus more precise forecasts by utilizing all available data, out-of-sample tests seem to be a more relevant standard for assessing genuine predictability in real time, which implicitly examine the stability of the data-generating process and guard against in-sample over-fitting. In particular, Welch and Goyal (2008) show that numerous economic variables with in-sample predictive ability fail to deliver consistent out-of-sample forecasts in stock market. Paye (2012) shows that economic variables contain robust out-of-sample volatility forecasting power in the U.S. stock market.

In this section, we test the out-of-sample predictive power of U.S. economic variables for the Chinese stock market volatility. We estimate our predictive regression models recursively, and compare the out-of-sample performance of the forecasts generated by the regression model based on U.S. economic variables with the benchmark forecasts, following the framework in Campbell and Thompson (2008) and Welch and Goyal (2008). In our out-of-sample analysis, we use three alternative benchmark models, including the historical average model, the autoregressive (AR) model incorporating the lagged Chinese and U.S. volatilities, and the Chinese economic variables augmented AR model. To carry out the out-of-sample test, we start with an initial training period of 1997:01 to 1999:12 and estimate the predictive regressions recursively to produce the first out-of-sample forecast on January 2000. We then expand the estimation window and repeat the above steps to obtain out-of-sample forecasts for the next period and continue in this way until we reach the end of the sample period. The out-of-sample forecast evaluation period spans 2000:01 to 2012:12. The length of the initial in-sample estimation period balances the desire for having enough observations for precisely estimating the initial parameters with the desire for a relatively long out-of-sample period for forecast evaluation.[9]

The out-of-sample R^2 (R^2_{OS}) of Campbell and Thompson (2008) is calculated as follow:

$$R^2_{OS} = 1 - \frac{\sum_{t=n}^{T-1}\left(LVOL_{t+1} - \hat{LVOL}_{t+1}\right)^2}{\sum_{t=n}^{T-1}\left(LVOL_{t+1} - \tilde{LVOL}_{t+1}\right)^2}, \tag{5}$$

where T denotes the full sample size, n is the initial training period, $LVOL_{t+1}$ is the actual log volatility at period $t+1$, $\hat{LVOL}_{t+1}$ is the volatility forecast generated by the regression model of interest, and $\tilde{LVOL}_{t+1}$ represents the benchmark forecast. The R^2_{OS} statistic lies in the range $(-\infty, 1]$; when $R^2_{OS} > 0$, the predictive regression forecast $\hat{LVOL}_{t+1}$ outperforms the $\tilde{LVOL}_{t+1}$ in terms of the mean squared forecasting errors (MSFE).

We use Clark and West (2007)'s *MSFE-adjusted* statistic to test the null hypothesis that the MSFE of benchmark model is less than or equal to that of the regression forecast based on U.S. economic variables against the one-sided (upper-tail) alternative hypothesis that the MSFE of benchmark model is greater than that of the regression forecast based on U.S. economic variables. Clark and West (2007) develop the *MSFE-adjusted* statistic by modifying the familiar Diebold and Mariano (1995) and West (1996) statistic so that it has a standard normal asymptotic distribution when comparing forecasts with the nested models.[10] Clark and West (2007) demonstrate that the *MSFE-adjusted* statistic performs reasonably well in terms of size and power when comparing forecasts from nested linear models for a variety of sample sizes.

Panel A of Table 5 presents the out-of-sample performance of the 17 individual U.S. economic variables for the Chinese stock market volatility over the 2000:01 to 2012:12 forecast evaluation period. In comparison with the historical average forecast, six U.S. economic variables (BM, NTIS, DP, DY, IP, and PPIVOL) generate positive R^2_{OS} statistics ranging from 0.16% to 16.28%, which are statistically significant and economically large according to the *MSFE-adjusted* statistics. Therefore, the predictive regression volatility forecasts based on these six U.S. economic variables produce substantially smaller MSFE than forecasts based on historical average.

In further tests, when comparing with alternative benchmark forecasts based on the AR model or the Chinese economic variables augmented AR model, U.S. economic variables like DP and DY still produce positive R^2_{OS} statistics. They are statistically significant and economically large according to the *MSFE-adjusted* statistics. We hence conclude that incorporating U.S. economic variables can highly improve the out-of-sample forecast of the Chinese stock market volatility, consistent with our in-sample findings.

