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Can US Economic Variables Predict Chinese Stock Market?

Jeremy C. GOH
Singapore Management University, jeremygoh@smu.edu.sg

Fuwei JIANG
Singapore Management University, fwjiang.2010@smu.edu.sg

Jun TU
Singapore Management University, tujun@smu.edu.sg

Yuchen WANG
Singapore Management University, yuchen.wang.2011@pbs.smu.edu.sg
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Can US economic variables predict the Chinese stock market?

Jeremy C. Goh, Fuwei Jiang, Jun Tu *, Yuchen Wang

Singapore Management University, Singapore

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ABSTRACT

In the last few decades, we observed a significant increase in global economic activities and these activities may have an impact on both China's economy and stock market. Given the potential impact, we empirically examine whether US economic variables are leading indicators of the Chinese stock market. Prior to China joining the World Trade Organization (WTO) in the end of 2001, we find no statistical relationship between US economic variables and the Chinese stock market returns. However, we find US economic variables have statistically significant predictive power for periods after China's admission into the WTO. In addition, we show that the combination of US and China economic variables is more superior in terms of forecasting ability than either single country economic variables. These findings are of economic importance from an investment perspective.

1. Introduction

There is an ongoing debate as to whether there is a decoupling between economic activities in emerging markets with those in mature markets. Studies supporting the notion that markets are integrated are many. For example, Gultekin et al. (1989), Bekaert and Harvey (1995), Bekaert et al. (2010), and Bracker et al. (1999) find that the stock markets contemporaneously co-move among economically integrated countries. In addition, Carrieri et al. (2007) find evidence suggesting that, notwithstanding the substantial differences and time variations in integration, none of the emerging markets are completely segmented from the global market. However, Chinese stock market seems to be different. In particular, Huang et al. (2000) find no co-integration and casual relationship between Chinese and American stock markets. It is important to note that their sample period is from October 1992 to June 1997, which happens to coincide with the period before China joined the World Trade Organization (WTO).

* Corresponding author at: 50 Stamford Road, Lee Kong Chian School of Business, Singapore Management University, Singapore, 178899. Tel.: +65 6828 0764; fax: +65 6828 0427.
E-mail address: tujun@smu.edu.sg (J. Tu)

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In a recent study, Johansson (2009) documents evidence suggesting that China is showing an increasing level of integration with several major financial markets during the last decade. Incidentally, this study's sample includes the period after China's admission into the WTO. It may not be surprising that joining the WTO may be a turning point for the Chinese economy. For example, studies have shown that the importance of the global economy on the Chinese economy has increased significantly after joining the WTO in December 2001. (e.g., Canova and Dellas, 1993; Sachs and Warner, 1995; Frankel and Romer, 1999; Rumbaugh and Blancher, 2004).

In addition, a close relationship exists between economic activity and stock prices (e.g., Schwert (1990) and Roll (1992) for the US economy, and Canova and De Nicolo (1995) for European economies). Hence, it is plausible that the Chinese stock market may be affected by global economic activities through a transmission mechanism from the Global to the Chinese economy, and then from the Chinese economy to the Chinese stock market.[1] Since the US is the world's largest economy and is China's largest trading partner, it is reasonable to use US economic variables as a proxy for global economic activity.[2] In this paper, we investigate whether US economic variables, such as the dividend–price ratio, earnings–price ratio, as well as the term and default spreads can predict Chinese stock market behavior. We also explore whether US economic variables can provide additional information beyond that contained in Chinese economic variables in predicting the Chinese stock market.

Investigating the forecasting ability of US economic variables for the Chinese stock market is relevant for a number of reasons. First, it establishes the proper information set or benchmark for investors focusing on the Chinese stock market. For instance, if US economic variables can predict and provide additional forecasting information for the Chinese stock market beyond that contained in Chinese economic variables, investors should incorporate US economic variables into their information set to enhance the accuracy of their return forecasts. The enhancement of the return forecasts may be economically important from an investment perspective, and will therefore affect the benchmark used for measuring investment performance.

Second, analyzing the forecasting ability of US economic variables for the Chinese stock market could have important implications for the cross-sectional returns of the Chinese stock market. As shown by Ferson and Harvey (1999) for the US stock market, among others, economic variables that predict stock returns provide significant explanatory power for the cross-sectional stock returns. Hence, incorporating US economic variable may lead to better asset pricing modelling as well as better cost of capital measuring (e.g., Fama and French, 1997).

Third, an investigation of the forecasting ability of US economic variables for the Chinese stock market improves our understanding of the return predictability across countries. Since the extant voluminous literature on return predictability focuses almost exclusively on the US stock market, the present paper provides additional evidence across countries by examining the forecasting ability of the US economic variables for the Chinese stock market.

In this paper, we conduct the following analyses on the forecasting ability of the US economic variables for the Chinese stock market. First, we analyze the in-sample forecasting ability of the US economic variables for the Chinese stock market for the aggregate market portfolio and for a large number of component portfolios. Second, we employ an out-of-sample analysis, focusing on comparing the forecasting performance of the enhanced forecasts utilizing the US economic variables as additional predictors relative to the benchmark forecasts based on historical average and the benchmark forecasts based on the China economic variables alone, respectively. Third, we examine the economic importance of incorporating the US economic variables as additional predictors from an investment perspective.

Our analysis on the forecasting ability of the US economic variables for the Chinese stock market uncovers a number of interesting empirical facts. In-sample results reveal that although in the time period before China joined WTO, the US economic variables are unable to predict the Chinese stock market. These variables show significant predictive ability after China joined WTO. Following Rapach et al. (2011), we

[1] We recognize alternative transition mechanisms. For example, global economy may directly affect the degree of risk averse of Chinese stock market investors.

[2] Harvey (1991) and Bekaert and Harvey (1995) show that US economic variables are highly correlated with world economic variables.

also analyze the predictability of the US variables on the Chinese stock markets not only for the Chinese aggregate market portfolio but also for thirteen Chinese industry portfolios. Our results document a similar pattern – significant increase in the predicting power after China joined WTO – except for one industry, AGRIC (Agriculture, Forestry, and Fishing).

Our results seem to suggest that China's admission into the WTO may have an effect on the integration of China economy with the world economy. The increase in integration between the two economies may have contributed to one of our key findings, that is, the US economic variables gain significant predicting power on the Chinese stock market after China joined WTO. Furthermore, we show that the US economic variables can be used in conjunction with the China economic variables to improve return forecasts. In other words, the US economic variables provide useful forecasting information beyond that contained in the China economic variables. In addition, our out-of-sample results further reveal extensive predictability in real time for both the aggregate market portfolio and the thirteen industry portfolios. Finally, in terms of Sharpe ratio and utility gains, including the US economic variables as additional predictors relative to the benchmark forecasts turns out to be economically significant from an investment perspective.

This study complements the growing body of knowledge on the Chinese economy and market. For example, Lee and Rui (2000) document some evidence of predictability of China's stock market based on data ending in 1997 for only the market portfolio. Phylaktis and Ravazzolo (2002) find that economic integration provides a channel for financial integration, which explains the high degree of financial integration even in the presence of foreign exchange control for a group of Pacific-Basin countries by analyzing the covariance of excess returns on national stock markets over the period from 1980 to 1998. Wang and Cheng (2004) study the cross sectional predicting power of turnover in the Chinese stock market. Wang and Firth (2004) provide evidence that there is unidirectional contemporaneous, but not one-period lagged, return spillover from developed markets to China market using daily price data from 1994 to 2001. Tian (2007) finds weak co-integration and casual relationship between China and US at the post Asian financial crisis period. Wang and Di Iorio (2007) show that there is an increasing integration between China's A-share market and Hong Kong's stock market, but that there is no evidence that the Chinese A-share market is becoming more integrated with the world market. Masson et al. (2008) review the China's financial liberalization progress since its accession to the WTO. Jiang et al. (2011) investigate the predictability of Chinese market and component portfolios based on China economic variables. Chen et al. (2010) examine stock return predictability in China at the firm level.

Hence, this paper's results documenting return predictability using US economic variables as leading indicators adds to the understanding of the Chinese economy and stock market, especially after the admission into the WTO. The remainder of the paper is organized as follows. Section 2 illustrates the statistical methodology. Data is described in Section 3, while Section 4 reports the empirical results. Section 5 concludes.

2. Predictability measure

In this section, we describe the predictive regression model framework. Following the literature, we analyze stock return predictability in the context of a standard predictive regression model:

$$r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}, \tag{1}$$

where $r_{i,t}$ is the return on portfolio i in excess of the risk-free interest rate, $x_{j,t}$ is a potential predictor variable, and $e_{i,t}$ is a zero-mean disturbance term. In contrast to the vast literature on return predictability for the US data, in which $r_{i,t}$ is the excess return on a US stock, we are interested in return predictability of the US economic variables when $r_{i,t}$ is replaced with the excess return of a Chinese stock. More specifically, we analyze return predictability for the aggregate market portfolio and its thirteen industry portfolios for the Chinese stock market (The data are described in detail below).

