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The Quality of Analysts' Cash Flow Forecasts in China*

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Abstract

There is a growing literature discussing the incentives of analysts to disseminate cash flow forecasts and the quality of these forecasts. Most studies support the 'demand hypothesis' and suggest that cash flow forecasts contain information additional to that provided in earnings forecasts. In contrast, Givoly *et al.* (2009) show that cash flow forecasts are just a simple extrapolation of analysts' earnings forecasts. In response to this challenge, Call *et al.* (2013) point out that the regression tests in Givoly *et al*. (2009) are non-diagnostic due to the measurement problem contained in the US dataset. We suggest that Givoly *et al.'s* (2009) method can be well applied in China since Chinese data do not have the same measurement problem as that contained in US data. By replicating the studies of Givoly *et al*. (2009) and Call *et al*. (2013), we find results consistent with Givoly *et al*. (2009) that analysts' cash flow forecasts appear to be naïve extensions of their earnings forecasts in China.

Keywords: Analyst, Analysts' Forecast, Cash Flow Forecast, Earnings Forecast, China

I. Introduction

DeFond and Hung (2003) document an increasing trend in analysts disseminating cash flow forecasts. To explain this finding, they suggest the 'demand hypothesis', that is, cash flow forecasts are provided in response to a demand by investors in cases where earnings management is likely to be severe. Most of the follow-up studies support their view and provide further evidence to show the incremental value of cash flow forecasts relative to earnings forecasts. For example, DeFond and Hung (2007) show that analysts are more likely to disseminate their cash flow forecasts in countries with weak investor protection. McInnis and Collins (2011) show a monitoring role of cash flow forecasts, namely that firms manage earnings less after they receive cash flow forecasts. It has also been found that earnings forecasts issued together with cash flow forecasts are more

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accurate (Call *et al*., 2009). The ability to beat analysts' cash flow forecasts is informative regarding the quality of reported earnings (Brown *et al*., 2013). There are also positive returns surrounding cash flow revisions (Call *et al*., 2013).

While most studies in this area directly or indirectly suggest that analysts' cash flow forecasts contain incremental information, Givoly *et al*. (2009; hereinafter GHL) challenge this view by showing that analysts' cash flow forecasts are less accurate than their earnings forecasts and cash flow forecasts are not much different from naïve forecasts, which are simply earnings forecasts adjusted for depreciation expense. Thus, the validity of all the existing research on analysts' cash flow forecasts is called into question. In response, Call *et al*. (2013) (hereinafter, CCT) point out the problem in GHL's methodology by showing that even a 'perfect foresight' cash flow forecast (i.e., a cash flow forecast that equals actual cash from operations as reported by I/B/E/S) would not be deemed sophisticated by the regression tests used in GHL. This problem is caused by the data measurement problem. The numbers reported by Compustat are GAAP based and are not consistent with what analysts forecast. Therefore, the regression tests in GHL are non-diagnostic. Although CCT provide further evidence to show that analysts' cash flow forecasts at least outperform naïve forecasts, which are simply earnings forecasts adjusted for depreciation expense, the quality of cash flow forecasts in the US is still questionable.

In this study, we investigate the sophistication of analysts' cash flow forecasts in China. Unlike US data, Chinese data do not contain the measurement problem. The actual values of earnings and cash flows reported in the financial statements are consistent with what analysts forecast in China. Therefore, GHL's regression tests can be safely carried out using Chinese data.

We first replicate the regression tests in GHL and CCT using US data and find results consistent with CCT's findings that both cash flow forecasts and actual cash flows reported in I/B/E/S are weakly associated with actual accruals reported in Compustat. This finding echoes CCT's question about the validity of GHL's tests. Then, we repeat the same regression tests using Chinese data. We find that actual cash flows are strongly, but analysts' cash flow forecasts are weakly, associated with actual accruals. This is consistent with GHL's conjecture that analysts' cash flow forecasts are merely a simple extrapolation of analysts' earnings forecasts. Next, we compare the accuracy of analysts' cash flow forecasts with the accuracy of naïve cash flow forecasts. Our results indicate that cash flow forecasts are not more accurate than the corresponding naïve forecasts. Finally, we examine the performance of star analysts and analysts with substantial industry expertise. We find that although the cash flow forecasts issued by star analysts and industry experts are more sophisticated than those issued by typical analysts, they still fail to significantly outperform the corresponding naïve cash flow forecasts. Our findings suggest that the 'demand hypothesis' cannot fully explain the incentive of analysts disseminating cash flow forecasts in China.

In the next section, we review the existing literature on analysts' cash flow forecasts. We specify the regression models used in GHL and CCT in Section III. In Section IV, we present our replication results of GHL and CCT's tests with both US and Chinese data. We present our conclusion in Section V.

II. Existing Research on Analysts' Cash Flow Forecasts

2.1 Research in the US

DeFond and Hung (2003) find that while few financial analysts produced cash flow forecasts before the 1990s, their propensity to disseminate cash flow forecasts increased quickly in the late 1990s. To explain this phenomenon, they argue that more analysts are providing cash flow forecasts in response to demand by investors increasingly concerned about earnings quality. They support their argument with the finding that the chance to receive analysts' cash flow forecasts is higher for firms with large accruals, heterogeneous accounting choices relative to industry peers, high earnings volatility, high capital intensity, and poor financial health. Moreover, it has also been found that analysts in countries with weak investor protection and low earnings quality are more likely to issue cash flow forecasts (DeFond and Hung, 2007).

In line with this 'demand hypothesis', cash flow forecasts are found to be accompanied by strong market reactions. Brown *et al*. (2013) show that the market reaction to earnings surprise is stronger if the firm also beats analysts' cash flow forecasts. Call *et al*. (2013) find abnormal returns surrounding cash flow forecast revisions. Because analysts' cash flow forecasts contain the information about accrual quality, managers of firms receiving analysts' cash flow forecasts are less likely to manipulate earnings (McInnis and Collins, 2008).

Several studies have investigated the determinants of cash flow forecast accuracy. It has been found that the quality of analysts' cash flow forecasts can be largely explained by cash flow forecasting frequency, cash flow forecasting experience, the number of companies followed, forecast horizon, and past cash flow forecasting performance (Pae and Yoon, 2011; Yoo and Pae, 2011).

