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Shareholder Coordination, Information Diffusion and Stock Returns

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Abstract

We show that the quality of information-sharing networks linking firms' institutional investors has stock return predictability implications. We find that firms with high shareholder coordination experience less local comovement and less post-earnings announcement drift, consistent with the notion that information-sharing networks facilitate information diffusion and improve stock price efficiency. In support of the view that coordination acts as an information diffusion channel, we document that the stock return performance of firms with high shareholder coordination leads that of firms with low shareholder coordination.

1. Introduction

Firms with good corporate governance are less prone to information asymmetries and should be less difficult for outside investors to analyze. Institutional investors are instrumental in shaping corporate

governance and are generally regarded as important promoters of sound corporate policies, transparency (Ajinkya, Bhojraj and Sengupta, **2005**), and stock price informativeness (Piotroski and Roulstone, **2004**). However, since institutional investors are not a homogeneous group, but rather a collection of clusters of institutions with different investment orientations and horizons, their ability to improve corporate governance and firms' information environment relies not just on their mere size and resources, but also on their capacity to share information with other institutional shareholders.¹ The transmission of value-relevant information across the set of a firm's institutional investors can be greatly facilitated by the strength of professional and social networks that may exist among institutions. There is recent evidence (Huang, **2013a,b**; Kim, Pantzalis and Wang, **2015**) suggesting that coordination among institutions improves corporate governance. What remains an unexplored question, and the core emphasis of this paper, is whether the strength of information-sharing networks facilitating coordination among institutional investors has return predictability implications. The notion that coordination among institutional investors can help predict returns relies on the premise that institutional investors' information-sharing network can be viewed as a flow channel. This channel allows market value-relevant information to be transmitted to stock prices of firms lacking shareholder coordination after it has been impounded in stock prices of peer firms enjoying shareholder coordination.²

Theory suggests that informed investors may have an effect on the speed of price adjustments to new information. For example, Holden and Subrahmanyam (**1992**) and Foster and Viswanathan (**1993**) extend the classic model of Kyle (**1985**) and show that stock prices reflect new information more rapidly as the number of informed investors increases. Empirical evidence confirms that stocks of firms with more informed investors adjust to common information faster than stocks of firms with less informed traders (Brennan, Jegadeesh and Swaminathan, **1993**; Badrinath, Kale and Noe, **1995**).

Information-sharing networks play an important role in enhancing market efficiency. For example, Colla and Mele (**2010**) find that price informativeness increases in the presence of information-sharing networks among individual traders. Pareek (**2012**) finds that strength of information-sharing networks between mutual fund managers affects the response time of stock prices to common information. Therefore, we conjecture that firms with strong information-sharing networks will adjust to common information faster than those with weak information-sharing networks. More specifically, we posit that cross-sectional variation in the ability of information-sharing networks to facilitate coordination among institutional investors reflects differences in the degree of skill-based information acquisition and processing costs faced by investors. Intuitively, investor specialization, more often than not, adversely affects investors' capability to acquire and process new information, which thereby plays an important role in the information diffusion (Menzly and Ozbas, **2010**). On the arrival of an information shock, information-sharing networks could break down the informational barriers among the institutional investors with different specializations and cause a quick and adequate response to it.

We demonstrate that institutional shareholder coordination improves investors' information environment. Specifically, we show that firms with high (low) shareholder coordination experience weak (strong) local comovement and post-earnings announcement drift. This is consistent with the notion that coordination reduces friction in public information processing and encourages the collection of and trading on private information.³

Previous studies utilize the Shapley value of existing shareholders as a proxy for shareholder coordination. Shapley value was first introduced as a solution to solve the problem of how to fairly distribute gains and costs among players in a cooperative game theory (Milnor and Shapley, 1978). Zingales (1994) and Nenova (2003) use Shapley value to capture the control value of shareholders' voting rights. Using shareholder-voting-based Shapley value as a proxy for coordination frictions among the existing shareholders, Chakraborty and Gantchev (2013) find that private investments in public equity can improve the equity coordination, leading to favorable debt renegotiation outcomes. In spite of the merits of the Shapley value and given the research question we try to answer in this paper, we believe that an information-sharing-network-based measure of shareholder coordination is more appropriate than a voting-rights-based one. Therefore, to measure the degree of coordination among institutional shareholders, we follow Huang (2013a,b) and devise two proxies that rely on the premise that the likelihood and strength of social connections increases with geographic proximity and similarity of values, attitudes, and beliefs comprising an institutional shareholders' corporate investment philosophy.⁴ Social network literature suggests that social ties and relationships are more likely to develop when there is homophily, that is, the tendency of individuals to associate and bond with others driven by familiarity, often rooted in geographic proximity or sharing of common values (McPherson, Smith-Lovin and Cook, 2001). Geographic proximity is shown to be influential in the development of close relationships, such as friendship and marriage (Bossard, 1932), in the forming of interlocked corporate boards (Kono, Palmer, Friedland and Zafonte, 1998), in dealings among floor traders (Baker, 1984), and in investment patterns of venture capital firms (Sorenson and Stuart, 2001). In addition to propinquity, studies show that social connections are more likely when individuals share similar backgrounds, demographic characteristics, and values (Marsden, 1988; McPherson, Smith-Lovin and Cook, 2001).

To generate clean tests of the hypothesis that institutional shareholder coordination acts as an information flow channel, we develop our coordination measures by accounting for the fact that the degree of institutional shareholder coordination can be strongly correlated with firm characteristics such as firm size and headquarters location. Accordingly, we first estimate coordination in a regression model that includes several firm characteristics as independent variables and extract the residual. These residual shareholder coordination measures (RES_COORD_PROX and RES_COORD_PORT) capture the unobservable part of coordination and serve as our main variables of interest in the return predictability tests.

The slow information diffusion hypothesis tests are first performed as they pertain to industry-specific information. In this case, the appropriate test assets are industry-based portfolios. Specifically, at the end of June in each year, we first sort all firms in each of the Fama-French 48 industries into three size terciles. We then separate each of these industry-size portfolios into three shareholder coordination terciles and define firms in the top (bottom) tercile as high (low) coordination firms. This sorting technique generates the two sets of our test assets (144 high shareholder coordination and 144 low shareholder coordination portfolios) and ensures that our results will not be contaminated by the previously documented lead-lag effects in stock returns between big and small firms within an industry (Lo and MacKinlay, 1990). After having matched each low shareholder coordination portfolio with its corresponding high coordination "clone" within each industry-size portfolio, we proceed to calculate clones' one-month-lagged return performance, and rank them into month $t - 1$ return quintiles.

Following Cohen and Lou (2012), we assign each of the low coordination portfolios to the quintile where its high coordination clone is located. We then calculate value-weighted returns in month t of the quintile portfolios consisting of low coordination test assets. We find evidence of strong return predictability, consistent with the notion that shareholder coordination serves as an information diffusion channel.

The zero-cost investment portfolio that buys low shareholder coordination firms, whose corresponding high coordination clones performed best in the prior month, and sells low shareholder coordination test assets, whose corresponding high coordination clones performed worst in the prior month, has a value-weighted return that is above 58 basis points per month. We repeat the test using alternate test assets that would be more appropriate in a more general setting where the value-relevant information has market-wide rather than industry-specific implications. Specifically, we construct two sets (i.e., high and low coordination) of 125 portfolios based on the method outlined in Daniel, Grinblatt, Titman and Wermers (1997) (hereafter DGTW) which entails combinations of size, book-to-market and momentum quintiles. This procedure of building test assets allows us to remove the effect of common factors on stock prices and provides a clean testing ground to investigate how shareholder coordination serves as a market-wide information diffusion channel. We document consistent evidence that the zero-cost investment portfolio delivers a value-weighted return about 68 basis points per month, which is an economically sizeable effect. Our results hold in a cross-sectional test setting where we control for other factors, such as size, book-to-market, past return, and liquidity.

Although our findings suggest that information-sharing networks captured by coordination among institutional investors have return predictability implications, the evidence is not conclusive. We outline the potential alternative explanations in the following: (1) Correlated informative signals. It is plausible that the two coordination measures capture correlated information which drives return predictability. In other words, correlated informative signals lead to correlated institutional portfolio holdings, which are reflected in shareholder coordination measures. Chan (1993) finds that correlated signals providing more precise market-wide information can explain cross-autocorrelations among stock returns. (2) Investor specialization. Our shareholder coordination measures may also correlate with investor specialization. More specifically, shareholder coordination may capture a degree of specialization diversity of informed investors within a firm. Menzly and Ozbas (2010) point out that specialization of investors in their information acquisition and processing effort can lead to informationally segmented markets and consequently stock return predictability. Therefore, firms with a group of investors with more diverse specializations will react faster to information shocks than those with a group of investors with less diverse specifications. (3) Unobserved firm characteristics. Our finding of a link between information-sharing network and future returns may simply be driven by unobserved firm characteristics that correlate with shareholder coordination and are also the main cause of return predictability. If this is the case, our findings may suggest a correlation between coordination and stock returns rather than a causal effect. Overall, we view our work as an initial attempt to carefully study the relation between shareholder coordination and return predictability. We hope that future work can further analyze the issue of causality and the topic of why the correlation between coordination and return predictability exists.

The rest of the paper is organized as follows. Section **2.** presents related literature. Section **3.** describes the sample and variables construction. Section **4.** contains the empirical results. Section **5.** provides concluding remarks.