[9] Hansen and Timmermann (2012) and Barbara and Inoue (2012) show that out-of-sample tests of predictive ability have better size properties when the forecast evaluation period is a relatively large proportion of the available sample, as in our case.

[10] While the Diebold and Mariano (1995) and West (1996) statistic has a standard normal asymptotic distribution when comparing forecasts from non-nested models, Clark and McCracken (2001) and McCracken (2007) show that it has a non-standard distribution when comparing forecasts from nested models. The non-standard distribution can lead the Diebold and Mariano (1995) and West (1996) statistic to be severely undersized when comparing forecasts from nested models, thereby substantially reducing power.

Table 5
Out-of-sample forecasting results.
This table reports the out-of-sample R^2_{OS} statistics of Campbell and Thompson (2008) for U.S. economic variables. Panels A and B present the forecasting results for individual forecasts and combination forecasts, respectively. To calculate the R^2_{OS} statistics, we use the historical average (HA), lagged Chinese and U.S. volatilities (AR), and AR model augmented with the lagged Chinese economic PLS factor extracted from 14 Chinese economic variables (AR + CN) as our benchmark models, respectively. All of the predictive regression slopes in out-of-sample forecasts are estimated recursively using the data available through period of forecast formation *t*. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, according to Clark and West (2007)'s *MSFE-adjusted* statistic. The out-of-sample evaluation period extends from January 2000 through December 2012.

	HA	AR	AR + CN		HA	AR	AR + CN
Panel A: Individual forecasts							
BM	1.44**	−2.59	−1.08	DE	−3.08	−6.07	−3.30
TBL	−5.30	−6.38	−2.48	TMS	−7.48	−8.12	−5.48
LTY	−6.69	−5.72	−4.61	DFY	−0.99	−4.88	−1.77
NTIS	15.02***	−0.91	−2.34	DFR	−0.36	−1.83	−2.10
INFL	−2.41	−2.52	−2.02	CP	−0.50	−3.93	−4.31
LTR	−1.67	0.04	0.41	IP	1.47**	−2.59	0.36*
DP	16.28***	2.17**	7.42***	IPVOL	−3.52	−3.52	−3.73
DY	15.39***	1.85**	6.89***	PPIVOL	0.16***	−5.49	−1.92
EP	−4.76	−3.82	−3.23				
Panel B: Combination forecasts							
Mean	10.42***	0.83	3.88**	Trimmed mean	9.48***	1.05	4.09***
Median	5.77***	0.67	3.45***	PLS	15.36***	1.58**	6.82***

We next construct out-of-sample combination forecasts to pool the information in all individual predictors together and to improve upon the univariate predictive regression forecasts. We consider four out-of-sample combination methods:

- Mean combination (Mean): uses the simple "1/N" rule that sets equal weight for each individual predictive regression model forecast, which is used in Rapach et al. (2010).
- Median combination (Median): uses the median value of all individual predictive regression model forecasts, which is used in Rapach et al. (2010).
- Trimmed mean combination (Trimmed mean): sets weight of zero for the individual forecasts with the smallest and largest values and "1/(N-2)" for the remaining individual forecasts, which is used in Rapach et al. (2010).
- Partial least square (PLS): extracts a relevant common factor from the individual predictors according to covariance between economic variables and stock volatilities, as in Kelly and Pruitt (2013, 2015) and Huang et al. (2015).