Although most studies in this literature indicate that analysts' cash flow forecasts contain incremental information, GHL question the quality of cash flow forecasts and directly challenge the 'demand hypothesis'. They find that analysts' cash flow forecasts have lower accuracy and a slower improvement rate than their earnings forecasts. Moreover, they find that cash flow forecasts are not associated with strong investor reaction and have little value in terms of detecting earnings management. More importantly, GHL show that cash flow forecasts are only weakly correlated with working capital and other accrual adjustments, which suggests that analysts' cash flow forecasts are merely naïve extensions of their earnings forecasts by adjusting for estimated depreciation and amortisation. Through a detailed study of how analysts produce their 'street' cash flow from operations (CFO) numbers, Brown and Christensen (2014) find that many analysts ignore working capital and other accruals when adjusting forecasted earnings. Their findings are consistent with GHL's results.

However, CCT point out that the regression tests applied by GHL are not diagnostic. They show that even I/B/E/S actual cash flows are only weakly correlated with working capital and other accrual adjustments. The problem is largely due to the discrepancies between I/B/E/S actual values and Compustat values. CCT further show that analysts do take accruals into consideration when they issue cash flow forecasts, cash flow forecasts are superior to the time-series cash flow forecasts, and cash flow forecast revisions are associated with investor strong reaction. They conclude that cash flow forecasts are sophisticated.

As mentioned by Mangen (2013), research on cash flow forecasts is still in its infancy. This emerging area is awaiting further exploration.

2.2 Research in China

So far, there have been few studies on analysts' cash flow forecasts in China. Among the few studies conducted, Guo *et al*. (2011) and Zhang (2007) find that firms have the intention to manipulate their cash flows. However, their incentive to beat analysts' cash flow forecasts through cash flow manipulation activities is very weak. By replicating DeFond and Hung's (2003) study with Chinese data, Wang *et al*. (2012) show that analysts are more likely to issue cash flow forecasts for firms with high investor demand for cash flow information (e.g. non-state-owned enterprises). Their finding is consistent with the 'demand hypothesis'.

III. Methodology

3.1 Regression models in GHL and CCT

The main regression model in GHL is

$$CFF_{it} = \alpha_0 + \beta_1 EF_{it} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it}, \qquad (1)$$

where CFF_{it} is consensus cash flow forecasts for firm i in year t, EF_{it} is consensus earnings forecasts for firm i in year t, DEP_{it} is actual depreciation and amortisation expense, ΔWC_{it} is change in working capital, and $OTHER_{it}$ is other adjustments needed to reconcile actual earnings with actual cash from operations. *CFF* and *EF* are forecast values as reported by I/B/E/S, while *DEP*, ΔWC, and *OTHER* are actual values as reported by Compustat. All variables are scaled by average total assets and truncated at the top and bottom percentiles.

GHL find that while β_1 and β_2 are very close to one, β_3 and β_4 are far below one. They suggest that this is consistent with the notion that analysts fail to adjust for changes in working capital and other accruals when they make cash flow forecasts.

CCT show the effect of the data measurement problem through the following regression:

$$CFO_{it}^{IBES} = \alpha_0 + \beta_1 EF_{it} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it}, \qquad (2)$$

where CFO_{it}^{IBES} is actual operating cash flows, as reported by I/B/E/S, for firm i in year t and other variables are as previously defined.

They find that similar to the results of regression (1), β_1 and β_2 are very close to one. But β_3 and β_4 are still far below one even when the dependent variable is changed to actual cash flows. Even cash flow forecasts without any forecast error would be deemed to lack sophistication on the basis of GHL regression tests. As pointed out by CCT, the problem is mainly driven by the data measurement issue.

The actual cash flows and earnings reported by Compustat, which are GAAP based, are different from the numbers reported by I/B/E/S. This indicates that analysts make some adjustments to the cash flow and earnings numbers they are forecasting. The actual numbers reported by Compustat are not consistent with what analysts forecast. Thus, it is problematic to examine the quality of analysts' forecasts of accruals using accruals reported by Compustat (i.e. values of ΔWC and *OTHER* in equation 1).

3.2 Analysts' forecast data in China

In China, all financial reports are required to use the Chinese Accounting Standards (CAS). The CAS largely converges with the International Financial Reporting Standards (IFRS). The use of the CAS in communications is a common practice for companies, investors, analysts, and regulators in China (Liu, 2010). We randomly interviewed 10 analysts, and all of them claimed that they were using the CAS to produce forecasts.

Therefore, the actual values reported in the financial reports are consistent with what analysts forecast in China. Chinese data do not contain the same measurement problem as that in US data. By replicating GHL's and CTT's studies using Chinese data, we expect to provide convincing evidence on the quality of analysts' cash flow forecasts in China.

IV. Empirical Tests with both US Data and Chinese Data

4.1 Data

We obtain data on analysts' one-year-ahead earnings and cash flow forecasts and their respective actual values for US firms from the I/B/E/S Detail History database for the period 1993-2012. Table 1 reports the availability of analysts' cash flow forecasts. The number of observations in our sample, as reported in Table 1-2, is much smaller than that in CCT for the sample period 1993-2008. It seems that I/B/E/S has removed a lot of observations from the dataset (Ljungqvist *et al*., 2009). Despite this difference, we show a trend in analysts issuing cash flow forecasts consistent with that found by CCT. There are sudden increases in cash flow forecasts in 1994, 1999, 2002, and 2003.

We obtain data on analysts' forecasts for Chinese A-share firms from the China Securities Market and Accounting Research (CSMAR) Analyst Forecast Research database. There is little forecast data for periods before 2003 in CSMAR. Therefore, we choose 2003-2012 as our sample period. As reported in Table 1-3, there is also an increasing trend in analysts disseminating cash flow forecasts in China. The number and percentage of firms with cash flow forecasts and the percentage of analysts issuing cash flow forecasts rise sharply in 2004, 2008, and 2010.