2. Literature review

Our paper relates to the literature on stock return predictability, one strand which investigates the lead-lag pattern in returns across stocks with different characteristics and the role of informed traders in explaining the pattern. Lo and MacKinlay (1990) document that returns of small firms correlate with past returns of large firms, but not vice versa. Badrinath, Kale and Noe (1995) find that past returns of stocks held by informed institutional traders positively correlate with returns of stocks held by uninformed retail traders. Brennan, Jegadeesh and Swaminathan (1993) provide evidence that returns on portfolios of stocks followed by many analysts tend to lead returns on portfolios of stocks followed by few analysts. Their findings can be explained by the faster adjustment to common information due to the presence of informed traders such as analysts and institutional investors. Motivated by this strand of literature, we examine whether cross-sectional variation in shareholder coordination facilitated by information-sharing networks can cause predictable patterns of variation in the speed of price adjustment to common information. Our paper also relates to the literature on information-sharing networks. Cohen, Frazzini and Malloy (2008) find that mutual fund managers place more weight in their portfolios on firms they are connected to through their network. Hong, Kubik and Stein (2005) find that mutual funds managers in the same city are more likely to make similar investment decisions because they share information through word-of-mouth communication. Colla and Mele (2010) find that in the presence of information-sharing networks among individual traders, price informativeness increases. Pareek (2012) finds that strength of information-sharing networks between mutual fund managers affects the response speed of stock prices to market-wide information. Our paper extends this line of literature by studying the implications of information-sharing networks for stock return predictability.

3. Sample and variables construction

Sample selection

Our analysis uses stock return data from CRSP, accounting data from COMPUSTAT, analyst forecast data from Institutional Brokers' Estimate System (I/B/E/S) and the institutional holding data from Thomson Reuters F13. Our sample period is from January 1994 to December 2010. We apply the following screens to create the sample. First, we restrict the sample to institutional shareholders located in the United States. Second, we exclude closed-end funds, real estate investment trusts, American depositary receipts, and foreign stocks, only retaining stocks with CRSP share code 10 or 11. Third, to ensure that accounting information is publicly available before we conduct stock return predictability tests, we impose at least a six-month gap between the firm's fiscal-year ends and the beginning of stock return intervals. Finally, to further alleviate market microstructure-related concerns, we require that the stock price must be greater or equal to five dollars per share at the beginning of the holding period.

Variables

3.2.1. Shareholder coordination

Following Huang (2013a,b), we construct two measures of institutional shareholder coordination: *COORD_PROX* and *COORD_PORT*. The first measure, *COORD_PROX*, is constructed as the weighted average geographical distance among institutional shareholders of a firm. The rationale behind this measure is that the likelihood of casual social interactions and networking increases with geographic proximity (McPherson, Smith-Lovin and Cook, 2001). For example, Hong, Kubik and Stein (2005) find that a mutual fund manager's investment decisions are more likely to be affected by the investment decisions of other managers in the same city through the word-of-mouth effects. To measure the distance between two institutions, we first identify the location of institutions by collecting the headquarter zip code information from the Securities and Exchange Commission (SEC) documents (SEC Edgar) and the Nelson's Directory of Investment Managers. We then obtain the latitude and longitude for each of the zip codes from the U.S. Census Bureau's Gazetteer Place and Zip Code Database. Following prior research (Coval and Moskowitz, 2001), we calculate the distance between institution i and j using the following standard formula:

$$DIST_{i,j} = r \times \arccos\{\cos(\text{lat}_i) \cos(\text{lon}_i) \cos(\text{lat}_j) \cos(\text{lon}_j) + \cos(\text{lat}_i) \sin(\text{lon}_i) \cos(\text{lat}_j) \sin(\text{lon}_j) + \sin(\text{lat}_i) \sin(\text{lat}_j)\},$$

where $DIST_{i,j}$ is distance in statutory miles, r denotes the radius of the Earth (approximately 3,963 statutory miles), and lat and lon are institution latitudes and longitudes.

For each firm-quarter, we calculate the distance of each institutional shareholder and all institutional shareholders of the firm, weighted by their respective fractional holdings of the total institutional ownership in the firm. To obtain the geographic-proximity-based shareholder coordination measure, we then take the logarithm-transformed fractional holdings' weighted average of these distances across all institutional shareholders of the firm. Since higher values of the raw geographic-proximity-based coordination measure indicate greater distance, they imply that institutions are less likely to coordinate. Thus, we take the inverse value to make sure that high (low) values of this measure indicate strong (weak) shareholder coordination. The weighting scheme aims to deliver a more accurate gauge of coordination than the simple average of the distances among institutions, because it accounts for the fact that institutions with large shareholdings typically have a more substantial impact on corporate behavior. Specifically, the geographical-proximity-based institutional shareholder coordination measure is designed as follows:

$$COORD_PROX = (-1)\text{LOG} \left(1 + \sum_{i \in a} w_i \sum_{j \in a} w_j DIST_{i,j} \right),$$

where a is the set of institutional investors, w_i is the ownership weight of institution i in the total ownership held by all institutions in a firm at the end of each quarter, and $DIST_{i,j}$ is the geographical

distance between institution i and j . The logarithm transformation, $\log(1 + \text{weighted average of geographical distance among institutions})$ serves the purpose of reducing the skewness of distribution for this measure.

The second measure, $COORD_PORT$, is the weighted average correlation between institutions' portfolios of stock holdings. The intuition behind this measure is based on the premise that institutions with similar portfolio allocations are more likely to share common investment philosophies. Therefore they are more likely to have developed social links that lead to better coordination. For example, to examine the effect of information-sharing networks on stock returns, Pareek (2012) classifies mutual managers who have large common portions in their portfolios as informationally connected. To calculate the portfolio correlation between two institutional shareholders for each firm-quarter, we first identify the stocks held by each institutional investor at the end of each quarter, and then calculate the correlation of the excess portfolio weights⁵ on the stocks held by both institutions. For each institutional shareholder of the firm, we calculate the correlation of its portfolio with that of all other institutions, weighted by their respective fractional holdings of the total institutional ownership in the firm. As in the geographical-proximity-based institutional shareholder coordination measure, we take the fractional holdings weighted average of these portfolio correlations across all institutional shareholders of the firm to obtain the portfolio-correlation-based institutional shareholder coordination measure for each firm-quarter. Specifically,

$$COORD_PORT = \sum_{i \in a} w_i \sum_{j \in a} w_j CORR_{i,j},$$

where a is the set of institutional investors, w_i is the ownership weight of institution i in the total ownership held by all institutions in a firm at the end of each quarter, and $CORR_{i,j}$ is the correlation coefficient of the excess portfolio weight (measured as the actual weight relative to the weight in the market portfolio) allocated to common holdings between institutions i and j at quarter t .

3.2.2. Unobservable shareholder coordination

To derive a clearer picture of a causal link between shareholder coordination and other variables of interest, we build a prediction model for shareholder coordination and examine the impact of the unexplained portion (i.e., the residual) shareholder coordination on stock return predictability. The rationale for this procedure is that, by construction, the predicted shareholder coordination is a linear combination of firm characteristics. Literature has shown that return predictability can be explained by variables such as firm size, institutional ownership, analyst coverage, and trading volume. Therefore, to alleviate the concern that our results are driven by these already established variables that contribute to return predictability, we focus on the unexplained part of shareholder coordination, that is, the residual from a prediction model. Moreover, the residual measure represents the unobservable part of coordination, that is, the part that the outside investors cannot easily recognize, which is a complicated information absorption mechanism from their perspective. Therefore, intuitively it is more appropriate to conduct the analysis based on residual institutional shareholder coordination. Similar methodology has been used in other influential studies. For example, using residual analyst coverage obtained from a prediction model, Hong, Lim and Stein (2000) examine the association between analyst coverage and

momentum strategy. Likewise, Nagel (2005) finds that short-sale constraints, proxied by residual institutional ownership, can explain cross-sectional stock return anomalies.

To design the prediction model for shareholder coordination, we include a battery of variables that reflect firm characteristics (e.g., firm size, accounting performance [return on asset (ROA)], and market performance [book-to-market ratio (BM), Beta and BHRET12]). We also include the percentage of institutional ownership and institutional ownership concentration to control for their potential impact on the degree of shareholder coordination. To mitigate the confounding effects on stock return predictability caused by analyst coverage (Brennan, Jegadeesh and Swaminathan, 1993) and trading volume (Chordia and Swaminathan, 2000), we add analyst coverage (Analyst) and stock turnover (Turnover) to the prediction model. We add a dividend yield dummy (Dividend) to control for the relation between dividends and institutional ownership (Ferreira and Matos, 2008). To capture the effect of local bias as suggested in Coval and Moskowitz (2001), we control the geographical distance between a firm's headquarters and its institutional investors. Finally, we add metropolitan statistical area (MSA)-city fixed effects. The prediction model of shareholder coordination emerges as follows:

$$\begin{aligned}
 COORD_ = & a_0 + a_1 Size + a_2 BM + a_3 Beta + a_4 ROA + a_5 Leverage \\
 & + a_6 Sale\ growth + a_7 Firm\ age + a_8 IO + a_9 IO_HHI + a_{10} BHRET12 \\
 & + a_{11} Analyst + a_{12} Turnover + a_{13} Dividend \\
 & + a_{14} Dist_Inst_Headquarter + d_i + d_j + d_k + \varepsilon,
 \end{aligned}$$