We analyze the predictive ability of $x_{j,t}$ with respect to $r_{i,t}$ by investigating the t-statistic corresponding to $\hat{b}_{i,j}$, the ordinary least squares (OLS) estimate of $b_{i,j}$ in Eq. (1). Under the null hypothesis of no predictability, $b_{i,j}=0$, the expected excess return is constant ($r_{i,t}=a_i+ {}_{i,t}$). In contrast, under the alternative hypothesis, $b_{i,j}$ is different from zero, hence $x_{j,t}$ contains information useful for predicting $r_{i,t}$, and the expected excess return becomes time-varying. However, estimating Eq. (1) may subject to potentially severe small-sample bias due to the fact that $x_{j,t}$ is not an exogenous regressor (Stambaugh, 1986, 1999). Therefore, we make our inference based on a bootstrap procedure similar to the procedures used by, among others, Nelson and Kim (1993), Mark (1995), Kothari and Shanken (1997), Kilian (1999), Rapach and Wohar (2006), and recently Rapach et al. (2011).

3. Data

We analyze stock returns predictability for the Chinese aggregate market portfolio and its thirteen industry portfolios. The stock market data are from RESSET including all normal (without Special Treatment symbol issued by China Securities Regulatory Commission (CSRC)) China A-share stocks listed in Shanghai and Shenzhen stock exchanges. For the aggregate market portfolio return, we use the value-weighted returns from 1993:07 to 2008:12. Second, for the industry portfolio returns, we use monthly returns on thirteen industry portfolios from 1993:07 to 2008:12 available in RESSET[3]: AGRIC (Agriculture, Forestry, and Fishing), MINES (Mining), MANUF (Manufacturing Industries), UTILS (Electric, Gas, Water production and Supply), CNSTR (Construction), TRANS (Transportation and Storage), INFTK (Information Technology), WHTSL (Wholesale and Retail Store), MONEY (Finance and Insurance), PROPT (Real Estate), SRVC (Service Industry), MEDIA (Communication and Cultural Industries), MULTP (Conglomerate and other Industries). These industry portfolios are constructed at the end of June using the June industry classification. The risk-free interest rate is also obtained from RESSET to construct excess stock returns. The risk-free rate for the sample period between February 2002 and 2009 is set to be the rate of the three-month China central bank bills. For periods before February 2002, we use one-year bank deposit rate as the risk-free rate, since there was no risk-free short-term debt prior to February 2002.

For the US economic variables used for predicting Chinese stock market, we consider a set of fourteen economic variables as used by Goyal and Welch (2008).

- Dividend-payout ratio (log), D/E: difference between the log of dividends and log of earnings on the S&P 500 index.
- Stock variance, SVAR: sum of squared daily returns on the S&P 500 index.
- Default return spread, DFR: difference between long-term corporate bond and long-term government bond returns.
- Long-term yield, LTY: long-term government bond yield.
- Long-term return, LTR: return on long-term government bonds.
- Inflation, INFL: calculated from the CPI (all urban consumers); following Goyal and Welch (2008), since inflation rate data are released in the following month, we use $x_{i,t-2}$ in (1) for inflation.
- Term spread, TMS: difference between the long-term yield and Treasury bill rate.
- Treasury bill rate, TBL: interest rate on a 3-month Treasury bill (secondary market).
- Default yield spread, DFY: difference between BAA- and AAA-rated corporate bond yields.
- Dividend–price ratio (log), D/P: difference between the log of dividends paid on the S&P 500 index and log of prices (S&P 500 index), where dividends are measured using a one-year moving sum.
- Dividend yield (log), D/Y: difference between the log of dividends and log of lagged prices.
- Earnings–price ratio (log), E/P: difference between the log of earnings on the S&P 500 index and log of prices, where earnings are measured using a one-year moving sum.
- Book-to-market ratio, B/M: ratio of book value to market value for the Dow Jones Industrial Average.
- Net equity expansion, NTIS: ratio of twelve-month moving sums of net issues by NYSE-listed stocks to total end-of-year market capitalization of NYSE stocks.

These fourteen variables, especially the valuation ratios (D/P, D/Y, E/P, and B/M) and interest rate variables (LTY, TMS, TBL, and DFY) are documented in the literature to have predicting power for the US stock returns. The data are monthly and described in more detail in Goyal and Welch (2008).[4]

In addition to analyzing the forecasting ability of the US economic variables when used alone, we would also like to analyze the forecasting ability of the US economic variables when used together with

[3] AGRIC and MINES start from 1996:07 and CNSTR starts from 1994:07. The stocks are grouped into industry portfolios by following the industry classification determined by China Securities Regulatory Commission (CSRC).

[4] The data are available at http://www.bus.emory.edu/AGoyal/Research.html.

China economic variables. The nine China economic variables used here are a subset of the fourteen economic variables of Goyal and Welch (2008) by excluding the economic variables that we do not have the data for the China case.

- Dividend-payout ratio (log), D/E: difference between the log of dividends and log 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.
- Stock variance, SVAR: sum of squared daily returns on the Value-weighted A-share market return.
- Inflation, INF: calculated from the CPI from the China Bureau of Statistics.
- Dividend–price ratio (log), D/P: difference between the log of dividends and log 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 yield (log), D/Y: difference between the log of dividends and log of lagged prices, where dividends are measured using a one-year moving sum.
- Earnings–price ratio (log), E/P: difference between the log of earnings and log 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, B/M: ratio of book value to market value for A-share stocks listed in Shanghai and Shenzhen stock exchanges. Book values from the annual reports and interim reports are from RESSET. For the months of January to March, this is computed by dividing book value of June of previous year by the price at the end of the current month. For the months of April to September, this is computed by dividing book value at the end of previous year by the price at the end of the current month. For the months of October to December, this is computed by dividing book value of June of current year by the price at the end of the current month.
- Net equity expansion, NTIS: ratio of twelve-month moving sums of new equity issues to market capitalization at the end of the current month by A-share stocks listed in Shanghai and Shenzhen stock exchanges. New equity issues are from China Securities Regulatory Commission (CSRC).
- Turnover, TO: ratio of trading value to market capitalization for A-share stocks listed in Shanghai and Shenzhen stock exchanges. Trading value and market capitalization are from CEIC.[5]

4. Empirical applications

In our empirical applications, we first analyze whether the individual US economic variables can predict the Chinese stock market before China joined the WTO and after China joined WTO separately by considering two time periods: (i) the time period before China joined the WTO covering 1993:07–2001:12; (ii) the time period after China joined the WTO covering 2002:01–2008:12. Then we apply a principal component approach to tractably incorporate information from a large number of US economic variables simultaneously. Furthermore, we implement out-of-sample analysis to check the real time predictability and conduct portfolio analysis to measure the economic importance of incorporating the US economic variables in predicting Chinese stock market.

4.1. Predictability of individual US economic variables

First, we consider the Chinese aggregate market portfolio. The MKT row of Table 1 reports the estimation results for the predictive regression of Eq. (1) using one of the fourteen US economic variables to predict the excess return of the Chinese aggregate market portfolio for the period from 1993:07 to 2001:12 before China joined the WTO. The entries in the table report the *t*-statistic corresponding to $b_{i,j}$ in Eq. (1) (top number) and R^2 statistic (bottom number) for each return/predictor combination. The fourteen individual US economic variables have little predictive power for the Chinese aggregate market

[5] Turnover is not included in the 14 US economic variables of Goyal and Welch (2008). However, Gervais et al. (2001), among others, demonstrate that trading volume predicts the stock market returns at the firm level, while Wang and Cheng (2004) provide China stock market evidence. Recent studies like Mei et al. (2009) and Xiong and Yu (2011) show that turnover is related to the asset prices bubbles in China stock and warrant markets.

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Table 1
Regression results based on fourteen US economic variables, 1993:07–2001:12. The entries in this table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t}=a_i+b_{i,j}x_{j,t-1}+e_{i,t}$, where $r_{i,t}$ is the excess return for the value-weighted market or industry portfolio given in the row heading and $x_{j,t-1}$ is the US economic variable given in the column heading. The MKT row reports results for the excess return on the China A-Share aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1993:07–2001:12 sample period. * indicates statistical significance at the 5% level. Sig.(5%) indicates the number of industries for which the t-statistic is significant at the 5% level for the predictor given in the column heading. Avg. R^2 is the row or column average of the R^2 statistics; the row average exclude MKT.

