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Does news on real Chinese GDP growth impact stock markets?†

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Real Gross Domestic Product (GDP) growth in China follows a random walk. Also, it has often been suggested that China 'cooks its books', that is to say that governmental officials in China manipulate economic statistics, such as GDP growth rate to present the outside world a rosy picture (Foreign Policy, 3 September 2009). If such unreliability is known to stock traders, news on GDP should not impact stock market fluctuations or their volatility. We test this hypothesis for 12 series with daily stock market returns for the years 2006 to and including 2009.

I. Introduction

The quarterly real Gross Domestic Product (GDP) growth data for China have interesting properties. One of these is that they are released quite rapidly after the relevant quarter, although China tends to have quite significant revisions of annual economic growth at a 1-year lag. Second, real GDP growth follows random walk properties, which means that the growth rates cannot be predicted through mere extrapolation. Third, it is often suggested that statistics in China are manipulated and therefore unreliable. The *Wall Street Journal* pointed out the discrepancy between Chinese GDP growth data and data on oil and electricity demand (29 May 2009). In the first quarter of 2009, for example, 6.1% GDP growth coincided with a mere 3.0% growth in energy consumption. The Financial Times reported that the tally of GDP estimates provided by the 31 provincial and municipal governments for the first half of 2009 was significantly higher, about 10%, than the GDP figure released by the National Bureau of Statistics (5 August 2009).

We study the consequences of these properties on stock market fluctuations. For this, we analyse an Exponential General Autoregressive Conditional Heteroscedastic (EGARCH) model (see Engle, 1982; Nelson, 1991) which includes 16 dummies concerning the announcement dates in the level equation and in the conditional volatility equation. The model is fitted to daily stock market returns data for eight Asian stock markets and four US stock markets. According to the Efficient Market Hypothesis (EHM), financial markets should respond only tepidly to news on GDP that is deemed unreliable.

The outline of this article is as follows. In Section II, we describe a few features of real GDP growth rates of China. In Section III, we discuss our methodology and we present the results. Section IV provides the general conclusion. Our main finding is that Chinese news has only a limited and also nonsystematic impact on stock market fluctuations.

II. Real GDP Growth in China

Figure 1 gives the nominal levels of GDP in China as they are published each quarter. The data are cumulated, which means that the first quarter reports

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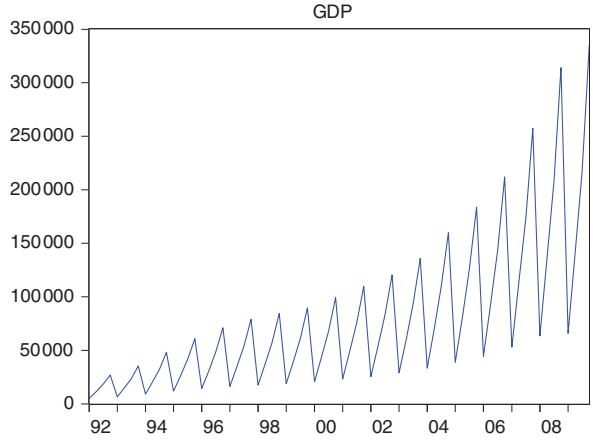

Fig. 1. Nominal GDP (levels) in China, 1992Q1–2009Q4

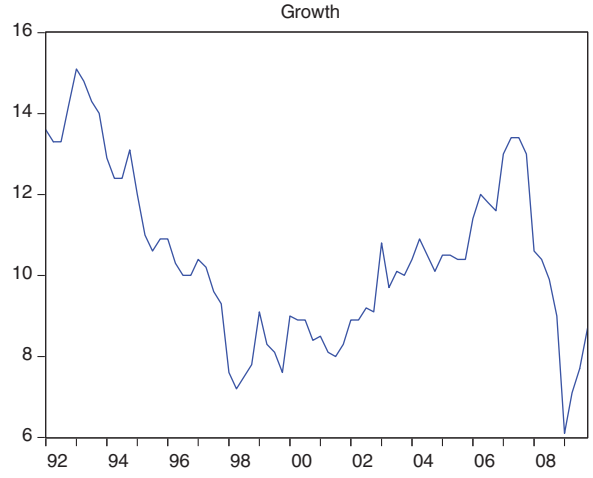

Fig. 2. Quarterly real growth rates of GDP in China, 1992Q1–2009Q4

the data on the first quarter, whereas the second quarter concerns the sum of output in the first two quarters, and so on.