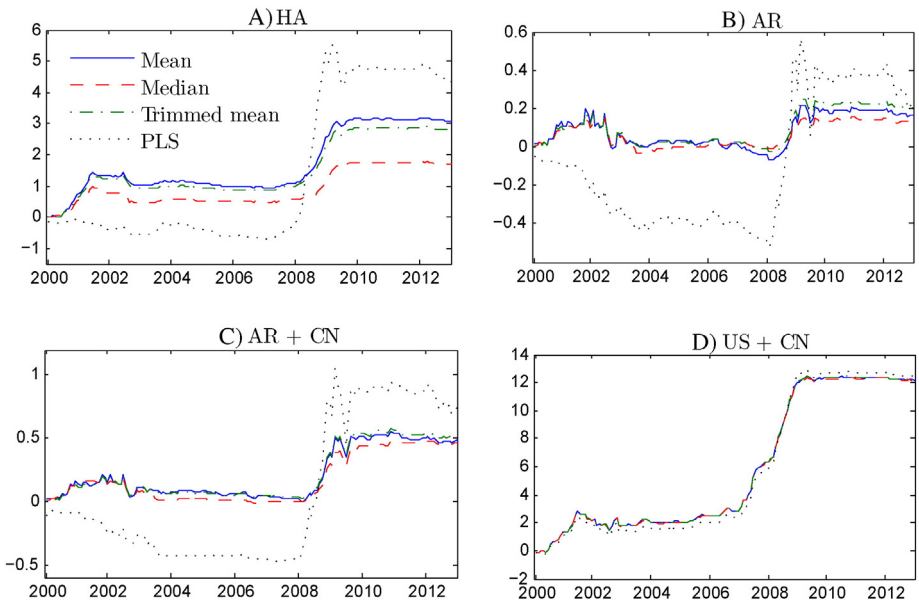

Fig. 2. The difference in cumulative squared forecast error (CSFE). The figures depict the differences between the cumulative squared forecast error (CSFE) for the benchmark forecasts and the CSFE for the out-of-sample predictive regression forecasts based on the U.S. economic variables using the mean, median, trimmed mean, and partial least square (PLS) forecasting combination methods, respectively. Panel A, Panel B, and Panel C illustrate the results for the benchmark forecasts based on historical average (HA), lagged Chinese and U.S. volatilities (AR), and AR model augmented with lagged Chinese economic variables (AR + CN), respectively. Panel D plots the differences in CSFE for combination forecasts using both the Chinese and U.S. economic variables relative to the HA benchmark (US + CN).

Panel B of Table 5 demonstrates the usefulness of combination forecasts based on the U.S. economic variables. The mean, median, trimmed mean, and PLS combination forecasts all deliver positive ΔR^2_{OS} statistics in comparison with the forecasts generated by three benchmark models, ranging from 0.67% to 15.36%. The ΔR^2_{OS} statistics of mean, median, and trimmed mean combination forecasts are statistically significant for the benchmark forecasts of historical average and Chinese economic variable augmented AR model, while the ΔR^2_{OS} statistics of PLS combination forecasts are statistically significant for all three benchmark forecasts at the 5% or better levels. The combination forecasts generated by the four methods outperform most of forecasts based on individual U.S. variables. This result is consistent with the literature showing that successful combination forecasting strategies incorporate information from multiple predictors and stabilize the forecasts in a manner that accommodates model uncertainty and parameter instability, therefore leading to superior forecasting performance.

Following Welch and Goyal (2008) and Rapach et al. (2010), Fig. 2 presents the time-series plots of the differences between the cumulative squared forecast error (CSFE) for the benchmark forecasts and the CSFE for the predictive regression forecasts based on the combined U.S. economic variables over the out-of-sample period 2000:01–2012:12. This time-series plot is an informative graphical device on the consistency of out-of-sample forecasting performance over time. When the difference in CSFE increases, the model forecast outperforms that based on the benchmark model, while the opposite holds when the curve decreases. It thus illustrates whether the forecasts based on U.S. economic variables have a lower MSFE than the benchmark forecasts of the historical average, the AR model with lagged Chinese and U.S. volatilities, and the AR model augmented with Chinese economic variables, respectively.

Panels A, B, and C show the differences in CSFE for combined U.S. economic variables relative to the benchmark forecasts based on the historical average, the AR model, and the Chinese economic variables augmented AR model, respectively. Panel D displays the differences in CSFE for combination forecasts using both the Chinese and U.S. economic variables relative to the historical average benchmark. Clearly, the curves in all four panels generally increase monotonically over time, especially during the period of financial crisis (i.e., tech bubble and recent subprime crisis), consistent with Rapach et al. (2010). Hence, incorporating U.S. economic variables into the benchmark models can improve the out-of-sample forecast for the Chinese stock market volatility, especially during the economic downturn.

3.4. Forecasting Industry Portfolios Volatilities

In this section, we investigate the forecasting power of U.S. economic variables for the industry portfolios volatilities. We focus on the monthly log volatilities of 13 Chinese industry portfolios formed on the industry classification of China Securities Regulatory Commission (CSRC) and the sample period extends from January 2002 to December 2012. Table 6 reports the summary statistics. In Panel A, the average volatilities for industry portfolios range from −2.72 (UTILS) to −2.43 (MEDIA), the skewness statistics range from −0.03 (MEDIA) to 0.49 (CNSTR), and the kurtosis statistics range from 2.15 (MINES) to 2.88 (UTILS). Panel B presents the correlation matrix for the 13 Chinese industry portfolios volatilities. The correlation coefficients range from 0.69 to 0.98.