Table 1 Availability of analysts' cash flow forecasts

Table 1-1 CCT Original Results

Year	# of firms with CFF	% of firms with EF & CFF	% of analysts issuing EF & CFF
1993	233	4.8	1.8
1994	469	8.5	3.9
1995	682	11.5	6.1
1996	848	12.4	9.5
1997	973	13.2	10.2
1998	1,089	15.0	11.0
1999	1,712	24.6	13.4
2000	1,678	26.2	12.7
2001	925	17.2	10.2
2002	1,933	37.4	15.3
2003	2,526	49.0	21.7
2004	2,986	40.3	23.1
2005	3,332	54.8	22.7
2006	3,481	55.3	22.6
2007	3,591	55.9	22.9
2008	3,375	56.4	23.8
Total	29,833	29.9	14.8

Table 1-2 Replication of Table 1 with US Data

Year	# of firms with CFF	% of firms with EF & CFF	% of analysts issuing EF & CFF
1993	22	0.48	0.05
1994	503	9.88	3.18
1995	561	10.16	4.44
1996	462	7.37	4.70
1997	503	7.59	5.16
1998	546	8.54	5.07
1999	953	15.19	5.58
2000	886	15.60	5.51
2001	584	12.05	5.68
2002	906	19.55	7.91
2003	1666	37.10	13.44
2004	1823	38.27	14.45
2005	2021	41.12	13.85
2006	2106	41.79	13.99
2007	2188	42.45	14.52
2008	2101	44.07	15.40
2009	2036	44.97	16.61
2010	2429	52.69	19.12
2011	2474	53.42	20.64
2012	2396	52.58	20.57
Total	27,166	26.36	10.64

Notes:
This table presents the descriptive statistics on the availability of analysts' cash flow forecasts in the I/B/E/S Detail History data file during the period 1993-2012. The first column presents the number of firms with at least one analyst's cash flow forecast (i.e. CFF). The second column presents the percentage of firms with earnings forecasts (i.e. EF) that also have at least one cash flow forecast. The final column presents the percentage of analysts who accompany their earnings forecasts with a cash flow forecast for the same firm.

Table 1-3 Replication of Table 1 with Chinese Data

Year	# of firms with CFF	% of firms with EF & CFF	% of analysts issuing EF & CFF
2003	41	10.38	2.84
2004	150	34.88	16.59
2005	256	42.88	10.62
2006	312	41.09	11.77
2007	357	41.30	9.39
2008	630	58.77	11.45
2009	716	51.55	9.15
2010	1,298	75.83	22.42
2011	1,501	76.43	28.13
2012	1,531	79.37	37.95
Total	6,792	61.17	16.03

Notes:
This table presents the descriptive statistics on the availability of analysts' cash flow forecasts in the CSMAR analyst forecast research database during the period 2003–2012. The first column presents the number of firms with at least one analyst's cash flow forecast (i.e. CFF). The second column presents the percentage of firms with earnings forecasts (i.e. EF) that also have at least one cash flow forecast. The final column presents the percentage of analysts who accompany their earnings forecasts with a cash flow forecast for the same firm.

Financial statement information for US firms and Chinese firms is taken from Compustat and the CSMAR Financial Statements Database respectively. Table 2 reports the descriptive statistics for the main components of operating cash flows. By comparing Table 2-1 and Table 2-2, we find that earnings account for a much larger percentage of operating cash flows in China than in the US (78.8% vs. 44.6%). Change in working capital is more important to operating cash flows in China than in the US (-16.5% vs. -6.8%); however, it is also much more volatile in China than in the US (Standard deviation: 2.740 vs. 0.551). Therefore, it seems cost efficient for financial analysts in China to focus more on earnings and less on change in working capital when they produce cash flow forecasts.

Table 2 Descriptive statistics for operating cash flow components

Table 2-1 US Data

	Mean	Median	Std Dev
IBC	0.446	0.520	0.990
DEP	0.465	0.394	0.576
ΔWC	-0.068	-0.027	0.551
Other	0.157	0.106	0.802

Income before extraordinary items (IBC) is Compustat data item 123. Depreciation and amortisation (DEP) is Compustat data item 125. Change in working capital (ΔWC) is equal to the sum of Compustat data items 302, 303, and 304. Other adjustments, OTHER, is equal to Compustat data item 308 minus the sum of Compustat data items 123, 125, 302, 303, and 304. All variables are deflated by net cash flow from operating activities and are truncated at the top and bottom percentiles.

Table 2-2 Chinese Data

	Mean	Median	Std Dev
IBC	0.788	0.707	2.060
DEP	0.316	0.271	0.760
ΔWC	-0.165	-0.075	2.740
Other	0.061	0.047	0.673

Net income (IBC) is CSMAR data item D000101000. Depreciation and amortisation (DEP) is equal to the sum of CSMAR data items D000103000, D000104000, and D000105000. Change in working capital (ΔWC) is equal to the sum of CSMAR data items D000113000, D000114000, and D000115000. Other adjustments, OTHER, is equal to CSMAR data item D000100000 minus the sum of CSMAR data items D000101000, D000103000, D000104000, D000105000, D000113000, D000114000, and D000115000. All variables are deflated by net cash flow from operating activities and are truncated at the top and bottom percentiles.

4.2 Sophistication of analysts' cash flow forecasts

We follow CCT in choosing our sample for regression tests. We select those firm years with at least one one-year-ahead cash flow forecast issued during the year, excluding those without accompanying earnings forecasts by the same analyst. Among the cash flow forecasts made by each individual analyst for each firm year, we keep the last forecast issued before the earnings announcement. Following GHL, we exclude stale forecasts (i.e. forecasts outstanding more than 90 days from the issuance date). The consensus cash flow forecast for each firm year is the median of all cash flow forecasts for that firm year outstanding immediately prior to the earnings announcement.

Different from the results reported in CCT, we find that there is not much difference between the number of firm-year observations in the first regression model test (reported in Table 3-2, panel A) and that in the other three tests (reported in Table 3-2, panels B, C, and D). It seems that I/B/E/S has substantially supplemented its actual value database in recent years. Our results are qualitatively similar to the results in CCT. Specifically, we find that β_1 and β_2 are significantly positive and very close to one, but β_3 and β_4 are far below one and sometime even close to zero no matter whether the dependent variable is analysts' consensus cash flow forecast or actual cash flow from operations reported by I/B/E/S. The results reconfirm CCT's finding that the tests in GHL are not diagnostic.