Figure 2 gives the real GDP growth rates. In Franses and Mees (2010) it is documented that this series follows a random walk. This is quite an unusual finding as most growth rates of real GDP data for industrialized countries can be described by simple time-series models like Autoregressive Moving Average (ARMA), which implies that these figures can be predicted to some extent through extrapolation. When the data are a random walk, the best forecast is the most recent observation, hence a no-change forecast. In Table 1, we present the actual data and the no-change forecasts, as well as the forecast errors. Later on, we will classify these forecast errors as negative or positive news to see if such news has an impact on stock market returns or stock market volatility.

In Table 2, we give the announcement dates for the growth rates of real GDP for the US and for China.

Table 1. The real GDP figures, as they are available from the National Bureau of Statistics of China, and the forecasts that follow from a random walk

Quarter	Real growth	No – change forecast	Forecast error
2005Q4	10.4	10.4	0.0
2006Q1	11.4	10.4	1.0
2006Q2	12.0	11.4	0.6
2006Q3	11.8	12.0	−0.2
2006Q4	11.6	11.8	−0.2
2007Q1	13.0	11.6	1.4
2007Q2	13.4	13.0	0.4
2007Q3	13.4	13.4	0.0
2007Q4	13.0	13.4	−0.4
2008Q1	10.6	13.0	−2.4
2008Q2	10.4	10.6	−0.2
2008Q3	9.90	10.4	−0.5
2008Q4	9.00	9.90	−0.9
2009Q1	6.10	9.00	−2.9
2009Q2	7.10	6.10	1.0
2009Q3	7.70	7.10	0.6
2009Q4	8.70	7.70	1.0

Source: http://www.stats.gov.cn/english (accessed 22 January 2010).
Note: The data in this table are calculated at constant prices, and are relative to the same period of the preceding year = 100.

Table 2. Dates with first announcements concerning the flash values of GDP growth in the previous quarter

Year	USA	China	Difference
2006	27 January	25 January	2
	28 April	20 April	8
	28 July	20 July	8
	27 October	24 October	3
2007	31 January	25 January	6
	27 April	18 April	9
	27 July	18 July	9
	31 October	23 October	8
2008	30 January	24 January	6
	30 April	17 April	13
	31 July	17 July	14
	30 October	21 October	9
2009	30 January	22 January	8
	29 April	16 April	13
	31 July	16 July	15
	29 October	22 October	7

The actual dates will be used to create associated zero–one dummy variables in the models below. We observe that the release dates for the Chinese data lead the dates of US announcements.

As said, the best forecast for real growth rates for Chinese GDP using extrapolation is the no-change forecast. This implies that traders all can rely on the same information concerning expected growth rates. Surprises in announcements would then be equally important for all traders, and nobody can make better forecasts. The distribution of past forecast errors can be instrumental to assign whether new GDP quotes are large or small surprises. In the analysis below, we will take absolute forecast errors exceeding 1.0 as large. So, traders may assign different interpretation to forecast errors, but they will not be able to create better forecasts than the no-change forecasts.

Professional traders generally will not rely exclusively on historic GDP data to make forecasts for real GDP growth. Data regarding payrolls, manufacturing, exports and other leading economic indicators will help traders to make their predictions. If the official GDP data are considered to be untrustworthy, however, financial markets should only respond tepidly to surprises in announcements of official data.

