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Firm-specific or market-wide information: How does analyst coverage influence stock price synchronicity?

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Abstract

This study shows that analysts generate firm-specific information, rather than market-wide information. Whereas previous studies report only the positive relationship between stock price synchronicity and analyst coverage, we suggest that the positive relation can be attributed to the interaction between analyst coverage and firm performance cyclicality. After controlling for the interaction effect between the analyst coverage and cyclicality, synchronicity decreases with the analyst coverage. Both effects diminish with the high analyst forecast dispersion, namely, we observe the decreasing effect of increasing analyst coverage on synchronicity and the increasing effect of interaction between analyst coverage and cyclicality.

JEL classification: G14; G15; G19

Keywords: Analyst coverage; Cyclicality; Firm performance; Firm-specific information; Stock price synchronicity

1. Introduction

Although the relationship between stock price synchronicity and analyst coverage has been studied extensively, no consensus has been reached on the drivers of this association in the extant finance literature. Some studies argue that analysts generate market-wide information and that stock price synchronicity is positively related to analyst coverage (Feng, Hu, & Johansson, 2016; Gao, Lin, Yang, & Chan, 2020; Piotroski & Roulstone, 2004). Considering that greater analyst coverage enhances firm transparency (Ben-Nasr, Bouslimi, Ebrahim, & Zhong, 2020; Kim, Ryu, & Yang, 2019; Kim, Ryu, & Yu, 2021; Lang, Lins, & Miller, 2004; Rolustone, 2003), the relationship between analyst coverage and stock price synchronicity is associated with the effect of firm transparency on synchronicity. For example, Dasgupta, Gan, and Gao (2010) and Hutton, Marcus, and Tehranian (2009) find that stock return synchronicity increases when firm transparency improves.

Other studies argue that analysts produce firm-specific information (Admati & Pfleiderer, 1986; Diamond & Verrecchia, 1981; Grossman & Stiglitz, 1980). Liu (2011) argues that analysts are motivated to benefit brokerage firms by increasing the value of research through the gathering of private information due to the positive relationship between the analyst's reward and the commission fees their research earns for brokerage clients. Crawford, Roulstone, and So (2012) show that, although increases in analyst coverage for firms with existing analyst coverage cause decreases in stock price synchronicity, analyst coverage initiation for firms without existing analyst coverage increases synchronicity. They interpret the results as meaning that analysts have incentives for providing market-wide information about newly covered firms because the cost of gathering information is relatively low but

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potentially valuable to investors. However, for firms with existing analyst coverage, analysts tend to provide firm-specific information because market-wide information has already been provided by other analysts. Bai, Wang, and Zhang (2016) find that in the Chinese stock market stock price synchronicity decreases as analyst coverage increases. Other related studies also provide evidence that stock price synchronicity is negatively related to analyst coverage (Brown, 1978; O'Brien, 1988; O'Brien & Bhushan, 1990). Extending this argument, the seminal study by Jin and Myers (2006) shows that stock price synchronicity is related to opaqueness (lack of transparency). Our research motivation is simple: To clarify these conflicting strands of evidence and illuminate the reasons for different findings, we investigate whether analyst coverage produces market-wide or firm-specific information and how this influences synchronicity in an elaborate setting.

This study builds on the work by Jin and Myers (2006), which indicates that an increase in the degree of opaqueness can lead to higher stock price synchronicity. Opaqueness is defined as the lack of information that prevents investors from perceiving the operating cash flow and income (Kim, Ryu, & Yang, 2021). Because outside investors have limited access to firm-specific information, internal managers might have an incentive to capture some of the firm's operating cash flow, namely, earnings management. The amount of cash flow captured depends on the expectations of outside investors about the firm's cash flow, which is imperfect. That is, insiders' capture increases (decreases) when the firm's operating cash is greater (less) than the expectations of outside investors, which implies income smoothing by firms. Increased capture of the operating cash flows reduces the firm-specific variance, so the ratio of market-to-total risk, stock price synchronicity, increases. Beidleman (1973) also contends that income smoothing might reduce the correlation between an individual firm's expected stock returns and the market portfolio returns. However, analysts are generally expected to make the firm more transparent (Chang, Khanna, & Palepu, 2000) by playing a role in the revelation of hidden information about operating cash flow captured by internal managers (Yu, 2008), implying that analyst coverage is negatively correlated with stock price synchronicity.

By extending the model of Jin and Myers (2006), we reexamine the role of analysts in revealing information about hidden cash flow. Consider a simple example. Suppose that an analyst reveals firm-specific confidential information in the cash flow of a pro-cyclical firm. The direction of the earning information revealed will be aligned with the market movement, and, consequently, synchronicity increases. This process suggests that stock price synchronicity increases with analyst coverage, even if the analysts disclose firm-specific information. These inferences are not consistent with the findings of previous empirical studies, which overlook the interaction effect between analyst coverage and the cyclicality of earnings performance. Related studies also state that firms' cyclicality affects incentives and the ability to manipulate their earnings. Givoly and Lakonishok (1984) find that unpredictability or variability of earnings is associated with measures of market risk, such as beta, implying that earnings uncertainty might raise firms' cost of capital. Lev and Kunitzky (1974) mention that the correlation in net earnings between one firm and all other firms is positive, and this relationship is also associated with the market beta. By conjecturing that a firm's income-smoothing behavior reduces this correlation, they examine the relationship between income smoothing and risk measures. Their empirical results show that earnings smoothing is negatively related to each firm's beta obtained with the market model. Beidleman (1973) and Gordon (1964) state that investors believe stable earnings, rather than fluctuating earnings, lead to higher dividends, implying that income smoothing might lead to higher stock prices. Moses (1987) also argues that firms with greater unpredictability of earnings might have greater incentives for smoothing them and show that smoothing behavior increases the gap between actual earnings and expectations. Ashari, Koh, Tan, and Wong (1994) claim that firms in riskier industries, which are expected to have higher cyclicality or market beta, tend to smooth their earnings. Mahmud (2012) also finds that manufacturing and high-technology companies smooth their income more than other industries. Therefore, we investigate whether analysts generate firm-specific information or market-wide information by considering a missing link, namely, the interaction effect. After controlling for the interaction effect, we find that synchronicity decreases as analyst coverage increases. Furthermore, we show that stock return synchronicity decreases as analyst coverage increases, and it increases with the interaction between analysts and cyclicality, diminishing when analyst forecast dispersion is high.