(1)

where i, j and k are index year, industry and MSA-city, respectively. We estimate this cross-sectional regression of coordination every quarter with lagged independent variables and obtain coefficient estimations of each controlling variable, which we then use to obtain predicted institutional shareholder coordination for each firm and each quarter according to the following equation:

$$\begin{aligned}
 P_COORD_ = & \frac{est}{\widehat{a}_0} + \frac{est}{\widehat{a}_1} Size + \frac{est}{\widehat{a}_2} BM + \frac{est}{\widehat{a}_3} Beta + \frac{est}{\widehat{a}_4} ROA + \frac{est}{\widehat{a}_5} Leverage \\
 & + \frac{est}{\widehat{a}_6} Sale\ growth + \frac{est}{\widehat{a}_7} Firm\ age + \frac{est}{\widehat{a}_8} IO + \frac{est}{\widehat{a}_9} IO_HHI \\
 & + \frac{est}{\widehat{a}_{10}} BHRET12 + \frac{est}{\widehat{a}_{11}} Analyst + \frac{est}{\widehat{a}_{12}} Turnover + \frac{est}{\widehat{a}_{13}} Dividend \\
 & + \frac{est}{\widehat{a}_{14}} Dist_Inst_Headquarter.
 \end{aligned}$$

(2)

After obtaining the predicted shareholder coordination, we obtain the unexplained (residual) part for geographical-proximity-based (hereafter RES_COORD_PROX) and portfolio-correlation-based (hereafter RES_COORD_PORT) institutional shareholder coordination as follows:

$$RES_COORD_ = COORD_ - P_COORD_$$

(3)

In this paper, we use RES_COORD_PROX and RES_COORD_PORT as the main shareholder coordination variables. One caveat is that it is still plausible that there are some salient factors that correlate with

shareholder coordination, although we try to exhaust the variables in the literature that have been proven to drive return predictability. In Section 4.1., we show that shareholder coordination is positively associated with corporate information environment, which suggests the validity of coordination measures. However, the evidence is not conclusive.

Table 1 presents summary statistics for the main variables as well as other controlling variables used in the regressions (refer to the caption of Table 1 for detailed variable definitions).

Panel A of Table 2 reports the regression results of the coordination prediction model. It is noteworthy that the adjusted R^2 for both coordination measures (COORD_PROX, 0.629; COORD_PORT, 0.782) indicates that the controlling variables in the prediction model explain a considerable part of variation in the coordination variables. In other words, after purging out the effects of relevant determinants, we obtain the pure shareholder coordination measures. It is not surprising to see that firm size is significantly and negatively related with shareholder coordination in that the visibility of large firms is more likely to attract a large number of different types of institutional investors. The positive relation between institutional ownership concentration and shareholder coordination indicates that dispersed institutional ownership imposes more barriers on the coordination among institutional investors. The results further suggest that prior market and accounting performance have substantial effects on shareholder coordination. Analyst coverage is negatively related to both shareholder coordination measures. This could be due to the positive correlation between firm size and analyst coverage. We also find that the fractional holdings' weighted average geographic distance between a firm's headquarters and institutions has a negative impact on shareholder coordination. Panel B of Table 2 reports the correlation matrix for the raw and refined shareholder coordination measures. The Pearson's correlation between COORD_PROX and RES_COORD_PROX is 0.6932, which indicates that although the two measures are highly correlated, they are not exactly the same, which is in line with the view that our prediction model of shareholder coordination successfully captures the noisy part in the raw coordination measures. The positive correlation between COORD_PORT and RES_COORD_PORT (0.5617) further confirms the above argument. The large correlation between COORD_PROX and COORD_PORT (0.6477), RES_COORD_PROX and RES_COORD_PORT (0.3496) supports the idea that the geographical-proximity-based and portfolio-correlation-based coordination measures capture, to a large extent, different aspects of the same phenomenon.

Table 1. Summary statistics

This table reports the descriptive statistics of main variables in the sample during January 1994–December 2010. COORD_PROX is the inverse of the natural logarithm of 1+ weighted average geographical distance among institutional shareholders of the firm in each firm-quarter, where the weight is the ratio of ownership held by the institution to the total ownership held by all institutions in a firm at each calendar quarter. COORD_PORT is the weighted average excess portfolio correlation among institutional shareholders of the firm in each firm-quarter, where the weight is the ratio of ownership held by the institution to the total ownership held by all institutions in a firm at each calendar quarter, and excess portfolio is the actual weight relative to the weight in market portfolio. RES_COORD_PROX is the residual of the quarterly cross-sectional regression of COORD_PROX on a series of firm characteristics. RES_COORD_PORT is residual of the quarterly cross-sectional regression of COORD_PORT on a series of firm characteristics (see Panel A of Table 2). Size is the natural logarithm of the stock market value at the end of each June. BM is the natural logarithm of the fiscal year-end book value of common equity divided by the calendar year-end stock market value. Beta is estimated from the market model over 36 months prior to the beginning of the current period. ROA is the return on asset measured as the ratio of

earnings before extraordinary items. Leverage is long-term debt scaled by total assets. Sale_Growth is the annual sale growth in percentage. Firm_age is the natural logarithm of firm age defined as the number of years since the firm was included in the COMPUSTAT database. IO is the ratio of institutional holdings of a firm to shares outstanding. IO_HHI is the Herfindahl Index of institutional ownership concentration based on percentages of institutional holdings by all 13F institutions. Leverage is the ratio of long-term debt plus current debt in liabilities to total asset. BHRET12 is the compound gross return in last 12 months. Turnover is average monthly trading volume of a firm scaled by the average number of shares outstanding over a one-year period. Analyst is the number of analysts following the stock in that quarter. Dividend is a dummy variable that equals 1 if a firm paid dividends. Dist_Inst_Headquarter is fractional holding weighted geographical distance between a firm's headquarters and its institutional investors. Ret (-2, -7) is the compound gross return from month $t - 7$ to $t - 2$.

	N	Mean	SD	Median	P25	P75
Shareholder coordination						
COORD_PROX	213,517	-5.9766	1.2515	-6.3789	-6.6743	-5.8009
COORD_PORT	213,517	0.2813	0.1789	0.2311	0.1531	0.3605
RES_COORD_PROX	213,517	0.0000	0.8675	-0.0365	-0.3719	0.2723
RES_COORD_PORT	213,517	0.0000	0.1005	-0.0056	-0.0548	0.0428
Firm characteristics						
Size	213,517	12.4465	1.9401	12.3218	11.0094	13.7169
BM	213,517	-0.7712	0.9001	-0.7221	-1.3036	-0.1800
Beta	213,517	1.2397	0.9082	1.0842	0.6265	1.6955
ROA	213,517	-0.0243	0.2221	0.0354	-0.0318	0.0791
Leverage	213,517	0.1933	0.1870	0.1551	0.0129	0.3187
Sale_Growth	213,517	0.2617	0.7692	0.1059	-0.0066	0.2836
Firm_age	213,517	2.5639	0.7853	2.4849	1.9459	3.1781
IO	213,517	0.4719	0.2964	0.4651	0.2060	0.7192
IO_HHI	213,517	0.0223	0.0219	0.0175	0.0069	0.0310
BHRET12	213,517	0.1763	0.7478	0.0390	-0.2695	0.3993
Turnover	213,517	0.1483	0.1410	0.1059	0.0541	0.1941
Analyst	213,517	1.6348	1.0741	1.7918	0.6931	2.4849
Dividend	213,517	0.2873	0.4525	0.0000	0.0000	1.0000
Dist_Inst_Headquarter	213,517	5.1942	1.9108	5.7619	4.5711	6.4026
Ret (-2, -7)	213,517	0.0889	0.6635	0.0015	-0.2222	0.2596

Table 2. The determinants of shareholder coordination

Panel A: Panel regression		
	COORD_PROX	COORD_PORT
Size	-0.0715***	-0.0361
	(-10.97)	(-38.36)
BM	0.0346***	-0.0025**
	(4.25)	(-2.35)
Beta	-0.0257***	-0.0071***
	(-3.86)	(-8.10)
ROA	0.0684**	0.0088**
	(2.55)	(2.48)
Leverage	0.1655***	0.01744***
	(4.63)	(3.16)

Sale_Growth	-0.0189***	0.0021***
	(-3.40)	(2.91)
Firm_age	0.0590***	-0.0082***
	(5.78)	(-6.10)
IO	-0.1388***	-0.1480***
	(-3.42)	(-28.18)
IO_HHI	3.9945***	2.6079***
	(10.44)	(43.48)
BHRET12	-0.0014	0.0021***
	(-0.25)	(3.11)
Turnover	0.3579***	-0.0027
	(8.78)	(-0.49)
Analyst	-0.0557***	-0.0072***
	(-5.67)	(-5.65)
Dividend	-0.0095	-0.0013
	(-0.67)	(-0.64)
Dist_Inst_Headquarter	-0.3760***	-0.0271***
	(-51.72)	(-34.81)
Constant	-3.3397***	0.8907***
	(-30.32)	(64.46)
Time FE	Yes	Yes
Industry FE	Yes	Yes
MSA_City_FE	Yes	Yes
Observations	213,517	213,517
R ²	0.629	0.782

Panel B: Correlation matrix				
		Correlation matrix (Pearson's correlations)		
	COORD_PROX	COORD_PORT	RES_COORD_PROX	RES_COORD_PORT
COORD_PROX	1			
COORD_PORT	0.6477	1		
RES_COORD_PROX	0.6932	0.1964	1	
RES_COORD_PORT	0.2424	0.5617	0.3496	1

Panel C: Shareholder coordination and synchronization in institutional training		
	(1)	(2)
RES_COORD_PROX	-0.1333***	
	(-3.78)	
RES_COORD_PORT		-1.7141***
		(-5.19)
Size	1.5916***	1.5896***
	(36.67)	(36.70)
BM	0.2830***	0.2810***
	(4.63)	(4.60)

IO	2.5886***	2.5811***
	(8.20)	(8.16)
IO_HHI	-17.4762***	-17.4975***
	(-6.56)	(-6.53)
Turnover	9.0168***	9.0150
	(21.89)	(21.90)
Ret (-2, -7)	0.0624	0.0621
	(1.28)	(1.27)
Constant	-21.6855***	-21.6527***
	(-44.71)	(-44.77)
Time FE	Yes	Yes
Industry FE	Yes	Yes
Observations	213,517	213,517
R ²	0.128	0.128

***, **, * indicate a two-tailed test significance at the 0.01, 0.05 and 0.10 level, respectively.

Finally, if our measures of institutional shareholder coordination capture the strength of links between institutions within an information-sharing network, they should be positively associated with the degree of synchronization in institutional trading. In other words, if higher coordination leads to greater harmony of institutional investors' information sets about a particular firm's stock performance, we should observe greater synchronization across institutional shareholders' trades leading to lower diversity in changes of institutional shareholder stakes. We test whether this is indeed the case by examining the relation between our residual coordination measures and the SD of the changes in the quarterly stakes of a firm's different institutional shareholders, controlling for other firm characteristics. Panel C of Table 2 shows a strong relation between coordination and synchronization in institutional trading. This provides support for the notion that our residual coordination measures indeed capture the ability of institutions to share market value-relevant information about the firm.