Portfolio	D/E	SVAR	DFR	LTY	LTR	INFL	TMS	TBL	DFY	D/P	D/Y	E/P	B/M	NTIS	Avg. R^2
MKT	−1.00	−0.12	−0.69	0.81	0.91	1.75*	−0.40	1.07	−0.38	−0.11	−0.03	0.53	−0.23	−0.04	
	0.98	0.01	0.47	0.65	0.82	2.98	0.16	1.13	0.14	0.01	0.00	0.28	0.05	0.00	0.55
AGRIC	−0.79	−0.89	−0.40	1.78*	−0.91	2.28*	−0.14	1.30	−0.98	1.49	1.30	2.02*	2.28*	1.77*	
	0.96	1.22	0.25	4.70	1.27	7.53	0.03	2.56	1.46	3.36	2.59	5.99	7.54	4.66	3.15
MINES	−0.60	−1.22	−0.06	1.11	−0.58	1.32	−0.36	1.07	−1.11	0.10	0.15	0.50	0.88	1.09	
	0.56	2.28	0.01	1.90	0.52	2.65	0.20	1.76	1.90	0.01	0.03	0.38	1.18	1.82	1.09
MANUF	−1.20	−0.02	−0.79	0.68	1.11	1.60	−0.67	1.27	−0.34	−0.23	−0.13	0.52	−0.32	−0.33	
	1.41	0.00	0.62	0.46	1.22	2.49	0.44	1.60	0.12	0.05	0.02	0.27	0.10	0.11	0.64
UTILS	−1.79*	0.32	−0.49	0.90	0.49	1.76*	−0.82	1.63	−0.26	−0.60	−0.51	0.43	−0.80	−0.56	
	3.09	0.10	0.24	0.80	0.23	2.99	0.67	2.58	0.07	0.36	0.26	0.19	0.64	0.31	0.90
CNSTR	0.85	−0.78	−0.33	1.26	0.71	1.72*	1.39	−0.32	−0.28	0.98	1.07	0.68	1.08	1.21	
	0.81	0.68	0.12	1.76	0.58	3.24	2.15	0.12	0.09	1.07	1.29	0.52	1.31	1.63	1.10
TRANS	−1.14	0.00	−0.99	0.50	1.31	1.73*	−0.67	1.14	−0.25	−0.35	−0.26	0.33	−0.54	−0.25	
	1.29	0.00	0.98	0.25	1.69	2.91	0.45	1.29	0.06	0.12	0.07	0.11	0.29	0.06	0.68
INFTK	−0.58	−0.66	−0.25	1.01	0.05	2.02*	0.07	0.71	−0.64	0.19	0.24	0.62	0.00	0.46	
	0.33	0.43	0.06	1.01	0.00	3.91	0.00	0.49	0.41	0.03	0.06	0.39	0.00	0.21	0.52
WHTSL	−1.09	−0.03	−0.78	0.70	1.14	1.55	−0.52	1.13	−0.51	−0.31	−0.21	0.35	−0.38	−0.11	
	1.18	0.00	0.61	0.49	1.29	2.34	0.27	1.27	0.26	0.10	0.04	0.12	0.15	0.01	0.58
MONEY	−0.65	−0.44	−0.01	1.18	−0.53	2.02*	0.16	0.73	−0.26	0.38	0.40	0.92	−0.02	0.11	
	0.42	0.19	0.00	1.37	0.28	3.92	0.03	0.53	0.07	0.15	0.16	0.85	0.00	0.01	0.57
PROPT	−0.23	−0.40	−0.60	1.05	0.87	1.88*	0.32	0.45	−0.24	0.47	0.55	0.75	0.38	0.64	
	0.05	0.16	0.36	1.08	0.76	3.40	0.10	0.20	0.06	0.22	0.31	0.56	0.14	0.40	0.56
SRVC	−0.64	−0.11	−0.79	1.06	0.92	1.65	−0.02	0.84	−0.63	0.16	0.23	0.63	0.07	0.35	
	0.41	0.01	0.62	1.11	0.84	2.66	0.00	0.71	0.40	0.02	0.05	0.40	0.01	0.12	0.53
MEDIA	−0.14	−0.46	−0.55	0.73	0.61	1.36	0.28	0.26	−0.55	0.20	0.27	0.34	0.16	0.86	
	0.02	0.21	0.30	0.53	0.37	1.83	0.08	0.06	0.30	0.04	0.07	0.12	0.03	0.73	0.34
MULTP	−0.73	−0.08	−1.01	0.61	1.17	1.72*	−0.27	0.77	−0.26	−0.25	−0.19	0.18	−0.32	0.27	
	0.53	0.01	1.01	0.37	1.34	2.88	0.07	0.59	0.07	0.06	0.03	0.03	0.10	0.07	0.51
Sig.(5%)	1	0	0	1	0	8	0	0	0	0	0	1	1	1	
Avg. R^2	0.85	0.41	0.40	1.22	0.80	3.29	0.35	1.06	0.40	0.43	0.38	0.76	0.88	0.78	

portfolio. Among the fourteen US economic variables considered, only one US economic variable – INFL – is significant at 5% level. In addition, twelve of the fourteen US economic variables have R^2 below 1.00%, and the average R^2 is only of 0.55% as shown in the last column. Overall, the predictability on the Chinese aggregate market portfolio of the fourteen US economic variables over the time period before China joined the WTO is not clearly evident.[6]

In contrast to the results in the MKT row of Table 1 for the sample period before China joined the WTO, as shown in the MKT row of Table 2, there is an obvious increase in the predictability on the Chinese aggregate market return using the fourteen individual US economic variables over the sample period from 2002:01 to 2008:12 after China joined the WTO. For instance, among the fourteen individual US economic variables considered, the R^2 statistics for thirteen US economic variables become larger, and five US economic variables including D/E, TMS, TBL, and E/P are significant predictors for the Chinese aggregate market portfolio with R^2 statistics of 9.24%, 15.82%, 19.78%, and 6.55%, respectively. The average R^2 of 4.64% over the sample period after China joined the WTO is around eight times larger than that for the sample period before China joined the WTO. Overall, we find that although in the time period before China joined WTO, the US economic variables generally are not that useful in predicting the Chinese aggregate market portfolio, they provide much more significant predictability in the time period after China joined WTO.

Now, we consider the industry portfolios of the Chinese stock market. The remaining rows of Table 1 report the estimation results for the predictive regression of Eq. (1) using one of the fourteen US economic variables to predict the excess return for an individual industry portfolio for the period before China joined the WTO. Average R^2 statistics across predictors (industries) are shown in the last column (row). The Sig.(5%) row reports the number of industries for which a given predictor is significant in (1) at the 5% level.

As shown in the second to the last row of Table 1, only one US economic variable (INFL) is significant for the industry portfolios before China joined the WTO, which is also the only significant predictor for the aggregate market portfolio. From this perspective, there seems a link between aggregate market predictability and predictability for individual industries. In addition, eleven US economic variables have average R^2 below 1.00%. Moreover, the last column of Table 1 reveals that ten of thirteen industry portfolios have average R^2 smaller than 1.00%. Overall, similar to the case of the Chinese aggregate market portfolio, there is no clear evidence that the fourteen US economic variables can significantly predict the majority of the thirteen industry portfolios over the time period before China joined the WTO.

The remaining rows of Table 2 present results for industry portfolios using the fourteen US economic variables as predictors over the period from after China joined the WTO. As shown in the second to the last row, four US economic variables, D/E, TMS, TBL, and E/P, are significant predictors for twelve, thirteen, thirteen, and nine industry portfolios, respectively. In the last row of Table 2, we find that the average R^2 statistics for the fourteen US economic variables predictors range from 0.17% (LTR) to 14.73% (TBL), and eight of them have average R^2 above 1.00%. The last column of Table 2 shows that eight of the thirteen industry portfolios have average R^2 greater than 3.00%, and all of the thirteen industry portfolios have average R^2 statistics above 1.00%. Moreover, nine of fourteen average R^2 for the US economic variables and twelve of thirteen average R^2 for industry portfolios over the period after China joined the WTO are larger than the corresponding average R^2 before China joined the WTO.[7] Overall, similar to the case of the Chinese aggregate market portfolio, the predictability of US economic variables on the Chinese industry portfolios has increased sharply after China joined the WTO.

An important issue on the large increase of the predictability of US economic variables for Chinese stock market after the China WTO accession is whether such significant increase is not only driven by the WTO event but also by other explanations. To examine if the significant increase is driven by the closer

[6] Stock market returns indeed may deviate from fundamentals during crises (e.g., Boyer et al., 2006). To examine whether the insignificant predictive power of US economic variables in the sample period before WTO accession is due to the 1997 Asian financial crisis, we re-run the predictive regression by dropping the data in 1997 period. With the crisis period excluded, we still cannot find significant predictive power of US economic variables. For instance, the average R^2 of the individual US economic variables for the China market portfolio in the last column of Table 1 only marginally increases from 0.55% to 0.58% after excluding the Asian financial crisis period.

[7] AGRIC is the only industry portfolio becoming less predictable by the US economic variables after China joined the WTO, with the average R^2 decreasing from 3.15% to 2.57%.

Table 2
Regression results based on fourteen US economic variables, 2002:01–2008:12. The entries in this table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t}=a_i+b_{i,j}x_{j,t-1}+e_{i,t}$, where $r_{i,t}$ is the excess return for the value-weighted market or industry portfolio given in the row heading and $x_{j,t-1}$ is the US economic variable given in the column heading. The MKT row reports results for the excess return on the China A-Share aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 2002:01–2008:12 sample period. * indicates statistical significance at the 5% level. Sig.(5%) indicates the number of industries for which the t-statistic is significant at the 5% level for the predictor given in the column heading. Avg. R^2 is the row or column average of the R^2 statistics; the row average exclude MKT.