The rest of the paper is organized as follows. Section 2 describes the data and variables included in the empirical test. Section 3 discusses our empirical findings. Section 4 presents our robustness tests. Section 5 concludes.

2. Sample data and research variables

To perform empirical analyses, we create a dataset that includes all ordinary common shares (codes 10 and 11) traded on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) during the long sample period from 1986 to 2021. We gather the stock price, number of trades, shares outstanding, and market index data from the database of the Center for Research in Security Prices (CRSP) and accounting data from COMPUSTAT. We also identify the number of analysts and forecast data for each company from the Institutional Brokers' Estimate (I/B/E/S).

To measure stock price synchronicity (*Sync*), we follow Chan and Hameed (2006), Morck, Yeung, and Yu (2000), Todea and Buglea (2017), and Xu and Zhang (2018). These studies suggest using R^2 to proxy for the firm-specific and market-wide information incorporated into stock prices. R^2 is defined as the degree of comovement between individual stock prices and the market estimated from the market model. A high R^2 implies that more market-wide information than firm-specific information is incorporated into stock prices.

We first regress individual firms' weekly stock returns on the market index return in a given year.

$$R_{i,w} = \beta_{i0} + \beta_{i1} R_{m,w} + \varepsilon_{i,w} \quad (1)$$

where $R_{i,w}$ denotes the weekly stock returns for firm *i* in week *w*, and $R_{m,w}$ is the market index return in week *w*.[1] We then calculate stock price synchronicity, *Sync*, as follows:

$$Sync_{i,t} = log\left(\frac{R^2}{1 - R^2}\right) \quad (2)$$

where R^2 is the coefficient of determination for firm *i* in year *t* estimated from Eq. (1). Because *Sync* increases as R^2 increases, a high *Sync* indicates a high correlation between an individual firm's return and the market index return, that is, high stock price synchronicity. We include analyst coverage, firm size, trading volume, firm age, market beta, book-to-market ratio, and return on assets as explanatory variables, based on prior literature. Analyst coverage (*Analyst*) is defined as the natural logarithm of one plus the number of analysts covering an individual firm, following Bai et al. (2016), Crawford et al. (2012), and Kang, Li, and Su (2018). We equate the number of analysts with the number of earnings forecasts during a given calendar year, assigning a value of zero to firms with no earnings forecasts. As discussed, we mainly investigate the effect of *Analyst* on *Sync* after controlling for the interaction effect between analyst coverage and cyclicality in firm performance. Given that stock prices immediately reflect information about firm performance in the market, we use market beta as a proxy for the cyclicality of firm performance. Because we want to measure the relative degree of cyclicality among firms, rather than merely how much an individual firm responds to the market, we adopt post-ranking beta rather than pre-ranking beta. We construct the post-ranking beta following the procedure suggested by Fama and French (1992). We hypothesize that managers of pro-cyclical firms, which are more sensitive to market fluctuation, have an incentive to conceal some of the operating cash flow. We therefore construct a dummy variable (*CycDum*) as a proxy for pro-cyclicality in firm performance. The dummy variable equals one if the estimated post-ranking beta is higher than one, and zero otherwise.

To measure the firm size (*Size*), we use the firm's market capitalization at the end of the trading day, and trading volume (*Volume*) is the sum of the dollar trading volume in a given year. The book-to-market ratio (*BM*) is calculated following Fama and French (1992). The return on assets (*ROA*) is defined as income scaled by total assets. Firm age (*Age*) is the number of years since its initial public offering (IPO) in natural log form, following Meng, Clements, and Padgett (2018). Dasgupta et al. (2010) find that firm age is positively related to stock price synchronicity because the market learns more about the firm's time-invariant intrinsic quality. We adopt *BM*, *Size*, and *Volume* in natural log form. We add share turnover (*Turnover*) and return volatility, such as systematic volatility (*SysVol*) and idiosyncratic volatility (*IdioVol*), as instrumental variables in the *Analyst* equation (see Eq. (4)). To measure *SysVol* and *IdioVol*, we calculate the square root of the explained variation and the standard deviation of residual returns in the market-model regression in a given year, following Chan, Hameed, and Kang (2013). *Turnover* is defined as the average number of shares traded relative to the number of shares outstanding in natural log form in a given year. Dasgupta et al. (2010) argue that although it is not necessary to control for the beta effect because the aggregate beta is precisely one in country-level studies, higher market beta might cause higher stock price synchronicity in a firm-level analysis. We therefore add the estimated coefficient (*Beta*) from Eq. (1) to the regression model, which is distinguished from *CycDum* estimated from the post-ranking beta. Earnings forecast dispersion is calculated as the standard deviation of analysts' forecasts normalized by the mean value of forecasts and divided by the square root of the number of analysts, following Jin and Myers (2006). If the calculated dispersion is greater than the average value in the given year, the dispersion dummy variable (*DispersDum*) is set at one. Firms with zero analyst coverage or dispersion are excluded.