4. Empirical results

Shareholder coordination and information environment

Colla and Mele (2010) find that price informativeness increases in the presence of information-sharing networks among individual traders. Pareek (2012) finds that strength of information-sharing networks between mutual fund managers affects the response time of stock prices to market-wide information. We examine whether information-sharing networks that facilitate coordination among institutional investors affect price efficiency. More specifically, we examine the impact of shareholder coordination on local comovement of stock returns and post-earnings announcement drift. Pirinsky and Wang (2006) document that stock returns exhibit strong local comovement and attribute the phenomenon to the trading pattern of local residents whose information sets are effectively segmented from that of outside investors.⁶ If firms with stronger information-sharing networks adjust to common information faster, then stock price will be more informative, indicating lower local comovement of stock returns.

Therefore, we hypothesize that firms with high shareholder coordination have a low degree of comovement with local stocks. To test this hypothesis, following Pirinsky and Wang (2006), we construct local stock return indices for each MSA by equally weighting the returns of all stocks within each MSA. To obtain the sensitivity of stock returns to local stock return indices, we estimate time

series regressions of monthly stock returns on the returns of the corresponding local index and the market portfolio for each stock. Specifically, we estimate the following model:

$$R_{i,t} = \alpha_i + \beta_i^{local} R_t^{local} + \beta_i^{market} R_t^{market} + \varepsilon_{i,t}$$

(4)

where $R_{i,t}$ is the monthly return of stock i , R_t^{local} is the monthly return of the stock's corresponding MSA local stock returns index, and R_t^{market} is the monthly return of the market portfolio. All returns are in excess of monthly Treasury bill rates. To avoid spurious correlations, we exclude the return of stock i when we construct the local stock returns indices. After we obtain β_i^{local} for each stock, we then regress it on shareholder coordination and other variables that capture firm and regional characteristics that correlate with local bias. Specifically, we control for size (the natural logarithm of market capitalization at the end of the previous year), leverage (the ratio of total debt to asset), MB (market to book ratio equity ratio), ROA, advertising (advertising expenditures), the number of shareholders (the natural logarithm of number of shareholders), and IO (institutional ownership). We include as controls regional characteristics, such as the industry agglomeration by MSA (Industry HHI, a Herfindahl index), investment income (the per capita investment income in an MSA), and personal income (the per capita personal income in an MSA).

The results in Panel A of Table 3 indicate that shareholder coordination has a strong negative impact on local comovement. Take RES_COORD_PORT, for example, a 10% increase in shareholder coordination results in an approximate 5.5 percentage decline in local beta, ceteris paribus. The results still hold after the inclusion of regional characteristics. Consistent with the findings in Pirinsky and Wang (2006), we also find a negative effect of size, ROA, and industry concentration on local beta. In contrast, the institutional ownership coefficient is negative, albeit not statistically significant. To further justify our shareholder coordination measures, we identify a mechanism that facilitates information incorporation into stock prices, namely stock liquidity (O'Hara, 2003). More specifically, we speculate that the impact of information-sharing networks on price efficiency will be enhanced when stocks are more liquid. Stock liquidity encourages informed investors to trade value-relevant information in large volumes so that firms with strong information-sharing networks will adjust to the common information even faster. We use the decimalization in early 2001 as an exogenous shock to stock liquidity. The main variable of interest is the interaction term between shareholder coordination and decimalization dummy variable. Panel B of Table 3 shows these results. The coefficient estimates on the interaction term between shareholder coordination and decimalization indicate that the impact of information-sharing networks on price efficiency is enhanced when stocks are more liquid. This result provides support for the view that our main variables indeed capture coordination among institutional shareholders.

Table 3. Cross-sectional determinants of local comovement

In Panel A, for each firm in the sample, we estimate time series regressions of monthly stock returns on the returns of a local index and the market portfolio for three periods: 1994–1999, 2000–2004, and 2005–2010. We then regress the estimated local beta on firm and regional characteristics. The main independent variable of interest is shareholder coordination (RES_COORD_PROX / RES_COORD_PORT). In Panel B, we estimate time series regressions of monthly stock returns on the returns of a local index and the market portfolio for two periods: pre- and post-decimalization. Decimalization is an indicator variable that takes the value 1 for firm years with fiscal year ends after January 2001. Dividend yield is the dividend payout divided by the market value of

equity; MTB is the market to book ratio. Advertising is the natural logarithm of advertising expenditures. Number of shareholders is the natural logarithm of number of shareholders. Number of firms is the total number of firms in one MSA; Industry HHI is the Herfindahl index calculated based on the percentage of firms in one industry for an MSA; Personal income is the per capita personal income for the MSA; Investment income is the per capita investment income for the MSA. Other control variables are defined in Table 1. All independent variables are the averages over the three periods. Time fixed effects are also included. t-Statistics are reported in parentheses below coefficient estimates.

Panel A: Determinants of local comovement		
	(1)	(2)
RES_COORD_PROX	-0.0208*	
	(-1.66)	
RES_COORD_PORT		-0.4221***
		(-3.82)
Size	-0.0954***	-0.0968***
	(-12.70)	(-12.88)
MB	0.0000	0.0000
	(0.13)	(0.13)
Dividend yield	0.0328	0.0335
	(0.49)	(0.50)
Leverage	0.1043**	0.1056**
	(2.34)	(2.37)
ROA	-0.4619***	-0.4614***
	(-17.25)	(-17.24)
Advertising	0.0010	0.0010
	(0.83)	(0.84)
Number of shareholders	0.0049	0.0054
	(0.83)	(0.92)
IO	-0.0339	-0.0365
	(0.072)	(-0.78)
Industry HHI	-0.4049***	-0.4030***
	(-11.66)	(-11.61)
Number of firms	0.0013***	0.0013***
	(12.02)	(12.06)
Investment income	-0.1782**	-0.1798**
	(-2.15)	(-2.17)
Personal income	0.1520**	0.1534**
	(2.20)	(2.22)
Constant	2.4656***	2.4885***
	(19.96)	(20.13)
Observations	11,430	11,430
R ²	0.112	0.113

Panel B: Effects of decimalization				
	(1)	(2)	(3)	(4)
RES_COORD_PROX*Decimalization		-0.1046***		
		(-3.16)		

RES_COORD_PROX	-0.0417***	-0.0084		
	(-2.71)	(-0.45)		
RES_COORD_PORT*Decimalization				-0.5266**
				(-2.05)
RES_COORD_PORT			-0.5506***	-0.3487**
			(-4.38)	(-2.19)
Decimalization		-0.0362*		-0.0346
		(-1.67)		(-1.59)
Size	-0.0880***	-0.0860***	-0.0902***	-0.0887***
	(-10.79)	(-10.53)	(-11.03)	(-10.84)
MB	0.0000	0.0000	0.0000	0.0000
	(0.12)	(0.11)	(0.10)	(0.06)
Dividend yield	-0.0566	-0.0530	-0.0591	-0.0573
	(-0.89)	(-0.83)	(-0.93)	(-0.90)
Leverage	0.0201	0.0166	0.0197	0.0172
	(0.53)	(0.44)	(0.52)	(0.45)
ROA	-0.3574***	-0.3622***	-0.3573***	-0.3621***
	(-14.67)	(-14.72)	(-14.67)	(-14.72)
Advertising	0.0002	0.0005	0.0002	0.0005
	(0.11)	(0.37)	(0.13)	(0.38)
Number of shareholders	-0.0006	-0.0018	0.0000	-0.0007
	(-0.09)	(-0.27)	(0.00)	(-0.10)
IO	-0.0317	-0.0143	-0.0284	-0.0203
	(-0.59)	(-0.26)	(-0.53)	(-0.37)
Industry HHI	-0.4154***	-0.4189***	-0.4138***	-0.4174
	(-10.99)	(-11.06)	(-10.95)	(-11.03)
Number of firms	0.0013***	0.0012***	0.0013***	0.0012***
	(10.56)	(9.94)	(10.57)	(9.95)
Investment income	-0.0546	-0.0721	-0.0543	-0.0722
	(-0.58)	(-0.77)	(-0.58)	(-0.77)
Personal income	0.0494	0.0638	0.0493	0.0639
	(0.64)	(0.82)	(0.63)	(0.82)
Constant	2.3980***	2.3845***	2.4340***	2.4305***
	(17.76)	(17.59)	(17.99)	(17.88)
Observations	8,443	8,443	8,443	8,443
R ²	0.114	0.115	0.115	0.116

***, **, * indicate a two-tailed test significance at the 0.01, 0.05 and 0.10 level, respectively.

Next, we examine whether shareholder coordination plays a role in explaining post-earnings announcement drift. Earnings surprises are measured as the difference between actual earnings as reported by I/B/E/S ($e_{i,q}$) and consensus earnings forecast ($F_{i,q}$), defined as the median of forecasts reported to I/B/E/S in the 90-day period prior to the earnings announcement. We then normalize the difference by the stock price at the end of the corresponding quarter q :⁷

$$UE_FERROR_{i,q} = \frac{e_{i,q} - F_{i,q}}{P_{i,q}}$$

(5)

If an analyst made multiple forecasts during a 90-day period, we use the most recent earnings forecast.