To replicate the results with Chinese data, we use the same sample selection procedure. Unlike the I/B/E/S database, CSMAR provides all the actual values for all firm years. The majority of these actual values (more than 95% of the total) are the same as the values reported by the CSMAR Financial Reports database. As reported in Table 3-3, we find that consistent with what GHL and CCT find in the US, β_1 and β_2 are very close to one in all the tests. Different from the US findings, however, we further find that although β_3 and β_4 are still far below one when the dependent variable is analysts' consensus cash flow forecast, they are very close to one when the dependent variable is actual cash from operations. This indicates that without the data measurement problem, GHL tests can be well applied using Chinese data. The results are consistent with the notion that analysts' cash flow forecasts are naïve extensions of their earnings forecasts adjusted for their projected depreciation expense.

As an alternative way to examine the sophistication of analysts' cash flow forecasts, we analyse 20 randomly selected full-text analysts' forecast reports, which contain cash flow forecasts, from the WIND database. We fail to find any explicit adjustments for working capital and other accruals in any of the 20 reports.

Table 3 Regression tests

Table 3-1 CCT Original Results

Panel A: Replicating GHL Table 10 using all possible observations

Model: $CFF_{it} = \alpha_0 + \beta_1 EF_{it} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it}$ (1)

	Coefficients (*t*-statistics)					
Intercept	*EF*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	n
0.001 (43.76)	1.106 (120.41)				62.1%	8,869
0.000 (6.05)	0.944 (141.29)	0.912 (95.14)			81.2%	8,869
0.000 (6.18)	0.946 (139.53)	0.912 (95.16)	0.026 (2.00)		81.2%	8,869
0.000 (4.27)	0.951 (142.28)	0.878 (90.93)	0.059 (4.66)	0.177 (16.68)	81.8%	8,869

Panel B: Replicating GHL Table 10 using observations with I/B/E/S actual cash flows

Model: $CFF_{it} = \alpha_0 + \beta_1 EF_{it} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it}$ (1)

	Coefficients (*t*-statistics)					
Intercept	*EF*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	n
0.001 (20.75)	1.298 (63.76)				61.1%	2,587
0.000 (1.25)	1.030 (83.21)	0.980 (71.56)			87.0%	2,587
0.000 (1.24)	1.029 (80.74)	0.980 (71.55)	-0.007 (-0.32)		87.0%	2,587
0.000 (0.84)	1.028 (81.66)	0.948 (66.86)	0.010 (0.45)	0.145 (7.82)	87.3%	2,587

Panel C: Using I/B/E/S actual cash flows (*CFO*) as the dependent variable

Model: $$CFO_{it}^{IBES} = \alpha_0 + \beta_1 EF_{it} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it} \quad (2)$$

	Coefficients (*t*-statistics)					
Intercept	*EF*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	n
0.001 (21.25)	1.255 (59.55)				57.8%	2,587
0.000 (2.68)	0.984 (73.29)	0.989 (66.52)			84.5%	2,587
0.000 (2.65)	0.980 (70.89)	0.989 (66.53)	-0.031 (-1.33)		84.5%	2,587
0.000 (1.98)	0.979 (73.72)	0.924 (61.84)	0.001 (0.06)	0.287 (14.63)	85.6%	2,587

Panel D: Using actual values for the dependent variable and all independent variables

Model: $$CFO_{it}^{IBES} = \alpha_0 + \beta_1 EARN_{it}^{IBES} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it} \quad (3)$$

	Coefficients (*t*-statistics)					
Intercept	*EARN*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	n
0.001 (24.43)	1.104 (52.64)				52.0%	2,558
0.000 (4.22)	0.897 (70.68)	1.070 (69.51)			83.4%	2,558
0.000 (4.17)	0.893 (68.39)	1.069 (69.45)	-0.035 (-1.40)		83.4%	2,558
0.000 (3.03)	0.913 (75.05)	0.973 (64.60)	0.013 (0.56)	0.405 (20.26)	85.7%	2,558

Table 3-2 Replication of Table 2 with US Data

Panel A: Replicating GHL Table 10 using all possible observations

Model: $$CFF_{it} = \alpha_0 + \beta_1 EF_{it} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it} \quad (1)$$

	Coefficients (t-statistics)					
Intercept	*EF*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	n
0.001 (36.28)	1.093 (89.65)				53.37%	7,022
0.000 (4.74)	0.960 (118.17)	0.934 (96.16)			79.88%	7,022
0.000 (4.65)	0.959 (116.99)	0.933 (95.86)	-0.021 (-1.18)		79.88%	7,022
0.000 (3.21)	0.963 (118.83)	0.786 (53.28)	-0.115 (-6.13)	0.120 (13.15)	80.36%	7,022

Panel B: Replicating GHL Table 10 using observations with I/B/E/S actual cash flows

Model: $$CFF_{it} = \alpha_0 + \beta_1 EF_{it} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it} \quad (1)$$

	Coefficients (t-statistics)					
Intercept	*EF*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	n
0.001 (29.15)	1.168 (82.69)				54.55%	5,698
0.000 (3.68)	0.980 (99.46)	0.944 (81.78)			79.09%	5,698
0.000 (3.69)	0.981 (98.14)	0.945 (81.69)	0.006 (0.27)		79.09%	5,698
0.000 (2.15)	0.983 (99.96)	0.768 (44.52)	-0.103 (-4.69)	0.141 (13.58)	79.74%	5,698

Panel C: Using I/B/E/S actual cash flows (CFO) as the dependent variable

Model: $$CFO_{it}^{IBES} = \alpha_0 + \beta_1 EF_{it} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it} \quad (2)$$

	Coefficients (t-statistics)					
Intercept	*EF*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	n
0.001 (17.01)	1.338 (56.29)				35.73%	5,698
0.000 (3.64)	1.178 (51.89)	0.798 (30.00)			44.49%	5,698
0.000 (3.76)	1.188 (51.61)	0.802 (30.09)	0.115 (2.41)		44.54%	5,698
0.000 (2.55)	1.192 (52.30)	0.486 (12.15)	-0.079 (-1.55)	0.253 (10.48)	45.58%	5,698

Panel D: Using actual values for the dependent variable and all independent variables

Model: $CFO_{it}^{IBES} = \alpha_0 + \beta_1 EARN_{it}^{IBES} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it}$ (3)

	Coefficients (t-statistics)					
Intercept	*EARN*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	n
0.001 (19.98)	1.190 (54.44)				34.25%	5,688
0.000 (5.00)	1.057 (51.52)	0.850 (32.18)			44.37%	5,688
0.000 (5.08)	1.062 (51.18)	0.852 (32.22)	0.077 (1.61)		44.39%	5,688
0.000 (3.37)	1.083 (52.88)	0.436 (10.94)	-0.172 (-3.43)	0.331 (13.77)	46.17%	5,688