Table 1 provides the descriptive statistics of the variables. Panel A reports the summary statistics, including the means and standard deviations as well as the 5th, 25th, 50th, 75th, and 95th percentile values. The median value of *Analyst* is 1.386, represented in natural log form. This means that the median number of analysts among the sample firms is three. Because we include firms with zero analysts, the 5th and 25th percentile values are zero. Similar distributions of analysts are reported by Crawford et al. (2012), Feng et al. (2016), and Piotroski and Roulstone (2004). The median *Age* is 2.872, which implies that the median number of years since the IPO of the sample firms is 17.7. We report the correlation matrix of the explanatory variables in Panel B. The correlation coefficient for *Analyst* and *Size* is relatively high, 0.661, which is consistent with that found by Chan and Hameed (2006) and Piotroski and Roulstone (2004). They state that larger firms have a greater demand for analysts, given that larger firms have a high number of shareholders and that private information about larger firms, rather than smaller firms, can be more valuable to investors. The correlation coefficient between *Beta* and *CycDum* is relatively low, 0.104, further showing that *CycDum* is distinguished from *Beta,* which is directly estimated from Eq. (1).[2]

[1] To construct market index returns, we use the daily CRSP total market value index, which is made up of the total market value of the NYSE, AMEX, NASDAQ (National Association of Securities Dealers Automated Quotations), and ARCA (Archipelago Exchange) for all non-ADR securities with valid prices. We calculate individual firms' weekly returns and the market weekly return from Wednesday close to Wednesday close to avoid possible problems of nonsynchronous trading and the weekend effect.

[2] One could argue that *CycDum* has a relatively low correlation coefficient with *Beta* because *CycDum* is a dummy variable. However, the post-ranking beta estimated from our samples also shows a distinguished distribution from *Beta*. Whereas the estimated post-ranking beta ranges from 0.581 (5th percentile) to 1.674 (95th percentile), *Beta* ranges from −0.203 (5th percentile) to 2.129 (95th percentile). The correlation coefficient between these two variables is only 0.131, which is similar to the correlation coefficient between *CycDum* and *Beta*. This result indicates that *CycDum* is not mechanically related to *Sync*.

Table 1
Descriptive statistics.

Panel A. Summary statistics

	Mean	Std. Dev.	Percentile				
			5th	25th	50th	75th	95th
Sync	−2.471	2.105	−7.040	−3.393	−2.062	−1.007	0.066
Analyst	1.410	1.146	0.000	0.000	1.386	2.398	3.178
Size	13.245	2.311	9.323	11.604	13.411	14.858	16.910
Volume	19.642	2.749	14.929	17.705	19.768	21.690	23.973
Beta	0.868	1.678	−0.203	0.412	0.807	1.259	2.129
BM	0.884	16.424	0.032	0.291	0.549	0.936	2.364
ROA	−0.004	0.525	−0.230	0.003	0.034	0.069	0.148
Age	2.539	1.133	0.288	1.910	2.872	3.370	3.832
Turnover	2.299	6.938	−0.659	0.550	1.327	2.168	8.601
SysVol	0.021	0.030	0.002	0.009	0.016	0.027	0.053
IdioVol	0.061	0.159	0.020	0.030	0.044	0.070	0.125
CycDum	0.593	0.491	0.000	0.000	1.000	1.000	1.000
DispersDum	0.667	0.471	0.000	0.000	1.000	1.000	1.000

Panel B. Correlation matrix

	Sync	Analyst	Size	Volume	Beta	BM	ROA	Age	Turnover	SysVol	IdioVol	CycDum
Analyst	0.280											
Size	0.377	0.661										
Volume	0.470	0.620	0.853									
Beta	0.248	0.034	0.030	0.123								
BM	−0.079	−0.211	−0.360	−0.309	−0.020							
ROA	0.070	0.089	0.126	0.098	0.009	0.005						
Age	0.119	0.165	0.240	0.189	−0.018	0.101	0.078					
Turnover	0.014	0.161	0.136	0.109	−0.028	−0.063	−0.054	−0.005				
SysVol	0.317	0.015	−0.013	0.112	0.191	0.036	−0.038	−0.034	0.001			
IdioVol	−0.115	−0.102	−0.151	−0.100	0.235	0.040	−0.062	−0.054	−0.017	0.584		
CycDum	0.097	0.044	−0.052	0.030	0.104	0.001	−0.020	−0.111	0.075	0.130	0.031	
DispersDum	−0.209	−0.626	−0.472	−0.429	−0.002	0.227	−0.063	−0.150	−0.106	0.018	0.077	0.033

Note: Panel A reports the summary statistics of the dependent and the explanatory variables. *Sync* is stock price synchronicity estimated from the CRSP total market value index. *Analyst* is analyst coverage defined as the natural logarithm of one plus the number of analysts covering the individual firm. *Size* denotes the natural logarithm of market capitalization. *Beta* is the estimated coefficient from the market-model regression. *Volume* and *BM* are the dollar trading volume and book-to-market ratio in natural log form, respectively. *ROA* denotes return on assets. *Age* denotes firm age defined as the number of years since the initial public offering (IPO) in natural log form. *Turnover* denotes the average number of shares traded relative to the number of shares outstanding in natural log form in a given year. *SysVol* and *IdioVol* are measured by the square root of the explained variation and the standard deviation of residual returns of the market-model regression, respectively. *CycDum* is the firm's cyclicality dummy variable equal to one if post-ranking market beta is higher than one. Panel B presents the pair-wise correlation matrix of the dependent variable and explanatory variables. *DispersDum* is the earnings forecast dispersion dummy variable defined as one if the calculated dispersion is higher than the average in the given year.