The cumulative abnormal returns over the post-announcement window from day 2 to 61 (BHAR[2, 61]) are defined as the difference between the buy-and-hold return of the announcing firm and that of a size and book-to-market matching portfolio over the window [2, 61]⁸ in trading days relative to the announcement date.

$$BHAR[2, 61]_{i,q} = \prod_{k=t+2}^{t+61} (1 + R_{i,k}) - \prod_{k=t+2}^{t+61} (1 + R_{p,k})$$

(6)

where $R_{i,k}$ and $R_{p,k}$ are the return of firm i and the return of size and book-to-market matching portfolio on day k relative to the announcement date t in quarter q .

Over the period from 1994 to 2010, we perform quarterly sorts based on each firm's earnings surprises. We independently sort stocks into quintiles based on the most recent corresponding shareholder coordination. We run a regression of 60-day post-announcement abnormal returns (BHAR[2, 61]) on the earnings surprise quintile rank (ES), the shareholder coordination quintile rank (RES_COORD_Rank), the interaction term $ES \times RES_COORD_Rank$, and control variables, also interacted with ES. We suggest that the post-announcement return is less sensitive to earnings news when information-sharing networks are strong. Thus, we expect that the coefficient estimate of the interaction term $ES \times RES_COORD_Rank$ is significantly negative. Previous research shows that investor reactions to earnings news vary with firm size, book-to-market, market beta, number of analysts following, institutional ownership, institutional ownership concentration, earnings volatility, share turnover and number of announcements on an earnings announcement day (Chambers and Penman, 1984; Hirshleifer, Lim and Teoh, 2009). Thus, we include these variables as control variables in the regressions.

Table 4. Shareholder coordination and post-earnings announcement drift

For each quarter from 1994 to 2010, we sort firms into quintiles based on corresponding earnings surprises proxied by analyst forecast error (FE). ES is the earnings surprise quintile (ES=1: lowest, 5: highest). We further independently sort firms into quintiles based on shareholder coordination. RES_COORD_Rank is the shareholder coordination quintile (RES_COORD_Rank = 1: lowest, 5: highest). We calculate the buy-and-hold cumulative abnormal return over the window [2, 61] relative to announcement date for each firm-quarter. The buy-and-hold cumulative abnormal returns are defined as the difference between the buy- and-hold return of the announcing firm and that of a size and book-to-market (BM) matching portfolio. Control variables include size and book-to-market deciles, market beta (Beta), analyst coverage (log (1 + # Analysts)), institutional ownership (IO), institutional ownership concentration (IO_HHI), earnings volatility (Volatility), share turnover (Turnover), number of announcements on an earnings announcement day (# Announcement) and indicator variables for year, month, day of week, and industry classification (Fama-French 48 industry classification). All control variables are interacted with ES. t -Statistics adjusted for heteroskedasticity and clustering by the day of announcement are reported in parentheses below coefficient estimates.

	RES_COORD_PROX		RES_COORD_PORT	
Variables	(1)	(2)	(3)	(4)
ES*RES_COORD_Rank	-0.0010***	-0.0009***	-0.0094***	-0.0185***

	(-16.63)	(-11.75)	(-2.67)	(-4.63)
ES*RES_COORD_RANK*Decimalization		-0.0001		-0.0201***
		(-1.57)		(-4.72)
RES_COORD_RANK	0.0071***	0.0071***	0.0019***	0.0017***
	(15.64)	(15.63)	(3.61)	(3.24)
ES	0.0076***	0.0076***	0.0055**	0.0055**
	(2.93)	(2.93)	(2.15)	(2.13)
Controls, interacted with ES	Yes	Yes	Yes	Yes
Constant	-0.1839***	-0.1860***	-0.1806***	0.1806***
	(-9.91)	(-9.97)	(-9.73)	(-9.73)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	125,531	125,531	125,531	125,531
R ²	0.078	0.078	0.075	0.075

***, **, * indicate a two-tailed test significance at the 0.01, 0.05 and 0.10 level, respectively.

Columns 1 and 3 of Table 4 report the results. Consistent with our prediction, the coefficient estimates on the interaction term $ES \times RES_COORD_Rank$ are significantly negative, which indicates that post-earnings announcement drift is weaker (stronger) when information-sharing networks are stronger (weaker). In a similar spirit, we examine the role of stock liquidity in the impact of shareholder coordination on post-earnings announcement drift. We suggest that as stock liquidity increases, the negative effect of shareholder coordination on the sensitivity of stock returns to earnings surprises becomes stronger. Therefore, the coefficient estimate of the triple interaction term $ES \times RES_COORD_Rank \times Decimalization$ should be negatively significant. The results in columns 2 and 4 of Table 4 show some supporting evidence. Although the coefficient estimate of the triple interaction term $ES \times RES_COORD_Rank \times Decimalization$ is not significant for the geographic-proximity-based shareholder coordination measure (RES_COORD_PROX), we find that it is significantly negative for the portfolio-correlation-based shareholder coordination measure (RES_COORD_PORT).

Shareholder coordination and information diffusion

We examine whether shareholder coordination serves as an information transmission channel thereby giving rise to lead-lag return phenomena between firms with strong and weak information-sharing networks. Social network literature suggests that informal ties are likely to develop when there is homophily, that is, the tendency of individuals to associate and bond with others driven by familiarity, often rooted in geographic proximity or the sharing of common values (McPherson, Smith-Lovin and Cook, 2001). The stronger the informal ties among institutional shareholders, the more likely they are to build up information-sharing networks that facilitate the diffusion of value-relevant information into the market. Accordingly, stock prices of firms with high shareholder coordination will respond faster to information shocks than firms with low shareholder coordination. We hypothesize that there exists a lead-lag effect wherein stock returns of firms with high levels of shareholder coordination will lead those of firms with low shareholder coordination.

We test the aforementioned return predictability implications of slow information diffusion as it pertains to both industry and market-wide information. We start with testing return predictability arising from slow diffusion of industry information. At the end of June in each year, we first sort firms into 144 portfolios corresponding to the 48 Fama-French industry portfolios, each split into three size portfolios (i.e., $48 \times 3 = 144$). We further independently sort firms into two portfolios based on whether the average residual shareholder coordination over the past four quarters was high (i.e., ranking in the top coordination tercile) or low (i.e., ranking in the bottom coordination tercile). This sorting technique insulates our results from the previously documented intraindustry lead-lag effect that exists between big and small firms (Lo and MacKinlay **1990**; Hou, **2007**). We then use the high coordination portfolios as the benchmarks and match them with stocks in the low coordination portfolios within each industry-size portfolio. The performance of each benchmark portfolio is measured by averaging the stock returns of firms each month. Following Cohen and Lou (**2012**), at the beginning of each month (starting in July), we sort stocks in low coordination portfolios into quintiles based on the returns of their corresponding high coordination benchmarks in the previous month. The quintile portfolios are rebalanced at the beginning of each month.

We employ the Fama-French-Carhart four-factor model that includes the market, size, book-to-market and momentum factors to examine the risk-adjusted return performance of portfolios (Fama and French, 1992, 1993; Carhart, 1997).

$$R_m^P - R_m^F = \beta_0 + \beta_1(R_m^M - R_m^F) + \beta_2SMB_m + \beta_3HML_m + \beta_4UMD_m + e_m$$

(7)

where R_m^P is a particular portfolio's monthly return, R_m^F is the one-month Treasury bill rate, R_m^M is the value-weighted market return, SMB (small minus big) is the difference between the monthly returns of the small and big firms' portfolios, HML (high minus low) is the difference between the monthly returns of high book-to-market and low book-to-market firms' portfolios, and UMD (up minus down) is the momentum factor computed as the monthly return differential between a portfolio of winners and a portfolio of losers. For the test of the performance on zero-cost investment portfolios, we also use the same four-factor model:

$$R_m^H - R_m^L = \beta_0 + \beta_1(R_m^M - R_m^F) + \beta_2SMB_m + \beta_3HML_m + \beta_4UMD_m + e_m$$

(8)

where R_m^H is the monthly return of the portfolio with stocks in the top shareholder coordination quintile, and R_m^L is the monthly return of the portfolio with stocks in the bottom shareholder coordination quintile.

If shareholder coordination serves as an information diffusion channel, the information update in stock prices of high coordination firms should predict the information update in stock prices of low coordination firms. We test this prediction in Table 5. As we can see, we find strong evidence consistent with the notion that shareholder coordination affects the speed at which information is impounded into stock prices. After controlling other common stock returns determinants, such as the market excess return (MKTRF), size (SMB), book-to-market (HML), and momentum (UMD), the zero-cost investment portfolio that buys (sells) low coordination firms whose corresponding high coordination

benchmarks performed best (worst) in the prior month has a value-weighted return of 69 basis points ($t = 1.76$) for RES_COORD_PROX and 58 basis points ($t = 1.92$) for RES_COORD_PORT per month, roughly 8.6% and 7.2% per year.