Notes:
CFF_{it} is analysts' consensus cash flow forecast for firm *i* in year *t*; EF_{it} is analysts' consensus earnings forecast for firm *i* in year *t*; CFO_{it}^{IBES} is actual cash from operations, as reported by I/B/E/S, for firm *i* in year *t*; DEP_{it} is actual depreciation and amortisation expense, as reported by COMPUSTAT, for firm *i* in year *t*; ΔWC_{it} is the change in working capital, as reported by COMPUSTAT, for firm *i* in year *t*, measured as the change in accounts receivable, inventory, and accounts payable; $OTHER_{it}$ is all other adjustments needed to reconcile cash from operations to earnings, as reported by COMPUSTAT, for firm *i* in year *t*; and $EARN_{it}^{IBES}$ is actual earnings, as reported by I/B/E/S, for firm *i* in year *t*. Forecasts outstanding more than 90 days from the date of issuance are excluded. We truncate all variables at the 1% and 99% levels.

Table 3-3 Replication of Table 2 with Chinese Data

Panel A: Replicating GHL Table 10 using all possible observations

Model: $CFF_{it} = \alpha_0 + \beta_1 EF_{it} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it}$ (1)

	Coefficients (t-statistics)					
Intercept	*EF*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	n
0.000 (4.98)	0.837 (32.12)				36.42%	1,801
0.000 (1.29)	0.703 (23.34)	0.903 (8.39)			38.78%	1,801
0.000 (2.22)	0.830 (26.10)	0.884 (8.44)	0.255 (10.25)		42.13%	1,801
0.000 (2.20)	0.841 (25.93)	0.810 (7.21)	0.268 (10.35)	0.246 (1.80)	42.20%	1,801

Panel B: Replicating GHL Table 10 using observations with CSMAR analyst forecasts of actual cash flows

Same as Panel A

Panel C: Using CSMAR actual cash flows (CFO) as the dependent variable

Model: $CFO_{it}^{CSMAR} = \alpha_0 + \beta_1 EF_{it} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it}$ (2)

	Coefficients (t-statistics)					
Intercept	*EF*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	N
0.000 (3.41)	0.657 (25.52)				26.53%	1,801
-0.000 (-2.19)	0.449 (15.52)	1.408 (13.64)			33.38%	1,801
0.000 (4.14)	0.935 (91.40)	1.333 (39.55)	0.985 (122.88)		92.91%	1,801
0.000 (4.57)	0.983 (111.16)	1.034 (33.76)	1.038 (146.85)	0.996 (26.69)	94.92%	1,801

Panel D: Using actual values for the dependent variable and all independent variables

Model: $CFO_{it}^{CSMAR} = \alpha_0 + \beta_1 EARN_{it}^{CSMAR} + \beta_2 DEP_{it} + \beta_3 \Delta WC_{it} + \beta_4 OTHER_{it} + \varepsilon_{it}$ (3)

	Coefficients (t-statistics)					
Intercept	*EARN*	*DEP*	*ΔWC*	*OTHER*	Adj. R^2	N
0.000 (2.74)	0.702 (27.29)				29.24%	1,801
-0.000 (-2.70)	0.503 (17.42)	1.329 (13.11)			35.37%	1,801
0.000 (4.27)	0.982 (121.85)	1.291 (49.23)	0.986 (158.37)		95.68%	1,801
0.000 (5.54)	1.032 (177.01)	0.983 (49.28)	1.040 (226.48)	1.031 (42.25)	97.83%	1,801

Notes:
CFF_{it} is analysts' consensus cash flow forecast for firm *i* in year *t*; EF_{it} is analysts' consensus earnings forecast for firm *i* in year *t*; CFO_{it}^{CSMAR} is actual cash from operations, as reported by CSMAR analyst forecast research database, for firm *i* in year *t*; DEP_{it} is actual depreciation and amortisation expense, as reported by CSMAR financial statements database, for firm *i* in year *t*; ΔWC_{it} is the change in working capital, as reported by CSMAR financial statements database, for firm *i* in year *t*, measured as the change in accounts receivable, inventory, and accounts payable; $OTHER_{it}$ is all other adjustments needed to reconcile cash from operations to earnings, as reported by CSMAR financial statements database, for firm *i* in year *t*; and $EARN_{it}^{CSMAR}$ is actual earnings, as reported by CSMAR analyst forecast research database, for firm *i* in year *t*. Forecasts outstanding more than 90 days from the date of issuance are excluded. We truncate all variables at the 1% and 99% levels.

4.3 Performance of analysts' cash flow forecasts versus naïve cash flow forecasts

Both GHL and CCT compare the accuracy of analysts' cash flow forecasts with that of naïve cash flow forecasts. While GHL find that there is no significant difference between the two, CCT show the opposite. The main difference between the two methods is that GHL compare the mean and median forecast errors, but CCT evaluate the frequency and magnitude of the superiority of one type of forecast over the other. Following the two studies, we calculate forecast error as

$$CFF\_Error_{it} = | CFF_{it} - CFO_{it}^{IBES} | / | CFO_{it}^{IBES} | \tag{4}$$

$$NaiveCFF_{it} = EF_{it} + DEP_{it} \tag{5}$$

$$Naive\_Error_{it} = | NaiveCFF_{it} - CFO_{it}^{IBES} | / | CFO_{it}^{IBES} | \tag{6}$$

Table 4 reports the descriptive statistics. It shows that while CFF_Error is on average smaller than Naïve_Error in the US (0.296 vs. 0.336 and 0.382), CFF_Error in China is even larger than Naïve_Error on average (1.713 vs. 1.652 and 1.628). CFF_Error is positively associated with EF_Error both in the US and in China. But this positive association is weaker in China than in the US.

Then, we replicate CCT's Table 3 with both US data and Chinese data. The results are reported in Table 5. Our US results are largely consistent with CCT, in which analysts' cash flow forecasts are found to be more accurate than naïve cash flow forecasts. Specifically, we find that analysts' individual and consensus cash flow forecasts outperform the corresponding naïve cash flow forecasts both in the frequency and the magnitude of their superiority in terms of accuracy.