3. Methodology and empirical findings

Our main goal is to investigate whether analysts generate firm-specific information or market-wide information that influences synchronicity. To this end, we reexamine the effect of analyst coverage and the interaction effect between analyst coverage and cyclicality of earnings performance on stock price synchronicity. As discussed, the interaction term between analyst coverage and cyclicality indicates the potential degree of firm performance revealed by the analysts.

3.1. The effect of firm cyclicality and analyst coverage

We regress stock price synchronicity on analyst coverage using US equity market data. Chan and Hameed (2006) show a positive relationship between stock price synchronicity and the number of analysts by examining data on 45 emerging markets. We first check whether this positive relationship is consistently detected in the US market and then reinvestigate the effect of analyst coverage on stock price synchronicity, after controlling for the interaction effect between the cyclicality of a firm's earnings performance and analyst coverage. We construct a panel regression model for firm i in year t as follows:

$$\begin{aligned} Sync_{i,t} = \alpha + \beta_1 \cdot Analyst_{i,t} + \beta_2 \cdot Analyst_{i,t} \times CycDum_{i,t} \\ + \beta_3 \cdot CycDum_{i,t} + \beta_4 \cdot Size_{i,t} + \beta_5 \cdot Volume_{i,t} \\ + \beta_6 \cdot Beta_{i,t} + \beta_7 \cdot BM_{i,t} + \beta_8 \cdot ROA_{i,t} + \beta_9 \cdot Age_{i,t} \\ + \lambda \cdot ExcDum_{i,t} + \sum \delta_l \cdot YearDum_{i,t} + \sum \varphi_m \cdot IDum_{i,t} \\ + \varepsilon_{i,t} \end{aligned} \quad (3)$$

where $Sync_{i,t}$ is the stock price synchronicity for firm i in year t calculated based on Eq. (2). Among the independent variables, $Analyst_{i,t}$ is the analyst coverage for firm i in year t. The interaction term, $Analyst_{i,t} \times CycDum_{i,t}$, implies the effect of analyst coverage that reveals firm-specific hidden information on cash flow for firm i in year t. $Size_{i,t}$, $Volume_{i,t}$, and $BM_{i,t}$ are the natural log of firm size, trading volume, and the book-to-

Table 2
Effect of firms' cyclicality and analyst coverage.

	Model 1	Model 2	Model 3	Model 4
Analyst	0.012*	0.020**	−0.011	−0.009
	(1.700)	(2.513)	(−1.114)	(−0.823)
Analyst × *CycDum*			0.034***	0.048***
			(3.069)	(4.011)
CycDum			0.238***	0.236***
			(7.515)	(6.825)
Size	0.132***	0.103***	0.163***	0.133***
	(8.162)	(5.096)	(12.139)	(7.845)
Volume	0.191***	0.214***	0.166***	0.189***
	(10.385)	(9.514)	(10.658)	(9.884)
Beta	0.174**	0.173*	0.160*	0.159*
	(1.964)	(1.730)	(1.932)	(1.705)
BM		0.039***		0.035***
		(4.326)		(3.694)
ROA		0.101**		0.094**
		(2.409)		(2.212)
Age		0.057***		0.065***
		(6.772)		(6.811)
Constant	−8.072***	−8.148***	−8.331***	1.232***
	(−31.526)	(−25.187)	(−20.914)	(57.486)
Fixed Effects	Yes	Yes	Yes	Yes
No. of Observations	63,553	55,607	60,574	53,223

Note: This table reports the estimated coefficients from the panel regression. The dependent variable is *Sync*, which is stock price synchronicity estimated from the CRSP total market value index. *Analyst* is analyst coverage defined as the natural logarithm of one plus the number of analysts covering the individual firm. *Size* denotes the natural logarithm of market capitalization. *Beta* is the estimated coefficient from the market-model regression. *Volume* and *BM* are the dollar trading volume and book-to-market ratio in natural log form, respectively. *ROA* denotes return on assets. *Age* denotes firm age defined as the number of years since the initial public offering (IPO) in natural log form. *CycDum* is the firm's cyclicality dummy variable equal to one if post ranking market beta is higher than one. Year, industry, and stock exchange fixed effects are included in the regression model. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

market ratio of firm i in year t, respectively. $Beta_{i,t}$ is the estimated coefficient from Eq. (2) using the weekly returns of firm i in year t. Similarly, $ROA_{i,t}$ and $Age_{i,t}$ denote the ROA ratio and firm age of firm i in year t, respectively.[3] *ExcDum*, *YearDum*, and *IDum* are dummy variables that control for the exchange, year, and industry effects.

We report the panel regression results of Eq. (3) in Table 2. Consistent with Chan and Hameed (2006) and Piotroski and Roulstone (2004), Models 1 and 2 show that the coefficients on *Analyst* are positive and significant. This result supports the hypothesis in the prior literature that analysts generate market-wide information and, therefore, increase stock price synchronicity. The coefficient on *Size* is also positive and significant at the 1 percent level, similar to the empirical findings by Piotroski and Roulstone (2004). Although Chan and Hameed (2006) also predict that firm size has a positive sign because the stock market indexes are value weighted, their empirical results using international data have an insignificant negative coefficient for firm size. The coefficient on *Volume* is significantly positive, supporting the hypothesis that greater trading activity increases the speed of price adjustment (Mech, 1993). The coefficients on *Age* and *Beta* are positive and significant, consistent with the findings by Dasgupta et al. (2010). They state that the market learns more about firm characteristics (e.g., intrinsic firm qualities), and firm fundamentals are more stable as firms age; thus, older firms show more comovement with the market.

Based on these findings, we reexamine the relation between stock price synchronicity and analyst coverage after controlling for the interaction effect between the pro-cyclicality of firm performance and analyst coverage. The estimation results are reported in Models 3 and 4 of Table 2. The coefficient on the

Table 3
Effect of firm cyclicality and analyst coverage (three-stage least squares).