Table 5. Stock return predictability time series test: FF48 \times 3Size = 144 portfolios

At the end of June in each year from 1994 to 2010, we first sort firms into three size portfolios within each Fama-French 48 industries. The firms are independently sorted into three portfolios based on the simple average of shareholder coordination over the past four quarters. We then construct the clone firm for each low shareholder coordination firm (firms in bottom tercile) with the portfolio of firms with high shareholder coordination (stocks in top tercile) in the same industry-size portfolio. At the beginning of every calendar month, all low shareholder coordination firms are ranked into quintiles in an ascending order on the basis of stock returns of their corresponding clone firms in the previous month. All stocks are value-weighted within a given portfolio, and the portfolios are rebalanced every calendar month. Panels A and B report the results for RES_COORD_PROX and RES_COORD_PORT, respectively. The explanatory variables are MKTRF (the value-weighted market return in excess of one-month Treasury bill rate), SMB (small minus big is the difference between the monthly returns of the small and big firms' portfolios), HML (the monthly difference of the returns on a portfolio of high book-to-market and low book-to-market firms), and UMD (the momentum factor computed on a monthly basis as the return difference between a portfolio of winners and a portfolio of losers). LIQ is the monthly innovation in aggregate liquidity. High/Low is the zero-cost investment portfolio of low shareholder coordination firms that longs the clone firms with the top quintile returns and shorts the clone firms with the bottom quintile returns in the previous month. t -Statistics are reported in parentheses below coefficient estimates.

<i>Panel A:</i>							
<i>RES_COORD_PROX</i>							
	Constant	MKTRF	SMB	HML	UMD	LIQ	R^2
Low	-0.0016 (-0.44)	1.2164*** (15.50)	0.5946*** (6.25)	-0.0304 (-0.30)	-0.3660*** (-5.98)	-0.0409 (-0.95)	0.733
2	-0.0027 (-1.01)	1.0581*** (15.65)	0.5227*** (6.38)	-0.0832 (-0.94)	-0.2074*** (-3.93)	-0.1516*** (-4.07)	0.719
3	0.0025 (0.73)	1.0648*** (14.40)	0.7330*** (8.18)	-0.1386 (-1.44)	-0.2751*** (-4.77)	-0.0154 (-0.38)	0.730
4	0.0043* (1.77)	0.9298*** (17.76)	0.6282*** (9.90)	-0.0194 (-0.28)	-0.0819** (-2.01)	0.0600** (2.08)	0.786
High	0.0053** (2.05)	0.9557*** (13.07)	0.8450*** (9.53)	0.1336 (1.40)	-0.1321** (-2.32)	0.0237 (0.59)	0.687
High -- Low	0.0069* (1.76)	-0.2607** (-2.12)	0.2504* (1.68)	0.1640 (1.02)	0.2339** (2.44)	0.0646 (0.95)	0.091
<i>Panel B:</i>							
<i>RES_COORD_PORT</i>							
	Constant	MKTRF	SMB	HML	UMD	LIQ	R^2
Low	-0.0007 (-0.32)	1.1993*** (23.61)	0.3842*** (6.24)	-0.1109* (-1.68)	-0.0532 (-1.34)	-0.0117 (-0.42)	0.830
2	0.0018 (0.52)	1.0102*** (13.13)	0.5848*** (6.27)	0.1221 (1.22)	-0.3806*** (-6.34)	-0.0466 (-1.10)	0.680
3	0.0028 (1.03)	1.1947*** (20.49)	0.3332*** (4.71)	0.1165 (1.53)	-0.2193*** (-4.82)	-0.0150 (-0.47)	0.789
4	0.0025 (0.86)	1.0173*** (16.39)	0.7585*** (10.08)	0.2197*** (2.72)	0.0352 (0.73)	-0.0055 (-0.16)	0.734
High	0.0050**	0.6491***	0.3645***	0.0635	-0.0042	-0.0099	0.757

	(2.58)	(15.41)	(7.14)	(1.16)	(-0.13)	(-0.43)	
High -- Low	0.0058*	-0.5502***	-0.0198	0.1744**	0.0491	0.0018	0.386
	(1.92)	(-8.47)	(-0.25)	(2.06)	(0.97)	(0.05)	

***, **, * indicate a two-tailed test significance at the 0.01, 0.05 and 0.10 level, respectively.

Next, we test the information diffusion hypothesis in a more general setting where we use test assets more appropriate for testing whether coordination can affect the diffusion of market-wide rather than industry-specific, value-relevant information. Specifically, at the end of June in each year, we sort firms into 125 portfolios (DGTW 125) based on size, book-to-market, and momentum characteristics (Daniel, Grinblatt, Titman and Wermers, 1997). We independently sort firms based on shareholder coordination and identify the portfolio of stocks with high shareholder coordination (top coordination tercile) and the matching portfolio of otherwise similar stocks with low shareholder coordination (bottom coordination tercile). This sorting and matching technique isolates the impact of stock characteristics and allows us to test whether market-wide information shocks travel from prices of firms with high shareholder coordination to those of firms with low shareholder coordination. We replicate the tests in Table 5 using the DGTW 125 portfolios as test assets and report the results in Table 6. As we can see, there is again strong evidence that shareholder coordination serves as an information diffusion channel. Take RES_COORD_PROX, for example: after controlling other common factors, the zero-cost investment portfolio that buys (sells) low coordination firms whose corresponding high coordination benchmarks performed best (worst) in the prior month delivers a value-weighted return of 68 basis points ($t = 2.04$) per month, about 8.5% per year. Finally, RES_COORD_PORT generates quantitatively similar results. Given transaction costs associated with monthly portfolio rebalancing (Novy-Marx and Velikov, 2016), we believe that the net annual return of zero-cost investment portfolios will not be as large as the gross return documented in this paper.

Table 6. Stock return predictability time series test: DGTW 125 portfolios

At the end of June in each year from 1994 to 2010, we independently sort firms into the DGTW 125 portfolios and three portfolios based on the simple average of shareholder coordination over the past four quarters. We then construct the clone firm for each low shareholder coordination firm (firms in bottom tercile) with the portfolio of high shareholder coordination firms (stocks in top tercile) within the same DGTW 125 portfolios. At the beginning of every calendar month, all low shareholder coordination firms are ranked into quintiles in an ascending order on the basis of stock returns of their corresponding clone firms in the previous month. All stocks are value-weighted within a given portfolio, and the portfolios are rebalanced every calendar month. Panels A and B report the results for RES_COORD_PROX and RES_COORD_PORT, respectively. The explanatory variables are MKTRF (the value-weighted market return in excess of one-month Treasury bill rate), SMB (small minus big is the difference between the monthly returns of the small and big firms' portfolios), HML (the monthly difference if the returns on a portfolio of high book-to-market and low book-to-market firms), and UMD (the momentum factor computed on a monthly basis as the return difference between a portfolio of winners and a portfolio of losers). LIQ is the monthly innovation in aggregate liquidity. High/Low is the zero-cost investment portfolio of firms with low coordination that longs the clone firms with the top quintile returns and shorts the clone firms with the bottom quintile returns in the previous month. t -Statistics are reported in parentheses below coefficient estimates.

<i>Panel A:</i>							
<i>RES_COORD_PROX</i>							
	Constant	MKTRF	SMB	HML	UMD	LIQ	R^2
Low	-0.0010	1.0584***	0.6229***	0.0212	-0.3624***	0.0481	0.748

	(-0.32)	(14.84)	(7.22)	(0.23)	(-6.69)	(1.24)	
2	0.0018	0.8909***	0.4981***	-0.1483*	-0.0942**	0.0099	0.702
	(0.63)	(14.24)	(6.58)	(-1.81)	(1.98)	(0.29)	
3	0.0035	0.9405***	0.4916***	0.0129	-0.3392***	-0.0285	0.738
	(1.20)	(14.85)	(6.42)	(0.16)	(-7.05)	(-0.83)	
4	0.0038	1.0310***	0.5974***	0.0007	-0.3365***	-0.0407	0.753
	(1.25)	(15.49)	(7.42)	(0.01)	(-6.66)	(-1.13)	
High	0.0058***	1.0758***	0.5184***	0.1454**	-0.1770***	0.0256	0.838
	(2.62)	(22.42)	(8.93)	(2.31)	(-4.86)	(0.98)	
High-Low	0.0068**	0.0174	-0.1045	0.1242	0.1854***	-0.0225	0.053
	(2.04)	(0.19)	(-0.96)	(1.05)	(2.71)	(-0.46)	
<i>Panel B:</i>							
<i>RES_COORD_PORT</i>							
	Constant	MKTRF	SMB	HML	UMD	LIQ	R^2
Low	-0.0022	1.1131***	0.3928***	0.3011***	-0.2794***	-0.0638**	0.782
	(-0.89)	(20.72)	(5.99)	(4.24)	(-6.82)	(-2.19)	
2	-0.0019	1.2363***	0.4781***	0.0453	-0.1518***	-0.0468	0.782
	(-0.70)	(20.28)	(6.42)	(0.56)	(-3.26)	(-1.41)	
3	0.0004	1.0174***	0.5362***	0.1975***	-0.2091***	0.0296	0.799
	(0.18)	(19.89)	(8.58)	(2.92)	(-5.36)	(1.07)	
4	0.0011	1.0970***	0.7200***	0.2093***	-0.2900***	0.0049	0.825
	(0.46)	(20.43)	(10.98)	(2.95)	(-7.08)	(0.17)	
High	0.0047**	1.0362***	0.7002***	0.2960***	-0.3380***	0.0102	0.821
	(2.14)	(19.64)	(10.87)	(4.24)	(-8.40)	(0.36)	
High-Low	0.0069**	-0.0769	0.3074	-0.0051	-0.0586	0.0740*	0.086
	(2.14)	(-1.10)	(3.58)	(-0.05)	(-1.09)	(1.94)	