The Chinese results are different from the US results. Although analysts' consensus cash flow forecasts are more accurate than the corresponding naïve cash flow forecasts (the superiority is significant in magnitude but not in frequency), analysts' individual cash flow forecasts are less accurate than the corresponding naïve cash flow forecasts (the inferiority is significant in magnitude but not in frequency). Our evidence indicates that analysts' cash flow forecasts in China are not more accurate than the naïve cash flow forecasts, which are simply analysts' earnings forecasts adjusted for their projection of depreciation expense.

Table 4 Descriptive statistics for forecast errors

Table 4-1 US Data

Panel A: Performance of analysts' cash flow forecasts, naïve cash flow forecasts, and analysts' earnings forecasts

	Individual forecasts			Consensus forecasts		
	Mean	Median	Std Dev	Mean	Median	Std Dev
CFF_Error	0.296	0.113	0.580	0.400	0.157	0.820
Naïve_Error[a]	0.336[a]	0.172	0.581	0.440[c]	0.178	0.863
Naïve_Error[b]	0.382[b]	0.209	0.628	0.471[d]	0.198	0.910
EF_Error	0.156	0.042	0.362	0.137	0.032	0.323

This table reports the forecast errors of analysts' cash flow forecasts, naïve cash flow forecasts, and earnings forecasts.

CFF_Error = $|CFF_{it} - CFO^{IBES}_{it}| / |CFO^{IBES}_{it}|$; Naïve_Error = $|EF_{it} + DEP_{it} - CFO^{IBES}_{it}| / |CFO^{IBES}_{it}|$ or $|EF_{it} + DEP_{it-1} - CFO^{IBES}_{it}| / |CFO^{IBES}_{it}|$; EF_Error = $| EF_{it} - EARN^{IBES}_{it}| / |EARN^{IBES}_{it}|$. DEP is the amount of depreciation and amortisation on a per share basis. Forecasts outstanding more than 90 days from the date of issuance are excluded. All variables are truncated at the top percentile.

[a] The number of observations is 23,349, using actual depreciation to define the naïve cash flow forecasts.

[b] The number of observations is 23,869, using lagged depreciation to define the naïve cash flow forecasts.

[c] The number of observations is 10,212, using actual depreciation to define the naïve cash flow forecasts.

[d] The number of observations is 10,325, using lagged depreciation to define the naïve cash flow forecasts.

Panel B: Correlation coefficients between forecast errors

	Individual forecasts	Consensus forecasts
	Analysts' Cash Flow Forecast Errors	Analysts' Cash Flow Forecast Errors
Analysts' Earnings Forecast Errors	0.125 (< 0.01)	0.105 (< 0.01)

This table reports the Pearson correlation coefficients between the signed errors. Forecasts outstanding more than 90 days from the date of issuance are excluded. All variables are truncated at the top percentile.

Table 4-2 Chinese Data

Panel A: Performance of analysts' cash flow forecasts, naïve cash flow forecasts, and analysts' earnings forecasts

	Individual forecasts			Consensus forecasts		
	Mean	Median	Std Dev	Mean	Median	Std Dev
CFF_Error	1.713	0.656	3.088	1.778	0.648	3.332
Naïve_Error	1.652[a]	0.622	2.921	1.790[c]	0.657	3.285
Naïve_Error	1.628[b]	0.565	3.150	1.736[d]	0.594	3.327
EF_Error	0.111	0.054	0.171	0.129	0.059	0.225

This table reports on the absolute errors of analysts' cash flow forecasts, naïve cash flow forecasts, and earnings forecasts.

$CFF\_Error = |CFF_{it} - CFO^{CSMAR}_{it}| / |CFO^{CSMAR}_{it}|$; $Naïve\_Error = |EF_{it} + DEP_{it} - CFO^{CSMAR}_{it}| / |CFO^{CSMAR}_{it}|$ or $|EF_{it} + DEP_{it-1} - CFO^{CSMAR}_{it}| / |CFO^{CSMAR}_{it}|$; $EF\_Error = | EF_{it} - EARN^{CSMAR}_{it}| / |EARN^{CSMAR}_{it}|$. DEP is the amount of depreciation and amortisation on a per share basis. Forecasts outstanding more than 90 days from the date of issuance are excluded. All variables are truncated at the top percentile.

[a] The number of observations is 3,671, using actual depreciation to define the naïve cash flow forecasts.
[b] The number of observations is 3,160, using lagged depreciation to define the naïve cash flow forecasts.
[c] The number of observations is 2,188, using actual depreciation to define the naïve cash flow forecasts.
[d] The number of observations is 1,888, using lagged depreciation to define the naïve cash flow forecasts.

Panel B: Correlation coefficients between forecast errors

	Individual forecasts	Consensus forecasts
	Analysts' Cash Flow Forecast Errors	Analysts' Cash Flow Forecast Errors
Analysts' Earnings Forecast Errors	0.091 (< 0.01)	0.063 (< 0.01)

This table reports the Pearson correlation coefficients between the signed errors. Forecasts outstanding more than 90 days from the date of issuance are excluded. All variables are truncated at the top percentile.

Table 5 Forecast accuracy: Analysts' cash flow forecasts vs. naïve cash flow forecasts

Table 5-1 CCT Original Results

Superiority of analysts' cash flow forecasts over naïve cash flow forecasts

Panel A: Accuracy of analysts' versus naïve cash flow forecasts, using actual depreciation to define the naïve cash flow forecast

	Individual cash flow forecasts		Consensus cash flow forecasts	
	Analysts' cash flow forecasts	Naïve cash flow forecasts	Analysts' cash flow forecasts	Naïve cash flow forecasts
Frequency of superiority[a]	62.5%***	37.5%***	57.7%***	42.3%***
Magnitude of superiority[b]	69.1%***		86.5%**	
n	21,096		4,608	

Panel B: Accuracy of analysts' versus naïve cash flow forecasts, using lagged depreciation to define the naïve cash flow forecast

	Individual cash flow forecasts		Consensus cash flow forecasts	
	Analysts' cash flow forecasts	Naïve cash flow forecasts	Analysts' cash flow forecasts	Naïve cash flow forecasts
Frequency of superiority[a]	66.2%***	33.8%***	60.8%***	39.2%***
Magnitude of superiority[b]	59.9%***		77.1%***	
n	21,126		4,608	