Table 6
Summary statistics of industry portfolios volatilities.
Panel A reports the mean, standard deviation (Std. Dev.), skewness (Skew.), and kurtosis (Kurt.) of the log volatilities for the 13 Chinese industry portfolios. Panel B presents the correlation matrix for the 13 industry portfolios volatilities. Our data sample period for the Chinese industry portfolios extends from January 2002 through December 2012.

Panel A: Descriptive statistics of industry portfolios volatilities.

	Mean	Std. Dev.	Skew.	Kurt.		Mean	Std. Dev.	Skew.	Kurt.		Mean	Std. Dev.	Skew.	Kurt.
AGRIC	−2.51	0.42	0.20	2.64	TRANS	−2.70	0.44	0.45	2.41	PROPT	−2.44	0.41	0.19	2.57
MINES	−2.60	0.44	0.17	2.15	INFTK	−2.57	0.37	0.37	2.62	SRVC	−2.59	0.43	0.36	2.68
MANUF	−2.66	0.41	0.24	2.57	WHTSL	−2.65	0.41	0.21	2.59	MEDIA	−2.43	0.40	−0.03	2.73
UTILS	−2.72	0.41	0.48	2.88	MONEY	−2.57	0.42	0.26	2.41	MULTP	−2.57	0.41	0.26	2.57
CNSTR	−2.58	0.39	0.49	2.75										

Panel B: Correlation matrix for industry portfolios volatilities

	AGRIC	MINES	MANUF	UTILS	CNSTR	TRANS	INFTK	WHTSL	MONEY	PROPT	SRVC	MEDIA	MULTP
AGRIC	1	0.85	0.97	0.87	0.91	0.91	0.92	0.96	0.71	0.91	0.94	0.85	0.95
MINES		1	0.86	0.88	0.85	0.92	0.83	0.85	0.83	0.86	0.86	0.80	0.83
MANUF			1	0.91	0.94	0.94	0.93	0.98	0.71	0.92	0.95	0.85	0.98
UTILS				1	0.91	0.92	0.88	0.89	0.79	0.85	0.89	0.82	0.89
CNSTR					1	0.91	0.90	0.93	0.79	0.88	0.93	0.85	0.92
TRANS						1	0.90	0.92	0.81	0.90	0.93	0.82	0.92
INFTK							1	0.91	0.74	0.85	0.89	0.88	0.92
WHTSL								1	0.72	0.92	0.96	0.85	0.97
MONEY									1	0.75	0.75	0.72	0.69
PROPT										1	0.93	0.83	0.90
SRVC											1	0.85	0.95
MEDIA												1	0.85
MULTP													1

Table 7
In-sample forecasts for industry portfolios volatilities.
This table presents the in-sample forecasting results for the Chinese industry portfolios volatilities (given in the column heading) using 17 U.S. economic variables (given in the row heading) as predictors over the period from January 2002 through December 2012. The combined factor estimated from the 17 U.S. economic variables using the PLS method is denoted as US. To save space, for each economic variable, we only present the increases in R^2 values (in percentage) relative to benchmark AR model incorporating the lagged Chinese and U.S. volatilities.