	Synch	Analyst
Analyst	−34.441***	
	(−7.979)	
Analyst × *CycDum*	14.902***	
	(4.838)	
CycDum	−20.938***	0.010
	(−4.733)	(1.229)
Sync		0.031***
		(3.164)
Size	3.696***	0.141***
	(10.806)	(27.316)
Volume	4.638***	0.152***
	(9.545)	(34.499)
Beta	0.161***	
	(3.612)	
BM	−0.069	0.006
	(−0.752)	(1.302)
ROA	0.922***	0.048***
	(3.925)	(3.667)
Age	−0.379***	
	(−3.282)	
Turnover		0.002***
		(2.686)
SysVol		−1.468***
		(−5.732)
IdioVol		0.209***
		(5.109)
Constant	−83.345***	−3.004***
	(−11.409)	(−13.640)
Fixed Effects	Yes	Yes
No. of Observations	53,223	53,223

Note: This table reports the estimated coefficients from the three-stage least squares with two simultaneous equation models. *Sync* is stock price synchronicity estimated from the CRSP total market value index. *Analyst* is analyst coverage defined as the natural logarithm of one plus the number of analysts covering the individual firm. *Size* denotes the natural logarithm of market capitalization. *Beta* is the estimated coefficient from the market-model regression. *Volume* and *BM* are the dollar trading volume and book-to-market ratio in natural log form, respectively. *ROA* denotes return on assets. *Age* denotes firm age defined as the number of years since the initial public offering (IPO) in natural log form. *Turnover* denotes the average number of shares traded relative to the number of shares outstanding in natural log form in a given year. *SysVol* and *IdioVol* are measured by the square root of the explained variation and the standard deviation of residual returns of the market-model regression, respectively. *CycDum* is the firm's cyclicality dummy variable equal to one if post ranking market beta is higher than one. Year, industry, and stock exchange fixed effects are included in the regression model. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

[3] We incorporate the control variables into the model, following previous studies (Kim, Batten, & Ryu, 2020; Laeven & Levine, 2007).

interaction term is positive and significant at the 1 percent level, which supports our hypothesis that analysts reveal the actual cash flow of a pro-cyclical firm, which internal managers want to capture (Jin & Myers, 2006). If analysts reveal the captured cash flow of pro-cyclical firms, this firm-specific information is likely to align with market movement. Therefore, when more analysts follow firms with pro-cyclicality, synchronicity in the market is higher, although analysts disseminate firm-specific information to the public. The sign of the estimated coefficient on *Analyst* changes from positive to negative after the interaction between the pro-cyclicality of firm performance and analyst coverage is controlled for. This result also supports the possibility of a positive relationship between synchronicity and analyst coverage that prior studies attribute to this interaction effect, that is, the effect in which analysts reveal hidden cash flow.

Because previous studies state that stock price synchronicity might be endogenous with analyst coverage (Feng et al., 2016; Roulstone, 2003), the estimated coefficients reported in Table 2 are likely to be biased. We, therefore, construct the simultaneous equation model using *Sync* and *Analyst* as endogenous variables. The regression equation for *Analyst* is as follows:

$$\begin{aligned} Analyst_{i,t} = \alpha &+ \beta_1 \cdot Sync_{i,t} + \beta_2 \cdot Size_{i,t} + \beta_3 \cdot Volume_{i,t} \\ &+ \beta_4 \cdot BM_{i,t} + \beta_5 \cdot ROA_{i,t} + \beta_6 \cdot Turnover_{i,t} \\ &+ \beta_7 \cdot SysVol_{i,t} + \beta_8 IdioVol + \beta_9 \cdot CycDum_{i,t} \\ &+ \lambda \cdot ExcDum_{i,t} + \sum \delta_l \cdot YearDum_{i,t} \\ &+ \sum \varphi_m \cdot IDum_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where $Turnover_{i,t}$ is the turnover ratio. $SysVol_{i,t}$ and $IdioVol_{i,t}$ are the systematic and idiosyncratic volatility for firm i in year t, respectively. We then estimate the coefficients using the three-stage least squares estimation between Eqs. (3) and (4). Table 3 shows the estimation results of the simultaneous equation model. After the possible effect of endogeneity is controlled for, the coefficient on *Analyst* is still negative and significant at the 1 percent level, which is an enhanced result over that in Table 2. The coefficient on the interaction term between *Analyst* and *CycDum* is also consistent in being positive and significant at the 1 percent level. The economic implication of the results in Table 3 can be explained as follows: in the case of a pro-cyclical firm ($CycDum = 1$), we find that the overall effect of $Analyst \times CycDum$ and *CycDum* on *Sync* turns positive when *Analyst* exceeds 1.405 (= 20.938/14.902). This implies that the negative effect of analyst coverage on stock price synchronicity diminishes when the number of analysts is greater than 3.08, because *Analyst* is defined as the logarithm of one plus the number of analysts. In other words, this result can be interpreted as the problem of earnings forecast dispersion, which may be caused by having coverage by too few analysts. As shown in Fig. 1, the estimated earnings forecast dispersion drops by 45.4 percent as the number of analysts increases from 2 to 3, which is the largest decrease among all intervals. Chalmers, Clinch, Godfrey, and Wei (2012) also show that the earnings forecast dispersion is negatively correlated with the number of analysts.