Portfolio	D/E	SVAR	DFR	LTY	LTR	INFL	TMS	TBL	DFY	D/P	D/Y	E/P	B/M	NTIS	Avg. R^2
MKT	−2.89*	−0.55	1.52	0.95	0.00	−1.62	−3.93*	4.50*	−1.28	−1.17	−1.17	2.40*	0.36	0.85	
	9.24	0.36	2.73	1.08	0.00	3.09	15.82	19.78	1.96	1.65	1.64	6.55	0.16	0.88	4.64
AGRIC	−1.82*	0.64	0.17	−0.04	0.11	−1.34	−3.23*	3.39*	−0.19	0.13	−0.22	1.99*	0.40	−0.87	
	3.89	0.50	0.03	0.00	0.01	2.13	11.27	12.29	0.05	0.02	0.06	4.59	0.20	0.92	2.57
MINES	−2.94*	−0.97	1.91*	0.78	−0.27	−0.89	−3.17*	3.60*	−1.51	−1.48	−1.27	2.28*	−0.44	0.76	
	9.52	1.14	4.27	0.73	0.09	0.96	10.90	13.62	2.72	2.61	1.92	5.97	0.24	0.70	3.96
MANUF	−2.37*	0.25	1.17	0.79	0.08	−1.68*	−3.63*	4.11*	−0.68	−0.75	−0.95	2.09*	0.58	0.59	
	6.39	0.07	1.63	0.76	0.01	3.33	13.82	17.06	0.56	0.68	1.08	5.05	0.41	0.42	3.66
UTILS	−1.67*	0.43	0.94	0.69	−0.39	−0.91	−2.61*	2.96*	−0.42	−0.49	−0.60	1.51	0.17	0.41	
	3.31	0.22	1.07	0.58	0.18	1.01	7.69	9.68	0.22	0.29	0.43	2.69	0.04	0.21	1.97
CNSTR	−1.91*	0.83	0.41	0.54	−0.41	−0.87	−3.62*	4.01*	−0.15	0.19	−0.15	2.11*	0.72	−0.50	
	4.24	0.83	0.21	0.35	0.21	0.92	13.80	16.42	0.03	0.04	0.03	5.13	0.64	0.31	3.08
TRANS	−2.86*	−1.11	1.65	1.41	0.08	−1.16	−3.25*	3.90*	−1.90*	−1.81*	−1.82*	2.04*	−0.05	1.49	
	9.09	1.47	3.20	2.36	0.01	1.60	11.43	15.65	4.20	3.83	3.87	4.84	0.00	2.64	4.59
INFTK	−1.87*	0.45	1.28	0.01	0.96	−2.18*	−3.12*	3.29*	−0.18	−0.37	−0.43	1.77	0.44	0.13	
	4.07	0.25	1.95	0.00	1.12	5.50	10.62	11.69	0.04	0.17	0.23	3.67	0.24	0.02	2.83
WHTSL	−2.32*	0.07	1.14	0.58	0.09	−1.35	−3.61*	4.02*	−0.57	−0.57	−0.74	2.14*	0.76	0.23	
	6.18	0.01	1.55	0.41	0.01	2.18	13.71	16.43	0.39	0.39	0.66	5.29	0.71	0.06	3.43
MONEY	−2.91*	−1.23	1.39	0.70	0.11	−1.47	−3.90*	4.38*	−1.74*	−1.03	−0.90	2.50*	0.98	1.23	
	9.38	1.82	2.29	0.59	0.01	2.56	15.64	18.94	3.56	1.28	0.98	7.07	1.16	1.80	4.79
PROPT	−2.68*	0.07	1.09	1.01	0.08	−1.10	−4.10*	4.71*	−0.80	−0.84	−1.05	2.36*	0.56	0.58	
	8.07	0.01	1.43	1.23	0.01	1.46	16.99	21.32	0.78	0.85	1.32	6.38	0.38	0.41	4.33
SRVC	−2.60*	−0.13	1.34	0.90	0.08	−1.14	−3.69*	4.22*	−0.87	−0.98	−1.14	2.21*	0.65	0.72	
	7.64	0.02	2.13	0.97	0.01	1.56	14.26	17.83	0.92	1.15	1.55	5.62	0.51	0.62	3.91
MEDIA	−1.42	0.49	0.27	0.19	0.66	−1.42	−2.49*	2.68*	0.02	−0.01	−0.13	1.49	0.81	0.09	
	2.42	0.30	0.09	0.04	0.52	2.41	7.03	8.03	0.00	0.00	0.02	2.64	0.80	0.01	1.74
MULTP	−1.88*	0.24	0.76	0.74	−0.07	−1.11	−3.02*	3.42*	−0.39	−0.54	−0.83	1.70	0.74	0.42	
	4.14	0.07	0.69	0.66	0.01	1.49	10.00	12.48	0.19	0.36	0.84	3.39	0.67	0.21	2.51
Sig.(5%)	12	0	1	0	0	2	13	13	2	1	1	9	0	0	
Avg. R^2	6.03	0.52	1.58	0.67	0.17	2.09	12.09	14.73	1.05	0.90	1.00	4.79	0.46	0.64	

linkage between Chinese economic activity and stock market, we compare the predictability of China economic variables for Chinese stock market before and after the WTO accession. Based on results not reported, we actually did not find significant change in the predictability of China economic variables for the Chinese stock market. Thus it seems not clear whether there is a closer linkage between Chinese economic activity and stock market in recent years. In addition, another potential cause for the sharp improvement in predictability of US economic variables for China stock market is a structural change in the predictability of US economic variables for US stock market. However, to our knowledge, there is no study that has documented significant structural change in the predictability of US economic variables for the US stock market around the China WTO accession date. For example, recent studies such as Campbell and Thompson (2008) and Goyal and Welch (2008) do not document any structural change around 2001 when China jointed WTO. As for the other alternative explanations such as rapid development of Chinese financial markets in information environments, security regulations, and institutional investments, it is difficult to disentangle them empirically. While beyond the scope of the present paper, it would be interesting in future research to further examine the economic explanations for the time-varying predictability of US economic variables for the Chinese stock market.

4.2. Principle component forecast

Heretofore, we have generated return forecasts for the Chinese stock market using individual US economic variables. Then it is natural to ask whether the fourteen US economic variables can be used collectively in forecasting returns. In addition, it is interesting to examine whether the US economic variables contain incremental forecasting information for Chinese stock market beyond that contained in China economic variables. In other words, can collectively employing both the US and the China economic variables as predictors produce better return forecasts than employing the China economic variables as predictors alone? However, although likely generating a very good in-sample fit, including a large number of predictors simultaneously in a multiple regression model often leads to over-fitting with poor out-of-sample forecasting power.

To tractably incorporate information from a large number of predictors while avoiding over-fitting, following Ludvigson and Ng (2007, 2009), we apply a principal component (PC) approach. Let $x_t = (x_{1,t}, \ldots, x_{N,t})'$, $t = 1, \ldots, T$, denote an N-vector of potential economic predictors. And let $\hat{F}_k = \left(\hat{F}_{1,k}, \ldots, \hat{F}_{J,k}\right)$ for $k = 1, \ldots, T$ represent a vector comprised of the first J principal components of x_t estimated using data up to time k, $x_k = (x_{1,k}, \ldots, x_{N,k})'$ for $k = 1, \ldots, T$, where $J \ll N$. To make J relatively small to avoid an overly parameterized model, at the same time, not to include too few principal components, thereby neglecting important information in x_t, we use information criteria developed in Bai and Ng (2002) to determine the number of common factors, J. The principal components conveniently detect the key comovements in x_t, while filtering out much of the noise in individual predictors. We then use a predictive regression framework to forecast the Chinese stock market based on principal component (PC) factors $\hat{F}_{t-1}$ estimated from x_{t-1}:

$$r_{i,t} = a_i + b_{i,\hat{F}} \hat{F}_{t-1} + u_{i,t}. \tag{2}$$

4.2.1. In-sample analysis

Tables 3 and 4 present the results for in-sample predictive regressions of Eq. (2) for the Chinese stock market with the US PC factors $\hat{F}^{US}$ and the China PC factors $\hat{F}^{CN}$ serving as predictors over the 1993:07–2001:12 and 2002:01–2008:12 sample periods, respectively. The US PC factors $\hat{F}^{US}$ and the China PC factors $\hat{F}^{CN}$ are estimated from the fourteen US economic variables and the nine China economic variables, respectively.[8] The PC factors before and after year 2001 when China joined the WTO are estimated over the 1993:07–2001:12 and 2002:01–2008:12 sample periods, respectively. Three predictive

[8] An alternative set of economic PC factors can be estimated on the panel of twenty three US and China economic variables by pooling the fourteen US economic variables and nine China economic variables together. The factors estimated from the this alternative method is often criticized for being difficult to interpret. Because we are interested to investigate whether the US economic variables are useful for forecasting China stock market, grouping data separately into US and China groups permits us to easily name the factors estimated from each group of data. We do not report the results for the this alternative method, however, factors estimated from both methods tend to have similar general results.