	AGRIC	MINES	MANUF	UTILS	CNSTR	TRANS	INFTK	WHTSL	MONEY	PROPT	SRVC	MEDIA	MULTP
BM	−0.23	−0.12	−0.41	0.04	−0.30	−0.25	−0.23	−0.38	0.30	−0.33	−0.30	0.00	−0.40
TBL	0.29	0.56	0.23	1.00	1.58	0.46	0.39	0.40	1.50	0.35	0.80	0.69	0.31
LTY	−0.46	0.07	−0.44	0.10	−0.09	−0.18	−0.17	−0.47	0.69	−0.37	−0.34	−0.09	−0.46
NYIS	5.82	1.84	4.96	2.74	4.60	3.27	6.20	5.82	2.05	4.87	4.66	4.02	5.38
INFL	−0.29	−0.28	−0.32	−0.14	−0.23	−0.38	−0.56	−0.22	−0.05	−0.17	0.20	−0.42	0.10
LTR	0.96	0.63	0.99	1.01	1.00	0.82	1.46	1.89	−0.04	0.72	0.72	0.61	1.50
DP	0.16	0.26	0.23	−0.17	−0.16	0.13	−0.08	0.49	−0.31	0.54	0.07	−0.02	0.40
DY	0.32	0.51	0.25	−0.05	−0.19	0.20	−0.11	0.52	−0.29	0.60	0.00	0.02	0.26
EP	−0.42	−0.01	−0.44	−0.28	−0.47	−0.35	−0.56	−0.49	−0.09	−0.36	−0.40	−0.48	−0.45
DE	−0.46	0.19	−0.44	−0.19	−0.44	−0.23	−0.55	−0.42	−0.07	−0.26	−0.41	−0.43	−0.46
TMS	0.59	0.07	0.36	0.28	0.98	0.15	−0.06	0.58	0.18	0.58	0.83	0.21	0.46
DFY	−0.42	−0.22	−0.46	−0.46	−0.47	−0.39	−0.56	−0.47	−0.38	−0.26	−0.40	−0.49	−0.47
DFR	−0.46	−0.27	−0.45	−0.34	−0.33	−0.37	−0.51	−0.49	−0.13	−0.32	−0.34	−0.48	−0.41
CP	2.48	1.19	2.26	2.04	3.43	1.76	5.35	2.05	1.37	1.45	1.42	2.53	2.02
IP	−0.18	0.64	−0.07	0.21	−0.09	0.35	−0.12	0.24	0.32	0.19	−0.04	0.23	0.05
IPVOL	−0.45	−0.36	−0.45	−0.44	−0.02	−0.41	−0.33	−0.48	−0.03	−0.36	−0.40	−0.35	0.47
PPIVOL	−0.23	−0.24	−0.19	−0.45	−0.46	−0.31	−0.48	−0.07	−0.35	−0.13	−0.20	−0.31	−0.14
US	3.91	2.60	3.59	2.02	3.11	2.93	4.05	4.68	1.72	4.28	3.33	3.30	3.94

We repeat the in-sample and out-of-sample tests for the industry portfolio volatilities. Table 7 reports the increases in R^2 statistics (ΔR^2) of in-sample predictive regression model based on U.S. economic variables in comparison with the benchmark AR model incorporating the lagged Chinese and U.S. volatilities. As is shown, U.S. economic variables of TBL, NYIS, and CP produce positive ΔR^2 statistics across all the 13 industries, while LTY, LTR, DP, DY, TMS, and IP generate positive ΔR^2 statistics for most of the industry portfolios. When combining all U.S. economic variables together using the PLS combining method, the ΔR^2 statistics are positive across all industry portfolios and rang from a low of 1.72% (MONEY industry) to a high of 4.68% (WHTSL industry). Thus, U.S. economic variables indeed contain important information for the industry portfolio volatility forecasting, consistent with our previous results for the Chinese market volatility.

Table 8 presents the out-of-sample ΔR^2_{OS} for combination forecasts of Chinese industry portfolio volatilities based on U.S. economic variables over the 2005:01 to 2012:12 forecast evaluation period. As is shown in Panel A, when comparing with the historical average benchmark, all ΔR^2_{OS} statistics for the four combining methods are positive and sizable across all the 13 industry portfolios. The ΔR^2_{OS} statistics range from 2.72% (median forecast for the UTILS industry) to 44.32% (PLS forecast for the PROPT

Table 8
Out-of-sample forecasts for industry portfolios volatilities.
This table reports the out-of-sample R^2_{OS} statistics of Campbell and Thompson (2008) for the predictive regression forecasts based on the 17 U.S. economic variables using the mean, median, trimmed mean, and partial least square (PLS) forecasting combination methods for the 13 Chinese industry portfolios volatilities (given in the column heading), respectively. Panel A, Panel B, and Panel C present the forecasting results relative to the benchmark forecasts based on the historical average (HA), lagged Chinese and U.S. volatilities (AR), and the AR model augmented with the lagged Chinese economic PLS factor extracted from 14 Chinese economic variables (AR + CN), respectively. All of the predictive regression slopes in out-of-sample forecasts are estimated recursively using the data available through period of forecast formation t. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on the one-sided Clark and West (2007) statistic. The out-of-sample evaluation period extends from January 2005 through December 2012.