Taking altogether this suggests that news on real GDP growth rates of China would not have a large impact on stock market returns nor on stock market volatility. We will put this suggestion to a test in the following section.

III. Modelling Stock Markets

In the section, we analyse whether the announcements concerning real GDP growth in China has an impact on stock market returns or stock market volatility.

The data and the model

We consider 4 years of daily stock market returns. These are India BSE, Nikkei 225, Hang Seng, Straits (Singapore), Korea, LQ45 (Indonesia), Shanghai and Shenzhen as the leading Asian stock markets, and the S&P500, Nasdaq, Dow Jones and Russell 2000 as the US stock markets. For the levels equation for the returns y_t, we consider

$$y_t = \mu + \sum_{i=1}^{16} \delta_i^{\text{USA}} D_{i,t}^{\text{USA}} + \sum_{i=1}^{16} \delta_i^{\text{China}} D_{i,t}^{\text{China}} + u_t \quad (1)$$

where the zero–one dummy variables $D_{i,t}^{\text{USA}}$ correspond to the dates in the second column of Table 2 and the zero–one dummy variables $D_{i,t}^{\text{China}}$ to the dates in the third column. Below, we will be interested in the hypotheses that $\delta_1^{\text{USA}} = \cdots = \delta_{16}^{\text{USA}} = 0$ and that $\delta_1^{\text{China}} = \cdots = \delta_{16}^{\text{China}} = 0$, and for that we will use a joint Wald test. Note that we import the dates such that they match the proper time zones. Chinese news will reach Asia during the very same day, while it reaches the American time zone the next day. The reverse holds for US news.

The next model we consider as in EGARCH(1, 1) equation, which comprises the following two equations, that is

$$y_t = \mu + z_t \sqrt{h_t} \quad (2)$$

with

$$\log h_t = \omega + \theta z_t + \lambda(|z_t| - E(|z_t|)) + \alpha \log h_{t-1} + \sum_{i=1}^{16} \lambda_i^{\text{USA}} D_{i,t}^{\text{USA}} + \sum_{i=1}^{16} \lambda_i^{\text{China}} D_{i,t}^{\text{China}} \quad (3)$$

Below, we are interested in the hypotheses $\lambda_1^{\text{USA}} = \cdots = \lambda_{16}^{\text{USA}} = 0$ and $\lambda_1^{\text{China}} = \cdots = \lambda_{16}^{\text{China}} = 0$, and again we will use a Wald test. Estimation will be carried out using the Eviews program. Note that we cannot replace (2) by (1), as then the parameters for the dummy variables are not identified.

The results, general

The Wald test values for the hypotheses concerning the conditional volatility equations are given in Table 3. We see that stock market returns in four of the eight Asian indexes react to US news, while this occurs for only two of the eight concerning Chinese news. At the same time, US stock market returns do not significantly react to US news or to Chinese news.

It is well-known that at the very same day of presentation of national accounts figures, the response at the level of returns can be small, but perhaps more response is there to be expected at the level of volatility. Table 4 presents the relevant Wald test results, and indeed, news announcements do seem to have more effect on volatility than on returns. For five of the 12 stock markets, Chinese news (and US news alike) has an impact on volatility. The S&P500 and Nasdaq respond similar to both US and Chinese news. This also holds for the LQ45 of Indonesia, where news seems to imply the largest effects for volatility.