Table 3
Regression results based on principle component factors, 1993:07–2001:12. The table reports the regression coefficients, t-statistics (in parenthesis), and R^2 statistic (in percent) for the factor-augmented predictive regression model, $r_{i,t} = a_i + b_{i,F}\hat{F}_{t-1} + u_{i,t}$, where $r_{i,t}$ is the excess return for the value-weighted market or industry portfolio given in the row heading and $\hat{F}_{t-1}$ is the principle component factors given in the column heading. Principle component factors $\hat{F}^{US}_{j,t-1}$ and $\hat{F}^{CN}_{j,t-1}$ are estimated from fourteen U.S. economic variables and nine China economic variables over 1993:07–2001:12 sample period, respectively. The number of factors are selected using Bai and Ng (2002) criterion. The MKT panel reports results for the excess return on the China A-Share aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation over 1993:07–2001:12 sample period. A constant is always included in the regression, though its estimate is not reported in this table.

Portfolio		$\hat{F}^{US}_{1,t-1}$		$\hat{F}^{US}_{2,t-1}$		$\hat{F}^{US}_{3,t-1}$		$\hat{F}^{CN}_{1,t-1}$		$\hat{F}^{CN}_{2,t-1}$		$\hat{F}^{CN}_{3,t-1}$		R^2
MKT	(1)	0.00	(0.03)	0.02	(2.58)	0.00	(−0.23)							1.66
	(2)	0.02	(1.13)	0.01	(0.48)	−0.01	(−0.66)	0.04	(1.46)	0.01	(1.68)	0.02	(1.57)	8.51
	(3)							0.04	(1.51)	0.02	(4.71)	0.01	(1.20)	7.61
AGRIC	(1)	−0.03	(−2.70)	0.02	(2.44)	0.01	(1.24)							8.15
	(2)	0.03	(1.49)	0.03	(5.09)	0.01	(2.05)	0.11	(6.69)	−0.03	(−1.43)	0.02	(1.10)	22.38
	(3)							0.05	(−5.07)	−0.05	(−2.24)	0.01	(0.83)	15.38
MINES	(1)	−0.02	(−0.85)	0.02	(1.69)	0.01	(1.46)							3.01
	(2)	0.00	(0.13)	0.03	(1.96)	0.01	(2.05)	0.06	(1.26)	−0.02	(−0.76)	0.04	(2.14)	12.40
	(3)							0.03	(1.42)	−0.04	(−1.54)	0.04	(1.75)	8.25
MANUF	(1)	0.00	(0.19)	0.02	(2.84)	0.00	(−0.36)							2.24
	(2)	0.02	(1.17)	0.01	(0.65)	−0.01	(−0.78)	0.04	(1.49)	0.01	(2.30)	0.02	(1.39)	9.66
	(3)							0.04	(1.56)	0.02	(6.31)	0.01	(0.96)	8.48
UTILS	(1)	0.01	(0.52)	0.03	(2.53)	0.01	(0.38)							2.93
	(2)	0.03	(1.65)	0.01	(0.79)	0.00	(−0.20)	0.05	(1.79)	0.01	(0.46)	0.01	(1.12)	10.16
	(3)							0.04	(1.72)	0.02	(2.87)	0.01	(0.52)	8.59
CNSTR	(1)	−0.04	(−0.93)	−0.01	(−0.43)	−0.01	(−0.49)							2.16

	(2)	−0.01	(−0.19)	−0.01	(−0.44)	−0.01	(−0.50)	0.03	(0.69)	−0.01	(−1.26)	0.06	(3.17)	8.92
	(3)							0.03	(0.86)	−0.01	(−0.78)	0.06	(3.10)	8.62
TRANS	(1)	0.00	(0.30)	0.02	(2.41)	−0.01	(−0.65)							2.23
	(2)	0.02	(1.68)	0.00	(0.30)	−0.02	(−1.08)	0.04	(1.78)	0.00	(0.16)	0.01	(1.04)	8.77
	(3)							0.03	(1.68)	0.02	(3.46)	0.00	(0.38)	6.66
INFTK	(1)	−0.01	(−0.37)	0.02	(1.71)	0.01	(0.46)							1.13
	(2)	0.01	(0.25)	0.00	(0.08)	0.00	(−0.03)	0.05	(1.35)	0.02	(1.19)	0.02	(1.04)	6.33
	(3)							0.04	(1.61)	0.02	(1.95)	0.01	(1.04)	6.29
WHTSL	(1)	0.00	(0.18)	0.02	(2.77)	−0.01	(−0.47)							1.93
	(2)	0.02	(1.26)	0.01	(0.66)	−0.01	(−0.79)	0.04	(1.33)	0.01	(1.76)	0.02	(1.58)	8.13
	(3)							0.03	(1.38)	0.02	(3.81)	0.01	(1.15)	6.89
MONEY	(1)	−0.01	(−0.37)	0.02	(1.32)	0.01	(0.87)							1.68
	(2)	0.01	(0.74)	−0.01	(−0.77)	0.00	(0.19)	0.06	(2.04)	0.01	(1.11)	0.01	(0.50)	12.92
	(3)							0.05	(2.01)	0.02	(2.77)	0.00	(0.44)	12.27
PROPT	(1)	−0.01	(−0.53)	0.02	(1.70)	−0.01	(−0.40)							1.10
	(2)	0.01	(0.62)	0.00	(0.12)	−0.01	(−0.72)	0.04	(1.25)	0.00	(0.50)	0.02	(1.79)	6.61
	(3)							0.04	(1.31)	0.01	(1.37)	0.02	(1.57)	6.01
SRVC	(1)	−0.01	(−0.23)	0.02	(2.46)	−0.01	(−0.47)							1.52
	(2)	0.02	(1.23)	0.01	(0.53)	−0.01	(−0.76)	0.05	(1.21)	0.00	(−0.40)	0.02	(1.73)	6.29
	(3)							0.04	(1.24)	0.01	(1.38)	0.01	(1.32)	5.12
MEDIA	(1)	−0.01	(−0.44)	0.01	(1.13)	−0.01	(−0.48)							0.59
	(2)	0.01	(0.55)	0.00	(0.05)	−0.01	(−0.73)	0.03	(1.13)	0.01	(0.86)	0.03	(2.25)	6.13
	(3)							0.03	(1.15)	0.01	(1.94)	0.03	(2.43)	5.63
MULTP	(1)	0.00	(0.09)	0.02	(1.86)	−0.01	(−0.83)							1.40
	(2)	0.02	(1.04)	0.00	(0.20)	−0.02	(−1.06)	0.04	(1.33)	0.01	(1.43)	0.02	(1.56)	6.88
	(3)							0.03	(1.28)	0.02	(3.44)	0.01	(1.28)	5.51

Table 4

Regression results based on principle component factors, 2002:01–2008:12. The table reports the regression coefficients, t-statistics (in parenthesis), and R^2 statistic (in percent) for the factor-augmented predictive regression model, $r_{i,t} = a_i + b_{i,\hat{F}}\hat{F}_{t-1} + u_{i,t}$, where $r_{i,t}$ is the excess return for the value-weighted market or industry portfolio given in the row heading and $\hat{F}_{t-1}$ is the principle component factors given in the column heading. Principle component factors $\hat{F}^{US}_{j,t-1}$ and $\hat{F}^{CN}_{j,t-1}$ are estimated from fourteen U.S. economic variables and nine China economic variables over 2002:01–2008:12 sample period, respectively. The number of factors are selected using Bai and Ng (2002) criterion. The MKT panel reports results for the excess return on the China A-Share aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation over 2002:01–2008:12 sample periods. A constant is always included in the regression, though its estimate is not reported in this table.