	AGRIC	MINES	MANUF	UTILS	CNSTR	TRANS	INFTK	WHTSL	MONEY	PROPT	SRVC	MEDIA	MULTP
Panel A: The historical average benchmark (HA)													
Mean	17.30***	18.38***	16.99***	11.79***	15.86***	18.39***	11.98***	15.86***	15.96***	24.36***	20.37***	15.05***	16.45***
Median	5.15***	8.33***	4.93***	2.72***	3.85***	6.29***	3.83***	5.50***	7.04***	8.81***	7.07***	6.50***	4.40***
Trimmed mean	14.29***	15.97***	13.77***	8.96***	13.28***	15.21***	9.63***	12.94***	13.88***	20.51***	17.13***	12.70***	13.42***
PLS	32.18***	34.42***	30.65***	15.16***	26.60***	35.14***	22.29***	31.48***	28.88***	44.32***	36.94***	24.98***	28.99***
Panel B: The lagged volatilities benchmark (AR)													
Mean	2.30**	2.83**	1.95**	0.92	2.96**	1.67*	1.53*	1.99**	2.44**	3.85***	2.56**	1.05	1.88**
Median	0.24	0.55	0.49	−0.17	1.20*	−0.20	−0.01	0.80*	0.00	1.10	0.76	−0.15	0.45
Trimmed mean	1.29*	2.07**	1.02*	0.51	2.15**	0.66	0.83	1.16*	1.46*	2.75**	1.73**	0.36	1.12*
PLS	4.55***	4.18***	4.91***	−0.18	3.76**	3.54***	4.01**	6.96***	1.04**	9.66***	4.22***	4.77**	4.95***
Panel C: The lagged volatilities and Chinese economic variables benchmark (AR + CN)													
Mean	4.48***	5.82***	4.81***	3.41**	4.78***	8.09***	2.02*	5.62***	5.39***	12.76***	7.63***	2.20*	4.79*
Median	0.36	2.98***	1.71*	1.60*	3.14**	3.99***	0.78	2.28*	2.31**	5.91***	2.91**	0.94	1.80
Trimmed mean	3.89**	5.23***	4.29**	3.33**	4.65***	7.35***	2.00*	5.09***	4.94***	10.98***	7.01***	2.13*	4.46**
PLS	7.86***	7.02***	9.12***	4.74**	9.76***	11.94***	5.43**	11.42***	4.11***	22.94***	13.13***	5.90**	9.06***

industry). It indicates that the industry portfolio volatility forecasts based on U.S. economic variables produce substantially smaller MSFE than forecasts generated by the historical average model. Similarly, in Panels B and C, all the four combining methods generate positive ΔR^2_{OS} statistics for most industry volatilities relative to the AR model benchmark and the Chinese economic variables augmented AR model benchmark, respectively. In particular, the PLS combination forecasts generate positive and significant ΔR^2_{OS} statistics for 12 out of 13 industry volatilities in Panel B. Thus, the combined U.S. economic predictors have strong out-of-sample forecasting power for Chinese industry portfolios volatilities too, consistent with our analysis for the Chinese aggregate market volatility.

4. Conclusions

This paper examines whether the U.S. economic variables contain additional forecasting information for the Chinese stock market volatility beyond that embedded in the Chinese domestic predictors. Our empirical results show that a number of U.S. economic variables significantly forecast the future Chinese stock market volatility after controlling for the lagged Chinese stock market volatilities, and U.S. market volatilities, and various Chinese economic variables. The predictive power is statistically significant and economically large. The finding suggests that bad U.S. economic conditions would lead to higher volatility in the Chinese stock market too.

Further out-of-sample tests show that the regressive models based on lagged U.S. economic variables outperform the historical average model, AR model incorporating Chinese and U.S. lagged volatilities, and the Chinese economic variables augmented AR model, respectively. The findings are consistent with our in-sample results, and confirm the important role of U.S. economic variables in predicting the time-varying volatility of Chinese stock market. Given the critical role of volatility risk in finance, our study hence has potentially important implications for risk management, asset pricing, option trading, and asset allocation in Chinese stock market.

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