The results, more refined

Finally, we examine which of the announcement dates for Chinese news have most impact, and whether

Table 3. Wald test values (and *p*-values) for joint significance of 16 dummy variables measuring days with GDP announcements *for the levels equation* of regression model (with an intercept) model for stock returns, 3 January 2006 to 24 November 2009 (correcting for time zones)

	US news	Chinese news
Stock market		
India BSE	12.41 (0.715)	13.96 (0.602)
Nikkei 225	41.89 (0.000)*	10.60 (0.833)
Hang Seng	44.10 (0.000)*	38.16 (0.001)*
Straits (Singapore)	40.26 (0.001)*	21.60 (0.157)
Korea	125.9 (0.000)*	13.12 (0.664)
LQ45 (Indonesia)	20.45 (0.201)	34.45 (0.005)*
Shanghai	18.85 (0.276)	10.98 (0.811)
Shenzhen	18.03 (0.322)	11.47 (0.780)
S&P500	10.28 (0.852)	7.811 (0.954)
Nasdaq	8.743 (0.924)	16.51 (0.418)
Dow Jones	8.818 (0.921)	8.376 (0.937)
Russell 2000	12.63 (0.700)	10.31 (0.850)

Note: *Denotes significance at the 5% level.

Table 4. Wald test values (and *p*-values) for joint significance of 16 dummy variables measuring days with GDP announcements *for the conditional volatility equation* of an EGARCH(1,1) model for stock returns, 3 January 2006 to 24 November 2009, with *t*-distributed innovations (correcting for time zones)

	US news	Chinese news
Stock market		
India BSE	29.81 (0.019)*	24.65 (0.076)
Nikkei 225	362.4 (0.000)*	21.12 (0.174)
Hang Seng	24.80 (0.073)	373.1 (0.000)*
Straits (Singapore)	6.919 (0.975)	7.084 (0.972)
Korea	17.01 (0.385)	7.318 (0.967)
LQ45 (Indonesia)	745.6 (0.000)*	597.5 (0.000)*
Shanghai	2.425 (1.000)	0.243 (1.000)
Shenzhen	2.131 (1.000)	32.20 (0.009)*
S&P500	36.50 (0.003)*	30.61 (0.015)*
Nasdaq	173.2 (0.000)*	49.09 (0.000)*
Dow Jones	24.93 (0.071)	21.13 (0.174)
Russell 2000	9.084 (0.910)	15.64 (0.478)

Note: *Denotes significance at the 5% level.

this news could have been considered as positive or negative. In Table 5, we classify the forecast errors of real GDP growth accordingly. In Table 6, we give the dates for which the news has an individual significant impact on stock market volatility.

Table 6 shows that if news has an impact on conditional volatility, it usually makes this volatility to decrease, and hence to calm down stock market fluctuations. A second observation of Table 6 is that it does not seem to matter much whether this news is positive or negative. In the panel for an increase in

Table 5. Dates with first announcements concerning the flash values of GDP growth in the previous quarter and indication if realization was higher

Year		Nature of the news
2006	25 January	0
	20 April	+
	20 July	+
	24 October	−
2007	25 January	−
	18 April	++
	18 July	+
	23 October	0
2008	24 January	−
	17 April	−−
	17 July	−
	21 October	−
2009	22 January	−
	16 April	−−
	16 July	+
	22 October	+

Notes: ++ for larger than 1.0 forecast errors, or + for forecast errors in between 0.0 and 1.0 or lower; −− for larger than −1.0 forecast errors or − forecast errors in between 0 and −1.0 than expected (based on random walk forecast for real GDP growth, see Table 1).

Table 6. Detailed results concerning increase of decrease in conditional volatility due to Chinese news on specific days (increase in volatility is due to worse than expected news, and a decrease in volatility due to better than expected news)

Stock market	Increase	Decrease
Asia		
India BSE		25 January 2007 (−)
		17 April 2008 (−−)
Nikkei 225		20 July 2006 (+)
		23 October 2007 (−)
Hang Seng	16 July 2009 (++)	20 July 2006 (+)
		18 April 2007 (++)
LQ45 (Indonesia)		25 January 2006 (0)
		24 October 2006 (−)
		25 January 2007 (−)
		18 April 2007 (++)
		21 October 2008 (−)
		16 April 2009 (−−)
		22 October 2009 (+)
Shenzhen	25 January 2006 (0)	18 July 2007 (+)
USA		
S&P500		17 April 2008 (−−)
		21 October 2008 (−)
Nasdaq	20 April 2006 (+)	25 January 2006 (0)
		18 July 2007 (+)
		22 October 2009 (+)
Dow Jones		24 October 2006 (−)
Russell 2000	18 July 2007 (+)	