3.2. Effect of earnings forecast dispersion

Lower levels of cash-flow disclosure increase information asymmetry and reduce investors' ability to forecast future cash flows (Cheng & Hollie, 2008; Kent & Bu, 2020). Consequently, analysts' earnings forecasts vary according to the quality and method of firms' earnings disclosure. Earnings forecasts with higher dispersion indicate less agreement about future earnings among analysts, implying investor uncertainty

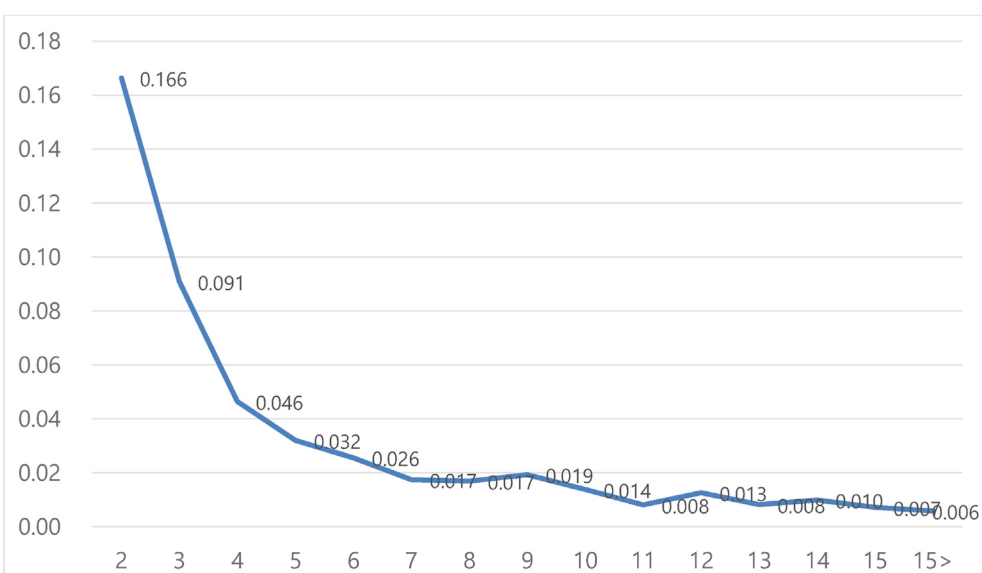

Fig. 1. Earnings forecast dispersions of analyst forecasts. *Note:* Fig. 1 plots the average earnings forecast dispersion of analyst forecasts as the number of analysts increases over the period from 1986 to 2021. Earnings forecast dispersion is calculated as the standard deviation of analysts' forecasts normalized by the mean value of forecasts and divided by the square root of the number of analysts, following Jin and Myers (2006).

about the firm's cash flow revealed by analysts; therefore, the effect of the interaction between the pro-cyclicality of firm performance and analyst coverage as well as analyst coverage on stock price synchronicity declines. Chan and Hameed (2006) show that the dispersion of earnings forecasts muddies the effect of analyst coverage; that is, according to their hypothesis, it reduces synchronicity. Truong, Shane, and Zhao (2016) also argue that information in the tails of the distribution of analysts' earnings forecasts affects market prices. Thus, we investigate whether the dispersion of earnings

Table 4
Effect of earnings forecast dispersion (three-stage least squares).

	Model 1		Model 2	
	Synch	Analyst	Synch	Analyst
Analyst	−5.806***		−11.303***	
	(−21.326)		(−14.861)	
Analyst × *DispersDum*	5.143***		10.856***	
	(21.488)		(14.619)	
DispersDum	−12.756***		−27.883***	
	(−21.502)		(−14.564)	
Analyst × *CycDum*	0.781***		9.825***	
	(18.970)		(14.145)	
CycDum	−0.993***	−0.047***	−25.289***	−0.026***
	(−13.740)	(−4.580)	(−13.922)	(−2.670)
Analyst × *CycDum* × *DispersDum*			−9.829***	
			(−14.142)	
CycDum × *DispersDum*			25.583***	
			(14.076)	
Sync		0.267***		0.189***
		(21.653)		(16.066)
Size	0.680***	0.091***	0.721***	0.101***
	(23.441)	(13.450)	(17.449)	(15.530)
Volume	0.206***	0.124***	0.238***	0.136***
	(16.013)	(20.765)	(13.943)	(23.872)
Beta	0.144***		0.148***	
	(23.521)		(18.192)	
BM	0.233***	0.013**	0.293***	0.015***
	(13.976)	(2.209)	(11.688)	(2.774)
ROA	−0.176***	0.065***	−0.103	0.075***
	(−3.022)	(2.679)	(−1.341)	(3.219)
Age	0.103***		0.094***	
	(6.915)		(4.786)	
Turnover		0.001		0.001
		(0.731)		(0.762)
SysVol		−7.308***		−5.618***
		(−18.437)		(−14.842)
IdioVol		1.636***		1.201***
		(15.690)		(12.055)
Δ*Ret*		−0.028***		−0.020***
		(−8.759)		(−6.351)
Δ*Anal_num*		0.041***		0.040***
		(25.151)		(25.406)
EM		−0.022*		−0.021*
		(−1.804)		(−1.795)
Constant	−2.387***	−0.784**	10.575***	−1.411***
	(−3.073)	(−2.507)	(6.323)	(−4.698)
Fixed Effects	Yes	Yes	Yes	Yes
No. of Observations	45,895	45,895	45,895	45,895

Note: This table reports the estimated coefficients from the three-stage least squares with the two simultaneous equation models. *Sync* is stock price synchronicity estimated from the CRSP total market value index. *Analyst* is analyst coverage defined as the natural logarithm of one plus the number of analysts covering the individual firm. *DispersDum* is the earnings forecast dispersion dummy variable defined as one if the calculated dispersion is higher than the average in the given year. *Size* denotes the natural logarithm of market capitalization. *Beta* is the estimated coefficient from the market-model regression. *Volume* and *BM* are the dollar trading volume and book-to-market ratio in natural log form, respectively. *ROA* denotes return on assets. *Age* denotes firm age defined as the number of years since the initial public offering (IPO) in natural log form. *Turnover* denotes the average number of shares traded relative to the number of shares outstanding in natural log form in a given year. *SysVol* and *IdioVol* are measured by the square root of the explained variation and the standard deviation of residual returns of the market-model regression, respectively. Δ*Ret* and Δ*Anal_num* denote the change in stock returns and in the number of analysts following between year $t-1$ and t, respectively. *EM* is earning management estimated using the modified Jones model. *CycDum* is the firm's cyclicality dummy variable equal to one if post ranking market beta is higher than one. Year, industry, and stock exchange fixed effects are included in the regression model. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

forecasts reduces the effect of analyst coverage as well as the interaction effect of analyst coverage and pro-cyclicality.