Portfolio		$\hat{F}^{US}_{1,t-1}$		$\hat{F}^{US}_{2,t-1}$		$\hat{F}^{US}_{3,t-1}$		$\hat{F}^{CN}_{1,t-1}$		$\hat{F}^{CN}_{2,t-1}$		$\hat{F}^{CN}_{3,t-1}$		R^2
MKT	(1)	−0.02	(−1.28)	0.02	(1.93)	0.02	(3.23)							14.43
	(2)	0.00	(−1.10)	−0.02	(−1.65)	0.03	(3.54)	0.02	(2.40)	−0.03	(−3.28)	−0.04	(−4.56)	30.33
	(3)							0.02	(2.98)	0.00	(−0.30)	−0.04	(−4.12)	24.19
AGRIC	(1)	−0.01	(−0.48)	0.03	(2.05)	0.01	(0.82)							6.46
	(2)	0.00	(0.33)	0.00	(0.05)	0.02	(1.32)	0.01	(0.29)	−0.02	(−1.69)	−0.03	(−1.62)	12.72
	(3)							0.01	(0.89)	−0.02	(−1.74)	−0.04	(−2.07)	11.30
MINES	(1)	−0.03	(−1.78)	0.02	(1.69)	0.02	(1.91)							11.39
	(2)	−0.01	(−3.08)	−0.02	(−1.82)	0.04	(3.02)	0.01	(0.70)	−0.04	(−4.61)	−0.05	(−3.55)	28.19
	(3)							0.01	(0.74)	−0.01	(−1.18)	−0.05	(−3.59)	19.98
MANUF	(1)	−0.01	(−0.72)	0.02	(1.88)	0.02	(2.88)							10.74
	(2)	0.00	(0.39)	−0.02	(−1.01)	0.03	(2.76)	0.02	(1.42)	−0.02	(−2.60)	−0.04	(−3.60)	24.39
	(3)							0.02	(2.30)	0.00	(−0.41)	−0.04	(−3.59)	19.98
UTILS	(1)	−0.01	(−0.86)	0.01	(1.38)	0.01	(1.21)							4.62
	(2)	0.00	(−1.36)	−0.02	(−1.81)	0.02	(1.36)	0.02	(1.96)	−0.02	(−2.13)	−0.04	(−3.20)	17.84
	(3)							0.01	(1.98)	−0.01	(−0.91)	−0.04	(−2.72)	15.47
CNSTR	(1)	−0.01	(−0.77)	0.03	(2.21)	0.00	(0.50)							7.31
	(2)	−0.01	(−0.99)	−0.02	(−1.50)	0.01	(0.84)	0.03	(2.59)	−0.03	(−3.13)	−0.05	(−3.76)	24.24
	(3)							0.02	(3.23)	−0.02	(−3.03)	−0.04	(−3.29)	22.64
TRANS	(1)	−0.02	(−1.95)	0.01	(1.41)	0.02	(4.20)							14.44
	(2)	−0.01	(−3.44)	−0.02	(−1.65)	0.03	(4.66)	0.01	(0.86)	−0.02	(−2.79)	−0.04	(−3.77)	28.03
	(3)							0.01	(1.17)	0.00	(0.37)	−0.04	(−3.65)	20.36
INFTK	(1)	0.00	(0.00)	0.02	(2.02)	0.03	(4.51)							11.06
	(2)	0.01	(1.43)	−0.01	(−0.76)	0.04	(3.80)	0.01	(0.92)	−0.03	(−2.52)	−0.03	(−2.52)	21.86
	(3)							0.02	(1.91)	0.00	(−0.70)	−0.03	(−3.05)	13.65
WHTSL	(1)	−0.01	(−0.60)	0.02	(1.91)	0.02	(2.80)							10.25
	(2)	0.00	(0.10)	−0.02	(−0.91)	0.03	(2.68)	0.02	(1.47)	−0.03	(−2.74)	−0.04	(−3.12)	22.82
	(3)							0.02	(2.32)	−0.01	(−0.84)	−0.04	(−3.26)	18.83
MONEY	(1)	−0.02	(−1.99)	0.02	(2.08)	0.03	(2.87)							17.70
	(2)	−0.01	(−1.11)	0.00	(−0.32)	0.04	(3.58)	0.01	(2.64)	−0.02	(−1.28)	−0.04	(−4.19)	26.15
	(3)							0.02	(2.50)	0.00	(0.34)	−0.04	(−3.71)	19.78
PROPT	(1)	−0.02	(−1.00)	0.03	(1.92)	0.02	(1.86)							11.85
	(2)	0.00	(−0.27)	−0.02	(−1.53)	0.03	(2.41)	0.03	(2.50)	−0.03	(−3.51)	−0.05	(−4.64)	28.90
	(3)							0.03	(3.53)	−0.01	(−0.64)	−0.05	(−4.31)	25.09
SRVC	(1)	−0.02	(−0.86)	0.02	(1.72)	0.02	(2.86)							11.68
	(2)	0.00	(−0.44)	−0.02	(−1.25)	0.03	(3.18)	0.02	(1.85)	−0.03	(−3.40)	−0.04	(−2.99)	25.24
	(3)							0.02	(2.92)	0.00	(−0.51)	−0.04	(−2.89)	20.39
MEDIA	(1)	0.00	(−0.03)	0.02	(1.87)	0.02	(2.42)							5.85
	(2)	0.01	(0.81)	−0.02	(−0.85)	0.03	(2.04)	0.02	(1.44)	−0.03	(−1.80)	−0.04	(−2.29)	14.13
	(3)							0.02	(2.28)	−0.01	(−0.76)	−0.04	(−2.22)	11.04
MULTP	(1)	−0.01	(−0.65)	0.02	(1.55)	0.02	(2.56)							6.87
	(2)	0.00	(0.36)	−0.02	(−1.31)	0.02	(2.27)	0.03	(1.96)	−0.03	(−2.41)	−0.05	(−2.91)	20.36
	(3)							0.02	(2.62)	−0.01	(−0.71)	−0.04	(−2.74)	17.38

regressions are run for each return series $r_{i,t}$. To examine the predictive power of the US economic variables, we run a regression with only $\hat{F}^{US}$ included as the predictor. Then, to investigate whether the US economic variables contain incremental forecasting information for Chinese stock market beyond that contained in the China economic variables, we run two regressions and compare their performances: one with only $\hat{F}^{CN}$ included as the predictor and the other with both $\hat{F}^{US}$ and $\hat{F}^{CN}$ included as predictors.

Panel MKT of Table 3 reports the results for the Chinese aggregate market portfolio over the 1993:07–2001:12 sample period before China joined the WTO. Row (1) shows that $F^{US}_{1,t-1}$ and $F^{US}_{3,t-1}$ are insignificant in predicting the Chinese aggregate market portfolio. Although $F^{US}_{2,t-1}$ in row (1) is statistically significant, row (2) shows that it loses its predictive power once the $\hat{F}^{CN}$ is included in regression. Furthermore, the last entries of rows (2) and (3) present that the R^2 is only marginally improved by less than 1% when adding $\hat{F}^{US}$ as additional predictors, suggesting that the US economic variables have not much incremental forecasting power for Chinese stock market beyond the China economic variables. Hence, similar to the previous results using individual predictors, the results under the PC factor approach also indicate that the US economic variables are not that useful for predicting the Chinese aggregate market portfolio over the sample period before China joined WTO.

In contrast, similar to the previous results using individual predictors, the US economic variables have much more significant predictive power for the Chinese aggregate market portfolio over the 2002:01–2008:12 sample period after China joined WTO. This is evident in Panel MKT of Table 4, which reports the results for the Chinese aggregate market portfolio under the PC factor approach over the 2002:01–2008:12 sample period. Row (1) shows that US PC factors $F_{2,t-1}^{US}$ and $F_{3,t-1}^{US}$ are statistically significant in predicting Chinese aggregate market portfolio. In addition, row (2) shows that they do not lose their predictive power when the $\hat{F}^{CN}$ are included in the regression. Furthermore, the US economic variables contain significant incremental forecasting information for the Chinese aggregate market portfolio beyond that contained in China economic variables, as shown by comparing the last entries of rows (2) and (3), where the increase of R^2 from 24.19% to 30.33% is more than 6% once the $\hat{F}^{US}$ are included as additional predictors.

The remaining panels of Tables 3 and 4 report the results of the Chinese industry portfolios under the PC factor approach during the 1993:07–2002:12 and 2002:01–2008:12 sample periods, respectively. Although there are significant variation in predictability among the thirteen Chinese industry portfolios, the results regarding the predictability of the US economic variables on the industry portfolios are generally similar to those on the Chinese aggregate market portfolio. For instance, for the 1993:07–2002:12 sample period, rows (1) of the remaining panels of Table 3 show that $F_{1,t-1}^{US}$ and $F_{3,t-1}^{US}$ are generally not statistically significant. Although $F_{2,t-1}^{US}$ in rows (1) can be statistically significant for some industries, rows (2) show that it loses its predictive power once the $\hat{F}^{CN}$ is included in the regression. Moreover, the US economic variables have little incremental predictability for most Chinese industry portfolios beyond that of the China economic variables, with economically small increase of R^2 when including $\hat{F}^{US}$ as additional predictors. On the contrast, for the 2002:01–2008:12 sample period, as shown by the remaining panels of Table 4, the predictive power of US PC factors $\hat{F}^{US}$ is substantially improved after China joined the WTO, with statistical and economic significance.

The predictability of US economic variables varies a lot across the Chinese industries. For example, industries like MONEY (17.70%) and TRANS (14.44%) are significantly more predictable than many other industries, as shown in Table 4. In the literature, cross-industry differences in predictability have been related to the differences in market betas (e.g., Ferson and Korajczyk, 1995). Industries with higher market betas tend to be more predictable by economic variables. Our empirical results also find a positive relationship between the predictabilities for Chinese industry portfolios and their betas on the US stock market. Intuitively, with increasing integration between China and US economy and stock market, US economic variables may have stronger predictive power for Chinese industries more exposed to the US stock market. Therefore, differences in the exposure to the US stock market help to explain the cross-industry differences in predictability. While it is out of the scope of this current paper, it is worth investigating further in future research the underlying mechanism that links the cross-industry differences in predictability for Chinese stocks with their differences in the exposure to the US stock market. [9]

Altogether, similar to the findings using individual predictors, our results under the principle component analysis find consistently that, the predicting ability of the US economic variables for the Chinese stock market is substantially improved after China joined the WTO in 2001. Furthermore, after China joined the WTO, the US economic variables contain substantial incremental information in predicting the Chinese stock market beyond that contained in the China economic variables. Therefore, the US economic variables may be used in conjunction with the China economic variables to improve return forecasts for the Chinese stock market.