Table 5-2 Replication of Table 3 with US data

Superiority of analysts' cash flow forecasts over naïve cash flow forecasts

Panel A: Accuracy of analysts' versus naïve cash flow forecasts, using actual depreciation to define the naïve cash flow forecast

	Individual cash flow forecasts		Consensus cash flow forecasts	
	Analysts' cash flow forecasts	Naïve cash flow forecasts	Analysts' cash flow forecasts	Naïve cash flow forecasts
Frequency of superiority[a]	57.71%***	42.29%***	54.18%***	45.82%***
Magnitude of superiority[b]	68.44%***		86.72%***	
N	23,648		10,351	

Panel B: Accuracy of analysts' versus naïve cash flow forecasts, using lagged depreciation to define the naïve cash flow forecast

	Individual cash flow forecasts		Consensus cash flow forecasts	
	Analysts' cash flow forecasts	Naïve cash flow forecasts	Analysts' cash flow forecasts	Naïve cash flow forecasts
Frequency of superiority[a]	62.84%***	37.16%***	56.85%***	43.15%***
Magnitude of superiority[b]	59.26%***		79.92%	
N	23,594		10,316	

Notes:

Frequency of superiority is the percentage of individual analysts (firms) where the analyst's individual (consensus) cash flow forecast outperforms the naïve cash flow forecast, and vice versa. The naïve cash flow forecast is defined as follows: Naïve $CFF_{it} = EF_{it} + DEP_{it}$, where EF_{it} is the analyst's own earnings forecast for firm i in year t and DEP_{it} is actual depreciation and amortisation expense, as reported by COMPUSTAT, for firm *i* in year *t*. Alternatively, in panel B, we use depreciation and amortisation expense for firm *i* in year $t - 1$ to define the naïve cash flow forecast. Magnitude of superiority is the ratio of the analyst's individual (consensus) cash flow forecast error to the naïve cash flow forecast error expressed as a percentage. Percentages smaller than 100% are consistent with analysts' cash flow forecasts being more accurate than the corresponding naïve cash flow forecasts. Forecasts outstanding more than 90 days from the date of issuance are excluded. All variables are truncated at the top percentile. *, **, ***: significant at 10%, 5%, 1% level.

[a] *p*-values are two-sided and are associated with the Binomial test for differences in proportion.

[b] *p*-values are two-sided and are associated with the Wilcoxon signed-rank test for differences in medians.

Table 5-3 Replication of Table 3 with Chinese data

Superiority of analysts' cash flow forecasts over naïve cash flow forecasts

Panel A: Accuracy of analysts' versus naïve cash flow forecasts, using actual depreciation to define the naïve cash flow forecast

	Individual cash flow forecasts		Consensus cash flow forecasts	
	Analysts' cash flow forecasts	Naïve cash flow forecasts	Analysts' cash flow forecasts	Naïve cash flow forecasts
Frequency of superiority[a]	49.10%	50.90%	51.02%	48.98%
Magnitude of superiority[b]	101.47%***		98.90%***	
N	3,709		2,211	

Panel B: Accuracy of analysts' versus naïve cash flow forecasts, using lagged depreciation to define the naïve cash flow forecast

	Individual cash flow forecasts		Consensus cash flow forecasts	
	Analysts' cash flow forecasts	Naïve cash flow forecasts	Analysts' cash flow forecasts	Naïve cash flow forecasts
Frequency of superiority[a]	48.78%	51.22%	50.19%	49.81%
Magnitude of superiority[b]	101.66%***		98.16%***	
N	3,143		1,875	

Notes:

Frequency of superiority is the percentage of individual analysts (firms) where the analyst's individual (consensus) cash flow forecast outperforms the naïve cash flow forecast, and vice versa. The naïve cash flow forecast is defined as follows: Naïve $CFF_{it}=EF_{it} + DEP_{it}$, where EF_{it} is the analyst's own earnings forecast for firm i in year t and DEP_{it} is actual depreciation and amortisation expense, as reported by CSMAR, for firm *i* in year *t*. Alternatively, in panel B, we use depreciation and amortisation expense for firm *i* in year *t* -1 to define the naïve cash flow forecast. Magnitude of superiority is the ratio of the analyst's individual (consensus) cash flow forecast error to the naïve cash flow forecast error expressed as a percentage. Percentages smaller than 100% are consistent with analysts' cash flow forecasts being more accurate than the corresponding naïve cash flow forecasts. Forecasts outstanding more than 90 days from the date of issuance are excluded. All variables are truncated at the top percentile. *, **, ***: significant at 10%, 5%, 1% level.

[a] *p*-values are two-sided and are associated with the Binomial test for differences in proportion.

[b] *p*-values are two-sided and are associated with the Wilcoxon signed-rank test for differences in medians.

4.4 The quality of cash flow forecasts issued by star analysts and industry experts

In addition, we also investigate whether star analysts and analysts with substantial industry expertise can issue more sophisticated cash flow forecasts. Analysts are classified as star analysts in a particular year if their names are in "Xin Cai Fu" magazine's top rated analysts list in that year. An analyst is regarded as an industry expert in a particular year if the number of firms in an industry he or she follows is larger than the median number of firms in that industry covered by all financial analysts in that year.

Our results (untabulated) indicate that while star analysts and industry experts do, to a certain extent, take change in working capital and other accruals into consideration when they produce cash flow forecasts, their forecasts still fail to outperform the corresponding naïve cash flow forecasts.

4.5 Discussion

On the basis of our tests, analysts' cash flow forecasts in the US are at least superior to naïve cash flow forecasts, but in China, analysts' cash flow forecasts even fail to outperform naïve cash flow forecasts. Below, we consider several possible explanations.

First, investors in China do not demand cash flow forecasts. Obviously, this explanation is inconsistent with the 'demand hypothesis' since the Chinese market used to be regarded as a market with a serious earnings management problem. However, it is consistent with the literature that documents the special features of the Chinese stock market. For example, it has been found that Chinese investors are inexperienced (e.g. Chen *et al.*, 2007) and react to new earnings information slowly (e.g. Su, 2003). Furthermore, the Chinese market is largely driven by government policies and therefore stock prices frequently deviate from the fundamentals (e.g. Lu and Zou, 2007). If Chinese investors pay little attention to fundamental factors such as cash flows, analysts will have a weak incentive to produce high quality cash flow forecasts.