Table 7. Number of days (out of the 16) where US and German news have a significant impact on conditional volatility

	US news	German news
India BSE	2	2
Nikkei 225	10	2
Hang Seng	1	2
Straits (Singapore)	1	1
Korea	2	1
LQ45 (Indonesia)	11	1
Shanghai	0	2
Shenzhen	0	3
S&P500	3	2
Nasdaq	5	2
Dow Jones	2	1
Russell 2000	1	1

Table 8. GDP values in current US dollars (billions)

	China	Germany	US
2006	2657.84	2919.51	13398.93
2007	3382.45	3328.18	14007.65
2008	4327.45	3673.11	14441.43
2009	4757.74	3235.46	14266.20
2006–2009	15125.48	13156.26	56184.21

volatility, we see that it is only positive or no news that makes volatility increase (in, as must be said, a very small amount of cases). Table 6 also shows that out of the 16 (news dates) times 12 (stock markets) possibly significant outcomes, only 24 are significant, which amounts to a fraction of 12.5%. Table 7 shows that this percentage for US news is 19.8% while for Germany it is 10.4%. At the same time, we observe from Table 6 that the nature of the news that makes volatility to decrease can be positive or negative, and there is no systematic pattern.

IV. Conclusion

There is a limited effect of Chinese news on world stock markets (12.5% of the news dates there is a significant impact) compared to US news (19.8% of the news dates there is a significant impact). Stock market returns in four of the eight Asian stock indexes react to US news, while they react in only two of the eight Asian stock indexes to Chinese news. US stock market returns do not significantly react to either US news or to Chinese news. US and Chinese news have a similar impact on stock market volatility.

Table 9. GDP values based on PPP as share of world GDP (%)

	China	Germany	US
2006	10.06	4.39	21.66
2007	10.72	4.29	21.07
2008	11.35	4.21	20.61
2009	12.05	4.09	20.02
2006–2009	11.05	4.24	20.84

Source: International Monetary Fund (IMF).
Note: PPP, Purchasing Power Parity.

We started this article discussing the fact that Chinese real GDP follow a random walk, and the fact that Chinese data are often deemed as not trustworthy. We suggested that these properties imply that stock markets respond only tepidly to Chinese news as traders might be expected to take the official announcements with a pinch of salt. Indeed, we found that stock markets respond less to Chinese news than to US news.

An alternative explanation for the fact that stock markets respond more tepidly to Chinese news than to US news may be the size of the Chinese economy. We included, in the last batch (Table 7), German data that could serve as a benchmark to this hypothesis. The German authorities are known for their punctuality. Hence, few traders will doubt the trustworthiness of the German GDP data.

The stock market's timid response to the German data shows that the relative size of the economy is a quite plausible explanation. Stock indexes respond less to German news than to US news while German and US data are deemed equally reliable. German GDP is about a quarter of US GDP.

Measured in current US dollars, the German economy is almost equal the size of the Chinese economy (Table 8). German and Chinese news significantly impacted world stock markets on 10.4% and 12.5% of the news dates, respectively, (compared to 19.8% for US news). The relative size of the Chinese economy measured in current US dollars may be a plausible explanation for the fact that stock markets respond less often to Chinese news (12.5%) than to US news (19.8%).

If GDP is measured on a PPP base, the Chinese economy is three times the size of the German economy (Table 9). In that case, the size of the Chinese economy cannot fully account for the fact that stock markets respond less often to Chinese news

(12.5%) than to US news (19.8%). The unpredictability/unreliability of Chinese GDP data may then serve as an additional explanation.

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