[9] The needed industry level data on economic and financial integration, such as the international business operation, FDI flows, international investor portfolio investment for each industry etc., are not available to us at this moment.

4.2.2. Out-of-sample analysis

Although in-sample analysis may have more testing power, out-of-sample analysis seems to be a more relevant standard for assessing genuine return predictability in real time, as argued for example by Goyal and Welch (2008).[10] Following Campbell and Thompson (2008), we analyze the out-of-sample predictive ability using R^2_{OS} statistic, which measures the reduction in mean squared predictive error (MSPE) for a competing predictive model (e.g., a model including the US PC factors $\hat{F}^{US}$ as additional predictors) relative to the corresponding restricted benchmark (e.g., a model excluding $\hat{F}^{US}$). To avoid look-ahead bias, the principle component factors and regression coefficients are estimated recursively using only the data available through time t for forecasting at time $t+1$. More specifically, we calculate the R^2_{OS} statistic for the predictive regression model using the PC factors estimated from both the US and China economic variables, $\hat{F}^{US}$ and $\hat{F}^{CN}$, relative to the benchmark predictive regression model using the PC factors based only on the China economic variables, $\hat{F}^{CN}$,

$$R^2_{OS} = 1 - \frac{\sum_{k=1}^{m} (r_k - \hat{r}_k)^2}{\sum_{k=1}^{m} (r_k - \hat{r}^R_k)^2}, \tag{3}$$

where $\hat{r}_k$ represents an excess return forecast including the US PC factors, $\hat{F}^{US}$, as predictors, and $\hat{r}^R_k$ represents the corresponding restricted forecast benchmark excluding the US PC factors, $\hat{F}^{US}$. Thus, when $R^2_{OS} > 0$, the competing forecast including the US PC factors, $\hat{F}^{US}$, outperforms the forecast benchmark in term of MSPE. Comparing the forecast including the US economic variables with the corresponding restricted forecast benchmark excluding the US economic variables entails comparing nested models. Hence, we employ the Clark and West (2007) *MSPE-adjusted* statistic to test the null hypothesis that the MSPE of the competing model is greater than or equal to the MSPE of the restricted forecast benchmark, against the one-sided alternative hypothesis that the competing forecast has lower MSPE, corresponding to H_0: $R^2_{OS} \leq 0$ against H_A : $R^2_{OS} > 0$. Clark and West (2007) develop the *MSPE-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 from nested models.[11]

We report the R^2_{OS} statistics of US PC factors $\hat{F}^{US}$ for two cases: (i) the R^2_{OS} statistic for a competing model including the PC factors based on the US economic variables, $\hat{F}^{US}$, and constant relative to the historical mean forecast benchmark corresponding to the constant expected return model; (ii) the R^2_{OS} statistic for a competing model including both the PC factors based on the US economic variables and the PC factors based on the China economic variables, $\hat{F}^{CN}$ and $\hat{F}^{US}$, relative to the corresponding benchmark model only including the PC factors based on the China economic variables, $\hat{F}^{CN}$ for assessing the incremental out-of-sample predictability of US economic variables beyond that of the China economic variables.

Table 5 reports the out-of-sample predictive performance of the US economic variables for the Chinese stock market over the 2002:01–2008:12 out-of-sample forecast evaluation period.[12] According to the MKT row under the "US vs. const" column, the US PC factors, $\hat{F}^{US}$, produce positive significant R^2_{OS} of 3.72% relative to the historical mean benchmark for the Chinese aggregate market portfolio, indicating significant out-of-sample forecasting power for the China aggregate market portfolio.[13] As for the industry portfolios, MINES, TRANS, and MONEY have large R^2_{OS} statistics of 5.91%, 4.73%, and 4.58%, respectively,

[10] See Lettau and Ludvigson (2009) for literature review on in-sample and out-of-sample return predictability tests.

[11] 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 complicated 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.

[12] The data in the 1993:07–2001:12 period are used for estimating the predictive regression parameters.

[13] We also studied the out-of-sample predictability of the China economic variables. In general, although the China economic variables are significant in in-sample regressions, their out-of-sample predictive power is weak. For example, the R^2_{OS} of China economic variables PC factors is 0.96% for the China market portfolio over the 2002:01–2008:12 out-of-sample evaluation period, which is significantly smaller than that of the US economic variables. This is may be due to the well-known unreliability of the Chinese macroeconomic and accounting data.

Table 5

Out-of-sample R^2_{OS} statistics. This table reports the out-of-sample R^2_{OS} statistics of principle component forecast based on US economic variables for the China market and industry excess returns. R^2_{OS} statistics measure the reduction in mean square prediction error (MSPE) for a competing model including US economic variables relative to the forecast benchmark. "US vs. const" columns report the R^2_{OS} statistics for a model including US economic variables as predictors relative to the historical mean forecast benchmark. "US + China vs. China" columns report the R^2_{OS} statistics for a model including China and US economic variables as predictors relative to the benchmark model including just the China economic variables. All the factors and parameters are estimated recursively using only the information available through period t. R^2_{OS} statistics are computed for the 2002:01–2008:12 full forecast evaluation period. Statistical significance is assessed with Clark and West (2007) *MSPE-adjusted* statistics corresponding to H_0: $R^2_{OS} \le 0$ against H_A: $R^2_{OS} > 0$. *, **, and *** indicate significance at the 10%, 5%,and 1% levels, respectively.

(1)	(2)	(3)
	US vs. const	US + China vs. China
MKT	3.72**	6.65**
AGRIC	0.21	1.93**
MINES	5.91***	6.67***
MANUF	0.15	3.18*
UTILS	−2.04	3.09*
CNSTR	−1.45	1.64*
TRANS	4.73**	8.61***
INFTK	−4.23	5.98**
WHTSL	0.55*	1.28*
MONEY	4.58***	6.81***
PROPT	1.32	2.45*
SRVC	0.91	3.82**
MEDIA	−2.61	0.43
MULTP	−1.41	0.42

among the thirteen industry portfolios. In addition, four of the eight positive R^2_{OS} statistics for industry portfolios are significant at 10% or better level.[14]

We then move on to investigate whether the US economic variables contain incremental predictive information beyond that contained in the China economic variables. For the aggregate market portfolio, the "US + China vs. China" column reports that a forecasting model including both the US and the China economic variables produces a significant positive R^2_{OS} statistic of 6.65% over the 2002:01–2008:12 period relative to the restricted forecast benchmark model including only the China economic variables. This indicates that the US economic variables contain significant amount of incremental forecasting information beyond that contained in the China economic variables that is useful in out-of-sample prediction. All of the thirteen industry portfolios have positive R^2_{OS} statistics, and eleven of them are significant at 10% or better level. MINES, TRANS and MONEY have large R^2_{OS} statistics of 6.67%, 8.61% and 6.81%, respectively.

We also investigate the out-of-sample predictability of US economic variables separately for the 2002:01–2006:12 non-bubble period and the 2007:01–2008:12 bubble period, respectively.[15] In an

[14] To make our results easier to compare with those of the recent literature, such as Campbell and Thompson (2008) and Goyal and Welch (2008), in the paper, we only report the results based on historical mean benchmark. Indeed, Fama and French (1988), among others, documented significant autocorrelation in stock market returns. Thus a time series model can be used as an alternative forecasting benchmark. We compare the out-of-sample forecasting performance of US economic variables relative to the AR(1) benchmark model, which utilizes the lag returns as predictors. The empirical results show that the predictability of US economic variables remains significant relative to the AR(1) benchmark . For instance, the out-of-sample R^2_{os} of US economic variables relative to AR(1) model for the Chinese aggregate market portfolio is 3.23%, of the similar statistical and economic significance with that relative to the historical average benchmark (3.72%). Furthermore, including both US and China economic variables improves the R^2_{os} to 5.92% relative to the AR(1) benchmark. Therefore, the results are qualitatively the same when the time series model is used as benchmark, and the forecasts including both China and US economic variables can substantially outperform the time series models.

[15] The bubble mentioned in this paper refers to the bubble in China stock market and not in the US market. In general, the 2007:01–2008:12 period tends to experience more severe overpricing concerns than the 2002:01–2006:12 period. Hence, we split the entire out-of-sample period of 2002:01–2008:12 into two subperiods and label the 2007:01–2008:12 period as a bubble period and the 2002:01–2006:12 period as a non-bubble period, respectively.

unreported table, we find that the US economic variables tend to have larger out-of-sample predictive power during the bubble period than during the non-bubble period. For example, the R^2_{OS} statistics for the aggregate market portfolio relative to the benchmark model with China economic variables are 9.20% and 2.16% during the bubble period and the non-bubble period, respectively. Moreover, nine of thirteen the industries have larger R^2_{OS} statistics during the bubble period than during the non-bubble period. We attribute the higher predictive power of US economic variables for China stock market during the recent bubble period to two reasons: (1) we detect a significant structural break on the association between the US economic variables and China stock market around the WTO accession. The bubble period has relatively more new regime data (after WTO period) to estimate the parameters recursively than the non-bubble period. Therefore, the parameters estimation in the bubble period is likely to be less biased and has smaller estimation error, resulting in better forecasting performance. (2) The US sub-prime bubble, which largely overlapped with the China stock market bubble, spread from US to the rest of the world, including China. This overlap results in the US economic variables potentially having more predictive power during this bubble period.