We modify the panel regression model (Eq. (3)) by including an interaction term between analyst coverage and the dispersion dummy variable (*Analyst* × *DisperDum*) and a triple interaction term involving analyst coverage, cyclicality in firm performance, and the dispersion dummy (*Analyst* × *CycDum* × *DisperDum*) as follows:

Table 5
Robustness check: Alternative cyclicality measure (three-stage least squares).

	Model 1		Model 2	
	Synch	Analyst	Synch	Analyst
Analyst	−5.043***		−8.112***	
	(−19.484)		(−15.611)	
Analyst × DispersDum	4.602***		8.068***	
	(20.645)		(15.915)	
DispersDum	−11.446***		−20.478***	
	(−20.553)		(−15.856)	
Analyst × CycDum_ROA	0.797***		7.191***	
	(17.629)		(15.047)	
CycDum_ROA	−1.198***	−0.011	−18.527***	−0.013
	(−16.963)	(−1.086)	(−15.047)	(−1.286)
Analyst × CycDum_ROA × DispersDum			−7.167***	
			(−15.028)	
CycDum_ROA × DispersDum			18.503***	
			(15.027)	
Sync		0.312***		0.211***
		(22.858)		(16.423)
Size	0.556***	0.079***	0.424***	0.090***
	(21.048)	(10.072)	(17.588)	(11.974)
Volume	0.194***	0.122***	0.251***	0.141***
	(15.062)	(17.281)	(16.854)	(21.148)
Beta	0.120***		0.126***	
	(21.492)		(20.745)	
BM	0.235***	0.014**	0.177***	0.018***
	(14.069)	(2.186)	(10.465)	(2.837)
ROA	−0.115**	0.071**	−0.064	0.080***
	(−2.042)	(2.521)	(−1.047)	(3.023)
Age	0.032*		0.026	
	(1.928)		(1.425)	
Turnover		0.002		0.002
		(1.159)		(0.958)
SysVol		−7.032***		−5.026***
		(−16.663)		(−12.654)
IdioVol		1.627***		1.089***
		(14.243)		(10.122)
Δ*Ret*		−0.031***		−0.020***
		(−8.734)		(−5.845)
Δ*Anal_num*		0.041***		0.040***
		(22.682)		(23.015)
EM		−0.025*		−0.023*
		(−1.843)		(−1.781)
Constant	−1.426	0.092	7.714***	−0.657
	(−1.353)	(0.187)	(5.235)	(−1.402)
Fixed Effects	Yes	Yes	Yes	Yes
No. of Observations	40,187	40,187	40,187	40,187

Note: This table reports the estimated coefficients from the three-stage least squares with the two simultaneous equation models. *Sync* is stock price synchronicity estimated from the CRSP total market value index. *Analyst* is analyst coverage defined as the natural logarithm of one plus the number of analysts covering the individual firm. *DispersDum* is the earnings forecast dispersion dummy variable defined as one if the calculated dispersion is higher than the average in the given year. *Size* denotes the natural logarithm of market capitalization. *Beta* is the estimated coefficient from the market-model regression. *Volume* and *BM* are the dollar trading volume and book-to-market ratio in natural log form, respectively. *ROA* denotes return on assets. *Age* denotes firm age defined as the number of years since the initial public offering (IPO) in natural log form. *Turnover* denotes the average number of shares traded relative to the number of shares outstanding in natural log form in a given year. *SysVol* and *IdioVol* are measured by the square root of the explained variation and the standard deviation of residual returns of the market-model regression, respectively. Δ*Ret* and Δ*Anal_num* denote the change in stock returns and in the number of analysts following between year *t*-1 and *t*, respectively. *EM* is earning management estimated using the modified Jones model. *CycDum_ROA* is the firm's cyclicality dummy variable equal to one if the regression coefficient of the individual firm's ROA on market value-weighted ROA is higher than zero. Year, industry, and stock exchange fixed effects are included in the regression model. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

$$\begin{aligned}Sync_{i,t} = {} & \alpha + \beta_1 \cdot Analyst_{i,t} + \beta_2 \cdot Analyst_{i,t} \times DisperDum_{i,t} \\ & + \beta_3 \cdot DisperDum_{i,t} + \beta_4 \cdot Analyst_{i,t} \times CycDum_{i,t} \\ & + \beta_5 \cdot CycDum_{i,t} + \beta_6 \cdot Analyst_{i,t} \times CycDum_{i,t} \\ & \times DisperDum_{i,t} + \beta_7 \cdot CycDum_{i,t} \times DisperDum_{i,t} \\ & + \beta_8 \cdot Size_{i,t} + \beta_9 \cdot Volume_{i,t} + \beta_{10} \cdot Beta_{i,t} + \beta_{11} \cdot BM_{i,t} \\ & + \beta_{12} \cdot ROA_{i,t} + \beta_{13} \cdot Age_{i,t} + \lambda \cdot ExcDum_{i,t} \\ & + \sum \delta_l \cdot YearDum_{i,t} + \sum \varphi_m \cdot IDum_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{5}$$