Second, it is a much more difficult job to forecast change in working capital in China than it is in the US. Operating in a developing economy, Chinese companies heavily rely on working capital. As we mentioned in section 4.1 and showed in Table 2, the fluctuation on ΔWC is much higher in China than in the US. In China, the cost for analysts to produce accurate ΔWC forecasts is likely to dominate the benefit.

Finally, as pointed out by Mangen (2013), it is not even clear whether the actual cash flows reported by companies are a good benchmark by which to evaluate analysts' cash flow forecasts. Due to cash flow management, the reported cash flow values can still deviate from the actual values. A better measure for the quality of analysts' cash flow forecasts is needed.

In summary, although our empirical evidence suggests that there seems to be a quality difference in cash flow forecasts between US analysts and Chinese analysts, we have little knowledge on its causes and consequences. Follow-up studies are required to fill this gap.

V. Conclusion

This study replicates GHL's and CCT's tests on the quality of analysts' cash flow forecasts with both US and Chinese data. Our US results are largely consistent with GHL's and CCT's findings. Specifically, we find that although analysts' cash flow forecasts are only weakly associated with change in working capital and other accrual adjustments, this weak association is largely due to the measurement problem contained in the US data. Analysts' cash flow forecasts are at least more accurate than naïve cash flow forecasts (analysts' earnings forecasts plus depreciation and amortisation expense). Chinese data do not contain the same measurement problem as US data. Therefore GHL's method can be well applied using Chinese data. We find that consistent with GHL's finding, analysts' cash flow forecasts are only weakly associated with change in working capital and other accrual adjustments. This indicates that analysts in China do not exert sufficient effort to estimate change in working capital and other accruals. We also find further evidence suggesting that analysts' cash flow forecasts are not more accurate than naïve cash flow forecasts. But what is causing the increasing trend in analysts issuing cash flow forecasts in China? How do investors in China react to analysts' cash flow forecasts? How can the informativeness of analysts' cash flow forecasts be improved? These unanswered but interesting questions are left for future research endeavours.

References

Brown, L. D., Huang, K., and Pinello, A. S. (2013), 'To Beat or not to Beat? The Importance of Analysts' Cash Flow Forecasts', *Review of Quantitative Finance and Accounting* 41 (4): 723-752.

Brown, N. C. and Christensen, T. E. (2014), 'The Quality of Street Cash Flow From Operations', *Review of Accounting Studies.* Forthcoming.

Call, A. C. (2009), 'Analysts' Cash Flow Forecasts and the Properties and Pricing of Operating Cash Flows', Working Paper, University of Georgia.

Call, A. C., Chen, S., and Tong, Y. H. (2009), 'Are Analysts' Earnings Forecasts More Accurate when Accompanied by Cash Flow forecasts?', *Review of Accounting Studies* 14 (2-3): 358-391.

Call, A. C., Chen, S., and Tong, Y. H. (2013), 'Are Analysts' Cash Flow Forecasts Naïve Extensions of their Own Earnings Forecasts?', *Contemporary Accounting Research* 30 (2): 438-465.

Chen, G., Kim, K., Nofsinger, J., and Rui, O. (2007), 'Trading Performance, Disposition Effect, Overconfidence, Representativeness Bias, and Experience of Emerging Market Investors', *Journal of Behavioral Decision Making* 20 (1): 425-451.

DeFond, M. and Hung, M. (2003), 'An Empirical Analysis of Analysts' Cash Flow Forecasts', *Journal of Accounting and Economics* 35 (1): 73-100.

DeFond, M. and Hung, M. (2007), 'Investor Protection and Analysts' Cash Flow Forecasts around the World', *Review of Accounting Studies* 12 (2-3): 377-419.

Givoly, D., Hayn, C., and Lehavy, R. (2009), 'The Quality of Analysts' Cash Flow Forecasts', *The Accounting Review* 84 (6): 1877-1911.

Givoly, D. and Lakonishok, J. (1979), 'The Information Content of Financial Analysts' Forecasts of Earnings: Some Evidence on Semi-Strong Inefficiency', *Journal of Accounting and Economics* 1 (3): 165-185.

Guo, H., Zhang, J., and Li, B. (2011), 'Research on Motivation Selection of Cash Flow Manipulation in Listed Companies', *Journal of Management Science* (in Chinese) 24 (5): 89-98.

Liu, Y. (2010), 'The Experience of China's Accounting Standards Setting and its Convergence with IFRSs', presentation by Director-General of Accounting Regulatory Department, Ministry of Finance, China, available at http://ec.europa.eu/internal_market/accounting/docs/conference20100208/presentation-liu_en.pdf.

Ljungqvist, A., Malloy, C., and Marston, F. (2009), 'Rewriting History', *Journal of Finance* 64 (4): 1935-1960.

Lu, Z. and Zou, H. (2007), 'Momentum and Reversal in China Stock Market', *Economic Research Journal* (in Chinese) 9: 145-155.

Mangen, C. (2013), 'Discussion of "Are Analysts' Cash Flow Forecasts Naïve Extensions of Their Own Earnings Forecasts?"', *Contemporary Accounting Research* 30 (2): 466-481.

McInnis, J. and Collins, D. (2011), 'The Effect of Cash Flow Forecasts on Accrual Quality and Benchmark Beating', *Journal of Accounting and Economics* 51 (3): 219-239.

Pae, J. (2007), 'Unexpected Accruals and Conditional Accounting Conservatism', *Journal of Business Finance and Accounting* 34 (5-6): 681-704.

Pae, J. and Yoon, S. (2011), 'Determinants of Analysts' Cash Flow Forecast Accuracy', *Journal of Accounting, Auditing, and Finance* 27 (1): 123-144.

Su, D. (2003), 'Stock Price Reactions to Earnings Announcements: Evidence from Chinese Markets', *Review of Financial Economics* 12 (3): 271-286.

Wang, H., Zhang, R., and Zhang, P. (2012), 'Why do Analysts Selectively Announce Cash Flow Forecasts?', *Investment Research* (in Chinese) 31 (7): 27-40.

Zhang, R. (2007), 'Cash Flow Management in the Chinese Stock Market - Comparing with Cash Flow Management in the U.S. Market', *China Accounting Review* (in Chinese) 5 (3): 381-400.