***, **, * indicate a two-tailed test significance at the 0.01, 0.05 and 0.10 level, respectively.

We then test our hypothesis in a cross-sectional framework, using Fama-MacBeth regressions (Fama and MacBeth, 1973). The dependent variable is the stock return for low shareholder coordination firms in month t (Ret_t). The main independent variable is the stock return of the high shareholder coordination benchmark in month $t - 1$ (i.e., the return of a “clone” portfolio of otherwise similar firms with high coordination, $Clone_ret_{t-1}$). Other independent variables include the low shareholder coordination firm's own return in month $t - 1$ (Ret_{t-1}) to control for the short-term reversal effect (Jegadeesh, 1990). To mitigate the concern that our findings could be driven by industry momentum effects documented in Moskowitz and Grinblatt (1999), we include lagged value-weighted industry returns (Ind_ret_{t-1}). We also control for firm size (Size), BM, Beta, momentum ($Ret(-2,-7)$), and liquidity (Turnover and CV_Turnover). We run cross-sectional regressions every month and adjust the times series standard errors for heteroskedasticity and autocorrelation up to 12 lags (Newey and West, 1987). Consistent with the portfolio results, we find that $Clone_ret_{t-1}$ is a strong and significant predictor of next month's stock return of matched low shareholder coordination firms. Take, for example, RES_COORD_PROX in specification 1, in Panel A of Table 7: the coefficient on $Clone_ret_{t-1}$ is 0.0233 with a t -statistics of 2.37, indicating that one SD increase in the high coordination benchmark portfolio return in the month $t - 1$ leads to a 26 basis point increase in the return of low shareholder coordination firms in month t . In short, both our time series and cross-sectional tests provide strong,

consistent evidence in support of the hypothesis that good (poor) institutional shareholder coordination facilitates (slows) the diffusion of information into market prices.

Table 7. Stock return predictability cross-sectional test: Fama-MacBeth regressions

This table reports Fama-MacBeth forecasting regressions of stock returns. The dependent variable is the monthly stock return of the firms with low shareholder coordination. In Panel A, columns 1 and 3, the main independent variable is the lagged monthly return of corresponding clone firms (Clone_ret) constructed using the portfolio of firms with high coordination in the same industry-size portfolio at the end of each June. In Panel A, columns 2 and 4, we further include the monthly return of corresponding clone firms at deeper lags (e.g., month $t - 2$ and month $t - 3$). In Panel A, columns 5 and 7, the main independent variable is the lagged monthly return of corresponding clone firms (Clone_ret) constructed using the portfolio of firms with high coordination in the same DGTW 125 portfolio at the end of each June. In Panel A, columns 6 and 8, we further include the monthly return of corresponding clone firms at deeper lags (e.g., month $t - 2$ and month $t - 3$ of Panel A with additional control variables: IO_ret $_{t-1}$ (lagged monthly return on the portfolio of firms with highest institutional ownership (top quintile) or Analyst_ret $_{t-1}$ lagged monthly return on the portfolio of firms with largest analyst coverage (top quintile). Panel C reports the results of the replication of Panel A with wee data. Refer to Table 1 for detailed variable definitions. Cross-sectional regressions are run every calendar month or week and the time series standard errors are adjusted for heteroskedasticity and autocorrelation (up to 12 lags). t -Statistics are reported in parentheses below coefficient estimates.

Panel A: Fama- MacBeth regressions								
	FF48 3SIZE				DGTW125			
	RES_COORD_PRO X		RES_COORD_POR T		RES_COORD_PRO X		RES_COORD_POR T	
	1	2	3	4	5	6	7	8
Clone_ret $_{t-1}$	0.0233**	0.0225**	0.0251***	0.0229**	0.0195***	0.0217** *	0.0151*	0.0137*
	(2.37)	(2.35)	(2.75)	(2.53)	(2.65)	(2.97)	(1.84)	(1.66)
Clone_ret $_{t-2}$		0.0166		0.0110		-0.0003		0.0070
		(1.02)		(1.31)		(-0.04)		(0.85)
Clone_ret $_{t-3}$		0.0050		0.0126		-0.0048		0.0026
		(0.60)		(0.75)		(-0.60)		(0.16)
Ind_ret $_{t-1}$	0.0731***	0.0736** *	0.0433**	0.0452**	0.0751***	0.0695** *	0.0848***	0.0848** *
	(3.79)	(3.66)	(2.17)	(2.33)	(4.09)	(3.72)	(3.29)	(3.22)
Size	-0.0036***	- 0.0036** *	-0.0034***	- 0.0031** *	-0.0019**	-0.0018**	-0.0034***	- 0.0033** *
	(-3.64)	(-3.60)	(-3.15)	(-2.86)	(-2.15)	(-2.02)	(-3.66)	(-3.50)
BM	0.0010	0.0010	0.0007	0.0007	0.0008	0.0008	0.0007	0.0009
	(1.00)	(1.01)	(0.721)	(0.70)	(0.95)	(0.88)	(0.79)	(1.04)

Beta	0.0022 (1.21)	0.0021 (1.17)	0.0011 (0.60)	0.0011 (0.62)	0.0015 (1.06)	0.0015 (1.06)	0.0015 (1.04)	0.0015 (1.09)
Ret (-2, -7)	0.0060 (1.37)	0.0060 (1.37)	0.0057 (1.30)	0.0055 (1.25)	0.0102*** (3.21)	0.0103** * (3.22)	0.0098*** (3.59)	0.0098** * (3.60)
Ret _{t-1}	-0.0546*** (-8.12)	- 0.0541** * (-7.93)	-0.0534*** (-8.40)	- 0.0528** * (-8.06)	-0.0486*** (-9.05)	- 0.0471** * (-8.76)	-0.0429*** (-9.32)	- 0.0428** * (-9.29)
Turnover	0.0002 (0.15)	0.0001 (0.07)	0.0002 (0.11)	-0.0002 (-0.14)	-0.0002 (-0.13)	-0.0003 (-0.20)	-0.0024* (-1.97)	-0.0024* (-1.92)
CV_Turnover	-0.0065*** (-3.60)	- 0.0068** * (-3.75)	-0.0061*** (-3.94)	- 0.0059** * (-3.77)	-0.0064*** (-4.50)	- 0.0058** * (-3.99)	-0.0076*** (-4.96)	- 0.0078** * (-4.98)
Constant	0.0492*** (3.29)	0.0480** * (3.15)	0.0471*** (2.91)	0.0424** (2.60)	0.0290** (2.20)	0.0278** (2.07)	0.0428** (3.17)	0.0438** * (3.15)
Observations	199,206	195,546	199,206	195,546	190,417	181,237	190,417	181,237
Adjusted R ²	0.050	0.050	0.031	0.026	0.046	0.046	0.047	0.047
<i>Panel B: Fama- MacBeth regressions with additional control variables</i>								
	FF48 3SIZE				DGTW 125			
	RES_COORD_PRO X		RES_COORD+POR T		RES_COORD_PRO X		RES_COORD_POR T	
	1	2	3	4	5	6	7	8
Clone_ret _{t-1}	0.01910* (1.88)	0.0243** (2.35)	0.0212** (2.28)	0.0252** (2.59)	0.0200* (1.97)	0.0211** (2.25)	0.0119 (1.29)	0.0164* (1.68)
Analyst_ret _{t-1}	0.0291 (1.44)		0.0331* (1.72)		0.0041 (0.22)		0.0115 (0.70)	

IO_ret _{t-1}		0.0019		0.0035		0.0009		-0.0160
		(0.12)		(0.23)		(0.06)		(-0.98)
Ind_ret _{t-1}	0.0701***	0.0738** *	0.0418**	0.0432**	0.0843***	0.0852** *	0.0709***	0.0711** *
	(3.67)	(3.80)	(2.11)	(2.18)	(4.08)	(4.12)	(3.56)	(3.57)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.0538***	0.0517** *	0.0507***	0.0497** *	0.0594***	0.0570** *	0.0771***	0.0760** *
	(3.59)	(3.48)	(3.13)	(3.09)	(3.69)	(3.59)	(4.55)	(4.54)
Observations	199,206	199,206	199,206	199,206	190,417	190,417	190,417	190,417
Adjusted R ²	0.050	0.050	0.050	0.050	0.050	0.050	0.042	0.047

***, **, * indicate a two-tailed test significance at the 0.01, 0.05 and 0.10 level, respectively.

The results from the time series tests in Tables 5 and 6 and from the cross-sectional tests in columns 1, 3, 5 and 7 of Table 7, Panel A, document a lead-lag effect in asset prices between firms with high and low shareholder coordination. This implies that investors gradually update prices of firms lacking coordination based on observation of prices of firms with coordination. The natural question to ask is how long this information flow process lasts. In columns 2, 4, 6 and 8 of Table 7, Panel A, we test whether stock returns of high shareholder coordination benchmarks in deeper lags (e.g., month $t - 2$ and month $t - 3$) have the ability to predict current stock returns of firms with low shareholder coordination. The tests are conducted for both industry-level (columns 2 and 4) and market-level information shocks (columns 6 and 8), that is, using the 125 DGTW and 144 industry-size portfolios as test assets, respectively. The results show that there is no predictive power of high shareholder coordination benchmarks in deeper lags, implying that investors update prices of firms lacking coordination over a period of approximately one month after the common information arrives. To differentiate our information diffusion channel from the clientele and analyst coverage effects, we follow Brennan, Jegadeesh and Swaminathan (1993) and Badrinath, Kale and Noe (1995). We construct IO_ret_{t-1} , the lagged monthly return on the portfolio of firms with highest institutional ownership (top quintile) and $Analyst_ret_{t-1}$, the lagged monthly return on the portfolio of firms with largest analyst coverage (top quintile). The results in Panel B show that $Clone_ret_{t-1}$ continues to be significantly positive after controlling IO_ret_{t-1} and $Analyst_ret_{t-1}$, suggesting that the role of information-sharing networks is different from that of informed traders proxied by institutional ownership and analyst coverage in explaining stock return predictability. We also dissect the monthly return predictability pattern into weekly return effects. The results in Panel C show that $Clone_ret_{t-1}$ is a significant predictor of next week's stock return of matched low shareholder coordination firms, confirming that our return predictability pattern remains economically and statistically significant using a different frequency of stock returns.