We then look at the effect of earnings forecast dispersion using the simultaneous equation model to avoid possible endogeneity problems between synchronicity and analyst coverage. We also include instrumental variables, such as a change in stock returns (ΔRet), a change in the number of analysts following ($\Delta Anal\_num$), and earning management (EM), in the *Analyst* equation as follows:

$$\begin{aligned}Analyst_{i,t} = {} & \alpha + \beta_1 \cdot Sync_{i,t} + \beta_2 \cdot Size_{i,t} + \beta_3 \cdot Volume_{i,t} + \beta_4 \cdot BM_{i,t} \\ & + \beta_5 \cdot ROA_{i,t} + \beta_6 \cdot Turnover_{i,t} + \beta_7 \cdot SysVol_{i,t} \\ & + \beta_8 \cdot IdioVol_{i,t} + \beta_9 \cdot CycDum_{i,t} + \beta_{10} \cdot \Delta Ret_{i,t} \\ & + \beta_{11} \cdot \Delta Anal\_num_{i,t} + \beta_{12}\, EM_{i,t} + \lambda \cdot ExcDum_{i,t} \\ & + \sum \delta_l \cdot YearDum_{i,t} + \sum \varphi \cdot IDum_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{6}$$

where $\Delta Ret_{i,t}$ and $\Delta Anal\_num_{i,t}$ are calculated as any difference in returns and the number of analysts at time t and t-1, respectively. We estimate the discretionary accruals (EM) from the regression of total accruals on changes in sales and on property, plant, and equipment in industries as a proxy for earnings management using the modified version of the Jones model (Dechow, Sloan, & Sweeney, 1995; Pham, Chung, Roca, & Bao, 2019; Yu, 2008). Table 4 presents the results of the simultaneous equation model using Eqs. (5) and (6). First, we find that the estimated coefficients on *Analyst* and $Analyst \times CycDum$ are still significant at the 1 percent level, and the signs remain unchanged in Models 1–2. That is, the estimated results in Table 4 support our hypothesis that analysts produce firm-specific information even after controlling for the effect of the dispersion of earnings forecasts. We find as well that the coefficient on $Analyst \times CycDum \times DisperDum$ is negative and significant at the 1 percent level. In sum, the results in Table 4 support our hypothesis that when we consider the effect of the dispersion of analyst forecasts, the effects of *Analyst* and $Analyst \times CycDum$ diminish after the potential effect of endogeneity is controlled for.[4] That is, when analysts have less agreement about earnings forecasts, investor uncertainty will emerge about uncovered cash flow. Consequently, the effects of analyst coverage and the interaction effect between a firm's pro-cyclicality and analyst coverage diminish.[5]

4. Robustness tests

In this section, we confirm the robustness of the results by adopting an alternative cyclicality measure and performing the regression simultaneously. In the main analysis in Section 3, we use the market beta as a proxy for the cyclicality of firm performance. Although the market beta is appropriate for capturing the sensitivity of an individual firm's stock return to market return movement, it can be regarded as an indirect measure of cyclicality in terms of earnings performance. Therefore, we adopt ROA-beta in the regression test to directly capture the effect of a firm's earnings cyclicality. To obtain ROA-beta, we regress an individual firm's ROA on value-weighted ROA (ROA_{vw}) on a quarterly basis as follows:

$$ROA_{i,t} = \alpha + \beta \cdot ROA_{vw,t} + \varepsilon_{i,t} \tag{7}$$

We run the regression in Eq. (7) using six years (24 quarters) of individual firms' ROA. Firms included in the data set have at least 20 out of 24 quarters of ROA data. We then construct a dummy variable, *CycDum_ROA*, which equals one if the estimated ROA-beta is higher than zero, and zero otherwise.

We report the regression results using *CycDum_ROA* in Table 5, and they are consistent with those in Table 4, showing that the estimated coefficient on *Analyst* is negative and significant, and the coefficient on $Analyst \times CycDum\_ROA$ is positive and significant at the 1 percent level. We also find that the coefficient on $Analyst \times CycDum\_ROA \times DisperDum$ is negatively significant at the 1 percent level. These results support our hypothesis even when the alternative measure of cyclicality is adopted in the regression model.

5. Conclusion

In this paper, we present our study on whether analysts produce firm-specific information or market-wide information that affects synchronicity. Extending the model suggested by Jin and Myers (2006), which states that outside investors have limited information, and thus internal managers have an incentive to capture some of the firm's operating cash flow, we analyze the impact of analysts' revelation of firm-specific cash flow captured by internal managers. Consequently, we find supportive evidence that analysts generate firm-specific information, rather than market-wide information. Ultimately, stock price synchronicity is negatively related to analyst coverage when we control for the interaction effect between the pro-cyclicality of firm performance and analyst coverage. Furthermore, both effects, stock return synchronicity

[4] To check the influence of correlation between interaction terms and dummy variables on the estimated coefficients, we exclude dummy variables, such as *CycDum* and *DispersDum,* from the regression model and rerun the regression analyses in Table 4. We find that the results are quantitatively and qualitatively consistent and robust. The results are not reported here for the sake of brevity, but are available upon request.

[5] We additionally implement the subperiod analysis in Table 4. Considering the Global Analyst Research Settlement in 2003, we set the period during 1986–2003 as subperiod 1 and the period during 2004–2021 as subperiod 2. The regression results are qualitatively and quantitatively robust. The results are not reported here for the sake of brevity, but are available upon request.

decreasing with increased analyst coverage and increasing with the interaction between analysts and pro-cyclicality, diminish when analyst forecast dispersion is high. These results are robust when we calculate stock price synchronicity with an alternative market index and simultaneously regress the estimation models to avoid potential endogeneity problems.

Declaration of competing interest

There is no conflict of interest.

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