4.2.3. Portfolio analysis

We have used regression analysis based R^2_{OS} statistics to analyze the out-of-sample predictive power of the US economic variables for the Chinese stock market. However, a relatively small R^2_{OS} statistic can still be economically important for an investor (Kandel and Stambaugh, 1996; Xu, 2004; Campbell and Thompson, 2008).[16] In this subsection, we study the economic value of using the US economic variables to forecast the Chinese stock market from an asset allocation perspective. Studies such as Kandel and Stambaugh (1996), Campbell and Thompson (2008), and Neely et al. (2011) analyze the importance of aggregate market return predictability for asset allocation, while Avramov (2004), Avramov and Chordia (2006), Avramov and Wermers (2006), and Wei and Zhang (2008) investigate the relevance of component return predictability for portfolio management. Along the line of these studies, we compute out-of-sample utility gain and Sharpe ratio gain, for a mean-variance investor who monthly allocates between Chinese risky stocks and risk-free asset based on stock return forecasts, from using the US economic variables in forecasting returns compared with not using the US economic variables in forecasting returns.

We assume a mean-variance investor with risk aversion coefficient of five. And we restrict the portfolio weight on stocks to lie between 0 and 150% to avoid short sell and leverage above 50%. In addition, following Campbell and Thompson (2008), we assume that the investor uses a five-year moving window of past monthly returns to estimate the variance of returns. We conduct two comparisons. First, we compute the economic gains of using forecasts based on the US economic variables relative to the benchmark forecasts based on the historical mean. The utility gain is the difference between the utility of the portfolio formed on out-of-sample principle component forecasts based on the US economic variables and that of the benchmark portfolio formed on the historical mean forecasts. We report annualized utility gain that can be interpreted as the annual percentage management fee that a investor would be willing to pay to utilize the US economic variables into forecasting the Chinese aggregate market and industry excess returns. Second, we compute the economic gains of using forecasts based on both the US and the China economic variables relative to the benchmark forecasts of using the forecasts based only on the China economic variables. The utility gain is the difference between the utility of the portfolio formed on out-of-sample principle component forecasts based on both the US and the China economic variables and that of the benchmark portfolio formed on out-of-sample principle component forecasts based only on the China economic variables. The second comparison assesses the economic value of utilizing both the US and the China economic variables compared with utilizing only the China economic variables.

Table 6 reports the utility gain and Sharpe ratio gain, which is calculated in the same way as the utility gain, for the China aggregate market and industry portfolio excess returns over the 2002:01–2008:12 period. The MKT row of the second column shows that incorporating the US economic variables into

[16] Actually, R^2_{OS} statistics are typically small for stock return forecasts, since stock return inherently contains a large unpredictable component. For instance, Cochrane (2008) addresses the issue that out-of-sample predictability could appear weak.

Table 6

Utility gains and Sharpe ratio gains. This table reports the utility gains (Δ) and Sharpe ratio gains (SR). Columns denoted "US vs. const" report the Sharpe ratio gain and utility gain (in annualized percentage) for a mean-variance investor with risk aversion coefficient of five as the difference between the Sharpe ratio and utility of the portfolio based on the US economic variables out-of-sample principle component forecast and the Sharpe ratio and utility of the benchmark portfolio based on historical mean forecast, respectively. Columns denoted "US + China vs. China" report the Sharpe ratio gain and utility gain (in annualized percentage) as the difference between the Sharpe ratio and utility of the portfolio based on both the US and the China economic variables out-of-sample principle component forecast and those of the benchmark portfolio based on just the China economic variables out-of-sample principle component forecast, respectively. All the factors and parameters are estimated recursively using only the information available through period t. The MKT row reports results for the excess return on the China A-Share aggregate value-weighted market portfolio. Sharpe ratio gain and utility gain are computed for the 2002:01–2008:12 out-of-sample forecast evaluation period.

(1)	(2)	(3)	(4)	(5)
	US vs. const		US + China vs. China	
	Δ (ann. %)	SR	Δ (ann. %)	SR
MKT	3.02	0.15	8.78	0.07
AGRIC	1.52	0.18	15.33	0.06
MINES	−1.48	0.07	8.75	0.06
MANUF	4.19	0.17	9.24	0.08
UTILS	−1.89	0.07	7.82	0.02
CNSTR	4.52	0.18	1.26	0.02
TRANS	−4.12	0.09	10.90	0.06
INFTK	2.91	0.15	11.36	0.09
WHTSL	6.22	0.19	8.14	0.09
MONEY	1.44	0.11	7.07	0.06
PROPT	4.77	0.20	11.42	0.07
SRVC	0.97	0.15	7.75	0.07
MEDIA	3.10	0.14	9.25	0.10
MULTP	−0.85	0.12	8.32	0.03

return forecasts improve the utility by 3.02% over using the historical mean benchmark for the China aggregate market portfolio, which are economically sizable. Therefore, the investor would be willing to pay an annual management fee up to 3.02% to have assess to the principle component forecasts for the China aggregate market portfolio based on the US economic variables relative to the historical mean forecasts. The remaining rows show that nine of the thirteen utility gains for industry portfolios are nearly above 1.00% or better, and MANUF, CNSTR, WHTSL and PROPT have the largest utility gains. The results for the Sharpe ratio are similar. For instance, the MKT row of the third column shows that incorporating the US economic variables into return forecasts improve the Sharpe ratio significantly by 0.15 over using the historical mean benchmark forecasts that only has a Sharpe ratio of 0.08, for the Chinese aggregate market portfolio. And all the Sharpe ratios for the thirteen industry portfolios are nearly doubled. The substantially larger utilities and Sharpe ratios obtained by using the forecasts based on the US economic variables relative to the historical mean forecasts indicate sizable economic gains from exploiting the US economic variables in predicting the China aggregate market portfolio and industry portfolios.[17]

The "US + China vs. China" columns in Table 6 report the utility gain and Sharpe ratio gain of utilizing both the US and the China economic variables relative to the benchmark utilizing only the China economic variables. As shown by the fourth column, the utility gains are 8.78% for the aggregate market portfolio and above 7.00% for twelve of the thirteen industry portfolios. Furthermore, the sharp ratio gains are 0.07 for the aggregate market portfolio and nearly doubled for ten industry portfolios. In summary, these results suggest that the significant predictive power of the US economic variables indicated by R^2_{OS} statistics in Table 5 turns out to be economically important as well from an investment perspective.

[17] Similar to the results for R^2_{OS}, the utility gain and Sharpe ratio gain are also larger during the bubble period than those corresponding to the non-bubble period. For example, the average utility gain and Sharpe ratio gain relative to the historical mean benchmark for the market portfolio are 9.97% and 0.26 during the bubble period, respectively, while they are only 1.95% and 0.09 during the non-bubble period.

5. Conclusion

The relative importance of the world economy for China has increased significantly over the last few decades, especially after China officially entered the WTO in December 2001. Joining the WTO meant more international trade for Chinese exporters. As a result of this move, it is not surprising to see increased integration between the Chinese and Global economy. Another effect of joining the WTO is the establishment of a freer and open financial market.[18] Hence, it is plausible that China joining the WTO may result in the Chinese stock market may be significantly affected by the world economy and/or the US economy.

In this paper, we examine whether the US economic variables are leading indicators of the Chinese stock market, especially after 2001. Our results show that US economic variables are indeed good leading indicators for the Chinese stock market after China joined the WTO. Prior to that, the predictive ability of these variables are statistically insignificant. One explanation for our findings is the increased integration of the Chinese economy to the world economy after China joined the WTO in 2001. In addition, we show that the US economic variables can be used in conjunction with the China economic variables to enhance return forecasts for the Chinese stock market. Finally, our out-of-sample results indicate extensive predictive power of the US economic variables in real time, which turns out to be economically important from an investment perspective as indicated by significant utility and Sharpe ratio gains.

Our findings suggest that conventional predictive regression models for Chinese stock market ignore important information in US (global) economic variables, and investors interested in investing in the Chinese stock market should pay attention to both US and China economic variables. Our results also have potentially important implications for asset pricing models for the Chinese stock market as well as cost of capital calculation.

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[18] An interesting research topic is to examine the relative importance of economic and financial channels on the time-varying integration between China and global market. In particular, Chinese B-share stock market was accessible to the international investors before China joined the WTO, thus it is interesting to compare the predictability of the Chinese A-share stock market against that of the B-share stock market. We leave these extensions to future research.

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