To further test whether there exists a lead-lag relation between firms with high shareholder coordination and firms with low shareholder coordination, we employ the vector autoregression (VAR) model to examine the cross-stock return dynamics based on earlier studies in the literature that show significant lead-lag relations among U.S. stock returns (Lo and MacKinlay, 1990; Chordia and Swaminathan, 2000; Hou, 2007).

To construct shareholder coordination portfolios, at the end of June in each year, we first sort firms into two portfolios based on whether the average residual shareholder coordination over the past four quarters was high (i.e., ranking in the top coordination tercile) or low (i.e., ranking in the bottom coordination tercile). We then independently sort firms into 144 portfolios corresponding to the 48 Fama-French industry portfolios, and split each into three portfolios (i.e., $48 \times 3 = 144$). After partitioning firms into double-sorted portfolios, we compute the monthly returns for each portfolio. We replicate the same sorting procedure for DGTW 125 portfolios. We estimate the following VAR model jointly across industry-size 144 or DGTW 125 portfolios.

$$R_{LI,t} = \alpha_0 + a_1 R_{LI,t-1} + a_2 R_{HI,t-1} + u_t,$$

(9)

$$R_{HI,t} = \alpha_1 + b_1 R_{LI,t-1} + b_2 R_{HI,t-1} + v_t,$$

(10)

where $R_{LI,t}$ and $R_{HI,t}$ represent the low and high shareholder coordination portfolio returns at time t , respectively. This bivariate VAR system allows us to test whether the lagged returns on the high shareholder coordination portfolio in Equation 9 have any significant power in predicting the current returns of the low shareholder coordination portfolio by testing the hypothesis that $a_2 = 0$. In addition, this system allows us to examine whether there is any asymmetry in the cross-autocorrelations across the high and low shareholder coordination portfolios by testing the hypothesis that $a_2 - b_1 = 0$.

In Panels A and B of Table 8, we present the estimation results for industry-size 144 and DGTW 125 groups, respectively. The results indicate that the lagged returns on the high shareholder coordination portfolio predict the current returns on the low shareholder coordination portfolio. Interestingly, the coefficient estimates of the lagged return on the low shareholder coordination in predicting the current return on the high shareholder coordination are significantly positive. However, their magnitude is smaller in comparison with that of the lagged returns on the high coordination portfolio in predicting current returns on the low coordination portfolio. Additionally, the cross-equation coefficient equality test confirms that the differences between the coefficients of the lagged returns on high coordination portfolio in predicting the current returns on the low coordination portfolio and those of the lagged returns on low coordination portfolio in predicting the current returns on the high coordination portfolio are positive and statistically significant. Therefore, our results indicate a potential lead-lag relation in stock returns across shareholder coordination portfolios.

Table 8. Vector autoregression test of intraportfolio lead-lag effect

This table presents the estimation results of vector autoregression (VAR) model using monthly returns on the industry&size144-coordination and DGTW 125 coordination portfolios. At the end of each June, stocks are sorted into terciles according to the average shareholder coordination over past four quarters. In addition, stocks are independently sorted into three size groups within each of 48 industries based on their latest available market capitalization or DGTW 125 portfolios, respectively. Then, returns of low coordination portfolio and high coordination portfolio are computed within each industry-size or DGTW 125 group, respectively. Finally, the following VAR is estimated jointly across all industry&size144 or DGTW 125 group.

$$\begin{aligned} R_{LI,t} &= \alpha_0 + a_1 R_{LI,t-1} + a_2 R_{HI,t-1} + u_t, \\ R_{HI,t} &= \alpha_1 + b_1 R_{LI,t-1} + b_2 R_{HI,t-1} + v_t, \end{aligned}$$

where $R_{LI,t}$ and $R_{HI,t}$ are the month t return on the low and high coordination portfolio, respectively. Panels A and B report the VAR estimation for low and high coordination portfolio returns controlling for industry-size and DGTW firm characteristics, respectively. The F -values are reported for the cross-equation test of null hypotheses: $a_2 - b_1 = 0$, and for the within-equation test of null hypotheses: $a_2 - a_1 = 0$ and $b_2 - b_1 = 0$, respectively. The t -statistics are in parentheses.

		Independent variables		Cross-equation test	Within-equation test	
Groups	Dependent variables	$R_{LI,t-1}$	$R_{HI,t-1}$	$a_2 - b_1 = 0$	$a_2 - a_1 = 0$	$b_2 - b_1 = 0$
FF48 × 3SIZE			<i>Panel A1:</i> <i>RES_COORD_PROX</i>			
	$R_{LI,t}$	0.0289*** (3.88)	0.0893*** (11.58)	9.66***	22.50***	0.09
	$R_{HI,t}$	0.0538*** (7.40)	0.0501*** (6.67)			

FF48 × 3SIZE			<i>Panel A2:</i> <i>RES_COORD_PORT</i>			
	$R_{LI,t}$	0.0439*** (5.79)	0.0993*** 6.03**	(9.62)	13.47***	0.56
	$R_{HI,t}$	0.0657*** (8.88)	0.0744*** (7.29)			
DGTW 125			<i>Panel B1:</i> <i>RES_COORD_PROX</i>			
	$R_{LI,t}$	0.0418*** (5.20)	0.0958*** 14.12***	(10.88)	14.00***	3.78*
	$R_{HI,t}$	0.0484*** (6.61)	0.0740*** (9.22)			
DGTW 125			<i>Panel B2:</i> <i>RES_COORD_PORT</i>			
	$R_{LI,t}$	0.0525*** (6.54)	0.10671*** 6.30**	(10.36)	11.97***	0.15
	$R_{HI,t}$	0.0708*** (8.81)	0.0768*** (7.44)			

***, **, * indicate a two-tailed test significance at the 0.01, 0.05 and 0.10 level, respectively. Numbers of interest are boldfaced.

5. Conclusions

Institutional shareholder coordination, that is, the existence of information-sharing networks linking institutional investors of a particular firm, shows to be an effective mechanism that improves corporate governance. In this paper, we attempt to focus on the asset prices implications of shareholder coordination. We start by showing that local comovement and post-earnings announcement drift are weaker in the presence of shareholder coordination, in support of the notion that information-sharing networks facilitate information diffusion and improve stock price efficiency. We then examine whether shareholder coordination serves as an information diffusion channel across firms. Following Cohen and Lou (2012), we devise time series and cross-sectional tests that yield strong evidence of a lead-lag effect in stock returns between firms with and without coordination, consistent with the view that information shocks travel from firms with high shareholder coordination to firms with low shareholder coordination.

We find that information-sharing network among institutional investors serves as an information diffusion channel. Our results extend the literature that studies return predictability as a result of slow information diffusion that results from various sources.

Notes

- 1 The alignment in institutions' monitoring practices is catching practitioners' and researchers' attention. For example, McCahery, Sautner and Starks (2010) provide survey evidence that 59% of institutional investors among respondents consider coordination with other institutional investors to improve monitoring their managers. Huang (2013a,b) finds that shareholder coordination has a positive and significant impact on the market for corporate control and corporate governance. Kim, Pantzalis and Wang (2015) find that firms with high shareholder coordination have better earnings quality and stronger stock price informativeness.

- 2 Throughout this paper, we use the terms “institutional shareholder coordination,” “shareholder coordination,” and “coordination” interchangeably.
- 3 Jin and Myers (2006) find that opaque stocks are associated with high stock price synchronicity. Zhang (2006) argues that investors underreact more to public information when there is more information uncertainty.
- 4 The first proxy is the inverse of the weighted average of the geographic distance among institutional shareholders (hereafter COORD_PROX) and the second one is the weighted average correlation among institutions’ portfolios of stock holdings (hereafter COORD_PORT).
- 5 The excess portfolio weight allocated to stock i in quarter t is given by: $EW_{ipt} = \frac{W_{ipt} - W_{imt}}{W_{imt}} \times 100$, where W_{ipt} is the actual weight assigned to stock i in the institution's portfolio p in quarter t and W_{imt} is the weight of stock i in the aggregate market portfolio in quarter t .
- 6 An alternative explanation provided by Pirinsky and Wang (2006) is that local comovement is rooted on local investors’ preferences toward local stocks stemming from familiarity and/or loyalty.
- 7 To avoid the potential rounding issues in I/B/E/S adjusted data described in Payne and Thomas (2003), we use the I/B/E/S unadjusted detail history data that do not have adjustments for stock splits and stock dividends, and put both forecast and actual earnings on the same per share basis to accurately calculate analyst-based earnings surprise using the CRSP adjustment factor.
- 8 Bernard and Thomas (1989) document that the post-earnings announcement drift primarily concentrate on the 60 trading days period after the earnings announcement.

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